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Masters in strategic and information
system Management

Predictive Maintenance for Optimizing Assets Management in Oil & Gas Field

Case: Halliburton Algeria

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Abstract

In asset-intensive industries like oil and gas, maintenance strategies are central to operational performance. This thesis investigates the feasibility of implementing predictive maintenance (PdM) at Halliburton Algeria, using a qualitative case study approach. The research is structured into three main chapters: a combined literature review and theoretical framework; a methodological framework including a company overview; and an empirical study comprising findings, discussion, and recommendations.

The study explores the evolution from traditional maintenance to data-driven strategies enabled by IoT and AI. It reveals that although Halliburton uses preventive and corrective methods supported by SAP, it lacks the digital infrastructure, organizational readiness, and workforce training required for PdM. The thesis introduces a PdM Readiness Framework based on strategic, technical, and human dimensions, offering practical steps toward phased adoption.

This work contributes to understanding the real-world barriers to PdM and emphasizes the need for a holistic transformation across systems, skills, and strategy in brownfield environments.

Keywords: Predictive maintenance, Halliburton, asset management, IoT, AI, SAP, digital transformation.

Résumé

Dans les industries à forte intensité d'actifs, comme le secteur pétrolier et gazier, les stratégies de maintenance sont essentielles à la performance opérationnelle. Ce mémoire examine la faisabilité de la mise en œuvre de la maintenance prédictive (PdM) chez Halliburton Algérie, à travers une étude de cas qualitative. Le travail est structuré en trois chapitres principaux : une revue de littérature accompagnée d'un cadre théorique, un cadre méthodologique incluant la présentation de l'entreprise, et une étude empirique comprenant les résultats, la discussion et les recommandations.

L'étude explore l'évolution des pratiques traditionnelles de maintenance vers des approches intelligentes et basées sur les données, rendues possibles grâce à l'IoT et à l'intelligence artificielle. Les résultats montrent que, bien qu'Halliburton applique des méthodes préventives et correctives appuyées par le système SAP, elle ne dispose pas de l'infrastructure numérique, de la préparation organisationnelle ni des compétences nécessaires pour adopter la PdM. Le mémoire propose un cadre d'évaluation de la maturité PdM, reposant sur des dimensions stratégiques, techniques et humaines, offrant ainsi des étapes concrètes pour une adoption progressive.

Ce travail contribue à mieux comprendre les obstacles réels à la mise en œuvre de la PdM et souligne la nécessité d'une transformation globale des systèmes, des compétences et de la stratégie dans les environnements à équipement ancien.

Mots-clés : Maintenance prédictive, Halliburton, gestion des actifs, IoT, IA, SAP, transformation numérique.

الملخص

في الصناعات المعتمدة على الأصول مثل قطاع النفط والغاز، تُعد استراتيجيات الصيانة ضرورية لتحقيق الأداء التشغيلي. يتناول هذا البحث إمكانية تطبيق **الصيانة التنبؤية في** شركة هاليبرتون الجزائر، من خلال دراسة حالة نوعية. ينقسم البحث إلى ثلاثة فصول رئيسية: مراجعة أدبية مع إطار نظري، إطار منهجي يتضمن عرضًا للشركة، ودراسة ميدانية تحتوي على النتائج والتحليل والمناقشة والتوصيات.

تتناول الدراسة التحول من ممارسات الصيانة التقليدية إلى استراتيجيات ذكية تعتمد على البيانات، بدعم من إنترنت الأشياء والذكاء الاصطناعي. وتظهر النتائج أن هاليبرتون تستخدم حالياً صيانة وقائية وتصحيحية تعتمد على نظام **SAP**، لكنها تفتقر للبنية التحتية الرقمية، والجاهزية التنظيمية، وتدريب الموظفين الضروري لتطبيق الصيانة التنبؤية. يقترح البحث **إطار جاهزية لتنفيذPdM** ، يستند إلى محاور استراتيجية وتقنية وبشرية، ويقدم خطوات عملية للتطبيق التدريجي.

يساهم هذا العمل في فهم الحواجز الواقعية التي تعيق تطبيق**PdM** ، ويؤكد على ضرورة التحول الشامل على مستوى الأنظمة والمهارات والاستراتيجية، خصوصًا في البيئات الصناعية ذات المعدات القديمة.

الكلمات المفتاحية :الصيانة التنبؤية، هاليبرتون، إدارة الأصول، إنترنت الأشياء، الذكاء الاصطناعي، **SAP**، التحول الرقمي.

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This thesis is not just the result of academic work, it is the fruit of love, patience, friendship, and faith. From the depths of my heart, thank you all.

RAHMANI Taha

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To my friends, I wouldn’t trade the moments we shared together for all the treasures in the world.

LAIMECHE Mohamed Lotfi

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List of Abbreviations

AI: Artificial Intelligence

AM: Asset Management

APA: Advanced Protection Analytics

AR: Augmented Reality

CBM: Condition-Based Maintenance

CMMS: Computerized Maintenance Management

CSV: Comma-Separated Values

DCS: Distributed Control System

ERP: Enterprise Resource Planning

FMEA : Failure Mode and Effects Analysis

HMI: Human-Machine Interface

HTML : HyperText Markup Language

IEM : Internal Equipment Maintenance

IoT: Internet of Things

IT : Information Technology

JSA : Job Safety Assessment

KPI: Key Performance Indicator

ML: Machine Learning

PdM: Predictive Maintenance

PSL: Product Service Line

ROI: Return on Investment

RUL: Remaining Useful Life

SAP: Systems, Applications and Products in Data Processing

SAX: Symbolic Aggregate approXimation

SCADA : Supervisory Control and Data Acquisition

SQL : Structured Query Language

SWOT: Strengths, Weaknesses, Opportunities, Threats

XML : eXtensible Markup Language (Langage de Balisage Extensible)

GENERAL INTRODUCTION

1. Research background

The oil and gas industry are under constant pressure to optimize operations, reduce costs, and improve safety and environmental outcomes. Within this context, the efficiency and reliability of equipment play a critical role in ensuring continuous production and minimizing unplanned downtime. Traditional maintenance strategies such as reactive and preventive approaches, have long been the standard in the sector. However, these methods are increasingly seen as insufficient in meeting the demands of modern industrial operations, particularly in remote and harsh environments.

Predictive maintenance (PdM) has emerged as a promising alternative that leverages data analytics, artificial intelligence (AI), and Internet of Things (IoT) technologies to anticipate equipment failures before they occur. While the potential benefits of PdM are widely recognized such as reduced downtime, optimized asset utilization, and lower maintenance costs, many companies are still at an early stage of exploring or adopting these technologies. This thesis focuses on Halliburton's operations in South Algeria, a region characterized by environmental extremes and logistical challenges. As of now, predictive maintenance has not been implemented in these operations, making this study an opportunity to investigate the current maintenance practices, identify technological and organizational gaps, and evaluate the feasibility of adopting a PdM strategy. By doing so, the research aims to develop a tailored framework that can guide Halliburton and similar organizations, toward a more proactive and data-driven approach to asset management.

The study adopts a qualitative case study methodology, drawing insights from interviews with operational and technical staff to understand both the potential and the limitations of implementing PdM in such a setting. The outcomes of this research are intended to support strategic decision-making and contribute to the broader discourse on digital transformation in the energy sector.

2. Research Objectives

The primary aim of this research is to assess the potential for implementing predictive maintenance PdM within Halliburton's operations in South Algeria, where such a system is not currently in place. Rather than evaluating an existing infrastructure, the study seeks to understand the current maintenance landscape, explore the feasibility of introducing data-driven approaches, and develop a practical framework tailored to the company's operational context.

To achieve this, the research is guided by the following specific objectives:

1. **Analyze Existing Maintenance Practices:** Examine the current maintenance strategies used at Halliburton and assess their strengths, limitations, and operational impact.
2. **Identify Technological and Organizational Gaps:** Explore the readiness of Halliburton's infrastructure, workforce, and systems for adopting predictive maintenance technologies such as AI, IoT, and machine learning.
3. **Assess Opportunities and Barriers:** Investigate the perceived benefits and potential challenges technical, logistical, and managerial, associated with implementing PdM in the South Algerian oilfield context.
4. **Develop a Strategic Implementation Framework:** Propose a structured, context-sensitive framework that outlines the steps and conditions necessary for successfully integrating predictive maintenance into Halliburton's maintenance operations.

3. Research questions:

In light of the research objectives, this study seeks to answer the following key questions:

1. **What maintenance strategies are currently used at Halliburton in South Algeria, and what are their limitations?**
   This question explores the present state of asset maintenance in the field and helps establish a baseline for assessing potential improvements.
2. **What technological and organizational factors affect Halliburton's readiness to implement predictive maintenance?**
   This includes evaluating data availability, existing IT systems, staff expertise, and openness to innovation.
3. **What are the main opportunities and challenges in adopting predictive maintenance in this specific context?**
   These addresses both internal and external barriers, as well as the anticipated benefits from the perspective of key stakeholders.
4. **How can a practical and effective framework be developed to support the implementation of predictive maintenance at Halliburton?**

The final question aims to synthesize findings into actionable guidance that fits the realities of oilfield operations in South Algeria.

4. Significance of the Study

This research holds importance both in academic and practical terms, especially as the oil and gas industry continues to explore digital solutions to improve efficiency and asset reliability.

From an **academic perspective,** the study contributes to a growing body of literature on predictive maintenance and digital transformation in industrial settings. Unlike many studies that focus on companies already using PdM, this research investigates a context where such technologies have not yet been implemented. By doing so, it highlights the early-stage considerations that often go unexamined such as organizational readiness, environmental constraints, and the practical steps needed for adoption. The case of Halliburton in South Algeria offers a valuable real-world example of how theory can meet operational reality.

On an **industrial level**, the findings provide actionable insights for decision-makers seeking to modernize maintenance strategies. For companies like Halliburton, operating in complex and remote environments, adopting a data-driven maintenance model could unlock substantial value, but only if tailored to their specific context. The framework proposed in this study aims to offer a practical roadmap that addresses both technical and managerial needs, helping organizations plan and execute a smooth transition to predictive maintenance.

In addition, the research carries **strategic implications**. As the energy sector faces growing pressure to optimize costs, reduce downtime, and enhance sustainability, smarter maintenance practices will become increasingly critical. By identifying opportunities and constraints at the ground level, this study equips companies with the foresight needed to invest in future-ready systems that support long-term operational resilience.

5. Structure of the Thesis

This thesis is structured into three main chapters, each divided into two sections, to provide a coherent and progressive exploration of predictive maintenance (PdM) and its potential implementation at Halliburton Algeria. The structure moves from theoretical foundations to methodological design and finally to empirical investigation and applied recommendations

Chapter 1: Literature Review and Theoretical Framework

- **Section 1: Literature Review**

  This section provides a critical analysis of existing research on maintenance strategies in the oil and gas industry, with an emphasis on the evolution toward predictive maintenance. It explores the integration of digital technologies such as IoT, artificial intelligence, and machine learning in asset management, while also identifying research gaps and debates relevant to the study.

- **Section 1: Theoretical Framework**

  This section outlines the conceptual foundations guiding the research. It covers strategic asset management, maintenance theory, and the enabling role of digital infrastructure. The framework serves as the analytical lens for interpreting the case study findings.

Chater 2: Methodological Framework

- **Section 1: Research Methodology**

  This section details the qualitative case study approach used in the research. It discusses the research design, data collection techniques (e.g., interviews, internal documentation), participant selection, and data analysis methods. Ethical considerations are also addressed.

- **Section 2: Case Study Context – Halliburton Algeria**

  This section presents the organizational and operational context of Halliburton Algeria, the host company for the case study. It outlines its system infrastructure, and organizational structure to contextualize the subsequent empirical analysis.

Chapter 3: Empirical Study

- **Section 1: Findings and Analysis**

  This section presents the main empirical findings drawn from interviews and document analysis. It explores Halliburton Algeria's current maintenance practices, technological infrastructure, data usage, and staff readiness in relation to predictive maintenance. The analysis is structured based on the key theoretical and literature-based themes.

- **Section 2: Discussion and Recommendations**

  This section compares the empirical findings with insights from the academic literature, highlighting similarities and deviations. It also presents a tailored set of recommendations, including a Predictive Maintenance Implementation Readiness 3Framework, and concludes with actionable strategies to support PdM deployment in similar operational contexts

CHAPTER 1: LITERATURE REVIEW AND THEORETICAL FRAMEWORK

Section 1: Literature Review

This section examines the academic discourse surrounding predictive maintenance (PdM) within industrial asset management, with a particular focus on the oil and gas sector. It traces the evolution of maintenance strategies and reviews technological advancements such as IoT, AI, and machine learning. The aim is to identify critical gaps and practical challenges that frame the need for this study.

1.1. Introduction

The literature on predictive maintenance in asset management, particularly within the oil and gas sector, has undergone significant developments and advancements in recent years. This evolution reflects a growing recognition of the immense potential that predictive maintenance holds to enhance operational efficiency and substantially reduce overall costs across various operations. In the year 2020, researchers Tan Jing Yu and Law Wing-Keung delved into the economic implications of implementing predictive maintenance strategies, highlighting the fact that many companies within the industry have yet to adopt this proactive approach. This hesitation is largely attributed to the substantial costs associated with the initial implementation of such advanced maintenance systems. Their comprehensive study emphasizes the critical need for a robust financial model that can effectively justify the transition from traditional corrective and preventive maintenance strategies. These conventional approaches often lead to unplanned downtimes and significant revenue losses, further underscoring the importance of understanding the economic benefits that predictive maintenance can bring to organizations striving for improved efficiency and sustainability in their operations.(Jing Yu & Nanyang Business School Assoc Law Wing-Keung, 2020).

Building on this foundation, (Bouabdallaoui et al., 2021) presented a machine learning-based approach to predictive maintenance in building facilities, underscoring the importance of condition monitoring data in predicting potential failures. They noted that while predictive maintenance can significantly reduce unplanned failures and associated costs, challenges remain in connecting physical assets and developing effective predictive algorithms. This highlights the necessity for further advancements in data extraction and analysis techniques to fully realize the benefits of predictive maintenance (Bouabdallaoui et al., 2021).

Afridi, Ahmad, and Hassan (Afridi et al., 2022) expanded the discussion by reviewing artificial intelligence techniques in prognostic maintenance systems. Their work underscores the role of complex data analytics and machine learning in enhancing the efficiency of predictive maintenance, while also addressing challenges related to data availability, quality, and interpretability. This review indicates that despite the potential of AI-driven approaches, significant hurdles must be overcome to implement robust predictive maintenance systems effectively (Afridi et al., 2022).

(Kane et al., 2022) focused on the application of machine learning to predictive maintenance, emphasizing the need for data collection over time to identify patterns that can predict equipment failures. They argued that traditional scheduled maintenance often leads to increased downtime and costs, advocating for smart systems that employ predictive maintenance strategies to optimize equipment availability and reduce operational disruptions (Kane et al., 2022).

Most recently, (Latrach, 2023) examined the application of deep learning techniques for predictive maintenance in oilfield equipment. His research highlights the evolution of maintenance practices from unplanned corrective actions to more strategic predictive approaches, which can foresee and mitigate equipment failures. This transition is crucial in maintaining operational efficiency in the oil and gas industry, where equipment reliability is paramount. (Latrach, 2023).

Lastly, (Molęda et al., 2023) conducted a systematic review of machine learning methods for predictive maintenance in the power industry, identifying current trends, challenges, and opportunities. Their findings reinforce the importance of data-driven approaches in enhancing maintenance practices, particularly in complex industrial environments.(Molęda et al., 2023).

Collectively, these studies reveal a clear trajectory towards the adoption of predictive maintenance practices, driven by advancements in technology and data analytics. However, they also underscore the challenges that remain, particularly in the oil and gas sector, where the implementation of such systems is critical for optimizing asset management and ensuring operational continuity.

1.2. Critical Analysis

The article "An Economic Perspective on Predictive Maintenance of Filtration Units" by Tan Jing Yu and Law Wing-Keung provides a comprehensive examination of the economic implications of implementing predictive maintenance (PdM) in the context of filtration units, which is particularly relevant for asset management in the oil and gas sector. The authors highlight a critical gap in the current practices of maintenance, noting that many companies have yet to adopt predictive maintenance strategies. This is particularly concerning given that maintenance operations can account for a substantial portion of overall operational expenses, ranging from 15% to 70%. (Jing Yu & Nanyang Business School Assoc Law Wing-Keung, 2020).

The article effectively underscores the necessity for a robust economic justification for transitioning to a predictive maintenance program. The authors present a financial model designed to analyze the costs and benefits associated with such a transition. This model is crucial as it addresses the significant upfront investment required for implementing PdM technologies, which often includes the installation of sensors and data analytics systems. By providing a detailed economic framework, the authors facilitate a better understanding of how predictive maintenance can potentially reduce the long-term operational costs associated with unplanned downtimes and maintenance inefficiencies.

Moreover, the article contrasts the traditional maintenance strategies, corrective and preventive maintenance, with predictive maintenance. The authors argue that while corrective and preventive maintenance are widely used, they are inherently reactive and often lack the foresight necessary to prevent equipment failures. This lack of proactive measures can lead to unanticipated breakdowns, resulting in production halts that can adversely affect revenue streams (Jing Yu & Nanyang Business School Assoc Law Wing-Keung, 2020). In contrast, predictive maintenance leverages advanced sensor technologies to continuously monitor the condition of equipment, allowing for timely interventions before failures occur. This proactive approach not only enhances operational efficiency but also aligns with the growing need for industries to optimize asset management strategies.

The article titled "Predictive Maintenance in Building Facilities: A Machine Learning-Based Approach" by Yassine Bouabdallaoui et al. presents a comprehensive exploration of predictive maintenance, emphasizing its relevance in enhancing asset management through condition monitoring data. The authors articulate that predictive maintenance is fundamentally about forecasting the future health of machines, which is crucial for preemptively addressing potential failures in various components. This insight is particularly pertinent to sectors such as oil and gas, where the reliability of machinery is critical for operational efficiency and safety.

A significant strength of the article lies in its detailed examination of the benefits associated with predictive maintenance. The authors highlight how this approach can lead to reduced unplanned failures and lower maintenance costs, which are vital outcomes for asset management in the oil and gas industry. By leveraging predictive maintenance, organizations can not only enhance operational efficiency but also improve safety and comfort for personnel, which is an essential consideration in high-stakes environments like oil and gas fields.

However, the article does not shy away from discussing the challenges inherent in implementing a predictive maintenance framework. The authors identify key obstacles such as the necessity for effective connectivity between physical assets, the extraction of valuable data from these assets, and the development of accurate predictive algorithms. These challenges are particularly relevant in the context of the oil and gas sector, where the complexity of equipment and the harsh operational environments can hinder the implementation of such advanced maintenance strategies.

Additionally, the article could benefit from a deeper exploration of specific case studies or empirical data that illustrate the successful application of predictive maintenance in the oil and gas industry. While the theoretical framework is robust, practical examples could provide readers with a clearer understanding of how these concepts translate into real-world applications.

The article "Artificial Intelligence Based Prognostic Maintenance of Renewable Energy Systems: A Review of Techniques, Challenges, and Future Research Directions" by Yasir Saleem Afridi, Kashif Ahmad, and Laiq Hassan provides a comprehensive overview of the advancements in prognostic maintenance systems, particularly through the lens of artificial intelligence (AI) and machine learning (ML) techniques. The authors emphasize the critical role of effective Operation Maintenance (OM) systems in ensuring uninterrupted power supply and minimizing equipment downtime, which is particularly relevant in the context of asset management in the oil and gas sector.

One of the key insights from the article is the emphasis on the development of robust prognostic maintenance frameworks that can proactively identify potential faults before they manifest. This proactive approach is essential for optimizing asset management, as it allows for timely interventions that can prevent costly downtimes and enhance the overall reliability of operations. The authors discuss various algorithms and techniques that have been introduced to improve the efficiency of these systems, highlighting the importance of complex data analytics in achieving these goals.

The article also addresses several challenges associated with implementing prognostic maintenance systems. Data-related issues, such as the availability and quality of data, pose significant hurdles. The authors note that effective feature engineering is crucial for the success of these systems, as it directly impacts the interpretability and accuracy of the predictive models. Furthermore, the discussion on security issues is particularly pertinent, as the reliance on data-driven approaches necessitates robust measures to protect sensitive information.

(Afridi et al., 2022) also provide an overview of commonly used publicly available datasets in the domain, which can serve as valuable resources for researchers and practitioners looking to develop and refine their predictive maintenance models. The identification of key future research directions is another significant contribution of this article, as it encourages ongoing exploration and innovation in the field.

The article titled "Artificial intelligence-based human-centric decision support framework: an application to predictive maintenance in asset management under pandemic environments" by Chen et al. presents a comprehensive examination of the role of predictive maintenance in asset management, particularly within the context of complex systems. The authors emphasize the critical nature of condition monitoring and predictive maintenance, highlighting their significance for businesses striving for operational efficiency and effectiveness.

The study underscores the evolution of predictive maintenance approaches, particularly through the integration of artificial intelligence (AI) and data analytics. The authors argue that condition monitoring and fault diagnostics are essential for failure detection and prediction, which are vital for maintaining the operational integrity of assets in the oil and gas sector. By leveraging data extracted from machines and processes, organizations can enhance their diagnostic and prognostic capabilities, thus minimizing downtime and optimizing asset performance.

(Chen et al., 2021) reference various studies that contribute to the understanding of predictive maintenance frameworks. For instance, Bengtsson's work on feature classification within condition-based maintenance systems illustrates the importance of creating a case library with previously classified measurements, which can aid in more accurate failure prediction. Similarly, Vachtsevanos and Wang's development of a condition monitoring framework highlights the necessity of human intervention, suggesting that domain experts play a crucial role in interpreting data and making informed decisions based on diagnostic results.

Moreover, Traini's proposed predictive maintenance framework for milling operations serves as a pertinent example of how predictive maintenance can prevent unexpected breakdowns and enhance human-machine interaction. This aspect is particularly relevant in the oil and gas industry, where equipment reliability is paramount for safety and productivity.

The article effectively captures the multi-faceted nature of predictive maintenance, particularly in the context of the ongoing challenges posed by pandemic environments. The authors advocate for a human-centric approach, suggesting that while AI and data-driven models are invaluable, the expertise of human operators remains irreplaceable in the decision-making process.

The article "Predictive Maintenance using Machine Learning" by Kane et al. provides a comprehensive examination of how predictive maintenance, driven by machine learning techniques, can significantly enhance asset management in the oil and gas sector. The authors underscore the critical importance of monitoring equipment states through data collection over time, which enables the identification of correlations that can forecast potential failures. This approach is particularly pertinent in industries like oil and gas, where equipment reliability is essential for operational efficiency.

One of the key insights from the article is the contrast between traditional scheduled maintenance and predictive maintenance. The authors argue that conventional maintenance practices often lead to unexpected downtimes and increased costs, as they rely on fixed intervals rather than the actual condition of the equipment. This is especially relevant in the oil and gas industry, where unplanned downtimes can result in significant financial losses and reduced productivity, estimated between 5% to 20%. By adopting predictive maintenance strategies, organizations can mitigate these risks by anticipating failures and scheduling maintenance proactively, thereby enhancing equipment availability and reducing downtime costs.

The authors also highlight the application of machine learning techniques in analyzing historical data to predict potential failures. This predictive capability allows for more informed decision-making regarding maintenance schedules, which can be tailored to the specific needs of the equipment rather than adhering to arbitrary timelines. The development of a web application that processes machine sensor data to forecast downtimes exemplifies a practical implementation of these concepts, offering benefits not only to machine operators but also to managers and stakeholders who seek to optimize asset management.

Moreover, the article effectively illustrates the broader implications of predictive maintenance beyond mere cost savings. By improving equipment reliability, organizations in the oil and gas sector can enhance overall productivity and operational resilience. The authors emphasize that equipment deterioration is a critical concern, as it can lead to shutdowns or unavailability, thus reinforcing the necessity for advanced maintenance strategies.

In the article "Application of Deep Learning for Predictive Maintenance of Oilfield Equipment," Abdeldjalil Latrach explores the critical role of predictive maintenance in the oil and gas industry, particularly focusing on the degradation of equipment over time. The author emphasizes that all machinery is susceptible to wear and tear, which can culminate in failures that adversely affect economic viability, human safety, and environmental integrity. This insight is essential for stakeholders in the oil and gas sector, as it underscores the necessity of proactive measures to ensure operational reliability.

Latrach delineates the evolution of maintenance strategies, highlighting the transition from unplanned corrective maintenance, reactive measures taken after equipment failure-to preventive maintenance, which aims to mitigate the probability of such failures. This shift is particularly relevant in high-stakes environments like oilfields, where equipment reliability is paramount. The author argues that leveraging advanced technologies, such as deep learning, can significantly enhance predictive maintenance efforts. By employing data-driven approaches, organizations can better anticipate equipment failures before they occur, thereby minimizing downtime and associated costs.

The article critically evaluates the methodologies involved in implementing deep learning for predictive maintenance. Latrach discusses the data requirements and the importance of historical performance data in training predictive models. This aspect is crucial, as the quality and quantity of data directly influence the accuracy of predictions. Moreover, the author addresses potential challenges, such as the integration of deep learning systems into existing maintenance frameworks and the need for skilled personnel to interpret and act upon the insights generated.

The article titled "From Corrective to Predictive Maintenance—A Review of Maintenance Approaches for the Power Industry" by Molęda et al. provides a comprehensive examination of the transition from traditional corrective maintenance strategies to more advanced predictive maintenance approaches, particularly in the context of the power industry. The authors conduct a systematic literature review that highlights the application of machine learning methods to predictive maintenance, which is crucial for optimizing asset management in sectors such as oil and gas.

One of the key insights from the article is the emphasis on data-driven methods for predictive maintenance of industrial equipment. The authors explore various machine learning techniques that have been employed to enhance predictive maintenance frameworks, specifically focusing on pump systems and thermal power plants. This is particularly relevant for the oil and gas industry, where the reliability of pump systems is critical for operational efficiency and safety. The review indicates that predictive maintenance can significantly reduce downtime and maintenance costs by anticipating failures before they occur, thereby allowing for timely interventions.

