Scilight

Journal of Mechanical Engineering and Manufacturing
https://www.sciltp.com/journals/jmem



Article

Check for updates

An Integrated Lean Maintenance 4.0 Framework for Preventive Maintenance Redesign: Evidence from a Food Manufacturing Case Study

Teresa Mendes [1], Bruno Silva [1], Rafaela Casais [1], André F. V. Pedroso [1,2,*], Naiara Sebbe [1] and Isabel Pinto [1,3]

[1] CIDEM, ISEP, Polytechnic of Porto, Rua Dr. António Bernardino de Almeida, 4249-015 Porto, Portugal
[2] Department of Mechanical Engineering, Faculty of Engineering, University of Porto, Rua Dr Roberto Frias, 400, 4200-465 Porto, Portugal
[3] LEMA, ISEP, Polytechnic of Porto, Rua Dr. António Bernardino de Almeida, 4249-015 Porto, Portugal
* Correspondence: afvpe@isep.ipp.pt; Tel.: +351-22-83-40-500

How To Cite: Mendes, T.; Silva, B.; Casais, R.; et al. An Integrated Lean Maintenance 4.0 Framework for Preventive Maintenance Redesign: Evidence from a Food Manufacturing Case Study. *Journal of Mechanical Engineering and Manufacturing* **2026**. https://doi.org/10.53941/jmem.2026.100038

Received: 3 April 2026
Revised: 3 August 2026
Accepted: 19 August 2026
Published: 19 October 2026

Abstract: Maintenance management has evolved from a predominantly reactive support activity into a strategic engineering discipline that directly influences equipment reliability, operational efficiency and manufacturing competitiveness. Despite substantial advances in predictive maintenance, digital technologies and Industry 4.0, many industrial organisations continue to rely on preventive maintenance programmes that are insufficiently structured, poorly prioritised and weakly integrated with operational decision-making. This study proposes and validates an integrated engineering framework for preventive maintenance redesign that combines Lean maintenance principles, asset criticality analysis, Failure Mode and Effects Analysis (FMEA), digital information management and Maintenance 4.0 concepts within an Action Research methodology. The research was conducted in a food manufacturing company, where the existing preventive maintenance system was systematically analysed, redesigned and implemented under real industrial conditions. The proposed framework incorporated equipment criticality assessment, maintenance standardisation, digital checklists, Computerised Maintenance Management System (CMMS) optimisation and structured maintenance planning to improve maintenance effectiveness while strengthening information traceability and organisational learning. The industrial implementation demonstrated that the integrated maintenance redesign significantly enhanced maintenance planning, improved maintenance information management, increased process standardisation and supported more efficient maintenance decision-making. The findings further indicate that meaningful maintenance transformation is achieved not through the isolated adoption of digital technologies, but through their systematic integration with structured engineering methodologies and continuous-improvement principles. The principal scientific contribution of this work lies in demonstrating how established maintenance engineering methodologies can be integrated into a unified Maintenance 4.0 framework validated through Action Research in a real industrial environment. Beyond the specific case study, the proposed framework provides a transferable engineering methodology capable of supporting maintenance transformation across manufacturing sectors seeking more intelligent, resilient and data-driven maintenance systems.

Copyright: © 2026 by the authors. This is an open access article under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).
Publisher's Note: Scilight stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Keywords: preventive maintenance; lean maintenance; maintenance 4.0; action research; failure mode and effects analysis; asset criticality analysis; computerised maintenance management system; food manufacturing

1. Introduction

Maintenance management has evolved from supporting operational activity into a strategic function that directly influences industrial competitiveness, equipment availability, production efficiency and organisational sustainability [1]. In modern manufacturing systems, where production increasingly depends on highly automated and interconnected equipment, maintenance performance has become intrinsically linked to operational excellence. Equipment failures no longer result solely in production interruptions; they also compromise product quality, increase operational costs, reduce resource utilisation and affect the overall resilience of manufacturing systems [1,2]. Consequently, maintenance is increasingly recognised as a value-generating activity whose effectiveness directly influences both operational and business performance.

The evolution of industrial maintenance reflects the growing complexity of manufacturing systems. Early maintenance practices were predominantly corrective, where interventions were performed only after equipment failure had occurred. Although this approach minimised immediate maintenance effort, it resulted in unpredictable downtime, unstable production schedules and elevated maintenance costs. The subsequent adoption of preventive maintenance (PM) introduced scheduled interventions at predefined intervals to reduce failure probability and improve equipment reliability [2,3]. More recently, condition-based and predictive maintenance strategies have further extended this evolution by incorporating equipment condition, operational history and real-time monitoring into maintenance planning, thereby overcoming many of the limitations associated with purely time-based maintenance policies [2–10].

Despite these advances, preventive maintenance remains the dominant strategy in a considerable number of industrial organisations. However, many preventive maintenance programmes continue to rely on historical schedules that have evolved incrementally over time rather than through systematic engineering analysis. Consequently, maintenance plans frequently become excessively conservative, operationally inefficient or poorly aligned with the actual criticality and condition of industrial assets [3,4]. Such limitations often result in unnecessary maintenance interventions, inefficient allocation of maintenance resources, reduced equipment availability and increased operational costs. Improving preventive maintenance planning therefore remains one of the most significant challenges in contemporary maintenance management.

The emergence of Industry 4.0 has profoundly transformed the maintenance landscape by enabling the continuous acquisition, processing and interpretation of operational information. Technologies such as Industrial Internet of Things (IIoT), intelligent sensors, cloud computing, machine learning and advanced data analytics have significantly expanded the capability to monitor equipment health, detect degradation patterns and support predictive maintenance strategies [2,11–14]. These technologies have progressively shifted maintenance from reactive decision-making towards data-driven asset management, giving rise to the broader concept of Maintenance 4.0, where maintenance activities are increasingly supported by digital information, intelligent analytics and integrated decision-support systems.

Nevertheless, digital technologies alone do not guarantee improvements in maintenance performance. Their successful implementation depends fundamentally on the existence of structured maintenance processes capable of transforming large volumes of operational data into effective engineering decisions. Without appropriate maintenance planning, equipment criticality assessment and systematic failure analysis, digital infrastructures frequently become sophisticated data repositories with limited practical impact on maintenance effectiveness [7,8,12]. Consequently, Maintenance 4.0 should not be interpreted simply as the adoption of digital technologies, but rather as the integration of digital information with structured maintenance engineering methodologies that support continuous operational improvement.

From this perspective, maintenance management has progressively evolved towards an integrated analytical framework combining operational performance evaluation, maintenance information management and systematic failure analysis. Among the most widely adopted performance indicators, Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR) and Overall Equipment Effectiveness (OEE) provide complementary information regarding equipment reliability, maintainability and production performance [5,6]. When integrated with Business Intelligence (BI) platforms and digital monitoring systems, these indicators become powerful decision-support tools capable of transforming maintenance data into actionable engineering knowledge [5,7].

Similarly, Computerised Maintenance Management Systems (CMMS) have become fundamental components of modern maintenance organisations by supporting work-order management, preventive maintenance scheduling, spare-parts control and maintenance documentation [8]. Nevertheless, several studies indicate that many CMMS implementations remain underutilised, functioning primarily as operational databases rather than as strategic decision-support platforms capable of supporting maintenance optimisation [7,8]. Consequently, the availability of digital information alone does not necessarily translate into improved maintenance performance unless accompanied by appropriate analytical methodologies.

Failure analysis constitutes another essential component of modern maintenance management. Failure Mode and Effects Analysis (FMEA) remains one of the most widely applied techniques for identifying potential failure mechanisms, evaluating associated risks and prioritising maintenance actions [9,10]. Although the traditional Risk Priority Number (RPN) methodology presents recognised limitations regarding ranking consistency and sensitivity, FMEA continues to represent an effective engineering tool, particularly when integrated with complementary approaches such as fuzzy logic, multi-criteria decision-making techniques and structured asset criticality analysis [9–11].

Among the various approaches proposed to strengthen maintenance effectiveness, three complementary dimensions consistently emerge throughout the literature: performance measurement, maintenance information management and systematic failure analysis. Rather than functioning as isolated activities, these dimensions form the analytical backbone of contemporary maintenance management by enabling organisations to monitor equipment behaviour, prioritise interventions and continuously improve maintenance strategies.

Performance measurement constitutes the first pillar of this framework. Key Performance Indicators (KPIs), including Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR) and Overall Equipment Effectiveness (OEE), provide quantitative measures of equipment reliability, maintainability and production efficiency [5,6]. These indicators allow maintenance managers not only to evaluate historical performance but also to identify trends, detect emerging operational problems and support evidence-based decision-making. When integrated with Business Intelligence (BI) platforms and digital monitoring environments, maintenance data evolve from simple operational records into strategic assets capable of supporting continuous performance improvement [5,7].

The second pillar concerns maintenance information management. Computerised Maintenance Management Systems (CMMS) have become indispensable tools for coordinating preventive maintenance schedules, managing work orders, controlling spare-parts inventories and documenting maintenance interventions [8]. Nevertheless, several studies emphasise that the potential of CMMS platforms remains only partially exploited in many industrial organisations. Instead of serving as comprehensive decision-support systems, they frequently operate as repositories of historical maintenance information, with limited analytical capabilities and insufficient integration with operational decision-making processes [7,8]. Consequently, improving maintenance effectiveness requires not only the availability of digital information but also methodologies capable of transforming that information into actionable engineering knowledge.

The third analytical dimension involves systematic failure analysis. Failure Mode and Effects Analysis (FMEA) remains one of the most widely adopted engineering methodologies for identifying potential failure mechanisms, assessing associated risks and prioritising corrective actions [9,10]. Although the conventional Risk Priority Number (RPN) methodology has been criticised for its limited sensitivity and ranking inconsistencies, FMEA continues to represent an effective decision-support framework when complemented by advanced approaches, including fuzzy logic, multi-criteria decision-making techniques and structured asset criticality analysis [9–11]. These developments reinforce the role of FMEA not merely as a risk assessment tool, but as a strategic instrument for redesigning maintenance policies based on engineering evidence.

The increasing digitalisation of manufacturing systems has further expanded the capabilities of maintenance management by enabling continuous equipment monitoring and data-driven decision-making. Technologies associated with Industry 4.0—including Industrial Internet of Things (IIoT), intelligent sensors, cyber-physical systems, machine learning algorithms and advanced data analytics—provide unprecedented opportunities for real-time condition monitoring, anomaly detection and predictive maintenance [2,12–14]. Sensor-based monitoring systems allow maintenance decisions to be progressively based on the actual condition of industrial assets rather than exclusively on predefined maintenance intervals, thereby improving intervention timing and reducing unnecessary maintenance activities [2,11].

However, the successful implementation of Maintenance 4.0 extends well beyond technological adoption. Digital technologies deliver sustainable benefits only when embedded within structured maintenance systems capable of integrating equipment criticality assessment, preventive planning, failure analysis and operational decision-making [12,13]. In the absence of such engineering foundations, even sophisticated digital infrastructures frequently fail to generate measurable improvements in equipment reliability or maintenance performance.

Consequently, the transition towards Maintenance 4.0 should be understood as an organisational transformation in which digital technologies support, rather than replace, structured maintenance engineering.

To better contextualise the evolution of maintenance strategies and position the present research within the current scientific landscape, Figure 1 summarises the transition from traditional maintenance approaches towards digitally enabled Maintenance 4.0. The figure highlights the progressive integration of Lean principles, Industry 4.0 technologies and data-driven decision-making, while simultaneously identifying the existing research gap addressed by the proposed framework.

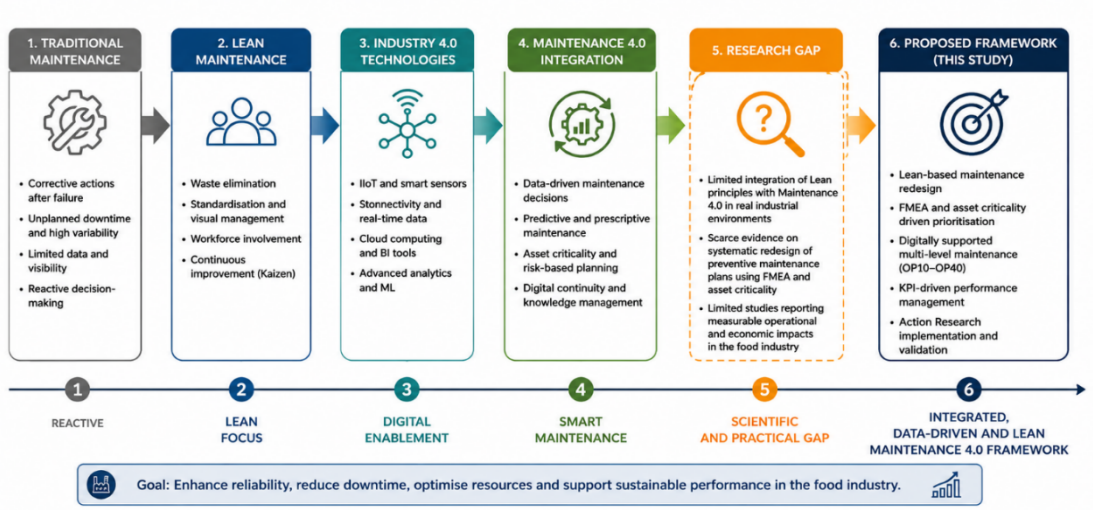


Figure 1. Evolution of maintenance paradigms, identification of the research gap and positioning of the proposed maintenance framework.

As illustrated in Figure 1, the evolution of maintenance has extended beyond the simple adoption of new technologies towards the development of integrated maintenance ecosystems that combine engineering methodologies, digital infrastructures and continuous-improvement philosophies. While considerable progress has been achieved in predictive maintenance and digital monitoring, the systematic integration of Lean maintenance, asset criticality analysis, FMEA and Maintenance 4.0 principles remains comparatively underexplored in real industrial environments. This observation provides the scientific motivation for the present study, which proposes and validates an integrated maintenance redesign framework through an Action Research implementation in the food manufacturing industry.

Beyond technological development, maintenance performance is inherently connected with other operational functions across manufacturing systems. Effective maintenance planning directly influences production scheduling, resource allocation and manufacturing flexibility [15,16], while efficient spare-parts management contributes to reducing maintenance delays, inventory costs and equipment downtime [17]. Increasing attention has therefore been devoted to integrated maintenance frameworks that combine operational planning, reliability engineering and continuous improvement methodologies.

Within this context, Lean Maintenance and Total Productive Maintenance (TPM) have become fundamental components of modern maintenance management. Both approaches emphasise waste elimination, equipment ownership, workforce involvement and systematic continuous improvement, promoting maintenance as an integral element of operational excellence rather than as an isolated technical function [18]. When supported by digital information, structured analytical methods and performance measurement systems, Lean and TPM principles provide the organisational mechanisms required to convert maintenance data into sustainable operational improvements, thereby establishing the foundation of contemporary Maintenance 4.0 strategies [19,20].

Figure 2 synthesises the conceptual relationships between the principal dimensions of modern maintenance management discussed throughout the literature. Rather than representing independent maintenance practices, the framework illustrates how performance measurement, maintenance information systems, failure analysis methodologies, Lean principles and digital technologies interact synergistically to support data-driven decision-making and continuous maintenance improvement within a Maintenance 4.0 perspective.

The conceptual framework highlights that maintenance excellence is not achieved through the isolated adoption of individual tools or technologies. Instead, it emerges from the systematic integration of analytical methodologies, digital infrastructures and continuous-improvement principles into a coherent maintenance management strategy capable of supporting informed engineering decisions and long-term operational performance.

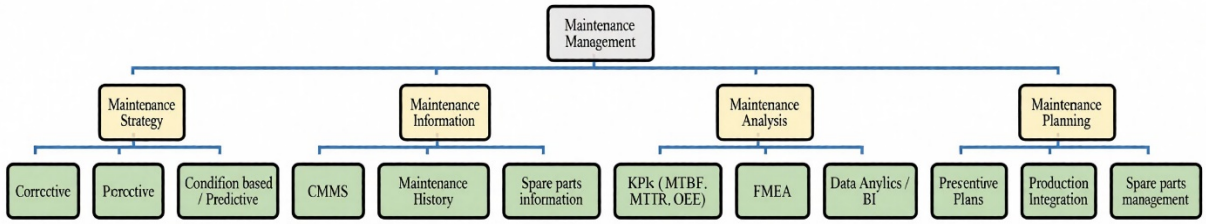


Figure 2. Conceptual framework of maintenance management dimensions and supporting analytical tools.

