الجمهـــوريـــــة الجزائـــريـــــة الديمقـــراطيـــة الشـعبيـــة
People's Democratic Republic of Algeria
وزارة التـــعلـــيـــــم العـــــالـــــي والبـــحـــــث العـلمـــــي
Ministry of Higher Education and Scientific Research

جامعة وهران 2 محمد بن أ حمد
University of Oran 2 Mohamed Ben Ahmed

معهد الصيانة و الأمن الصناعي
Institute of Maintenance and Industrial security

Département de maintenance en électromécanique

MÉMOIRE

Pour l'obtention du diplôme de Master

Filière : Électromécanique
Spécialité : Maintenance Industriel Électromécanique

Thème

Optimisation De La Gestion Des Stocks De Pièces De Rechange : Une Approche Multicritère

Présenté et soutenu publiquement par :

KHELLADI ABDELMADJID

SANDID MOHAMED IMAD-EDDINE

Devant le jury composé de :

Nom et Prénom	Grade	Etablissement	Qualité
ACHACHE Habib	PR	Université d'Oran 2 MBA	**Président**
BOUCHAALA Mohammed Abdelghani	MCB	Université d'Oran 2 MBA	**Encadreur**
METAHRI Dhiyaeddine	MCB	Université d'Oran 2 MBA	**Examinateur**

Année 2024/2025

الجمهـــوريـــــة الجزائـــريـــــة الديمقـــراطيـــــة الشـعبيـــة
People's Democratic Republic of Algeria
وزارة التـــعلـــيـــــم العـــــالـــــي والبـــحـــــث العـلمـــــي
Ministry of Higher Education and Scientific Research

جامعة وهران 2 محمد بن أ حمد
University of Oran 2 Mohamed Ben Ahmed

معهد الصيانة و الأمن الصناعي
Institute of Maintenance and Industrial security
Department of Electromechanical Maintenance

THESIS

For the attainment of the Master's degree

Field: Electromechanics
Specialization: Industrial Electromechanical Maintenance

Topic

Optimization Of Spare Parts Inventory Management: A Multicriteria Approach

Presented and publicly defended by:

KHELLADI ABDELMADJID

SANDID MOHAMED IMAD-EDDINE

Before the jury composed of:

Last and First Name	Grade	Institution	Position
ACHACHE Habib	PR	Université d'Oran 2 MBA	**President**
BOUCHAALA Mohammed Abdelghani	MCB	Université d'Oran 2 MBA	**Supervisor**
METAHRI Dhiyaeddine	MCB	Université d'Oran 2 MBA	**Examiner**

Year 2024/2025

Optimisation de la gestion des stocks de pièces de rechange : Une approche multicritère

Résumé :

La gestion des stocks représente un levier essentiel dans la performance des entreprises industrielles, influençant directement leur rentabilité et leur efficacité opérationnelle. Parmi les différents types de stocks, celui des pièces de rechange occupe une place particulière en raison de son rôle déterminant dans le soutien aux opérations de maintenance et la continuité de la production. Cependant, cette catégorie de stock pose plusieurs défis majeurs, au premier rang desquels figure la nécessité de minimiser les coûts de stockage tout en assurant la disponibilité des pièces critiques en cas de panne. La variabilité du niveau de criticité des pièces vient complexifier davantage cette gestion.

Ce mémoire propose un modèle d'optimisation basé sur la programmation linéaire en nombres entiers mixtes (MILP), visant à déterminer les quantités à acquérir sous contraintes de budget et de capacité de stockage. Les priorités d'acquisition sont établies selon un score de criticité défini par un modèle multicritère, intégrant l'impact opérationnel, la disponibilité sur le marché et les contraintes d'approvisionnement, avec une pondération issue de la méthode AHP. L'approche est validée à travers un cas d'application réel, permettant de formuler des recommandations efficientes pour une gestion plus efficace des pièces de rechange.

Mots clés : AHP, criticité des pièces, gestion des stocks, maintenance, MILP, multicritère, optimisation, pièces de rechange.

Optimizing spare parts inventory management: A multi-criteria approach

Abstract:

Inventory management is a key lever in the performance of industrial companies, directly influencing their profitability and operational efficiency. Among the different types of inventories, spare parts management holds a special place due to its crucial role in supporting maintenance operations and ensuring production continuity. However, this category poses several major challenges, chief among them the need to minimize storage costs while ensuring the availability of critical parts in the event of failure. The varying levels of part criticality further complicate this management.

This thesis proposes an optimization model based on Mixed-Integer Linear Programming (MILP), aimed at determining the optimal quantities to acquire under budget and storage capacity constraints. Acquisition priorities are established according to a criticality score derived from a multicriteria model, which integrates operational impact, market availability, and supply constraints, with weighting performed using the AHP (Analytic Hierarchy Process) method. The approach is validated through a real-world application case, leading to efficient recommendations for more efficient spare parts management.

Key-words: AHP, parts criticality, inventory management, maintenance, MILP, multicriteria, optimization, spare parts.

تحسين إدارة مخزون قطع الغيار: نهج متعدد المعايير

الملخص:

تعد إدارة المخزون رافعة أساسية في أداء الشركات الصناعية، حيث تؤثر بشكل مباشر على ربحيتها وكفاءتها التشغيلية. ومن بين مختلف أنواع المخزون، يحتل مخزون قطع الغيار مكانة خاصة نظرًا لدوره الحاسم في دعم عمليات الصيانة وضمان استمرارية الإنتاج. ومع ذلك، تواجه هذه الفئة من المخزون تحديات كبيرة، أبرزها ضرورة تقليل تكاليف التخزين مع ضمان توفر القطع الحيوية في حال حدوث أعطال. كما أن تفاوت درجة أهمية القطع يزيد من تعقيد إدارتها.

يقترح هذا البحث نموذجًا تحسينياً يعتمد على البرمجة الخطية المختلطة بالأعداد الصحيحة (MILP)، بهدف تحديد الكميات المثلى الواجب اقتناؤها ضمن قيود الميزانية وسعة التخزين. وتُحدَّد أولويات الشراء استنادًا إلى درجة الأهمية المستخرجة من نموذج متعدد المعايير، يأخذ في الاعتبار الأثر التشغيلي وتوفر القطع في السوق وصعوبات التوريد، مع اعتماد أوزان المعايير من خلال طريقة التسلسل الهرمي التحليلي (AHP). وقد تم اختبار هذا النموذج على حالة تطبيق حقيقية، ما أتاح تقديم توصيات فعالة لتحسين إدارة مخزون قطع الغيار في المؤسسات الصناعية.

كلمات مفتاحية: AHP، أهمية القطع، إدارة المخزون، التحسين، الصيانة، قطع الغيار، متعدد المعايير، MILP.

Dedication

To my beloved parents, whose unwavering love, silent sacrifices, and constant encouragement have carried me through every challenge. Your faith in me has been the light guiding my every step

To my Brother , Sisters & My Nephew , for their constant encouragement and presence in every step of my journey.

To my friends, Lahbib , Djaafar , Ayoub , Oussama , Ahmed , Farouk . To Bahaa , Mourad , Khaled, Dr Djihad , Merzak , ihab , Ali & Mobaraq. To Khelladi , Attab , Meyara , Boularas , Djakani & Brik Families for their support, motivation, and the moments that lightened the path. (❤️)

And to all those who helped me, guided me, and believed in me. Your support, whether big or small, meant more than words can express.

This accomplishment is yours as much as it is mine. Thank you.

-KHELLADI Abdelmadjid

To my beloved mother, whose strength and patience are forged from something stronger than steel, your unwavering support made this journey possible.

To my four siblings, my first companions in life, whose presence continues to shape who I am.

To my father.

To the dear friends I was blessed to meet during my college years, your sincerity and companionship have been priceless.

And to the entire Islamic Ummah, a global family united in faith may this humble effort serve as a small contribution toward knowledge and progress.

-SANDID Mohammed Imadeddine

Acknowledgment

First and foremost, we express our deepest gratitude to God Almighty, whose endless mercy and blessings have guided and strengthened us throughout the journey of this research. Without His divine support, none of this would have been possible.

We are sincerely thankful to our families, who stood by us with patience, encouragement, and unconditional support. Their love and sacrifices were the foundation upon which this work was built.

Our heartfelt appreciation goes to our supervisor, Dr. Bouchaala Mohammed Abdelghani, for his continuous guidance, insightful advice, and generous availability. His mentorship played a crucial role in shaping the direction and quality of our thesis.

We would also like to thank the members of the jury for their time, evaluation, and valuable feedback, which will undoubtedly help us improve and enrich this work.

We extend our special thanks to the team at In Salah Gas, where we completed our internship. Their collaboration, resources, and professional environment contributed significantly to the success of our practical research.

Table of Contents

Dedication i
Acknowledgment ii
Table of Contents iii
Liste of Figures vi
Liste of Tables vii
Acronyms and Abbreviations viii
Notations ix
Introduction 1
Chapter 1: Fundamentals and Basic Concepts 3
1.1 Introduction 4
1.2 Fundamental concepts of management 4
1.3 Basic principles of inventory management 4
1.3.1 Definition of Inventory 4
1.3.2 Objectives of Inventory Management 5
1.3.3 Types of Inventories 5
1.3.4 Core Stock Parameters 6
1.3.5 Impact of Inventory Level on Finances and Equipment 7
1.4 General overview of maintenance 8
1.4.1 Definition of Maintenance 8
1.4.2 Maintenance Function 8
1.4.3 Objectives of Maintenance 9
1.4.4 Main Types of Maintenance 10
1.4.5 Maintenance Key Performance indicators 12
1.5 Specificities of spare parts management 14
1.5.1 Definition and Role of Spare Parts 14
1.5.2 Particular Characteristics of Spare Parts 14
Random or Sporadic Demand 14
Importance of Availability (Criticality) 14
Obsolescence and Life Cycle Management 15
1.5.3 Impact of Poor Spare Parts Management 15
1.6 Objectives and challenges of spare parts management 16
1.6.1 Ensuring Equipment Availability 16
1.6.2 Reducing Inventory Costs 17
1.6.3 Maintaining Production Performance 17
1.6.4 Optimizing Logistical and Financial Resources 17
1.7 Conclusion 17
Chapter 2: Spare Parts Inventory Management Methods 18
2.1 Introduction 19
2.2 Classical inventory management methods 19
2.2.1 Reorder Point Model (ROP) 19
2.2.2 Safety Stock and Minimum Stock Level Models 20

2.2.3 Economic Order Quantity Model (EOQ) 21
2.2.4 Periodic Replenishment Systems 22
2.2.5 Inventory Classification Methods 23

2.3 Methods adapted for rare usage high importance items 25
2.3.1 Criticality-Based Spare Parts Management 25
2.3.2 Methods for Managing Sporadic or Intermittent Demand 27
Probabilistic Approaches 27
Croston-Based Methods 29
2.3.3 Rotating Stock vs. Dormant Stock 30

2.4 Multicriteria decision-making methods 30
2.4.1 Analytic Hierarchy Process (AHP) 30
Hierarchy Construction 31
Pairwise Comparisons & Priority Weights 31
Consistency Check 31
Alternative Scoring & Synthesis 31
2.4.2 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) 32
2.4.3 Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE) 33
2.4.4 Multi-Objective Optimization Problem (MOOP) 35

2.5 Modern and Intelligent Methods 37
2.5.1 Artificial Intelligence (AI)-Based Approaches 37
2.5.2 Big Data and IoT in Predictive Parts Management 38
2.5.3 Expert Systems and Simulation Tools 38

2.6 Comparative synthesis of methods 41

2.7 Conclusion 43

Chapter 3: Multicriteria Optimization of Spare Parts Inventory 44

3.1 Introduction 45

3.2 Targeted work: context, motıvatıons, objectıves, and challenges 45
3.2.1 Context 45
3.2.2 Motivations 45
3.2.3 Objectives 46
3.2.4 Challenges 46

3.3 Description of the proposed methodology 47
3.3.1 Concept of the proposed study 47
3.3.2 Presentation of the case study 48
Presentation of the host company 48
Problem Specification and Criteria Selection 48
3.3.3 Data acquisition 49
3.3.4 Modelling spare parts criticality 50
3.3.5 MILP-based Optimization of Spare Parts Acquisition 51
Indices 52
Parameters 52
Constraints 52

3.4 Implementation of the methodology 53
3.4.1 Data preprocessing 53
3.4.2 Criticality quantification using the adopted model 55
3.4.3 Implementation of the proposed MILP 57
Software Presentation 57
Solving the model: technical specifications 58
Results: 59

3.5 Results Discussion and Interpretation 60

3.5.1 Discussion of the AHP-driven criticality weights 60
3.5.2 Discussion of the obtained criticality scores 62
3.5.3 Discussion of the MILP-driven parts orders 63
3.5.4 Validation of the results 65
Testing the criticality model robustness 65
Solver-based validation of the MILP model 66
Stress-testing feasibility and constraint compliance 67
3.6 Conclusion 69
Conclusion and perspectives 70
References 71

Liste of Figures

Figure 1.1 Types of maintenance 12
Figure 2.2 Reorder Point (ROP) Inventory Management Cycle 20
Figure 2.2 Inventory Cost Analysis: EOQ Model and Re-Order Quantity Components 22
Figure 2.3 a graph demonstrating ABC inventory classification 23
Figure 2.4 ABC XYZ Analysis in Inventory Management (Medium.com, 2023) 24
Figure 2.5 VED analysis cumulative curve (Mahesh Devnani, 2010) 25
Figure 2.6 Spare Parts Criticality Decision Diagram (Molenaers et al., 2012) 26
Figure 3.1 Diagram of methodology adopted 47
Figure 3.2 Location of IN SALEH GAS wells and fields in Algeria 48
Figure 3.3 VP185 NEW Diesel Engine 2005 Year of Build 50
Figure 3.4 Expert-Choice Interface 55
Figure 3.5 Pairwise Comparaison Matrix 56
Figure 3.6 AHP Calculation and Weights Output 56
Figure 3.7 Logiciel CPLEX 58
Figure 3.8 CPLEX interface 58
Figure 3.9 Resolution Time 58
Figure 3.10 Inventory Status and Stock Level Analysis per Part 59
Figure 3.11 Budget Proportion 60
Figure 3.12 Inventory Proportion 60
Figure 3.13 Normalized Comparison of Spare Part Parameters and Resulting Criticality 62
Figure 3.14 Coverage bar chart 64

Liste of Tables

Table 2.1 Criticality-based classification 27
Table 2.2 Croston-based methods 29
Table 2.3 Stock Management Strategies Based on Usage Frequency 30
Table 2.4 Use case of mentioned Intelligent methods 40
Table 2.5 Comparative synthesis of methods 42
Table 2.6 Best-Fit Inventory Management Methods by Industry/Environment 43
Table 3.1 Pre-Processed inputs 54
Table 3.2 Computed Criticality Scores 57
Table 3.3 Results of Spare parts Optimisation 63
Table 3.4 Criticality & Ordered results on two scenarios 65
Table 3.5 Optimization Results under Budget-Sensitive and Capacity-Sensitive Scenarios 68

Acronyms and Abbreviations

- **ABC**: Activity-Based Classification
- **AHP**: Analytic Hierarchy Process
- **AI**: Artificial Intelligence
- **BRB**: Belief Rule Base
- **CBR**: Case-Based Reasoning
- **CI**: Consistency Index
- **CR**: Consistency Ratio
- **DES**: Discrete Event Simulation
- **EOQ**: Economic Order Quantity
- **HES**: Hyperbolic-Exponential Smoothing
- **IoT**: Internet of Things
- **MILP**: Mixed Integer Linear Programming
- **MCDM**: Multi-Criteria Decision Making
- **MOOP**: Multi-Objective Optimization Problem
- **MTBF**: Mean Time Between Failures
- **MTTR**: Mean Time To Repair
- **PROMETHEE**: Preference Ranking Organization Method for Enrichment Evaluation
- **ROP**: Reorder Point
- **SBA**: Syntetos–Boylan Approximation
- **SS**: Safety Stock
- **TSB**: Teunter–Syntetos–Babai
- **TOPSIS**: Technique for Order Preference by Similarity to Ideal Solution
- **VED**: Vital, Essential, Desirable Classification
- **XYZ**: Classification by Demand Variability

Notations

• **i:** Index of spare parts

• **Ci**: Unit cost of part i ($)

• **Vi**: Volume of part i (cm3)

• **Ii**: Initial inventory level of part i (units)

• **Li**: Lead time of part i (days)

• **Ui**: Annual usage of part i (units/year)

• **Si**: Number of suppliers for part i

• **MinStocki**: Minimum stock level of part i (units)

• **MaxStocki**: Maximum stock level of part i (units)

• **Bi**: Budget constraint ($)

• **K**: Storage capacity (cm3)

• **Xi**: Decision variable (ordered quantity of part i)

• **CRi**: Criticality score of part i

• **w1**, **w2**, **w3**: Weights of criticality criteria (Operational Impact, Supply Constraints, Market Availability)

• **Z**: Objective function to be maximized (total weighted inventory)

Introduction

Stock management is a crucial issue for industrial companies, as it directly impacts their performance and profitability. Effective management not only reduces costs but also improves the smoothness of operations and customer satisfaction. Among the various categories of stock, spare parts hold a strategic position due to their essential role in equipment maintenance and the continuity of industrial activities. However, managing them is a significant challenge, especially given the need to balance availability with cost control. Indeed, insufficient stock can lead to costly production interruptions, while overstocking generates significant financial and logistical costs.
Optimizing spare parts stock relies on a complex balance between several factors: reducing storage costs, ensuring the immediate availability of critical parts, and prioritizing supplies based on the importance of each part in the production process. This issue raises several key questions: How can storage costs be minimized without compromising the availability of essential parts? What criteria should be considered to classify parts based on their criticality? What tools and methods effectively optimize spare parts stock management?

In this context, a multicriteria approach seems to be a relevant solution. It considers various decision-making parameters such as cost, lead time, usage frequency, and part criticality. This approach aims to propose an optimized management solution tailored to the needs of industrial companies, ensuring better cost control and adequate availability of strategic parts.
The main objective of this thesis is to propose an optimized spare parts stock management model based on a multicriteria approach. To achieve this goal, several steps will be followed: initially, a literature review will explore the different existing approaches and models in stock management. Next, an analysis of industrial practices will identify the most relevant criteria for stock optimization. Based on this, a multicriteria management model will be proposed and applied to a real case to evaluate its effectiveness. Finally, an analysis of the results will lead to recommendations for improving stock management in an industrial context.

This thesis is structured into three main chapters:

- The first chapter is dedicated to the literature review on stock management and existing optimization methods.

- The second chapter presents the multicriteria approach and its application to spare parts management.
- The third chapter focuses on the practical application of the proposed model to a real case and the evaluation of the results.

Finally, A general conclusion is presented, summarizing the main contributions and suggesting some interesting perspectives for future work.

Chapter 1: Fundamentals and Basic Concepts

1.1 Introduction

In an increasingly competitive industrial environment, the performance of production systems depends heavily on the availability and reliability of equipment. Effective inventory management, particularly of spare parts, plays a crucial role in ensuring operational continuity, reducing unexpected downtime, and optimizing costs. This first chapter aims to present the fundamental concepts of management and inventory control, with a particular emphasis on the specificities of spare parts management.

1.2 Fundamental concepts of management

Management is the set of techniques and practices used to plan, organize, direct, and control an organization's resources to achieve its goals (Koontz & Weihrich, 2010). In the industrial sector, this includes managing human, financial, and material resources—particularly inventory. Functions such as procurement, production planning, maintenance, and logistics all rely on efficient inventory management. Effective inventory management ensures that materials are available in the right quantity, at the right time, and at optimal cost. Poor management can lead to stockouts, production delays, and increased costs, while good practices improve service levels and operational efficiency. This is especially important for spare parts, where shortages can halt production and cause significant downtime. To meet these challenges, industries use various tools and models, such as EOQ, safety stock calculations, and classification methods like ABC or VED. Increasingly, modern inventory systems are supported by technologies like ERP software and data analytics to enhance decision-making. Thus, inventory management is a strategic function that supports the overall performance and competitiveness of industrial operations

1.3 Basic principles of inventory management

1.3.1 Definition of Inventory

Inventory refers to all goods, raw materials, semi-finished or finished products held by a company awaiting use or sale. It serves as a link between procurement, production, and distribution (Paul Fournie . 2019).

According to Arnold et al. (2008), "*Inventory is an accumulation of material resources waiting to be used or sold.*" In industrial logistics, it plays a strategic role in maintaining the continuity of production and maintenance activities.

1.3.2 Objectives of Inventory Management

Inventory management aims to strike a balance between availability, cost efficiency, and operational effectiveness. Its key objectives include:

- **Ensure product availability:** One of the primary goals is to prevent stockouts by ensuring that essential items are available when needed. This is especially critical in production and maintenance contexts, where the absence of a single component can halt operations and result in costly downtime.
- **Reduce inventory-related costs:** Inventory management seeks to minimize the total cost associated with inventory, including storage costs (such as warehousing and insurance), ordering costs (procurement and administrative efforts), and stockout costs (lost sales, production stoppages, or service disruptions). Efficient inventory control helps organizations operate within tighter budgets and avoid unnecessary expenses.
- **Optimize stock levels:** Maintaining an optimal level of inventory is crucial to minimize capital tied up in stock while still ensuring service continuity. This involves accurately forecasting demand, adjusting reorder points, and setting appropriate safety stock levels (Christopher, 2011). Well-calibrated stock levels support a lean inventory approach without compromising service quality.
- **Improve inventory turnover:** High inventory turnover indicates efficient use of resources, as it reflects how often stock is replenished within a given time period. Improving turnover reduces the risk of obsolescence, lowers holding costs, and increases responsiveness to market changes or customer needs.