The article also addresses the state-of-the-art in predictive maintenance, identifying current trends and challenges faced by industries in implementing these advanced methodologies. For instance, the authors discuss the obstacles related to data quality and availability, which are essential for training effective predictive models. This is a critical point, as the oil and gas sector often deal with large volumes of data generated from various sensors and equipment, necessitating robust data management and analysis strategies to leverage predictive maintenance effectively.

Furthermore, the review highlights the opportunities presented by deep learning models for machinery fault detection and diagnosis. These models have shown promise in improving the accuracy of predictive maintenance predictions, which can lead to better decision-making and resource allocation. However, the authors caution that while deep learning offers significant potential, there are still challenges to be addressed, such as the need for extensive labeled datasets and the complexity of model interpretability.

1.3. Conclusion

The literature on predictive maintenance in the oil and gas sector illustrates a significant shift towards leveraging advanced technologies and data analytics to optimize asset management. The studies reviewed reveal a clear consensus on the advantages of predictive maintenance, including reduced downtime, improved equipment reliability, and enhanced operational efficiency. However, they also highlight persistent challenges that must be addressed for successful implementation.

(Jing Yu & Nanyang Business School Assoc Law Wing-Keung, 2020) emphasize the economic justification needed for transitioning from traditional maintenance strategies to predictive maintenance. Their financial model aims to clarify the long-term benefits of predictive maintenance, particularly in reducing unplanned downtimes that can severely impact revenue. This foundational work sets the stage for subsequent studies that explore the techical aspects of predictive maintenance.

(Bouabdallaoui et al., 2021) discuss the importance of condition monitoring data in predictive maintenance, noting the potential for machine learning to predict failures. They identify challenges in developing effective predictive algorithms and integrating physical assets with data systems. This highlights the need for advancements in data extraction and analysis methods, which are echoed in the work of (Afridi et al., 2022). They review artificial intelligence techniques in prognostic maintenance systems, underscoring the significance of data quality and availability in enhancing predictive maintenance efficiency.

(Kane et al., 2022a) further this discussion by advocating for the adoption of machine learning techniques to identify patterns that predict equipment failures. They critique traditional maintenance schedules, arguing for a shift towards predictive strategies that can enhance equipment availability and minimize operational disruptions. (Latrach, 2023) extends this narrative by examining the application of deep learning techniques specifically in oilfield equipment, emphasizing the transition from reactive to proactive maintenance strategies.

Lastly, (Molęda et al., 2023a) provide a systematic review of machine learning methods for predictive maintenance, highlighting current trends and challenges while reinforcing the necessity of data-driven approaches in optimizing maintenance practices. Their findings indicate that while deep learning models hold promise for improving predictive maintenance accuracy, challenges related to data quality and model interpretability remain.

In conclusion, the reviewed literature collectively underscores the transformative potential of predictive maintenance in the oil and gas sector. The integration of advanced technologies such as machine learning and deep learning can significantly enhance asset management strategies, leading to improved operational efficiency and reduced costs. However, for these benefits to be fully realized, the industry must address challenges related to data quality, algorithm development, and the economic justification of predictive maintenance initiatives.

Section 2: Theoretical Framework

This section presents the conceptual tools used to guide the research analysis. Drawing on theories of strategic asset management and digital transformation, it explores how PdM can be integrated into broader maintenance strategies. It also reviews models of data collection and infrastructure readiness relevant to digital implementation.

2.1. Understanding Asset Management

Asset management represents a crucial managerial activity that exists in all organizations, irrespective of their size or industry focus. This comprehensive definition highlights the two key components encompassed within the term Asset Management. The initial segment of this definition focuses on the Art and Science involved in making well-informed decisions concerning each asset. This includes but is not limited to determining the most suitable career path for the asset, clearly defining its purpose, creating effective structures, wisely investing funds, and managing the dynamics associated with Value Delivery. This encompasses ongoing responsibilities such as Upgrades, Refurbishments, and ultimately the Decommissioning and Disposal processes of assets. Each of these pivotal decisions will inevitably be influenced by the timing of evaluation, for example, identifying when it is appropriate to dispose of an asset. The second segment of the definition underscores the continuous management of assets throughout the life cycle of the organization, emphasizing that the objective is to ensure that the delivery of value can be consistently realized and maximized, thereby supporting the organization's broader goals and objectives.

Physical asset management is an integrated and holistic management approach of the hard assets of a company, which acknowledges the critical need for and significance of an integrated and holistic management approach revolving around the hard assets. This approach concentrates on effectively achieving essential business goals through the optimization of the management processes involving an organization’s assets. These essential components are quite similar to those that are found in any standard management framework; however, they also include specific elements that pertain to the Asset Lifecycle and Physical Asset Management domains. These domains are unique and central to the focus of this discussion, representing the foundational aspects that guide the strategic handling of physical assets throughout their entire lifecycle. This enhances sustainability and operational efficiency across the organization’s activities.

A maintenance action is defined as any activity that is planned to take place within a specified time frame, regardless of the current state of the machines and the operating conditions that may or may not necessitate such maintenance intervention. In this context, a maintenance action may encompass a range of activities including, but not limited to, cleaning processes, meticulous calibration, the replacement of particular spare parts, the changing of oil, and other similar tasks. Maintenance intervention policies that fit within this category are typically put into practice during the operation of machines, functioning as preventive actions to avert potential breakdowns or failures. However, this proactive approach to maintenance can have significant financial implications, potentially resulting in extremely high costs due to the excessive frequency of maintenance actions being performed. Such costs may not be justifiable when weighed against the potential benefits of minimizing the depreciation of valuable assets. Consequently, effective asset management becomes crucial and requires careful consideration and improvement to better align maintenance practices with actual needs. It has been observed through various studies that when maintenance companies undertake actions that diverge from their established policies, it often leads to a decline in profitability. Nevertheless, under certain suitable conditions, maintaining the status quo could potentially safeguard net profits, positively impacting the bottom line or, in contrast, could also lead to negative financial outcomes over extended periods.

2.2. The Oil and Gas Industry Landscape

The oil and gas industry are of great significance to the global economy, exerting influence on nearly every aspect of daily life, even in the face of the ongoing transition towards sustainable energy sources. The oil and gas sector, in conjunction with the broader field of petrochemicals, stands as the most crucial industry on a global scale. The operations within the oil industry encompass a wide range of activities, starting from the extraction of raw materials all the way to their processing and eventual sale of various products. This sector includes numerous diverse areas of management and production, which can be categorized into different segments such as oil extraction, refining processes, gas compression, and transportation, as well as the production and distribution of petrochemicals. Moreover, the complex transportation networks for oil and gas products play an essential role within this industry. In the oil and gas sector, a multitude of systems and devices are essential for the effective management and synchronization of operations, which highlight its intricate nature. Consequently, the oil and gas industry are characterized as a multifaceted and multitasking domain that holds immense economic importance in the modern world. (Volkodavova & Tomazova, 2019).

In today's oil and gas industry, the management of equipment maintenance has become an increasingly critical issue and priority challenge that organizations must address. Recent approximate calculations reveal that as much as 90% of the overall production costs incurred by oil and gas companies can be directly linked to the management processes implemented during the production stage. Ineffective management of the assets owned by oil and gas companies often results in prolonged idle time, periodic losses in production due to unexpected equipment failures, and ultimately drives the need for substantial increases in the budgets allocated to developing and managing a comprehensive technical asset portfolio. Furthermore, many existing management systems utilized by these companies are struggling to effectively collect and leverage information regarding the current operational state of their equipment. Commonly, for a significant number of oil and gas companies, the range of controlled indicators tends to be severely limited, focusing primarily on metrics such as the level of oil and gas production, the registration of equipment failures, and instances of non-conformance with established quality standards in both product output and resource utilization. As a direct result of this narrow scope, and compounded by the prevalence of obsolete equipment, the lack of high-quality, timely preventive maintenance and repairs, along with inefficient current maintenance management practices, the overall durability and lifespan of the equipment is drastically diminished. This leads to notable production losses, alongside an escalating proportion of the total costs that are attributed specifically to maintenance management activities. Consequently, it is paramount for oil and gas companies to reevaluate their current practices and invest in improved systems and processes that ensure more effective oversight, maintenance, and management of their extensive equipment portfolios. This strategic shift is essential for optimizing efficiency and sustaining profitability in a highly competitive market landscape. (Chin et al., 2020).

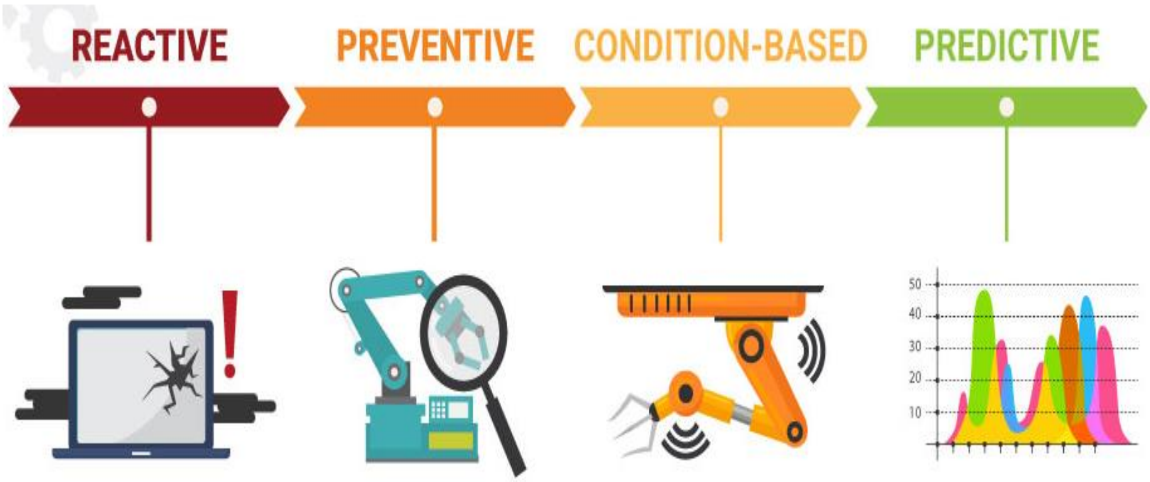
2.3. Introduction to Predictive Maintenance

Predictive maintenance has been an integral part of the manufacturing industry for an extended period. Its diverse applications encompass various types of machinery, including but not limited to rolling mills, electric motors, and hydraulic presses. These systems are monitored for a range of variables, including vibration, temperature, pressure, and the quantity of diesel. Extensive research has been conducted to understand and apply these monitoring techniques effectively. Data is systematically gathered over a defined time frame to enable continuous observation of the machine's operational status. The primary aim is to identify correlations and patterns within this data, which can subsequently inform users about potential failures, allowing for predictive measures that can prevent issues before they escalate. This intelligence-driven approach to maintenance is significantly more effective than traditional scheduled maintenance, which may not always align with actual machine performance. On one hand, predictive maintenance minimizes the risks associated with unexpected downtime that can occur due to the failure of machine components, which are often unforeseen and require extended repair time after they occur. On the other hand, it plays a crucial role in eliminating unnecessary inspections of machinery that remain in sound operating condition and reduces the frequency and costs associated with the premature replacement of components that are still functional. In recent years, the use of smart machines has rapidly increased within the manufacturing sector, integrating advanced technologies and sensors that facilitate this predictive approach. Despite this advancement, it is worth noting that many machines are still operated without any structured maintenance plan in place. Consequently, the existing fault detection and diagnosis techniques predominantly rely on the experience and intuition of human operators. Often, the acceptable limits on operational parameters, such as temperature and vibration intensity levels, are established based on the subjective experiences of these operators. The operators typically prepare an emergency response plan, ready to implement it promptly when an alarm is triggered, dealing with each issue as it arises. This reliance on human judgment highlights a gap in the proactive identification of potential failures, emphasizing the continuing need for the advancement of predictive maintenance strategies in modern manufacturing environments. (Aremu et al., 2018; Kane et al., 2022).

There are two approaches to maintenance. The first is scheduled maintenance, referring to a maintenance procedure that will check the condition of the machine, replace some components, and do a thorough cleaning after a fixed time interval. As most of the moving components in a machine are subject to wear and tear, excessive work/maintenance will help prevent failure and long down time, but it will also increase the time that the machine is non-functioning, meaning waste of its capability to do work. The second is predictive maintenance, where the configuration of the machine is continuously monitored and the condition of the machine is predicted using this information. A key component for such a system is a mathematical model that captures the relationship between the observable behavior and the hidden state of the system. The conventional approach to achieve this is model-based reasoning, which is essentially a bottom-up approach, where models and simulation programs of the system behavior are built based on the physics of the system. Such models act as a digital twin of the physical system to be monitored.

2.4. Comparative Analysis with Other Maintenance Strategies

Figure 1: Evolution of Maintenance Strategies



Source: (Rubiales Mena, 2024)

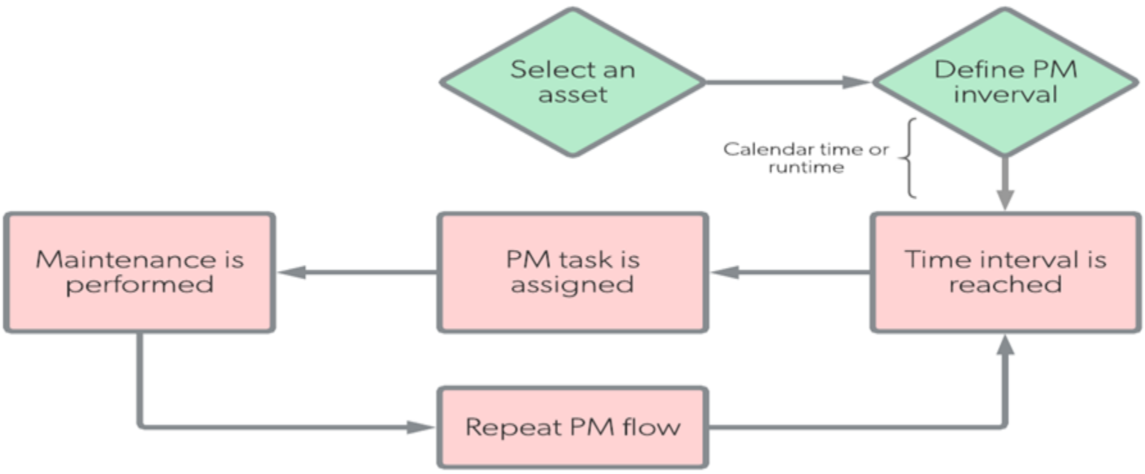
There are different types of maintenance strategies. Choosing a suitable maintenance strategy is crucial for companies. Therefore, there are different strategies to follow which cover various sectors under different conditions. For example, these approaches for maintenance in the electrical power generation industry were chosen since equipment failures are critical due to severe economic losses. On the other hand, the failures are rare, and therefore predictive maintenance is costly. Consequently, companies need to avoid potential downtimes in smart ways. Monthly and quarterly reviews of protection devices and HDVC systems are examples of the potential downtimes' sophisticated avoidance. In the paper a detailed review of equipment monitoring systems including AI is presented. AI-based modeling often outperforms classical solutions but data-driven methods are highly demanding in terms of input data and knowledge about the equipment being monitored. Approaches analyzing periodic work quality checks, e.g., maintenance of switchgears in the Polish power generation sector, seem more realistically acceptable. Deeper analysis of available data from companies may uncover additional and still unexplored dependencies between the data being monitored (Hamasha et al., 2023). A comparison of the advantages and disadvantages of maintenance strategies were described. Selection of the maintenance method differs depending on certain aspects in a large facility. Studying the literature, a comparison of main data was analyzed, including feasibility, availability, economy and reliability. Comparative analysis was completed under different conditions with consideration for the important aspects. Furthermore, linear heuristic rules were proposed for strategical selection of the maintenance type when imprecise data is available, which included a numerical demonstration for better understanding.

2.4.1. Preventive Maintenance

Since industrial machines are designed to run continuously, the maintenance of industrial machines is crucial for the uninterrupted operation of a production line. Many companies pursue maintenance strategies on their machines to keep them in good condition for the production process. The most typical maintenance strategies are corrective, preventive, and predictive maintenance strategies. Maintenance of machines can be classified as corrective and preventive maintenance. In a corrective maintenance strategy, the maintenance can be executed only when a failure occurs (Guillaume, Vrain, & Elloumi, 2020). When a failure occurs, several maintenance actions can be performed to fix the machine or assembly.

In a preventive maintenance strategy, maintenance is performed on a machine or assembly after fixed intervals of time either by preventive replacements or preventive repairs regardless of the state of the machine. While the corrective maintenance strategy may minimize maintenance personnel and material costs, it incurs serious productivity and customer satisfaction costs. On the other hand, preventive maintenance checks, repairs, and even replacement often occur on non-faulty equipment since the maintenance actions are based on fixed time intervals, resulting in potentially excessive costs and unnecessary downtime (Kane et al., 2022). Therefore, smart systems with predictive maintenance strategies have become the norm in industry.

Figure 2: Preventive Maintenance Work Flow



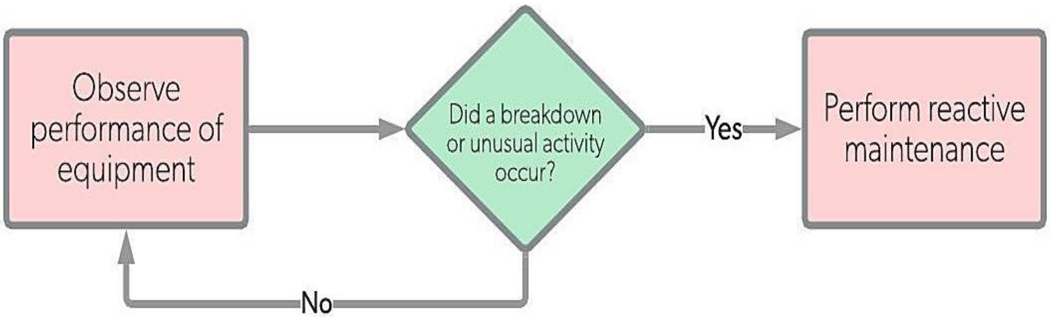
Source: (UpKeep, s.d.)

2.4.2. Reactive Maintenance

The process of re-establishing components, assemblies, or systems in a state in which they can perform the required functions is known as maintenance. Its goal is to preserve the condition of production facilities as they exist. Physical repairs or reinstatements are some of the ways maintenance is executed. Maintenance can be preventive, curative, or condition-based. Others refer to these as "scheduled maintenance." Under preventive maintenance, routine tasks are performed with sufficient frequency to minimize equipment problems. Curative maintenance is either repairs that are made after a fault has occurred or replacement of failed components or systems. Forecasting is used in predictive maintenance to service equipment just prior to failure.

Reactive or curative maintenance assumes that a faulty component will be repaired after the fault is detected or the equipment or component has become faulty. There are several distinct steps in the process of repair maintenance. The first step tends to involve the detection of failure in the initial stages of breakdown. This may arise from vibrations of machinery going beyond a threshold range, unexpected noise from factory equipment, or temperature of the component arising beyond a pre-determined threshold. The second step is the collection of knowledge about the malfunctioning component in the system. Important information includes the type of breakdown, the degree of severity, the past history of the component which may involve how often and what type of repair has been done in the past, the time at which the fault was detected, overall or partial failure, threshold at which the component went faulty. The final stage of the proactive strategy is called corrective or reactive maintenance, which is the process of repairing the faulty component assembly. To maintain the quality of production, the repair of breakdown components is inevitable and consists of concurrent actions by the initial supplier, the system owner, and maintenance contractor. The ability to complete such complex repair maintenance highly depends upon the capability and reliability of each component supplier. It also relies on the maintenance method applied by the owner and contractors and their proficiency.

Figure 3: Reactive Maintenance Work Flow



Source: (UpKeep, s.d.)

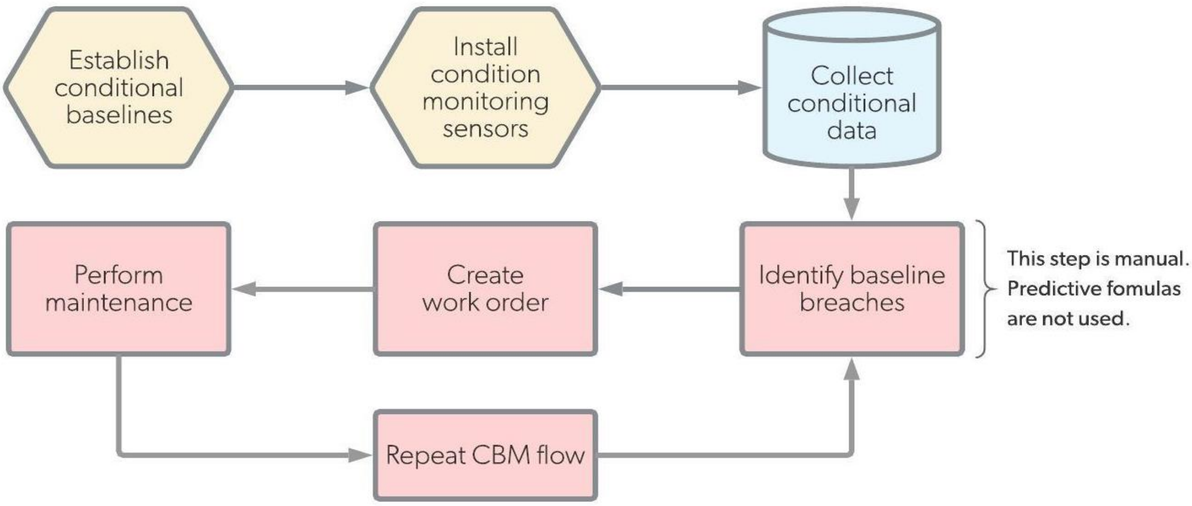
2.4.3. Condition-Based Maintenance

As equipment age, plant owners will face the problem of maintenance throughout the life cycle of the equipment in order to mitigate the risk of critical equipment failure. Among many maintenance strategies, condition-based maintenance is widely recognized by many experts and practitioners in recent years. CBM is a maintenance program that is based on the understanding that equipment goes through multiple degraded states before failure (B. Rong Wu, 2009). The degraded states can be identified through condition monitoring. In CBM, actions are decided upon after monitoring each equipment (or area). A well-designed program will take away unnecessary maintenance tasks by taking action only when there is evidence that failure is approaching. It is also called monitoring, and on-condition maintenance (Raza & Ulansky, 2019).

CBM is intended to avoid sequence or time-based preventive maintenance tasks and to maximize the efficiency of maintenance resources allocated by plant owners. It avoids unexpected failures by deciding actions based on condition monitoring data. CBM has been developed in such a way that condition monitoring data is interpreted using machine learning methods in both frequency and time domain to identify warning levels (or near failures). CBM has been widely implemented in aerial, military, mining, petroleum, and power generation industries. Equipment such as pumps, turbines, fans, and electric motors are usually monitored for sound, vibration, and temperature using time domain and frequency domain data.

The concept of CBM can be effective in many cases but is complex and only effective in some areas. Though mathematical models have been well-established, implementations have caused challenges for many companies. CBM techniques have been combined with other optimization-based theory focusing on decision-making and evaluation of data gathering to enhance the efficiency and effectiveness of the program. On the other hand, a treatment on existing CBM application cases is beneficial for understanding its implementation in practice.

Figure 4: CBM Work Flow



Source: (UpKeep, s.d.)

2.5. Importance of Predictive Maintenance in Oil and Gas

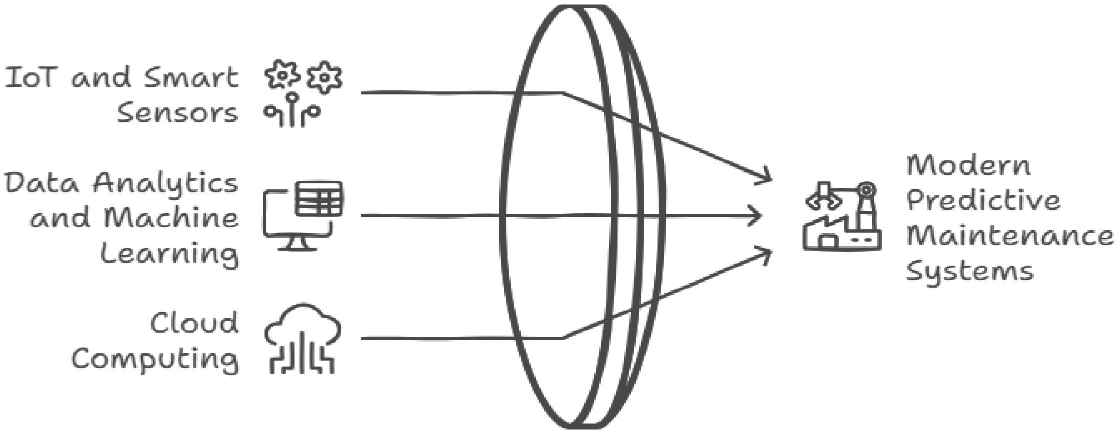
The oil and gas sector plays a pivotal role in the global economy, often regarded as the backbone of industrial operations. It is an energy-intensive industry characterized by aging infrastructure, competitive global consumption pressures, and fluctuating energy prices. These dynamics place significant demands on asset performance, operational efficiency, and strategic decision-making. Recent developments have highlighted both the challenges and opportunities related to real-time asset monitoring, adaptive asset management (AM) planning, and accurate reliability assessment.

To address these demands, predictive maintenance offers a compelling approach. It enables the transition from reactive and time-based maintenance to data-driven strategies that predict failures before they occur. This shift supports improved operational uptime, reduced maintenance costs, and more effective resource allocation. The implementation of PdM also introduces technical challenges that spur innovation, particularly in integrating concepts from Mechanism Design Theory and Hybrid Systems Theory into management science frameworks.

Given its organizational structure and capital-intensive nature, the oil and gas industry is well-positioned to lead the development of advanced AM models. These models must evolve to incorporate predictive capabilities, allowing for continuous condition monitoring and timely interventions. Ultimately, adopting PdM methodologies is not only feasible but increasingly essential to meet the industry's technical, economic, and environmental challenges.(Molęda et al., 2023)

2.6. Key Technologies for Predictive Maintenance

Figure 5: Technologies involved in PdM



Source: Elaborated by the students

In today's industrial landscape, predictive maintenance has emerged as a powerful strategy for improving operational efficiency, reducing costs, and avoiding unplanned downtime. Unlike traditional maintenance approaches which rely on scheduled checkups or respond only after a breakdown, predictive maintenance uses real-time data and intelligent tools to anticipate when equipment is likely to fail. This allows organizations to intervene at the right time, keeping assets in peak condition while minimizing unnecessary maintenance efforts.