2. Literature Review

2.1. The Evolution of Industrial Maintenance Paradigms: From 1.0 to 4.0

The evolution of industrial maintenance is characterised by a profound transformation in its conceptualisation, shifting from a mere technical necessity to a strategic business function. Historically, this progression has been analysed through temporal phases, evolving from traditional reactive models to highly integrated digital systems [21]. This development is categorised into four distinct generations, starting with the corrective "run-to-failure" approach of Maintenance 1.0 and culminating in the current Maintenance 4.0 paradigm, underpinned by the standardised terminology of the NP EN 13306:2021 [22]. The official classification of these maintenance strategies, defined in NP EN 13306:2021, is illustrated in Figure 3. This terminology provides the standard conceptual basis adopted throughout the remainder of the manuscript, including the redesign of the preventive maintenance framework presented in the industrial case study.

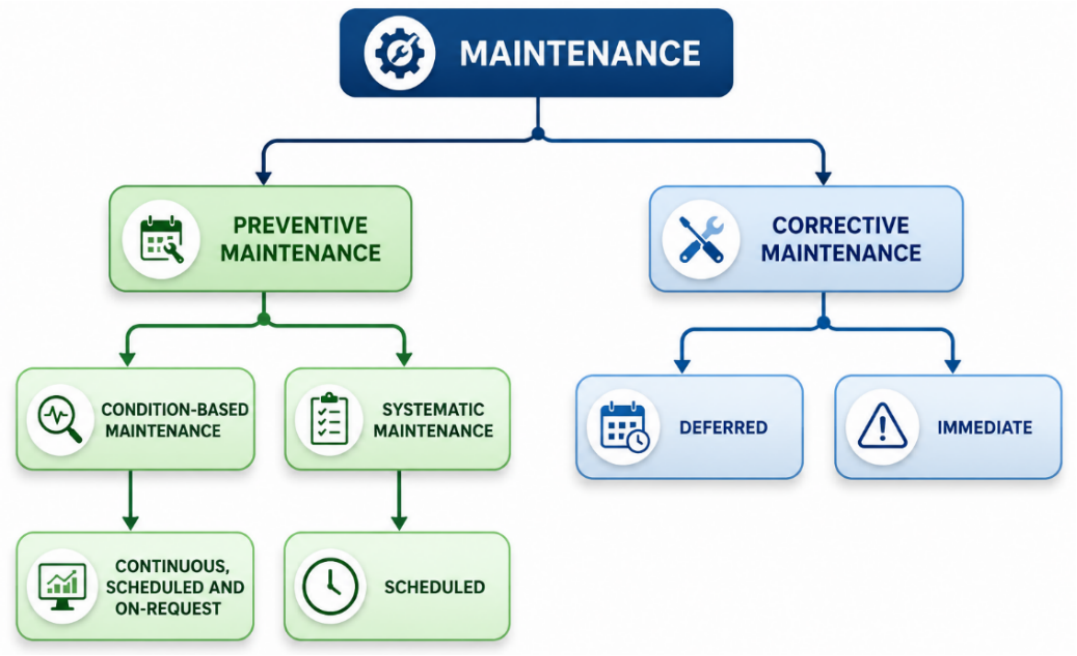


Figure 3. Classification of maintenance types according to NP EN 13306:2021 (adapted from [22]).

While concepts such as e-maintenance, intelligent maintenance (IM), and smart maintenance (SM) are often used interchangeably, they represent distinct milestones in the technology-based transformation of the field [23]. For instance, IM focuses on decision-making support since the late 1980s, while SM is a more recent development emphasising data-driven decision-making and human capital. To validate the impact of these evolutionary steps, it is essential to implement sophisticated Key Performance Indicators (KPIs) capable of measuring actual gains in operational reliability [5].

A pivotal organisational shift occurred with the introduction of Total Productive Maintenance (TPM), which aims to maximise equipment effectiveness through a proactive system involving the entire workforce [24]. As shown in Figure 4, the TPM methodology is traditionally structured around eight pillars that support the goal of achieving zero breakdowns and zero defects, establishing a foundation for operational excellence [25].

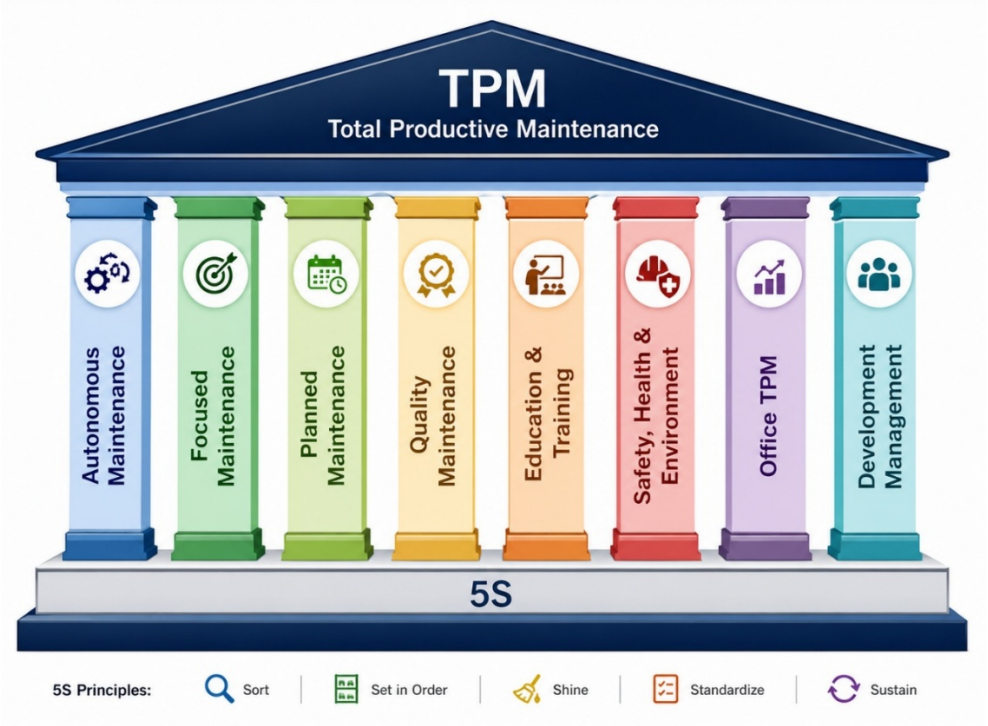


Figure 4. The eight pillars of Total Productive Maintenance (adapted from [25]).

Complementing this shift is the mathematical rigour of Reliability Engineering, utilising indicators such as Mean Time Between Failures (MTBF) and Mean Time to Repair (MTTR) to manage variation [26]. The design and application of these metrics provide the empirical evidence necessary to justify the transition towards digital transformation initiatives [5]. This path leads to a future of "digital continuity" and predictive adaptability [23].

2.2. Performance Measurement and Key Indicators in Maintenance

The effectiveness of any maintenance strategy is contingent upon a robust performance measurement system. Defining and selecting appropriate Key Performance Indicators (KPIs) is vital for measuring and monitoring performance, adhering to the management principle that operations can only be managed and improved if they are measured. These indicators provide a quantitative framework that translates operational data into actionable insights for strategic decision-making [5].

2.2.1. Reliability and Maintainability Metrics: MTBF and MTTR

Reliability and maintainability are fundamental parameters in technical asset management, utilised to ensure the high availability of production equipment. The Mean Time Between Failures (MTBF) represents the average time an equipment unit functions before failure, reflecting system reliability, while the Mean Time to Repair (MTTR) measures the average time required to restore functionality after a fault has occurred [26].

In the dairy industry, minimising MTTR is critical, as the continuous 3 × 8 labour mode and the fragility of the technological process do not support sudden stops without affecting the organoleptic and bacteriological quality of food materials [27]. While these metrics are essential for diagnosing technical health, they also provide important information for evaluating equipment performance and maintenance effectiveness.

2.2.2. Overall Equipment Effectiveness (OEE)

Overall Equipment Effectiveness (OEE) is a quantitative measure widely accepted for observing and controlling the productivity of equipment. The Availability (A) component of OEE is directly influenced by maintenance performance and is commonly determined as the ratio between operating time and planned production time. Consequently, improvements in indicators such as MTBF and MTTR contribute directly to increasing the Availability component and, therefore, the overall OEE. Originally introduced within the Total Productive Maintenance (TPM) philosophy by Nakajima [24], OEE is calculated as the product of three independent factors: Availability, Performance, and Quality. As shown in Figure 5, this metric identifies the "six big losses", such as breakdowns and reduced speed, that impact the bottom line [28].

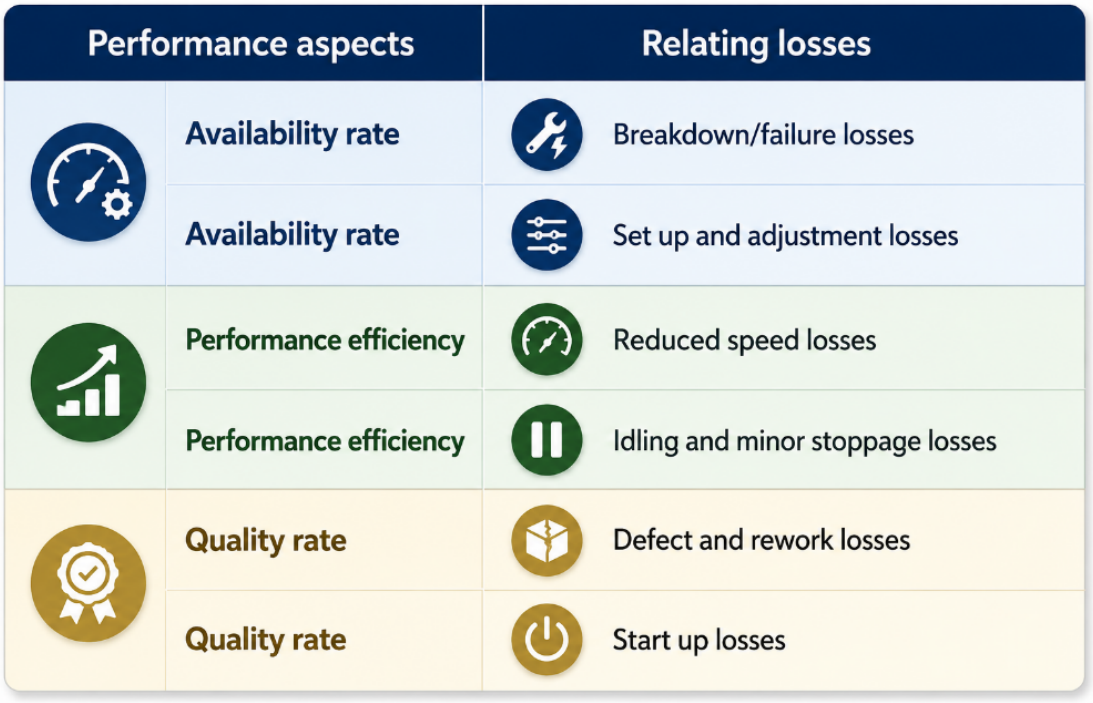


Figure 5. Components of OEE and their associated production losses (adapted from [28]).

While a "world-class" OEE is typically targeted at 85%, research indicates that many production lines operate at lower levels, highlighting significant opportunities for improvement. In the dairy sector, achieving high OEE is particularly vital due to the perishability of raw materials and stringent hygiene requirements [27]. Furthermore, modern TPM reviews emphasise that these goals are achieved through a proactive system involving the entire workforce to ensure zero defects [25,28].

2.2.3. Asset Criticality and Prioritisation in the Food Industry

Given the competitive environment of the food industry, unexpected failures leading to emergency stoppages must be avoided to ensure compliance with production plans. A structured method of equipment criticality classification is required to focus resources on vital equipment, typically categorised into Category A (high criticality), Category B (moderate), and Category C (low). The classification is based on a multi-criteria assessment in which each asset is evaluated according to five dimensions: Quality, Availability, Safety and Environment, Costs, and Technological Complexity. Each criterion is assigned a predefined weighting according to its operational significance, and the combined score determines the overall criticality level of the equipment. This structured approach supports objective decision-making by ensuring that maintenance resources are prioritised according to the potential operational impact of equipment failures.

This prioritisation, based on the criteria shown in Figure 6, evaluates assets across five key dimensions: Quality, Availability, Safety and Environment, Costs, and Technological Complexity. By applying these specific weights, the framework allows for the implementation of targeted strategies, such as Reliability Centred Maintenance (RCM), to the most critical units, thereby maximising the global reliability of the plant [29].



Figure 6. Asset priority model for maintenance management in the food industry (adapted from [29]).

2.3. Operational Excellence and Lean Maintenance Frameworks

To transform maintenance from a cost centre into a strategic function, organisations must adopt philosophies that focus on value creation and the systematic elimination of waste. In the food industry, this is typically achieved

through the integration of Lean Thinking and Total Productive Maintenance (TPM), providing a structured approach to continuous improvement [24,28]. Modern frameworks now increasingly incorporate AI-driven optimisation and real-time sensor data to enhance these traditional methodologies, aligning them with Industry 4.0 and 5.0 standards [30,31].

2.3.1. Lean Thinking and the Elimination of Waste (Muda)

The Lean philosophy, rooted in the Toyota Production System (TPS), defines value solely from the perspective of the final customer. Any activity or expenditure that does not add value is classified as waste, or *Muda*. According to the established Lean framework, there are seven primary wastes in production: overproduction, waiting, unnecessary transport, over-processing, excess inventory, motion, and defects [28].

In maintenance management, these wastes often manifest as "waiting" for spare parts or "defects" that lead to rework. Recent research suggests that multi-objective optimisation approaches can significantly reduce these wastes by balancing high Overall Equipment Effectiveness (OEE) with energy sustainability and reduced resource consumption [30]. Furthermore, modern Lean thinking identifies an eighth waste: the under-utilisation of human talent and skills, which is critical for fostering innovation in maintenance teams [25].

2.3.2. Total Productive Maintenance (TPM) and "Smart" Foundation

Total Productive Maintenance (TPM) is a holistic approach that aims to maximise equipment effectiveness by involving the entire workforce, from top management to shop-floor operators [24]. The goal of TPM is to achieve "three zeros": zero breakdowns, zero defects, and zero accidents [24,25]. This philosophy is traditionally supported by eight technical pillars, including Autonomous Maintenance, Planned Maintenance, and Quality Maintenance [24].

The implementation of TPM begins with the 5S methodology (Sort, Set in order, Shine, Standardise, and Sustain), which serves as the foundation for a disciplined and organised work environment. However, in the modern dairy industry, this foundation is being augmented by "Smart Food Safety" technologies. As illustrated in Figure 7, the conceptual architecture of an integrated Electronic Nose (E-Nose) system with AI-based recognition and cloud analytics allows for real-time, non-destructive quality assessment [32]. This directly supports the Quality Maintenance pillar of TPM by automating the detection of product spoilage or contamination through IoT sensors.

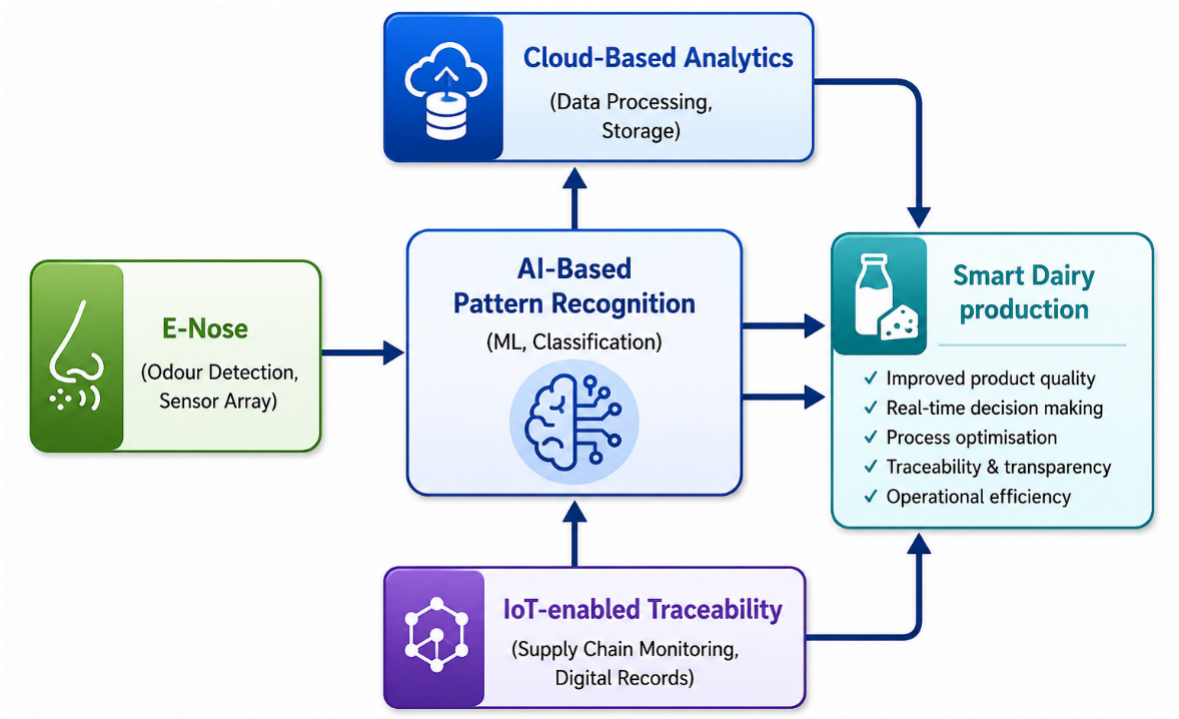


Figure 7. Conceptual architecture of an integrated E-Nose system with AI-based recognition and cloud analytics for smart dairy production (adapted from [32]).

