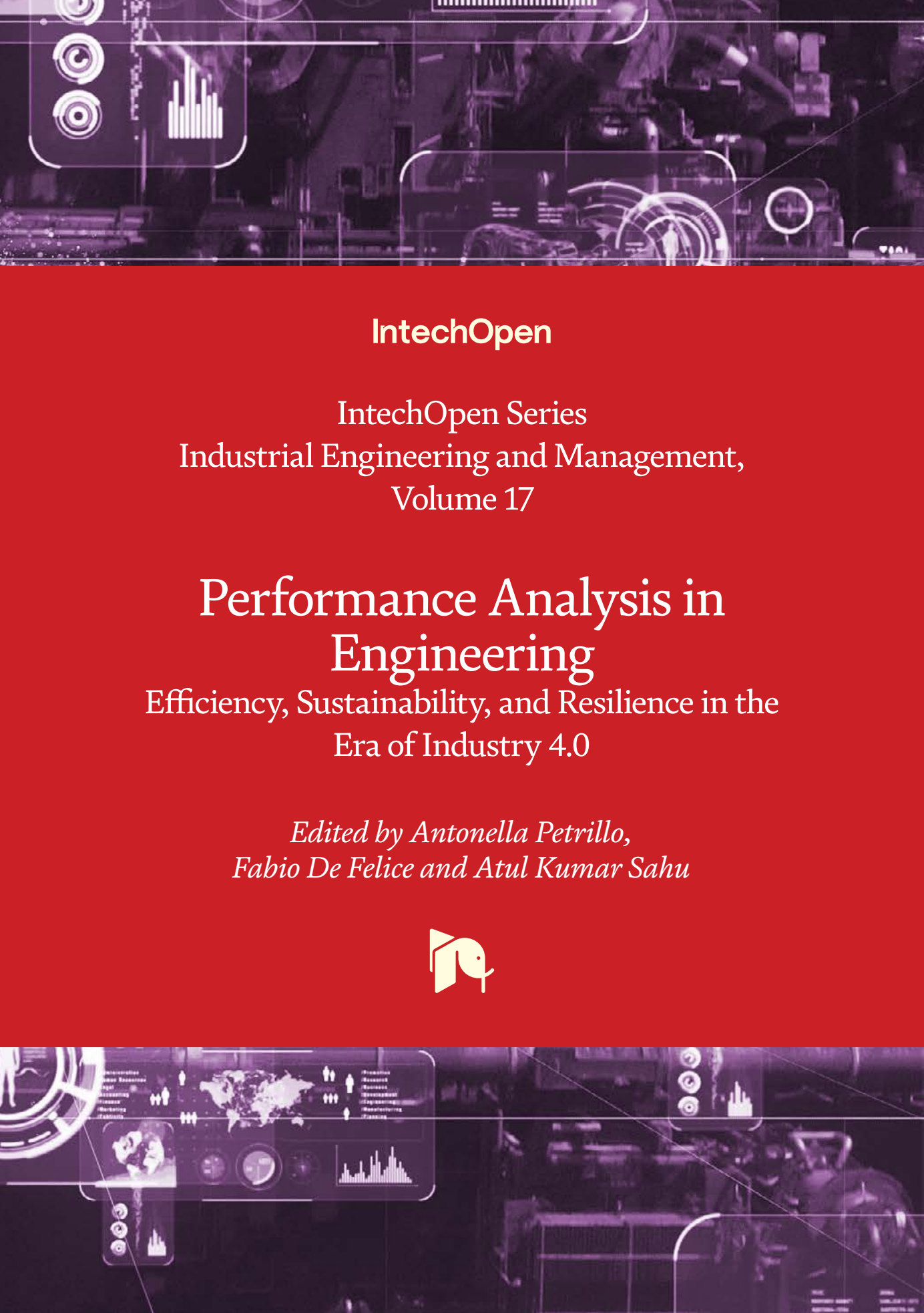


The background of the cover is a dark, industrial scene with various mechanical parts and structures. Overlaid on this are several semi-transparent, futuristic data visualization elements. In the top left, there are three concentric circles and a bar chart. In the top right, there are more concentric circles and a bar chart. In the bottom left, there is a circular gauge and a bar chart. In the bottom right, there is a bar chart. The overall aesthetic is high-tech and modern.

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Performance Analysis in Engineering

Efficiency, Sustainability, and Resilience in the
Era of Industry 4.0

*Edited by Antonella Petrillo,
Fabio De Felice and Atul Kumar Sahu*



Performance Analysis in Engineering - Efficiency, Sustainability, and Resilience in the Era of Industry 4.0

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Aims and Scope of the Series

Industrial Engineering and Management (IEM) is a discipline that focuses on optimizing complex processes and systems within various industries. It involves the integration of engineering, business, economics, mathematics, and behavioral sciences to improve efficiency, productivity, quality, and overall performance in organizations. Key aspects of Industrial Engineering and Management include: Process Optimization; System Analysis and Design; Quality Control and Management; Supply Chain Management; Operations Management; Human Factors and Ergonomics; Project Management; Cost Analysis and Financial Management; Decision Analysis.

Overall, Industrial Engineering and Management aims to optimize resources, improve processes, enhance productivity, and ensure the effective and efficient utilization of all elements involved in the production or delivery of goods and services. It is crucial in today's competitive business environment for organizations to stay efficient and competitive.