The success of predictive maintenance depends on the integration of several key technologies that work together to support a smarter, more responsive approach to asset management. These technologies are not only reshaping maintenance processes, but also transforming the way industries monitor, understand, and interact with their equipment.

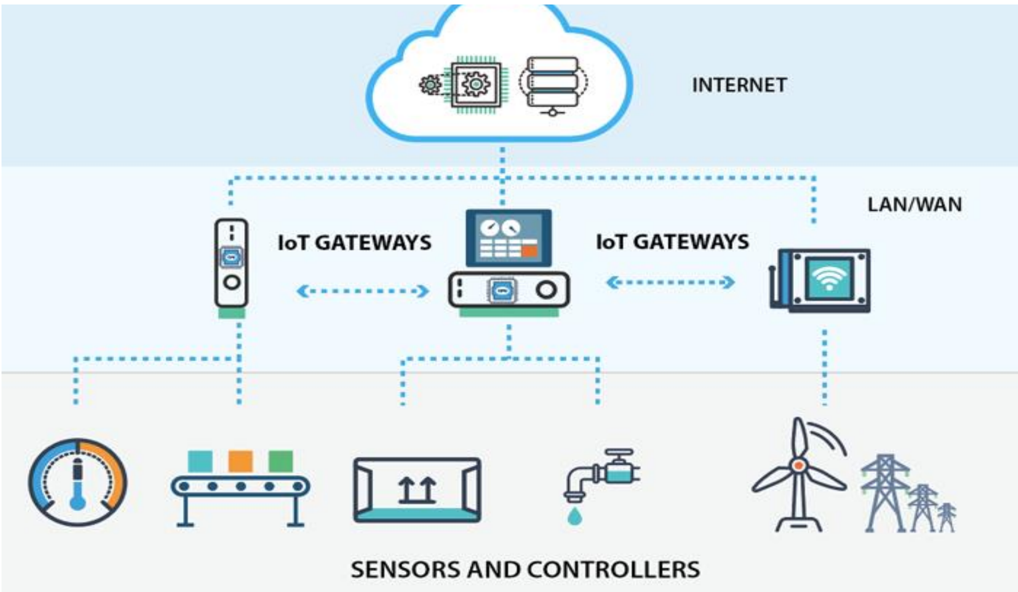
One of the driving forces behind this transformation is the growing availability of real-time operational data. Advanced sensors embedded in machines now continuously monitor variables such as temperature, vibration, pressure, and fluid levels. These sensors form the physical backbone of predictive maintenance, making it possible to observe equipment behavior in a detailed and dynamic way. The expansion of the Internet of Things (IoT) which connects these smart sensors to digital platforms has been a game-changer, especially in complex sectors like oil and gas where equipment is often located in remote or hazardous environments.

Yet, collecting data alone is not enough. The volume of information generated by connected assets can be overwhelming without the means to process and interpret it effectively. This is where data analytics and machine learning come into play. These technologies analyze historical and real-time data to detect patterns, uncover hidden correlations, and generate accurate failure predictions. Over time, machine learning models improve through continuous exposure to new data, enabling even more precise and reliable insights. However, predictive maintenance would not be feasible without scalable and efficient infrastructure to store, manage, and access vast amounts of data. This is made possible through cloud computing and storage solutions, which provide flexible platforms for data integration, advanced analytics, and collaborative decision-making. Cloud environments support high-performance computing tasks without requiring significant investment in on-site infrastructure. They also enable remote access to insights, which is particularly valuable for industries like oil and gas, where decision-makers often need to coordinate across locations. These three technological pillars: IoT and smart sensors, data analytics and machine learning, and cloud computing together form the foundation of modern predictive maintenance systems. Their combined capabilities make it possible to move from reactive problem-solving to proactive planning. By identifying early warning signs of wear and failure, these systems allow operators to prioritize critical interventions, schedule maintenance more efficiently, and reduce the risk of costly shutdowns.

2.6.1. IoT and Sensor Technologies

In recent years, IoT (Internet of Things) and smart sensors have become essential tools for improving maintenance strategies, especially in complex and high-risk industries like oil and gas. These technologies are changing the way companies monitor equipment, moving from scheduled inspections and reactive repairs to a much more proactive, data-driven approach. At the heart of this transformation are sensors installed on equipment throughout the production field. These small but powerful devices track key indicators such as pressure, temperature, and flow rate, helping operators keep an eye on equipment health in real time. But sensors don’t work in isolation; they’re part of a larger ecosystem. Once the data is collected, IoT technologies step in to send this information from the field to edge devices, where it’s quickly processed and filtered. From there, the data travels to the cloud, where more advanced analysis and visualization take place, often using tools like machine learning to detect early warning signs of failure.

Figure 6: IOT Ecosysteme



Source: (Assayed, 2023)

Whenever something unusual is spotted (like a sudden drop in pressure or abnormal vibration) maintenance staff can be alerted right away. This ability to react before a problem escalates is one of the biggest advantages of predictive maintenance.

In a typical oil or gas extraction site, wells are connected to enclosed monitoring units that contain various meters and sensors. These units gather a steady stream of operational data. However, getting all this equipment to "speak the same language" is not always straightforward. That's where communication protocols come in. Choosing a widely supported protocol makes integration much easier, especially when dealing with older systems or equipment from different manufacturers. The setup of these communication networks is heavily influenced by the type of gathering station in use, so decisions made during the design phase are critical for long-term efficiency and scalability.

Beyond equipment monitoring, modern sensor systems can even track environmental factors, such as weather conditions. In places like desert oilfields or offshore platforms, weather can have a serious impact on machinery. By incorporating weather data into the maintenance analysis either through direct sensing or external forecasts, companies can make even more informed predictions. Of course, the reliability of such data matters. If the weather information is accurate enough, it can be restructured and merged with operational data to strengthen predictive models. A crucial consideration is that predictive maintenance can only function effectively once condition monitoring is in place. In many cases, especially in mining or remote oilfields, historical maintenance data may be limited or non-existent. As such, organizations often require an initial period of data collection and operational experience to determine which parameters should be monitored, at what frequencies, and under what thresholds. Over time, maintenance teams gain deeper insights into common failure modes and operational patterns, enabling them to fine-tune their monitoring strategies and expand predictive capabilities.

In early stages, some sensor-equipped devices may only provide rough estimates or temporary insights, especially when applied to older or less sophisticated installations. However, these initial deployments lay the groundwork for broader integration into larger, more advanced systems. As IoT networks mature and sensor technologies improve, predictive maintenance will become increasingly precise, data-driven, and capable of preventing costly failures across complex oil and gas infrastructures.

2.6.2. Data Analytics and Machine Learning

These technologies offer the ability to make sense of vast amounts of operational data generated by equipment across its life cycle. However, while the potential is significant, applying AI to real-world maintenance problems is not without its challenges.

In most industrial settings, raw data comes from a variety of sources such as sensors, control terminals, physics-based simulation models, and field tests. This data holds valuable insights, but it is also complex, often unstructured, and highly variable. A single asset, for example, can generate a continuous stream of data that varies not only in volume but also in nature over time. The way an asset is used, how it's maintained, and even how it was originally designed or tested can cause its data patterns to evolve in unpredictable ways.

These patterns are rarely simple. The raw data typically includes multiple overlapping variables that change in frequency, amplitude, shape, and other dimensions. Moreover, every asset or group of assets might develop a unique data “signature” depending on its usage history and context. This makes it difficult for machine learning models to work effectively without first preparing and simplifying the data.

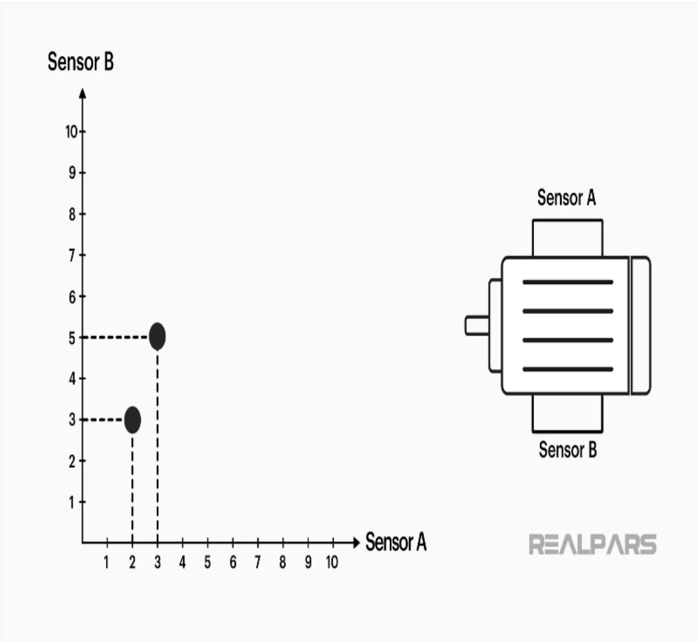
One of the biggest obstacles here is what's known as the “curse of dimensionality”, a common issue in machine learning where data has so many variables (or dimensions) that it becomes sparse and difficult to analyze effectively (Aremu et al., 2018). To illustrate, imagine a data table with 100 rows and 200 features per row. This leads to a total of 20,000 dimensions, far more than most ML algorithms can handle efficiently. In such cases, the data becomes too thinly spread across the available space, which makes it hard for the algorithm to find patterns or make reliable predictions.

This high dimensionality not only affects the accuracy of predictive models, but also increases the risk of making poor operational decisions. If not handled properly, it could even lead to serious economic consequences due to mismanagement of critical assets.

To address this, the development of better data preparation frameworks is essential. One promising approach involves transforming complex life cycle data into a more compact format reducing the number of variables without losing important information. This enables ML algorithms to work more efficiently and produce more reliable results. The goal is to reshape the raw, multivariate data into something more usable for predictive tools, ensuring that PdM systems powered by AI can deliver accurate, timely insights that support better maintenance and asset management decisions.

The following is an example of how ML algorithms are applied for PdM:

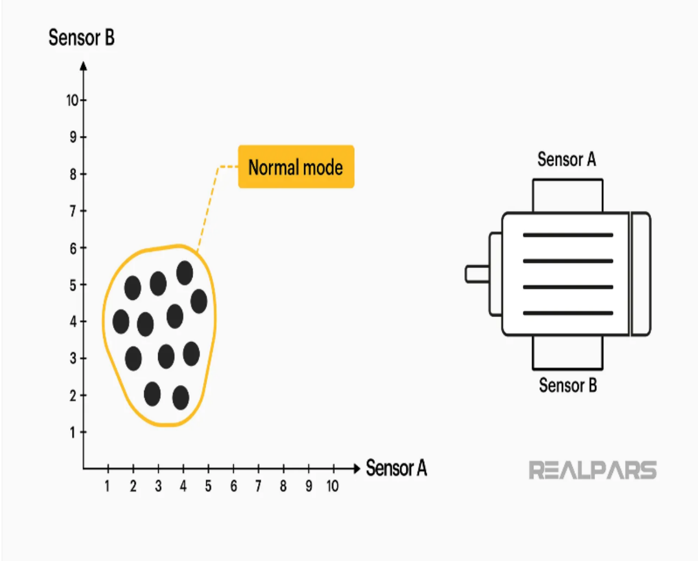
Figure 7: Measurements of normal behavior



Source: (REALPARS, s.d.)

This figure illustrates the data collection phase, where simultaneous vibration measurements from two sensors (A and B) are recorded during the motor’s normal operation. By gathering several of these paired values over time, a pattern or "normal operating zone" is formed, which defines the expected vibration behavior under healthy conditions.

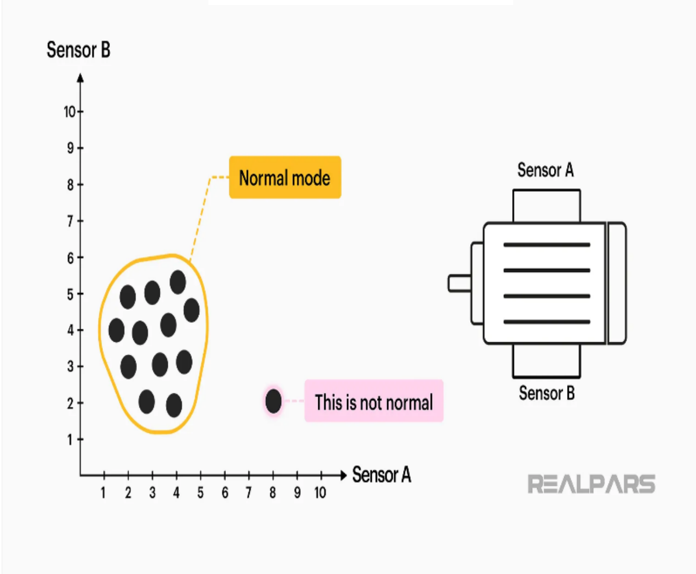
Figure 8: Normal Operating Mode



Source: (REALPARS, s.d.)

The second figure shows how repeated sensor readings form a cluster or zone often visualized as a colored area (like yellow), representing typical vibration behavior. This zone serves as the machine learning model's reference for identifying future anomalies. Any new data point falling within this area is considered normal.

Figure 9: Abnormal Mode



Source: (REALPARS, s.d.)

In this figure, a new set of sensor values is plotted (e.g., Sensor A = 8, Sensor B = 2), clearly falling outside the previously learned "normal zone." This deviation signals abnormal behavior. The model flags this as a potential fault, showing how even basic machine learning techniques can identify early signs of equipment failure.

2.6.3. Cloud Computing and Storage Solutions

Cloud computing is playing an increasingly important role in predictive maintenance across the oil and gas industry. As highlighted by (Khodabakhsh et al., 2017), the sector from upstream operations like offshore platforms and drilling to downstream activities such as refining and distribution, relies heavily on automated, mission-critical equipment. These systems generate vast amounts of data, much of which comes from interconnected components like pumps, compressors, valves, and geophysical instruments.

A key element in managing this complexity is the use of Distributed Control Systems (DCS). These systems include centralized controllers and visual interfaces known as Human-Machine Interfaces (HMIs), which help monitor operations and make real-time decisions. However, rather than uploading all the continuous data from these systems to the cloud, only the most critical information such as alerts, alarms, or relevant sensor readings is sent. This selective approach reduces bandwidth load and ensures that essential insights are available quickly across various user platforms, including desktops and mobile devices.

Additionally, newer technologies are enabling the use of virtual sensors that work alongside industry-standard protocols. This allows for easier integration and the creation of interactive dashboards that present data in intuitive and user-friendly formats. These dashboards can support advanced analytics modules, such as real-time fault detection, alarm management, and even business intelligence tools (TOMA & POPA, 2018).

Behind the scenes, software platforms like Neo4J, a graph-based database integrated into the cloud, support these functions. This technology makes it possible to perform complex queries on process and network data efficiently. Combined with mobile access, it allows maintenance and operations teams to detect issues remotely and act quickly. Other cloud-based solutions include enterprise-level architectures that can classify faults, suppress irrelevant data, and handle the challenges of big data through smart compression and removal techniques.

2.7. Data Collection for Predictive Maintenance

This section explores various data collection methods and techniques used in predictive maintenance, particularly within the context of asset management. It covers structured, semi-structured, and unstructured data types, examines both active and passive data acquisition techniques, and touches on data streaming protocols essential for edge computing. The aim is to provide a comprehensive look at how data is gathered and used to support predictive maintenance, from traditional approaches to more modern, technologically advanced methods.

2.7.1. Data Collection Methods

Data used in predictive maintenance comes in different formats, generally categorized as structured, semi-structured, or unstructured:

- **Structured data** refers to well-organized and easily searchable datasets typically found in relational databases, spreadsheets, or standardized text formats like CSV.

These formats use tables composed of rows and columns, often with defined relationships maintained via keys, ensuring a high degree of data integrity (Guillaume, Vrain, & Wael, 2020).

– **Semi-structured data** offers more flexibility. It uses tags or markers (like XML or HTML) to describe data, which allows for some organization but without the rigidity of tables. This type of data is useful in dynamic environments where data formats may change.
– **Unstructured data**, on the other hand, lacks a predefined format and includes information such as multimedia files, emails, images, or even free-form text. While harder to process, unstructured data often holds rich insights when properly analyzed.

Table 1: Data Types

Data Type	**Examples**	**Advantages**	**Disadvantages**
Structured Data	Relational databases (SQL), spreadsheets, CSV files	- Easily searchable and queryable - High data integrity - Efficient storage and processing	- Limited flexibility due to a strict schema - Requires upfront data modeling and may not adapt well to changing data types
Semi-Structured Data	XML, JSON, HTML	- Offers flexibility in data representation - Easier integration of heterogeneous data sources	- Querying and indexing can be less efficient compared to structured data - May need extra processing to extract useful information
Unstructured Data	Text documents, images, videos, emails	- Highly flexible and rich in content - Can capture complex real-world phenomena	- Difficult to search and analyze with traditional tools - Requires specialized techniques (e.g., natural language processing, image analysis) for processing

Source: Elaborated by the students

2.7.2. Data Acquisition Techniques

When it comes to how data is actually collected, we can distinguish between two main approaches: active and passive.

- **Active acquisition** involves installing hardware such as accelerometers or vibration sensors directly onto machinery. These sensors continuously record operational parameters, providing valuable real-time insight into machine health. This method is widely used in industries with complex equipment, especially when historical data is limited.
- **Passive acquisition**, by contrast, relies on existing datasets. These might come from archived records, previous maintenance logs, or historical monitoring systems. This method is more cost-effective but depends heavily on data quality and availability.

Table 2: Types of Data Acquisition Methodes

Acquisition Type	Examples	Advantages	Disadvantages
Passive Acquisition	-Archived maintenance logs - Historical sensor data - Data from legacy systems	- Cost-effective, since it utilizes already available data - Easier integration with existing records - No need for new sensor installations	- May not reflect real-time operational conditions - Data can be outdated or incomplete - Less granularity for immediate fault detection
Active Acquisition	- Real-time sensor measurements - Continuous monitoring systems - Automated data capture from newly installed IoT devices	- Provides up-to-date and high-resolution data - Enhances the ability to detect anomalies as they occur - Suitable for real-time decision-making	- Higher initial cost for sensor installation and system integration - May require frequent maintenance and calibration - Can increase system complexity

Source: Elaborated by the students

2.7.3. Real-time Monitoring

In the oil and gas sector, collecting real-time monitoring data for individual components (especially offshore) is often costly and technically challenging. Operators prioritize critical systems for sensor deployment, while less vital equipment may only be monitored through basic indicators like pressure sensors. For example, pressure monitoring is commonly used on liquid-gas separators, but more advanced sensor arrays are reserved for high-value assets (Guillaume, Vrain, & Wael, 2020).

Despite these challenges, there's growing industry recognition of the benefits that predictive maintenance can bring. But a fully automated PdM system typically requires building a mathematical model of the process and integrating it with SCADA (Supervisory Control and Data Acquisition) systems. Machine learning tools are particularly effective in settings where sensor data is already available.

Figure 10: Example of Real Time Assets Tracking using CYBRA's EdgeInfinity IOT

Source: (Tracking, s.d.)

In remote or offshore facilities, turbulent environments can limit the usefulness of certain PdM techniques. Instead of relying on complex models or rare data inputs, many operators adopt simplified monitoring strategies based on key pressure and mixture readings. While not optimal, this trade-off helps balance reliability and cost.

Still, the path toward effective predictive maintenance includes installing more sensors and establishing strong links between data collection systems and analytics platforms. Not all operators have the resources to make this leap, but without it, achieving competitive advantage in the oil and gas industry is unlikely.

2.7.4. Historical Data Analysis

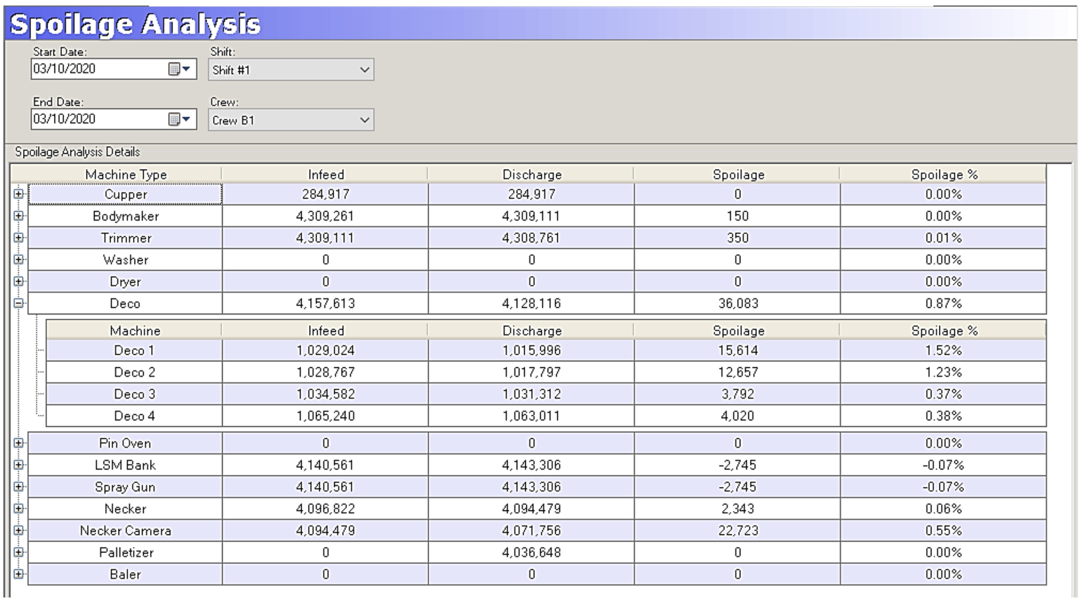
The oil and gas industry plays a vital role in many national economies. In the UK alone, it contributes roughly £22 billion annually. As a data-intensive and asset-heavy sector, it's a prime candidate for advanced asset management solutions. However, rising operational costs have pushed companies to rethink how they manage and maintain assets (Guillaume, Vrain, & Wael, 2020).

Using historical data effectively can lead to significant improvements in predictive maintenance. By analyzing past failures or performance trends, companies can identify weak points and preemptively address them. A common practice is to allocate about 70% of the available data for fault prediction covering both equipment breakdowns and process disruptions.

For example, one case study involving drill rig #195 demonstrated how a customized analysis program could be developed using historical datasets. The system highlighted both the potential and limitations of predictive maintenance especially in brownfield (already operational) facilities. Reengineering PdM systems in these contexts means solving problems related to data quality, algorithmic efficiency, and system adaptability.

In short, while historical data is a rich resource, maximizing its value requires thoughtful design and a willingness to invest in customization and computational optimization.

Figure 11: Example of a Historical Data Report made using Acumence



Machine Type	Infeed	Discharge	Spoilage	Spoilage %
Cupper	284,917	284,917	0	0.00%
Bodymaker	4,309,261	4,309,111	150	0.00%
Trimmer	4,309,111	4,308,761	350	0.01%
Washer	0	0	0	0.00%
Dryer	0	0	0	0.00%
Deco	4,157,613	4,128,116	36,083	0.87%

Machine	Infeed	Discharge	Spoilage	Spoilage %
Deco 1	1,029,024	1,015,996	15,614	1.52%
Deco 2	1,028,767	1,017,797	12,657	1.23%
Deco 3	1,034,582	1,031,312	3,792	0.37%
Deco 4	1,065,240	1,063,011	4,020	0.38%

Machine Type	Infeed	Discharge	Spoilage	Spoilage %
Pin Oven	0	0	0	0.00%
LSM Bank	4,140,561	4,143,306	-2,745	-0.07%
Spray Gun	4,140,561	4,143,306	-2,745	-0.07%
Necker	4,096,822	4,094,479	2,343	0.06%
Necker Camera	4,094,479	4,071,756	22,723	0.55%
Palletizer	0	4,036,648	0	0.00%
Baler	0	0	0	0.00%

Source: (Acumence, s.d.)

2.7.5. Condition Monitoring Techniques

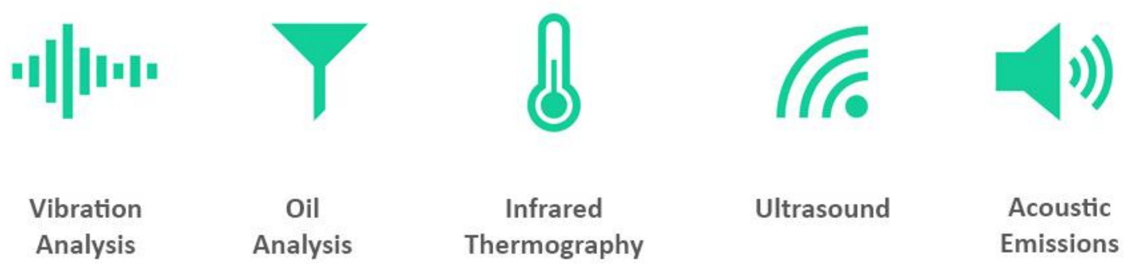
Condition monitoring is at the heart of predictive maintenance. It involves continuously checking equipment status to detect early signs of failure and avoid unplanned downtime. This process typically includes two main stages: feature extraction and condition classification.

In feature extraction, parameters like vibration, noise, temperature, or acoustic signals are gathered and used to assess machine health. The classification stage involves categorizing the machine's status into fault types or operational conditions (Marwala & Busisiwe Vilakazi, 2007).

Condition monitoring helps facilities schedule maintenance in a way that minimizes disruptions. Its importance has grown alongside global industrial competition, deregulation, and the demand for cost-efficient operations. Today's machinery is more complex and often built to be flexible, which has made reliance on sensor-based monitoring all the more necessary.

Modern condition monitoring often incorporates computational intelligence techniques such as machine learning. These tools can handle the complex and varied data streams generated by industrial machinery and provide actionable insights. Current maintenance challenges ranging from design and production to resource planning, can be addressed through intelligent condition monitoring systems (Scheu et al., 2019).

Figure 12: Basic Condition Monitering Techniques



Source: (Ghaisas, s.d.)