2.3.3. Proactive Decision-Making: From A3 to AI-Driven Prediction

While traditional organisations use systematic problem-solving tools like the A3 methodology for identifying root causes through "5 Whys" [28], the "State of the Art" is moving towards proactive optimisation. Current studies demonstrate that integrating data simulation with Machine Learning (ML) algorithms, such as Random Forest, can predict critical operational parameters and OEE values before failures occur [31].

The effectiveness of this AI-driven approach is demonstrated in Figure 8, where Random Forest models show a near-perfect alignment between true and predicted values for availability, performance, and quality [31]. In dairy production, where perishability is a critical factor, these predictive solutions enable real-time monitoring of machine settings and help prevent downtime. This shifts traditional reactive maintenance practices towards a data-driven approach, in which predictive analytics inform maintenance plans and support equipment availability and energy efficiency throughout the production cycle [30,31].

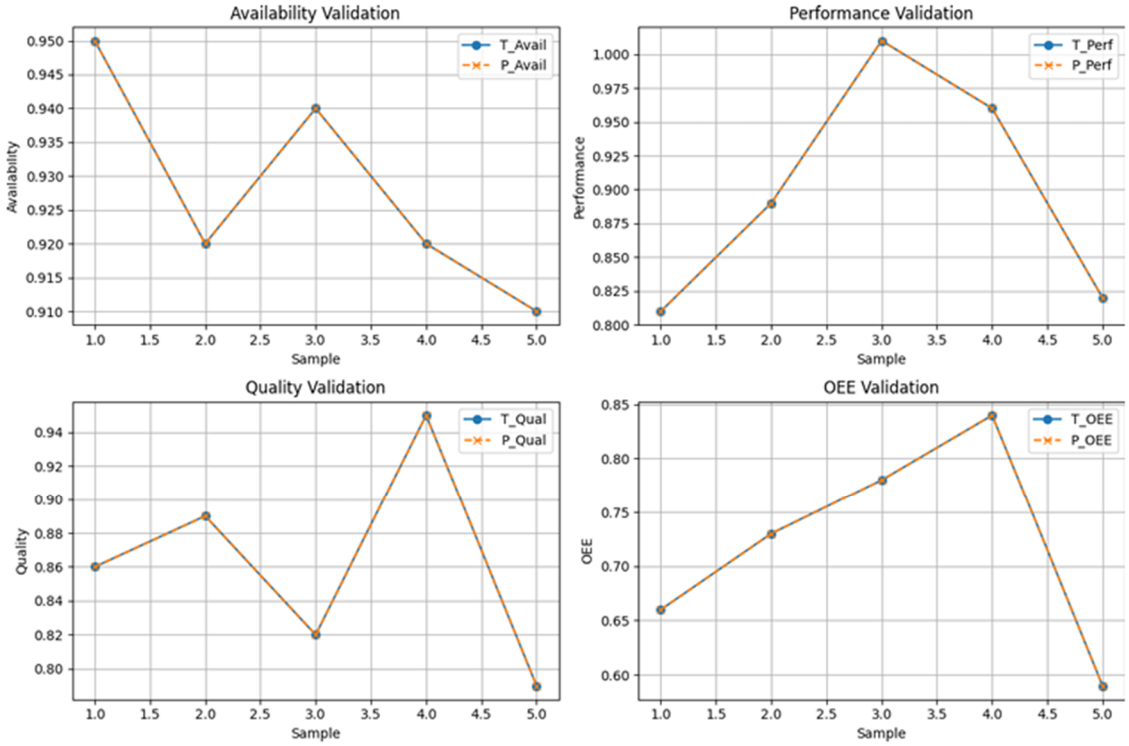


Figure 8. Example of AI-driven OEE prediction reported in the literature, illustrating the alignment between true and predicted operational values (adapted from [31]).

Although the AI-based validation presented in Figure 7 was reported by previous research [31] and does not correspond to data generated in the present case study, it is included to illustrate the technological evolution of Maintenance 4.0 and the growing role of predictive analytics in maintenance decision support. In the present research, these concepts were not directly implemented; instead, they provide the conceptual background for the proposed framework, which establishes the structured maintenance processes, digital information management, and standardised operational procedures required for the future adoption of AI-driven predictive maintenance techniques.

In the present research, Lean was not considered as an isolated philosophy but rather as an operational enabler of the Maintenance 4.0 transition. The redesign combined several complementary Lean tools, each addressing a specific source of maintenance waste. The 5S methodology supported workplace organisation and standardised inspection conditions; Total Productive Maintenance (TPM) promoted operator involvement through Autonomous Maintenance activities; Pareto analysis enabled the identification of the critical assets responsible for the majority of failures; Failure Mode and Effects Analysis (FMEA) prioritized maintenance actions according to technical risk; A3 thinking supported structured problem solving during the redesign cycles; and continuous improvement principles guided the iterative refinement of maintenance plans throughout the Action Research process. Together, these tools established a stable operational foundation upon which digital technologies such as QR-code documentation and SharePoint integration could generate sustainable value.

The maintenance management and Lean tools integrated into the proposed framework, together with their respective roles in the research, are summarized in Figure 9.

Tool	Purpose	Application in this research
TPM	Improve equipment effectiveness	Autonomous Maintenance
FMEA	Risk prioritization	Selection of OP10–OP40 tasks
Pareto	Identify critical assets	Selection of Condifilm/Cefma
KPI analysis	Performance evaluation	MTBF, MTTR, PTU, OEE
5S	Standardization	Maintenance documentation
A3	Structured problem solving	Action Research cycles
QR codes	Digital information management	Digital manuals
MRP	Spare parts optimization	L05/L06 classification

Figure 9. Maintenance management and Lean tools employed in the proposed framework.

3. Methodology

This study adopts an Action Research (AR) approach combined with an industrial case study, allowing for the implementation and evaluation of maintenance improvements in a real manufacturing environment. AR is widely recognised for integrating scientific investigation with practical problem-solving in organisational contexts, promoting collaboration between researchers and practitioners. To provide a comprehensive overview of the research design, Figure 10 summarises the methodological architecture adopted in this study. The framework illustrates the sequential integration of Action Research, data collection, maintenance analysis, redesign, implementation and performance evaluation, highlighting how these complementary stages collectively support the development and validation of the proposed Maintenance 4.0 framework.

The research was conducted in an industrial manufacturing environment where maintenance management practices were analysed with the objective of improving preventive maintenance planning and supporting data-driven decision-making. Maintenance data were collected from the maintenance management system, including equipment failure history, maintenance records and operational performance indicators. The use of operational data to support maintenance decision-making has been widely highlighted in recent studies on predictive maintenance and Industry 4.0 environments [33–35].

The data analysis phase included the evaluation of key performance indicators commonly used in maintenance management, such as Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR) and Overall Equipment Effectiveness (OEE). These indicators allow the assessment of equipment reliability and operational performance and are commonly used in data-driven maintenance frameworks and Total Productive Maintenance strategies [18].

Additionally, Failure Mode and Effects Analysis (FMEA) was applied to identify potential failure modes and prioritise improvement actions based on risk and operational impact. The integration of analytical methods and operational data supports the development of more effective maintenance strategies aligned with Industry 4.0 principles and predictive maintenance approaches [12,34]. Specifically, real-time sensor data and Bayesian updating enable predictive models to be updated as new operational evidence becomes available [33].

Based on the results obtained during the diagnostic phase, preventive maintenance plans were reviewed and redesigned in order to improve maintenance scheduling, optimize resource allocation and reduce equipment downtime. The proposed improvements were implemented in the organisation's maintenance processes, allowing the evaluation of their impact on operational performance. The results obtained were subsequently analysed in terms of maintenance reliability indicators, maintenance costs and operational efficiency.

The overall research process followed an iterative improvement cycle typical of Action Research methodologies, where the analysis of operational data supports the identification of improvement opportunities and the implementation of corrective actions in the maintenance management system [19,36].

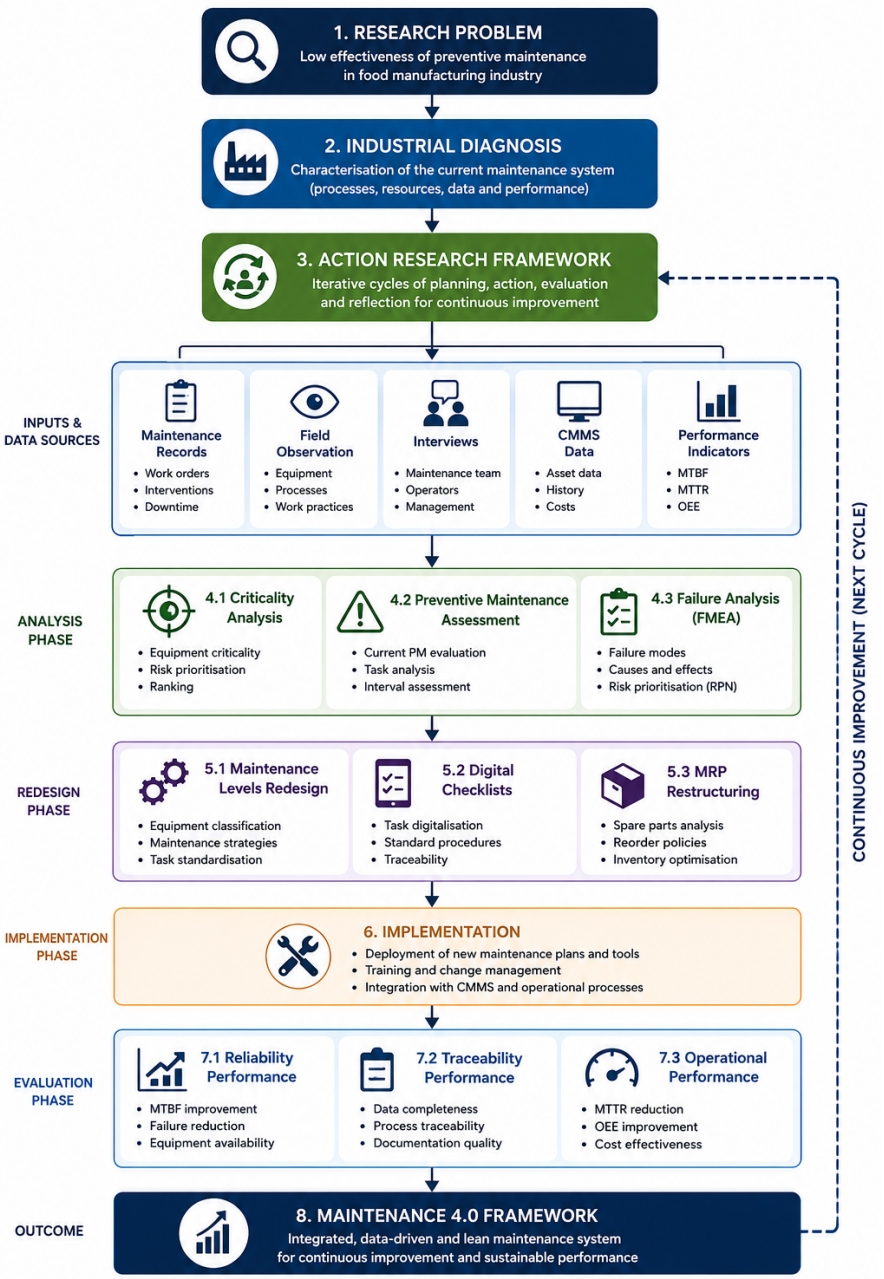


Figure 10. Overall methodological architecture of the maintenance redesign framework (adapted from [37]).

4. Industrial Case Study: Maintenance Framework Redesign

Following the Action Research (AR) methodology previously established, this chapter details the empirical application of the redesigned framework within the Lactogal production unit in Modivas, Portugal. As one of the largest dairy processing facilities in the Iberian Peninsula, the plant provides a complex operational environment ideal for bridging the gap between theoretical maintenance models and practical industrial problem-solving. By utilising the iterative cycles of diagnosis, intervention, and reflection [37], the study aims to deliver immediate process improvements while contributing to the scientific understanding of maintenance management in the process industry.

4.1. System Characterisation and Criticality Analysis

The Lactogal Modivas plant handles an annual volume of approximately 1200 million litres of milk. The production flow is characterised by high-speed automation, transitioning from raw material reception and UHT treatment to aseptic filling and secondary packaging. The packaging and distribution (DE) sector was identified as the primary operational bottleneck, consisting of 16 high-performance filling lines integrated with complex grouping and palletising systems.

As shown in Figure 11, the layout involves a high density of interconnected assets where a failure in a single secondary packaging machine can halt the entire upstream filling process. Maintenance policies must be explicitly aligned with manufacturing competitive priorities, particularly in the dairy industry, where product shelf-life and high-volume throughput are critical, making availability and reliability the dominant priorities [38].

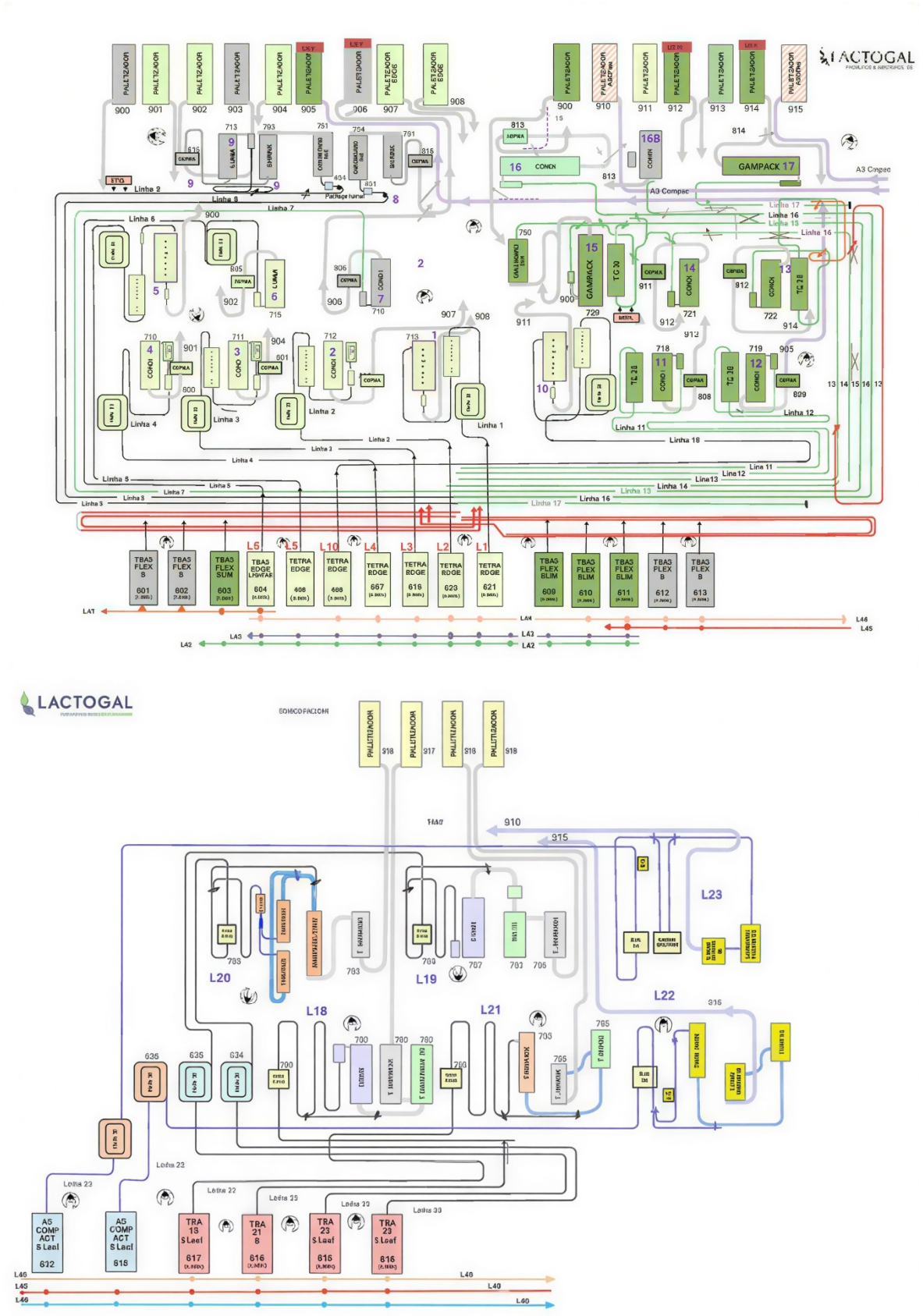


Figure 11. General Layout of the Filling and Distribution Sector.