Balancing these objectives is fundamental to effective and sustainable inventory management. Overemphasis on one aspect—such as minimizing stock levels—without regard to availability or service quality can lead to inefficiencies or operational risk. Therefore, inventory managers must continually assess performance indicators and adjust strategies to align with broader organizational goals, ensuring reliability, efficiency, and long-term value creation

1.3.3 Types of Inventories

Inventories can be classified in various ways depending on their function, status, or strategic importance. Understanding the different types of inventory is crucial for efficient stock control and for aligning inventory strategies with operational needs. The main types include:

- **In-transit stock:** These are goods currently being transported between two locations, such as from a supplier to a warehouse or between internal facilities. Though not yet physically available at the destination, they are considered part of the inventory and must be tracked to ensure visibility across the supply chain.
- **Average stock:** This represents the average quantity or value of inventory over a given period. It is often used in performance analysis, particularly to calculate inventory turnover ratios, which reflect how efficiently stock is being managed and renewed.
- **Safety stock:** Safety stock is a buffer quantity kept on hand to protect against uncertainties in demand or supply, such as unexpected customer orders or delivery delays. It ensures continuity in production and service, acting as a safeguard against stockouts.
- **Minimum stock:** Also known as the reorder point threshold, minimum stock defines the lowest acceptable inventory level before a replenishment order must be triggered. Falling below this level risks interrupting operations or failing to meet customer demand.
- **Maximum stock:** This is the upper limit of inventory that should be maintained to avoid overstocking, which can result in increased storage costs, risk of obsolescence, or inefficient use of capital. It is especially important in space-constrained or cost-sensitive environments.
- **Dead stock (obsolete stock):** These are items that have remained unused for a prolonged period and are no longer expected to be consumed or sold. Dead stock can accumulate due to poor forecasting, changes in product design, or discontinued operations. Identifying and minimizing dead stock is essential to reduce waste and free up storage capacity.
- **Strategic stock:** Strategic inventory is reserved for exceptional or unforeseen circumstances, such as natural disasters, supply chain disruptions, or seasonal demand peaks. It is typically held in larger quantities and managed with a long-term perspective to enhance organizational resilience.

Each type of inventory serves a distinct purpose and must be managed using appropriate policies and tools. A comprehensive understanding of these categories helps organizations optimize stock levels, reduce costs, and improve service reliability

1.3.4 Core Stock Parameters

- **Demand Rate:** Average quantity consumed per time period (e.g., 10 units/month).

- **Lead Time:** Time from placing an order to receiving parts (e.g., 2 weeks).
- **Reorder Point (ROP):** Inventory level triggering a new order

$$(ROP = Demand \times Lead\ Time + Safety\ Stock) \quad (1\text{-}1)$$

- **Average Inventory:** Average inventory estimates the typical stock level of a part, used to evaluate turnover and holding costs

$$\text{Average inventory} = \frac{\text{Max+Min}}{2} \quad (1\text{-}2)$$

- **Cycle Stock:** Inventory to cover demand between orders (excluding safety stock).
- **Max Stock Level:** Upper limit to avoid
- **Minimum Order Quantity (MOQ):** Smallest quantity a supplier allows
- **Annual Usage Value**: The total yearly value of consumption is calculated by multiplying annual demand by the unit price

$$Annual\ Usage\ Value = Annual\ Demand \times Price \quad (1\text{-}3)$$

- **Lead Time Demand:** Lead Time Demand represents the expected quantity needed during the replenishment period and is given by:

$$Lead\ time\ demand = (Annual\ Demand\ /\ 365) \times Lead\ Time \quad (1\text{-}4)$$

1.3.5 Impact of Inventory Level on Finances and Equipment

Inventory levels have a substantial impact on both a company's financial performance and the operational reliability of its equipment and processes. Managing inventory effectively means balancing various types of costs that are often in conflict. These include:

- **Storage costs:** High inventory levels lead to increased warehousing needs, along with associated expenses such as rent, energy, insurance, and labor. Over time, stored items may also suffer from depreciation, deterioration, or obsolescence—especially in fast-moving or high-tech industries—resulting in further financial losses.
- **Ordering costs:** These are incurred every time an order is placed and received. They include administrative tasks (such as purchase requisitions and approvals), transportation fees, receiving, and inspection. Placing frequent small orders can increase these costs, while bulk orders may reduce them but raise holding costs.
- **Stockout costs:** When inventory is insufficient to meet demand—whether for production, maintenance, or customer delivery—stockouts can lead to serious consequences. These may include halted operations, missed sales, emergency purchases at higher prices, or penalties for delayed service. In maintenance, a lack of spare parts may result in extended downtime for critical equipment.

- **Tied-up capital:** Inventory represents a form of capital investment. When too much stock is held, financial resources are immobilized and cannot be used for other productive purposes, such as R&D, expansion, or debt reduction. This reduces a company's financial agility and opportunity for growth (Arnold, T 2008).

From an operational perspective, poor inventory management—especially of spare or critical parts—can reduce equipment reliability, delay maintenance interventions, and extend downtime. This affects not only productivity but also long-term asset performance.

Therefore, good inventory management involves finding the optimal balance between availability and cost. By minimizing total inventory-related costs while maintaining service and production continuity, companies can ensure both financial efficiency and operational readiness. Tools like Economic Order Quantity (EOQ), safety stock calculations, and inventory classification help managers make informed decisions that align with strategic objectives

1.4 General overview of maintenance

1.4.1 Definition of Maintenance

Maintenance includes all actions aimed at keeping or restoring an asset to a specified condition so that it can perform its intended function. It involves a combination of technical, organizational, and human activities. According to Monchy and Vernier (2012), maintenance goes far beyond simple repair operations following a failure; it also encompasses preventive actions, predictive monitoring, and improvement measures designed to maintain and enhance system performance and reliability.

In this sense, maintenance is no longer considered a purely reactive or support activity. It has become a strategic function that contributes directly to the availability, efficiency, and safety of industrial installations. A well-structured maintenance strategy helps reduce unplanned downtime, extend equipment lifespan, and lower overall production costs. It also supports continuous improvement efforts by identifying and addressing root causes of recurring issues

1.4.2 Maintenance Function

The maintenance function plays a central role in ensuring the continuity of operations and the optimal performance of production systems. It aims to control the risks associated with technical failures while maximizing equipment availability and reliability. Maintenance operates transversally across the organization, working in close collaboration with other key departments

such as production, quality, safety, and logistics. As industrial processes become more complex and demanding, the expectations placed on maintenance have increased significantly. Its traditional role, focused primarily on corrective interventions after breakdowns, has evolved toward a more proactive and strategic orientation. Modern maintenance practices incorporate preventive, predictive, and even prescriptive approaches that anticipate failures and reduce their impact.

In addition to its direct impact on productivity and cost control, maintenance also plays a vital role in ensuring the safety of personnel, protecting assets, and maintaining compliance with regulatory standards. For example, regular inspections and maintenance are often legally required in sectors such as food processing, pharmaceuticals, and energy. Furthermore, maintenance contributes to environmental sustainability by reducing waste, energy consumption, and the environmental impact of equipment failures. It also supports innovation and competitiveness by integrating new technologies such as condition monitoring, remote diagnostics, and computerized maintenance management systems (CMMS).

In summary, the maintenance function is no longer just a technical necessity—it is a performance driver and a key pillar of industrial excellence. A well-managed maintenance strategy aligns with the organization's overall goals, supporting productivity, quality, safety, and long-term profitability.

1.4.3 Objectives of Maintenance

The primary goal of maintenance is to ensure that industrial assets operate efficiently, reliably, and safely over their useful life. In modern industrial environments, maintenance is seen as a strategic function that directly influences performance, cost, and safety. The core objectives include:

- **Ensure equipment availability and reliability:** Maintenance aims to maximize the operational availability of machines and systems by preventing unexpected failures and ensuring that equipment performs its intended functions without interruption. High reliability reduces the risk of production stoppages and ensures consistent output.
- **Reduce unplanned downtime:** One of the most critical goals is to minimize unplanned outages caused by equipment breakdowns. Through preventive and predictive maintenance strategies, organizations can detect early signs of wear or malfunction and address them before they escalate into costly disruptions.

- **Extend the lifespan of assets:** By performing regular inspections, servicing, and timely replacements of critical components, maintenance helps preserve the condition of equipment, slow down degradation, and delay the need for capital-intensive replacements. This enhances return on investment (ROI) and asset value over time.
- **Ensure safety and regulatory compliance:** Maintenance plays a vital role in ensuring the safety of both personnel and equipment. Properly maintained machines are less likely to cause accidents or hazardous situations. In many industries, regulatory bodies require systematic maintenance activities to comply with health, safety, and environmental standards.
- **Lower overall operating costs:** While maintenance itself involves costs, it ultimately contributes to cost reduction by preventing major failures, optimizing energy consumption, and reducing emergency repairs. A proactive maintenance strategy can significantly reduce the total cost of ownership (TCO) of equipment.
- **Maintain production quality:** Equipment that functions consistently and within specified parameters contributes to stable and high-quality production output. Faulty or poorly maintained machines can lead to defects, variability, or product recalls, affecting customer satisfaction and brand reputation.

In essence, maintenance is not merely a support activity but a critical driver of operational excellence. Achieving these objectives requires a structured approach that combines technical know-how, data analysis, strategic planning, and interdepartmental coordination. With the growing adoption of smart maintenance technologies (e.g., CMMS, IoT sensors, AI-based diagnostics), organizations are increasingly capable of meeting these goals more effectively and sustainably

1.4.4 Main Types of Maintenance

Maintenance activities can be categorized into different types depending on their timing, purpose, and methodology. A well-structured maintenance strategy often combines multiple types to align with the organization's operational, safety, and financial objectives. According to Monchy and Vernier (2012), the main categories of maintenance include:

1. **Corrective Maintenance:**
   This type of maintenance is performed after a fault has occurred. It can be:

- **Immediate (emergency):** Carried out as soon as a breakdown is detected, with the goal of restoring the equipment to service quickly and minimizing downtime. This is common for critical failures that halt production.
- **Deferred:** Postponed to a later time based on operational constraints or availability of resources. Deferred corrective maintenance is often scheduled during low-production periods or planned shutdowns.

While corrective maintenance is essential in some situations, relying solely on this approach can be costly due to unplanned downtime, emergency repairs, and potential safety risks.

2. **Preventive Maintenance:**
   Preventive maintenance is aimed at **anticipating and avoiding failures** before they occur. It includes several subcategories:
   - **Systematic maintenance:** Conducted at regular intervals based on time or usage (e.g., every 3 months or after every 1,000 hours of operation), regardless of the actual equipment condition. This is the traditional calendar-based approach.
   - **Conditional maintenance:** Triggered by indicators such as vibration, temperature, pressure, or wear levels. Maintenance is performed only when measurements suggest that the equipment is approaching failure.
   - **Predictive maintenance:** Uses data analysis, diagnostics, and sometimes machine learning to forecast potential failures with a high degree of accuracy. Techniques such as thermography, oil analysis, and vibration monitoring help determine the optimal timing for interventions.

Preventive maintenance helps reduce the frequency of breakdowns, increase equipment reliability, and optimize maintenance resources.

3. **Improvement Maintenance:**
   Also known as proactive maintenance, this approach aims to eliminate the root causes of failures and increase equipment reliability. It may involve:
   - Redesigning components or systems
   - Modifying maintenance procedures
   - Implementing feedback from failure analyses (e.g., FMEA or RCA)

Improvement maintenance contributes to continuous improvement and long-term cost reduction by reducing failure recurrence and optimizing system performance.

These types of maintenance are **not mutually exclusive**; in fact, the most effective maintenance strategies combine them into a **global, integrated maintenance plan** tailored to the company's operational needs, technical constraints, and strategic objectives. The right balance depends on several factors such as equipment criticality, production requirements, safety considerations, and available maintenance resources.

By integrating corrective, preventive, and improvement maintenance within a structured framework, organizations can enhance equipment reliability, reduce costs, and create a safer and more productive work environment.

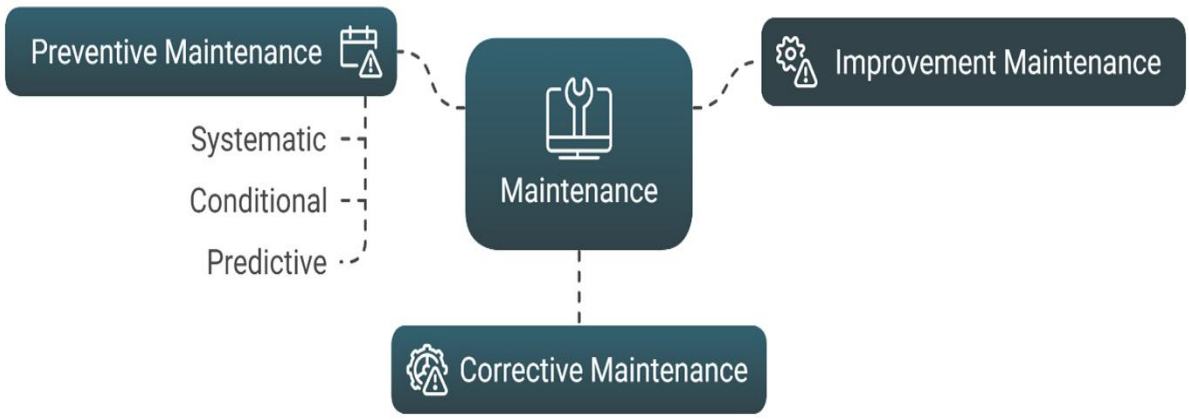


Figure 1.1 *Types of maintenance*

1.4.5 Maintenance Key Performance indicators

To evaluate the effectiveness and efficiency of a maintenance strategy, organizations rely on a set of Key Performance Indicators (KPIs)**.** These metrics provide valuable insights into equipment reliability, maintenance responsiveness, cost control, and overall operational stability. Proper monitoring of these indicators helps identify weaknesses, prioritize improvements, and ensure alignment with production goals.

Key maintenance performance indicators include:

- **MTBF (Mean Time Between Failures):**
  This measures the average operating time between two consecutive failures. A higher MTBF indicates better equipment reliability and fewer disruptions to production.
- **MTTR (Mean Time to Repair):**
  Represents the average time required to restore equipment to operational condition after a failure. A lower MTTR reflects efficient repair procedures, resource readiness, and effective team coordination.
- **Availability Rate:**
  This is the ratio of actual operational time to the total scheduled time, expressed as a percentage. It reflects how often a machine or system is available for use and is closely related to MTBF and MTTR.
- **Failure Rate:**
  Indicates the frequency of equipment failures over a specific period. High failure rates signal potential issues with design, usage, or maintenance practices.
- **Preventive Maintenance Rate:**
  Measures the **proportion of maintenance activities that are planned** (preventive or predictive) as opposed to unplanned (corrective). A high preventive rate suggests a proactive and controlled maintenance environment.
- **Maintenance Cost per Machine or Production Unit:**
  This KPI tracks the average maintenance expenditure relative to each piece of equipment or unit of production. It helps assess cost efficiency and identify cost-saving opportunities.
- **Backlog of Maintenance Work:**
  Refers to the accumulated number of maintenance tasks not yet completed**. a** growing backlog may indicate resource limitations or poor planning.
- • **Planned Maintenance Compliance (PMC):**
  Measures the percentage of scheduled maintenance tasks completed on time. It reflects the effectiveness of planning and execution.
- • **Downtime (Planned and Unplanned):**
  Tracks total equipment downtime**,** distinguishing between planned maintenance and unexpected stoppages. This helps identify reliability issues and optimize scheduling.

- **Wrench Time (Effective Maintenance Time):**
  The actual time maintenance personnel spend working on equipment**,** excluding delays, waiting, or administrative tasks. Higher wrench time indicates better productivity

1.5 Specificities of spare parts management

1.5.1 Definition and Role of Spare Parts

Spare parts are components or assemblies used to replace defective or worn elements of a technical system. They play a key role in ensuring equipment availability and reducing machine downtime. Efficient spare parts management ensures production continuity, prevents unexpected breakdowns, and controls maintenance costs (Monchy & Vernier, 2012).

Spare parts may include standard items (screws, bearings) or specific and expensive components often tailored to particular equipment. Their optimal management is essential to ensure reliability and prevent stockouts.

1.5.2 Particular Characteristics of Spare Parts

Random or Sporadic Demand

Spare parts demand often differs from regular products due to its random or sporadic nature. Unlike production parts with predictable usage, spare parts consumption depends on failures or wear, making it hard to forecast, this uncertainty poses a major challenge to inventory managers, who must balance storage costs with the risk of stockouts. (Pintelon et al. (2006))

Importance of Availability (Criticality)

The availability of spare parts is critical, especially for strategic equipment. Delays in supplying a spare part can lead to costly downtime and disruptions in production. Mobley (2002) emphasizes that spare parts inventory must guarantee component availability while minimizing lead-time impacts.

Effective management involves classifying parts by criticality to prioritize essential items. A key strategy includes maintaining safety stocks and establishing preventive maintenance contracts for critical components.

Obsolescence and Life Cycle Management

Another major challenge is managing obsolescence. As equipment ages and technologies evolve, some parts become scarce or obsolete. Obsolescence management involves forecasting, proactive inventory planning, and supplier partnerships.

It is essential to track a part's life cycle—from introduction to end-of-life. Parts must be replaced before becoming obsolete, considering production lead times and substitution costs (Ben-Daya et al., 2009).

1.5.3 Impact of Poor Spare Parts Management

Inefficient management of spare parts can have serious consequences on both the operational and financial performance of an industrial organization. Since spare parts are essential for maintaining equipment availability and ensuring quick repairs, any mismanagement can result in cascading negative effects across the entire production system. The main impacts include:

- **Extended Downtime:**
  One of the most immediate and critical consequences is the prolongation of equipment **downtime** due to the unavailability of essential spare parts. When a machine breaks down and the necessary components are not in stock, operations are halted until the part is sourced—often at the expense of production targets and delivery commitments.
- **Increased Operational Costs:**
  Poor inventory control often leads to emergency procurement**,** which is typically more expensive due to urgent shipping, last-minute sourcing, or purchasing at a premium price. In addition, frequent stockouts or overstocking of obsolete items result in inefficient use of capital and resources**.**
- **Inefficient Maintenance Processes:**
  When parts are not easily located or are missing from stock, maintenance teams lose valuable time searching for components, delaying interventions, or implementing temporary fixes. This reduces overall maintenance productivity and can lead to incomplete or unreliable repairs.
- **Reduced Equipment Availability and Reliability:**
  A lack of spare parts can prevent preventive or corrective maintenance from being performed on time, leading to a decline in equipment reliability and increased risk of unexpected failures. Over time, this can damage machinery and reduce its lifespan.

- **Poor Inventory Turnover and Obsolescence:**
  Without proper classification and forecasting, organizations may overstock low-demand or outdated parts while understocking critical ones. This results in capital tied up in unused inventory and higher risk of obsolescence**,** especially for fast-evolving equipment technologies.
- **Decreased Safety and Compliance:**
  In some cases, missing or incompatible spare parts may lead to non-standard repairs that compromise the safety of both equipment and personnel. Furthermore, delays in replacing worn or damaged components can result in non-compliance with safety regulations or internal standards.
- **Customer Dissatisfaction:**
  In industries with strict delivery schedules or high service expectations, equipment downtime caused by poor spare parts availability can lead to missed deadlines, penalties, and loss of customer trust. This can affect the company's reputation and competitiveness.
- **Lack of Traceability and Data for Decision-Making:**
  Inadequate spare parts management often goes hand-in-hand with poor record-keeping**,** making it difficult to analyze usage patterns, forecast demand, or optimize reorder levels. This leads to poor strategic planning and reactive, rather than proactive, inventory control

  Proper spare parts management is essential for supporting maintenance effectiveness, minimizing downtime, and controlling costs. Implementing structured classification systems (e.g., ABC, VED), accurate forecasting, and integrated inventory tracking tools (such as CMMS or ERP systems) allows organizations to ensure the right parts are available at the right time, supporting operational resilience and long-term performance.

1.6 Objectives and challenges of spare parts management

1.6.1 Ensuring Equipment Availability

The main goal is to ensure continuous equipment availability. A lack of spare parts can cause unplanned downtime, disrupt production and affect competitiveness. Efficient spare parts inventory management helps reduce downtime and supports preventive maintenance by ensuring rapid supply in case of failure (Monchy & Vernier, 2012).

1.6.2 Reducing Inventory Costs

Optimized spare parts management reduces inventory-related costs. High safety stock or excess reserves lead to excessive storage costs, while insufficient stock raises the risk of costly shortages. The key is to balance availability with cost control using models like ABC classification or Just-in-Time (JIT).

Mobley (2002) highlights the importance of analysing spare parts needs to streamline purchases and forecast future requirements based on equipment wear patterns.

1.6.3 Maintaining Production Performance

Efficient spare parts management supports equipment performance and avoids frequent production interruptions. Spare parts availability is not enough; they must also match equipment needs. Proper management maximizes equipment lifespan and ensures production quality (Pintelon et al., 2006).

1.6.4 Optimizing Logistical and Financial Resources

Optimizing logistical and financial resources is crucial. Good management helps streamline logistics flows, reduce transport costs, and limit risks such as obsolescence or overstocking. A proactive approach supported by inventory software enables informed decisions and demand forecasting based on equipment life cycles (Ben-Daya et al., 2009).