2.8. Implementation Strategies

To fully harness the potential of a predictive maintenance program, careful and structured implementation is crucial. This process requires an initial diagnostic assessment, guided by the following key questions:

- What is the current level of personnel expertise with the equipment designated for predictive maintenance?
- How proficient and reliable are the existing practices and skills in predictive maintenance techniques?
- What tools and technologies are available, and what funding is recommended for the program's scope?
- What format will be reporting and documentation follow?
- Do trained personnel exist to provide relevant task-specific training?
- Which techniques are considered operationally viable?
- What data filtering and processing mechanisms are in place?
- What specialized training is necessary, and who should receive it?
- Who is responsible for the implementation process? To what extent and in which locations?

Answering these and related questions honestly helps establish a baseline assessment of the current situation "where we are" before planning improvements "where we want to be". This evaluation will reveal potential gaps in either a structured or evolving strategy, which can then be fortified. Such an approach ensures that initial efforts are aligned with practical objectives without undermining the existing body of technical expertise.

Once the existing maintenance techniques are assessed and categorized by effectiveness, the Technical & Engineering teams can define both initial and ongoing strategies. The available toolkit for predictive maintenance is broad, and many techniques are highly effective if they are up to date, well-managed, and appropriately applied. However, some methods, while familiar to staff, may become ineffective over time due to complexity, time constraints, or reliability issues. Therefore, by leveraging a grading system of existing techniques, an implementation roadmap can be developed that prioritizes practical and impactful tools. This roadmap should include continuous evaluation to incorporate new and beneficial advancements as they arise.

2.8.1. Developing a Predictive Maintenance Plan

The long-term performance of oil and gas assets and ultimately the sustainability of operations relies on robust lifecycle asset management. As many industries assets approach or exceed their design lifespans, the risks of unexpected failures, safety incidents, environmental impacts, and financial losses increase. Predictive maintenance plays a key role in mitigating these risks by monitoring asset health and anticipating malfunctions before they escalate.

The sector is now entering the era of big data, where enhanced analytics can significantly improve business efficiency and operational effectiveness. Continuous technological advancement has enabled the broader adoption of condition-based maintenance, commonly known as predictive maintenance. Unlike time-based or failure-based strategies, predictive maintenance allows operators to make maintenance decisions based on the actual condition of equipment and systems. This proactive model is increasingly popular among industry leaders.

Implementation typically follows five key stages:

1. Data acquisition
2. Data processing and analysis
3. Prognostics (predicting future conditions)
4. Maintenance decision-making
5. Execution of maintenance actions

While the oil and gas industry has made considerable progress in the first three phases, the final two especially execution and decision implementation remain relatively underdeveloped.

2.8.2. Integrating with Existing Systems

In the complex operational ecosystem of the oil and gas industry, a variety of existing systems such as control systems, computerized maintenance management systems (CMMS), and data historians are used to ingest, store, and manage data for ongoing business activities. Understanding how and when data is captured is critical to implementing predictive maintenance.

A system becomes genuinely predictive only when enough quality data is collected to support accurate forecasting. Typically, this requires at least six months of historical data, logged at hourly intervals, to enable the creation of reliable predictive models. Analysts must ensure this data is both accessible and cleansed, as not all measurements may be suitable for model training due to preliminary filtering processes (Miller & Dubrawski, 2020). Additionally, any failed equipment events must be accompanied by structured, sequential data points to support root cause analysis.

Traditional inspection and diagnostic methods, while effective, often demand physical proximity to the asset and the use of specialized instruments. Once these traditional systems are integrated into a centralized monitoring platform with standardized calibration protocols, they serve as a strong foundation for developing predictive models for estimating remaining useful life (RUL) (Starr & Ball, 2005).

Advanced techniques such as fuzzy logic, neural networks, and hidden Markov models can be used to support complex decision-making processes, particularly under uncertain operating conditions or volatile markets. Machine learning algorithms may also be incorporated to enhance the predictive accuracy and timeliness of preventive actions. Additionally, operator contracts should be reviewed to identify how predictive models can influence and potentially reduce equipment tie-up costs.

2.8.3. Training and Skill Development

The successful implementation of predictive maintenance hinges on a well-trained workforce. Continuous learning and development programs not only improve operational capability but also ensure the transfer of institutional knowledge as experienced personnel approach retirement.

Training should be strategically designed to raise the competency levels of junior staff in particular. It is essential for new engineers to understand the baseline conditions of machinery, as unrealistic expectations or improper interpretation of early data can result in inaccurate predictions. For instance, during the initial startup phase, machinery may exhibit nonlinear behavior, high-amplitude oscillations, or transient operating states. These anomalies may trigger false alerts before the system stabilizes and a reliable reference baseline is established.

Care must also be taken when interpreting unfamiliar machinery behavior, particularly during follow-up diagnostics or action planning. Acting too quickly, without adequate understanding, can lead to costly errors or hazardous outcomes. Therefore, every case involving a maintenance decision should be thoroughly documented—including the observed conditions, rationale behind decisions, and resulting actions (Hall, 1983).

It is advisable to consult machinery manufacturers for surveys before implementing major actions on new purchases. Lessons from past cases should also be compiled into a centralized knowledge base. Such documentation becomes a valuable resource for training newer staff, who often face challenges in managing systems with which they have no prior experience.

2.9. Challenges in Predictive Maintenance Implementation

Predictive Maintenance is a maintenance strategy that leverages condition monitoring technology to determine the state of an asset and assess the need of maintenance actions on each individual asset (Miller & Dubrawski, 2020).

However, despite the promise of PdM, many assets have poor implementation or none at all. Common reasons for its failure include misunderstanding the business benefit and poor communication across departments. Implementing PdM should ideally be a cross-organizational effort involving both business and engineering teams. Engineering teams bring the technical expertise and knowledge necessary to design applications and algorithms that produce accurate predictions of asset failure probabilities. Nevertheless, these models are often dismissed by the business teams because they fail to consider how business profit will be affected if these predictions are utilized. For example, the engineering team may produce a highly accurate prediction model but fail to consider how adjustments are implemented into the maintenance scheduling. Finding the appropriate way to disrupt established practices while garnering trust from the field will be a large predictor of success for PdM applications. Ultimately, the business team must understand how dead asset time costs revenue. Likewise, the engineering team must understand how a PdM application affects many assets, and that at scale, a single, one-day increase in edge probability is a large disruption to maintenance practices and may result in excessive overtime, missed production, and accidents. Having a defined business case clarifies the goal of a PdM project and gives engineering teams something to work toward, allowing for more manageable expectations.

2.9.1. Data Quality and Management

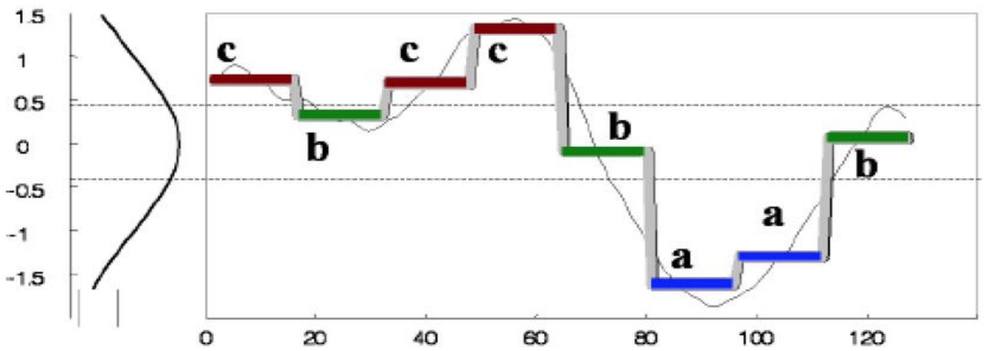
In predictive maintenance, data quality and management are central to achieving reliable, actionable insights. PdM systems depend on high volumes of operational data often in the form of time-series measurements and use ML algorithms to predict equipment failures, assess asset health, and optimize performance. However, the oil and gas industry present particular challenges due to the complexity, volume, and heterogeneity of its data environments.

A key issue lies in the fragmentation of data across organizational silos. Despite increasing investments in PdM technologies, much of the collected data and resulting analytical outputs remain underutilized or isolated within specific departments. This limits the potential for comprehensive, cross-functional insights and hinders the deployment of advanced analytics across the asset lifecycle.

To address these challenges, effective data transformation techniques are essential. One promising approach involves the discretization of time-series data to enhance critical features for machine learning. This process allows for the integration of both continuous and categorical covariates into predictive models. By converting raw sensor data into more structured forms, ML models can better interpret and act on the information, even in the absence of predefined user assumptions.

A notable technique in this domain is Symbolic Aggregate approximation (SAX), which transforms time-series data into symbolic representations while preserving key structural properties. SAX maintains the lower-bound distance measure of the original data, ensuring that important variations and trends are retained in the discretized output. This balance between simplification and information retention makes it highly suitable for PdM applications.

Figure 13: Example of The SAX Methode



Source: (Foteini K.K, 2018)

The ability to transform data effectively not only supports more accurate predictions but also enables comparative evaluations across different assets, teams, or operational contexts. It provides a framework for both qualitative interpretation and quantitative performance assessment, allowing organizations to benchmark and improve their PdM strategies.

However, implementing such data frameworks requires careful attention to data consistency, completeness, and interpretability. Feature transformation must be validated to avoid misrepresentation, and the resulting data must align with the specific requirements of ML algorithms used in PdM. In addition, as instrumentation for feature engineering evolves, organizations must invest in robust data governance and integration strategies to ensure that data remains accessible, high-quality, and meaningful.

Ultimately, overcoming data-related challenges in PdM is not only a technical task but also a managerial one. It demands coordinated efforts across IT, operations, and analytics functions to break down data silos, standardize processing techniques, and promote a culture of data-driven decision-making in asset management.

2.9.2. Cultural Resistance to Change

The effectiveness of PdM implementation is not solely dependent on technology or data infrastructure; it is also deeply influenced by the organizational culture in which it is deployed. Corporate culture plays a critical role in shaping maintenance practices and, ultimately, the success of PdM initiatives. As noted by (Eti et al., 2006), the maturity and effectiveness of maintenance strategies are strongly correlated with the prevailing corporate culture.

In many organizations (For example in Nigeria) there is a limited understanding of what it means to manage people effectively within the maintenance function. Management practices often focus narrowly on controlling activities, rather than fostering an environment that encourages accountability, collaboration, and long-term strategic thinking. True leadership in this context involves more than direction; it requires a visible and sustained commitment to organizational excellence, the alignment of maintenance culture with strategic goals, and the provision of necessary financial and operational resources for PdM (Eti et al., 2006)

Without these foundational elements, attempts to introduce quality-oriented or data-driven maintenance programs frequently fall short. Predictive maintenance, in particular, demands a shift in mindset and operations toward proactive decision-making, interdepartmental collaboration, and transparency in work processes. Resistance often arises when these shifts challenge established hierarchies, habits, or perceptions of job roles.

This resistance can manifest in several practical ways. For instance, PdM requires planning and scheduling tasks in advance, which can conflict with traditional reactive maintenance mindsets. Maintenance planners must ensure that work orders are properly formatted and communicated early enough to be integrated into operational schedules. In many organizations, a strong cultural preference for addressing urgent, unplanned work persists, often at the expense of strategic, scheduled maintenance.

As predictive maintenance becomes more central to organizational strategy, it becomes increasingly important to cultivate a culture that prioritizes long-term asset health over short-term responsiveness. This involves not only technical adjustments but also behavioral and procedural changes such as timely recognition, escalation, and resolution of breakdowns to avoid operational backlogs and increased risk exposure.

Ultimately, overcoming cultural resistance requires consistent leadership, clear communication, and a participatory approach that engages employees at all levels. Building an organizational culture that embraces change, supports continuous improvement, and values data-informed maintenance practices is essential to unlocking the full potential of predictive maintenance.

2.9.3. Cost Considerations

Implementing Predictive Maintenance involves more than technological integration,

it also requires careful financial planning. While PdM aims to reduce unplanned downtime and optimize asset performance, its cost implications must be thoroughly considered. One of its primary advantages of is its ability to use operational data and failure risk models by treating asset conditions as learning variables. This adaptive approach generates more dynamic and informative maintenance insights compared to traditional methods.

In the oil and gas industry, the costs associated with operating and maintaining assets such as pipelines, compressors, pumps, and fixed installations frequently exceed their initial capital expenditure. For example, in Norway, the annual risk-related operational cost of assets in use for oil and gas extraction has been estimated at approximately 900 million NOK surpassing the reinvestment requirement of 630 million NOK. Optimizing maintenance scheduling and scope can thus lead to substantial economic benefits (Menon et al., 2018)

A key area for cost optimization lies in enhancing Failure Mode Effects Analysis (FMEA) and improving work management systems, as maintenance activities account for roughly 63% of total operational costs in such industries (Menon et al., 2018). However, current schemes often rely on fixed repair intervals and assume static knowledge about asset conditions. These rigid frameworks result in suboptimal outcomes, as they ignore variability in equipment performance and the evolving nature of operational risks.

Instead, PdM enables more responsive maintenance by continuously treating asset states and risk estimates as learning variables within decision-making frameworks, such as Markov models. This approach facilitates targeted actions not only for monitored assets but also for those lacking real-time feedback, improving overall system reliability and cost-effectiveness.

Moreover, (Siemens AG, 2023) supports these claims by highlighting that predictive maintenance at scale can reduce maintenance costs by up to 30%, extend asset lifespans, and increase equipment utilization by 20%. These gains translate into an average ROI of 250%, particularly when PdM strategies are supported by robust data maturity and cultural readiness within the organization.

While installing additional sensors and monitoring equipment may initially seem costly, the Siemens report suggests that many organizations already possess sufficient data often through existing PLC systems (Programmable Logic Controllers) to launch effective PdM programs. Monitoring operational variables like current, torque, or vibration can provide early warnings of failures without expensive retrofits.

Another financial benefit of PdM lies in avoiding unnecessary interventions. Traditional maintenance schedules often prompt actions based on fixed intervals rather than actual equipment need, leading to wasteful practices. Predictive models, by contrast, help prevent these inefficiencies by providing data-driven decision support. As Siemens notes, preventing even one critical failure can result in “bankable value,” but the true ROI of PdM comes from the accumulation of avoided unnecessary maintenance tasks, reduced inventory holdings, and streamlined resource allocation.(Siemens AG, 2023)

Furthermore, scalable PdM minimizes dependency on third-party preventive services by enabling focused, in-house repairs. This shift not only reduces labor and contracting costs but also shortens average repair times and improves workforce utilization. The ability to detect and address problems before they escalate also improves safety, compliance, and overall operational resilience.

In summary, while the upfront investment in PdM infrastructure, training, and data systems may seem significant, the long-term savings and performance improvements far outweigh these costs. When implemented strategically, PdM offers a powerful lever for controlling maintenance expenses, reducing capital reinvestment needs, and maximizing return on assets, making it a financially sound strategy in modern asset management.

2.10. Case Studies of Successful Implementation

The oil and gas industry faces numerous challenges, including aging infrastructure, complex equipment, and the need for continuous, efficient operations. Traditional maintenance strategies, often reactive in nature, can lead to unplanned downtimes, increased costs, and safety risks. In response, PdM has emerged as a transformative approach, leveraging data analytics, machine learning, and real-time monitoring to anticipate equipment failures before they occur.

This subchapter presents a series of case studies that illustrate the successful implementation of predictive maintenance across various sectors within the oil and gas industry. Each case highlights the unique challenges faced, the technologies employed, and the tangible benefits realized, offering valuable insights into the practical applications of PdM.

2.10.1. Implementing Predictive Maintenance for Gas Compressors in Offshore Operations (VROC, 2022)

- **Industry**: Oil & Gas
- **Location**: Offshore platform
- **Technology Provider**: VROC

➢ **Background**

PETRONAS, a leading oil and gas operator, faced recurring issues with its gas compressors on the Dulang offshore platform. These issues led to frequent unplanned downtimes, increased maintenance costs, and production deferments. Traditional methods of identifying the root causes were time-consuming and often lacked precision. Engineers had to rely on standard reliability analysis, which took approximately 4,000 man-hours to identify the cause of the failure. Even after this extensive analysis, there was little confidence that the corrective measures would be successful during the limited 48-hour shutdown window available for maintenance.

➢ **Implementation**

To address these challenges, PETRONAS partnered with VROC to deploy an AI-driven predictive maintenance solution. VROC's platform ingested one year of historical data from the gas compressors and processed it in just 90 minutes. The AI model identified the root causes of the compressor issues 2,000 times faster than the standard reliability analysis. Additionally, the AI system uncovered factors that had not been identified by traditional methods, such as equipment being operated in incorrect modes.

➢ **Results**

1. **Enhanced Reliability**: The gas compressor's reliability was extended from a maximum of two weeks to four months.
2. **Cost Savings**: The improvements in uptime resulted in an estimated savings of USD 21.7 million.
3. **Operational Efficiency**: Root causes were identified 2,000 times faster than with standard methods, allowing for mre effective maintenance planning.
4. **Expanded Application**: Due to the success of this initiative, VROC was engaged to provide real-time predictive analytics for all equipment on the platform, further enhancing overall reliability.

➢ **Conclusion**

This case study demonstrates the significant benefits of implementing AI-driven predictive maintenance in offshore oil and gas operations. By leveraging advanced analytics, PETRONAS was able to improve equipment reliability, reduce costs, and enhance operational efficiency, setting a precedent for future applications of AI in the industry.

2.10.2. Predictive Maintenance for Centrifugal Compressors in Oil and Gas Operations (Yu et al., 2022)

- **Industry:** Oil & Gas
- **Location:** Global (case study data from China)
- **Technology Provider:** China Petroleum Planning & Engineering Institute

➢ **Background**

Centrifugal compressors are critical components in oil and gas operations, used for gas compression, reinjection, and transportation. However, their complex nature and transient operational behaviors make them prone to faults, leading to potential safety hazards and increased maintenance costs. Traditional maintenance strategies often rely on generic schedules, which may not align with the actual health of the equipment, resulting in either over-maintenance or under-maintenance.

➢ **Implementation**

To address these challenges, the China Petroleum Planning & Engineering Institute developed a data-driven methodology for the reliability analysis of natural gas compressor units. This approach involved collecting and analyzing extensive operational data to identify multiple failure modes and their corresponding symptoms. By integrating this data with advanced diagnostic techniques, the team aimed to enhance the accuracy of fault detection and improve maintenance planning

- **Results**

1. **Enhanced Fault Detection:** The data-driven methodology enabled more accurate identification of failure modes, leading to timely interventions and reduced downtime**.**
2. **Improved Maintenance Planning:** By aligning maintenance activities with the actual condition of the equipment, the approach optimized resource allocation and minimized unnecessary maintenance tasks.
3. **Increased Equipment Reliability:** The proactive maintenance strategy contributed to improved operational efficiency and extended the lifespan of the compressors.

- **Conclusion**

This case study demonstrates the effectiveness of implementing a data-driven predictive maintenance strategy for centrifugal compressors in the oil and gas industry. By leveraging operational data and advanced diagnostic techniques, operators can enhance fault detection, optimize maintenance planning, and improve overall equipment reliability.

2.10.3. Predictive Maintenance for Gas Compressors in Smart Manufacturing

(TTTech-Industrial, 2023)

- **Industry**: Oil & Gas
- **Location**: Global6
- **Technology Provider**: TTTech Industrial

- **Background**

A global oil and gas operator faced challenges in implementing predictive maintenance for its gas compressors due to varying configurations, high data rates, and the need for on-premises operation. Many installations were air-gapped for security reasons, limiting cloud access and necessitating remote commissioning without internet connectivity.

- **Implementation**

The operator partnered with TTTech Industrial to deploy the Nerve edge computing platform, which was installed on an industrial PC certified for hazardous environments. The platform enabled real-time sampling of compressor signals at 50 kHz, facilitating high-speed data acquisition. Nerve DNA simplified the configuration of numerous edge devices, allowing the operator to focus on developing predictive maintenance algorithms while the platform handled configuration and operation.

➢ **Results**

1. **Enhanced Reliability**: The predictive maintenance solution improved the reliability of gas compressors by enabling early detection of potential issues.
2. **Operational Efficiency**: The edge computing platform streamlined maintenance processes, reducing unplanned downtimes and associated costs.
3. **Scalability**: The system's design allowed for scalability, accommodating the growing data needs of the operator's extensive compressor network.

➢ **Conclusion**

This case study demonstrates the effectiveness of implementing predictive maintenance through smart manufacturing solutions in the oil and gas sector. By leveraging edge computing and real-time data analysis, operators can enhance the reliability and efficiency of their gas compressors, setting a precedent for future applications of predictive maintenance in similar operations.

2.11. Benefits of Predictive Maintenance

The context for adopting a PdM model to maximize availability, reliability, and utilization in managing assets in treatment plants is reviewed. The focus is on where narrow-band signals (data) can be captured from assets and how these data can be used to develop a PdM model. Today, changing economic conditions, energy usage, and environmental considerations mean a large part of the applied technology inventory must be modified to improve in-use efficiency, energy use, and reductions in carbon emissions. Most of these technologies either rely on rotating systems or select a narrow-band technology to produce the result set infrastructure. About 80% of the asset value is data and about 80% of waste is due to performing the wrong activity. An intelligent PdM capex decision support model for maximizing oil well delivery is pioneered. This incorporates a multitude of influences on asset uptime intelligence which include asset reliability prediction, fault clustering and behavior modeling, continual in-use condition monitoring and abnormality detection, maintenance and re-investment options, and economic conditions and business driver analytics. (Kane et al., 2022).

More generally, the benefits to different organizations from moving to PdM fit into two groups. The direct benefits relate to improved availability, utilization, and efficiency of assets and operations. The improved understanding of condition and life enables having the right amount of suitable back-up assets at the right time and leads to enhanced risk and investment decision-making choices. Less direct benefits relate to the management of the improvement initiatives and integration with business processes (Aremu et al., 2018). The assets needed to develop, implement, and operate a PdM model can, at some organizations, be large and difficult to procure, integrate, or operate on a 'just in case' basis. Importantly, many activities involve fundamental changes to the technology and knowledge if undertaken properly. There are also risks in the results. As a start, it is often prudent to be selective initially in modeling choices. This can focus on a specific type of asset and its reliability. A limited scope lets the organization learn quickly and realize benefits to fund more extensive deployment.

2.11.1. Cost Reduction

One of the most significant benefits of PdM is its ability to reduce operational and maintenance costs by optimizing asset usage and avoiding unnecessary interventions. Traditional maintenance modelling often relies on static or deterministic frameworks, which, although mathematically simpler, do not effectively capture the dynamic and uncertain conditions in real-world asset networks, especially in complex environments such as gas transport systems (Sinha et al., 2013).

To address this gap, recent approaches in maintenance modelling integrate principles from asset management theory with stochastic modelling techniques. These approaches aim to provide a more accurate representation of how gas networks behave under uncertain operating conditions. Instead of modelling uncertainty at the level of maintenance actions alone, the stochastic method models the uncertainties directly at the level of basic operational signal**s** that influence asset performance. This shift allows for a more detailed and computationally feasible analysis of future asset conditions and potential failures, leading to smarter, more cost-effective maintenance strategies.

The key advantage of this method lies in its ability to simulate and optimize maintenance policies based on probabilistic forecasts of asset usage and degradation. Such predictive capabilities enable organizations to anticipate potential failures before they occur, reducing unplanned downtime, minimizing reactive maintenance costs, and extending asset lifecycles. Case studies applying this stochastic modelling approach to natural gas transport pipelines have demonstrated its value. They reveal how predictive strategies, when embedded within simulation-optimization frameworks, significantly enhance cost-efficiency by targeting maintenance actions only when data indicates a high probability of failure. This results in better resource allocation, reduced emergency repairs, and improved operational continuity, all of which contribute to substantial cost savings (Aremu et al., 2018).

2.11.2. Increased Equipment Lifespan

Extending the lifetime of equipment is another anticipated benefit of predictive maintenance. Many proactive measures are now widely employed in oil and gas production, mainly as regular preventive maintenance, which forms fixed schedules for inspections, adjustments, overhauls, or repairs. However, in many cases, preventive maintenance does not outperform predictive maintenance. Some mechanical equipment is renewed at intervals shorter than optimal intervals due to inefficient preventive maintenance (too many adjustments, unnecessary overhauls, or repairs) or excessive wear caused by rust, cavitation, or other degrading processes. A planned approach is required to determine the nature and timing of preventive measures in order to guarantee minimal costs and maximum equipment lifetime. It is also well established that predictive maintenance can obtain considerable cost savings. Capital costs related to the replacement of broken units can be very high, in some cases 50% or more of operational costs. Other consequential costs incurred by blackouts can be even higher but are usually more difficult to quantify. Predictive maintenance measures taken to prolong the lifetime of high-cost equipment significantly reduce these costs.

2.11.3. Enhanced Safety Protocols

Incorporating PdM into asset management systems not only improves efficiency but also introduces new opportunities to enhance safety protocols. Given the potential for PdM algorithms to influence operational decisions, it is critical to ensure that safety measures are well-defined to prevent unintended failures or hazards resulting from misinterpretations or faulty predictions.

The first step in managing safety within these frameworks involves identifying which asset components and operational zones are subject to significant safety risks. For instance, while a sensor malfunction might be automatically flagged and diagnosed, areas involving direct human interaction with assets require additional precautionary layers. In such zones, the system must be designed to minimize physical intervention unless absolutely necessary. This may include utilizing remote monitoring or surveillance in place of manual inspections, especially where environmental factors (e.g., ice or dust) are known to compromise sensor accuracy.

PdM systems must also incorporate input validity checks processes that assess whether sensor data is trustworthy. If a sensor is likely to be contaminated or obstructed, the system should automatically signal degraded input quality. This alerts technicians that enhanced safety protocols apply in these cases. Such mechanisms help in categorizing maintenance actions into full-safety and half-safety requirements, depending on the level of risk and human involvement (A. M. Clapp, 1978).

- **Full-safety requirements** cover scenarios where predictive insights must be based on reliable, secure inputs. These systems must be capable of detecting sensor or system failures, flagging data compromised by malware or anomalies, and ensuring that predictions are only made on verified asset behavior. Outputs must clearly indicate prediction certainty and avoid false negatives, which can create significant safety threats.
- **Half-safety requirements** are associated more with the human-computer interface and the technician's ability to act on predictions. These include ensuring ergonomic design, clarity of information, and proper procedural guidance for responding to alerts. Similarly, actuators controlled by PdM outputs must be regularly checked to confirm they are reflecting the expected operational states.