Production Engineering and Operational Excellence are fields of study and practices that focus on optimizing and improving the manufacturing and production processes within an organization. It combines principles from engineering, management, and operational strategies to enhance productivity, efficiency, quality, safety, and sustainability in the production of goods and services.

Here are the key components of Production Engineering and Operational Excellence: Process Optimization; Operational Excellence; Manufacturing Systems Design; Quality Management; Supply Chain Optimization; Production Planning and Scheduling; Automation and Technology Integration; Health, Safety, and Environmental Management; Cost Management; Performance Measurement and Key Performance Indicators (KPIs); Continuous Improvement and Innovation. Production Engineering and Operational Excellence are crucial for organizations aiming to stay competitive in the global market by achieving high levels of efficiency, quality, and customer satisfaction while optimizing resources and minimizing waste. It is a multidisciplinary approach that encompasses engineering principles, management strategies, and the effective use of technology to drive operational success.

Meet the Series Editor



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Contents

Preface	XIII
Chapter 1 Scenario-Based Analysis on Digital Twin: Toward a Greener Industry 4.0 <i>by Fabio De Felice, Aniello Ferraro and Antonella Petrillo</i>	1
Chapter 2 Enhanced Economic Order Quantity Framework for Reliability-Critical Industries: The EOQdsd Model <i>by Deepak R. Chandran, Deepashri Sanath and Sanath Kumar</i>	21
Chapter 3 Engineering Performance in Industry 4.0: From Metrics to Methods for Sustainable Innovation <i>by Brindha Priyadarshini Jeyaraman</i>	61
Chapter 4 Implementing Lean Manufacturing in Food Companies: Impact on Productivity and Quality – A Case Study of an Ice Cream Manufacturer <i>by Maria Victoria de-la-Fuente Aragon and Lorenzo Ros-McDonnell</i>	87
Chapter 5 Maintenance Management Support for System Reliability and Sustainable Optimisation <i>by Věra Pelantová</i>	107
Chapter 6 Selection of Appropriate Predictive Maintenance Techniques <i>by Usman Mustafa Syed</i>	127
Chapter 7 Supersonic Ejector Performance Improvement through Contoured Mixing Chamber Design <i>by Amer Muzaber and Nadin Bassmaji</i>	155

Preface

In recent decades, engineering systems have undergone a profound transformation driven by rapid technological advancement, globalization, and the increasing urgency of environmental and societal challenges. The emergence of Industry 4.0 has redefined traditional paradigms, introducing interconnected, data-driven, and intelligent systems that demand new approaches to performance evaluation and optimization. Within this evolving context, the concepts of efficiency, sustainability, and resilience have become not only desirable attributes but essential requirements for modern engineering practice.

This book, *Performance Analysis in Engineering – Efficiency, Sustainability, and Resilience in the Era of Industry 4.0*, aims to provide a comprehensive framework for understanding and assessing performance across a wide range of engineering domains. It brings together theoretical foundations, methodological tools, and practical applications to address the complexities inherent in contemporary systems. By integrating classical engineering principles with emerging digital technologies, this work seeks to bridge the gap between established knowledge and future-oriented innovation.

A central objective of this book is to highlight the interdependence between efficiency, sustainability, and resilience. While efficiency has traditionally been associated with optimal resource utilization, sustainability expands the perspective to include long-term environmental and social impacts. Resilience, in turn, refers to a system's capacity to withstand, adapt to, and recover from disruptions. The convergence of these dimensions is particularly critical in the context of Industry 4.0, where cyber-physical systems, artificial intelligence, and big data analytics redefine system boundaries and performance metrics.

This work is intended for researchers, practitioners, and graduate students seeking to deepen their understanding of performance analysis in modern engineering environments. It encourages a multidisciplinary approach, recognizing that the challenges of the present era cannot be addressed within isolated disciplinary silos.

We would like to express our sincere gratitude to Mateo Belir, Publishing Process Manager, for his invaluable support, guidance, and professionalism throughout the publishing process. His dedication and attention to detail have been instrumental in bringing this work to fruition.

We hope this book will advance knowledge and foster innovation in engineering, supporting the development of systems that are not only efficient but also sustainable and resilient in an increasingly complex and uncertain world.

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Chapter 1

Scenario-Based Analysis on Digital Twin: Toward a Greener Industry 4.0

Fabio De Felice, Aniello Ferraro and Antonella Petrillo

Abstract

Digital Twin technology is increasingly recognized as a strategic enabler of Industry 4.0, combining efficiency, resilience, and sustainability. By replicating physical assets and processes in dynamic digital environments, Digital Twins enable real-time monitoring, predictive maintenance, and energy optimization. This chapter provides a scenario-based analysis on digital twin. Evidence from existing implementations shows measurable sustainability outcomes: energy savings of 15–30%, CO₂ emission reductions up to 25%, and maintenance cost decreases between 20 and 30%. These benefits are most evident in energy-intensive and complex industries, where Digital Twins have already demonstrated tangible impacts on operational performance and ecological transition. At the same time, barriers such as high initial costs, lack of standardization, and cybersecurity risks remain critical challenges. The chapter emphasizes the role of Digital Twins not only as technological tools but as catalysts of systemic transformation toward greener, more resilient industrial and urban models.