1.7 Conclusion

Spare parts management is vital for ensuring equipment availability and optimizing production performance. It reduces storage costs and ensures system reliability. However, poor management can cause stockouts, unplanned downtime, and extra costs, directly harming competitiveness.

The main goals are to reduce costs, guarantee availability, maintain performance, and optimize resources. Achieving these goals requires strategies tailored to the specific nature of spare parts, considering their demand variability, criticality, and lifecycle.

Companies must implement effective inventory models and use modern tools to anticipate needs and manage obsolescence. Successful spare parts management is a key factor in industrial performance and competitiveness

Chapter 2: Spare Parts Inventory Management Methods

2.1 Introduction

This chapter provides a comprehensive literature review and analysis of both traditional and contemporary approaches to spare parts inventory management, examining their respective strengths and limitations across various industrial contexts. It assesses how these methods address key factors such as cost efficiency, operational reliability, and adaptability to demand fluctuations. By synthesizing these insights, the review identifies best practices that align with organizational objectives and real-world constraints. This foundation supports the selection of a customized inventory management strategy for a real-world case study, ensuring coherence with specific goals, resource availability, and the dynamic nature of spare parts demand.

2.2 Classical inventory management methods

Classical inventory management methods have long provided decision-makers with quantitative frameworks for weighing the trade-offs between ordering costs, carrying costs, and shortage costs in manufacturing and supply-chain operations. By assuming relatively stable demand and predictable lead times, these approaches use straightforward formulas to determine when and how much to order to minimize total inventory expenses while maintaining desired service levels. Their transparency and ease of implementation allow practitioners to rapidly evaluate the financial impact of different stocking policies and to adjust parameters such as order frequency or safety margins, in response to shifts in demand variability or cost structures.

2.2.1 Reorder Point Model (ROP)

The “gas light” method, also called the reorder-point (ROP) approach, uses a warning-level threshold to signal when to replenish inventory. Much like refilling your car’s fuel tank when the warning light comes on, a business calculates the minimum stock level needed during supplier lead time and average usage; once inventory falls to that predefined level, a new order is placed. For example, a bakery might reorder flour as soon as only ten bags remain, ensuring they never run out before the next delivery arrives.

Key Formula:

$$Reorder\ Point\ =\ (Daily\ Usage\ \times\ Lead\ Time)\ +\ Safety\ Stock \qquad (2\text{-}1)$$

2.2.2 Safety Stock and Minimum Stock Level Models

Safety stock is the extra inventory carried to prevent stockouts caused by fluctuations in customer demand, forecast errors, or variability in supplier lead times. It acts as a buffer that a business holds above its cycle stock to absorb unexpected spikes in usage or delays in replenishment.

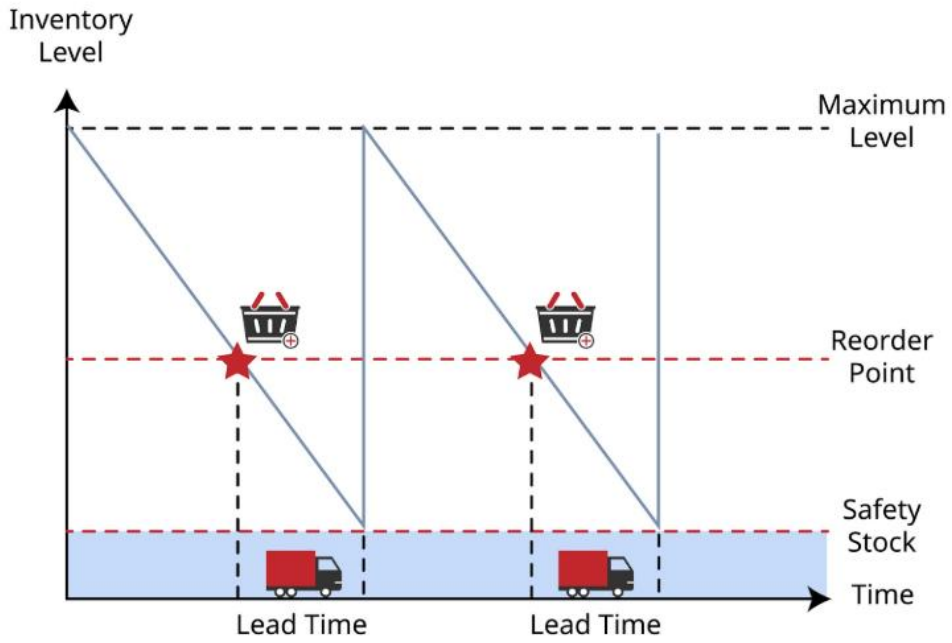


Figure 2.1 *Reorder Point (ROP) Inventory Management Cycle*

One common statistical formula for safety stock (SS) under uncertain demand and lead time is given as follows:

Key Formula:

$$SS = z\alpha \times \sqrt{[\,E(L)\,\sigma D^2 + [E(D)]^2\,\sigma L^2]} \qquad (2\text{-}2)$$

where $z\alpha$ is the service level factor, $E(D)$ and σD are the mean and standard deviation of demand, and $E(L)$ and σL are the mean and standard deviation of lead time.

A simpler heuristic formula often used by practitioners is:

$$SS = (Max\ Daily\ Sales \times Max\ Lead\ Time) - (Avg\ Daily\ Sales \times Avg\ Lead\ Time) \qquad (2\text{-}3)$$

Example: For a 90% service level (z=1.28), if demand's standard deviation is 15 units per day and lead time is 10 days, then: $SS = 1.28 \times 15 \times \sqrt{10} \approx 61\ units$.

This means that the company should hold about 61 units of extra stock as a safety buffer.

Calculation Methods

- **Lead Time Demand Method**:

$$Minimum\ Stock\ =\ Average\ Daily\ Demand\ \times\ Lead\ Time \quad (2\text{-}4)$$

  which covers expected consumption during replenishment delay.

- **Min/Max Method**:

$$MIN\ =\ Avg\ Sales\ \times\ (Lead\ Time\ +\ Safety\ Lead\ Time) \quad (2\text{-}5)$$

  where "safety lead time" adds extra buffer days.

The Safety Stock and Minimum Stock Level models play a critical role in ensuring the reliability and stability of inventory systems. By defining a minimum threshold for each item, these models help prevent stockouts during unexpected demand surges or supply delays. Safety stock acts as a buffer, absorbing variability in consumption and lead times, while the minimum stock level ensures that replenishment is triggered in time. Implementing these models reduces the risk of production stoppages, improves service levels, and enhances the overall efficiency of the supply chain. In highly dynamic environments, they are essential tools for maintaining operational continuity and customer satisfaction (*Inventory Planner, 2024).*

2.2.3 Economic Order Quantity Model (EOQ)

The Economic Order Quantity (EOQ) model is widely recognized as the "Goldilocks" approach to inventory management—aiming to determine the order quantity that is "just right." It seeks to strike a balance between two key types of costs: ordering costs (such as administrative labor, order processing, and delivery charges) and holding costs (including warehousing, insurance, depreciation, and opportunity costs). By calculating the optimal quantity that minimizes the total cost of ordering and storing inventory, EOQ helps organizations avoid both stockouts and excess inventory. For instance, in manufacturing environments, EOQ can guide the purchasing of spare parts like bearings or filters, ensuring that items are available when needed without tying up capital in unused stock. This method is particularly useful when demand, ordering cost, and holding cost are relatively stable and predictable. Ultimately, EOQ supports more efficient inventory control, cost savings, and smoother operations.

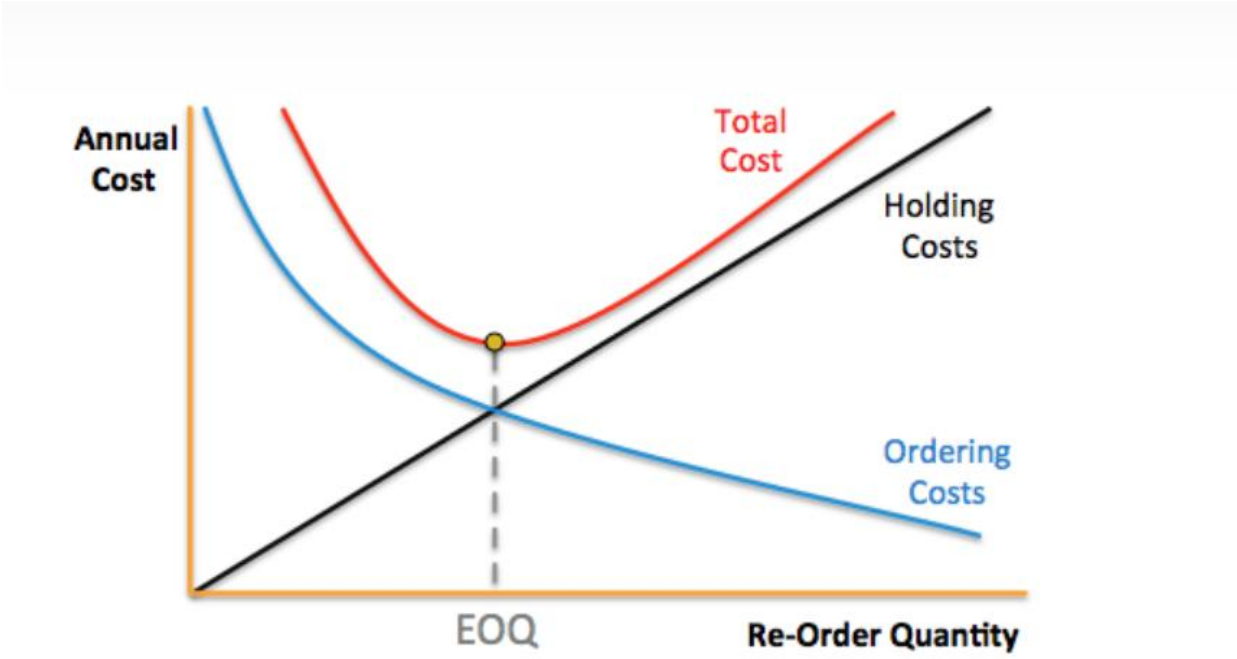


Figure 2.2 *Inventory Cost Analysis: EOQ Model and Re-Order Quantity Components*

Key Formula:

$$EOQ = \sqrt{[(2 \times Annual\ Demand \times Order\ Cost) / Holding\ Cost]} \qquad (2\text{-}6)$$

2.2.4 Periodic Replenishment Systems

The Periodic Review Inventory Model is particularly effective for managing industrial spare parts, especially those with irregular demand patterns or lower criticality. In this approach, inventory levels are assessed at fixed intervals (such as weekly or monthly) and replenishment orders are placed to restore stock to a predetermined target level. This method is advantageous in environments where continuous monitoring is impractical or where ordering processes are scheduled regularly.

Key Formula:

The order quantity in a periodic review system is determined by:

$$Order\ Quantity = Target\ Inventory\ Level - Current\ Inventory\ Level \qquad (2\text{-}7)$$

Where:

Target Inventory Level is calculated as the expected demand during the lead time plus the review period, plus a safety stock buffer to account for demand variability and supply delays.

$$Target\ Inventory\ Level = Average\ Demand \times (Lead\ Time + Review\ Period) + Safety\ Stock \quad (2\text{-}8)$$

This formula ensures that the inventory is sufficient to cover expected usage until the next review period, considering both the lead time for replenishment and any uncertainties in demand or supply.

2.2.5 Inventory Classification Methods

classification methods such as ABC, XYZ, and VED analyses are essential for optimizing stock control and ensuring operational efficiency.

ABC Analysis categorizes inventory based on the annual consumption value of items. 'A' items represent a small percentage of total inventory but account for a significant portion of the consumption value, necessitating tight control and accurate records. 'B' items are of moderate importance, requiring less stringent controls, while 'C' items are numerous but contribute minimally to the overall consumption value, allowing for simpler management (Kumbhar, S. V., & Dhavale, T. B. (2016)).

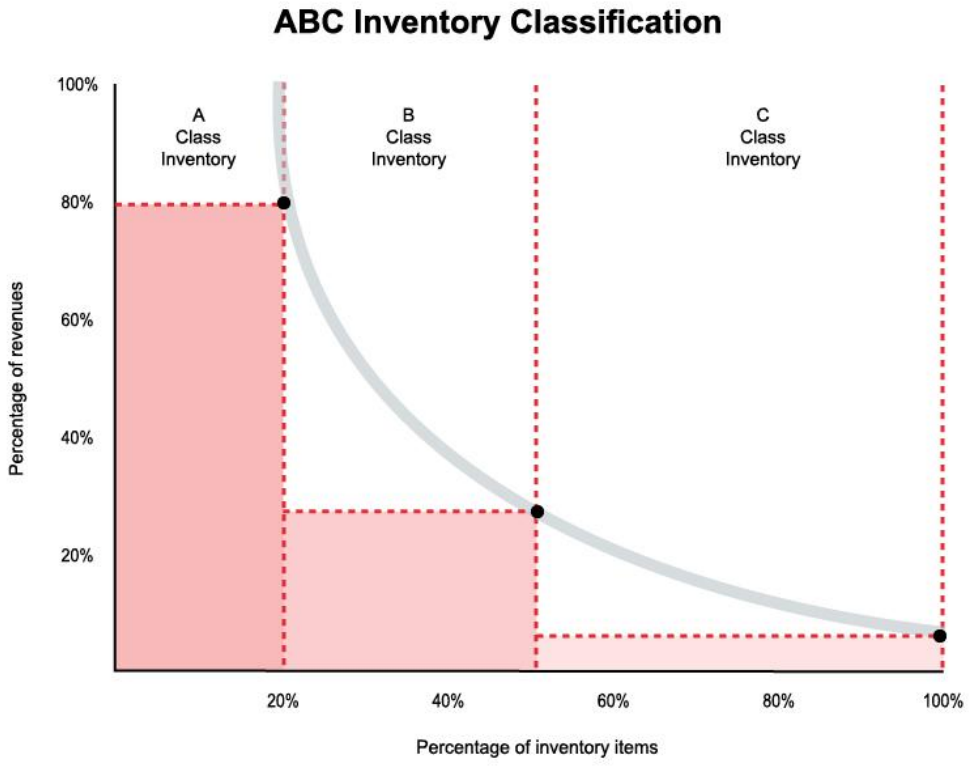


Figure 2.3 *a graph demonstrating ABC inventory classification*

XYZ Analysis focuses on the predictability of item demand. 'X' items have steady and predictable demand, making them suitable for automated inventory systems. 'Y' items exhibit moderate variability, often influenced by factors like seasonality, requiring more attentive monitoring. 'Z' items have highly unpredictable demand, necessitating flexible inventory strategies to prevent stockouts or overstocking (LeanDNA, 2024).

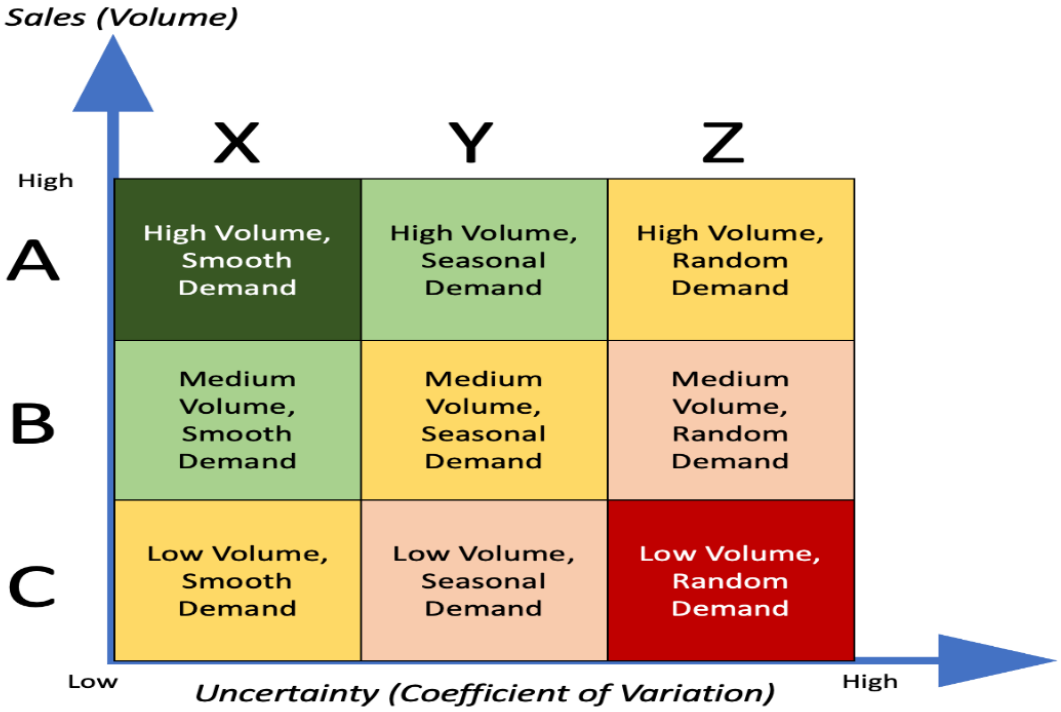


Figure 2.4 *ABC XYZ Analysis in Inventory Management (Medium.com, 2023)*

VED Analysis assesses the criticality of spare parts to operations. 'Vital' items are crucial for system functionality, and their absence can halt production, thus they must be readily available. 'Essential' items are important but not critical, and their temporary absence may cause minor disruptions. 'Desirable' items have minimal impact on operations, allowing for more lenient stocking policies (Kumbhar, S. V., & Dhavale, T. B. 2016).

By integrating these classification methods, industries can prioritize inventory management efforts, ensuring that critical and high-value items are adequately controlled, while optimizing resources allocated to less critical components.

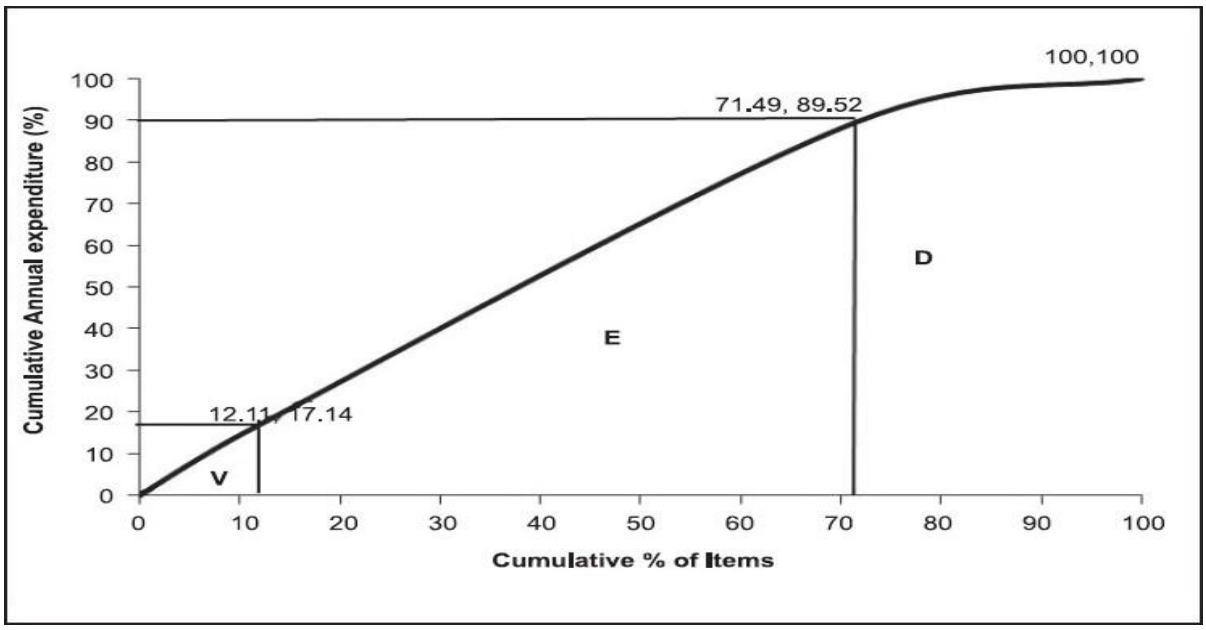


Figure 2.5 *VED analysis cumulative curve (Mahesh Devnani, 2010)*

2.3 Methods adapted for rare usage high importance items

Managing inventory for items that are infrequently used yet critically important such as specialized machine components, safety-related parts, or long-lead-time spares requires a strategic approach distinct from standard inventory practices. These items, while seldom needed, are vital for preventing operational disruptions and ensuring safety compliance. Traditional inventory methods may not suffice, as they often overlook the unique challenges posed by such items. Therefore, specialized strategies are essential to balance availability with cost-effectiveness.

2.3.1 Criticality-Based Spare Parts Management

Criticality Based Spare Parts Management is an inventory strategy that classifies and prioritizes spare parts according to their impact on operational continuity, ensuring that the most essential components are always available while optimizing overall inventory investment. This approach employs a criticality index: a composite metric that considers equipment importance, failure frequency, lead time, and the cost of downtime, to rank parts by urgency and value. By focusing resources on high criticality items, organizations can significantly reduce unplanned downtime, improve asset reliability, and lower carry costs associated with less critical stock.