The diagnostic phase identified a systemic failure in the legacy maintenance model, which relied on rigid, time-based preventive cycles of 1000 h. A logistical and mathematical evaluation conducted during this study revealed that performing these comprehensive overhauls across 16 lines would require 64 weeks of downtime per year. Given the 52-week calendar limit, this approach proved to be unsustainable, leading to a mounting maintenance backlog and a 42% increase in reactive interventions. This 'maintenance debt' significantly impacted the Mean Time to Repair (MTTR) and inflated operational costs due to emergency spare parts procurement.

To prioritise the redesign, a multi-criteria criticality analysis was performed using the Production Utilisation Time (PTU) indicator. Within this framework, KPIs must not only measure output but also reflect the health and obsolescence of the assets [6]. To assess the operational status during the diagnostic phase, performance indicators were calculated for the three primary production formats (Edge, Base, and Slim), as summarized in Figure 12.

Format	Machine	Filling (%)	Distribution (%)	PTU (%)
EDGE	F607	8.76	24.32	66.92
	F621	6.86	22.66	70.48
	F619	6.67	21.85	71.48
	F620	5.65	22.17	72.18
	F604	5.73	20.35	73.93
SLIM	F611	4.19	17.04	78.77
	F609	3.53	16.11	80.35
	F610	3.11	16.47	80.41
	F603	3.21	15.66	81.13
	F613	3.19	12.95	83.86
BASE	F612	4.03	14.76	81.21
	F602	3.55	14.72	81.73
	F601	3.03	12.93	84.04

Figure 12. Performance indicators for Edge, Slim, and Base formats.

A comparative analysis of these indicators reveals that while the 'Slim' and 'Base' formats achieved PTU values of 76.62% and 73.74% respectively, the 'Edge' format exhibited the facility's lowest performance, with a critical PTU of 66.92%. This significant performance gap validates the selection of the Edge lines as the primary focus for the maintenance framework redesign, as they represent the most substantial opportunity for improving overall equipment effectiveness (OEE).

To further deconstruct these inefficiencies, a Pareto analysis of the maintenance records was performed, the results of which are illustrated in Figure 13. This analytical step identifies the 'vital few' assets responsible for the majority of system instability. The findings indicate that the Condifilm shrink wrapper and the Cefma handle applicator are the primary drivers of disruption, collectively accounting for 86% of all maintenance work orders in this sector. By pinpointing these specific technical roots, the research successfully transitions from a broad diagnosis to a targeted action planning phase, ensuring that subsequent interventions are prioritised according to their operational impact [39].

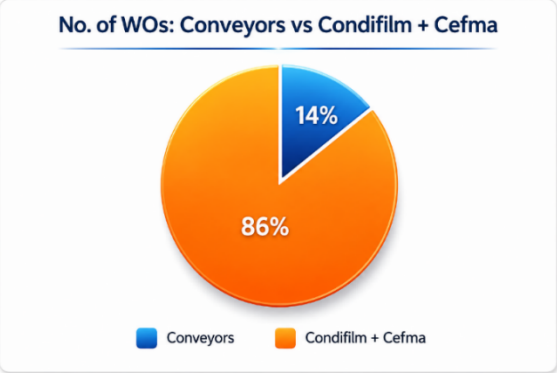


Figure 13. Distribution of Maintenance Work Orders by Equipment Type.

4.2. Failure Mode and Effects Analysis (FMEA) and Risk Management

Once the critical assets were identified, a Failure Mode and Effects Analysis (FMEA) was implemented to deconstruct the technical root causes of recurring stoppages. This phase is consistent with smart manufacturing frameworks that leverage data-driven diagnostics to transition from subjective, opinion-based assessments to objective, fact-based maintenance [40].

The FMEA was conducted by a cross-functional team comprising maintenance engineers, production supervisors, maintenance technicians, and process specialists with direct knowledge of the equipment under analysis. Severity (S), Occurrence (O), and Detection (D) ratings were assigned through expert consensus based on historical maintenance records, operational experience, and equipment failure data obtained from the maintenance management system. The assessment followed the conventional FMEA methodology, in which Severity reflects the impact of a failure, Occurrence estimates its likelihood, and Detection evaluates the probability of identifying the failure before it affects production. The resulting Risk Priority Number (RPN) was then used to prioritise maintenance actions according to the associated operational risk. Through the calculation of the Risk Priority Number (RPN), intervention thresholds were established to guide the strategy: an RPN exceeding 140 for the Condifilm shrink wrapper and 100 for the Cefma handle applicator. The decision-making process for selecting maintenance tasks followed the logic presented in the methodology flowchart in Figure 14.

The analysis revealed that mechanical issues, such as shaft fractures and belt misalignments, were the primary drivers of risk for the Cefma unit. Overall, 52% of Condifilm failure causes and 33% of Cefma causes exceeded the risk thresholds. By quantifying these risks, the study mitigated the subjectivity of legacy planning, ensuring that resources are strategically directed towards high-risk components rather than redundant inspections [39].

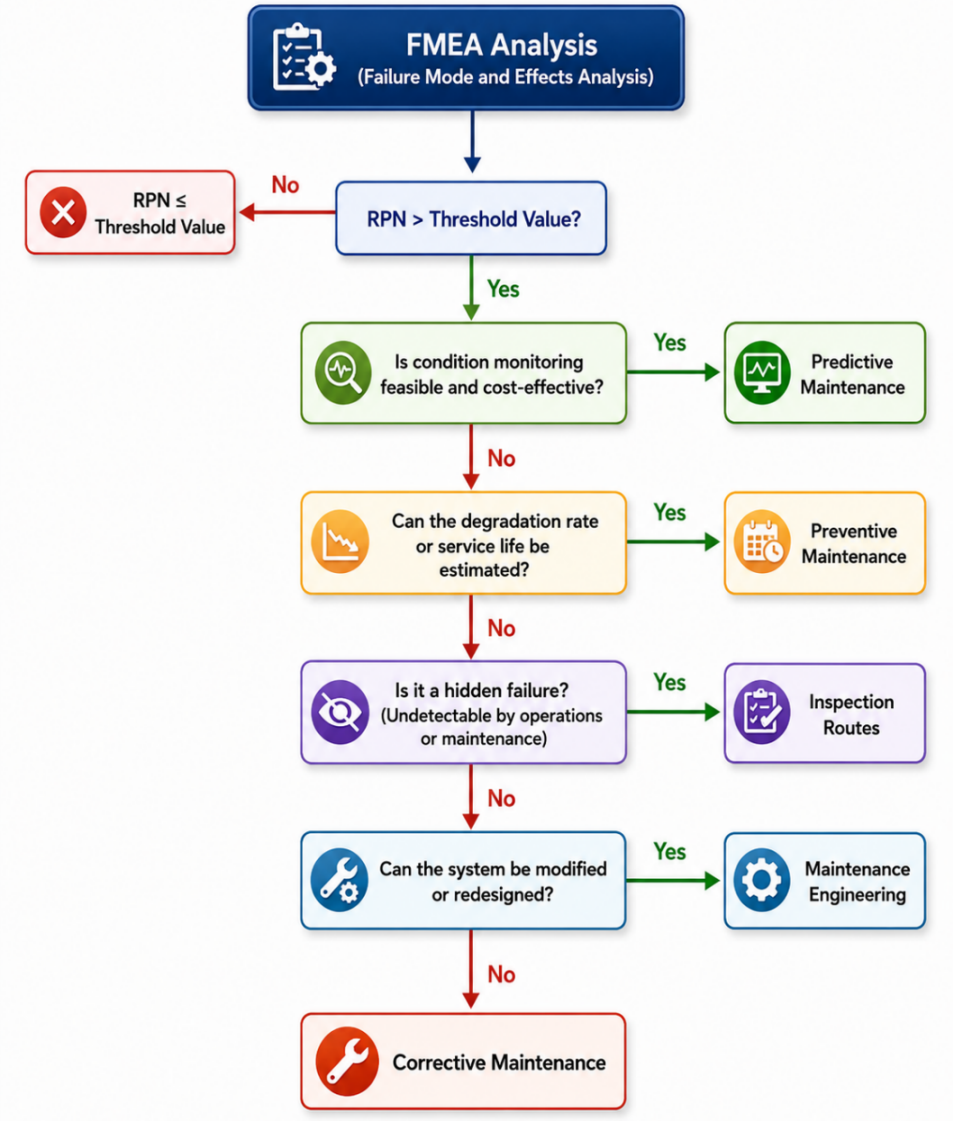


Figure 14. FMEA Methodology Flowchart.

Technical Analysis of Critical Failure Modes

To bridge the gap between risk identification and strategic action, Figure 15 synthesises the high-priority failure modes that dictated the redesign of the preventive plans. These specific technical roots were responsible for the majority of the unplanned downtime recorded during the diagnostic phase.

The data analysis reveals that the maximum Severity score of 10 was assigned to the Cefma infeed conveyor shaft fracture. This classification is justified because such a failure results in a total cessation of the production flow without the possibility of an operational bypass. Conversely, the high RPN for the Condifilm Cutting Group of 224 is driven by a high occurrence rate of 7 combined with moderate detection of 4. This indicates that the legacy 1000-h overhaul intervals were insufficient to monitor the accelerated wear of the cutting blades.

Furthermore, the low detection scores in components like the Cefma position sensors highlighted a critical gap in the legacy model. By identifying these specific risks, the research justifies the transition to the OP10 quarterly verification plans, which focus on early detection through visual and tactile standards. The implementation of the digital information layer via QR codes further addresses these risks by providing technicians with instantaneous access to structural rebuilding procedures, effectively lowering the Detection factor and reducing the overall risk profile of the Modivas plant packaging sector.

Equipment	Component/ System	Failure Mode	Potential Effect	S	O	D	RPN	Recommended Action
Cefma	Infeed Conveyor	Shaft fracture	Total line stoppage	10	4	5	200	Systematic replacement (OP30)
Condifilm	Cutting Group	Blade failure	Improper pack wrapping	8	7	4	224	Tactile inspection and adjustment (OP10)
Condifilm	Divider (Repartidor)	Broken support	Package crushing/stoppage	9	5	5	225	Systematic lubrication plan (OP10)
Cefma	Applicator Unit	Handle application failure	Quality rejection at palletizer	7	8	3	168	Tension verification via QR Code (OP10)
Cefma	Position Sensors	Sensor out of alignment	Intermittent line stops	6	9	2	108	Cleaning via Autonomous Maintenance

Figure 15. Detailed FMEA results for high-priority failure modes in Condifilm and Cefma units (Legend: S = Severity; O = Occurrence; D = Detection; RPN = S × O × D.).

4.3. Implementation of Solutions and Maintenance 4.0

The proposed solution involved a paradigm shift from a singular, exhaustive 1000-h cycle to a multi-level maintenance strategy. This hierarchical approach enables the application of varied inspection frequencies aligned with the specific degradation patterns of individual components [41]. Consequently, the new framework was structured into four distinct operational levels: OP10 (Quarterly), OP20 (Biannual), OP30 (Annual), and OP40 (Biennial).

The adoption of this hierarchical structure facilitates the frequent inspection of high-wear components, such as suction cups and chains, whilst reserving complex structural interventions for annual overhauls. This redistribution successfully reduced the required annual downtime per line from 4 weeks to 2.2 weeks, effectively resolving the previously identified logistical backlog and ensuring higher asset availability.

To further illustrate the transformation achieved through the proposed framework, Figure 16 compares the main characteristics of the legacy preventive maintenance approach with those of the proposed Maintenance 4.0 framework.

Aspect	Legacy maintenance	Proposed Maintenance 4.0
Maintenance philosophy	Time-based	Risk-based
Planning	Fixed 1000 h	Multi-level OP10–OP40
Information	Paper manuals	QR + SharePoint
Decision support	Experience	FMEA + KPIs
Scheduling	Uniform	Asset criticality
Spare parts	Conventional MRP	Optimized MRP
Workforce	Maintenance technicians	TPM + operators
Traceability	Limited	Digital
Flexibility	Low	High
Continuous improvement	Sporadic	Continuous through Action Research

Figure 16. Comparison between legacy preventive maintenance and the proposed Maintenance 4.0 framework.

Compared with the previous maintenance model, the proposed Maintenance 4.0 framework shifts maintenance planning from rigid calendar-based interventions towards a risk-driven and digitally supported decision-making process. Rather than increasing maintenance workload, the framework redistributes interventions according to asset degradation patterns, thereby reducing unnecessary activities while improving reliability and maintainability.

Furthermore, within the framework of Industry 4.0, a digital information layer was implemented by affixing QR codes to all critical assets, as illustrated in Figure 17, allowing technicians to supersede traditional paper-based manuals. Both information transparency and decentralised technical support are established as core pillars of the fourth industrial revolution [42,43].



Figure 17. QR Code Implementation on the Shop Floor.

Through these codes, maintenance personnel gain instantaneous access to a centralised SharePoint repository containing digital manuals, structural rebuilding procedures, and SAP-integrated maintenance history. This integration between the shop floor and the Computerised Maintenance Management System (CMMS) fulfils the requirements of the “Smart Monitoring” scenario within digital manufacturing [44].

Furthermore, the study involved restructuring the Material Requirements Planning (MRP) by analysing consumption patterns from 2023 to 2025. Spare parts were subsequently reclassified into L05 (automatic replenishment) and L06 (on-demand), an optimisation that ensures the availability of critical components. This approach reduces the Mean Time to Repair (MTTR) while simultaneously minimising the total inventory cost of non-critical items [6].

Finally, the introduction of Autonomous Maintenance (AM) plans empowered production operators to undertake basic cleaning and lubrication tasks. The implementation of Autonomous Maintenance (AM) plans directly operationalises the TPM strategic objectives defined in Section 2.3.2, allowing the technical team to focus on high-level predictive and condition-based tasks rather than basic preservation [45]. This structured data environment establishes the necessary foundation for the future integration of advanced predictive algorithms and machine learning models for asset health monitoring [46,47].

The implementation of the proposed framework combined several Lean tools throughout the Action Research cycles. Pareto analysis was used to identify the equipment responsible for the majority of maintenance work orders, FMEA supported the prioritisation of maintenance tasks according to technical risk, TPM principles were implemented through Autonomous Maintenance activities assigned to production operators, the 5S methodology supported the standardisation of maintenance documentation and workplace organisation, while A3 thinking guided the structured problem-solving process during successive redesign iterations. These Lean practices were integrated with digital technologies, including QR-code documentation and SharePoint-based information management, establishing the operational foundation of the proposed Maintenance 4.0 framework.

4.3.1. Standardization and Digital Checklist Architecture

The transition to a multi-level strategy required a complete standardization of technical documentation to eliminate subjectivity and ensure 'digital continuity'. By leveraging the expertise of maintenance specialists, the framework evolved from vague instructions into rigorous technical procedures. The technical architecture of these checklists was designed to guide technicians through a logic-driven sequence, ensuring full traceability for every action performed on the shop floor.

As illustrated in Figure 18, the digital checklist follows a modular data structure that links asset identification with specific technical methodologies and validation controls.