Keywords: Digital Twin, Industry 4.0, sustainability, green manufacturing, digitalization

1. Introduction

In recent years, Industry 4.0 has profoundly redefined the boundaries of industrial innovation, introducing a new vision of production based on interconnection, automation, and intelligent integration between the physical and digital worlds. In this context, industrial systems are no longer isolated but are in constant communication, generating and exchanging real-time data [1]. The foundation of this transformation lies in the integration of cyber-physical systems (CPS), the widespread adoption of the Internet of Things (IoT), and the use of advanced cloud infrastructures.

The use of these technologies is transforming processes, roles, and skills within production and organizational contexts. These elements have given rise to a highly connected and intelligent production environment, where distributed data processing enables continuous and predictive monitoring, analysis, and optimization of processes [2].

Within this transformation, the concept of the Digital Twin (DT) plays an increasingly central role. It represents a dynamic digital replica of a physical object, production process, or complex system, allowing continuous and interactive monitoring of its real-world counterpart. Unlike simple static simulations, the Digital Twin integrates real-time data from IoT sensors, connected machinery, and information systems, thus creating a constantly updated virtual environment [3, 4].

Operationally, a Digital Twin allows real-time data analysis, simulation of alternative production scenarios, prediction of failures, and inefficiencies, and supports strategic decisions based on accurate virtual simulations [5]. Its application is already consolidated in high-tech sectors such as automotive, renewable energy, and aerospace, where it enables modeling, anticipating, and optimizing the performance of products and processes before they are physically realized [6, 7]. These capabilities translate into tangible benefits: cost reduction, quality improvement, greater efficiency, and the ability to respond to market changes [8].

In the context of smart manufacturing, the Digital Twin is a key lever for resource optimization and achieving sustainability goals. Indeed, it not only reduces waste and energy consumption but also implements predictive maintenance strategies, increases the useful life of machinery, and improves traceability throughout the product lifecycle [9, 10]. The integration of the DT with emerging technologies such as artificial intelligence, machine learning, and big data analytics further amplifies its transformative potential [11].

However, the widespread adoption of this technology also presents significant challenges: from the need for reliable digital infrastructures to the secure and intelligent management of large volumes of data, to the demand for highly specialized skills in creating and maintaining complex Digital Twins [12, 13].

In this context, the interest in the integration of digital transformation and sustainability is increasingly pronounced. Companies are required to reconcile competitiveness with environmental responsibility, in a setting where regulations and social expectations are pushing toward more efficient, transparent, and resilient production models. Against this backdrop, the aim of this chapter is to analyze how Digital Twin can serve as a key enabler for the adoption of sustainable industrial practices, contributing to the transition toward more responsible, agile, and efficient production models. The analysis will focus specifically on the manufacturing sector, one of the most critical industries in terms of environmental impact yet rich in innovative potential.

To guide the reader in exploring the topic, the content is divided into three main parts, each dedicated to an essential aspect of Digital Twin technology and its impact on production processes. The rest of the chapter is organized as follows: Section 2 explores the Digital Twin as a strategic tool for digital transformation, examining the technologies that enable it (IoT, AI, cloud, and edge computing) and the continuous flow of data between the physical and digital worlds. It also highlights its impact on sustainability, improving energy efficiency and environmental monitoring. While Section 3 presents concrete examples of Digital Twin applications across various industrial sectors, highlighting the benefits in terms of efficiency, emission reduction, and production flexibility. Finally, the Conclusions summarize the transformative role of the Digital Twin for digitalization and sustainability, reflecting on future challenges such as digital infrastructure, data security, and the necessary skills required.

2. Digital twin: Synergy between physical and virtual

In an increasingly dynamic and competitive industrial context, the ability to innovate quickly, reduce waste, and anticipate problems becomes a crucial strategic advantage. The Digital Twin emerges as a key technology capable of revolutionizing the way products, processes, and systems are designed, managed, and optimized. The intensification of global competition, the growing complexity of markets, and the demand for customization driven by increasingly informed and demanding consumers [14] require companies to adopt a radically new approach to innovation and operational efficiency. In this scenario, the Digital Twin represents a concrete response to these challenges, offering a virtual environment synchronized with the real world, capable of reflecting the physical dynamics of objects, plants, and entire production systems in real time [15, 16]. Its value lies in the ability to simulate, test, and virtually optimize any stage of a product's lifecycle, anticipating malfunctions, improving design quality, and reducing the development time and costs [17, 18].

Far beyond a simple static digital twin, the Digital Twin is configured as a complex and dynamic system that integrates geometric modeling, data analysis, artificial intelligence, simulation technologies, Internet of Things, and cloud computing [19–21]. Its conceptual structure, formalized in the “Mirrored Spaces Model” and later evolved into the “Information Mirroring Model” by Michael Grieves [22, 23], includes three fundamental components: a physical space, a virtual space, and a bidirectional interconnection mechanism that ensures a continuous flow of data and information.

The “Mirrored Spaces Model,” proposed by Grieves in the early 2000s, represents the first attempt to conceptualize the relationship between the physical world and the digital world. In this model, it is imagined that for every physical object (product, component, system), there exists a corresponding “virtual space,” that is, a digital model that can faithfully represent its structural, functional, and operational characteristics. However, what makes this model innovative is not only the presence of a physical-digital pair but also the introduction of a bidirectional “connection channel” between the two spaces: Thanks to sensors, communication systems, and IoT platforms, it is possible to transfer real-time data from the physical space to the virtual model, which can in turn be used to influence and optimize the behavior of the real twin. In other words, the virtual is not just a passive copy but an active agent in the decision-making process.