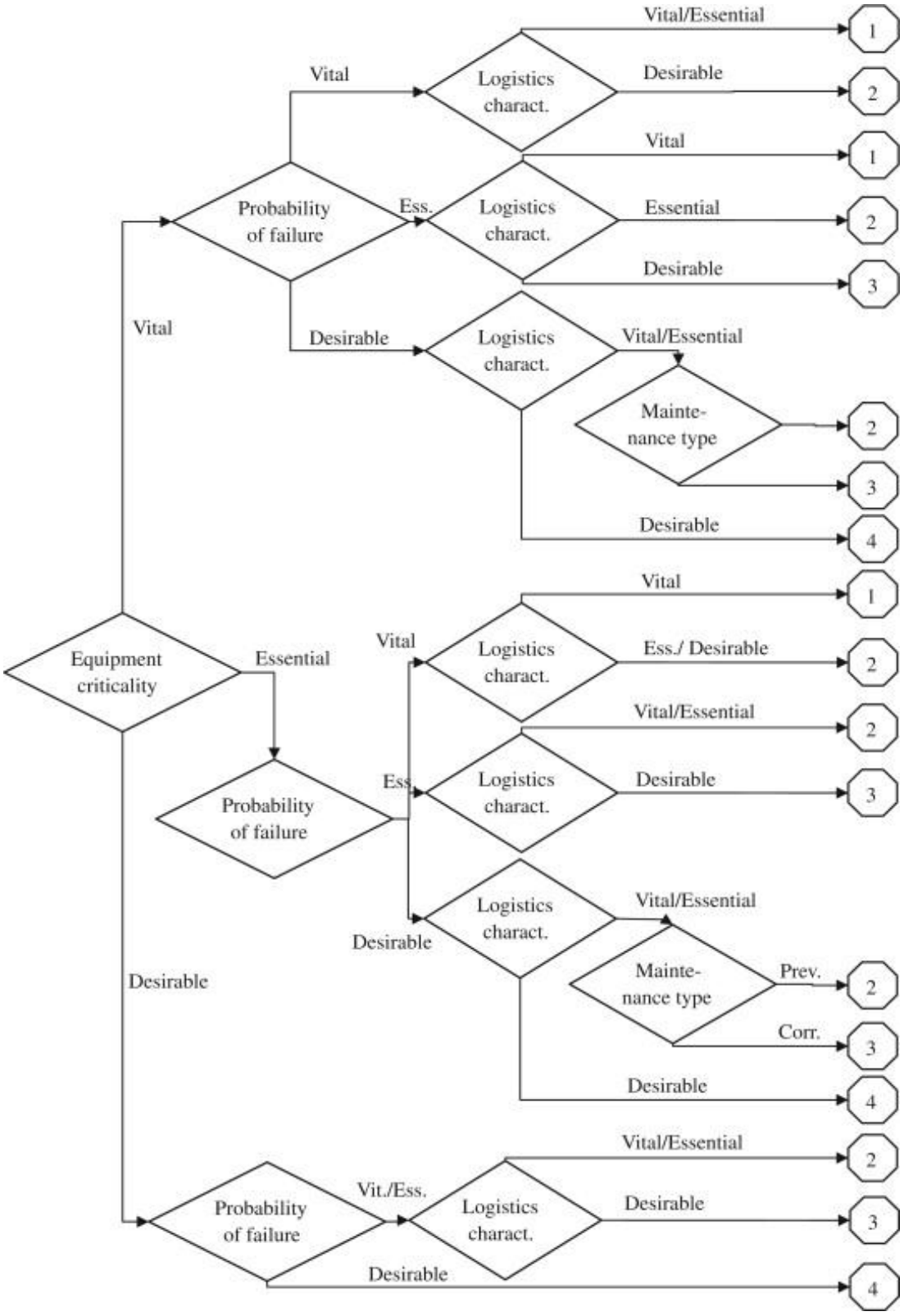


Figure 2.6 *Spare Parts Criticality Decision Diagram (Molenaers et al., 2012)*

- **How it works**:
    - **Step 1**: Analyse the impact of a part's failure on:
        - **Safety** (e.g., brakes in a train).
        - **Production** (e.g., a broken motor in a factory).
        - **Cost** (e.g., downtime costing 10m dzd/hour).

    - **Step 2**: Classify parts into three categories:

Category	Impact of Failure	Example
Mission-Critical	Halts operations entirely	Turbine blade in a power plant.
Operational	Reduces efficiency	Conveyor belt bearings.
Non-Critical	Minor or no disruption	Light bulbs in a warehouse.

Table 2.1 *Criticality-based classification*

- **Example**: An airline prioritizes jet engine parts (mission-critical) over cabin seat hinges (non-critical).

2.3.2 Methods for Managing Sporadic or Intermittent Demand

Managing inventory for items with sporadic or intermittent demand—such as spare parts, seasonal products, or niche components—presents unique challenges. Unlike items with steady demand, these products experience irregular and unpredictable usage patterns, making traditional forecasting methods less effective. Inaccurate forecasts can lead to either stockouts, disrupting operations, or overstocking, tying up capital and increasing holding costs.

Probabilistic Approaches

- **Poisson Distribution**: Used to estimate the probability of a part being demanded X times in a fixed period, ideal for modelling rare, independent failure/repair events (e.g., occasional sensor replacements in heavy machinery)..

- **Binomial Distribution:** Applies when there is a fixed number of trials (e.g., scheduled inspections) with two outcomes (failure or no failure); useful for predicting the count of part failures in maintenance cycles and sizing spare-parts orders accordingly. (*Krasimir Kalev, 2014)*

- **Normal Distribution:** Assumes demand over long periods is symmetrically distributed around a mean; commonly used in forecasting high-volume, regular-use parts (e.g., filters) where central-limit properties hold. (*Charmayne Smith, Normal Distribution Uses for Inventory Forecasting)*.
- **Exponential Distribution:** Models the time between independent failure events (e.g., time until next bearing failure), providing input for reliability-based reorder decisions and maintenance scheduling.
- **Weibull Distribution:** Captures a variety of failure-rate behaviours (increasing, constant, or decreasing hazard rates); widely used for life-cycle analysis of components like hydraulic seals or belts to forecast spare-parts needs.
- **Gamma Distribution:** Employed to model continuous demand during lead time when variability is significant; for example, forecasting total consumable usage (lubricants, gaskets) over replenishment lead times.
- **Log-Normal Distribution:** Reflects skewed demand patterns where most periods have low usage, but occasional spikes occur; suitable for forecasting intermittent demands of slow-moving parts (e.g., specialized electronics).
- **Uniform Distribution:** Assumes all demand levels within a given range are equally likely; used in simple "what-if" analyses and in Newsvendor models when only minimum and maximum demand are known.
- **Triangular Distribution:** An easy-to-parameterize model using minimum, most likely, and maximum demand estimates; often applied in Monte Carlo simulations of spare-parts consumption when data are scarce.
- **Beta Distribution:** Serves as a conjugate prior in Bayesian spare-parts forecasting (e.g., beta-binomial models) to update demand probability estimates as new failure data become available.
- **Negative Binomial Distribution:** Generalizes the Poisson for over-dispersed count data; useful for modelling the number of failures until a specified number of successes (or vice versa), especially in systems with clustered failures.

Croston-Based Methods: The following table classes Croston based methods Croston (1972), Syntetos and Boylan (2005), Boylan and Syntetos (2008), Teunter et al. (2011), Babai et al. (2014), Prestwich et al. (2014):

Method	Description	Purpose	Example
Croston's Method	Separately smooths nonzero demand sizes and inter-demand intervals using simple exponential smoothing to forecast intermittent demand	To generate forecasts for sporadic spare-parts demand by decoupling frequency and magnitude of demand events.	Estimating annual demand for rare sensors in a manufacturing plant (e.g., 0–2 replacements per year).
Syntetos–Boylan Approximation (SBA)	Introduces a correction factor (1−β2) into Croston's forecast formula to mitigate its upward bias on intermittent demand.	To improve forecast accuracy by adjusting for Croston's positive bias in demand rate estimates.	Forecasting bearing replacements in a steel mill, yielding more accurate order quantities compared to the original Croston method.
Teunter–Syntetos–Babai (TSB)	Smooths demand size and updates a smoothed probability of demand occurrence each period, allowing forecast decay during obsolescence.	To provide responsive forecasts that adjust both demand probability and size, especially when parts become obsolete.	Predicting valve failures per maintenance cycle in an oil refinery, where failure likelihood changes over time.
Hyperbolic-Exponential Smoothing (HES)	Combines exponential smoothing with a Bayesian hyperbolic decay mechanism, yielding unbiased forecasts for both intermittent and continuous demand and decaying during obsolescence	To handle obsolescence and maintain forecast accuracy across intermittent and non-intermittent demand scenarios	Anticipating declining demand for legacy electronic modules in industrial equipment, ensuring stocks are reduced as obsolescence occurs

Table 2.2 *Croston-based methods*

2.3.3 Rotating Stock vs. Dormant Stock

compares two distinct categories of inventory based on their usage frequency and management requirements. Rotating stock refers to items that are frequently used and require active tracking and efficient reordering strategies to maintain availability. In contrast, dormant stock consists of items that are seldom used and typically require less frequent attention, with a focus on cost-saving storage and preventing obsolescence. This section explores the differences in how each type of stock is managed and the strategies best suited to optimize their handling.

Stock Type	Usage Frequency	Management Strategy	Example
Rotating *(Active)*	High	- Track with sensors or logs. - Use ROP/EOQ for reordering.	Spark plugs in a car repair shop.
Dormant *(Inactive)*	Low	- Store centrally to save costs. - Audit yearly to prevent obsolescence.	Bolts for 20-year-old machinery.

Table 2.3 *Stock Management Strategies Based on Usage Frequency*

2.4 Multicriteria decision-making methods

Multicriteria Decision-Making (MCDM) encompasses a comprehensive suite of methodologies designed to evaluate and prioritize alternatives when faced with multiple, often conflicting, criteria. In the realm of spare parts management, MCDM is instrumental in addressing challenges such as balancing cost constraints, assessing the criticality of components, and managing supplier lead times. These methods provide a structured framework for decision-makers to analyze complex trade-offs and arrive at optimal solutions.

2.4.1 Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making technique that helps maintenance planners optimize spare-parts inventories by structuring the problem into a hierarchy, quantifying expert judgments, and computing a composite score for each part. Here's how it works in the context of spare-parts stock management:

Hierarchy Construction

- **Goal:** Optimize spare parts stocking policy.
- **Criteria:** e.g., failure consequence cost, lead time variability, demand frequency, part cost, and availability.
- **Alternatives:** The individual spare part items under consideration.

This three-level structure ensures a clear separation between what you want to achieve (minimize downtime and inventory cost), the factors that matter, and the candidate parts.

Pairwise Comparisons & Priority Weights

For each set of elements (criteria or alternatives under a criterion), experts fill out a pairwise comparison matrix A=[aij], such as :

$$aij = \frac{importance\ of\ element\ i}{importance\ of\ element\ j}\ , aij > 0\ , aji = \frac{1}{aij1} \qquad (2\text{-}9)$$

The priority vector (weight) w is then derived as the principal eigenvector:

$Aw = \lambda_{max} w$

These weights reflect the relative importance of each criterion (or alternative under that criterion)

Consistency Check

AHP includes a measure of judgment consistency. Calculate the Consistency Index (CI):

$$CI\ =\ \lambda_max/(n-1) \qquad (2\text{-}10)$$

and the Consistency Ratio (CR): $CR\ =\ CI/RI$

where RI is the Random Index (a tabulated value dependent on n). A CR below 0.10 indicates acceptable consistency

Alternative Scoring & Synthesis

Each spare part k is rated against every criterion i , producing a score matrix $V = [vik]$.

The overall **criticality score** S_k is the weighted sum is defined by:

$$S_k = \sum_{i=1}^{m} wi\ vik \qquad (2\text{-}11)$$

2.4.2 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a multi-criteria decision analysis method that ranks alternatives based on their geometric distance from a positive ideal solution and from a negative ideal solution. The positive ideal solution represents a hypothetical alternative with the best performance across all criteria, while the negative ideal embodies the worst performance levels. By calculating each alternative's relative closeness coefficient—measuring proximity to the ideal and remoteness from the negative ideal—TOPSIS helps decision makers choose the option that best balances multiple, often conflicting criteria. (Hwang, C. L., & Yoon, K. 1981). Steps in the implementation of the TOPSIS Method involve:

1) **Construct the Decision Matrix:** List all alternatives and their performance scores for each criterion.

2) **Normalize the Decision Matrix:** Convert different measurement units into a comparable scale, typically using vector normalization.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (2\text{-}12)$$

- xij: the value of alternative i for criterion j

- rij: the normalized value

3) **Apply Weighting:** Assign weights to each criterion based on their importance.

$$v_{ij} = w_{ij} \,.\, r_{ij} \quad (2\text{-}13)$$

- w_ij: weight (coefficient) of criterion.

- 〖r〗_ij: weighted normalized value

4) **Determine Ideal and Negative-Ideal Solutions:** Identify the best and worst values for each criterion across all alternatives.

For benefit criteria (higher is better):

- Ideal solution: $A^+ = \{\max(v_{ij})\}$
- Negative-ideal solution: $A^- = \{\max(v_{ij})\}$

5) **Calculate Separation Measures:** Compute the distance of each alternative from both the ideal and negative-ideal solutions.

Distance to the ideal solution: $S_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - A_j^+)^2}$ *(2-14)*

Compute the Relative Closeness: For each alternative, calculate a score that reflects its closeness to the ideal solution, (Considering cost lower is better).

$$C_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (2\text{-}15)$$

- C_i: the relative closeness coefficient (between 0 and 1)

- The higher C_i the better the alternative

6) **Rank the Alternatives:** Order the alternatives based on their relative closeness scores, the higher the score, the better the rank.

Example:

A retail chain uses TOPSIS to choose between three suppliers:

Supplier A: Low cost, long lead time.

Supplier B: High cost, short lead time.

Supplier C: Medium cost, medium lead time.

TOPSIS calculates which supplier best balances cost and speed.

2.4.3 Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE)

PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) is an outranking-based multi criteria decision making method that ranks a finite set of alternatives by comparing them pairwise across multiple criteria, using preference functions to calculate positive and negative outranking flows for each option. PROMETHEE I produces a partial ranking by considering both the strength (positive flow) and weakness (negative flow) of each alternative, while PROMETHEE II yields a complete ranking based on the net flow (positive minus negative). Its companion method, GAIA (Geometrical Analysis for Interactive Aid), offers a visual representation of conflicts and synergies among criteria, helping decision makers understand the multidimensional tradeoffs inherent in their choices (Priyam Verma, 2020; Bertrand Mareschal, 2005).

PROMETHEE I (Partial Ranking):

Preference Function Selection: For each criterion, a preference function is chosen to translate the difference between evaluations into a preference degree.

For two spare parts α and b and a criterion (e.g. cost of a part) j:

$$d_j(a,b) = f_j(a) - f_j(b) \quad (2\text{-}16)$$

Where

* $f_j(a)$: evaluation of a spare part α on the cost j

* $f_j(b)$: evaluation of a spare part b on the cost j

* $d_j(a,b)$: difference in evaluation for the cost j

Then apply a **preference function** $P_j(a,b)$ to this difference:

$$P_j(a,b) = H_j(d_j(a,b)) \quad (2\text{-}17)$$

Where H_j is one of the **preference function types** (e.g., usual, U-shape, V-shape, level, Gaussian, etc.).

Calculation of Preference Indices: Aggregates the preference degrees across all criteria to compute a global preference index for each pair of alternative spare parts .

The overall preference of spare part **α** over spare part **b** is calculated by aggregating across all criteria:

$$\boldsymbol{\pi(a,b) = \sum_{j=1}^{n} P_j(a,b)} \quad (2\text{-}18)$$

where**:**

*** wj:** weight of criterion j

*** $\boldsymbol{\pi(a,b) \in [0, 1]}$:** global preference of α over b

1. **Determination of Positive and Negative Flows:**

Positive Flow (φ⁺): Represents how much a spare part is preferred over all other parts.

$$\varphi^{+}(a) = \frac{1}{n-1}\sum_{b\in A, b\neq a} \pi\,(a,b) \quad (2\text{-}19)$$

Negative Flow (φ⁻): Indicates how much all-other parts are preferred over the given part.

$$\varphi^{-}(a) = \frac{1}{n-1}\sum_{b\in A, b\neq a} \pi\,(b,a) \quad (2\text{-}20)$$

Where A is the set of all alternatives, spare parts in this case

2. **Partial Ranking Formation:** Alternatives are compared based on their positive and negative flows, leading to a partial ranking where some alternatives may be

incomparable.

PROMETHEE II (Complete Ranking):

- **Objective:** Provides a complete ranking of alternatives by combining the positive and negative flows into a single net flow.
- **Process:**

1. **Net Flow Calculation:** For each alternative, the net flow (φ) is computed as the difference between the positive and negative flows:
$$\varphi = \varphi^{+} - \varphi^{-}$$
2. **Complete Ranking Formation:** Alternatives are ranked based on their net flow values, resulting in a complete preorder from the most to the least preferred alternative.
Combines the two flows for a complete ranking
$$\varphi(a) = \varphi^{+}(a) - \varphi^{-}(a)$$
3. *The higher $\varphi(a)$, the better the spare part
*PROMETHEE II ranks the parts from the more optimized to the less optimized using net flow.

2.4.4 Multi-Objective Optimization Problem (MOOP)

Multi-objective optimization, also known as Pareto optimization, involves solving problems with more than one objective function to be optimized simultaneously. In stock management, typical objectives include minimizing total inventory costs (ordering, holding, shortage costs), maximizing service levels, and minimizing environmental impacts from warehousing operations. MOOP has been widely applied in supply chain contexts, with literature reviews summarizing the latest research on conflicting objectives and solution approaches in inventory control problems metrics (Teunter, R. H., & Haneveld, W. K., 2008).

Mathematical Formulation:

Formally, a MOOP can be expressed as:

$$Minimize\ f(x) = [f1(x), f2(x), \dots, fK(x)] \qquad (2\text{-}21)$$

subject to $x \in X$, where X denotes the feasible region defined by inventory constraints (e.g., $xi \geq 0$, safety stock and service level requirements).

For example, common objective functions in inventory management include the total cost

function:

$$f1(x) = \sum_{i=1}^{N}(\frac{D_i}{Q_i}S_i + \frac{h_i Q_i}{2}) \quad (2\text{-}22)$$

which balances ordering cost Si and holding cost hi, and a stock-out risk function:

$$f2(x) = \sum_{i=1}^{N} P_{stockout,i} \times C_{stockout,i} \quad (2\text{-}23)$$

where $P_{stockout,i}$ is the probability of stock-out and $C_{stockout,i}$ is the associated penalty cost.

This field encompasses a diverse array of cross-disciplinary optimization methodologies. These approaches, while grounded in similar principles, exhibit variations in logic and application. Notable among these are:

- **Goal Programming (GP)**: An extension of linear programming, GP addresses multiple, often conflicting objectives by setting specific target values (goals) for each objective. The method then minimizes the deviations from these goals, allowing decision-makers to prioritize certain objectives over others based on their relative importance. *Towards AI, (2011) Multi-Objective Optimization Problem using Goal Programming*

- **Compromise Programming (CP)**: CP seeks solutions that are closest to an ideal point, representing the best possible values for each objective. By minimizing the distance to this ideal point, CP identifies solutions that offer a balanced trade-off among all objectives, making it particularly useful when no single objective can be optimized without compromising others.

- **Mixed Integer Linear Programming (MILP)**: The MILP method (Mixed-Integer Linear Programming) is an extension of linear programming that combines continuous variables with integer variables, thereby expanding its applicability to more complex and realistic optimization problems. This method is particularly useful in situations where some decisions must be made discretely (e.g., the number of units produced or the allocation of resources), while others can vary continuously (such as material quantities or costs). This flexibility makes MILP extremely useful in a wide range of fields, including supply chain management, scheduling, and energy management, among others.

A MILP problem is generally formulated as follows:

- Implementation of Multicriteria Modelling for Maintenance Optimization

Minimize (or maximize): $c^T x$

Subject to constraints: $Ax \leq b$

$x_j \in \mathbb{Z}^+$ (for some variables x_j)

$x_i \in \mathbb{R}^+$ (for the other variables x_i)

Where:

- X is the vector of decision variables
- C is the vector of coefficients in the objective function
- A is the matrix of constraint coefficients
- B is the vector of constants in the constraints

2.5 MODERN AND INTELLIGENT METHODS

2.5.1 Artificial Intelligence (AI)-Based Approaches

Artificial Intelligence–based approaches for spare parts management leverage advanced machine learning and neural network models to turn vast operational and sensor datasets into precise failure predictions and optimized stocking decisions. Neural networks (such as convolutional or recurrent architectures) can uncover complex, non-linear patterns in condition monitoring data (e.g., predicting conveyor motor failures from vibration and temperature sensors) by training on historical maintenance records. Machine learning algorithms, including random forests and gradient boosting machines, "learn" from warranty claim and usage datasets to forecast which engine components are most likely to fail next month, enabling automotive manufacturers to adjust spare parts inventories proactively and avoid excessive downtime. Beyond forecasting, reinforcement learning and prescriptive analytics frameworks can automate replenishment policies, balancing ordering costs and holding costs under uncertainty to recommend optimal order quantities and timing. For example, a major carmaker implemented an ML driven demand forecasting model that reduced stockouts by 30% while cutting inventory levels by 20%, demonstrating the transformative impact of AI on procurement efficiency. By embedding these AI models into maintenance and ERP systems, organizations shift from reactive spare parts

procurement to fully predictive, cost-efficient inventory management. Demand forecasting of spare parts with regression and machine learning methods. (Ghazanfari, M., Moosavi, A., & Fathi, M. 2021).