Proper safety protocol integration ensures that PdM systems are not only effective but reliable in mission-critical environments. Beyond algorithm accuracy, successful PdM deployment requires the implementation of dedicated maintenance routines, typically performed annually in addition to regular inspections. These protocols reinforce safety assurance and help establish a robust framework for decision-making in maintenance activities (A. M. Clapp, 1978).

2.12. Future Trends in Predictive Maintenance

Predictive maintenance continues to evolve as one of the most strategically valuable innovations in the oil and gas industry. Among technological investment priorities, PdM, especially when integrated with advanced analytics is consistently ranked among the top three focus areas for companies aiming to optimize operations, reduce risks, and extend asset lifespan (Molęda et al., 2023a). Its next frontier lies in the convergence of artificial intelligence (AI), advanced analytics, cloud computing, and secure digital infrastructures, forming what is increasingly referred to as Advanced Protection Analytics (APA).

This emerging direction goes beyond traditional asset health monitoring. It emphasizes predicting and preventing high-impact failures that could result in severe operational disruptions, regulatory non-compliance, or even catastrophic events such as ruptures, explosions, or large-scale downtime. The consequences of such failures are not just technical; they carry major financial, environmental, and reputational risks for oil and gas operators.

Future PdM systems will focus on two complementary approaches:

- **Asset-focused Analytics**, which enhance the detection and prediction of failure modes at the equipment level.
- **Process-focused Analytics**, which monitor and protect integrated systems and workflows from cascading failure or unsafe operation.

These two approaches will be powered by smart technologies, including IoTs, ML algorithms, and Bayesian inference models for risk estimation. While traditional performance monitoring has focused mainly on direct parameters such as temperature, pressure, or vibration, next-generation PdM will interpret broader patterns, environmental contexts, and interdependencies between multiple systems.

Additionally, decision-making models are expected to shift from reactive event analysis to predictive, probabilistic frameworks. Technologies like Bayesian Networks are gaining attention for their ability to incorporate uncertainty, assess risk scenarios, and guide maintenance actions based on likelihood rather than just historical precedent.

Crucially, the integration of PdM with strategic asset management must be accompanied by strong attention to safety, scalability, and digital governance. As these systems become more autonomous and data-reliant, cybersecurity, data integrity (e.g., via blockchain), and operator trust become vital considerations in the architecture and deployment of predictive maintenance solutions.

2.12.1. Artificial Intelligence Advancements

As a key technology of the fourth industrial revolution, AI has developed rapidly in recent years. AI doesn't possess general intelligence like human beings, but achieves its so-called “intelligence” by imitating parts of human behavior, such as analysis, reasoning, learning and decision-making (Wang et al., 2024). So far, various forms of AI technologies, including expert systems, decision trees, support vector machines, artificial neural networks, deep learning, model prediction, natural language processing, reinforcement learning, and knowledge graphs, have emerged. AI technology can be used to process and make sense of different types of massive and complex data in oil and gas field development. For example, a large number of geological, geophysical, and geochemical data can be analyzed to improve the accuracy and efficiency of exploration by using machine learning algorithms. By imitating human intuition with the huge amount of production data and the various types of measurements, intelligent production monitoring and optimization technology can be developed to detect abnormal situations, predict oil and gas production, and take corresponding measures to overcome challenges of intelligent production, improve production efficiency, and reduce production costs (Aremu et al., 2018). The structured asset data, types of regularity, and forms of biases have a great impact on the performance and accuracy of machine learning algorithms that drive smart predictive maintenance, so a mechanism for providing a standard method is required for structuring and screening asset data. Thus, the proposed asset data structure standard provides an initial foundation to aid asset management stakeholders in training and testing analytics ML algorithms, particularly after the key insights of the AI domain have been defined, an inventory of asset data types has been documented with their relations to failing modes together with their corresponding regularity and biases, and the architecture has also been defined in this work. Moreover, the influence of the proposed data structuring standard upon the machine learning algorithms have been demonstrated in designed experiments illustrating how usage of the standard improves modelling performance.

2.12.2. Blockchain for Data Integrity

PdM systems increasingly rely on real-time data from IoT-enabled devices installed across oil and gas pipelines, ensuring the trustworthiness and integrity of this data becomes critical. Once IoT sensors and monitoring software are deployed and operational, they enable continuous assessment of asset conditions and performance. However, the effectiveness of PdM relies heavily on the validity of the data sources and the reliability of the execution environment that supports these systems.

In complex, multi-organizational supply chains such as those found in oil and gas, establishing trust through centralized authorities is not always feasible. The industry’s distributed nature, involving multiple stakeholders across the value chain, creates a significant challenge in ensuring transparent and tamper-proof data exchange. To address this, blockchain technology offers a compelling solution. By using a decentralized architecture, blockchain enables the creation of a shared and immutable digital ledger that securely records events, transactions, and sensor data across all nodes in a network (Pincheira et al., 2022).

Blockchain is particularly valuable for verifying the identity and trustworthiness of IoT devices. In operational contexts where high-cost programmable systems coexist with lower-cost commercial-off-the-shelf devices, there is a need to ensure device authenticity and data traceability. Each data point collected must be tied to a verified source, enabling a clear chain of accountability from sensor to system output.

In this architecture, data integrity refers not only to the accuracy and completeness of the collected information but also to its provenance knowing precisely where the data came from and whether it can be trusted. Blockchain allows for this level of control by:

- Logging every device's activity in an immutable ledger.
- Validating data at the point of origin.
- Supporting outlier detection through transparent historical records.

In environments where the integration of diverse hardware is often dictated by economic or operational needs, blockchain ensures that even low-cost, non-proprietary devices are held to a common standard of accountability. This is essential for PdM systems, where inaccurate or tampered data can result in false alerts or overlooked failures.

In broader terms, blockchain represents a technological enabler of trust, much like foundational tools that shaped earlier phases of human progress. Just as writing and navigation enabled early systems of coordination and trust, blockchain underpins modern digital trust architectures, essential for autonomous systems and data-driven decision-making in maintenance operations.

By embedding blockchain in the digital infrastructure of PdM systems, companies in the oil and gas sector can ensure data security, transparency, and operational credibility, critical requirements for scaling predictive maintenance reliably across complex asset networks.

2.12.3. Augmented Reality in Maintenance

The integration of Augmented Reality (AR) into industrial maintenance is gaining momentum, particularly in sectors where equipment downtime results in high operational costs and safety risks. As more companies PdM to reduce failures and increase efficiency, AR has emerged as a valuable support tool especially in addressing workforce-related challenges and improving procedural accuracy.

PdM applications rely heavily on data collected from machines and field assets to forecast failures and schedule interventions. As sensor networks and data platforms become more embedded across industrial operations, these insights can be scaled to larger assets and even entire plants. However, scaling PdM also introduces new complexities for human operators. Technicians are often required to work on unfamiliar or newly upgraded equipment, which demands extensive training, contextual understanding, and interpretation of technical documentation like manuals and piping and instrumentation diagrams (P&IDs).

This is where AR becomes a strategic enabler. By overlaying digital information directly onto physical equipment through mobile devices or smart glasses, this technology provides real-time visual guidance, step-by-step instructions, and contextual cues. This can significantly reduce the cognitive burden on operators, enhance training effectiveness, and minimize human errors even after formal instruction. For example, AR can highlight the specific valve or component that requires maintenance, visualize sensor readings in situ, or warn technicians when safety thresholds are being approached.

Despite its widespread use in consumer markets ranging from gaming to interior design, AR's adoption in industrial maintenance is still limited, primarily due to the specificity and complexity of industrial systems. Nonetheless, the potential is substantial.(Manuri et al., 2019).

AR enables quicker interpretation of asset conditions, and guiding technicians through complex multi-step procedures. Furthermore, when paired with PdM systems, it can help visualize predictive alerts and automate corrective workflows, increasing overall equipment availability and reducing downtime.

In summary, as PdM becomes more data-driven and expansive, AR can serve as a bridge between digital insights and physical actions, enhancing human-machine interaction, reducing operator error, and facilitating safer, more efficient maintenance practices. Its growing role underscores the need for organizations to not only invest in digital infrastructure but also rethink training, documentation, and workforce readiness as part of the implementation framework.

➢ In this chapter, we explored how PdM fits into the broader landscape of asset management and how it can help organizations monitor and manage their equipment more effectively. PdM offers a smarter, data-driven alternative to traditional maintenance approaches by tracking key parameters and predicting failures before they happen. This allows companies to respond proactively rather than reactively saving time, cutting costs, and avoiding unexpected breakdowns.

We also looked at how prediction models can be built and adapted to different conditions, considering the changing environment and operational needs. As technology continues to advance, there's potential to monitor more types of data at different frequencies, making the models even more accurate and useful. Tools like neural networks, fuzzy logic, and cause-and-effect analysis will play a bigger role in future developments, helping us understand how different factors interact and improving the way we forecast equipment behavior.

Importantly, the research also shows that organizations don't always need to invest in entirely new systems. By making better use of existing sensors, data, and monitoring tools, many of which are already in place, companies can start building a PdM strategy without major new investments. This approach is especially helpful for industries like oil and gas, where budgets and resources can be limited, but equipment reliability is critical.

All in all, PdM isn't just about using advanced technology, it's about changing how organizations think about maintenance. By combining technical tools with strategic planning, companies can create a more efficient, reliable, and cost-effective way to manage their assets. The ideas in this chapter lay the groundwork for the next phase of this research, where we'll examine real-world practices and develop a practical framework to help companies like Halliburton successfully implement PdM on the ground.

CHAPTER 2: METHODOLOGICAL FRAMEWORK

Section 1: Research Methodology

This section details the research approach employed to investigate the feasibility of implementing PdM at Halliburton Algeria. It outlines the case study design, qualitative methods (interviews, field observation), and the epistemological foundations that justify the exploratory orientation of this work.

1.1. Introduction

This chapter outlines the methodological framework adopted to explore the current maintenance practices at Halliburton Algeria (Southern operations) and to evaluate both the feasibility and requirements for implementing predictive maintenance. Since this approach has not yet been deployed within the studied organization, the research follows an exploratory and qualitative approach. The goal is to develop a contextualized understanding grounded in operational realities by directly gathering insights from personnel involved in maintenance, operations, and information technology.

The methodology was designed to support a holistic understanding of the organization's technological maturity, the perceptions of its workforce, and the structure of its existing asset management processes.

1.2. Epistemological Foundations and Research Paradigm

This research is situated within an interpretivist paradigm, which acknowledges that organizational reality is socially constructed. As Mays and Pope (1995, p. 43) state, *"the purpose of qualitative research is to develop concepts that help us understand social phenomena in natural (rather than experimental) contexts, emphasizing the meanings, experiences, and viewpoints of all participants."*

This philosophical stance is particularly appropriate for examining industrial maintenance processes, which involve not only technical considerations but also human, organizational, and cultural dimensions. Adopting this epistemological perspective allows the study to explore how different actors within Halliburton interpret, implement, and potentially transform their maintenance practices, especially in light of emerging technologies such as predictive maintenance.

1.3. Research Design

This study follows a single-case qualitative design with embedded units of analysis. This structure is particularly suited for investigating complex phenomena within their real-life

context, especially when the boundaries between the phenomenon (predictive maintenance) and the context (Halliburton’s maintenance environment) are not clearly delineated.
The embedded design enables the inclusion of multiple units of analysis, namely:

- Maintenance engineers and technicians,
- Operations supervisors and managers,
- IT system administrators and technical support staff.

By integrating the viewpoints of these distinct stakeholder groups, the research captures a diverse range of operational realities and technical experiences. The case study strategy is especially appropriate for addressing “how” and “why” questions related to implementation processes, organizational readiness, and strategic alignment, all of which are central to the research objectives.

1.4.1. Participant Selection

Data was collected through semi-structured interviews conducted with 5 employees, distributed across three primary stakeholder groups A purposive sampling strategy was employed to identify participants most likely to offer meaningful insights, based on their day-to-day responsibilities and experience within the organization. This approach ensured that the data collected reflected both the practical realities and the contextual nuances of asset management within Halliburton’s operational environment.

Table 3: List of Interviewees

Name	Position	Department	Years of Experience	Relevance to Study
Hafidh Bounar	E-Tech Supervisor	Internal Equipment Maintenance	10 years	Provides insight into field-level maintenance execution
Mkharmech Haithem	Electronic Technician I	Internal Equipment Maintenance	2.5 years	Offers a junior technician’s view on work orders and tools
Riadh Gunaoua	Maintenance Manager	Internal Equipment Maintenance	15 years	Provides managerial perspective on strategy and challenges
Affaf Mahieddine	Operation Supervisor	Production Solutions	19 years	Familiar with PdM and operational coordination

Diabi Amane	SAP Expert	IT	21 years	Offers expertise on digital systems and SAP infrastructure

Source: Elaborated by the students

1.4.2. Semi-Structured Interviews: Definition and Methodological Justification

Semi-structured interviews constituted the primary method of data collection in this research. According to Pin (2023), *"the semi-structured interview is a widely used data collection technique in qualitative social science research."* It is a guided conversation initiated by the researcher, based on a flexible interview guide or question grid.

This method aims not only to collect information but also to document the participant's lived experience and worldview in a comprehensive manner. Unlike structured questionnaires, which aim to produce standardized data across a large population, semi-structured interviews allow for depth, adaptability, and the emergence of unanticipated themes.

As Lincoln (1995) explains, *"the semi-structured interview is a data collection technique that supports the development of knowledge rooted in qualitative and interpretive approaches, particularly within constructivist paradigms."* It is designed to capture the uniqueness of individuals' or groups' experiences in relation to others, institutions, or broader social phenomena.

In the specific context of this study at Halliburton Algeria, semi-structured interviews were chosen for several key reasons:

1. They allow for in-depth exploration of perceptions, attitudes, and lived experiences regarding current maintenance practices and the potential transition toward predictive maintenance.
2. Their flexibility enables the interviewer to tailor questions to each participant's profile and area of expertise, while maintaining consistency across interviews for comparative analysis.
3. They facilitate the emergence of previously unidentified but important themes relevant to Halliburton's specific operational environment.
4. They are particularly suited to complex organizational contexts where technical, human, and managerial dimensions are deeply intertwined.

The interviews conducted in this study can be classified as focused or targeted interviews, as they centered on a specific experience, namely, current maintenance practices and perspectives on predictive maintenance. This approach, grounded in a concrete case study, serves to better understand the broader phenomenon of digital transformation in the industrial sector.

1.4.3. Interview Protocol

An interview guide was developed based on themes identified in the literature and early field observations. The questions were open-ended and adapted for each stakeholder group to ensure contextual relevance and clarity. Interviews were conducted in French and/or English, depending on the participant's preference, and were audio-recorded with consent before being transcribed verbatim for analysis.

The protocol covered several core themes:

- Understanding of current maintenance processes
- Awareness and perception of predictive maintenance
- Data usage practices and SAP system integration
- Attitudes toward technological change and AI
- Skills, training needs, and perceived barriers to adoption

The interview guide was structured logically and thematically, moving from general questions to more specific topics. This structure provided a consistent framework for discussion while preserving the flexibility necessary to explore emergent insights during the conversation.

1.4.4. Observation: Definition and Methodological Justification

In addition to the semi-structured interviews, this research also employed qualitative observation as a complementary method. According to QuestionPro (2023), *"qualitative observation is a valuable research method that allows researchers to immerse themselves in the complexity of human experiences, gather data, and better understand the subjective aspects of a given phenomenon."* This method focuses primarily on capturing meaning, context, and subtle behavioral nuances, involving a systematic and detailed examination of situations, actions, and interactions.

Observation is widely used in qualitative research and provides direct access to the reality of field practices. It allows the researcher to describe behaviors, settings, routines, and interpersonal dynamics that may not be fully captured through interviews alone (Scribbr, 2019).

In the context of this study, two types of observation were applied:

1. Non-participant observation: The researcher did not intervene or take part in the observed social setting but closely observed maintenance operations, team interactions, and the use of information systems (e.g., SAP and MyPM) in practice.
2. Overt observation: All participants were informed in advance about the research process and the researcher’s presence, fostering an atmosphere of transparency and trust while maintaining methodological rigor.

This observation strategy was particularly useful for several reasons:

- It helped identify actual maintenance practices that sometimes diverged from formal procedures described in interviews.
- It facilitated a deeper understanding of cross-departmental interactions between maintenance, operations, and IT teams.
- It provided insight into technical and organizational challenges likely to influence the implementation of predictive maintenance.
- It revealed unspoken or tacit aspects of workplace behavior that are often critical in shaping organizational culture.

Observations were systematically documented using detailed field notes, including descriptions of observed processes, staff interactions, and preliminary analytical reflections. These notes were later integrated into the overall data corpus for thematic analysis.

1.5. Data Analysis

1.5.1. Thematic Coding

All interview transcripts were imported into NVivo, a qualitative data analysis software. An inductive coding strategy was used, meaning that themes and codes emerged directly from the data rather than being based on a pre-established framework. This approach was especially appropriate given the exploratory nature of the study and the limited exposure of participants to predictive technologies.

Codes were developed on both descriptive and interpretive levels, capturing what participants said and the underlying beliefs, assumptions, or attitudes embedded in their responses. As Pin (2023) emphasizes, such multi-layered coding allows researchers to *"produce data that help grasp the uniqueness of individuals' experiences, especially in their relationships with institutions, colleagues, and broader social phenomena."*

1.5.2. Stakeholder-Based Classification

Each participant was categorized in NVivo according to their stakeholder group (IT, Manager, Technician). This classification enabled group-based thematic comparison through features such as matrix coding queries and visual charts, facilitating a deeper understanding of how perceptions and concerns varied across organizational roles.

1.5.3. Inter-Group Comparison

To compare how different stakeholder groups addressed key themes, such as training needs, resistance to change, or data accessibility, matrix coding queries were performed. This technique highlighted which themes were emphasized by which groups, allowing the researcher to identify contrasts in perception, priorities, and expectations.

1.5.4. Data Triangulation

Triangulation was conducted by systematically comparing insights obtained through interviews, observations, and organizational documents. This strengthened the credibility and validity of the findings by corroborating themes across multiple sources. In alignment with the naturalistic observation approach (QuestionPro, 2023), triangulation grounded the analysis in the real context of the field and ensured consistency and interpretative reliability.

1.6. Ethical Considerations

All participants were informed in advance of the research objectives, the voluntary nature of their participation, and their right to withdraw at any time. Written consent was obtained before conducting each interview.

To ensure confidentiality, all personal identifiers were anonymized. Interview data and recordings were stored securely and used solely for academic purposes. The study was conducted in accordance with the ethical guidelines of the researcher's academic institution. Respecting participant anonymity and data confidentiality was especially critical in the sensitive industrial context of Halliburton, where information related to operational processes and maintenance strategies may have strategic implications. Pseudonyms were used in the presentation of results, and potentially identifying details were adjusted or generalized without compromising the substance of the data.

This ethical posture contributed to establishing a climate of trust with participants, which in turn enriched the depth and openness of the data collected.

1.7. Methodological Limitations

While the qualitative approach adopted in this study enabled a deep exploration of individual and group perspectives, it also presents certain limitations. First and foremost, the findings are context-specific and not intended to be statistically generalizable. The study's focus on a single organization (Halliburton Algeria) limits the direct applicability of the insights to other companies or sectors without careful contextualization.

Moreover, the reliance on self-reported data from interviews may introduce biases such as social desirability or selective memory. However, these limitations were mitigated through data triangulation, which involved comparing interview data with field observations and organizational documentation.

Specific limitations of the methods used include:

1. Semi-structured interviews may be influenced by power dynamics, especially in hierarchical environments like Halliburton, where participants might moderate their responses based on perceived expectations.
2. Observation, even when non-participant and overt, can lead to the so-called Hawthorne effect, where individuals alter their behavior because they are being observed. While this effect often diminishes over time, it must be acknowledged.
3. Subjectivity in qualitative analysis: Despite methodical coding and interpretation strategies, the analysis of qualitative data is inherently interpretive and influenced by the researcher's perspective. A reflexive attitude was maintained throughout the research process to limit this risk.

These methodological limitations were taken into account during the interpretation and presentation of findings. They are discussed transparently to provide a balanced and credible account of the study's strengths and constraints.

➢ The methodological framework adopted in this study combines complementary qualitative approaches, namely semi-structured interviews and field observation, to thoroughly explore current maintenance practices at Halliburton Algeria and assess the potential for implementing predictive maintenance.

Grounded in interpretivist epistemology and aligned with the principles of qualitative case study research, the methodology was carefully designed to capture the complexity of the phenomenon within its organizational context. Through purposive sampling, a diverse range of participants was selected, and through triangulation and thematic analysis, rich and credible insights were drawn from the collected data.

This rigorous and context-sensitive methodology has made it possible to amplify the voices of different stakeholders: technicians, IT experts, and managers, offering a nuanced understanding of the operational, technical, and human factors that would shape any future transition to predictive maintenance.

By anchoring the research in real field practices and fostering a deep interpretive understanding, this methodological framework provides a strong foundation for both the empirical findings and the practical recommendations that follow.

Section 2: Case study context: Halliburton Algeria

Founded in 1919 by Erle P. Halliburton in Duncan, Oklahoma, Halliburton is one of the world's oldest and largest oilfield service companies. The company's inception was rooted in a single innovation: a cementing process for oil wells that significantly improved well integrity and production efficiency. This technology marked the beginning of a century-long journey of innovation, expansion, and strategic leadership in the energy sector.

Today, Halliburton operates in over 70 countries, with a workforce of more than 40,000 employees. Its headquarters are based in Houston, Texas, with a prominent operational hub in Dubai, United Arab Emirates, reflecting its dual presence in both Western and Middle Eastern markets. The company delivers a broad range of products and services to the upstream oil and gas industry.

Throughout its history, Halliburton has played a central role in many of the world's largest oil and gas projects, earning a reputation for technological leadership and operational efficiency. The company has consistently invested in research and development, pioneering technologies in hydraulic fracturing, directional drilling, data analytics, and recently, AI and cloud-based asset monitoring.

Despite its success, Halliburton has also faced public scrutiny, particularly during the early 2000s due to its role in geopolitical and regulatory controversies. Nonetheless, the firm has demonstrated resilience, responding to challenges with corporate reforms and sustainability initiatives, particularly in the areas of safety, environmental compliance, and digital transformation.

In recent years, Halliburton has shifted its strategic focus toward energy efficiency, data-driven services, and digitalization, aligning itself with global trends toward more sustainable and intelligent energy systems. Its current innovation agenda includes predictive maintenance, remote operations, real-time analytics, and the integration of IoT devices into oilfield infrastructure.

Through its long-standing industry presence, global reach, and technological expertise, Halliburton remains a key player in the energy services sector, both as a solution provider and as a strategic partner in the digital transformation of oil and gas operations.

2.1. General Overview

- **Name:** Halliburton Company
- **Founded:** 1919
- **Headquarters:** Houston, Texas, United States
- **Type:** Public (NYSE: HAL)
- **Market cap:** $17.50 billion (2024)
- **Industry:** Oilfield Services and Energy Solutions
- **Global Presence:** Operations in over 70 countries
- **Employees:** Approximately 46,000 (as of recent estimates)

2.2. Business Focus

Halliburton is one of the world’s largest providers of products and services to the energy industry, with a comprehensive portfolio that spans the entire lifecycle of the oil and gas reservoir. Its offerings cover:

- Exploration and evaluation
- Well construction
- Production enhancement
- Asset maintenance and abandonment

The company works with national and international oil companies to deliver integrated, data-driven solutions that optimize performance, increase recovery, and reduce environmental impact.

Source: (Wikepedia, 2002)

Figure 15: Inside one of the company's sites

Source: (Badkar, 2009)

2.3. HESP (Halliburton Entreprise de Services aux Puits)

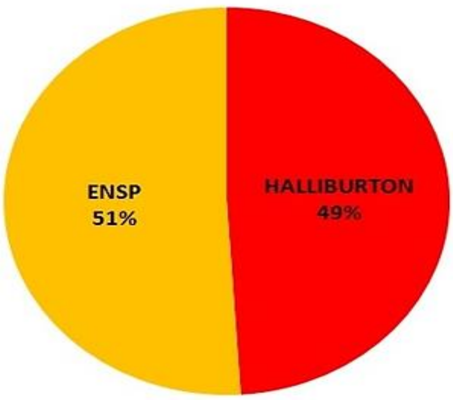
2.3.1 Legal and Organizational Structure

HESP is a joint venture company established in July 1999 and officially began operations on January 1, 2000. It operates in the oilfield services sector and is governed by a public-private partnership between:

- ENSP (Entreprise Nationale de Services aux Puits), holding 51% of shares
- Halliburton, holding 49% of shares

This ownership structure reflects both local content participation and international technical expertise, making HESP a strategic operator in Algeria's oil and gas service industry.

Figure 16: Shareholding Structure of Halliburton



Source: (HESP, 2010)

2.3.1. Core Activities

HESP is specialized in well servicing operations, particularly in high-precision services that are critical during both drilling and production phases of oil and gas wells. Its key operations include:

Logging (Diagraphies)

- Measurement and recording of resistivity, nuclear, and acoustic signals in oil wells (vertical and horizontal).
- These logs are used to analyze and evaluate reservoir characteristics such as porosity, fluid type, and formation boundaries.