This framework is further refined by Grieves with the subsequent model called the “Information Mirroring Model,” which delves into the critical role of information as the central element in the interaction between the physical space and the virtual space. Here, the Digital Twin is no longer just a geometric and functional representation of the physical asset, but a dynamic system constantly fed by structured information flows, including historical data, real-time data, and predictive data. The model emphasizes how this data is processed through a “informational mirroring” logic, meaning continuous reflection of the state and performance of the real object within the digital space. From this perspective, the Digital Twin is viewed as a “living” entity, evolving over time through data-driven learning and capable of supporting advanced decision-making processes, such as predictive maintenance, optimization of production cycles, simulation of alternative scenarios, or product lifecycle analysis.

The Information Mirroring Model also introduces a systemic perspective, where the Digital Twin is seen as an integral part of a multi-level architecture: At the base level are the data from sensors and devices (physical level), which are collected and

processed to update the virtual model in real time (digital level). On a third level, called the decision-making or cognitive level, reside artificial intelligence algorithms and simulation tools that transform the data into useful insights for guiding action. Therefore, this model does not merely describe the physical object, but also represents its behaviors, interactions, and operational context.

To make these concepts more accessible to those encountering them for the first time, consider the case of an automated production line: Each machine is equipped with sensors that monitor variables such as temperature, vibrations, and operating speed. This data is transmitted in real time to the machine's digital model (virtual space), which uses it to predict potential faults or inefficiencies. If the model detects an anomaly, it can simulate various intervention scenarios and suggest to the real system the most efficient action to take, such as a scheduled downtime for preventive maintenance. This continuous cycle of updating, simulation, and optimization is made possible by the conceptual architecture described by Grieves in his models.

A distinctive feature of these conceptual models is that they lay the theoretical foundations for a radical transformation of the role of information in the lifecycle of products and industrial systems: From being a simple support for documentation, information becomes a strategic asset that intelligently and responsively drives all stages of production and management activities.

This architecture enables not only a faithful but also an intelligent virtual replica of the real world, capable of learning and progressively improving through continuous data updates [24, 25].

Grieves' model has since been revisited, integrated, and expanded by numerous researchers, including Tao et al., who extended its scope by introducing the "Five-Dimensional Digital Twin Framework," explicitly incorporating, in addition to the physical and virtual spaces and their connection, the dimensions of data and services. These additions highlight the active role that the Digital Twin can assume as a service platform: from predictive analysis to operational optimization, and even strategic decision support [26, 27].

The applicability of the Digital Twin extends across the entire value chain: from the design phase, where it supports the development of customized products and the optimization of geometric tolerances [19, 28, 29], to production, where it enables real-time monitoring, bottleneck identification, process variation management, and quick adaptation to unforeseen operational conditions [30–32].

During design, the ability to create highly realistic virtual models allows for the early testing of various operational scenarios, significantly reducing the development time and costs. For example, in the manufacturing sector, frameworks have been developed that integrate real data, virtual resources, and simulations to support every stage of design, from initial concept to virtual prototype validation [33, 34].

In the field of production, the Digital Twin has accelerated the transition from traditional manufacturing to the so-called smart manufacturing. Thanks to the use of augmented reality, big data, and artificial intelligence, production systems based on Digital Twin technology can self-optimize in real time, reducing the gap between virtual design and the real product [35, 36]. Solutions are already in operation where optimization is entrusted to predictive models based on machine learning, capable of anticipating anomalies and correcting process deviations before they lead to physical defects [37, 38].

Even in logistics, the Digital Twin has proven its effectiveness in optimizing transportation, packaging, and warehouse management, improving resource allocation and material flow traceability [39, 40]. Furthermore, by simulating alternative

scenarios, the Digital Twin promotes a proactive approach to risk management, allowing for the development of risk mitigation plans during the design or operational phases [41–43].

In the field of maintenance, the combined use of physical data collected through sensors and virtual models enables the implementation of predictive maintenance strategies based on statistical analysis, Bayesian inference, and neural networks, providing a reliable estimate of the remaining useful life of components [44, 45]. The goal is not only to prevent failures but also to optimize the scheduling of maintenance interventions and minimize plant downtime.

Historically, the idea of creating a virtual counterpart of a physical system dates to the 1960s with NASA, which developed digital representations of space shuttles to monitor their performance during missions [46]. However, it was only in 2002 that the concept was systematized by Michael Grieves, marking the beginning of its theoretical development and industrial application [47].

A significant early example can be identified in the Apollo 13 mission, where a “physical twin” of the spacecraft was used to simulate the operational conditions and develop emergency strategies, laying the conceptual foundations for the current Digital Twin [48]. This approach then evolved with NASA’s official recognition in 2012, which included Digital Twin technology among the priority technologies for the future of the aerospace sector [49].

In the following years, with the spread of digital technologies and the integration of IoT, the Digital Twin found fertile ground to expand into sectors such as automotive, energy, logistics, and advanced manufacturing, supported by major companies like Siemens, IBM, and General Electric [15, 50]. Today, the rapid expansion of the global Digital Twin market, with a projected annual growth rate exceeding 60% and expected to surpass 73 billion dollars by 2027 [51], confirms the strategic importance of this technology as a pillar of industrial innovation.