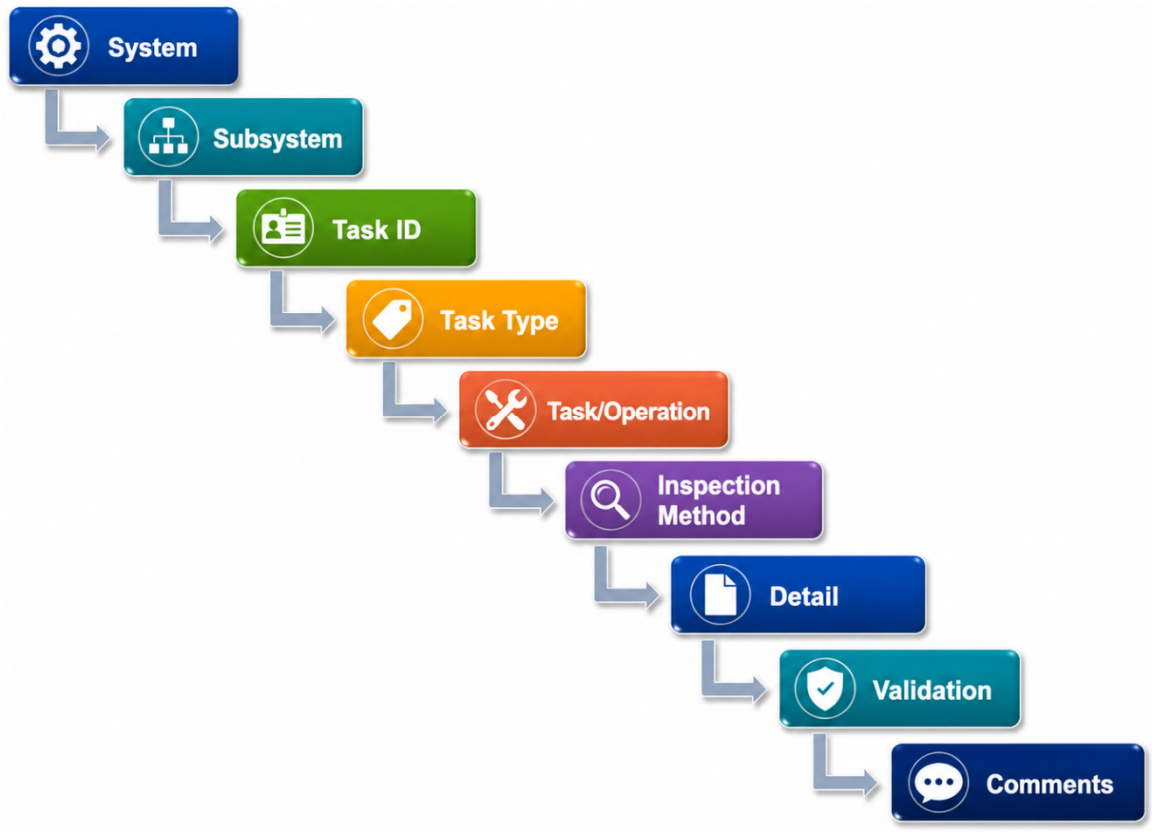


Figure 18. Logical architecture and data fields of the standardised digital maintenance checklists.

To facilitate correct execution and avoid omissions, each digital checklist was structured with specific operational fields:

- **Inspection Method:** Specifies the sensory or technical approach required, such as visual, auditory, tactile, or measurement-based inspections (e.g., using infrared thermometers for temperature checks or vibration sensors).

- **Detail/Instruction:** Provides a precise, step-by-step technical guide for each task. This field acts as a standardised 'on-the-spot' manual for complex structural rebuilding or fine-tuning, ensuring that the intervention quality is independent of the technician's experience level.
- **Validation (OK/NOK):** A binary status field that mandates a formal record of the component's condition. In the event of a 'NOK' (Not OK) status, the technician is required to record the findings in the observations field and trigger a corrective work order follow-up. This ensures that technical anomalies are addressed before they escalate into functional failures.

4.3.2. Technical Hierarchy: Differentiating OP10 and OP30

A fundamental pillar of this framework is the strategic differentiation between verification and restoration. This prevents the accumulation of 'maintenance debt' by focusing high-intensity resources only when necessary, while maintaining constant surveillance through non-intrusive routes.

- **OP10 (Quarterly—Verification Focus):** These tasks prioritize condition monitoring with minimal equipment intrusion. The goal is the early detection of wear patterns (e.g., chain elongation or seal leaks) without significant disassembly.
- **OP30 (Annual—Restoration Focus):** These are intrusive, high-depth interventions. Based on the FMEA risk profile, these cycles involve the systematic replacement of critical components (e.g., cutting blades or main drive belts) to reset the asset's reliability life cycle.

Figure 19 illustrates this differentiation with real-world tasks extracted from the redesigned maintenance plan for the Cefma handle applicator at the Modivas plant.

Level	Component	Task/Operation	Inspection Method	Detail/ Instruction
OP10	Drive Motor	Surface temperature check	Tactile/Technical	Use an infrared thermometer; verify if the housing temperature is below 60°C.
OP30	Cutting Unit	Systematic blade replacement	Technical/Manual	Disassemble the cutting head, replace blades, and recalibrate the zero-position sensor.
OP10	Pneumatic Unit	Air leak detection	Auditory/Visual	Inspect hoses and fittings; listen for air bypass during the cylinder compression cycle.
OP30	Conveyor	Main drive belt replacement	Technical/Manual	Remove safety guards, replace the timing belt, and verify tension using a sonic tension meter.

Figure 19. Comparison of task specifications between OP10 and OP30 cycles for the Cefma unit.

This standardised architecture ensures that every technical anomaly detected during an OP10 route is either immediately resolved or digitally scheduled for follow-up, maintaining a continuous feedback loop between the shop floor and the centralized SharePoint repository.

4.4. Economic Impact and Material Requirements Planning (MRP) Optimization

The transition to a multi-level maintenance strategy requires not only a shift in technical procedures but also a structural reorganisation of the logistical chain. As the new maintenance cycles (OP10 to OP40) demand high availability of specific spare parts, the study addressed the optimization of Material Requirements Planning (MRP) to ensure asset reliability without inflating inventory costs.

4.4.1. MRP Restructuring and Item Classification (L05 vs. L06)

A critical bottleneck identified in the legacy system was the lack of a standardised filter for spare parts procurement, leading to a "logistical backlog" and tied-up capital. To resolve this, a new governance model was implemented through the New Maintenance Item Form (FNAM), a technical document designed to validate the entry of any new component into the SAP system.

Based on an analysis of consumption patterns between 2023 and 2025, spare parts were reclassified into two distinct logistical flows:

- **L05 (Automatic Replenishment):** Reserved for high-rotation consumables and critical low-cost components (e.g., suction cups, seals, and sensors). These items are automatically restocked by the ERP system once a minimum threshold is reached, ensuring that the frequent OP10 and OP20 inspections are never delayed due to lack of material.
- **L06 (On-demand):** Applied to high-value or low-rotation components. These parts are only ordered specifically for scheduled major interventions (OP30 and OP40). This prevents expensive parts from sitting idle in the warehouse for years, effectively increasing the company's liquidity.

4.4.2. Financial Results and the "Inventory Paradox"

The implementation of this dual-logic MRP system resulted in what can be characterized as an "Inventory Paradox." Despite an increase in the total number of registered references to support the decentralized maintenance model, the total financial value of the inventory was reduced by 32%. This was achieved by eliminating obsolete high-value items and focusing on high-reliability, low-cost consumables.

Furthermore, the reallocation of technical resources led to significant savings in operational expenditures (OPEX). By empowering production operators through Autonomous Maintenance (AM), the technical team was able to shift its focus from basic cleaning and lubrication to high-level predictive tasks. This transition resulted in a 23% reduction in subcontracted labor costs and a 20% increase in internal labor efficiency, as detailed in Figure 20. The quantitative results presented in Figure 20 were obtained from maintenance work orders, production planning records, SAP inventory data, and operational KPIs collected throughout the Action Research implementation between 2023 and 2025. Percentage improvements were calculated by comparing the baseline maintenance system with the redesigned Maintenance 4.0 framework implemented in the case study. The underlying industrial records are confidential under the company's data-sharing agreement and therefore cannot be included as supplementary material.

Performance Metric	Baseline (Legacy)	Post-Implementation	Improvement
Total Inventory Value	100%	68%	-32%
Subcontracted Labor Cost	100%	77%	-23%
Internal Labor Efficiency	100%	120%	+20%
Annual Line Downtime	4 weeks	2.2 weeks	-45%

Figure 20. Summary of Financial and Operational Impact (2023 vs. 2025).

This financial optimization proves that the Maintenance 4.0 framework at the Modivas plant is not only a technical success but also a highly sustainable economic model, providing a clear Return on Investment (ROI) within the first year of implementation.

5. Results

This chapter details the evaluation phase of the Action Research cycle, focusing on the validation of the redesigned maintenance framework implemented at Lactogal's Modivas plant. While the presentation of quantitative gains is a significant contribution, the discussion is enriched by a structured, practical framework designed to guide practitioners in transitioning from reactive legacy models to Maintenance 4.0 environments [48]. The results demonstrate that the synergy between organisational redesign and digital tools is essential for sustainable operational excellence.

5.1. Framework for Maintenance Strategy Alignment

For a maintenance strategy to be effective in the dairy industry, the manufacturing context must be clearly defined to address challenges such as perishability and stringent hygiene [3]. The proposed framework identifies three pillars for aligning technical interventions with real-world production needs:

- **Asset Typology:** Distinguishing between bottleneck assets and auxiliary equipment. In this study, the Edge format's critical PTU of 66.92% validated its selection as the priority for digital monitoring. This approach ensures that technical resources are allocated where they generate the highest impact on global plant efficiency [49].
- **Performance Requirements:** Prioritising availability and reliability. By identifying the "vital few" assets through Pareto analysis, specifically the Condifilm and Cefma units, it was found that 86% of system instability originated from these specific points. This focus allowed for a surgical intervention rather than a generalized, less effective maintenance plan.
- **Operational Constraints:** Addressing the 'maintenance debt' accumulated by an outdated preventive plan. The legacy model's requirement of 4 weeks of annual downtime was theoretically sound but logistically unsustainable. The transition to a multi-level structure (OP10 to OP40) redistributed tasks, reducing annual downtime to 2.2 weeks per line, effectively resolving the conflict between maintenance windows and production targets.

5.2. Key Observations on Framework Implementation

Building on the review of Lean and Industry 4.0 synergies, the implementation addressed information precision and resource efficiency.

Key observations include:

- **Operational Performance:**
  - The tiered OP10-OP40 cycles led to a 71% reduction in Reactive Work Orders for critical assets, significantly reducing over-maintenance [50].
  - The DE03 sector achieved a 15.19% reduction in global PTU losses, demonstrating the impact of targeted technical interventions.
- **Digital and Maintainability Gains:**
  - The use of QR codes operationalises smart information systems, ensuring that technical knowledge is decentralised and accessible [51].
  - This digital continuity provided a documentary digital twin, reducing MTTR by 13% through instantaneous access to structural rebuilding procedures [49].
- **Economic Impact:**
  - Regaining internal control of the maintenance plan enabled a 50% reduction in external hourly rates.
  - The MRP restructuring resulted in a 32% increase in stock units but a 32% reduction in total inventory value, confirming that Industry 4.0 tools act as amplifiers for Lean practices [52].

Although the implementation required an initial investment in process mapping, workforce training, FMEA and digital infrastructure, these efforts were rapidly compensated by lower maintenance workload, improved planning efficiency and significant reductions in reactive interventions. Therefore, the proposed Maintenance 4.0 framework should be viewed as a transformation of maintenance philosophy rather than merely the adoption of digital technologies.

The principal quantitative improvements achieved following the implementation of the proposed framework are consolidated in Figure 21.

Figure 21 consolidates the principal quantitative outcomes obtained during the implementation of the proposed Maintenance 4.0 framework. The results demonstrate consistent improvements in operational performance, maintenance efficiency, and inventory management, providing objective evidence that the integration of Lean maintenance principles with digital technologies generated measurable technical and economic benefits. These consolidated findings provide the basis for the subsequent strategic assessment presented through the SWOT analysis.

Performance Indicator	Baseline	After Implementation	Improvement
Reactive Work Orders (critical assets)	100%	29%	↓ -71%
Annual downtime per production line	4 weeks	2.2 weeks	↓ -45%
Mean Time to Repair (MTTR)	100%	87%	↓ -13%
PTU losses (DE03 sector)	100%	84.81%	↓ -15.19%
External hourly maintenance costs	100%	50%	↓ -50%
Subcontracted labour cost	100%	77%	↓ -23%
Internal labour efficiency	100%	120%	↑ +20%
Inventory value	100%	68%	↓ -32%
Managed stock references	100%	132%	↑ +32%

Figure 21. Summary of the quantitative improvements obtained after implementing the proposed Maintenance 4.0 framework.

5.3. SWOT Analysis

To provide a comprehensive strategic overview of the framework's implementation, a SWOT analysis was conducted. This qualitative assessment, presented in Figure 22, synthesises the internal and external factors observed throughout the Action Research cycles at the Modivas plant. By categorising the strengths, weaknesses, opportunities, and threats, this analysis evaluates the sustainability of the Maintenance 4.0 transition and identifies the critical success factors required for its long-term viability within the dairy industry.

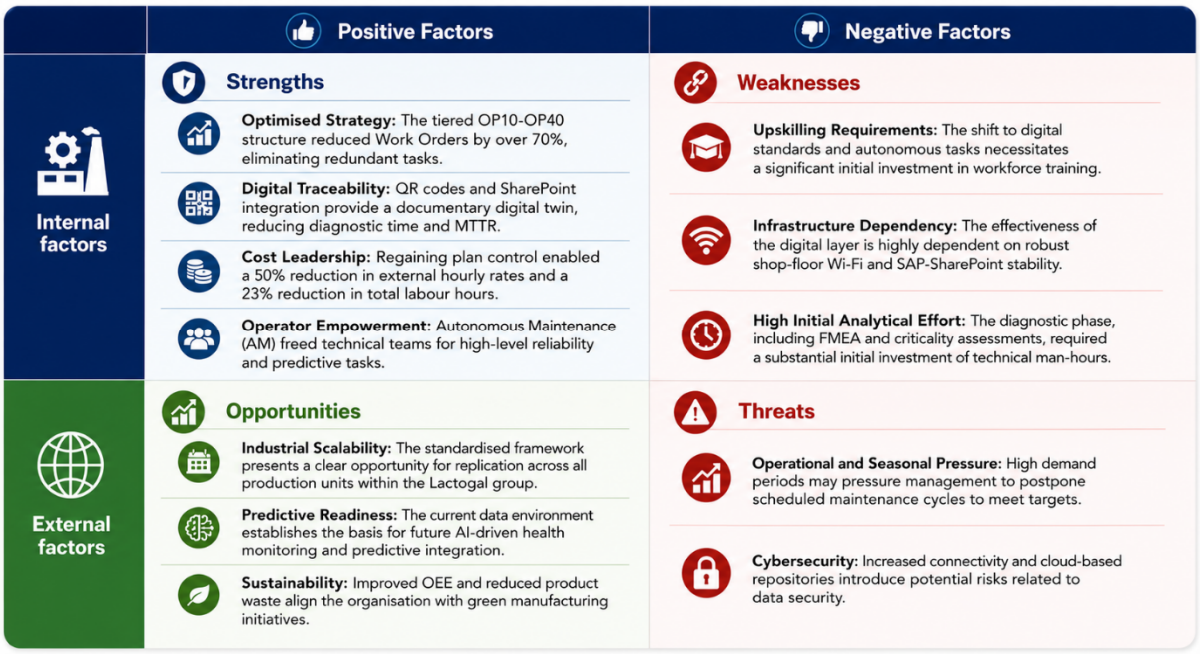


Figure 22. SWOT analysis of the redesigned Maintenance 4.0 framework at Lactogal.

5.4. Managerial Implications

The results of this study provide several practical implications for maintenance managers and manufacturing organisations undergoing digital transformation. First, digital technologies should not be implemented as isolated solutions but should complement robust maintenance processes supported by Lean principles and standardised procedures. Second, maintenance planning should be adapted according to asset criticality rather than relying on uniform preventive intervals recommended by equipment manufacturers. Third, integrating FMEA with KPIs such as MTBF, MTTR and OEE provides an objective basis for prioritising maintenance resources and investments. Finally, the implementation of QR-code documentation demonstrates that relatively low-cost digital solutions can significantly improve knowledge management, technician autonomy and maintenance traceability, representing an accessible first step towards Maintenance 4.0 for organisations with limited investment capacity.

From a strategic perspective, the proposed framework contributes to reducing maintenance debt, increasing organisational resilience and improving alignment between maintenance activities and production objectives. Consequently, practitioners may use the framework presented in this paper as a practical roadmap for progressively implementing Maintenance 4.0 in process industries.

5.5. Strategic Synthesis and Future Outlook

The findings evidence that higher adoption levels of Industry 4.0 are easier to achieve when Lean practices are extensively implemented [52]. By establishing digital continuity, the organisation has moved beyond a reactive mindset toward a strategic business function.