Perforation Services

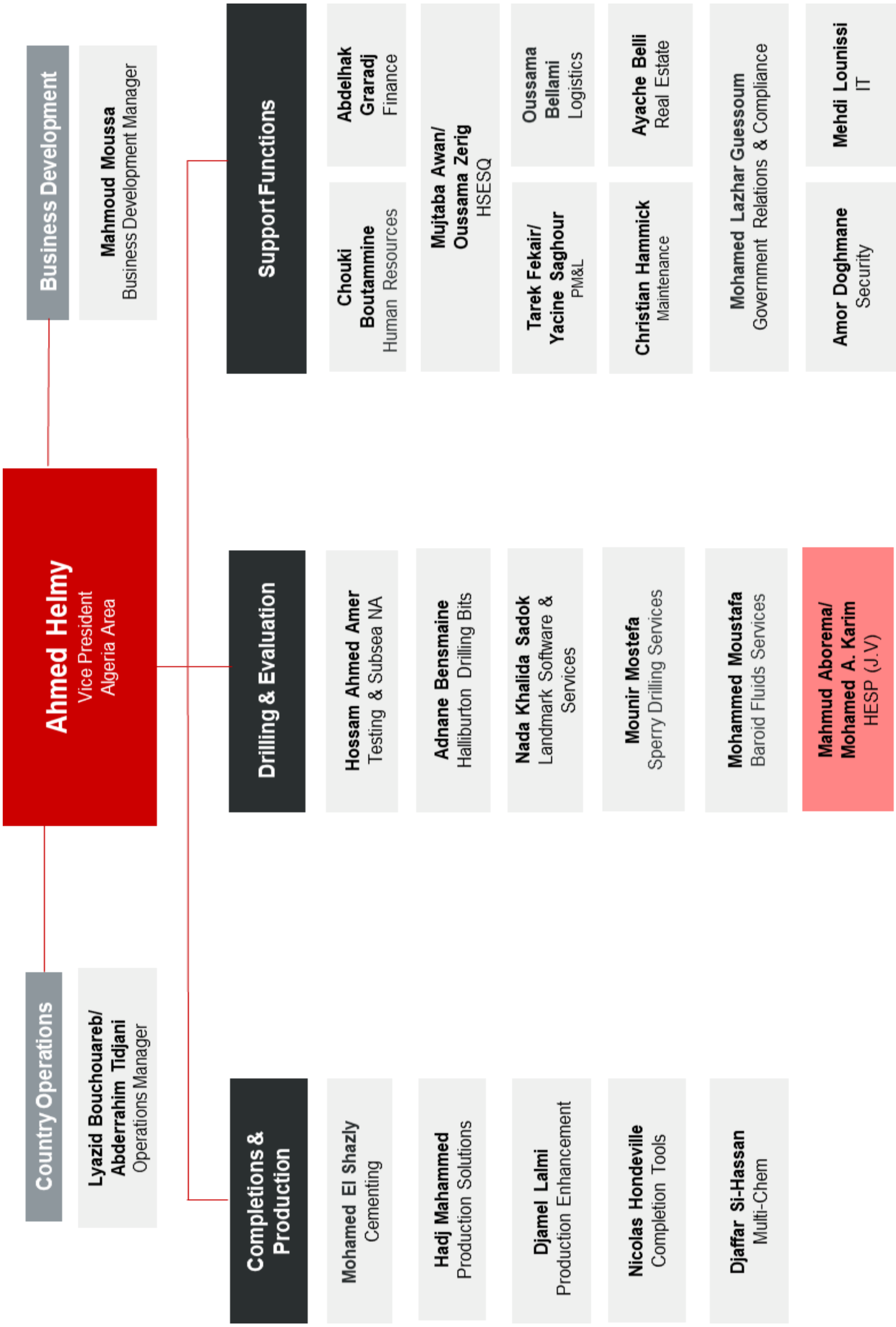
- Execution of perforation jobs essential for connecting the wellbore to the reservoir.
- Involves high-precision explosive charges to allow hydrocarbons to flow into the well.

Well Construction and Maintenance

- Supporting operations for well integrity, diagnostics, and interventions during the entire lifecycle of the well.

2.4. HESP organizational chart

Figure 17: Organizational Chart of HESP



Source: Internal Document

CHAPTER 3: EMPIRICAL STUDY

Section 1: Empirical Findings and Analysis

This section presents the empirical insights gathered from interviews and internal documentation. It analyzes maintenance practices, digital maturity, cultural attitudes, and organizational capabilities. The analysis is structured around cross-functional themes to capture a holistic view of PdM readiness.

1.1. Introduction

This chapter presents the results of the qualitative research conducted at Halliburton Algeria, based on a series of semi-structured interviews with key stakeholders, including managers, maintenance technicians, and IT/digital systems personnel. The objective of this chapter is to analyze the perceptions, practices, and readiness of the organization regarding the adoption of PdM, while also providing an in-depth understanding of the current maintenance process.

The analysis is organized around six cross-functional thematic axes derived from the interview guides:

- Current Maintenance Practices & Process Efficiency
- Data Infrastructure, Tools & Digital Maturity
- Awareness, Attitude & Cultural Readiness for PdM
- Organizational Readiness & Capability for Change
- Perceived Benefits, Concerns & Impact of PdM
- Implementation & Long-Term Outlook

Before diving into these themes, the chapter begins with a description of the existing maintenance process at Halliburton Algeria, highlighting the roles of systems like SAP and MyPM, and the general workflow across departments. This overview provides essential context for understanding the organization's operational baseline.

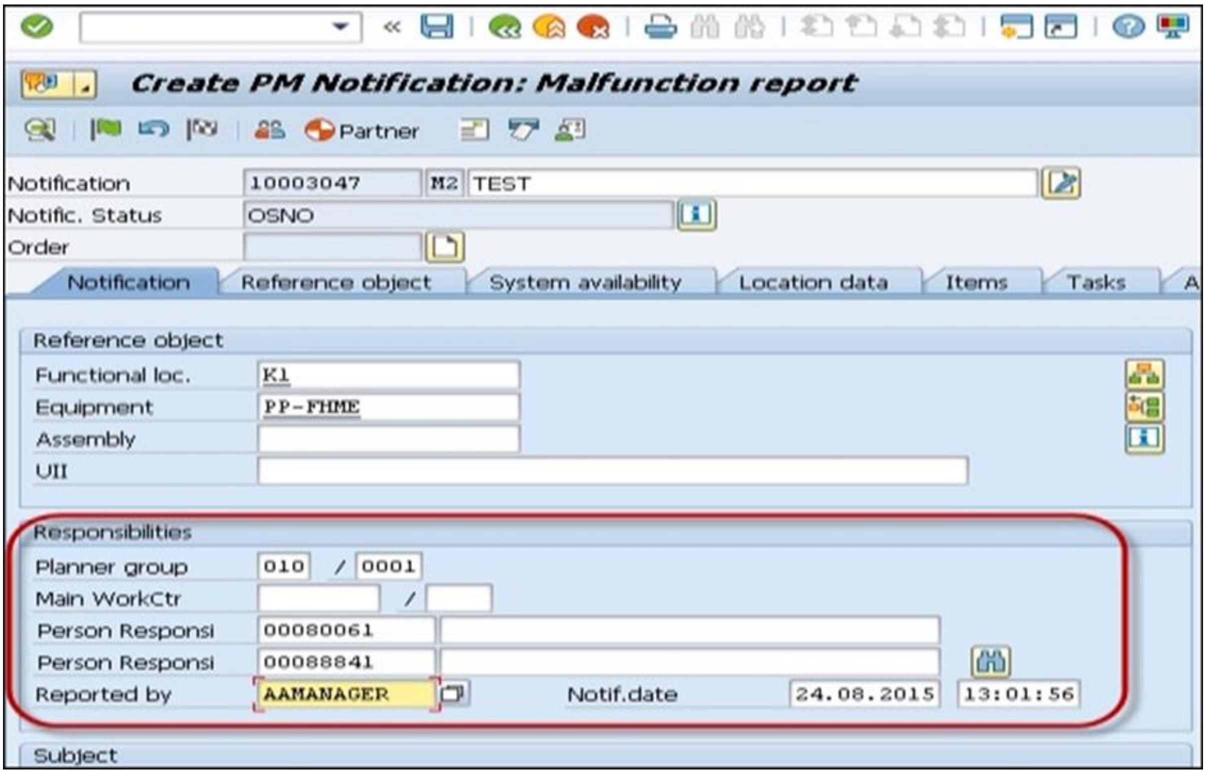
As the chapter progresses, each axis is examined in detail to uncover strengths, weaknesses, and recurring patterns. Particular attention is given to the obstacles, both technical and organizational, that may hinder the adoption of PdM, as well as areas of potential leverage, such as existing data systems or management support.

Through this cross-functional lens, the chapter aims to offer a nuanced interpretation of the organization’s current state, readiness for change, and the strategic implications of moving toward predictive maintenance. The analysis not only identifies key challenges but also highlights opportunities for improvement and alignment across departments.

1.2. Overview of Halliburton Maintenance Workflow

Based on the internal flow chart and field observations we can say that the maintenance process at Halliburton Algeria is a structured, multi-departmental system that blends both corrective and preventive maintenance strategies, aimed at ensuring operational efficiency, equipment integrity, and safety compliance. The workflow typically initiates when an equipment breakdown occurs within a Product Service Line (PSL), or when scheduled preventive maintenance is due. This triggers the creation of a Maintenance Request Form, which serves as the formal start of the process.

Figure 18: SAP Maintenance Notification Creation

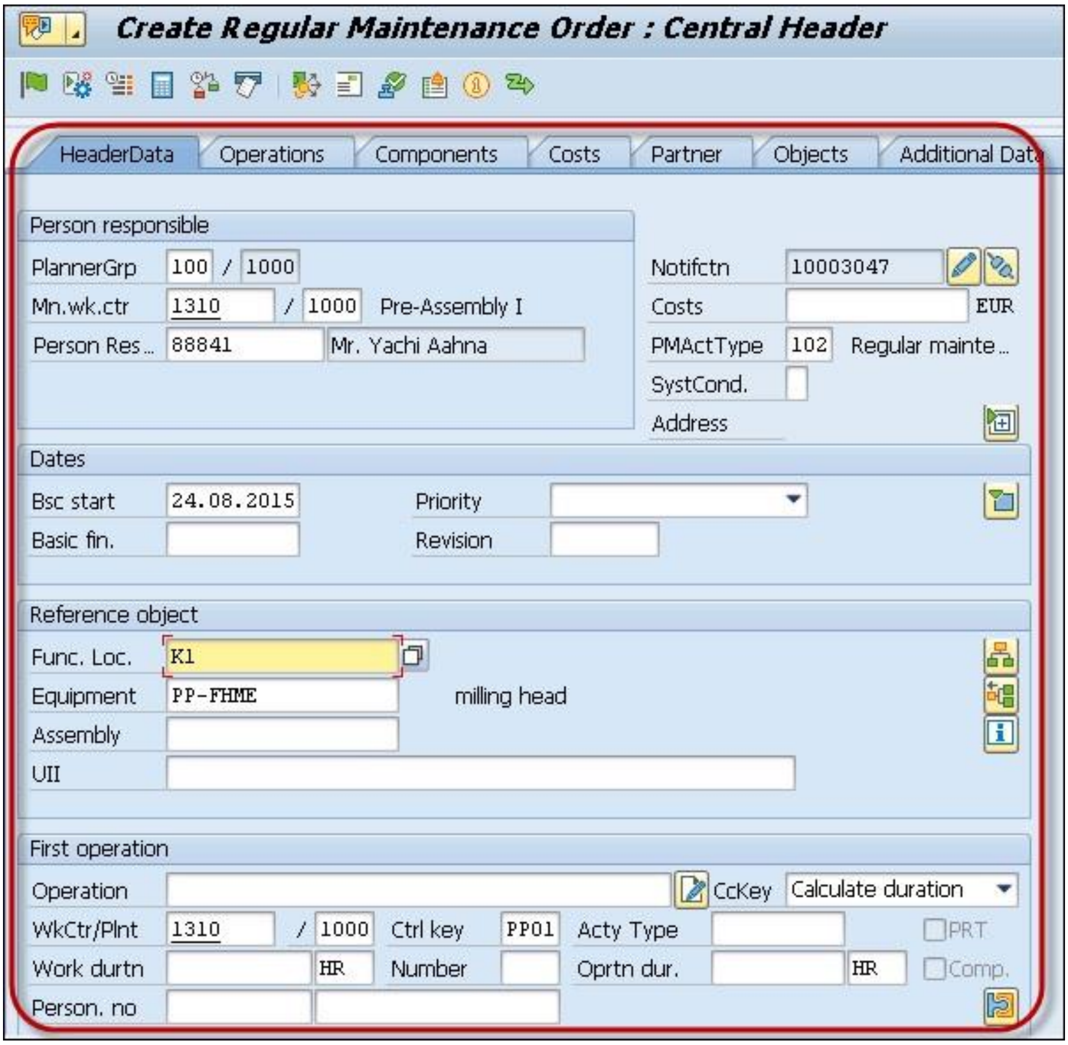


Source: (Ntirandekura, 2017)

From this point, the Planner/Scheduler steps in to review the request (categorized within the system under "2HOP") and proceeds to attach relevant notification details and generate a Work Order. They then assess the scope of work, define the required resources, and verify the availability of the targeted equipment.

Simultaneously, the Supply Chain team reviews the same maintenance request to ensure that all necessary parts are available. If missing, the team sources them either internally or from external vendors. Once secured, the parts are delivered to the technician via a Goods Issue tracked in SAP, ensuring traceability and accountability.

Figure 19: SAP Work Order

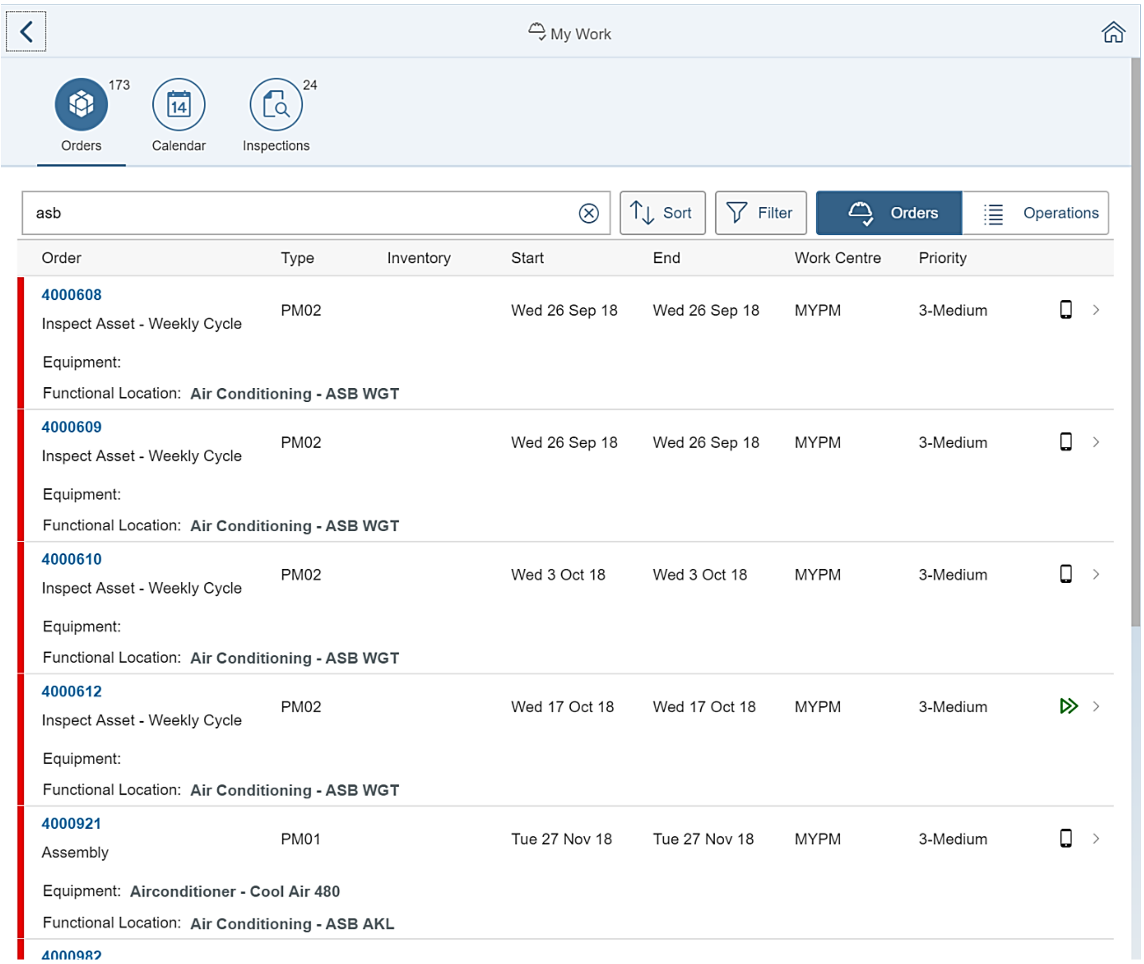


Source: (TutorialsPoint, s.d.)

With planning and procurement complete, the technician reviews the assigned task in MyPM; the digital maintenance platform used at Halliburton. Before beginning work, technicians are required to execute critical safety procedures, including Job Safety Analysis (JSA), Lockout/Tagout (LOTO) to isolate equipment energy sources, and a Permit to Work (PTW), especially for hazardous or high-risk tasks. Once safety measures are confirmed, the technician carries out the repair or preventive operation.

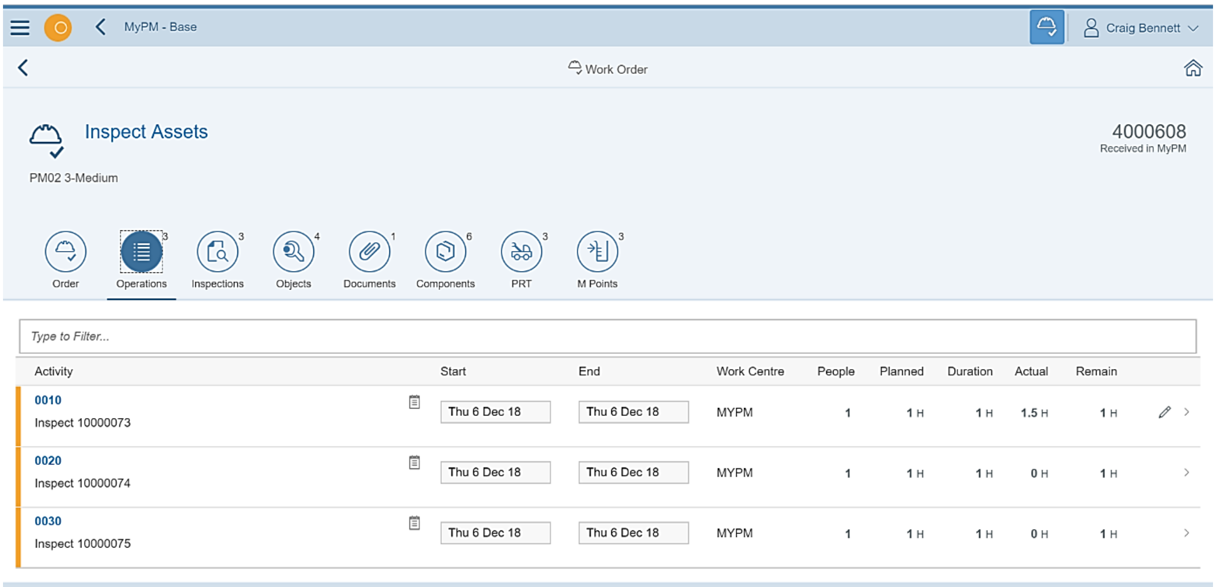
Upon completion of the initial task, the technician encounters a decision point: if a new issue is discovered, the workflow loops back to the planning stage with the creation of a new TECO (Technically Completed) Order to address the additional problem. If no further issues are detected, the technician finalizes the order details in MyPM and may initiate a Request for Engineering Change (RFEC), especially if technical modifications or system updates were made during the intervention. Another decision gate checks whether the process is fully complete; if not, the order moves into a holding pattern until all work is satisfactorily closed.

Figure 20: MyPM List of Orders



Source: (Bennet, 2019)

Figure 21:Example of a Work Order on MyPM



Source: (Bennet, 2019)

When function testing is required, the responsibility shifts back to the PSL, which creates a Function Test Order to validate that the equipment is operating correctly post-repair. The technician then performs this functional test, which may need to be repeated if the initial result is unsatisfactory. Only once the equipment passes the test can the technician attach the necessary documentation and update all related inputs into the system. The Planner/Scheduler then formally closes the Function Test Order, and the equipment is released back into operation. The final status in SAP is marked as "Complete," signifying the successful end of the maintenance cycle.

An additional note in the process documentation indicates that any authorized personnel can initiate or release a workflow, allowing flexibility and quick response to equipment needs. Throughout this system, SAP functions as the central coordination and archival platform assigning unique IDs to work orders, technicians, and equipment, managing costs by department (via cost centers), and ensuring traceability. MyPM serves as the frontline interface for technicians and supervisors to manage work instructions and execute

Figure 22: SAP Order Plan

PM Order Plan / Actuals Line Item Wise

PM Order Plan/Actuals Line Item WIse

PM Order No	Code	Mat/Ser Code	Mat/Ser Desc	Units	Plan Qty	Plan Cost	Act Qty	Act Cost
910000004004	Mat	OFO10004	Removed Transformer Oil	L	20.000	507.40	20.000	507.37
	Mat	SCR00004	Aluminium Scrap BTW	KG	30.600-	2,358.65-	30.600-	2,144.45-
	Mat	SCR00006	Brass Scrap	KG	0.200-	17.63-	0.200-	16.03-
	Ser	SOT00019	Replacement of MS Bolts&Nuts with washer	EA	6.000	18.00	6.000	18.00
	Ser	SOT00018	Replacement of LV Epoxy Bushings	EA	3.000	180.00	3.000	180.00
	Ser	SOT00017	Replacement of Conventional LV Bushings	EA	2.000	56.00	2.000	56.00
	Ser	SOT00015	Replacement of Conventional HV Bushings	EA	2.000	190.00	2.000	190.00
	Ser	SOT00014	Replacement of LV brass metal Parts	EA	3.000	69.00	3.000	69.00
	Ser	SOT00013	Replacement of HV brass metal Parts	EA	1.000	23.00	1.000	23.00
	Ser	SOT00012	Replacement of LVBushRods with washers	EA	3.000	165.00	3.000	165.00
	Ser	SOT00011	Replacement of HV BushRods with washers	EA	1.000	55.00	1.000	55.00
	Ser	SOT00023	Reinsulation of Aluminium Coils	KG	18.000	756.00	18.000	756.00
	Ser	SOT00002	Labour for Replacement of HV Coil Al.DTR	KG	40.200	1,286.40	40.200	1,286.40
	Ser	SOT00001	Replacing of HvCoil Material for Al.DTR	KG	40.200	7,839.00	80.400	10,974.60
	Ser	SWR00087	Transport of failed Units from SPM Sheds1	EA	1.000	1,842.00	1.000	1,842.00
910000004004						▪ 10,610.52		▪ 13,961.89
910000004005	Mat	SCR00006	Brass Scrap	KG	0.250-	22.03-	0.250-	20.03-
	Mat	SCR00004	Aluminium Scrap BTW	KG	35.100-	2,705.51-	35.100-	2,459.81-
	Mat	OFO10004	Removed Transformer Oil	L	25.000	634.25	25.000	634.21
	Ser	SWR00087	Transport of failed Units from SPM Sheds1	EA	1.000	1,842.00	1.000	1,842.00
	Ser	SOT00001	Replacing of HvCoil Material for Al.DTR	KG	45.000	8,775.00	90.000	12,285.00
	Ser	SOT00002	Labour for Replacement of HV Coil Al.DTR	KG	45.000	1,440.00	45.000	1,440.00
	Ser	SOT00023	Reinsulation of Aluminium Coils	KG	27.900	1,171.80	27.900	1,171.80
	Ser	SOT00011	Replacement of HV BushRods with washers	EA	2.000	110.00	2.000	110.00
	Ser	SOT00012	Replacement of LVBushRods with washers	EA	3.000	165.00	3.000	165.00
	Ser	SOT00013	Replacement of HV brass metal Parts	EA	2.000	46.00	2.000	46.00
	Ser	SOT00014	Replacement of LV brass metal Parts	EA	3.000	69.00	3.000	69.00
	Ser	SOT00015	Replacement of Conventional HV Bushings	EA	2.000	190.00	2.000	190.00
	Ser	SOT00017	Replacement of Conventional LV Bushings	EA	3.000	84.00	3.000	84.00
	Ser	SOT00018	Replacement of LV Epoxy Bushings	EA	3.000	180.00	3.000	180.00
	Ser	SOT00019	Replacement of MS Bolts&Nuts with washer	EA	4.000	12.00	4.000	12.00
910000004005						▪ 11,991.51		▪ 15,749.17
						▪▪ 22,602.03		▪▪ 29,711.06

Source: (SAP, 2019)

1.3. Lexical Analysis of Interview Data

To enrich the thematic findings, a lexical analysis of interview transcripts was conducted. By examining word frequency and usage, this method highlights recurring concerns, key priorities, and common language patterns related to predictive maintenance, helping to validate and complement earlier qualitative insights.

Figure 23:Words Cloud

Elaborated by the students using NVivo

Table 4: Words Frequency

Word	Count	Weighted Percentage (%)	Word	Count	Weighted Percentage (%)
Maintenance	58	2,87	PdM	23	1,14
Data	35	1,73	Training	23	1,14
Predictive	30	1,48	System	22	1,09
SAP	28	1,38	Need	21	1,04
Work	26	1,29	Time	18	0,89

Source: Elaborated by the students using NVivo

This Table and figure present a ranked list of the most commonly used terms across interview transcripts, offering a quantitative lens into the thematic focus of the respondents.

Key Observations:

- "Maintenance" dominates with 58 occurrences (2.87%), confirming the centrality of the topic throughout discussions. This aligns with the core theme of the study.
- "Data" and "Predictive" follow closely, reinforcing the ongoing shift from traditional to data-driven maintenance approaches. Their combined frequency (~3.21%) reflects how critical data is perceived in enabling PdM systems.
- "SAP", "Work", and "Training" emerge as recurrent themes, indicating that digital system integration and human resource preparedness are equally on stakeholders' minds.
- Words like "System", "Sensors", and "Real-time" suggest a shared awareness of the technological infrastructure required for implementation.

Implications:

The lexical weight of terms like training, implementation, and integration signals a recurring concern with change management and technical readiness. Simultaneously, the frequent appearance of alerts, failures, and planning points to a desire for better foresight and operational stability.

Table 5: Text search for the term "PdM"

Department	References	Coverage
Managers and Operators	42	9.35%
IT Department	15	3,75%
Technicians	36	8.98%

Source: Elaborated by the students using NVivo

This spreadsheet details how often specific keywords or themes were cited by different stakeholder groups, providing insight into the distribution of concerns and interests across roles.

Key Observations:

- Managers and Operators contributed 42 references, indicating strong involvement in strategic or operational decision-making regarding PdM.