The distinctive value of the Digital Twin lies not only in the virtual replication of a physical asset but in its ability to enable continuous decision-making processes, based on real-time updated data and accurate predictions [17, 52]. Its adoption results in increased responsiveness to changes, greater precision in planning, and a reduction of errors and inefficiencies throughout the product lifecycle. For this reason, this chapter aims to deeply analyze the structure of the Digital Twin, its technical functionalities, and the main application areas, highlighting how this technology can serve as a strategic lever for efficiency, reliability, and enhanced decision-making capabilities in the industrial sector.

2.1 Principles and architecture of the digital twin

The Digital Twin is a virtual representation of a physical object, process, or system, designed to reflect its real-time state, historical performance, and predicted behavior. At the core of the concept are three fundamental components: physical entity, the digital environment, and the data interfaces that link them. These elements are integrated into a continuous cycle of data acquisition, analysis, simulation, and decision support. The digital model is constantly synchronized with its physical counterpart through sensors and actuators, enabling a bidirectional flow of real-time information. This synchronization is what differentiates a Digital Twin from a simple static digital model or traditional simulation.

To support the operational complexity of DTs, a layered and well-defined architecture is necessary. An important proposal in this regard is a six-level architecture,

an extension of the 5C model (Connection, Conversion, Cyber, Cognition, Configuration) [53], initially designed for cyber-physical systems. This structured model facilitates the connection between physical devices and their respective digital twins, ensuring interoperability and consistency between the real and virtual worlds, as shown in **Figure 1**.

Layer 1 includes the actual physical devices, such as sensors, actuators, and machinery, while Layer 2 is dedicated to the data sources associated with the physical entity, collecting and transmitting the relevant information for subsequent processing.

Layers 1 and 2 constitute the physical domain of the Digital Twin.

Layer 3 serves as a communication interface and local data storage, supported by the OPC-UA standard, Open Platform Communication, Unified Architecture, which is crucial to ensure secure and standardized exchange of information across the various layers.

Layer 4 leverages IoT technologies to convert raw data into useful information. This information is then stored and made accessible through Layer 5, based on cloud solutions that offer scalability and high processing capabilities.

Layer 6, the cognitive layer, is dedicated to intelligent real-time monitoring, simulation, optimization, and decision support through artificial intelligence and predictive simulation tools (e.g., Siemens Tecnomatix, AI algorithms).

This layered approach enables the DT not only to monitor but also to anticipate problems and improve operational performance through continuous learning [54].

Tao and Zhang [20], who identify a five-dimensional model in a DT system, offer a complementary perspective on the structure of the Digital Twin. As illustrated in

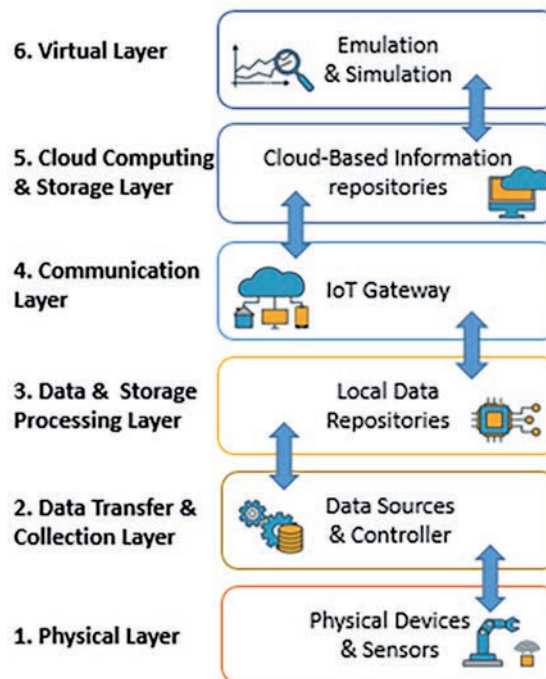


Figure 1.
Structured model of the digital twin (source: authors' elaboration).

Figure 2, this model emphasizes the dynamic interactions and relationships among the physical and virtual systems, the communication infrastructure, and the shared data environment that enables synchronization between the real and digital worlds.

The five dimensions of the model are as follows:

- Physical System (PS): the real system, including machinery, infrastructure, and materials;
- Virtual System (VS): the digital counterpart that constantly replicates the behavior of the physical system;
- Service System (SS): a communication infrastructure that enables the integration and exchange of data between the physical and digital environments;
- Digital Twin Data (DTD): the information ecosystem that contains all the data transmitted and shared between the physical and virtual models;
- Connections: these are the communication channels between physical entities, virtual models, data, and services, structured into six distinct links.

This breakdown highlights the interdependence between hardware, software, and data, emphasizing the importance of informational continuity throughout the Digital Twin's lifecycle. Real-time synchronization between the virtual model and the physical system is achieved through data collection from sensors, industrial devices, and connected machines, integrated into a continuous simulation platform [55–57].

For effective implementation of the Digital Twin in real-world contexts, it is essential to have a coordinated set of technologies that support data acquisition, simulation, analysis, and performance evaluation of the system [58–60].