2.5.2 Big Data and IoT in Predictive Parts Management

Combining Big Data and the Internet of Things (IoT) for predictive parts management involves harnessing vast datasets alongside networks of connected devices to anticipate maintenance needs before failures occur. Smart sensors such as vibration monitors on wind turbine bearings—continuously track equipment health in real time, feeding data into analytics platforms that identify early warning signs of wear or degradation. Predictive maintenance algorithms then use this sensor data to forecast component lifecycles, enabling maintenance teams to schedule repairs or part replacements like swapping out a hydraulic pump two weeks before its predicted failure to avert costly downtime (e.g., a a million DZD loss). By moving from reactive to proactive maintenance, organizations reduce unexpected breakdowns and optimize spare parts inventory, ordering only what's needed when it's needed.

2.5.3 Expert Systems and Simulation Tools

Software that replicates human expertise or tests scenarios in virtual environments.

- **Expert Systems:**
    - Fuzzy Rule Based Inference Modelling

Fuzzy expert systems extend traditional rule-based systems by representing knowledge with fuzzy sets and "if then" rules that handle imprecision and uncertainty in data (e.g., "If temperature is high, then fan speed is fast"); this allows gradual membership rather than binary logic. The inference engine applies fuzzy inference (e.g., Mamdani or Sugeno methods) to aggregate rule outputs and perform defuzzification, yielding a crisp decision or control action Fuzzy rule based

modelling is used in decision support for maintenance prioritization where sensor readings and expert judgments are inherently vague. (Sugeno, T., & Kang, G. T. 1988)

- Semantic Web Technologies Based Modelling

Semantic Web based expert systems leverage ontologies (OWL/RDF), semantic annotations, and SPARQL queries to represent domain knowledge as linked data on the Web. (Mostafa Nofal and Khaled M. Fouad, 2015).

By encoding concepts, properties, and relationships in formal ontologies, these systems enable reasoning engines (using description logic reasoners) to infer new facts and ensure

consistency across distributed knowledge sources. Applications include Web based diagnostic systems, context aware agents, and large-scale knowledge integration platforms where interoperability and reuse of domain vocabularies are critical.

- Rule Based Inference Engines

At the core of many expert systems is a production rule system: a knowledge base of IF–THEN rules combined with an inference engine that uses forward chaining (data driven reasoning) and backward chaining (goal driven reasoning) to draw conclusions from known facts. These engines employ conflict resolution strategies (e.g., specificity, recency) to select which rule to fire next and support explanation facilities that trace the reasoning. path Ajith Abraham, Rule-based Expert Systems. Rule based systems remain popular for well-defined domains such as medical diagnosis, credit scoring, and configuration management.

- Case Based Reasoning (CBR)

Case based expert systems solve new problems by retrieving and adapting solutions from a case library of past experiences. When a novel query is presented, the system finds the most similar historical case(s) using similarity metrics, reuses and adapts its solution, revises the proposed solution if needed, and retains the new experience for future reference Purdue Engineering, CBR - Case Based Reasoning. CBR is particularly effective in legal reasoning, customer support, and maintenance diagnostics where precedents or past resolutions closely map to emerging issues.

- Bayesian Networks

Bayesian network based expert systems model probabilistic relationships among variables using directed acyclic graphs, allowing inference under uncertainty by propagating beliefs via Bayes' theorem (PMC, 2016) Integrating Expert Knowledge with Data in Bayesian Networks. Expert knowledge is encoded in conditional probability tables, and inference algorithms (e.g., junction tree, variable elimination) compute posterior probabilities given evidence (Jinchang Wang, 2009) Inference-Guiding on Bayesian Knowledge-Based Systems. These systems are employed in risk assessment, medical decision support, and fault diagnosis where quantifying uncertainty and causal dependencies is essential.

- Belief Rule Base (BRB) Hybrid Systems

The Belief Rule Base framework merges rule-based logic with belief degree assignments to handle multiple types of uncertainty fuzziness, randomness, and ignorance through Dempster–Shafer theory and evidential reasoning (Karmi Derrik, 2024). BRB systems define rules of the

form “IF conditions THEN belief degrees in outcomes,” and aggregate them to derive a global assessment, making them suitable for complex nonlinear decision problems in reliability evaluation, network security, and professional services.

- Knowledge Graphs & Ontologies

Belongs within Semantic Web Technologies-based modelling. Knowledge graph driven systems represent domain knowledge as graph structures where entities and their relations form a semantic network, enabling graph-based querying and reasoning (e.g., via graph traversal algorithms) (GeeksforGeeks, 2024). Combined with ontology reasoning, these systems support rich semantic inference, data integration, and explainable AI, finding use in enterprise knowledge management, biomedical informatics, and smart manufacturing. By selecting and combining these techniques—each tailored to different knowledge representations and reasoning paradigms—knowledge engineers build robust expert systems capable of emulating human level decision making across diverse application domains.

- Simulation Tools:

Simulation tools enable organizations to model, analyze, and optimize complex systems by replicating real world processes in silico. Major approaches include Discrete Event Simulation (DES) for event driven processes, Monte Carlo Simulation for probabilistic risk and uncertainty analysis, System Dynamics for continuous feedback loop modeling, and Agent Based Modeling (ABM) for simulating autonomous entities. Hybrid platforms now integrate multiple paradigms, facilitating end to end scenarios such as manufacturing workflows, supply chain logistics, and maintenance planning.

Key Applications: Table 2.1 summarizes the key applications of the aforementioned methods in the field of spare parts management.

Method	Use Case	Example
AI/Neural Networks	Predicting part failures	Forecasting elevator motor replacements.
IoT Sensors	Real-time equipment monitoring	Detecting pipeline leaks in oil refineries.
Simulation Tools	Testing inventory strategies risk-free	Simulating warehouse layouts for faster part retrieval.

Table 2.4 *Use case of mentioned Intelligent methods*

2.6 Comparative synthesis of methods

The following is a comparison table: Advantages, Disadvantages, and Application Domains

Method	Advantages	Disadvantages	Application Domains
Reorder Point (ROP)	Simple to implement; prevents stockouts with minimal computation	Assumes constant demand; requires safety stock for variability; can increase ordering frequency	Retail and manufacturing with steady demand; consumables
Economic Order Quantity (EOQ)	Minimizes combined ordering and holding costs; straightforward analytical formula	Assumes constant demand and lead time; ignores quantity discounts and demand variability	Bulk procurement, raw materials, standardized spare parts
Safety Stock	Buffers against demand and supply variability; improves service levels	Increases carrying costs; risk of obsolescence; requires accurate variability data	Healthcare, critical spare parts industries, high service-level environments
ABC/XYZ/VED Classification	Prioritizes high-value, predictable, or critical items; allocates resources effectively	Subjective thresholds: static classification ignores dynamic demand; requires periodic review	All sectors for general inventory sorting; spare-parts categorization
Croston's Method	Handles intermittent demand by separating size and interval forecasting	Positive bias: updates only after demand occurs; complex for non-statisticians	Aerospace, rare spare parts, intermittent-demand items
AHP / TOPSIS	Balances multiple qualitative and quantitative criteria; transparent weighting and ranking	Time-consuming data collection; requires expert judgments; potential consistency issues	Healthcare, high-risk industrial parts selection; strategic spare-parts decision-making

Method	Advantages	Disadvantages	Application Domains
AI / ML Forecasting	Learns complex patterns; improves accuracy over time; automates replenishment decisions	Requires large, high-quality datasets; specialized expertise; integration challenges	Smart manufacturing, predictive maintenance, automotive warranty analysis
IoT / Big Data	Enables real-time monitoring and analytics; supports proactive maintenance	High infrastructure and integration costs; cybersecurity and data privacy risks	Energy, automotive, heavy machinery, utilities
Expert Systems	Encodes expert knowledge; provides explainable, rule-based recommendations	Limited to pre-programmed rules; difficult to update; lacks learning capability	Complex industrial troubleshooting, medical diagnostics, maintenance decision support
MOOP	Generates Pareto-optimal trade-offs; balances cost, service, and sustainability objectives	Computationally intensive; requires scalarization or heuristics; subjective solution selection	Sustainable supply chains, balancing inventory cost vs. environmental impact, multi-criteria stock optimization
PROMETHEE	User-friendly outranking; supports partial and complete rankings; flexible preference functions	Needs careful preference function and weight elicitation; sensitive to parameter choices	Supplier selection, multi-criteria decision-making in maintenance and spare-parts prioritization

Table 2.5 *Comparative synthesis of methods*

Adaptability to Specific Industrial Environments

Industry/Environment	Best-Fit Methods
High-Volume Manufacturing (e.g., Automotive)	• **EOQ** and **ROP** for cost efficiency. • **IoT** for real-time tracking.
Low-Demand, High-Criticality (e.g., Aerospace)	• **Croston's Method** for sporadic demand. • **MCDM** for prioritization. • **Safety Stock** for risk mitigation.
Healthcare/Pharma	• **VED Analysis** to prioritize vital supplies. • **MCDM** for criticality-based decisions.
Legacy Systems (e.g., Power Plants)	• **Expert Systems** for troubleshooting. • **Dormant Stock Management** for rare parts.

Table 2.6 *Best-Fit Inventory Management Methods by Industry/Environment*

2.7 Conclusion

This thesis has systematically explored a spectrum of inventory management methodologies, from classical models like ROP and EOQ to advanced techniques such as AI-driven forecasting and IoT-enabled predictive maintenance. While these methods provide valuable tools for optimizing stock levels and reducing costs, their limitations in addressing the multi-dimensional complexity of spare parts management—where decisions hinge on competing priorities like cost, criticality, risk, and demand uncertainty—underscore the need for a more holistic approach. Multi-Criteria Decision Making (MCDM) emerges not merely as a complementary tool but as the cornerstone of a forward-looking framework for spare parts optimization.

The future of spare parts management lies in transcending siloed, one-dimensional models. MCDM's ability to harmonize diverse criteria—while integrating seamlessly with modern technologies like AI and IoT—positions it as the linchpin of next-generation inventory systems. By anchoring this thesis in MCDM, we aim to bridge the gap between theoretical decision science and industrial pragmatism, delivering frameworks that are as robust in practice as they are elegant in theory.

Chapter 3: Multicriteria Optimization of Spare Parts Inventory

3.1 Introduction

This chapter is dedicated to the implementation of a novel multi-criteria approach for optimizing spare parts inventory management, marking the transition from theory to practice. The proposed methodology combines powerful decision-making tools such as the Analytic Hierarchy Process (AHP) for criteria weighting, a criticality calculation model, and a Mixed-Integer Linear Programming (MILP) model, solved using CPLEX. The goal is to enhance the availability of critical spare parts while minimizing storage costs and avoiding stockouts.

Through a real-world case study, this chapter presents the key implementation steps: from criteria selection and weighting to model formulation and result analysis. It aims not only to validate the relevance of the proposed approach but also to demonstrate its practical benefits in an industrial context. Additionally, we discuss the main challenges encountered during implementation, along with insights and recommendations for future improvements and broader application.

3.2 Targeted work: context, motıvatıons, objectıves, and challenges

3.2.1 Context

In asset-intensive industries, production continuity heavily relies on the prompt availability of spare parts. However, companies often face a paradox of overstocking low-priority items while suffering from stockouts of critical components. Overstocking ties up capital and consumes storage space, whereas understocking leads to costly downtime. To address this, a structured approach is essential — one that ranks spare parts based on multiple criteria (such as cost, failure frequency, lead time, and operational impact). This work aims to propose an optimal solution in this context by leveraging advanced mathematical optimization techniques, while accounting for the critical stakes involved.

3.2.2 Motivations

As with any approach aimed at optimizing inventory management, the motivations for this work are as follows:

- Reducing total costs: minimizing both inventory holding costs and production downtime.
- Improving part availability: ensuring that the most critical spare parts are always in stock.

- Rational resource allocation: directing financial and storage resources to the most impactful items.
- Structured decision-making: replacing intuitive, experience-based approaches with a robust multi-criteria evaluation system.
- Structured decision-making: replacing intuitive, experience-based approaches with a robust multi-criteria evaluation system.

3.2.3 Objectives

- Assess and quantify the criticality of spare parts reflecting their importance.
- To compute a criticality index for each spare part using a formula that incorporates AHP-derived weights.
- Formulate a robust multi-objective optimization model for spare parts management under resources constraints.
- Validate the proposed method through a case study and evaluate its performance in stock and resources management efficiency.

3.2.4 Challenges

- Data reliability and consistency: collecting, cleaning, and standardizing supply data might be required in such an approach.
- Criticality is an intangible factor which can be described following different perspectives and is therefore hard to quantify.
- Translating real-world budget, space, and service level constraints into a solvable mathematical model can be complex and hard to achieve.
- Identify the factors and criteria influencing the management of spare parts and transform them into quantifiable metrics that can serve modeling and solving purposes.
- Assuming the model is successfully formulated, it still needs to be streamlined to handle a large number of variables without compromising solution time or optimality.
- Practical acceptance: ensuring the proposed solution is understandable and acceptable to maintenance and inventory managers for real-world application.

3.3 DESCRIPTION OF THE PROPOSED METHODOLOGY

3.3.1 Concept of the proposed study

Based on the specific context of this study, a structured methodology has been designed to meet the defined objectives while addressing the challenges encountered along the way. Figure 3.1 illustrates the overall workflow of this methodology. Each step of the process is explained in detail in the subsections that follow, providing a clear understanding of the rationale behind the approach and how it contributes to the optimization of spare parts management.

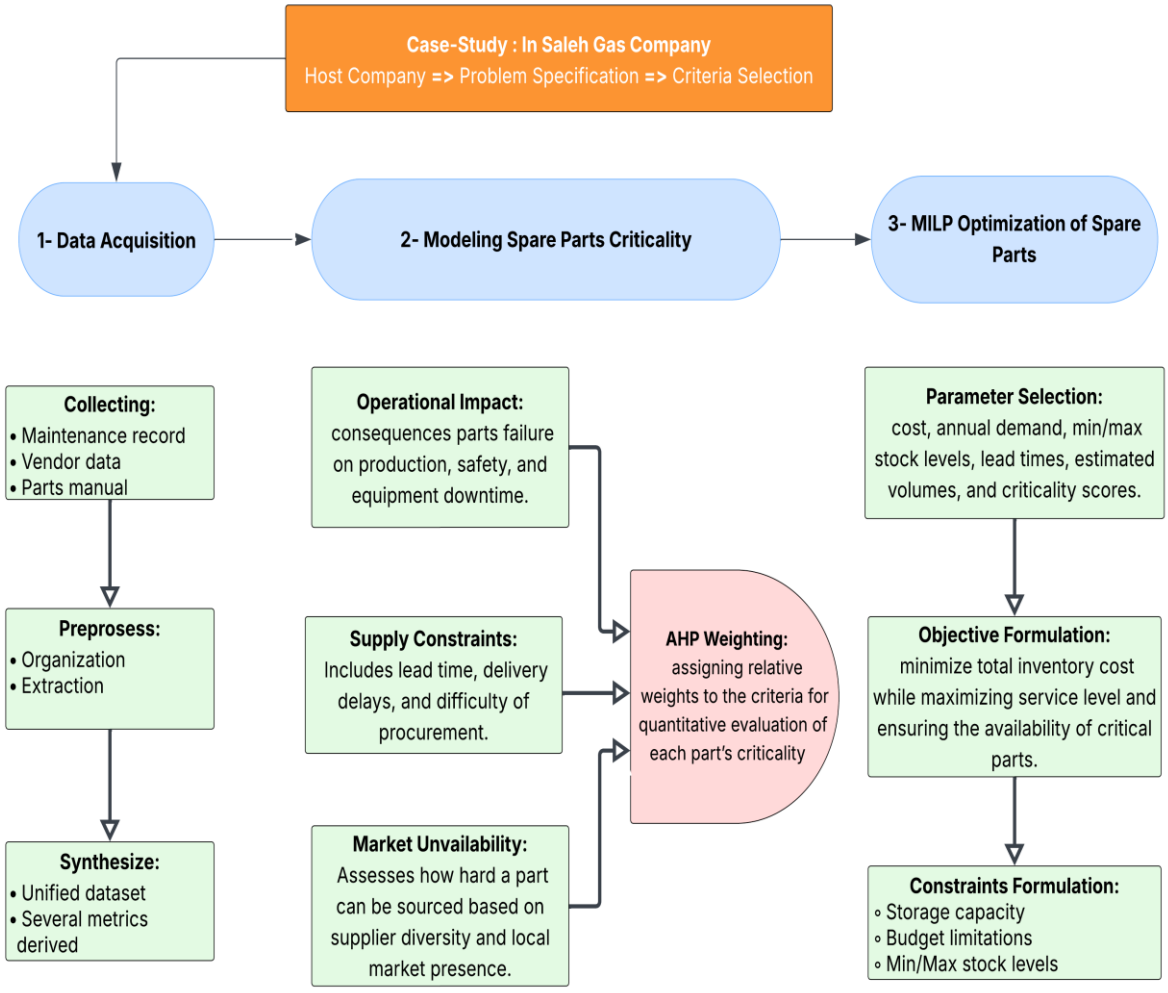


Figure 3.1 *Diagram of methodology adopted*

3.3.2 Presentation of the case study

Presentation of the host company

The company from which the data used in this study was obtained is In Salah Gas (ISG), a strategic joint venture primarily owned by Sonatrach, with the participation of international partners Equinor and Eni. ISG operates in the exploration, processing, and export of natural gas in southern Algeria and plays a significant role in the national and international energy markets. The company is known for its advanced infrastructure and high operational standards, which are essential for the continuity of gas production and supply.

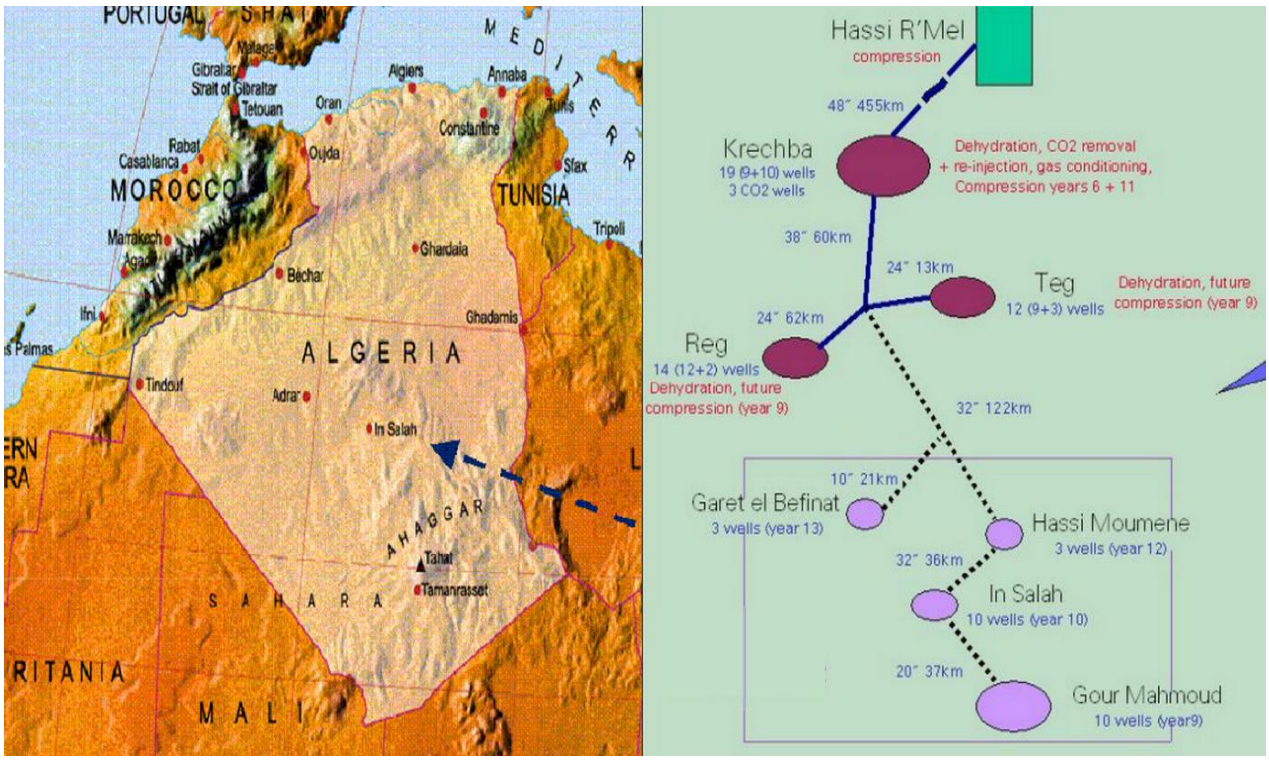


Figure 3.2 *Location of IN SALEH GAS wells and fields in Algeria*

Problem Specification and Criteria Selection

The main stock management issue at ISG is the frequent shortage of critical spare parts, posing risks of production stoppages and operational delays. Ensuring the availability of the right parts at the right time is therefore essential. To address this, a multicriteria decision-making approach was applied. This method enables a more balanced evaluation of various influencing factors, such as part criticality, lead time, and consumption rate. It supports better inventory

planning and prioritization. By integrating these criteria, ISG aims to reduce stockouts and enhance operational reliability.To build a model that reflects the complexity of the problem, the following decision criteria were selected:

- Cost: Including the purchase price and potential holding costs of the parts.
- Lead Time: Time required by suppliers to deliver the part, especially critical for imported or custom components.
- Availability of parts in the market: Availability of multiple sources for procurement, which affects supply reliability.
- Minimum and Maximum Storage Levels: Constraints related to warehouse capacity and safety stock policies.
- Annual Demand: Frequency of use or replacement, based on historical maintenance records. which is the lead factor in defining the criticality of parts.
- Volume: Physical space each part occupies, impacting storage and logistics planning.
- Current inventory: serving as a reference for assessing the need to order additional parts and determining the appropriate quantity to order.
- Logistical constraints: Represents the resources influencing the parts acquisition such as the allocated budget for ordering and the available warehouse storage capacity.