This transition represents a significant increase in the plant's technological maturity. The current structured data environment, supported by a documentary digital twin, establishes the necessary foundation for future advanced predictive integration, such as real-time condition monitoring and AI-driven failure forecasting [49]. This evolution positions the Modivas plant at the forefront of the Maintenance 4.0 paradigm within the food industry.

6. Discussion

6.1. Interpretation of the Maintenance Redesign Strategy

The improvements observed following the implementation of the redesigned maintenance framework demonstrate that maintenance performance should be interpreted as the outcome of a systematic engineering process rather than the isolated application of individual maintenance tools. Instead of relying on incremental modifications to existing preventive plans, the proposed framework restructured maintenance management through the combined application of asset criticality assessment, Failure Mode and Effects Analysis (FMEA), Lean maintenance principles and digitally supported maintenance processes. This integrated approach enabled maintenance activities to be prioritised according to operational importance, potential failure consequences and actual organisational needs, thereby improving the overall coherence and effectiveness of the maintenance system.

One of the most significant outcomes of the maintenance redesign was the transition from schedule-oriented maintenance towards risk-informed maintenance planning. Traditional preventive maintenance programmes frequently evolve over long periods through successive additions of maintenance tasks, often resulting in redundant interventions, inconsistent maintenance frequencies and inefficient resource allocation. By introducing structured criticality analysis and systematic FMEA, the redesigned framework established objective criteria for defining maintenance priorities, optimising inspection intervals and allocating maintenance resources where they generated the greatest operational value. Consequently, maintenance planning became progressively aligned with equipment criticality and production requirements rather than historical maintenance practices.

The results also highlight the complementary relationship between Lean maintenance principles and Maintenance 4.0 concepts. While Lean methodologies contributed to eliminating non-value-added maintenance activities, simplifying maintenance procedures and improving process standardisation, digital technologies enhanced information availability, traceability and decision support. Importantly, the present study demonstrates that digitalisation should not be regarded as an independent maintenance strategy but rather as an enabling mechanism that strengthens structured engineering methodologies. The effectiveness of digital maintenance systems ultimately depends on the quality of the maintenance processes they support.

Another important observation concerns the role of maintenance information management. The implementation of digital checklists, improved CMMS utilisation and the restructuring of maintenance documentation significantly increased process standardisation and information consistency. Beyond reducing administrative effort, these improvements enhanced organisational learning by ensuring that maintenance knowledge became systematically captured, shared and reused throughout the organisation. Such improvements

represent an essential prerequisite for the progressive evolution towards data-driven maintenance management and continuous organisational learning.

From an engineering perspective, the proposed maintenance redesign illustrates that sustainable maintenance improvements arise from the simultaneous optimisation of technical, organisational and informational dimensions. Equipment reliability depends not only on maintenance frequency but also on the quality of maintenance decisions, the prioritisation of critical assets, the availability of reliable maintenance information and the capability to continuously improve maintenance practices through structured analytical methods. This systems-oriented perspective differentiates the proposed framework from approaches that focus exclusively on isolated maintenance technologies or individual analytical tools.

Overall, the findings suggest that maintenance transformation should be understood as an organisational redesign process supported by engineering analysis, digital technologies and continuous-improvement philosophies. Rather than introducing fundamentally new maintenance techniques, the proposed framework demonstrates how the systematic integration of established methodologies can substantially improve maintenance effectiveness, providing a practical pathway towards the implementation of Maintenance 4.0 in industrial environments.

6.2. Comparison with Previous Studies

The maintenance redesign strategy proposed in this study is consistent with the growing body of research advocating the transition from conventional preventive maintenance towards more structured, data-driven maintenance systems. Previous studies have demonstrated that maintenance effectiveness can be significantly improved through the application of performance indicators, condition monitoring technologies, failure analysis methodologies and digital information systems [5–18]. Nevertheless, these approaches are frequently investigated independently, with comparatively limited attention devoted to their systematic integration within comprehensive maintenance redesign strategies implemented under real industrial conditions.

The present study extends existing knowledge by demonstrating that maintenance improvement is not solely dependent on the introduction of advanced digital technologies, but rather on the coordinated integration of engineering methodologies capable of supporting informed maintenance decision-making. While Industry 4.0 technologies provide unprecedented opportunities for real-time monitoring, predictive analytics and intelligent maintenance scheduling [12–14], their practical value ultimately depends on the quality of the maintenance strategies that govern maintenance planning and resource allocation. In this respect, the findings reinforce the growing consensus that digitalisation should be considered an enabler of maintenance excellence rather than an objective in itself.

The results also support previous research highlighting the importance of Lean maintenance and Total Productive Maintenance (TPM) in promoting continuous improvement and operational efficiency [18]. However, unlike many previous studies that primarily focus on waste reduction or workforce involvement, the present work integrates Lean principles with asset criticality analysis, structured FMEA and digitally supported maintenance management. This combination enables maintenance decisions to be prioritised according to operational risk, equipment importance and production requirements, thereby establishing a more comprehensive decision-support framework than those typically reported in the literature.

Similarly, previous investigations have consistently recognised the value of FMEA as a structured methodology for identifying potential failure modes and prioritising maintenance actions [9–11]. The present study confirms these findings while demonstrating that the practical benefits of FMEA become considerably greater when failure analysis is embedded within a broader maintenance redesign process incorporating criticality assessment, maintenance standardisation, digital documentation and continuous performance monitoring. Rather than functioning as an isolated analytical technique, FMEA becomes one component of an integrated maintenance management architecture.

Another distinguishing characteristic of the proposed framework concerns its industrial validation. A substantial proportion of Maintenance 4.0 research remains centred on conceptual models, predictive algorithms or simulation-based analyses [12–14]. Although these contributions have significantly advanced maintenance science, relatively fewer studies report the complete implementation of integrated maintenance redesign strategies within operational industrial environments, particularly in sectors characterised by continuous production, strict hygiene constraints and limited maintenance windows. By validating the proposed framework through an Action Research methodology conducted in a food manufacturing company, the present study provides practical evidence of how established engineering methodologies can be systematically combined to generate measurable organisational and operational improvements.

Overall, the findings suggest that the principal contribution of this work lies not in proposing entirely new maintenance tools, but in demonstrating how established methodologies can be integrated into a coherent maintenance management framework capable of supporting Maintenance 4.0 implementation. This systems-oriented perspective complements existing literature by bridging the gap between engineering analysis, digital transformation and continuous improvement, thereby contributing to the development of more resilient, data-driven and operationally sustainable maintenance systems.

6.3. Industrial Implications and Practical Applicability

The practical significance of the proposed maintenance redesign extends beyond improvements in individual maintenance indicators, demonstrating how structured maintenance engineering can directly enhance operational efficiency, organisational resilience and manufacturing competitiveness. Rather than focusing exclusively on increasing maintenance frequency or introducing isolated digital technologies, the proposed framework adopts a systems-oriented perspective in which maintenance planning, engineering analysis and digital information management are integrated to support evidence-based decision-making [1,5,6]. This holistic approach is consistent with the current evolution of maintenance management towards more intelligent, data-driven and value-oriented maintenance systems.

One of the principal industrial implications concerns the optimisation of maintenance resources. In industrial environments, maintenance departments typically operate under significant constraints regarding personnel availability, production schedules, maintenance windows and financial resources. Consequently, maintenance interventions should be prioritised according to equipment criticality and operational risk rather than uniformly distributed across all production assets. The combined application of asset criticality analysis and FMEA enabled maintenance activities to be systematically prioritised according to their expected impact on production continuity, equipment reliability and operational safety, thereby improving maintenance planning while reducing unnecessary interventions [3,9–11]. These findings are consistent with previous studies emphasising that risk-based maintenance planning contributes to more efficient resource allocation and improved operational performance.

The implementation of Lean maintenance principles further reinforced these improvements by eliminating non-value-added maintenance activities, simplifying maintenance procedures and promoting greater process standardisation [18]. Instead of treating maintenance as a collection of independent technical interventions, the redesigned framework establishes maintenance as an integrated operational process closely aligned with production requirements and continuous improvement objectives. This integration reduces process variability, improves workflow efficiency and supports a more proactive maintenance culture, in agreement with the fundamental principles of Total Productive Maintenance and Lean Manufacturing [18].

Another important implication concerns maintenance information management. Although Computerised Maintenance Management Systems (CMMS) have become standard tools within modern industrial organisations, their potential is frequently limited by incomplete data collection, inconsistent documentation and insufficient analytical utilisation [7,8]. The introduction of digital checklists, improved maintenance documentation and enhanced CMMS utilisation significantly strengthened maintenance traceability and information consistency throughout the organisation. Beyond reducing administrative effort, these improvements contributed to higher-quality maintenance records, facilitating faster engineering decision-making, improved maintenance scheduling and more effective continuous improvement initiatives [5,7,8]. This observation reinforces previous research indicating that digital transformation generates sustainable benefits only when supported by structured maintenance processes and reliable operational information [12,13].

The proposed framework also demonstrates that organisational learning represents a critical dimension of maintenance transformation. Maintenance knowledge is frequently dispersed among experienced technicians, making organisations vulnerable to knowledge loss and inconsistencies in maintenance execution. By standardising maintenance procedures, documenting engineering decisions and integrating digital information into routine maintenance activities, the redesigned framework contributes to the institutionalisation of maintenance knowledge and reduces dependence on individual experience. Such knowledge standardisation enhances organisational resilience while facilitating training, knowledge transfer and the long-term sustainability of maintenance improvement programmes [7,8,18].

From a strategic perspective, the present study further illustrates that the transition towards Maintenance 4.0 should be understood as a gradual organisational transformation rather than a purely technological upgrade. Although advanced technologies such as Industrial Internet of Things (IIoT), machine learning and predictive analytics considerably expand maintenance capabilities [12–14], their practical effectiveness depends fundamentally on robust engineering methodologies capable of translating operational data into structured

maintenance decisions. The framework proposed in this work demonstrates that digitalisation delivers its greatest industrial value when combined with criticality assessment, systematic failure analysis, Lean maintenance principles and continuous performance evaluation, thereby establishing a coherent decision-support architecture fully aligned with the Maintenance 4.0 paradigm [12–14].

Although the proposed framework was validated within a food manufacturing environment, its underlying methodological principles are sufficiently generic to support maintenance transformation across a broad spectrum of manufacturing sectors. Industries characterised by continuous production, high equipment utilisation, stringent quality requirements and limited maintenance opportunities may equally benefit from the systematic integration of criticality analysis, FMEA, Lean maintenance and digital information management. Consequently, the industrial contribution of this work extends beyond the specific case study by providing a transferable engineering methodology that can be adapted to different production environments while preserving its fundamental decision-support philosophy [15–18].

Overall, the industrial contribution of the proposed framework lies not in introducing entirely new maintenance techniques, but in demonstrating how established engineering methodologies can be systematically integrated into a coherent maintenance management architecture capable of improving reliability, maintenance efficiency, organisational learning and operational decision-making. This integrated perspective contributes to narrowing the gap between maintenance engineering, digital transformation and continuous improvement, offering industrial organisations a practical pathway towards more resilient, data-driven and sustainable maintenance systems [5,12,18].

6.4. Maintenance 4.0 Perspective and Digital Transformation

The findings of the present study reinforce the view that Maintenance 4.0 should not be interpreted solely as the digitalisation of maintenance activities, but rather as the systematic integration of engineering methodologies, operational knowledge and digital technologies into a coherent decision-support framework. Although Industry 4.0 technologies—including Industrial Internet of Things (IIoT), cyber-physical systems, cloud computing and advanced data analytics—have substantially expanded maintenance capabilities, their successful implementation depends fundamentally on the quality of the maintenance strategies that support engineering decision-making [2,12–14]. Consequently, digital transformation should be regarded as an enabling mechanism that strengthens maintenance engineering rather than as an isolated technological objective.

The maintenance redesign implemented in this study illustrates this principle by demonstrating that digital technologies generate the greatest operational value when integrated with structured maintenance methodologies. Asset criticality assessment, Failure Mode and Effects Analysis (FMEA), preventive maintenance optimisation and Lean maintenance principles collectively provide the engineering foundation upon which digital maintenance systems can effectively operate. Within this context, digital checklists, improved Computerised Maintenance Management System (CMMS) utilisation and enhanced maintenance documentation function not merely as information repositories, but as mechanisms for improving maintenance traceability, decision consistency and organisational learning [7,8,12].

These observations are consistent with recent Maintenance 4.0 literature, which emphasises that maintenance intelligence emerges from the interaction between data acquisition, engineering analysis and informed decision-making rather than from data collection alone [12–14]. While predictive maintenance algorithms and condition-monitoring technologies are capable of identifying equipment degradation and supporting maintenance scheduling, their practical effectiveness remains dependent on robust maintenance processes capable of interpreting operational information within the broader context of production requirements, equipment criticality and organisational priorities [2,11,13]. The present framework therefore complements existing Maintenance 4.0 research by demonstrating how digital technologies can be systematically embedded within an integrated maintenance management architecture.

An additional contribution of the proposed framework concerns the progressive nature of digital transformation. Many organisations perceive Maintenance 4.0 as requiring substantial technological investment before meaningful improvements can be achieved. However, the present study demonstrates that significant operational benefits can already be obtained through the systematic integration of existing maintenance engineering methodologies with relatively accessible digital tools. The enhancement of CMMS functionality, digital maintenance records, structured inspection procedures and standardised maintenance documentation represents an evolutionary pathway towards Maintenance 4.0 that is both technically feasible and economically realistic for many industrial organisations [7,8,12].

From an organisational perspective, the framework also supports the transition from reactive information management towards knowledge-driven maintenance. Digital maintenance systems become substantially more valuable when maintenance records are consistently structured, engineering decisions are formally documented and operational experience is progressively incorporated into future maintenance planning. This transformation enables maintenance organisations to evolve from executing predefined maintenance tasks towards continuously learning systems capable of improving maintenance strategies through accumulated operational knowledge and performance feedback [5,7,13].

Furthermore, the proposed framework aligns closely with the broader objectives of smart manufacturing by strengthening the integration between maintenance, production and operational management. Rather than functioning as an isolated support activity, maintenance becomes an active contributor to manufacturing performance through improved equipment reliability, enhanced resource allocation and more informed operational decision-making. Such integration is increasingly recognised as a defining characteristic of Maintenance 4.0 and represents an essential prerequisite for achieving resilient, flexible and data-driven manufacturing systems [12,14–16].

Overall, the Maintenance 4.0 perspective presented in this study demonstrates that sustainable digital transformation is achieved not through the isolated adoption of advanced technologies, but through the coordinated integration of structured maintenance engineering, digital information management and continuous-improvement principles. By combining Lean maintenance, asset criticality analysis, FMEA, enhanced CMMS utilisation and digital maintenance processes within a unified decision-support framework, the proposed methodology contributes to narrowing the gap between conventional preventive maintenance and the intelligent, connected and knowledge-driven maintenance systems envisaged within the Maintenance 4.0 paradigm [12–18].

6.5. Scientific Contributions and Research Implications

Beyond the operational improvements achieved in the industrial case study, the present research contributes to maintenance engineering by demonstrating that significant advances in maintenance performance can be obtained through the systematic integration of established engineering methodologies rather than through the isolated adoption of individual maintenance technologies. While the existing literature has extensively investigated preventive maintenance, Lean Maintenance, Failure Mode and Effects Analysis (FMEA), Computerised Maintenance Management Systems (CMMS) and Industry 4.0 technologies independently [5–18], comparatively fewer studies have examined how these complementary approaches can be combined within a unified maintenance redesign framework validated under real industrial conditions.

The first scientific contribution of this work lies in the development and validation of an integrated maintenance management framework that combines asset criticality analysis, structured FMEA, Lean maintenance principles and digitally supported maintenance processes within an Action Research methodology. Rather than proposing a new analytical technique, the study demonstrates how the coordinated application of established maintenance engineering methods can generate synergistic improvements in maintenance planning, information management and operational performance. This systems-oriented perspective complements previous maintenance studies by emphasising integration as a primary driver of maintenance effectiveness rather than technological sophistication alone [9–18].

A second contribution concerns the methodological approach adopted throughout the research. Action Research has increasingly been recognised as an appropriate methodology for addressing complex industrial problems because it simultaneously generates practical solutions and scientific knowledge [19,20]. In the present study, this methodology enabled the iterative development, implementation and evaluation of maintenance improvements under real production conditions, ensuring that the proposed framework was continuously refined through collaboration between researchers and industrial practitioners. Consequently, the research provides not only empirical evidence of maintenance improvement but also a reproducible methodological pathway for conducting maintenance redesign projects in industrial environments [19,20].