In recent years, technological advancements have enabled the integration of heterogeneous techniques within the Digital Twin architecture, allowing for increasingly efficient and scalable use. Among these are:

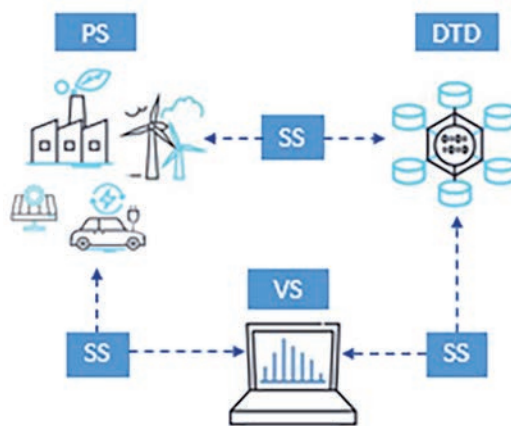


Figure 2.
Five-dimensional model of the Digital Twin (source: authors' elaboration).

- **Machine learning:** a rapidly evolving subdomain of artificial intelligence, it enables the Digital Twin to learn from data originating from both the physical and virtual models. Through advanced statistical techniques and hybrid algorithms, the DT can predict future behaviors, optimize operations, and generate real-time feedback, significantly enhancing the system's operational efficiency;
- **Internet of things (IoT):** ensures continuous connectivity between the various physical components of the system and the digital environment. Thanks to the widespread use of smart sensors and connected devices, it is possible to remotely monitor and control ongoing processes, reducing the need for manual intervention. This network of interconnected objects enables the real-time acquisition of essential operational data, continuously feeding the digital replica with up-to-date information;
- **Cloud computing:** serves as a strategic resource for the Digital Twin architecture, offering data storage, processing, and remote access services. Cloud platforms help reduce costs associated with purchasing dedicated hardware and software, making the creation of digital models sustainable even for small-scale systems. Moreover, the scalability of the cloud facilitates the management of large data volumes and supports complex operations;
- **Augmented reality (AR) and virtual reality (VR):** enhance the interaction between users and digital models. While VR allows for immersive exploration of the physical system in a simulated environment, AR overlays digital information onto the real world, improving perception and understanding of the system's functioning. In the context of the Digital Twin, these technologies enable a simultaneous and coherent view of physical and digital processes, supporting analysis and decision-making;
- **Application programming interfaces (API):** play a key role in enabling communication between sensors, databases, software, and network infrastructures. APIs simplify the integration of heterogeneous system components and facilitate adaptation to changes, reducing the need for complex reconfigurations.

The synergistic integration of these technologies enables operators and stakeholders to build Digital Twins capable of accurately reflecting system behavior, analyzing performance variations, and simulating complex operational scenarios.

The architecture of Digital Twins represents the convergence of physical systems, digital modeling, and intelligent computing. Through a layered architecture and the use of emerging technologies, DTs provide a powerful platform to simulate, monitor, and enhance the performance of physical systems in real time, generating significant value across various sectors, such as manufacturing, energy, healthcare, and transportation [20].

2.2 Digital Twin technology for sustainable industry

The Digital Twin is emerging as one of the most promising technologies for transforming production processes, offering companies advanced tools to optimize resource use, reduce emissions, and increase efficiency. Thanks to its ability to create interactive,

real-time updated digital replicas of assets, processes, or entire physical systems, the Digital Twin provides an unprecedented level of monitoring and simulation [61].

Integrated with IoT sensors and advanced data analytics systems, it enables the real-time collection of information, facilitating timely, data-driven decision-making.

This technology has a significant impact in terms of sustainability. Continuous analysis of operational data supports more efficient energy management, reducing waste and optimizing the product lifecycle. Predictive maintenance, one of the key features of the Digital Twin, helps prevent failures and extend asset life, reducing the need for replacements and, consequently, the consumption of resources for producing new equipment.

The Digital Twin stands out as an enabling technology that combines advanced analytics with practical applications to improve production operations and reduce the environmental impact.

Its applications, ranging from real-time monitoring to energy simulation and predictive asset management, make it a strategic tool for building more sustainable industrial models.

In the following sections of the chapter, the main functionalities that make the Digital Twin a strategic ally in developing more efficient, sustainable, and low-impact production models will be analyzed.

One of the most significant functionalities is real-time monitoring, which allows continuous collection and analysis of data on the behavior of production processes. Thanks to integration with IoT sensors and intelligent control systems, it is possible to obtain an accurate picture of the plant's condition, quickly identify inefficiencies, and take action to optimize the process.

The collection of operational data from various stages of production, such as temperature, pressure, and material flow, provides a complete and accurate overview of the system's status. This allows companies to optimize processes and reduce waste, thereby improving the overall sustainability of the production cycle [62].

For example, the Digital Twin can reveal imbalances in the workflow that result in suboptimal resource use.

By acting on this information, companies can reduce energy consumption and optimize the workflow, minimizing waste and improving overall efficiency [63].

Another key aspect is energy simulation and optimization. Thanks to the virtual replication of production processes, it is possible to simulate different scenarios and test the impact of various changes, such as the adoption of renewable energy sources, the integration of energy storage systems, or the optimization of production cycles to reduce energy consumption [64].

The simulations provided by Digital Twins allow for the optimization of energy use by testing configurations that can lead to lower energy costs and reduced carbon emissions. Additionally, data analysis from sensors can detect inefficiencies in consumption, such as unnecessary energy peaks, and enable timely adjustments to reduce them, contributing to lowering the plant's ecological footprint [65].