These criteria align with the goal of building a model that balances cost efficiency with operational reliability, ensuring the company maintains critical parts without overstocking.

3.3.3 Data acquisition

The adopted data acquisition protocol led to the assembly of an initial sample dataset comprising 22 spare parts belonging to the VP185 NEW Diesel Engine, manufactured in 2005. This piece of equipment is responsible for starting the three main generators during power outages and is considered crucial for ensuring the reliable performance of the production line. The retained data elements consist of 9 initial key parameters: part reference, designation, unit price, volume, annual demand, lead time (days), minimum stock, maximum stock and number of suppliers, selected with the involvement of experienced company personnel to ensure a reasonable variety among the different parts and to cover diverse scenarios, thereby supporting scalability. Subsequently, the collected data is pre-processed by estimating missing inputs and calculating derived key stock performance indicators with the aim of enabling broader opportunities for analysis and exploitation.

Figure 3.3 *VP185 NEW Diesel Engine 2005 Year of Build*

3.3.4 Modelling spare parts criticality

To quantify the relative importance of each spare part, a criticality score is computed using a weighted-sum formula that integrates three normalized components: usage value (U), lead time (L), and vendor availability (V). These components are defined and normalized such that the score lies between 0 and 1.

$$Criticality_i = w_1 \times \left(U_i/max(U)\right) + w_2 \times \left(L_i/max(L)\right) + w_3 \times \left(1 - N_i/max(N)\right) \qquad (3\text{-}1)$$

Where:

- U_i: Annual usage value of part i, defined as the product of its Annual demand and cost expressed in monetary value.

- L_i: Procurement Lead time for part i.

- N_i : Number of available suppliers for part i

- w_1, w_2, w_3: Respective weights of the three aforementioned components, reflecting their contribution to the overall criticality assessment based on their relative importance.

The adopted criticality model originates from the fact that the operational risk associated with a spare part increase with its high usage value, long replenishment lead time, and low supplier availability. These three criteria collectively represent key risk factors in spare parts management: high-cost or frequently used items can severely impact operations if out of stock; long lead times delay recovery in case of failure; and limited supplier options increase procurement vulnerability. The model thus enables a more objective prioritization of parts for inventory optimization.

The choice of these 3 main components is justified by their reasonable alignment with the problem specifications detailed in Section 3.2.1, as well as by the limitation of available data, which does not allow for more complex or granular models. Furthermore, this approach enables a multicriteria evaluation that is both reasonably efficient and balanced, while offering great flexibility thanks to the adaptable weights. These weights are systematically calculated using the Analytic Hierarchy Process (AHP), based on pairwise comparisons carried out by field experts. This ensures a robust weighting, aligning with context-specific preferences.

3.3.5 MILP-based Optimization of Spare Parts Acquisition

While Mixed-Integer Linear Programming (MILP) may not be commonly applied in spare parts management, its strong potential for solving complex optimization problems is well recognized. To efficiently optimize spare parts order quantities under resource constraints, we employ a tailored MILP model that leverages the outputs of the spare parts criticality assessment. The objective is to maximize the total inventory levels of parts, weighted by their pre-calculated criticality scores. This approach ensures that the most critical components—those with higher criticality—receive larger order quantities, while adhering to budgetary and storage capacity limits. In essence, it enables the strategic allocation of limited resources (budget and space) to improve operational readiness and minimize the risk of downtime. The model specifications are presented as follows:

Objective function: Maximize the total stock weighted by the criticality score:

$$Maximize \sum (Criticalityi \times (Li + Xi)) \quad (3\text{-}2)$$

Indices

- $i = 1, \ldots, n$: Spare part index

Parameters

- C_i: Unit cost ($).
- V_i: Unit Volume (cm³).
- Li: Current inventory (units).
- $Smin_i$ / $Smax_i$: Stock bounds (units), respectively defined as: Minimum required stock / Maximum allowed stock per part.
- B: Budget ($), representing the financial limit for the amount that can be spent on the parts.
- K: Storage capacity (cm³), representing the total volume that can be handled by the warehouse.

Derived parameter

- $Criticality_i$: Score ∈ [0, 1] combining usage value, lead time, vendor availability, resulting from equation n *(3-1)*

Decision Variable

- X_i: Order quantity of part i (integer ≥ 0)

Constraints

- $\sum C_i \times X_i \leq B$ (Budget Constraint): To ensure that the financial expenses implied can be covered.
- $\sum V_i \times X_i \leq K$ (Storage Capacity Constraint): To ensure that there is enough space to store the acquired parts.
- $(Li + Xi) \geq Smin_i$ (Minimum Stock Constraint): To ensure avoiding understocking.
- $(Li + Xi) \leq Smax_i$ (Maximum Stock Constraint): To ensure avoiding overstocking.
- $X_i \in \mathbb{Z}_+$ (Non-negative Integer Order Quantities): To ensure logical optimization.

3.4 Implementation of the methodology

3.4.1 Data preprocessing

As mentioned in Section 3.3.2, several key stock performance indicators are calculated to produce an extended and coherent dataset aligned with the modelling objectives. This step was carried out using Microsoft Excel, based on the equations presented in *(1-2) (1-3) (3-1),* respectively enabling the derivation of the Average Inventory, Annual Usage Value and Criticality parameters. In addition to the parts volumes which were estimated using generative artificial intelligence based on commonly similar components specifications. The resulting pre-processed inputs are listed in table below

SN	D	Article No	Price ($)	MAX	MIN	Lead time (days)	demand (unit/year)	Number of Suppliers	volume (m³)	Average Inventory (units)	Annual Usage Value ($)
1	ASSY-BREAKBACK LINK ASSEMBLY - BREAKBACK PN:YN27120D for PAXMAN generator	YN27120D	143.18	9	3	90	12	2	0.06	6	1718.16
2	SPRING TORSION SPRING FOR FLAP VALVE PN:18yn27711 for PAXMAN generator	18YN27711	10.79	3	1	35	6	1	0.005	2	64.74
3	LIPSEAL PN:OD32378P107 for PAXMAN generator	OD32378P107	59.39	3	1	20	12	3	0.002	2	712.68
4	WASHER PN:11/P441/1059/29 for PAXMAN generator	11/P441/1059/29	4.25	18	6	150	24	1	0.0003	12	102
5	GASKET PN:OD32730/11 for PAXMAN generator	OD32730/11	67.68	297	99	20	1188	3	0.01	198	80403.84
6	O RING PN:OD32270P124 for PAXMAN generator	OD32270P124	5.9	6	2	10	24	3	0.0005	4	141.6
7	O RING PN:OD32270P125 for PAXMAN generator	OD32270P125	9.29	3	1	10	12	3	0.0005	2	111.48
8	O' RING SEAL - SECONDARY PUMP PN:OD32271P109 for PAXMAN generator	OD32271P109	7.48	3	1	10	12	2	0.0005	2	89.76
9	ASSY-CONDENS.DRAIN PN:YN45109 for PAXMAN generator	YN45109	67.86	6	2	35	12	1	0.004	4	814.32
10	O RING FOR COMPRESSOR CASING PN:OD32401P121 for PAXMAN generator	OD32401P121	9.04	27	9	10	108	3	0.0005	18	976.32
11	LOCTITE GRADE 243 (50ml Bottle) PN:SD265/10 for PAXMAN generator	SD265/10	102.49	6	2	35	12	3	0.00005	4	1229.88
12	WASHER SEALING 1.000" BSP ALUMINIUM PN:ST012635 for PAXMAN generator	ST012635	2.46	3	1	10	12	3	0.0003	2	29.52
13	O RING SEAL DIA 785 MEAN PN:OD32381 for PAXMAN generator	OD32381	42	6	2	20	24	2	0.001	4	1008
14	LOCTITE GRADE 225 (50ml Bottle) PN: SD265/21 for PAXMAN generator	SD265/21	44.76	3	1	150	4	1	0.00005	2	179.04
15	LOCTITE 542 (50ML BOTTLE) PN:SD265/38 for PAXMAN generator	SD265/38	59.35	3	1	150	4	1	0.00005	2	237.4
16	LOCTITE GRADE 603 (10ml Bottle) PN:SD265/23 for PAXMAN generator	SD265/23	27.78	3	1	150	4	1	0.00005	2	111.12
17	LOCTITE 595 RTV Clear 100ml TO SK12136 PN:ST960001R for PAXMAN generator	ST960001R	13.02	6	2	150	8	1	0.0001	4	104.16
18	LOCTITE 518 PN:ST960001V for PAXMAN generator	ST960001V	326.94	6	2	150	8	1	0.0002	4	2615.52
19	CASTROL LMX GREASE PN:CO7/14 for PAXMAN generator	CO7/14	26.11	3	1	150	4	1	0.0003	2	104.44
20	JOINT SET OIL COOLER & THERMOSTAT PN:18YN72133 for PAXMAN generator	18YN72133	269.19	3	1	35	6	1	0.05	2	1615.14
21	JOINTING , PR:50RPD1185 (QA LC 24)	50RPD1185	399.98	108	36	150	144	1	0.002	72	57597.12
22	SIGMA SEAL, PAXMAN P/N: OD32032/52, FOR DIESEL ENGINE PAXMAN 18VP185, (QA CL24)	OD32032/52	235.59	27	9	150	36	1	0.003	18	8481.24

Table 3.1 *Pre-Processed inputs*

3.4.2 Criticality quantification using the adopted model

To assess the criticality of spare parts, the Analytic Hierarchy Process (AHP) was applied using Expert Choice, a decision-making software based on the Analytic Hierarchy Process. It helps users prioritize options by comparing criteria in pairs and calculating their relative importance. Widely used in industry and research, it simplifies complex decisions involving multiple factors.

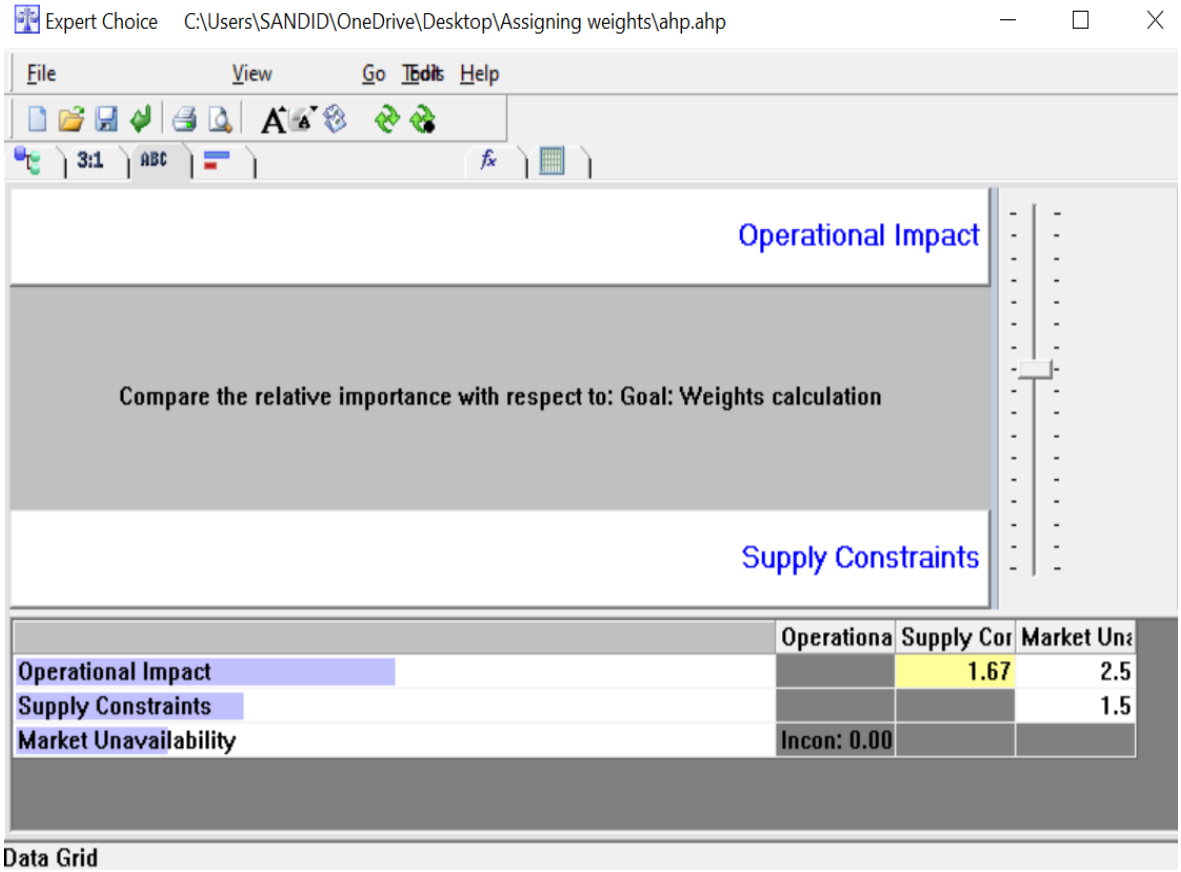


Figure 3.4 *Expert-Choice Interface*

This method allowed for the systematic evaluation and weighting of three key criteria that influence part criticality: Operational Impact, Supply Constraints, and Market Unavailability

Each criterion was compared in a pairwise matrix to establish its relative importance in the decision-making process. The pairwise comparison matrix used is presented below

Compare the relative importance with respect to: Goal: Weights calculation

	Operational Impact	Supply Constraints	Market Unavailability
Operational Impact		1.67	2.5
Supply Constraints			1.5
Market Unavailability	Incon: 0.00		

Figure 3.5 *Pairwise Comparaison Matrix*

Following the standard AHP methodology, the Expert Choice software computed the weights associated with each criterion. These weights—denoted as w_1, w_2, and w_3 for Annual Usage, Lead Time, and Supplier Availability respectively—reflect the influence of each factor on the overall criticality score.

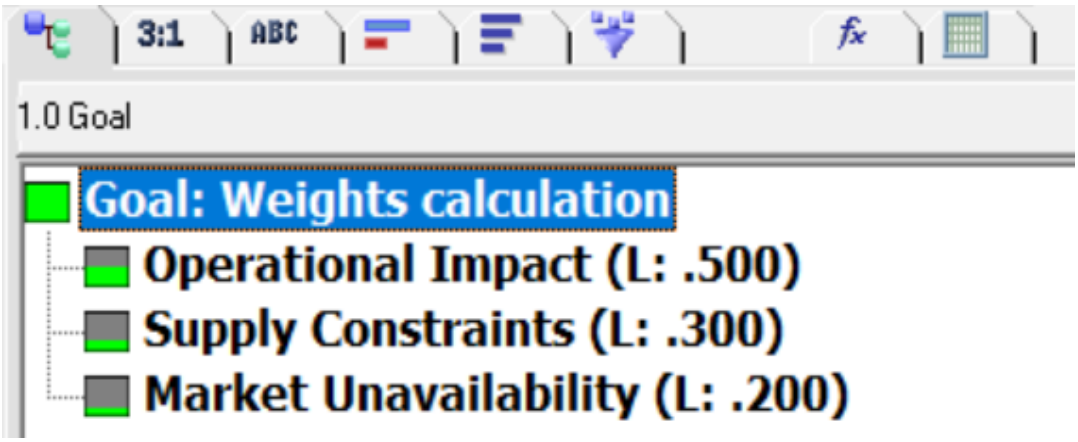


Figure 3.6 *AHP Calculation and Weights Output*

After determining the weights, the criticality of each of the 22 spare parts was calculated using the weighted sum model. This involved combining the normalized values of Operational Impact, Supply Constraints, and Market Unavailability. The method provided a structured way to assess part importance. The final scores are presented in the table below.

	D	Market Un-Availability	Supply Constraints	Operational Impact	Criticality
1	ASSY-BREAKBACK LINK ASSEMBLY - BREAKBACK PN:YN27120D for PAXMAN generator	0.333333333	0.6	0.021369129	0.257351231
2	SPRING TORSION SPRING FOR FLAP VALVE PN:18yn27711 for PAXMAN generator	0.666666667	0.233333333	0.000805185	0.203735926
3	LIPSEAL PN:OD32378P107 for PAXMAN generator	0	0.133333333	0.008863756	0.044431878
4	WASHER PN:11/P441/1059/29 for PAXMAN generator	0.666666667	1	0.001268596	0.433967631
5	GASKET PN:OD32730/11 for PAXMAN generator	0	0.133333333	1	0.54
6	O RING PN:OD32270P124 for PAXMAN generator	0	0.066666667	0.00176111	0.020880555
7	O RING PN:OD32270P125 for PAXMAN generator	0	0.066666667	0.001386501	0.02069325
8	O' RING SEAL - SECONDARY PUMP PN:OD32271P109 for PAXMAN generator	0.333333333	0.066666667	0.001116365	0.087224849
9	ASSY-CONDENS.DRAIN PN:YN45109 for PAXMAN generator	0.666666667	0.233333333	0.010127874	0.208397271
10	O RING FOR COMPRESSOR CASING PN:OD32401P121 for PAXMAN generator	0	0.066666667	0.012142704	0.026071352
11	LOCTITE GRADE 243 (50ml Bottle) PN:SD265/10 for PAXMAN generator	0	0.233333333	0.015296284	0.077648142
12	WASHER SEALING 1.000" BSP ALUMINIUM PN:ST012635 for PAXMAN generator	0	0.066666667	0.000367147	0.020183573
13	O RING SEAL DIA 785 MEAN PN:OD32381 for PAXMAN generator	0.333333333	0.133333333	0.012536715	0.112935024
14	LOCTITE GRADE 225 (50ml Bottle) PN: SD265/21 for PAXMAN generator	0.666666667	1	0.002226759	0.434446713
15	LOCTITE 542 (50ML BOTTLE) PN:SD265/38 for PAXMAN generator	0.666666667	1	0.002952595	0.434809631
16	LOCTITE GRADE 603 (10ml Bottle) PN:SD265/23 for PAXMAN generator	0.666666667	1	0.001382024	0.434024345
17	LOCTITE 595 RTV Clear 100ml TO SK12136 PN:ST960001R for PAXMAN generator	0.666666667	1	0.001295461	0.433981064
18	LOCTITE 518 PN:ST960001V for PAXMAN generator	0.666666667	1	0.03252979	0.449598228
19	CASTROL LMX GREASE PN:CO7/14 for PAXMAN generator	0.666666667	1	0.001298943	0.433982805
20	JOINT SET OIL COOLER & THERMOSTAT PN:18YN72133 for PAXMAN generator	0.666666667	0.233333333	0.020087847	0.213377257
21	JOINTING , PR:50RPD1185 (QA LC 24)	0.666666667	1	0.716347876	0.791507271
22	SIGMA SEAL, PAXMAN P/N: OD32032/52, FOR DIESEL ENGINE PAXMAN 18VP185, (QA CL24)	0.666666667	1	0.105483022	0.486074844

Table 3.2 *Computed Criticality Scores*

3.4.3 Implementation of the proposed MILP

Software Presentation

IBM ILOG CPLEX Optimization Studio is a powerful solver used for mathematical optimization problems such as linear and mixed-integer programming. In this study, it is used to solve the MILP model for spare parts inventory optimization.

CPLEX was chosen for its speed, reliability, and ability to handle real-world constraints like budget, storage capacity, and stock levels. The model was implemented using the DOcplex Python library, enabling seamless integration with data analysis and preprocessing tasks.

Figure 3.7 *Logiciel CPLEX*

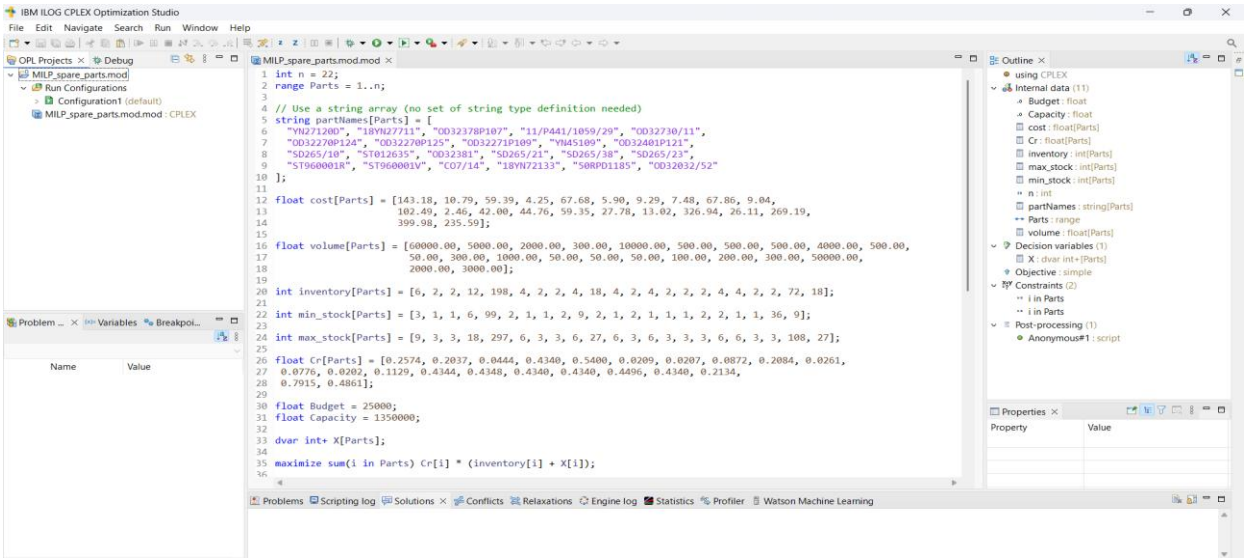


Figure 3.8 *CPLEX interface*

Solving the model: technical specifications

The MILP model was successfully solved using IBM ILOG CPLEX under two primary constraints: a budget limit of $25,000 and a storage capacity limit of 1,350,000 cm³. The solution was obtained in just 0.11 seconds (figure 16), demonstrating excellent computational performance.