The proposed framework also contributes to the evolving body of knowledge surrounding Maintenance 4.0. Current research frequently associates Maintenance 4.0 with predictive analytics, Industrial Internet of Things (IIoT), artificial intelligence and advanced sensing technologies [12–14]. Although these technologies undoubtedly represent essential components of digital maintenance, the present findings suggest that their effectiveness depends fundamentally on the existence of structured maintenance engineering processes capable of transforming operational information into informed maintenance decisions. The study therefore reinforces the concept that Maintenance 4.0 should be interpreted as the convergence of engineering methodologies, digital information management and continuous-improvement philosophies rather than as the implementation of isolated digital technologies [12–18].

Another relevant scientific implication concerns the role of maintenance information as an engineering asset. The results demonstrate that improvements in maintenance performance are influenced not only by maintenance interventions themselves but also by the quality, consistency and accessibility of maintenance information. Enhanced CMMS utilisation, digital documentation and standardised maintenance procedures facilitate organisational learning, improve maintenance traceability and strengthen decision-making capabilities, thereby supporting the transition from experience-based maintenance towards knowledge-driven maintenance management [5,7,8,12]. This observation complements previous studies highlighting the strategic importance of information management within intelligent manufacturing systems.

Furthermore, the findings contribute to bridging the traditional separation between maintenance engineering and operational management. Maintenance optimisation is frequently analysed from a purely technical perspective, focusing on equipment reliability or maintenance scheduling. The present framework demonstrates that maintenance redesign also generates broader organisational benefits through improved process standardisation, enhanced cross-functional integration and more efficient resource utilisation. Consequently, maintenance should be regarded not only as an engineering discipline but also as a strategic organisational capability that directly supports manufacturing competitiveness and operational resilience [1,5,15–18].

Finally, the proposed framework provides a transferable conceptual model that extends beyond the specific industrial case investigated. Although validated within a food manufacturing company, the methodological principles underpinning the framework—including structured criticality assessment, systematic failure analysis, Lean continuous improvement and digitally supported maintenance management—are sufficiently generic to be adapted to other manufacturing sectors characterised by complex production systems, high equipment utilisation and demanding reliability requirements. This transferability enhances the broader scientific relevance of the study and supports future research into integrated maintenance transformation across diverse industrial contexts [15–20].

Overall, the principal scientific contribution of this work resides in demonstrating that maintenance transformation should be understood as the coordinated integration of engineering analysis, organisational improvement and digital technologies within a unified maintenance management framework. By experimentally validating this integration through Action Research in a real industrial environment, the present study contributes to advancing maintenance engineering from isolated maintenance optimisation techniques towards comprehensive, data-driven and operationally sustainable Maintenance 4.0 systems [12–20].

6.6. Limitations and Future Research Directions

Although the proposed maintenance redesign framework demonstrated significant operational benefits within the investigated industrial environment, several limitations should be acknowledged when interpreting the present findings. First, the framework was validated through a single industrial case study conducted in the food manufacturing sector. While this sector represents a highly demanding production environment characterised by continuous operation, strict hygiene regulations and limited maintenance windows, the specific organisational characteristics and production constraints may influence the direct transferability of the quantitative results to other industrial contexts. Nevertheless, the engineering principles underpinning the proposed framework—including asset criticality assessment, structured FMEA, Lean maintenance and digitally supported maintenance management—are sufficiently generic to support adaptation across a broad range of manufacturing sectors [15–20].

A second limitation concerns the temporal scope of the industrial implementation. Maintenance transformation represents a continuous organisational process whose full benefits often become evident only after extended periods of operational maturity. Although the improvements reported in this study demonstrate the effectiveness of the proposed redesign during the implementation period, longer-term monitoring would provide additional evidence regarding the sustainability of the observed improvements, the evolution of maintenance performance indicators and the long-term organisational impact of the implemented maintenance strategies [5,6,18].

Another important consideration relates to the level of digital maturity of the maintenance system. The proposed framework incorporates digital maintenance records, enhanced CMMS utilisation and structured maintenance documentation, thereby establishing a solid foundation for Maintenance 4.0 implementation. However, the framework does not yet incorporate advanced predictive maintenance technologies such as Industrial Internet of Things (IIoT) sensor networks, machine learning algorithms, digital twins or autonomous maintenance optimisation systems, which are increasingly recognised as key components of next-generation intelligent maintenance environments [12–14]. Consequently, the present work should be regarded as an important intermediate stage in the progressive transition from structured preventive maintenance towards fully intelligent and predictive maintenance ecosystems.

The Action Research methodology adopted in this investigation also introduces inherent methodological characteristics that should be considered when interpreting the results. The close collaboration established between researchers and industrial practitioners represents one of the principal strengths of Action Research because it facilitates practical implementation while simultaneously generating scientific knowledge [19,20]. However, such collaboration also implies that organisational culture, management commitment and employee engagement may influence implementation effectiveness. Future studies involving multiple industrial organisations would therefore contribute to evaluating the robustness and generalisability of the proposed framework under different organisational conditions.

Building upon the findings of this study, several promising research directions emerge. Future investigations may explore the integration of real-time condition monitoring, Industrial Internet of Things (IIoT) infrastructures, artificial intelligence, machine learning and predictive analytics into the proposed maintenance framework, thereby extending its decision-support capabilities towards fully adaptive maintenance management systems [12–14]. Similarly, the incorporation of Digital Twin technologies may enable continuous simulation of equipment behaviour, optimisation of maintenance schedules and dynamic assessment of maintenance strategies under varying production conditions, further strengthening the alignment between maintenance engineering and smart manufacturing.

Another promising avenue concerns the application of the proposed framework to different industrial sectors characterised by distinct production systems, maintenance philosophies and operational constraints. Comparative studies involving discrete manufacturing, process industries, energy production or highly automated production environments would contribute to evaluating the scalability, adaptability and robustness of the integrated maintenance framework proposed in this research [15–20]. Such comparative analyses would further clarify how sector-specific characteristics influence the implementation and effectiveness of Maintenance 4.0 strategies.

Overall, the limitations identified do not diminish the scientific or industrial relevance of the present study. Instead, they define the natural boundaries of the current investigation while identifying clear opportunities for extending the proposed framework towards more intelligent, autonomous and data-driven maintenance systems. In this sense, the present research should be regarded as a robust engineering foundation upon which future developments in Maintenance 4.0 can be systematically constructed, combining structured maintenance engineering, digital transformation and continuous organisational improvement into increasingly resilient manufacturing systems [12–20].

6.7. Towards Intelligent and Sustainable Maintenance Engineering

The evolution of industrial maintenance increasingly reflects the broader transformation of manufacturing systems towards intelligent, connected and data-driven production environments. Within this context, maintenance can no longer be regarded as an isolated support function responsible solely for equipment repair or preventive interventions. Instead, it is progressively becoming a strategic engineering discipline that contributes directly to production continuity, operational resilience, resource efficiency and long-term industrial competitiveness [1,5,6].

The findings of the present study reinforce this emerging perspective by demonstrating that sustainable maintenance improvement is fundamentally achieved through the systematic integration of engineering methodologies, organisational learning and digital information management. Although advanced technologies such as Industrial Internet of Things (IIoT), artificial intelligence, machine learning and predictive analytics continue to reshape Maintenance 4.0, their successful implementation ultimately depends on robust maintenance engineering processes capable of transforming operational data into structured maintenance decisions [12–14]. Consequently, technological innovation should complement, rather than replace, established engineering methodologies such as asset criticality analysis, Failure Mode and Effects Analysis (FMEA), Lean maintenance and structured preventive maintenance planning [9–18].

An important implication of this work is that maintenance transformation should be viewed as a continuous organisational capability rather than as a discrete technological project. The transition towards Maintenance 4.0 requires organisations to progressively develop engineering knowledge, standardise maintenance processes, strengthen maintenance information management and cultivate a culture of continuous improvement capable of adapting to evolving production requirements [7,8,18]. In this sense, digital technologies represent powerful enablers of organisational learning, but their value is realised only when embedded within coherent maintenance management systems supported by reliable engineering practices.

The proposed framework also aligns closely with the growing emphasis on sustainable manufacturing. More efficient maintenance planning contributes directly to reducing unnecessary maintenance interventions, minimising equipment downtime, improving resource utilisation and extending asset service life, thereby supporting more sustainable production systems [1,5,15]. Beyond economic benefits, improved maintenance

effectiveness may also contribute to reducing material consumption, avoiding premature component replacement and enhancing overall production efficiency, all of which are increasingly recognised as important dimensions of sustainable industrial development [15–18].

From a broader research perspective, the present study illustrates the continuing convergence of maintenance engineering, digital transformation and operational excellence. Rather than treating reliability engineering, Lean Manufacturing, Maintenance 4.0 and data-driven decision-making as separate research domains, the proposed framework demonstrates how these complementary disciplines can be integrated into a unified maintenance management architecture capable of simultaneously improving technical performance, organisational efficiency and managerial decision-making. This integrated perspective contributes to addressing one of the principal challenges identified in recent maintenance literature, namely the need to bridge engineering methodologies with intelligent manufacturing systems through practical and industrially validated implementation strategies [12–20].

Ultimately, the long-term evolution of maintenance engineering will depend less on the development of isolated digital technologies than on the ability of organisations to integrate engineering knowledge, operational information and continuous improvement within adaptive maintenance ecosystems. The framework proposed in this research represents one step towards that objective by providing a structured methodology through which conventional preventive maintenance can progressively evolve into intelligent, knowledge-driven and operationally sustainable Maintenance 4.0 systems. In doing so, the study not only contributes to improving maintenance performance within the investigated industrial environment but also provides a transferable engineering framework capable of supporting future maintenance transformation across diverse manufacturing sectors [12–20].

To synthesise the principal findings discussed throughout this chapter, Figure 23 presents the integrated engineering framework emerging from the present investigation. The framework illustrates how structured maintenance engineering, digital technologies and continuous-improvement principles interact to support the transition from conventional preventive maintenance towards Maintenance 4.0.

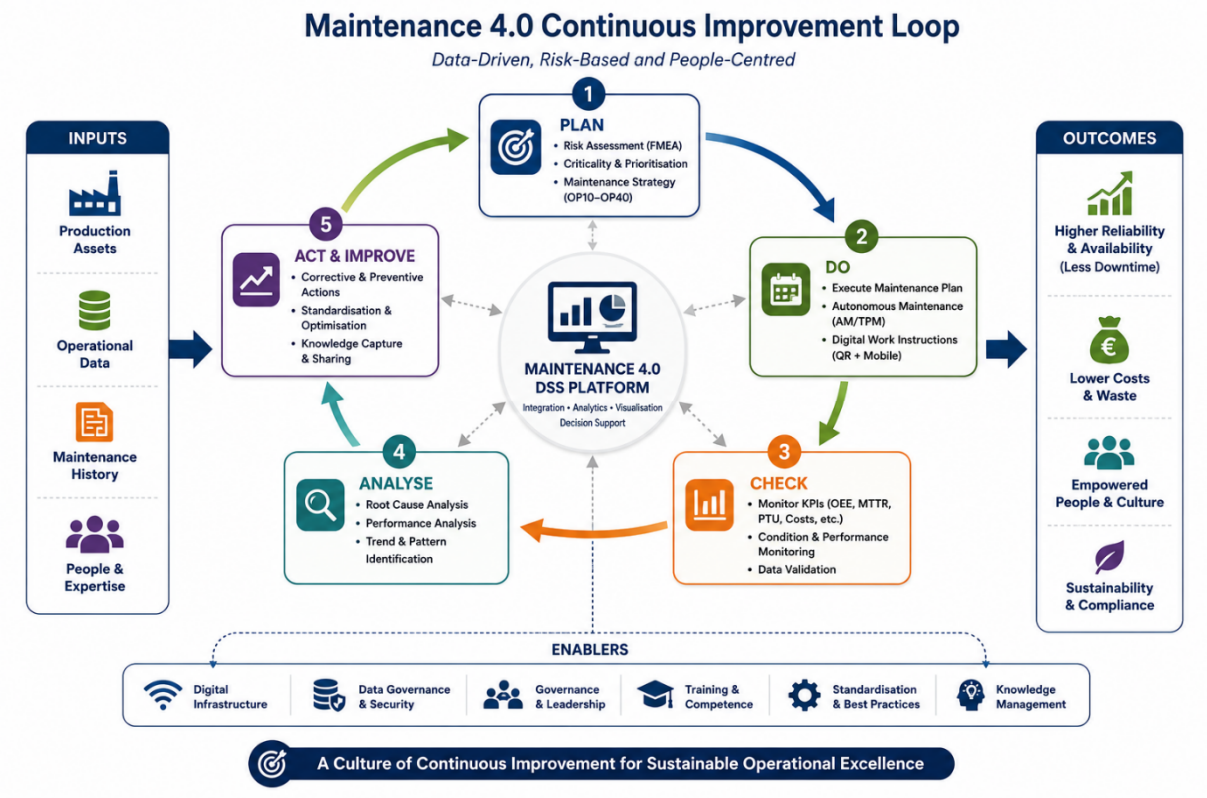


Figure 23. Integrated engineering framework for the transition from conventional preventive maintenance to Maintenance 4.0 through Lean maintenance redesign and data-driven decision support.

The framework highlights that maintenance transformation should be understood as a progressive organisational process in which engineering methodologies, digital information and operational knowledge are systematically integrated. Rather than relying on isolated technological solutions, the proposed approach

demonstrates that sustainable maintenance excellence emerges from the coordinated interaction between structured maintenance planning, data-driven decision-making and continuous organisational improvement.

7. Conclusions

This study demonstrated that preventive maintenance performance can be substantially enhanced through the systematic integration of engineering methodologies, Lean maintenance principles and digitally supported decision-making within a structured Maintenance 4.0 perspective. Rather than focusing on isolated maintenance optimisation techniques, the proposed framework combined asset criticality analysis, Failure Mode and Effects Analysis (FMEA), maintenance standardisation, digital information management and Action Research into a unified maintenance redesign strategy. The industrial implementation confirmed that the coordinated application of these complementary approaches significantly improved maintenance planning, information traceability, operational consistency and maintenance effectiveness within a food manufacturing environment.

From an engineering perspective, the results demonstrate that sustainable maintenance improvement depends less on increasing maintenance effort than on improving the quality of maintenance decisions. The integration of structured criticality assessment, systematic failure analysis and Lean maintenance principles enabled maintenance activities to be prioritised according to operational risk and production requirements, thereby improving resource allocation while reducing process variability and enhancing organisational responsiveness. These findings reinforce the importance of maintenance engineering as a strategic discipline that directly contributes to equipment reliability, operational resilience and manufacturing performance.

A principal scientific contribution of this research lies in demonstrating that Maintenance 4.0 should not be interpreted merely as the implementation of advanced digital technologies, but rather as the systematic integration of engineering analysis, organisational learning and digital information management within a coherent decision-support framework. While previous studies have extensively investigated predictive maintenance, CMMS platforms, Industry 4.0 technologies and Lean maintenance independently [5,18], the present study contributes by experimentally validating how these complementary methodologies can be integrated into a unified maintenance redesign framework under real industrial conditions through an Action Research methodology [19,20]. Consequently, the study helps bridge the gap between conceptual Maintenance 4.0 models and their practical implementation within manufacturing organisations.

The industrial implications of the proposed framework extend beyond the specific case study investigated. The methodological principles underpinning the framework—including asset criticality analysis, structured FMEA, Lean maintenance, digital documentation and continuous performance evaluation—are sufficiently generic to support maintenance transformation across diverse manufacturing sectors characterised by complex production systems, high equipment utilisation and demanding reliability requirements. By improving maintenance traceability, supporting risk-informed decision-making and promoting continuous organisational learning, the proposed methodology provides industrial organisations with a practical pathway towards more efficient, resilient and data-driven maintenance management systems.

The findings also highlight the increasingly strategic role of maintenance within modern manufacturing. As production systems continue to evolve towards intelligent, connected and digitally integrated environments, maintenance must progressively transition from a reactive support activity to an active contributor to operational excellence and sustainable industrial development. In this context, Maintenance 4.0 should be understood as the convergence of engineering methodologies, digital technologies and continuous-improvement philosophies, rather than as a purely technological transformation. The framework proposed in this research contributes to this transition by demonstrating how established maintenance engineering principles can be effectively combined with digital information management to generate measurable operational improvements.

Several limitations should nevertheless be acknowledged. The framework was validated within a single food manufacturing company, and although the underlying engineering principles are broadly transferable, additional validation across different industrial sectors would further strengthen its generalisability. Furthermore, the implementation focused primarily on preventive maintenance redesign supported by digital information management and did not incorporate advanced predictive technologies such as Industrial Internet of Things (IIoT) sensor networks, Digital Twins or artificial intelligence-based maintenance optimisation. These technologies represent promising opportunities for extending the proposed framework towards increasingly adaptive and autonomous maintenance systems.