The Digital Twin also enables the adoption of predictive maintenance approaches, based on early fault detection and real-time data analysis. Sensors connected to physical systems continuously transmit information that allows for the prediction of failures before they occur, improving the reliability and efficiency of facilities. This functionality is crucial for reducing downtime and extending the lifespan of assets, an aspect that directly supports sustainability by reducing the need for frequent equipment replacement and limiting resource consumption for manufacturing new systems [66].

Predictive maintenance, combined with optimized asset management, helps minimize resource consumption by extending the useful life of equipment and reducing the volume of electronic and industrial waste. This approach supports the adoption of more sustainable practices, as it lowers both operational costs and the environmental impact associated with the production and disposal of new machinery [67].

Moreover, the Digital Twin enables the optimization of resource use by mapping the entire production cycle to identify waste or inefficiencies. Simulations can guide changes in workflows or materials used, reducing the consumption of natural and energy resources [26, 63].

Another strategic value of the Digital Twin lies in its ability to support circular economy models, actively contributing to the recovery and reuse of resources within the production cycle. Thanks to the capability to monitor real-time data related to end-of-life products and materials used, companies can effectively plan resource recovery and reintegration into production processes. This approach not only reduces dependency on new natural resources but also significantly decreases the amount of waste generated [68].

In parallel, Digital Twins offer the ability to accurately simulate the benefits of adopting sustainable solutions, such as the use of recycled materials or the integration of renewable energy sources, without interfering with actual production. This ability to experiment in a virtual environment and optimize processes before practical implementation allows companies to reduce the risks associated with introducing technological innovations and to adopt sustainable strategies more quickly and effectively [69].

An additional crucial aspect is that the Digital Twin provides a solid foundation for data-driven decision-making. Access to detailed real-time information and the ability to simulate future scenarios enable business leaders to develop more informed and sustainability-oriented strategies. The collected data allow continuous monitoring of energy performance, the quality of materials used, and environmental outcomes, offering precise insights for identifying the most effective solutions to reduce emissions and improve the overall environmental impact of the production system [70].

The ability to compare and simulate different operational options, selecting the most efficient one, is particularly valuable for companies aiming to achieve climate neutrality and reduce their environmental impact. In this regard, the Digital Twin not only serves as a tool for improving operational efficiency but also emerges as a strategic ally for precisely and effectively achieving corporate sustainability goals [71].

Indeed, the applications of the Digital Twin go far beyond mere process optimization. They extend to a broader vision rooted in sustainability and environmental responsibility. Through continuous data analysis and the ability to simulate and optimize production operations, companies can make more informed choices aligned with global goals for emission reduction and climate neutrality.

Ultimately, the Digital Twin is not just a technological support for industry, it is a true enabler of systemic transformation, capable of profoundly and permanently influencing how companies operate and manage their environmental impacts.

3. Industrial applications and impacts of Digital Twin solutions

The Digital Twin is emerging as an enabling technology capable of translating into practice the architectures and theoretical models presented in Section 2, providing

concrete tools to improve operational efficiency, sustainability, and resilience of complex systems. Its applications are not limited to individual processes but extend across the entire lifecycle of assets and infrastructures, ranging from manufacturing to energy, from smart buildings to urban planning.

The analysis of case studies highlights the ability of the Digital Twin to generate measurable benefits: reduction of energy consumption, CO₂ emissions abatement, cost containment, and productivity growth. At the same time, some challenges remain open, mainly related to implementation costs, standardization, interoperability, and data security [16, 72].

3.1 Sectoral applications of the Digital Twin

Smart buildings and urban management:

In the building and urban infrastructure sectors, the integration of Digital Twin with Building Information Modeling (BIM) has shown a strong impact on energy management. Studies on public buildings and university campuses report energy savings of up to 30%, while simultaneously improving indoor comfort and air quality [73–75].

Similarly, in urban contexts, Digital Twin technology has been applied to the management of public services such as waste collection and street lighting, resulting in cost reductions of up to 35% and operational efficiency increases of around 20% [74, 75]. In a district-level energy planning case, the adoption of a Digital Twin enabled the simulation of decarbonization scenarios, guiding local policies to reduce CO₂ emissions [76].

3.2 Advanced manufacturing

Manufacturing represents one of the most mature fields of application. Digital Twins enable real-time monitoring of production lines, simulation of alternative scenarios, and optimization of logistics flows. The implementation of predictive maintenance strategies has led to machine downtime reductions between 20 and 30%, with cost savings of up to 30% in maintenance and 5–10% in operational costs [76, 77].

From an environmental perspective, the ability to simulate processes and optimize resource consumption translates into emission reductions of up to 25%. Furthermore, the ability to track materials across the product lifecycle facilitates circular economy practices, promoting reuse and reducing industrial waste.

3.3 Energy sector and smart grids

In the energy sector, Digital Twins are applied both to production and to distribution. Power plants, whether thermal or renewable, use digital models to optimize production cycles and prevent failures. A significant example is a 600 MW thermal power plant, where the introduction of a Digital Twin prevented the consumption of over 500,000 tons of coal in just 2 weeks, with direct impacts on both emission reduction and operational cost savings [77–79].

At the grid level, Digital Twins support the management of smart grids, integrating renewable energy sources, balancing supply and demand, and preventing overloads. These functionalities are essential steps toward resilient energy infrastructures and the transition to low-carbon systems [3, 56, 57, 60].