- Technicians followed closely with 36 references, which highlights their practical engagement and concerns with day-to-day maintenance challenges and tool usability.
- The IT Department accounted for 15 references, suggesting a more focused or specialized contribution, often related to integration and system architecture.

Implications:

The heavier input from technicians and operators suggests that implementation success or resistance will hinge on their experience. Managers, while equally engaged, seem to focus on organizational readiness, cost justification, and performance outcomes.

The lighter contribution from IT may reflect either a less central role in the current maintenance setup or a gap in interdisciplinary collaboration, especially critical since IT is expected to play a key enabling role in PdM systems (sensor integration, data flow, dashboarding, etc.).

Table 6:Pearson Correlation between the different stakeholders

Source A	Source B	Pearson correlation coefficient
Riadh	Affaf	0,730409
Haithem	Hafidh	0,7213
Riadh	Hafidh	0,511255
Hafidh	Affaf	0,470105
Riadh	Haithem	0,459186
Haithem	Affaf	0,441078
Riadh	Diabi	0,404118
Diabi	Affaf	0,389371
Hafidh	Diabi	0,387315
Haithem	Diabi	0,383076

Source: Elaborated by the students using Nvivo

This table shows Pearson correlation coefficients between pairs of internal sources, indicating how similar their word usage is (with 1 being identical and 0 being no similarity). Here’s the analysis based on the provided roles:

Key Observations:

Highest Similarity

- **Riadh & Affaf**: 0.73

  This suggests strong alignment in communication or documentation styles between the two managers, which is expected given their shared roles.
- **Haithem & Hafidh**: 0.72

  Their high correlation might indicate collaboration or similar functions as they're both Technicians in the same department
- **Riadh & Diabi**: 0.40

  Moderate similarity, possibly reflecting IT-related communications or projects involving Riadh.

Lower Correlations

- **Haithem/Hafidh with Affaf**: ~0.44–0.47

  Suggests these pairs interact less or have divergent documentation styles.
- **Diabi with Hafidh/Haithem**: ~0.38–0.39

  Indicates minimal overlap, typical as IT and technicians operate in distinct contexts.

1.4. Cross-Functional Interview Analysis

1.4.1. Current Maintenance Practices

Table 7: Technicians Daily Operations & Tools

	Bounar Hafidh	Mkharmech Haithem
Daily Operations & Tools	– I handle diagnostics, electrical inspections, and make sure preventive maintenance tasks are carried out according to schedule. – I also supervise technicians and coordinate with other departments through MyPM application and E-mail. – We usually find out from operators who report performance issues, or during routine inspections. – We don't get any real-time alerts, our equipment uses traditional sensors, not smart ones, so it's based on experience and visible signs. – We use MyPM to complete Work Orders, which include checklists. – Before completing a task, we follow a standard checklist for Job Safety Assessment (JSA) with photo evidence. – Everything gets logged into SAP later for tracking and cost purposes.	– I mostly handle routine inspections, small repairs, and electronic diagnostics. – I follow checklists provided in MyPM and report to my supervisors Mr Bounar. – Most of my work is preventive, but sometimes I help with emergency repairs too. – We're informed either through a work order or by an operator who noticed an issue. – Since we don't have smart sensors, we check based on visual signs, unusual noise, or readings from traditional instruments. – We use E-mail and MyPM to receive work orders, and we document our work with photos and checklists. – Everything gets uploaded and eventually recorded in SAP, which calculates costs and labor

Source: Elaborated by the students using Nvivo

Table 8: Technicians Challenges & Manual Efforts

	Bounar Hafidh	Mkharmech Haithem
Challenges & Manual Efforts	– Malfunctioning electrical components, wear and tear on motors or pumps, and issues with calibration. – Sometimes we replace parts that are still functional just to be safe, because we can't predict when they'll fail. – Definitely. – If we had real-time condition monitoring or alerts, we could have prevented several breakdowns. – But with our current setup, it's more about fixing things when they show clear signs of damage and preventing breakdowns at much as we could	– Sensor misreadings, wiring faults, and issues with electronic control systems – Sometimes the root cause isn't obvious, so we rely heavily on trial and error. – Yes, many times. – Some parts show early signs of fatigue that we miss because we don't have systems that monitor condition in real-time. – We end up doing curative work that could've been prevented.

Source: Elaborated by the students using NVivo

Table 9: Manages on Current Strategy & Practises

	Mahieddine Affaf	Gunaoua Riadh
Current Practices & Strategy	- We mostly rely on curative and preventive maintenance. - Preventive work is scheduled through SAP, while curative is done when something fails unexpectedly. - The preventive approach helps us reduce risks, but it's still not enough to avoid unplanned downtime completely. - Preventive tasks are scheduled based on usage: days, hours, or kilometrage. - If there's a breakdown, a maintenance request is sent to the IEM department, and also to the warehouse if spare parts are needed. - Everything gets documented in SAP. - Delays cause serious problems-production stops, projects get delayed, and we lose time and resources. - Sometimes maintenance is done too early or too late because there's no accurate way to judge equipment condition in real-time.	- We mainly use curative and preventive maintenance. - Curative is reactive, it's what we do when something breaks or malfunctions. - Preventive maintenance is scheduled and done according to usage criteria: days of operation, hours logged, or kilometrage. - This helps reduce breakdowns but doesn't fully prevent them. - It's mostly schedule-based. - SAP system generates Work Orders for preventive tasks based on the criteria I mentioned. - Failures, on the other hand, trigger emergency requests. - Everything is logged and tracked through SAP, which also monitors costs. - Unplanned downtime is the biggest issue. - When preventive tasks are delayed or when unexpected failures occur, it impacts equipment availability and operational planning. - We also face delays in sourcing spare parts if the warehouse isn't informed early.

Source: Elaborated by the students using NVivo

Table 10: IT on Current Infrastructure

	Diabi Amane
Current Infrastructure	– Our core system is SAP, which manages everything from maintenance work orders to cost control and inventory. Maintenance tasks are scheduled through MyPM, but SAP handles tracking, ID assignment, labor hours, and financial reporting. – Not really. – We have traditional sensors, but they're not "smart." They don't connect to the network or communicate with SAP. – So, there's no live data, only data entered manually after interventions.

Source: Elaborated by the students using NVivo

This axis focuses on how maintenance is currently carried out at Halliburton Algeria, highlighting strategies, tools, and recurring challenges shared across roles.

Several key themes emerged from the interviews regarding current maintenance practices:

- **Dual maintenance strategy**: All interviewees confirmed the use of both curative (reactive) and preventive (scheduled) maintenance, with preventive actions guided by predefined usage metrics such as operational days, hours, or kilometrage.
- **Role of digital systems**: The SAP system is central to maintenance management, handling work order generation, cost tracking, and ID assignments, while MyPM is used for completing tasks, checklists, and submitting documentation with photo evidence.
- **Lack of real-time monitoring**: A major limitation identified is the absence of smart sensors or condition-monitoring tools. Maintenance teams rely on operator feedback, visual inspections, and traditional instruments, leading to delays in detecting faults.
- **Proactive but imprecise scheduling**: Although preventive work is scheduled regularly, the inability to assess equipment condition in real time means that maintenance is sometimes performed too early or too late, reducing efficiency.
- **Common issues and breakdowns**: Interviewees frequently cited unplanned downtime, resource losses, and project delays caused by delayed maintenance or unexpected failures. Additionally, coordination with departments like IEM or the warehouse can be slow, impacting responsiveness.
- **Experience-based decisions**: Due to the lack of predictive tools, many decisions are based on technician experience and trial-and-error diagnostics, with some parts being replaced prematurely as a precaution.

Overall, the current system is structured and supported by SAP, but remains heavily reactive and constrained by technological gaps and communication delays.

1.4.2. Data Infrastructure & Digital Maturity

Fos this Axis we chose the previous *Table 5 + Table 8 and additionally:*

Table 11: IT Data Collection & Management & integration Challenges

	Diabi Amane		Diabi Amane
Data Collection & Management	– We store information related to work orders, equipment IDs, labor time, spare parts used, and costs. – So, we can say that our analysis is mostly always reactive or historical. – Data quality, system compatibility, and security. – Predictive models need clean, reliable input, and if sensors are inaccurate or offline, predictions won't be valid. – Also, data ownership and access rights would need to be managed.	**Integration Challenges**	– Technically, SAP can be integrated with external systems through middleware or APIs. – But it would require investment, IT coordination, and standardized data formats. Right now, we don't have a system for ingesting real-time sensor data. – Data quality, system compatibility, and security. – Predictive models need clean, reliable input, and if sensors are inaccurate or offline, predictions won't be valid. – Also, data ownership and access rights would need to be managed.

Source: Elaborated by the students using Nvivo

This axis explores the current state of digital tools, sensor infrastructure, data handling practices, and technological readiness at Halliburton Algeria, revealing significant constraints and opportunities.

- **Absence of real-time monitoring**: The company does not use smart sensors; instead, traditional instruments are used to detect anomalies through visual cues, noise, or operator reports. As a result, there are no automated alerts or real-time diagnostics.
- **Manual data collection and input**: Information from maintenance tasks, such as work orders, checklists, photos, and Job Safety Assessments, is first processed through MyPM and then manually uploaded to SAP. This creates a time lag and contributes to a reactive, post-event data culture.
- **Limited system integration**: While SAP is the backbone for operations like labor tracking, inventory, and cost control, it is not currently integrated with real-time sensor data or external PdM tools. Integration would require middleware, APIs, and IT coordination, which are not yet in place.
- **Reactive analytics and low digital maturity**: Because the data is collected after interventions, analysis tends to be reactive and historical. Predictive approaches are hindered by the lack of continuous, real-time data flows.

- **Technical and organizational constraints**: Concerns were raised about data quality, system compatibility, and security. Furthermore, the lack of protocols for managing data ownership and access rights poses additional barriers.

These factors collectively indicate that while some foundational systems are present (SAP and MyPM), significant improvements in sensor technology, integration capabilities, and data governance would be needed to support predictive maintenance

1.4.3. Awareness & Attitude Toward PdM

Table 12: Managers Awarness & Attitude toward PdM

	Mahieddine Affaf	Gunaoua Riadh
Awareness & Attitude Toward PdM	– Yes, I'm familiar with it and I strongly believe it can help us a lot. – Predictive maintenance allows for early detection of potential failures, meaning we can intervene before the problem escalates. – It's a proactive strategy that could improve efficiency and reduce emergency interventions. – It's been mentioned in high-level conversations, but there's been no official roadmap for implementation. – I think people are interested, but they don't fully understand how it works or what it requires.	– I'm aware of the concept, but it hasn't been implemented here. – It seems like a smart way to optimize interventions, especially by using real-time data. – But without proper tools and integration, it's just a theory to us for now. – Not seriously. – There's some curiosity, especially from technical staff who've heard about it during training, but we haven't had a structured discussion or pilot project.

Source: Elaborated by the students using NVivo

Table 13: Technicians Digital Readiness & Training

	Bounar Hafidh	Mkharmech Haithem
Digital Readiness & Training	– No, we got familiar with SAP and following digital checklists through experience, also no training on advanced diagnostics or predictive tools. – Everything we do is based on pre-set intervals or physical inspection. – We'd need clear guidance on how to read and trust the alerts, understand the logic behind the system, and integrate it into our daily workflow. – A test phase would be helpful.	– I've received basic SAP training, but not much about diagnostics beyond using handheld testers. – There's no training here on how to work with PdM systems or data interpretation. – I'd need a clear explanation of how the system works, how to read alerts, and how to act on them. – A mix of theoretical and practical training would help.

Source: Elaborated by the students using NVivo

Table 14: Technicians Understanding of PdM

	Bounar Hafidh	Mkharmech Haithem
Understanding of PdM	– I've heard the term during internal discussions, but we don't use it here. – From what I understand, it's about using data to predict failures before they happen, we don't have the tools or sensors for that yet. – I'm comfortable with MyPM and basic SAP functions. – But when it comes to reading graphs or interpreting sensor data, that would need some training.	– I've heard about it in discussions and training. – To me, it's a system that uses live data to predict when something will break down, so you can fix it before it does. – But we don't have anything like that here. – I'm comfortable with the basics: SAP, MyPM, and checklists. – But if we had PdM tools, I'd need extra training to interpret graphs or alerts. – It's not part of our current work culture yet.

Source: Elaborated by the students using NVivo

This axis explores the level of understanding, perceived benefits, and organizational readiness for implementing predictive maintenance at Halliburton Algeria.

- **General Awareness of PdM**: Most of the interviewees are somewhat familiar with the concept of predictive maintenance. They understand it as a strategy that uses data to anticipate failures before they occur, potentially improving efficiency and reducing emergency interventions.
- **No Current Implementation**: Although PdM has been mentioned in high-level conversations or during training sessions, there is no structured implementation, pilot project, or roadmap in place at Halliburton Algeria.
- **Lack of Technical Tools**: The absence of real-time data acquisition tools and smart sensors is a major barrier. The current system relies on traditional sensors, manual entries, and physical inspection.
- **Training and Skill Gaps**: Technicians and engineers reported that they have not received any formal training related to predictive tools, diagnostics, or data interpretation. They expressed the need for structured training, both theoretical and hands-on, if PdM were to be implemented.
- **Integration Concerns**: There is some uncertainty about how predictive maintenance would be integrated into existing workflows such as SAP and MyPM. Employees mentioned the importance of clear guidance on how to interpret and act on PdM alerts.

- **Cultural Readiness**: PdM is not yet embedded in the current maintenance culture. Employees recognize that adopting such a system would require not only technical changes but also a shift in mindset and work habits across the organization.

1.4.4. Organizational Readiness & Capability

For this axis we'll use the previous *Table 12* and the following:

Table 15: Managers Organizational Readiness

	Mahieddine Affaf	Gunaoua Riadh
Organizational Readiness	– We already have SAP and digital work orders. – If we could connect those with smart sensors and real-time data platforms, we'd be off to a good start. – Also, IT and engineering teams could help interpret the data, but training is essential. – Resistance to change, lack of real-time data, and limited awareness about how PdM works. – Some people worry it will make their jobs harder or obsolete. – And with no smart sensors in place yet, we're starting from scratch in terms of infrastructure.	– SAP could be a good backbone if connected to real-time sensors. – The IT team knows the system well, and some engineers are technically inclined, but we'd need training, a new layer of tools, and involvement from multiple departments – The main challenges are data integration, technician training, and change management. – Also, some of our equipment are old and not compatible with modern sensors. – We'd need investments and a mindset shift.

Source: Elaborated by the students using NVivo

Table 16: IT Organizational and Technical Alignment, plus Predictive Analytics Readiness

	Diabi Amane		
Organizational and Technical Alignment	– Collaboration happens, especially during system updates, but it's not structured for innovation. – We operate more as system support than as digital transformation drivers. – A major role. – IT would be responsible for system integration, data flow, sensor network management, and possibly helping interpret or visualize PdM outputs.	**Predictive Analytics Readiness**	– Not yet. – We've used dashboards for KPI reporting, but nothing that supports machine learning or predictive analytics. – That's still theoretical in our environment. – We'd need continuous input from vibration, temperature, and pressure sensors, along with historical maintenance data. – Then we could train a model to recognize failure patterns.

Source: Elaborated by the students using NVivo

This axis evaluates the internal capabilities, existing systems, and structural preparedness of Halliburton Algeria for adopting predictive maintenance technologies.

- **Existing Digital Foundations**: SAP and MyPM are well-integrated into daily workflows, serving as digital backbones for maintenance tracking, work orders, and cost management. Employees are familiar with these systems, which could be leveraged as a foundation for PdM.
- **Lack of Specialized Training**: Staff members across departments reported having little to no formal training in diagnostics, predictive tools, or data interpretation. Most gained SAP knowledge through experience rather than structured instruction, and PdM-related competencies are absent.
- **Training Requirements**: Interviewees consistently emphasized the need for both theoretical and hands-on training to help technicians understand PdM logic, interpret alerts, and apply insights effectively. A pilot phase with learning support was suggested as an ideal starting point.
- **Role of IT and Engineering Teams**: While IT teams are experienced in managing current systems, they function more as support rather than innovation drivers. However, they are well-positioned to contribute to PdM integration by managing sensor networks, data flow, and visualization tools.
- **Technological Gaps**: The absence of smart sensors and real-time data platforms is a major limiting factor. Most existing equipment is older and not compatible with modern sensor technology, requiring significant investment to upgrade infrastructure.
- **Change Management Barriers**: There is a recognized resistance to change among staff, with some expressing concern that PdM could complicate workflows or make roles obsolete. Overcoming these psychological and cultural barriers would require clear communication and inclusive planning.
- **Interdepartmental Collaboration**: While collaboration exists, particularly around system maintenance and updates, it is not structured around innovation or transformation. A more cross-functional and strategic approach will be necessary to drive PdM adoption.
- **Need for a Strategic Roadmap**: There is no current roadmap or strategic plan for PdM deployment. Stakeholders agree that a phased approach, with investment in tools, training, and cross-functional coordination will be essential for building organizational capability.

1.4.5. Perceived Benefits & Concerns

To fully cover this axis, we'll bring back *Table 12* and also:

Table 17: Managers Benefits & Concerns

	Mahieddine Affaf	Gunaoua Riadh
Benefits & Concerns	– It could bring fewer breakdowns, lower maintenance costs, and better planning. – It would also reduce unnecessary preventive work and give us more confidence in asset health. – It's a win for both safety and productivity. – Yes. – Technicians may resist at first due to lack of training or fear of automation. – Also, if the system is too complicated or gives false alerts, people will stop trusting it. – That's why proper implementation and communication are crucial.	– Better resource planning, reduced emergency interventions, and lower costs over time. – It would also improve reliability and allow us to focus on optimization rather than firefighting. – Yes, especially from technicians who aren't comfortable with digital tools. – There's a fear of complexity and lack of trust in automated systems. – Without proper onboarding, adoption could be slow.

Source: Elaborated by the students using NVivo

Table 18: Technicians Pratical Concerns

	Bounar Hafidh	Mkharmech Haithem
Practical Concerns	– It would help if it's accurate and easy to use. – Right now, we waste time checking things that don't need fixing or reacting too late. – But if it's too technical or unreliable, it'll just slow us down. – The ability to plan based on real data, not just usage estimates. – We need better visibility into actual equipment condition.	– It would help a lot if it's accurate. – now, we often react late or inspect things that don't really need work. – But if the system gives false alarms or is too complex, it could slow us down. – Real-time monitoring and better inputs. – We rely too much on historical data and routine checks. I think with better data, we could be more efficient.

Source: Elaborated by the students NVivo

Table 19: IT pov on Security, Budget & Scalability

	Diabi Amane
Security, Budget & Scalability	– Security would be a concern, especially if external cloud services are used. – But with the right protocols and internal governance, it's manageable. – The bigger issue is ensuring data accuracy and sensor health. – Yes, definitely. – New sensors, software licenses, training, they all have costs. – It would have to be presented as a long-term investment with measurable ROI.

Source: Elaborated by the students using Nvivo

This axis captures the perceived advantages of PdM as well as the reservations, fears, and practical challenges expressed by Halliburton Algeria personnel.

- **Recognized Benefits**: Across interviews, participants consistently acknowledged the potential value of PdM. Benefits include reduced breakdowns, improved equipment reliability, fewer unnecessary preventive interventions, better visibility into asset condition, and enhanced resource planning. Several interviewees highlighted that PdM could boost both safety and productivity while optimizing costs over time.
- **Improved Efficiency and Confidence**: Respondents expect that PdM will allow for better maintenance planning based on actual conditions rather than rough usage estimates. This shift could help reduce last-minute interventions, improve decision-making, and provide technicians with more confidence in asset health.
- **Concerns About Complexity and Trust**: A recurring concern is the potential complexity of PdM systems. If platforms are not user-friendly or generate false alerts, staff may lose trust and disengage. There's apprehension that complicated interfaces could overwhelm technicians or disrupt workflows.
- **Need for Clear Guidance**: Both technicians and engineers stated they would need clear explanations of how PdM works, how to interpret alerts, and how to integrate recommendations into their existing routines. Without this understanding, adoption is likely to be slow or ineffective.
- **Resistance to Change**: Cultural and psychological resistance emerged as a key barrier. Some technicians may feel threatened by automation, fear being replaced, or

simply be uncomfortable with digital systems. Overcoming this resistance requires proper onboarding, communication, and involvement in the change process.

- **False Alarms and Reliability Issues**: There's concern that PdM systems could trigger unnecessary alarms, leading to either overreaction or complete disregard. Ensuring data accuracy, alert precision, and sensor health will be crucial to long-term acceptance.
- **Data Security and Cost Implications**: From an IT perspective, cybersecurity was flagged as a concern, especially if PdM solutions rely on external cloud platforms. Moreover, the cost of sensors, software, and staff training needs to be framed as a long-term investment with clear ROI to gain management buy-in.
- **Call for a Test Phase**: A phased implementation, starting with pilot projects, was suggested as a way to test the reliability, ease of use, and organizational fit of PdM before full-scale deployment. This approach could also serve to build confidence and gather feedback early on.

1.4.6. Implementation & Future Outlook

Table 20: Managers Integration & Future Outlook

	Mahieddine Affaf	**Gunaoua Riadh**
Integration & Future Outlook	– Maintenance, obviously, but also operations, IT, and warehouse. – Everyone would need to work in sync. – Maintenance needs to react based on data, IT must ensure proper integration, and warehouse needs to be ready with the right parts. – First, we need modern sensors and infrastructure. – Then, staff training, internal alignment, and a step-by-step roadmap. – A pilot on selected assets would be a good starting point. – A system that is accurate, user-friendly, and well-integrated into SAP and MyPM. – Success would mean fewer unplanned downtimes, more efficient maintenance planning, and a workforce that's confident in using technology.	– Maintenance, IT, and Production would be the key players. – Everyone would need to work together, from data engineers to technicians to managers. – We'd need modernized equipment, a clear digital integration plan, staff training, and executive support. – A system that gives us real-time alerts, integrates with SAP, and is user-friendly for everyone. Success would mean fewer emergency breakdowns, more efficient planning, and better cost control.

Source: Elaborated by the students using Nvivo

Table 21: Technicians Expectations & Suggestions

	Bounar Hafidh	Mkharmech Haithem
Expectations & Suggestions	– Start using modern sensors, train staff, and link the data with SAP. – Even one or two critical machines with predictive features would make a big difference. – If it consistently helps us avoid breakdowns and doesn't generate too many false alarms. – Seeing it work on the ground is key. – Yes, absolutely. – But it has to come with proper training, technical support, and be integrated into our existing workflow.	– We should install modern sensors and start monitoring equipment health continuously. – That way, we can fix things before they break. – Also, improve communication between departments. – If it helps me do my job better and avoids surprises. – It needs to be simple to use, with clear, reliable alerts. – I'd also want to see it work in real examples first. – Absolutely. As long as we get support and training, I'd be happy to try something new that helps us stay ahead of problems.

Source: Elaborated by the students using NVivo

Table 22: IT's Future Outlook

	Diabi Amane
Future Outlook	– We'd need modern smart sensors, a data platform to collect and process live inputs, and integration with SAP or a dedicated PdM dashboard. – Not yet, but we have a foundation. – With proper planning, cross-department support, and the right tools, it's achievable in phases, starting with critical assets

Source: Elaborated by the students using NVivo

This axis outlines the practical steps, required conditions, and envisioned path for implementing PdM at Halliburton Algeria, as described by various staff members.

- **Cross-Department Collaboration**: Interviewees unanimously highlighted that successful PdM implementation will require coordinated efforts between Maintenance, IT, Operations, and the Warehouse. Maintenance teams need to act based on data, IT must ensure technical integration, operations should align with new workflows, and the warehouse must anticipate part availability based on real-time insights.

- **Infrastructure and Sensor Deployment**: A common prerequisite mentioned is the deployment of modern smart sensors capable of collecting live equipment data such as temperature, vibration, and pressure. Without this foundational infrastructure, PdM remains theoretical.
- **Integration with Existing Systems**: PdM solutions must seamlessly integrate with existing platforms like SAP and MyPM. Respondents emphasized the importance of user-friendly dashboards and interfaces that allow for efficient use and minimal disruption to current routines.
- **Staff Training and Cultural Shift**: Beyond tools, participants stressed the importance of training personnel, from technicians to managers, to understand, trust, and act on PdM alerts. Change management will be critical to overcoming resistance and ensuring adoption.
- **Phased Approach and Pilot Projects**: A gradual rollout, starting with pilot projects on a few critical assets, was recommended. This approach allows the company to test system accuracy, build internal trust, and demonstrate value without overwhelming staff.
- **Vision of Success**: Success was described in practical terms: fewer unplanned downtimes, more efficient and proactive maintenance planning, improved cost control, and a confident, tech-savvy workforce. For PdM to succeed, the system must be accurate, easy to use, and supported by adequate technical and managerial infrastructure.
- **Readiness and Optimism**: While PdM is not yet operational, respondents expressed cautious optimism. They believe the foundation exists, especially through SAP and digital checklists, and that with the right tools, planning, and support, implementation is feasible in structured phases

1.5. From Words to Strategy: Synthesizing Interview Insights and Lexical Trends

The combined insights from the thematic interviews and the lexical analysis reveal a consistent narrative across staff roles: predictive maintenance is understood as a valuable innovation, but its adoption faces structural, cultural, and technological challenges.

From the interviews, we observed:

- Operational knowledge is largely experiential, not formalized through structured training, especially for advanced digital systems.
- There's strong reliance on SAP and digital checklists, but little integration with real-time data or smart sensors.
- Most respondents recognize the potential benefits of PdM, such as reduced breakdowns, cost efficiency, and optimized planning, but emphasize the need for trust in the system, proper training, and phased implementation.

From the lexical analysis, frequent terms like *maintenance*, *data*, *system*, *training*, *SAP*, *predictive*, and *equipment* confirm that:

- Technical infrastructure and data quality are core concerns.
- Training and integration are recurring themes, pointing to gaps in knowledge and readiness.
- Keywords around *trust*, *real-time*, *alerts*, and *diagnostics* highlight the importance of usability and reliability in any future PdM system.

Together, these analyses point to a workforce that is aware of the change PdM implies and tentatively supportive, but in need of clear guidance, visible results, and active leadership support.