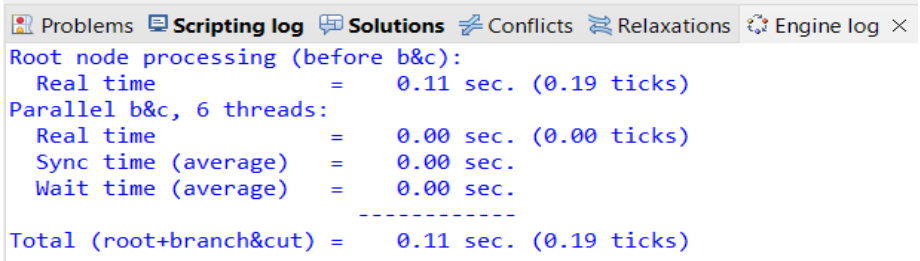


Figure 3.9 *Resolution Time*

Results:

The spare parts orders obtained from the MILP model are presented in the figure below. The disparity relative to the Min and Max stock levels is also illustrated to provide additional insight.

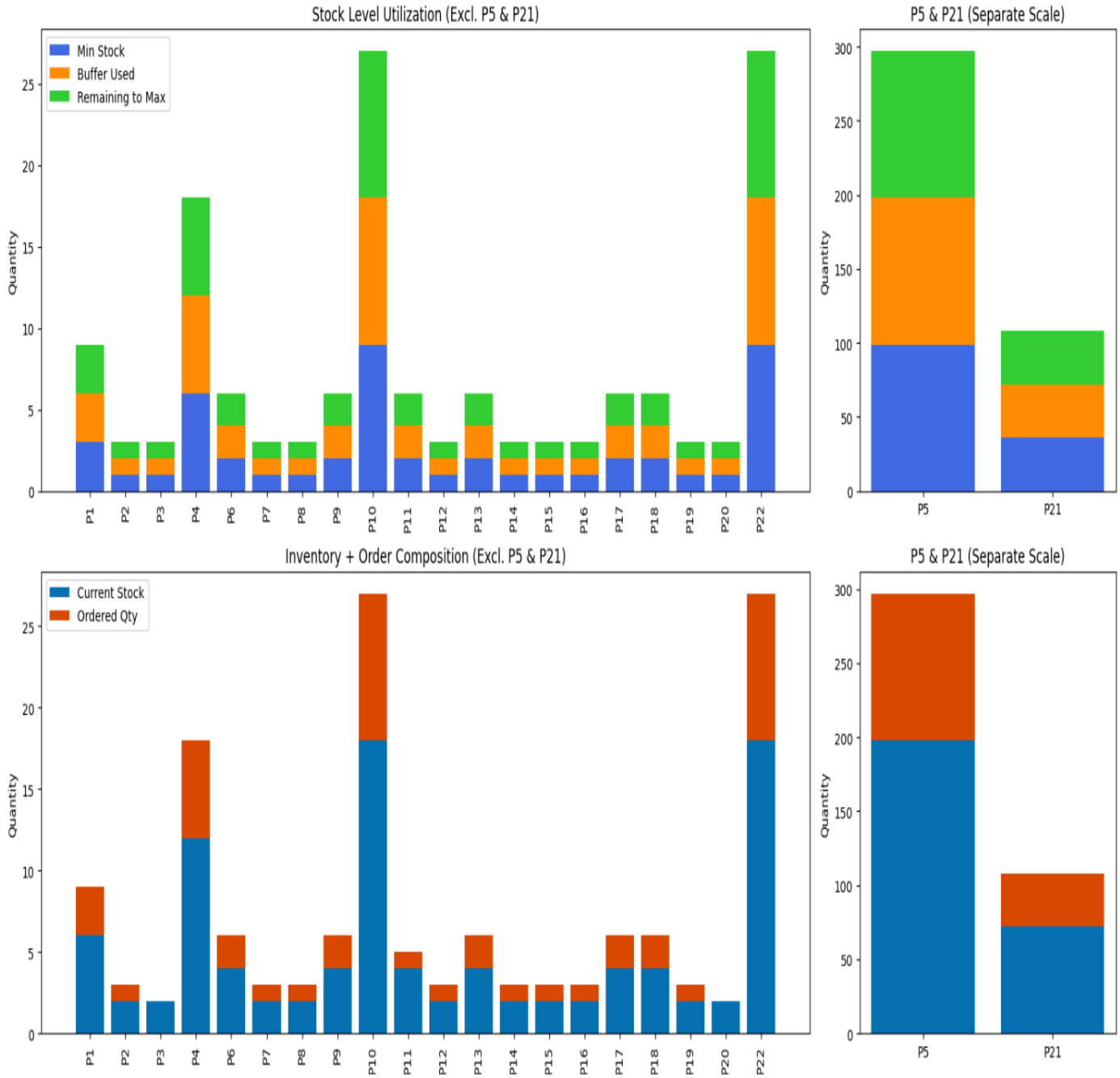
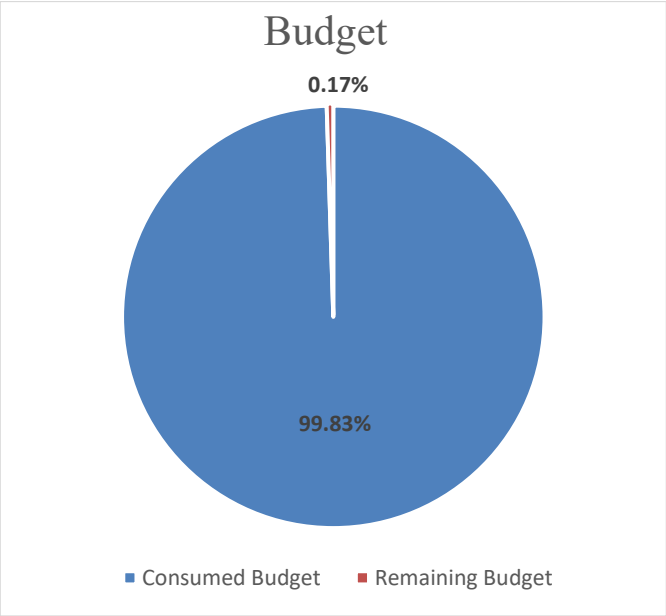


Figure 3.10 *Inventory Status and Stock Level Analysis per Part*

The resulting consumption of budget and storage resources is shown below:



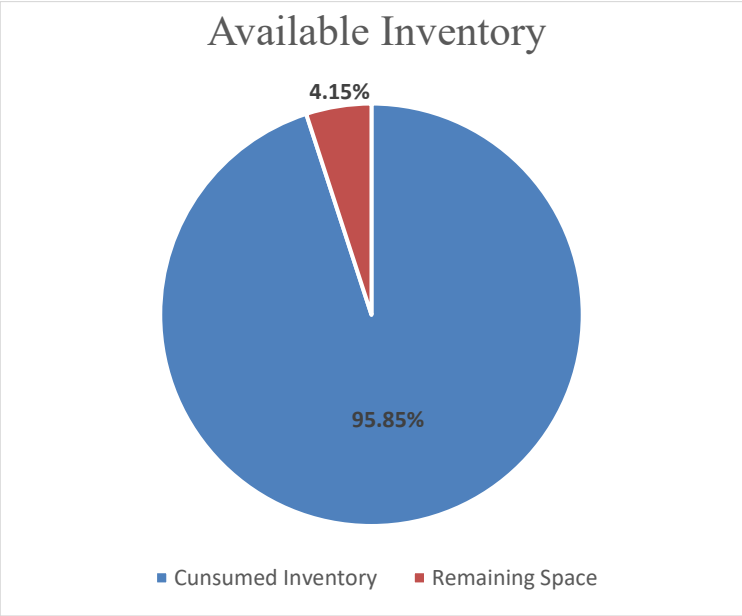


Figure 3.11 *Budget Proportion*

Figure 3.12 *Inventory Proportion*

3.5 Results Discussion and Interpretation

3.5.1 Discussion of the AHP-driven criticality weights

The results obtained through the application of the AHP method reveal a clear prioritization of the criteria according to their relative importance. The criterion Operational Impact received the highest weight with 50%, followed by Market Availability at 30%, and Supply Constraints at 20%. This distribution reflects a logical and reasonable weighting in the context of spare parts management.

Giving top priority to Operational Impact is justified, as a failure of a critical spare part can lead to equipment downtime, directly affecting the continuity of production or service. Therefore, emphasizing this criterion is both strategic and necessary.

Supply Constraints, ranked second, play a crucial role in the decision-making process. This criterion captures supplier-related risks such as delivery delays, which must be carefully considered during stock planning to minimize the risk of supply chain disruptions.

Market Unavailability, while receiving the lowest weight, remains relevant. The ease or difficulty of sourcing a part influences procurement and stocking strategies. Even if less critical

than operational or supply-related issues, parts with limited availability or long lead times still require careful attention to ensure continuity.

It is important to note that the final weighting depends on the preferences of the decision-maker, expressed through pairwise comparisons. A key strength of the AHP method is its flexibility to adjust these preferences based on strategic priorities or changing operational contexts. This is demonstrated through the following scenarios:

- **Scenario 1 – Market-Oriented Approach**: This scenario may be more suitable when spare parts are hard to find or supply chains are unstable.

	Market Unavailability	Operational Impact	Supply Constraints
Market Unavailability	1	2.4	4
Operational Impact	0.42	1	1.67
Supply Constraints	0.25	0.60	1

Resulting AHP-Weights:

Market Availability = 60%, Operational Impact = 25%, Supply Constraints = 15%

- **Scenario 2 – Time-Critical Approach**: In this case, the criticality is more oriented to the supply constraints, reflecting a desire to receive required parts as soon as possible.

	Market Unavailability	Operational Impact	Supply Constraints
Operational Impact	1	1	0.50
Market Unavailability	1	1	0.50
Supply Constraints	2.00	2.00	1

Resulting AHP-Weights:

Operational Impact = 25%, Market Unavailability = 25%, Supply Constraints = 50%

These scenarios demonstrate the adaptability of the AHP method and show how weightings can be modified to suit different priorities or decision-making contexts.

One of the key advantages of the AHP method is its ability to structure the weighting process in a rational and transparent way, relying on expert judgments through systematic pairwise comparisons. This helps to reduce the degree of uncertainty and subjectivity, while providing a solid analytical foundation for the decisions made.

In conclusion, the resulting prioritization is consistent with the challenges of spare parts inventory management. Thanks to AHP, the decision-making process becomes more structured, traceable, and adaptable to various operational realities.

3.5.2 Discussion of the obtained criticality scores

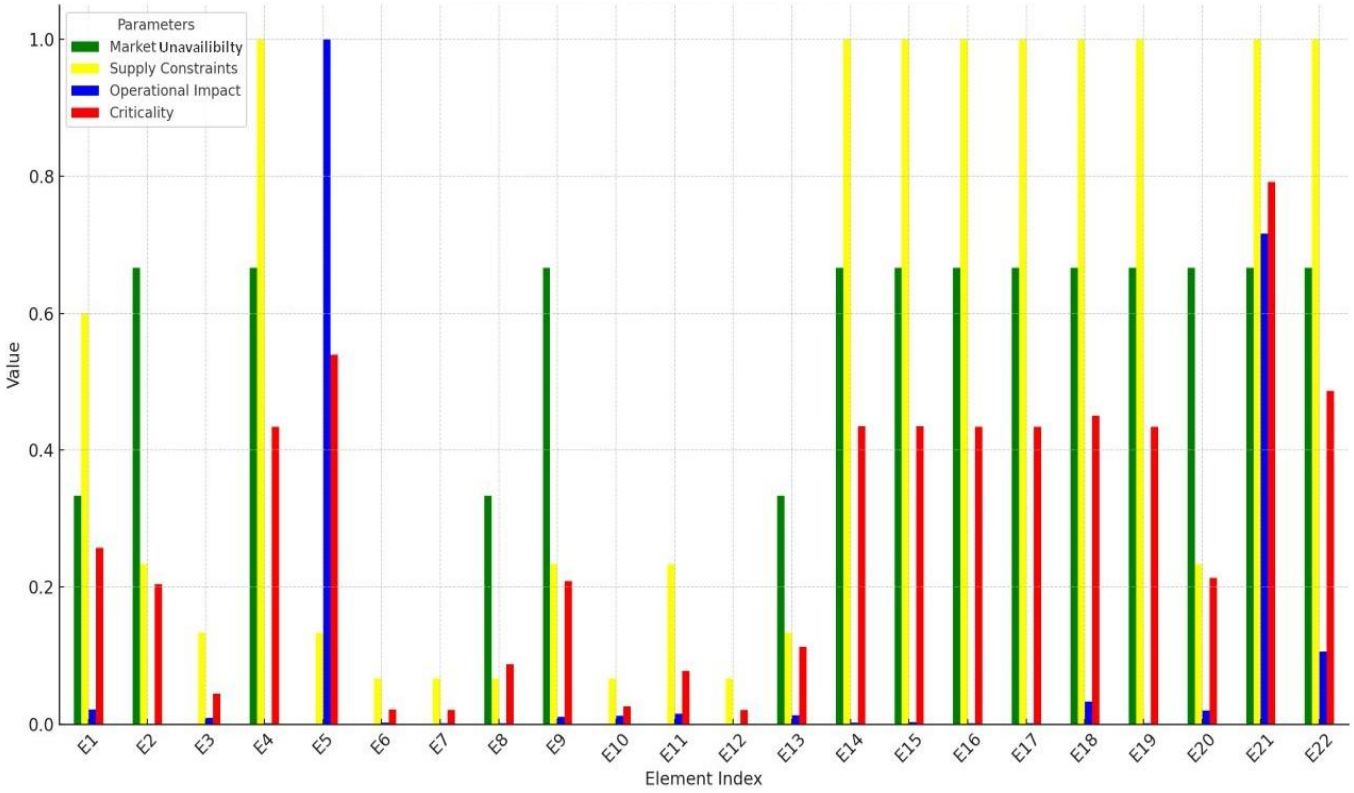


Figure 3.13 *Normalized Comparison of Spare Part Parameters and Resulting Criticality*

The bar chart illustrates the normalized values of four criteria across 22 Spare parts: Market Unavailability, Supply Constraints, Operational Impact, and the resulting Criticality (red). Although the first three parameters represent distinct dimensions of risk and are not directly comparable in value, their influence on the computed criticality is evident and consistent.

The Criticality score, derived using a structured weighting method such as AHP, reflects a balanced integration of the criteria. For example:

- Parts such as E5 and E21 show high Operational Impact and/or Market Unavailability, resulting in high criticality scores.
- Conversely, parts like E6, E7, and E8, which display low values across all criteria, correspondingly yield low criticality levels.

This alignment demonstrates the coherence of the quantified criticality with the adopted evaluation framework. It confirms that the multi-criteria decision-making process successfully captures the influence of each parameter and provides a reliable basis for spare parts prioritization.

3.5.3 Discussion of the MILP-driven parts orders

In order to thoroughly discuss the results of the spare parts optimization, several metrics are derived. These are listed in the table below:

SN	D	Artcle No	Inventory (units)	Ordered	Total stock	Ordered parts Volume (m^3)	Ordering Cost ($)	Buget Propotion	Inventory Propotion
1	ASSY-BREAKBACK LINK ASSEMBLY - BREAKBACK PN:YN27120D for PAXMAN generator	**YN27120D**	**6**	**3**	**9**	**0.18**	**429.54**	99.83%	95.85%
2	SPRING TORSION SPRING FOR FLAP VALVE PN:18yn27711 for PAXMAN generator	**18YN27711**	**2**	**1**	**3**	**0.005**	**10.79**		
3	LIPSEAL PN:OD32378P107 for PAXMAN generator	**OD32378P107**	**2**	**0**	**2**	**0**	**0**		
4	WASHER PN:11/P441/1059/29 for PAXMAN generator	**11/P441/1059/29**	**12**	**6**	**18**	**0.0018**	**25.5**		
5	GASKET PN:OD32730/11 for PAXMAN generator	**OD32730/11**	**198**	**99**	**297**	**0.99**	**6700.32**		
6	O RING PN:OD32270P124 for PAXMAN generator	**OD32270P124**	**4**	**2**	**6**	**0.001**	**11.8**		
7	O RING PN:OD32270P125 for PAXMAN generator	**OD32270P125**	**2**	**1**	**3**	**0.0005**	**9.29**		
8	O' RING SEAL - SECONDARY PUMP PN:OD32271P109 for PAXMAN generator	**OD32271P109**	**2**	**1**	**3**	**0.0005**	**7.48**		
9	ASSY-CONDENS.DRAIN PN:YN45109 for PAXMAN generator	**YN45109**	**4**	**2**	**6**	**0.008**	**135.72**		
10	O RING FOR COMPRESSOR CASING PN:OD32401P121 for PAXMAN generator	**OD32401P121**	**18**	**9**	**27**	**0.0045**	**81.36**		
11	LOCTITE GRADE 243 (50ml Bottle) PN:SD265/10 for PAXMAN generator	**SD265/10**	**4**	**1**	**5**	**0.00005**	**102.49**		
12	WASHER SEALING 1.000" BSP ALUMINIUM PN:ST012635 for PAXMAN generator	**ST012635**	**2**	**1**	**3**	**0.0003**	**2.46**		
13	O RING SEAL DIA 785 MEAN PN:OD32381 for PAXMAN generator	**OD32381**	**4**	**2**	**6**	**0.002**	**84**		
14	LOCTITE GRADE 225 (50ml Bottle) PN: SD265/21 for PAXMAN generator	**SD265/21**	**2**	**1**	**3**	**0.00005**	**44.76**		
15	LOCTITE 542 (50ML BOTTLE) PN:SD265/38 for PAXMAN generator	**SD265/38**	**2**	**1**	**3**	**0.00005**	**59.35**		
16	LOCTITE GRADE 603 (10ml Bottle) PN:SD265/23 for PAXMAN generator	**SD265/23**	**2**	**1**	**3**	**0.00005**	**27.78**		
17	LOCTITE 595 RTV Clear 100ml TO SK12136 PN:ST960001R for PAXMAN generator	**ST960001R**	**4**	**2**	**6**	**0.0002**	**26.04**		
18	LOCTITE 518 PN:ST960001V for PAXMAN generator	**ST960001V**	**4**	**2**	**6**	**0.0004**	**653.88**		
19	CASTROL LMX GREASE PN:CO7/14 for PAXMAN generator	**CO7/14**	**2**	**1**	**3**	**0.0003**	**26.11**		
20	JOINT SET OIL COOLER & THERMOSTAT PN:18YN72133 for PAXMAN generator	**18YN72133**	**2**	**0**	**2**	**0**	**0**		
21	JOINTING , PR:50RPD1185 (QA LC 24)	**50RPD1185**	**72**	**36**	**108**	**0.072**	**14399.28**		
22	SIGMA SEAL, PAXMAN P/N: OD32032/52, FOR DIESEL ENGINE PAXMAN 18VP185, (QA CL24)	**OD32032/52**	**18**	**9**	**27**	**0.027**	**2120.31**		

Table 3.3 *Results of Spare parts Optimisation*

The final analysis of the results highlights an optimized spare parts inventory management system, with an efficient budget utilization rate of 99.83% and a 95.85% satisfaction rate of inventory requirements. These indicators reflect a well-balanced trade-off between cost control and supply security.