Future research should therefore investigate the integration of real-time condition monitoring, Industrial Internet of Things (IIoT) infrastructures, machine learning, artificial intelligence, Digital Twin technologies and advanced predictive analytics within the proposed maintenance architecture. Comparative multi-sector studies would

also contribute to assessing the scalability and robustness of the framework under different organisational contexts, production systems and maintenance maturity levels. Such developments would further strengthen the convergence between maintenance engineering, intelligent manufacturing and sustainable industrial transformation.

In conclusion, the present study demonstrates that the successful evolution from conventional preventive maintenance towards Maintenance 4.0 depends fundamentally on the systematic integration of engineering knowledge, structured maintenance methodologies and digital decision-support systems. By combining Lean maintenance, asset criticality analysis, FMEA, enhanced maintenance information management and continuous organisational improvement within a unified engineering framework, this research provides both a scientifically grounded contribution to maintenance engineering and a practical roadmap for organisations seeking to implement intelligent, resilient and sustainable maintenance systems in the era of smart manufacturing.

8. Future Considerations

The framework developed in this study should be tested through replication in other production units within the Lactogal group to validate its scalability. Additionally, the following research directions are proposed:

- **Advanced Predictive Integration:** Transition from the current documentary digital twin to real-time condition monitoring using IoT sensors and Machine Learning algorithms (e.g., Random Forest) for failure forecasting.
- **Digital Maturity Benchmarking:** Develop a standardised index to evaluate the Maintenance 4.0 readiness of different manufacturing sectors before digital implementation.
- **Sustainability and Green Maintenance:** Establish metrics to quantify the environmental benefits of the redesigned plans, specifically focusing on energy consumption reduction and waste minimization.
- **Augmented Reality (AR):** Explore the use of AR interfaces to provide hands-on structural rebuilding guidance to technicians in real-time.
- **Cybersecurity Frameworks:** Develop specific protocols to protect decentralized technical repositories and cloud-based data from external threats.

Establishing these advanced predictive standards is vital for ensuring the long-term sustainability of the food industry. This work lays the groundwork for future advancements, contributing to the evolution of maintenance as a transformative solution for smart dairy production.

Author Contributions

Conceptualization: R.C. and I.P.; methodology: T.M., A.F.V.P. and N.S.; data curation, visualization: T.M.; writing—original draft preparation: B.S.; investigation: R.C.; supervision: I.P.; validation: B.S., N.S. and A.F.V.P.; writing—reviewing and editing: B.S. and T.M. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data are contained within the article.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

During the preparation of this work, the author(s) used Grammarly Premium v6.8.263 to verify and improve the British (UK English) language employed. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article."

References

1. Rakyta, M.; Bubenik, P.; Binasova, V.; et al. The Change in Maintenance Strategy on the Efficiency and Quality of the Production System. *Electronics* **2024**, *13*, 3449. https://doi.org/10.3390/electronics13173449.
2. Molęda, M.; Małysiak-Mrozek, B.; Ding, W.; et al. From Corrective to Predictive Maintenance—A Review of Maintenance Approaches for the Power Industry. *Sensors* **2023**, *23*, 5970. https://doi.org/10.3390/s23135970
3. Preventive Maintenance Strategies to Increase Industrial Machine Life. (2025). *Journal of Renewable Engineering*, *2*(2), 13-21. https://doi.org/10.62872/tg323p32
4. Mohan, V.N. Intelligent Preventive Maintenance: The Rise of Usage-Based Scheduling. *Journal of Computer Science and Technology Studies*, *7*(6), 1090-1095. https://doi.org/10.32996/jcsts.2025.7.129
5. Zis, T.P.V.; Psaraftis, H.N.; Reche-Vilanova, M. Design and Application of a Key Performance Indicator (KPI) Framework for Autonomous Shipping in Europe. *Marit. Transp. Res.* **2023**, *5*, 100095. https://doi.org/10.1016/j.martra.2023.100095.
6. Ferreira, S.; Silva, F.J.G.; Casais, R.B.; et al. KPI Development and Obsolescence Management in Industrial Maintenance. *Procedia Manuf.* **2019**, *38*, 1427–1435. https://doi.org/10.1016/j.promfg.2020.01.145.
7. Picozzi, P.; Nocco, U.; Pezzillo, A.; et al. The Use of Business Intelligence Software to Monitor Key Performance Indicators (KPIs) for the Evaluation of a Computerized Maintenance Management System (CMMS). *Electronics* **2024**, *13*, 2286. https://doi.org/10.3390/electronics13122286.
8. Wienker, M.; Henderson, K.; Volkerts, J. The Computerized Maintenance Management System an Essential Tool for World Class Maintenance. *Procedia Eng.* **2016**, *138*, 413–420. https://doi.org/10.1016/j.proeng.2016.02.100.
9. Huang, J.; You, J.X.; Liu, H.C.; et al. Failure Mode and Effect Analysis Improvement: A Systematic Literature Review and Future Research Agenda. *Reliab. Eng. Syst. Saf.* **2020**, *199*, 106885. https://doi.org/10.1016/j.ress.2020.106885.
10. Liu, H.C.; Liu, L.; Liu, N. Risk Evaluation Approaches in Failure Mode and Effects Analysis: A Literature Review. *Expert Syst. Appl.* **2013**, *40*, 828–838. https://doi.org/10.1016/j.eswa.2012.08.010.
11. Mazzoleni, M.; et al. A Fuzzy Logic-Based Approach for Fault Diagnosis and Condition Monitoring of Industry 4.0 Manufacturing Processes. *Eng. Appl. Artif. Intell.* **2022**, *115*, 105317. https://doi.org/10.1016/j.engappai.2022.105317.
12. Essalih, S.; El Haouat, Z.; Ramadany, M.; et al. A Model to Optimize Maintenance through Implementing Industry 4.0 Technologies. *Heliyon* **2025**, *11*, e42297. https://doi.org/10.1016/j.heliyon.2025.e42297.
13. Rakholia, R.; Suárez-Cetrulo, A.L.; Singh, M.; et al. Integrating AI and IoT for Predictive Maintenance in Industry 4.0 Manufacturing Environments: A Practical Approach. *Information* **2025**, *16*, 737. https://doi.org/10.3390/info16090737.
14. Rosati, R.; et al. From Knowledge-Based to Big Data Analytic Model: A Novel IoT and Machine Learning Based Decision Support System for Predictive Maintenance in Industry 4.0. *J. Intell. Manuf.* **2023**, *34*, 107–121. https://doi.org/10.1007/s10845-022-01960-x.
15. Penchev, P.; Vitliemov, P.; Georgiev, I. Optimization Model for Production Scheduling Taking into Account Preventive Maintenance in an Uncertainty-Based Production System. *Heliyon* **2023**, *9*, e17485. https://doi.org/10.1016/j.heliyon.2023.e17485.
16. Mifdal, L.; Hajej, Z.; Dellagi, S. Joint Optimization Approach of Maintenance Planning and Production Scheduling for a Multiple-Product Manufacturing System. *IFAC Proc. Vol.* **2014**, *47*, 8042–8047.
17. Zhu, S.; van Jaarsveld, W.; Dekker, R. Critical Project Planning and Spare Parts Inventory Management in Shutdown Maintenance. *Reliab. Eng. Syst. Saf.* **2022**, *219*, 108197. https://doi.org/10.1016/j.ress.2021.108197.
18. Lucantoni, L.; Antomarioni, S.; Ciarapica, F.E.; et al. A Data-Driven Framework for Supporting the Total Productive Maintenance Strategy. *Expert Syst. Appl.* **2025**, *268*, 126283. https://doi.org/10.1016/j.eswa.2024.126283.
19. Alfaro-Tanco, J.A.; Avella, L.; Moscoso, P.; et al. An Evaluation Framework for the Dual Contribution of Action Research: Opportunities and Challenges in the Field of Operations Management. *Int. J. Qual. Methods* **2021**, *20*, 16094069211017636. https://doi.org/10.1177/16094069211017636.
20. Amado, A.; Belfo, F.P. Maintenance and Support Model within the ERP Systems Lifecycle: Action Research in an Implementer Company. *Procedia Comput. Sci.* **2021**, *181*, 580–588. https://doi.org/10.1016/j.procs.2021.01.205.
21. Nowakowski, T.; Tubis, A.; Werbińska-Wojciechowska, S. Evolution of Technical Systems Maintenance Approaches—Review and a Case Study. In *Intelligent Systems in Production Engineering and Maintenance*; Springer: Cham, Switzerland, 2019; pp. 161–174. https://doi.org/10.1007/978-3-319-97490-3_16.

22. *NP EN 13306:2021*; Manutenção—Terminologia de Manutenção. IPQ (Instituto Português da Qualidade): Caparica, Portugal, 2021.
23. Roda, I.; Macchi, M. Maintenance Concepts Evolution: A Comparative Review towards Advanced Maintenance Conceptualization. *Comput. Ind.* **2021**, *133*, 103531. https://doi.org/10.1016/j.compind.2021.103531.
24. Nakajima, S. *Introduction to TPM: Total Productive Maintenance*; Productivity Press: Cambridge, UK, 1988.
25. Tewari, A. Total Productive Maintenance—A Review. *Int. J. Res. Appl. Sci. Eng. Technol.* **2017**, *5*, 406–410. https://doi.org/10.22214/ijraset.2017.4072.
26. O'Connor, P.D.T.; Kleyner, A. Front Matter. In *Practical Reliability Engineering*; Wiley: Hoboken, NJ, USA, 2011. https://doi.org/10.1002/9781119961260.fmatter.
27. Messaoud, B.; Dalila, T. Maintenance Optimization Policy in the Dairy Industry. a Case Study. *South Fla. J. Dev.* **2024**, *5*, e4803. https://doi.org/10.46932/sfjdv5n12-040.
28. Singh, R.K.; Clements, E.J.; Sonwaney, V.; et al. Measurement of overall equipment effectiveness to improve operational efficiency. *Int. J. Process Manag. Benchmarking* **2018**, *8*, 246–261.
29. Santos, T.; Silva, F.J.G.; Ramos, S.F.; et al. Asset Priority Setting for Maintenance Management in the Food Industry. *Procedia Manuf.* **2019**, *38*, 1623–1633. https://doi.org/10.1016/j.promfg.2020.01.122.
30. Nwoke, C.I.; Ikhuele, D.; Diemuodeke, E.O.; et al. Multi-Objective Optimization Approach for Enhancing Production System Efficiency in a Food Processing Industry. *IPS J. Eng. Technol.* **2025**, *1*, 119–127. https://doi.org/10.54117/ijet.v1i2.20.
31. Nwoke, C.I.; Ikhuele, D.; Diemuodeke, O. Integrating Data Simulation, Machine Learning, and Mathematical Modeling for Predicting Critical Operational Parameters and Evaluating Overall Equipment Effectiveness in Food Production. *IPS J. Eng. Technol.* **2025**, *1*, 111–118. https://doi.org/10.54117/ijet.v1i2.19.
32. Akimsha, R.; Sharmilan, T.; Wanniarachchi, D. Smart Food Safety in Dairy Production: Enose Technologies with Digital Traceability Systems—A Review. *Food Humanit.* **2026**, *6*, 100991. https://doi.org/10.1016/j.foohum.2025.100991.
33. Lu, B.; Chen, Z.; Zhao, X. Data-Driven Dynamic Predictive Maintenance for a Manufacturing System with Quality Deterioration and Online Sensors. *Reliab. Eng. Syst. Saf.* **2021**, *212*, 107628. https://doi.org/10.1016/j.ress.2021.107628.
34. Zonta, T.; da Costa, C.A.; da Rosa Righi, R.; et al. Predictive Maintenance in the Industry 4.0: A Systematic Literature Review. *Comput. Ind. Eng.* **2020**, *150*, 106889. https://doi.org/10.1016/j.cie.2020.106889.
35. Mallioris, P.; Aivazidou, E.; Bechtsis, D. Predictive Maintenance in Industry 4.0: A Systematic Multi-Sector Mapping. *CIRP J. Manuf. Sci. Technol.* **2024**, *50*, 80–103. https://doi.org/10.1016/j.cirpj.2024.02.003.
36. Salehi, F.; Yaghtin, A. Action Research Innovation Cycle: Lean Thinking as a Transformational System. *Procedia Soc. Behav. Sci.* **2015**, *181*, 293–302. https://doi.org/10.1016/j.sbspro.2015.04.891.
37. Williams, T.; Wiles, J.; Smith, M.; et al. Combining Action Research and Grounded Theory in Health Research: A Structured Narrative Review. *SSM-Qual. Res. Health* **2022**, *2*, 100093. https://doi.org/10.1016/j.ssmqr.2022.100093.
38. Sellitto, M.A. Expected Utility of Maintenance Policies under Different Manufacturing Competitive Priorities: A Case Study in the Process Industry. *CIRP J. Manuf. Sci. Technol.* **2022**, *38*, 717–723. https://doi.org/10.1016/j.cirpj.2022.06.012.
39. Pereira, J.; Silva, F.J.G.; Bastos, J.A.; et al. Application of the A3 Methodology for the Improvement of an Assembly Line. *Procedia Manuf.* **2019**, *38*, 745–754. https://doi.org/10.1016/j.promfg.2020.01.101.
40. Zheng, P.; Wang, H.; Sang, Z.; et al. Smart Manufacturing Systems for Industry 4.0: Conceptual Framework, Scenarios, and Future Perspectives. *Front. Mech. Eng.* **2018**, *13*, 137–150. https://doi.org/10.1007/s11465-018-0499-5.
41. Feng, Q.; Zhang, Y.; Sun, B.; et al. Multi-Level Predictive Maintenance of Smart Manufacturing Systems Driven by Digital Twin: A Matheuristics Approach. *J. Manuf. Syst.* **2023**, *68*, 443–454. https://doi.org/10.1016/j.jmsy.2023.05.004.
42. Shaheen, B.W.; Németh, I. Integration of Maintenance Management System Functions with Industry 4.0 Technologies and Features—A Review. *Processes* **2022**, *10*, 2173. https://doi.org/10.3390/pr10112173.
43. Cañas, H.; Mula, J.; Díaz-Madroñero, M.; et al. Implementing Industry 4.0 Principles. *Comput. Ind. Eng.* **2021**, *158*, 107379. https://doi.org/10.1016/j.cie.2021.107379.
44. Oztemel, E., Gursev, S. Literature review of Industry 4.0 and related technologies. *J. Intell. Manuf.* **2020**, *31*, 127–182. https://doi.org/10.1007/s10845-018-1433-8.
45. Pinto, G.; Silva, F.J.G.; Baptista, A.; et al. TPM Implementation and Maintenance Strategic Plan—A Case Study. *Procedia Manuf.* **2020**, *51*, 1423–1430. https://doi.org/10.1016/j.promfg.2020.10.198.
46. Carvalho, T.P.; Soares, F.A.; Vita, R.; et al. A Systematic Literature Review of Machine Learning Methods Applied to Predictive Maintenance. *Comput. Ind. Eng.* **2019**, *137*, 106024. https://doi.org/10.1016/j.cie.2019.106024.
47. Pavlyshenko, B.M. Machine-Learning Models for Sales Time Series Forecasting. *Data* **2019**, *4*, 15. https://doi.org/10.3390/data4010015.
48. Zahrah, S.F.; Yusof, Y.A.; Kumar, K.; et al. Maintenance in the Era of Industry 4.0. *J. Manag. Sci.* **2018**, *8*, 176–181. https://doi.org/10.26524/jms.2018.16.
49. van Dinter, R.; Tekinerdogan, B.; Catal, C. Predictive Maintenance Using Digital Twins: A Systematic Literature Review. *Inf. Softw. Technol.* **2022**, *151*, 107008. https://doi.org/10.1016/j.infsof.2022.107008.

50. ScienceDirect. 2020. Available online: www.sciencedirect.com (accessed on 1 January 2026).
51. Bokrantz, J.; Skoogh, A.; Berlin, C.; et al. Smart Maintenance: An Empirically Grounded Conceptualization. *Int. J. Prod. Econ.* **2020**, *223*, 107534. https://doi.org/10.1016/j.ijpe.2019.107534.
52. Rossini, M.; Costa, F.; Staudacher, A.P.; et al. Industry 4.0 and Lean Production: An Empirical Study. *IFAC-PapersOnLine* **2019**, *52*, 42–47. https://doi.org/10.1016/j.ifacol.2019.11.122.