→ To consolidate the insights gathered from both the interview findings and the lexical analysis, a SWOT analysis was conducted to evaluate Halliburton Algeria's preparedness for implementing predictive maintenance. This framework helps distill internal strengths and weaknesses, as well as external opportunities and threats, offering a strategic snapshot of the organization's current state and potential trajectory. The goal is to translate qualitative and lexical observations into actionable strategic insights that can inform decision-making and planning.

Table 23: SWOT matrix for implementing PdM at Halliburton

Strengths	Weaknesses
Existing digital backbone with SAP & MyPM	No current use of smart sensors or real-time data
Experienced maintenance teams	Low awareness or understanding of predictive systems
Structured workflows for Work Orders and cost tracking	Lack of formal training on PdM and diagnostics
Cross-department communication tools in place (Teams, SharePoint)	Equipment age and sensor compatibility limitations
Opportunities	**Threats**
Pilot projects to demonstrate value of PdM on selected assets	Resistance to change from technicians wary of automation
Training programs combining theory and practice	High initial investment in sensors, integration, and software
Stronger IT-engineering collaboration to manage data flows	Potential data overload or system mistrust if alerts are inaccurate
Aligning PdM with safety, cost savings, and performance goals	Cybersecurity and data integrity concerns if external cloud systems are used

Source: Elaborated by the students

Conclusion: The findings reveal a preventive-curative maintenance culture, aging infrastructure, and limited digital integration. However, latent opportunities exist through SAP systems and management support. These insights highlight both the constraints and potential levers for future PdM implementation.

Section 2: Discussion and Strategic Recommendations

This section interprets the findings through the lens of the theoretical framework and literature review. It contrasts academic expectations with on-the-ground realities and proposes a roadmap for PdM implementation at Halliburton, including a readiness framework and maturity model.

2.1. Discussion

The academic literature on PdM consistently highlights its transformative potential in asset-intensive industries, where operational efficiency, cost reduction, and equipment reliability are crucial. Scholars such as Bouabdallaoui et al. (2023) and Afridi et al. (2021) emphasize the growing importance of PdM as a strategic evolution beyond traditional maintenance models. PdM leverages AI, IoT, and advanced analytics to enable real-time equipment monitoring and early failure prediction, addressing the limitations of reactive and preventive strategies, which are often inefficient, costly, and fail to prevent unplanned downtime. However, these benefits are conditional upon the presence of an enabling digital ecosystem, an aspect frequently raised in the literature (Afridi et al., 2021; Latrach et al., 2022). Robust technological infrastructures, sensor integration, and organizational readiness are identified as critical enablers of PdM success.

Kane et al. (2022) and Latrach et al. (2022) further identify structural and organizational challenges that often obstruct PdM deployment, such as the misalignment between predictive technologies and legacy ERP systems like SAP. Mohamed et al. (2021) point out the incompatibility between older industrial assets and new predictive layers, while Tang et al. (2023) discuss the maturity of PdM solutions that rely on sophisticated digital twins, federated learning, and real-time feedback loops, features often unavailable in brownfield environments. These gaps reflect a broader issue: the divergence between theoretical potential and operational reality.

Against this backdrop, the findings from Halliburton Algeria reveal a practical manifestation of these gaps and serve as a grounded counterpoint to the more idealized portrayals found in the literature. The maintenance approach at Halliburton remains predominantly preventive and curative, relying on fixed usage intervals such as hours, days, or mileage, without dynamic condition-based adjustments. The equipment in use is relatively dated and lacks smart or IoT-enabled sensors, precluding the kind of real-time, high-frequency data collection essential for predictive models. These empirical observations echo the infrastructural limitations discussed by Mohamed et al. (2021) and confirm that digital retrofitting in brownfield sites remains a substantial challenge.

While SAP and MyPM are in place as digital tools to manage maintenance operations, their function remains descriptive and administrative rather than predictive or analytical. Almeida et al. (2019) stress that the true value of digital platforms lies in their evolution into decision-support systems powered by predictive analytics, an evolution not yet achieved at Halliburton Algeria. Although SAP integrates data across PSLs and handles work orders, cost centers, and safety documentation, it does not yet offer functionalities aligned with real-time anomaly detection or AI-driven diagnostics.

From an organizational standpoint, the lack of awareness and training in PdM among employees poses a significant barrier. Most technicians and engineers interviewed had limited or no exposure to predictive methodologies, with the exception of isolated individuals like Affaf. This lack of digital fluency and absence of PdM-related upskilling reflect the findings of Kane et al. (2022), who note that human capital and change management are often overlooked in digital maintenance transitions.

Moreover, communication channels within Halliburton Algeria, such as Microsoft Teams, SharePoint, and in-person meetings, although sufficient for traditional coordination, do not contribute to the data intelligence required for PdM. The absence of real-time monitoring and advanced diagnostics tools underscores the strategic misalignment identified in the literature between PdM ambitions and on-the-ground capabilities (Latrach et al., 2022; Afridi et al., 2021).

This thesis positions itself within this academic landscape as a case-based contribution that exposes the operational inertia and misalignment between PdM theory and practice. While the literature often explores PdM within advanced or experimental contexts, this study provides insight into a transitional industrial setting where aspirations for PdM exist but are hindered by technological, structural, and cultural constraints. In doing so, it contributes to a more nuanced understanding of the PdM implementation gap, particularly in the context of the oil and gas sector in developing or digitally lagging regions.

Unlike many existing studies that rely on simulation environments or well-funded PdM pilots, this research highlights the incremental, non-linear, and context-sensitive nature of PdM adoption. It also reinforces the notion that PdM implementation is not a purely technical matter but a strategic endeavor requiring alignment across data infrastructure, workforce capabilities, organizational readiness, and cross-functional collaboration. The findings affirm the core arguments of the literature while introducing a grounded, real-world example of how these challenges unfold in practice, offering valuable lessons for both scholars and practitioners seeking to bridge the gap between PdM potential and operational reality.

2.2. Recommendations

The findings from this case study at Halliburton Algeria highlight significant gaps between the theoretical benefits of predictive maintenance (PdM) and its practical implementation on the ground.

While academic literature points to PdM as a transformative tool for asset-intensive industries (Bouabdallaoui et al., 2023; Afridi et al., 2021), the empirical reality demonstrates that successful deployment requires not only technological upgrades but also organizational readiness, strategic alignment, and cultural change. Based on this observation, and drawing from established frameworks in the literature, the following recommendations are proposed to support a structured, feasible roadmap toward PdM implementation at Halliburton Algeria and comparable industrial contexts.

2.2.1. Adopt a Structured Readiness Framework

To ensure a coherent and sustainable adoption of PdM, organizations should begin by assessing their maturity across six key pillars using the Predictive Maintenance Implementation Readiness Checklist. This framework provides a diagnostic tool to evaluate readiness across strategic, technical, and organizational dimensions.

❖ **Strategic Alignment**

A clear misalignment currently exists between maintenance operations and Halliburton's broader digital transformation objectives. PdM initiatives should begin by defining business-aligned objectives (cost reduction, uptime improvement, safety enhancements), calculating expected ROI, and establishing KPIs to monitor impact.

➢ *Recommendation:* Conduct a strategic PdM alignment workshop with senior leadership to integrate PdM into the overall asset management strategy. Use the checklist to evaluate:
  - Are PdM goals linked to business strategy?
  - Is there a defined business case or ROI calculation?
  - Have KPIs for predictive maintenance success been developed?

❖ **Data Infrastructure and Integration**

The current dependence on SAP and MyPM without real-time data acquisition limits predictive capabilities. As supported by Mohamed et al. (2021) and Almeida et al. (2019), PdM depends on structured, accessible, and high-quality data integrated into existing IT architecture.

➢ *Recommendation:* Begin digitization of key equipment data flows and implement a centralized data repository. Gradually transition from checklist-based logs to sensor-based data collection where possible. Evaluate readiness through:
  - Do at least 6 months of historical failure and maintenance logs exist?
  - Can existing tools like SAP integrate with PdM modules?
  - Are data sources centralized and machine-readable?

- ❖ **Technical Capabilities**

The absence of IoT-enabled sensors and analytical tools at Halliburton is a critical bottleneck. As Bouabdallaoui et al. (2023) and Latrach et al. (2022) argue, PdM requires both hardware and analytical software to deliver value.

- ➢ *Recommendation:* Pilot a PdM solution using portable, non-intrusive sensors on a small fleet of high-value assets. Collaborate with external technology partners if internal capacity is limited. Readiness should be assessed by checking:
  - – Are monitoring devices available or can they be deployed temporarily?
  - – Do personnel have access to diagnostic dashboards or modeling tools?
  - – Is there technical expertise available internally or via partnerships?

- ❖ **Organizational Readiness**

The case study revealed limited awareness of PdM and its implications among employees. Resistance to change, or simple unfamiliarity, is often underestimated in implementation failures (Kane et al., 2022).

- ➢ *Recommendation:* Launch an internal communication campaign followed by a PdM awareness and alignment program targeting all PSLs. Use the readiness checklist to explore:
  - – Is there visible support from leadership?
  - – Do employees understand what PdM is and how it will affect them?
  - – Are change-resistant behaviors being acknowledged and addressed?

- ❖ **Skills and Training**

Current personnel are trained in preventive or curative maintenance but lack exposure to data-driven methodologies. This finding aligns with Latrach et al. (2022), who emphasize digital upskilling as essential for PdM success.

- ➢ *Recommendation:* Develop a phased training plan that includes:
  - – Basic PdM concepts for technicians
  - – Intermediate diagnostics and data analysis for engineers
  - – Leadership courses on change management and ROI assessment

Evaluate readiness by:

- – Are formal training programs documented?
- – Is there a mentoring or knowledge transfer mechanism?

– Do career paths support long-term digital competencies?

❖ **Governance and Change Management**

A PdM program needs designated ownership and accountability. At present, PdM lacks an internal champion at Halliburton Algeria.

➢ *Recommendation:* Assign a PdM Program Lead responsible for coordination between maintenance, IT, and management. Establish a continuous improvement loop with feedback from field technicians and periodic performance reviews. Readiness checks should include:

– Is ownership for PdM clearly defined?
– Is there a structured way to gather operational feedback?
– Are lessons learned incorporated into ongoing strategy?

2.2.2. Introduce a Maturity Model for Self-Evaluation

To track progress, it is recommended to use a Maturity Assessment Scale (1–5) for each of the six readiness pillars, allowing Halliburton to visualize its trajectory using a spider chart or heat map. This scalable tool supports iterative development and can serve as a communication aid for stakeholders and upper management.

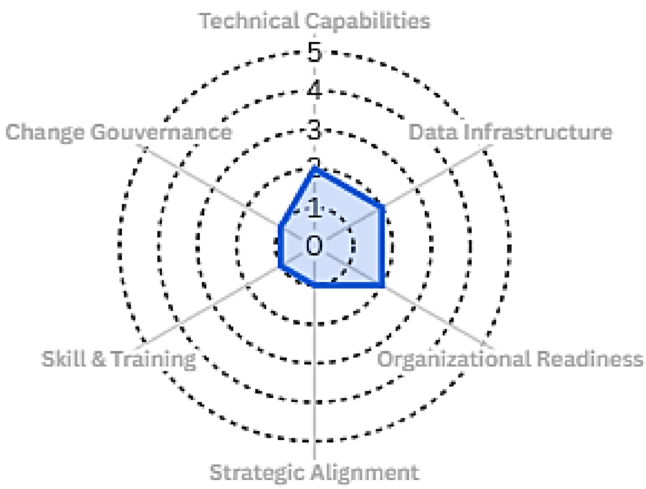
Table 24: Maturity Assessment Scale

Level	Description
1	Not started
2	Awareness phase
3	Pilot or partial roll-out
4	Operational in silos
5	Fully integrated system

Source: Elaborated by the students

Here is a spider chart visualizing the current readiness of Halliburton Algeria for implementing predictive maintenance across six critical dimensions. Each axis represents one pillar of readiness, scored out of 5

Figure 24: Spider Chart of Halliburton's PdM Implementation Readiness



Source: Elaborated by the students

- *Recommendation:* Conduct annual PdM maturity reviews, with self-scoring and departmental benchmarking, to identify progress, bottlenecks, and learning opportunities.

2.2.3. Start with a Focused Pilot Project

Given the current technological and organizational limitations, Halliburton should begin with a low-risk, high-value PdM pilot on a select group of critical assets. This phased approach allows theorganization to experiment with PdM in a controlled environment, gain internal credibility, and build capabilities incrementally.

- *Recommendation:* Identify one PSL and two to three high-failure assets for the pilot. Define scope, KPIs, and training needs. Use lessons learned to refine the approach before scaling.

Conclusion:

By applying this structured readiness framework and focusing on targeted pilot initiatives, Halliburton Algeria can progressively build the technological, cultural, and operational capabilities needed for PdM. This case reinforces the academic consensus that predictive maintenance requires not only advanced tools but strategic foresight, human-centered change management, and continuous capability building. While the path to full PdM integration may be gradual, these recommendations provide a concrete, staged roadmap to guide implementation and organizational transformation in alignment with both internal goals and global best practices

GENERAL CONCLUSION

This thesis explored the implementation of predictive maintenance (PdM) as a strategic approach to optimizing asset performance in oil field operations, with a focused case study on Halliburton Algeria. Through a combination of literature review, field observations, and qualitative interviews, the study examined the technological, organizational, and operational readiness of a major oilfield services provider to transition from traditional maintenance models toward data-driven, condition-based strategies.

The academic literature overwhelmingly supports the potential of PdM to reduce downtime, extend asset life, and improve operational efficiency by leveraging IoT, machine learning, and real-time data analytics. However, it also emphasizes that successful implementation depends on a robust digital infrastructure, skilled workforce, strategic alignment, and cultural readiness. These insights were juxtaposed with empirical findings from Halliburton Algeria, where maintenance practices remain largely preventive and curative, with limited use of smart sensors, constrained integration of digital systems, and low organizational awareness of PdM principles.

The analysis revealed a significant implementation gap between the theoretical promise of PdM and its practical application within the case company. While the enterprise system (SAP) is well integrated and capable of handling maintenance workflows and cost tracking, it lacks the real-time capabilities and advanced analytics functions that PdM demands. Moreover, limited technical expertise, insufficient training, and a lack of strategic prioritization further hinder readiness for digital transformation in maintenance.

To bridge this gap, the study proposed a structured implementation roadmap and introduced a readiness assessment framework based on six critical pillars: strategic alignment, data infrastructure, technical capabilities, organizational readiness, skills and training, and governance. A spider chart visualized Halliburton's current state, revealing critical deficiencies in key areas such as sensor technologies, data analytics, and change management.

In conclusion, while the concept of predictive maintenance holds great potential for asset optimization in the oil and gas sector, its realization at Halliburton Algeria requires a comprehensive, context-sensitive transformation. This includes phased investments in technology, cross-departmental collaboration, leadership commitment, and sustained capacity-building efforts. PdM is not a plug-and-play solution; it is a strategic evolution that must be gradually embedded into the fabric of the organization's operational and digital strategy.

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Appendix

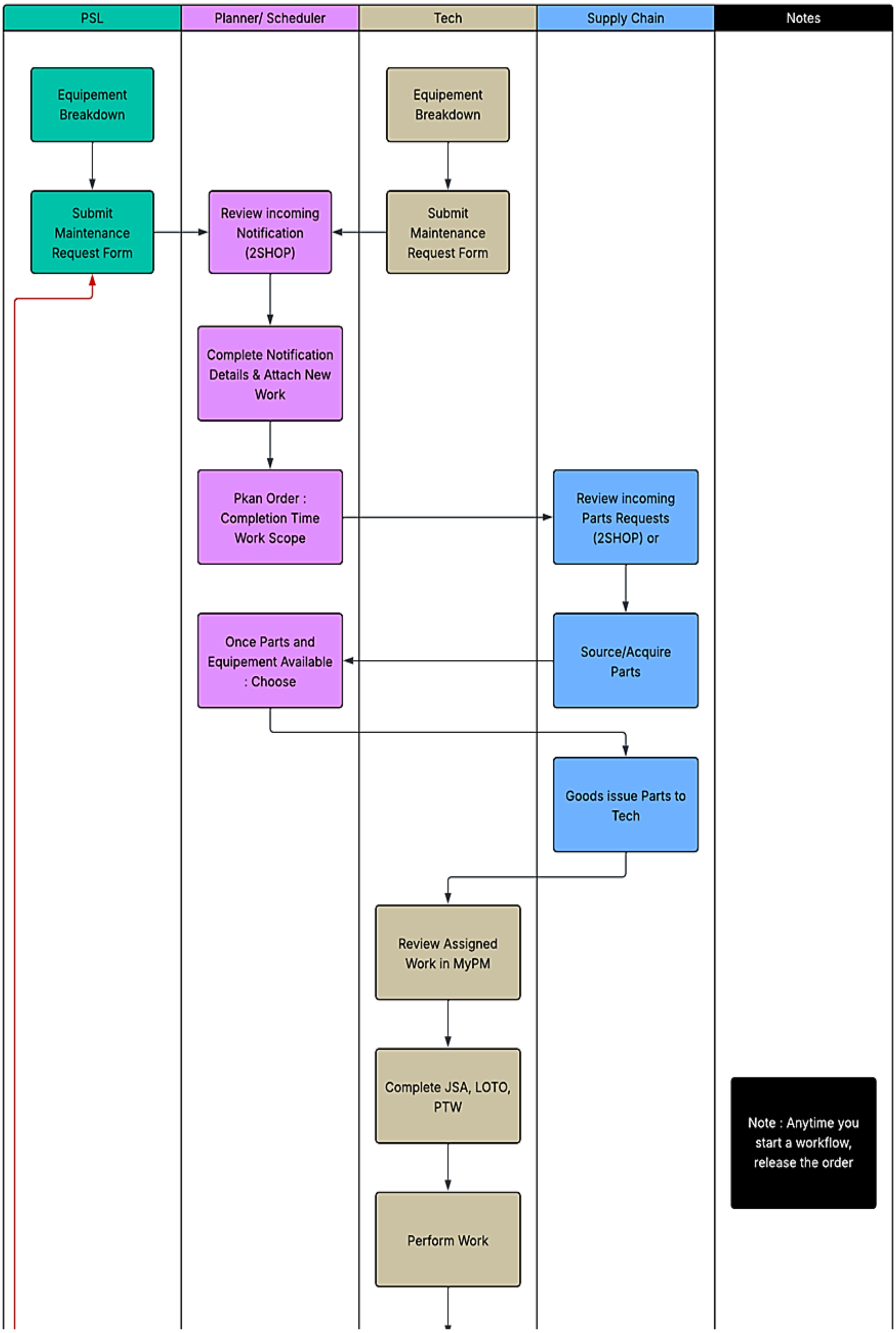
Appendix A: Interview Guide

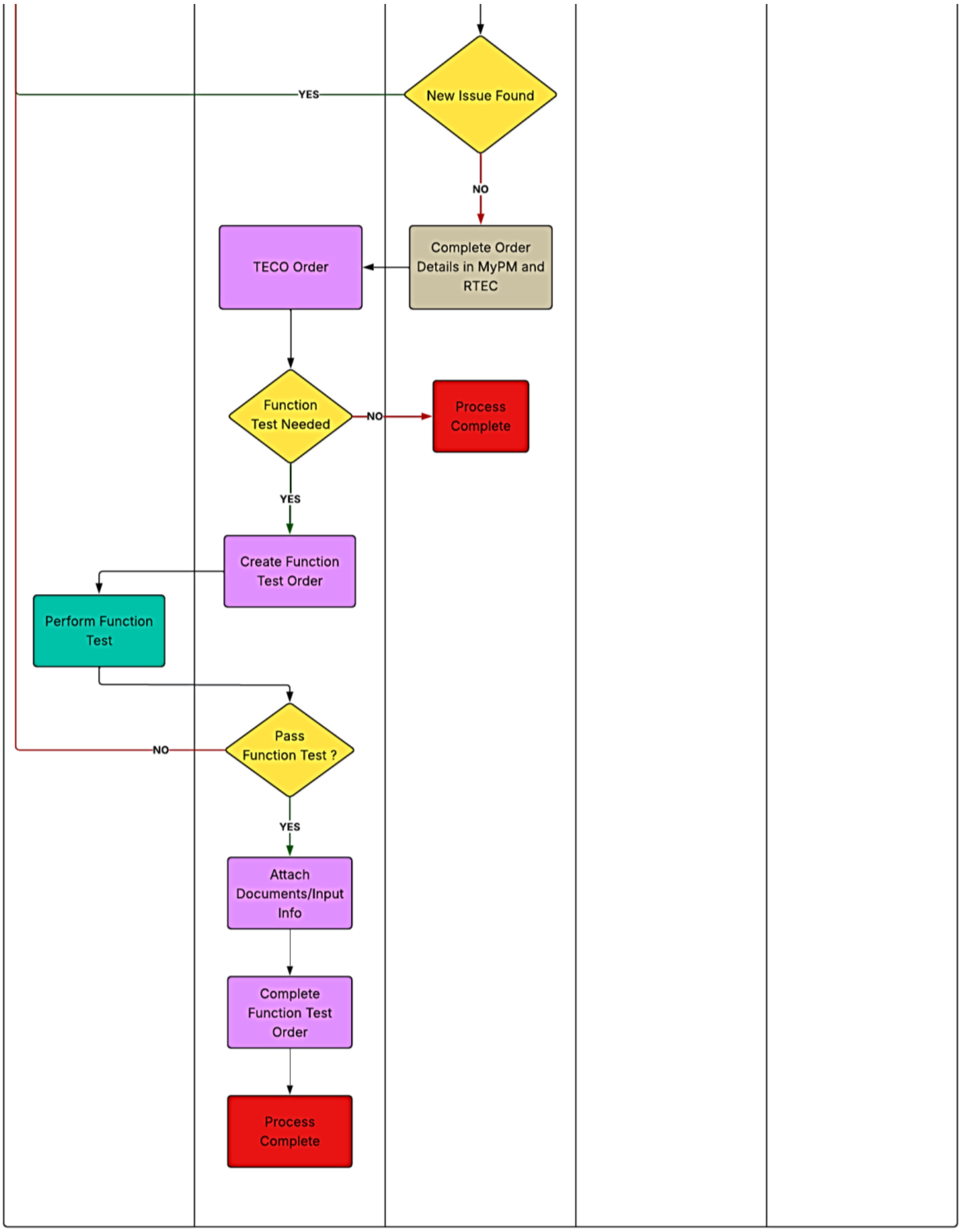
Stakeholder Group	Axis	Questions
Managers / Operations Supervisors	Current Practices & Strategy	- What types of maintenance strategies are currently used in your operations? - How is maintenance planning typically handled? - What are the most common issues or disruptions caused by maintenance delays or failures?
	Performance & Decision-Making	- What KPIs or indicators do you currently use to monitor asset performance? - How is maintenance performance reported or evaluated at the management level?
	Awareness & Attitude Toward PdM	- Are you familiar with the concept of predictive maintenance? - Has predictive maintenance been discussed or piloted within your department or company?
	Organizational Readiness	- What internal resources (tools, expertise, teams) could support PdM implementation? - What challenges do you anticipate in transitioning to predictive approaches?
	Benefits & Concerns	- What benefits do you expect PdM could bring to operations? - Do you foresee any risks or resistance from staff in adopting PdM?
	Integration & Future Outlook	- What departments or roles would be most affected by PdM implementation? - What conditions must be met for PdM adoption? - What would a successful PdM implementation look like?

Stakeholder Group	Axis	Questions
Maintenance Technicians / Engineers	Daily Operations & Tools	- What kind of maintenance tasks are you typically responsible for? - How do you detect or learn about equipment issues? - What tools or systems do you use to track or document work?
	Challenges & Manual Efforts	- What are the most common equipment problems you encounter? - Could failures have been avoided with earlier warnings?
	Understanding of PdM	- Have you heard of predictive maintenance? What does it mean to you? - Are you confident using digital systems or software to support maintenance?
	Digital Readiness & Training	- Have you received training related to SAP, data logging, or diagnostics? - What support or training would help you use predictive systems?
	Practical Concerns	- How would a predictive alert system help or complicate your work? - What's missing in the current approach to maintenance?
	Expectations & Suggestions	- What would make maintenance more proactive? - What would make you trust or rely on a PdM system? - Would you be open to piloting PdM tools?

Stakeholder Group	Axis	Questions
IT / Digital Systems Staff	**Current Infrastructure**	**- What IT systems are in place to support maintenance (e.g., SAP, CMMS)? - Are any assets equipped with IoT sensors or real-time monitoring?**
	Data Collection & Management	**- What kind of maintenance or operational data is collected and stored? - How is this data managed, processed, or analyzed across departments?**
	Integration Challenges	**- How easy would it be to integrate new data sources or models? - What are the main technical risks in deploying PdM infrastructure?**
	Predictive Analytics Readiness	**- Has your team explored analytics, dashboards, or machine learning for PdM? - What types of data are necessary to build reliable PdM systems?**
	Organizational & Technical Alignment	**- How well do IT and operations collaborate on system deployment? - What role would IT play in supporting PdM?**
	Security, Budget & Scalability	**- How would you assess data security or system reliability with PdM tools? - Do you foresee budget or procurement constraints?**
	Future Outlook	**- What infrastructure upgrades are needed for PdM? - Is Halliburton Algeria ready, technologically for predictive maintenance?**

Appendix B: Halliburton's Maintenance Flowchart




New Issue Found
YES
NO
Complete Order Details in MyPM and RTEC
TECO Order
Function Test Needed
NO
Process Complete
YES
Create Function Test Order
Perform Function Test
Pass Function Test ?
NO
YES
Attach Documents/Input Info
Complete Function Test Order
Process Complete

Appendix C: Pearson Correlation Coefficient Table

Source A	Source B	Pearson correlation coefficient
Internals\\Riadh	Internals\\Affaf	0,730409
Internals\\Haithem	Internals\\Hafidh	0,7213
Internals\\Riadh	Internals\\Hafidh	0,511255
Internals\\Hafidh	Internals\\Affaf	0,470105
Internals\\Riadh	Internals\\Haithem	0,459186
Internals\\Haithem	Internals\\Affaf	0,441078
Internals\\Riadh	Internals\\Diabi	0,404118
Internals\\Diabi	Internals\\Affaf	0,389371
Internals\\Hafidh	Internals\\Diabi	0,387315
Internals\\Haithem	Internals\\Diabi	0,383076