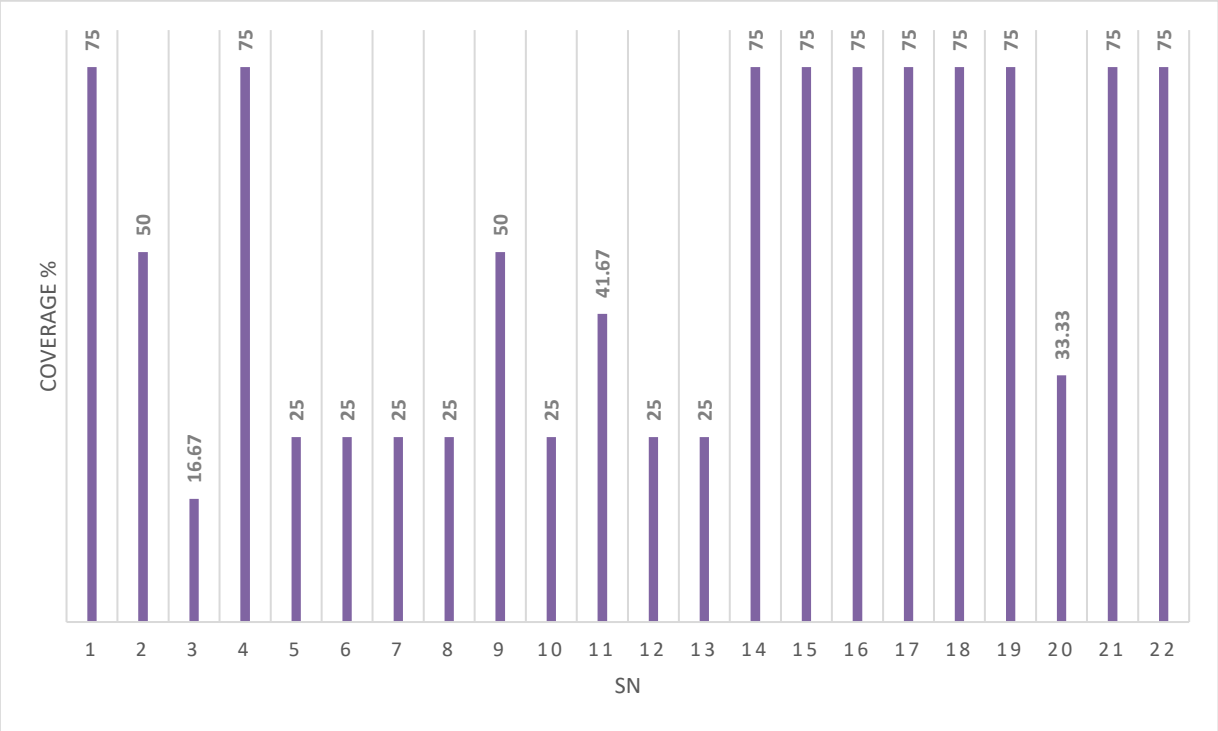


Figure 3.14 *Coverage bar chart*

The coverage rate (%) observed in the graph shows significant variations between different parts. Some items, such as washers and seals (e.g., WASHER PN:11/P441/1059/29, LOCTITE), display a high coverage (up to 75%), indicating a protection strategy for parts that are either frequently consumed or critical. Other items, less frequently used but more expensive, exhibit a more moderate coverage (25–50%), which helps avoid overstocking while maintaining an acceptable availability level.

The inclusion of low-volume but high-criticality parts, as well as costly components essential for proper functioning, confirms that the multi-criteria approach which incorporates operational impact, supply constraints, and market availability enabled a relevant prioritization. The diversity in stock levels and coverage rates results from a balanced arbitration between the risk of stockouts, ordering frequency, and storage cost.

In conclusion, the results demonstrate a clear consistency between the calculated criticality and the criteria used, proving the effectiveness of the optimization model in a real-world industrial management context.

3.5.4 Validation of the results

Testing the criticality model robustness

Using the two previously defined scenarios in section 3.6.1, we calculated new criticality values and applied them to our model to evaluate the relevance of the resulting order quantities. The results are shown in the table below:

		Scenario 1		Scenario 2	
SN	D	Criticality	Ordered	Criticality	Ordered
1	ASSY-BREAKBACK LINK ASSEMBLY - BREAKBACK PN:YN27120D for PAXMAN generator	0.295342282	0	0.417607159	2
2	SPRING TORSION SPRING FOR FLAP VALVE PN:18yn27711 for PAXMAN generator	0.435201296	1	0.295161037	0
3	LIPSEAL PN:OD32378P107 for PAXMAN generator	0.022215939	0	0.075106084	1
4	WASHER PN:11/P441/1059/29 for PAXMAN generator	0.550317149	5	0.716920386	6
5	GASKET PN:OD32730/11 for PAXMAN generator	0.27	87	0.273333333	95
6	O RING PN:OD32270P124 for PAXMAN generator	0.010440277	1	0.037018889	2
7	O RING PN:OD32270P125 for PAXMAN generator	0.010346625	0	0.036943967	1
8	O' RING SEAL - SECONDARY PUMP PN:OD32271P109 for PAXMAN generator	0.210279091	1	0.120223273	0
9	ASSY-CONDENS.DRAIN PN:YN45109 for PAXMAN generator	0.437531969	2	0.297025575	1
10	O RING FOR COMPRESSOR CASING PN:OD32401P121 for PAXMAN generator	0.013035676	3	0.039095207	9
11	LOCTITE GRADE 243 (50ml Bottle) PN:SD265/10 for PAXMAN generator	0.038824071	0	0.13139259	2
12	WASHER SEALING 1.000" BSP ALUMINIUM PN:ST012635 for PAXMAN generator	0.010091787	0	0.036740096	1
13	O RING SEAL DIA 785 MEAN PN:OD32381 for PAXMAN generator	0.223134179	2	0.15917401	2
14	LOCTITE GRADE 225 (50ml Bottle) PN: SD265/21 for PAXMAN generator	0.55055669	1	0.717112019	1
15	LOCTITE 542 (50ML BOTTLE) PN:SD265/38 for PAXMAN generator	0.550738149	1	0.717257186	1
16	LOCTITE GRADE 603 (10ml Bottle) PN:SD265/23 for PAXMAN generator	0.550345506	1	0.716943071	1
17	LOCTITE 595 RTV Clear 100ml TO SK12136 PN:ST960001R for PAXMAN generator	0.550323865	1	0.716925759	1
18	LOCTITE 518 PN:ST960001V for PAXMAN generator	0.558132447	1	0.723172625	2
19	CASTROL LMX GREASE PN:CO7/14 for PAXMAN generator	0.550324736	1	0.716926455	1
20	JOINT SET OIL COOLER & THERMOSTAT PN:18YN72133 for PAXMAN generator	0.440021962	1	0.299017569	0
21	JOINTING , PR:50RPD1185 (QA LC 24)	0.729086969	27	0.859936242	36
22	SIGMA SEAL, PAXMAN P/N: OD32032/52, FOR DIESEL ENGINE PAXMAN 18VP185, (QA CL24)	0.576370755	6	0.737763271	9

Table 3.4 *Criticality & Ordered results on two scenarios*

The results obtained from both scenarios clearly demonstrate the consistency and effectiveness of the proposed criticality model. Indeed, we observe that spare parts with high criticality values are systematically prioritized in the procurement decisions. This is reflected in higher order quantities for highly critical parts, such as item SN21 "JOINTING, PR:50RPD1185",

which shows the highest scores in both scenarios (0.729 and 0.860) and receives the largest order quantities (27 and 36 units respectively).

We also note that low-criticality items, such as O-rings (e.g., SN6 and SN7), with very low scores (around 0.01–0.03), are either ordered in minimal quantities or entirely excluded in scenario 1. This confirms the model's ability to filter out non-urgent parts, thereby optimizing the use of the available budget.

Moreover, the differences observed between the two scenarios illustrate the model's adaptability to strategic priorities:

- Scenario 1, based on market availability, tends to favor critical but rare items while limiting orders for replaceable or readily available parts.
- Scenario 2, more oriented toward time-criticality, prioritizes parts whose unavailability could cause immediate downtime, such as the "O RING FOR COMPRESSOR CASING" (SN10), whose order quantity increases from 3 to 9 despite only moderate criticality.

Finally, the comparison between criticality levels and ordered quantities in both scenarios shows that our multi-criteria weighting model (which incorporates operational impact, supply constraints, and market availability) provides a reliable and actionable prioritization. The results confirm that this model is a relevant decision-making tool for guiding spare parts procurement strategies.

Solver-based validation of the MILP model

Using CPLEX, it is possible to derive the main model specifications and key performance indicators from the statistics tab. These are listed and translated as follows:

- **Number of constraints (46):** This includes all model restrictions, such as stock bounds, budget, capacity, and any logical or operational constraints. The relatively low number suggests a moderate model complexity.
- **Number of variables (22):** These represent the decision variables in the model — the quantities of different spare parts to order. All of them are integer variables, indicating that fractional orders are not allowed, which is realistic for inventory decisions.
- **Non-zero coefficients in the matrix (88):** This is a measure of model sparsity. With 88 non-zero values in the constraint matrix, the model is relatively sparse and computationally efficient.

- **MIP Objective Value = 284.2854:** This is the optimal value achieved by the solver. It reflects the total "benefit" as defined in the objective function. It represents the maximum achievable value under the defined constraints.
- **Incumbent Solution Value = 284.2854:** This is the best solution found during the solving process, which in this case matches the final optimal value, confirming optimality.
- **Nodes processed = 1 and Remaining nodes = 0:** This shows that the solution was found at the root node without needing further branching in the branch-and-bound tree, indicating that the model is well-posed and easy to solve.
- **Iterations = 6:** Refers to the number of simplex or barrier method iterations used internally by the solver to process the relaxation of the model. A small number of iterations again confirms computational efficiency.
- **Number of solutions found = 3:** While CPLEX found 3 feasible solutions during the solving process, it correctly identified the best one as optimal.
- **Mean objective value = 252.771867:** This is the average of all feasible solutions found before reaching the optimal one. The difference between this mean and the optimal (≈ 31.5 units) reflects how much better the final solution is compared to early feasible ones.

Overall, the model was solved efficiently and accurately. The quick convergence (1 node, 6 iterations) and matching optimal and incumbent values confirm that the solution is robust and globally optimal under the current constraints and formulation. This suggests that the model is both well-structured and computationally tractable, making it suitable for practical applications in spare parts optimization.

Stress-testing feasibility and constraint compliance

The table summarizes the results of a sensitivity analysis on the spare parts inventory optimization model under two scenarios: one constrained by budget (max 12,500) and the other by storage capacity (max 850,000 cm^3). For each spare part, the number of units ordered, budget share, and storage usage are reported. This comparison highlights how changes in budget or space limitations impact order allocation and the model's effectiveness in maintaining critical spare parts coverage.

		Budget sensitive case			capacity sensitive case		
SN	D	Ordered	Buget Propotion	Inventory Propotion	Ordered	Buget Propotion	Inventory Propotion
1	ASSY-BREAKBACK LINK ASSEMBLY - BREAKBACK PN:YN27120D for PAXMAN generator	0	99.99%	77.96%	0	91.09%	99.97%
2	SPRING TORSION SPRING FOR FLAP VALVE PN:18yn27711 for PAXMAN generator	1			0		
3	LIPSEAL PN:OD32378P107 for PAXMAN generator	0			0		
4	WASHER PN:11/P441/1059/29 for PAXMAN generator	6			6		
5	GASKET PN:OD32730/11 for PAXMAN generator	99			74		
6	O RING PN:OD32270P124 for PAXMAN generator	2			1		
7	O RING PN:OD32270P125 for PAXMAN generator	1			1		
8	O' RING SEAL - SECONDARY PUMP PN:OD32271P109 for PAXMAN generator	1			1		
9	ASSY-CONDENS.DRAIN PN:YN45109 for PAXMAN generator	2			1		
#	O RING FOR COMPRESSOR CASING PN:OD32401P121 for PAXMAN generator	9			0		
#	LOCTITE GRADE 243 (50ml Bottle) PN:SD265/10 for PAXMAN generator	0			2		
#	WASHER SEALING 1.000" BSP ALUMINIUM PN:ST012635 for PAXMAN generator	0			1		
#	O RING SEAL DIA 785 MEAN PN:OD32381 for PAXMAN generator	2			2		
#	LOCTITE GRADE 225 (50ml Bottle) PN: SD265/21 for PAXMAN generator	1			1		
#	LOCTITE 542 (50ML BOTTLE) PN:SD265/38 for PAXMAN generator	1			1		
#	LOCTITE GRADE 603 (10ml Bottle) PN:SD265/23 for PAXMAN generator	1			1		
#	LOCTITE 595 RTV Clear 100ml TO SK12136 PN:ST960001R for PAXMAN generator	2			2		
#	LOCTITE 518 PN:ST960001V for PAXMAN generator	0			2		
#	CASTROL LMX GREASE PN:CO7/14 for PAXMAN generator	1			1		
#	JOINT SET OIL COOLER & THERMOSTAT PN:18YN72133 for PAXMAN generator	0			0		
#	JOINTING , PR:50RPD1185 (QA LC 24)	9			36		
#	SIGMA SEAL, PAXMAN P/N: OD32032/52, FOR DIESEL ENGINE PAXMAN 18VP185, (QA CL24)	7			9		

Table 3.5 *Optimization Results under Budget-Sensitive and Capacity-Sensitive Scenarios*

The sensitivity analysis highlights how changes in constraints budget and storage capacity affect the allocation of spare parts orders and the effectiveness of the stock optimization model.

In the budget-sensitive scenario, where financial resources are limited, the optimization model prioritizes high-criticality and cost-efficient items. This results in a total cost utilization of approximately 99.97%, ensuring nearly full exploitation of the available budget. However, the total inventory volume used reaches only 77.96%, reflecting a conservative allocation strategy focused on financial efficiency rather than full space utilization. In this case, low-cost yet critical components are favored, while some high-volume items are deprioritized to stay within budget constraints.

Conversely, in the capacity-sensitive scenario, the model is guided by a constraint on physical storage (volume), leading to a total volume utilization of 99.97%, with a slightly lower cost utilization of 91.09%. Here, space is maximized, allowing the inclusion of more bulky components. This scenario enables a broader coverage of spare parts, particularly those that are

frequently used or of medium criticality but low cost. As storage availability increases, the model allocates more orders across a wider range of components.

These observations demonstrate that tightening the budget forces the model to make more selective choices, often excluding larger or expensive items despite their criticality. On the other hand, limiting storage emphasizes compactness and cost-efficiency per volume, affecting the selection of high-volume parts even if they are affordable.

In summary, both constraints financial and spatial significantly influence the prioritization strategy. The model adapts accordingly, ensuring either cost or space is optimized, while still maintaining a coherent link between calculated criticality and ordering decisions. This validates the robustness and flexibility of the proposed multicriteria optimization approach.

3.6 Conclusion

This practical study allowed us to demonstrate the effectiveness of the multi-criteria approach in optimizing spare parts inventory management. By integrating criteria such as operational impact, supply constraints, and market availability, the criticality assessment model provided a solid foundation for prioritizing spare parts and guiding procurement decisions.

The use of Mixed Integer Linear Programming (MILP) enabled the development of optimal allocation strategies under various constraints, whether related to budget or storage capacity. The sensitivity analysis further showed how different scenarios significantly influence order distribution: budget constraints tend to reduce the coverage of critical parts by favoring lower-cost items, while storage limitations encourage better space utilization while maintaining appropriate coverage of priority items.

Ultimately, the results confirmed the coherence and robustness of the proposed model, as evidenced by the near-full use of available resources and the high satisfaction of essential inventory needs. These findings highlight the relevance and efficiency of the adopted methodology in a real industrial context.

Conclusion and perspectives

This thesis has addressed the complex and critical issue of spare parts inventory management by proposing a robust multicriteria optimization approach. By incorporating key factors such as operational impact, supply constraints, and market availability, the proposed model enables data-driven prioritization and efficient allocation of limited resources, namely budget and storage space. The integration of criticality assessment with Mixed Integer Linear Programming (MILP) ensures that the most essential parts are secured under various operational scenarios, while maintaining flexibility and scalability across different industrial contexts.

The results demonstrate significant strengths: the model is adaptable, does not rely on opaque historical failure data, and provides a clear, visualized decision-support system suitable for use in industrial environments such as energy, manufacturing, and transport. Moreover, the framework can serve dual purposes, not only in spare parts stock management but also in guiding investment and budget forecasting strategies.

Nonetheless, this work also acknowledges its limitations. The current model is static and deterministic, without accounting for uncertainties, demand variability, or multi-period planning, which are essential for real-world, long-term inventory strategies. These limitations open the door to several promising research perspectives.

Future enhancements could include incorporating stochastic or robust optimization techniques, dynamic reordering policies, and case-specific constraints such as batch sizes or item perishability. Additionally, hybridizing the model with predictive maintenance tools and machine learning could further elevate its operational relevance and predictive power.

In summary, this work lays a solid foundation for intelligent spare parts inventory management. It offers a flexible, scalable, and realistic approach to balancing cost, risk, and operational continuity—paving the way for smarter maintenance logistics in data-driven industrial systems.

References

Arnold, T., Chapman, S., & Clive, L. (2008). *Introduction to materials management* (6th ed.). Pearson Education. https://archive.org/details/introductiontoma0000arno?

Ben-Daya, M., Kumar, U., & Murthy, D. N. P. (2009). *Handbook of maintenance management and engineering*. Springer. https://doi.org/10.1007/978-1-84882-472-0

Boylan, J. E., & Syntetos, A. A. (2008). Forecasting for inventory management of service parts. In K. Kennedy & R. G. Wilson (Eds.), *Service parts management* (pp. 95–122). https://link.springer.com/chapter/10.1007/978-1-84800-011-7_20

Christopher, M. (2011). *Logistics & supply chain management* (4th ed.). Pearson Education. https://rudyct.com/supchn/Christopher%20Logistics%20and%20Supply%20Chain%20Management%204th%20txtbk.pdf

Croston, J. D. (1972). Forecasting and stock control for intermittent demands. *Operational Research Quarterly, 23*(3), 289–303. https://www.scirp.org/reference/referencespapers?referenceid=1695886

Paul Fournier , Caroline M (2019). Gestion de l'approvisionnement et des stocks, 5e édition https://www.cheneliere.ca/fr/gestion-de-lapprovisionnement-et-des-stocks-5supesup-edition-10876.html

Guitouni, A. (2001). *L'ingénierie du choix d'une procédure d'agrégation multicritère* (Doctoral dissertation). Université Laval. https://www.researchgate.net/publication/34764521_L%27ingenierie_du_choix_d%27une_procedure_d%27agregation_multicritere

Hwang, C. L., & Yoon, K. (1981). *Multiple attribute decision making: Methods and applications*. Springer-Verlag. https://link.springer.com/book/10.1007/978-3-642-48318-9

İfraz, M., Aktepe, A., Ersöz, S., & Çetinyokuş, T. (2023). Demand forecasting of spare parts with regression and machine learning methods: Application in a bus fleet. *Journal of Engineering Research, 11*(2), 100057. https://doi.org/10.1016/j.jer.2023.100057

Jameela, M. (2024). Types of inventory control methods: Detailed guide. *WareIQ*. https://wareiq.com/resources/blogs/types-of-inventory-control/

Jenkins, A. (2025). Safety stock: What it is & how to calculate. *NetSuite*. https://www.netsuite.com/portal/resource/articles/inventory-management/safety-stock.shtml

Kalev, K. (2014). Application of binomial distribution in logistics systems. *Logistics Review, 7*(1), 33–42. https://jsar.ftn.shu.bg/index.php/jsar/article/view/147/138

Koontz, H., & Weihrich, H. (2010). *Essentials of management* (8th ed.). McGraw-Hill. https://fr.scribd.com/document/675426135/Essentials-of-Management-Harold-Koontz

Mobley, R. K. (2002). *An introduction to predictive maintenance* (2nd ed.). https://www.sciencedirect.com /book/9780750675314/an-introduction-to-predictive-maintenance

Molenaers, A., Baets, H., Pintelon, L., & Waeyenbergh, G. (2012). Criticality classification of spare parts: A case study. *International Journal of Production Economics, 140*(2), 570–578. https://doi.org/10.1016/j.ijpe.2011.08.013

Monchy, H., & Vernier, P. (2012). *La maintenance industrielle* (5e éd.). Dunod. https://www.eyrolles.com/Entreprise/Livre/maintenance-9782100579679/

Pintelon, L., Pinjala, S. K., & Vereecke, A. (2006). Evaluating the effectiveness of maintenance strategies. *Journal of Quality in Maintenance Engineering, 12*(1), 7–20. https://www.emerald.com/insight/content/doi/10.1108/13552510610654501/full/html

Prestwich, S., Rossi, R., Tarim, S. A., & Hnich, B. (2014). HES: A new approach for forecasting intermittent demand. *International Journal of Production Research, 52*(22), 6654–6671. https://www.researchgate.net/publication/251232624_Forecasting_Intermittent_Demand_by_Hyperbolic-Exponential_Smoothing?

Roy, B. (1985). *Méthodologie multicritère d'aide à la décision*. Economica. https://www.persee.fr/doc/pomap_0758-1726_1986_num_4_3_1906_t1_0138_0000_1

Roy, B., & Bouyssou, D. (1993). *Aide multicritère à la décision : Méthodes et cas*. Economica.

Smith, C. (2011). Normal distribution uses in inventory forecasting. *Chron*. https://smallbusiness.chron.com/normal-distribution-uses-inventory-forecasting-37419.html

Sonal V. Kumbhar & T. B. Dhavale (2016) *Inventory Control using ABC and VED Analysis — construction materials case study*; montre la réduction des coûts de stock via la matrice ABC-VED https://pubmed.ncbi.nlm.nih.gov/27408040/

Syntetos, A. A., & Boylan, J. E. (2005). The accuracy of intermittent demand estimates. *International Journal of Forecasting, 21*(2), 303–314. https://www.sciencedirect.com/science/article/abs/pii/S0169207004000792

Teunter, R. H., & Haneveld, W. K. (2008). Inventory control with multiple service levels: Optimization formulations. *European Journal of Operational Research, 191*(2), 365–377. https://repub.eur.nl/pub/73148/

Trisna, T., Marimin, M., Arkeman, Y., & Sunarti, T. C. (2018). Multi-objective optimization for supply chain management problem: A literature review. *Decision Science Letters, 5*(2), 283–316. https://www.researchgate.net/publication/288857216_Multi-objective_optimization_for_supply_chain_management_problem_A_literature_review

Turrini, L., & Meissner, J. (2019). Spare parts inventory management: New evidence from distribution fitting. *European Journal of Operational Research, 273*(1), 118–130. https://www.sciencedirect.com/science/article/pii/S037722171730886X