3.4 Infrastructure and urban mobility

Applications in water networks, transportation, and urban mobility provide a systemic view of operations, enabling the simulation of flows and the prediction of congestion or malfunctions. Optimizing waste collection routes and smart traffic management has produced significant reductions in transport-related emissions, while also improving service levels [74, 75].

3.5 Benefits and advantages of Digital Twin technology

The main benefits of adopting Digital Twin technology across different sectors can be summarized as follows:

- **Energy efficiency:** savings between 15 and 30% in smart buildings and up to 10% in large thermoelectric plants [73].
- **Emission reduction:** decreases ranging from 15 to 25% in industrial and manufacturing processes, achieved through optimization and intelligent materials management [76].
- **Economic savings:** maintenance cost reductions of 20–30% and operational cost reductions between 5 and 10% in industrial contexts [76].
- **Productivity increase:** improvements estimated at 3–5% annually, resulting from enhanced system reliability and faster operational decision-making [75].
- **Support for the circular economy:** material tracking and reuse across the product lifecycle, with positive impacts on waste reduction and sustainable sourcing [74].

3.6 Challenges and prospects

Despite these promising results, large-scale adoption of Digital Twin technology still faces significant barriers. High initial costs, the need for advanced digital infrastructures, and the demand for specialized skills remain major obstacles, especially for small- and medium-sized enterprises [74].

Additional issues concern interoperability and standardization: The lack of universally recognized protocols hinders integration between different systems, thus limiting the potential for large-scale deployment [50, 51]. Moreover, secure data management and protection against cyber threats remain pressing challenges, particularly in critical sectors such as energy and public services.

4. Conclusions

The Digital Twin is now positioned as one of the most strategic technologies to tackle the contemporary challenges related to sustainability, energy efficiency, and the digital transformation of industries and cities. Its ability to dynamically connect the physical and digital worlds allows for real-time monitoring, the simulation of alternative scenarios, and the continuous optimization of complex system

performance, with tangible impacts on consumption, emissions, costs, and operational resilience.

The integration of IoT sensors, artificial intelligence algorithms, and advanced digital platforms enables Digital Twins to predict failures, improve maintenance, optimize production processes, and support faster, more informed decision-making. This proactive approach has already proven effective in diverse fields, from smart buildings to energy grids, advanced manufacturing to urban services. The benefits are numerous: improved energy efficiency, reduced CO₂ emissions, lowered operational costs, increased productivity, and strengthened overall sustainability.

However, the widespread adoption of Digital Twins is hindered by complex challenges. Integration with legacy infrastructures requires substantial modifications, in both hardware and software, which can be costly for small- and medium-sized enterprises. Additionally, high initial costs, the need for highly specialized skills, and the management of vast amounts of data, requiring security, consistency, and interoperability, present significant barriers.

Cybersecurity is also a critical concern, especially in sensitive sectors such as energy and public services, where attacks or unauthorized access could disrupt operational continuity.

Despite these obstacles, the prospects for Digital Twins remain highly promising. The evolution of artificial intelligence, IoT, and cloud computing is making digital modeling more accessible, scalable, and accurate. Technologies like edge computing and machine learning enable decentralized and predictive resource management. Meanwhile, the standardization of frameworks and protocols, along with public policies geared toward green and digital transitions, could stimulate investment and accelerate adoption, even in less structured environments.

Overall, Digital Twin technology enables sustainability by reducing energy consumption, lowering CO₂ emissions, and extending asset lifecycles through predictive maintenance and process optimization. Evidence of these impacts has already been documented in manufacturing, smart buildings, and the energy sector, where measurable results include energy savings of 15–30%, emission reductions up to 25%, and significant cost savings [73, 77]. These findings indicate that Digital Twins are best suited to industries with high energy intensity and complex operations—such as industrial manufacturing, energy generation and distribution, and urban infrastructure management—where their implementation has consistently delivered the most tangible sustainability benefits.

In this context, the Digital Twin emerges as a true enabler of ecological and digital transitions, capable of supporting the design of more resilient, efficient, and low-emission urban and industrial environments. Its implementation could become a key element in energy planning, the circular economy, and long-term sustainable development, confirming its role as a cornerstone technology for the future of engineering.

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Conflict of interest

The authors declare no conflict of interest.

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Enhanced Economic Order Quantity Framework for Reliability-Critical Industries: The EOQdsd Model

Deepak R. Chandran, Deepashri Sanath and Sanath Kumar

Abstract

This chapter introduces the economic order quantity (EOQ) for demand-supply-downtime (EOQdsd) framework, extending classical inventory theory by systematically integrating reliability engineering parameters. Traditional EOQ models fail to address failure-driven demand patterns, extended lead times, and equipment downtime costs prevalent in reliability-critical industries. The EOQdsd framework progresses from a three-component basic formulation incorporating cycle stock, safety buffer, and downtime protection, through comprehensive implementations integrating warranty considerations, FMEA risk assessment, Weibull lifecycle analysis, and dynamic stocking indices. Mathematical development demonstrates dimensional consistency and reduction to classical EOQ under limiting conditions. Application to electric vehicle charging infrastructure using manufacturer data (SIRIEM, 2024–2025) shows a 61% total cost reduction compared to traditional EOQ while improving service levels from 87% to 97%. The framework's scalability accommodates both high-volume operations and ultra-reliable systems where theoretical EOQ < 1 . Statistical validation ($p < 0.001$, $n = 730$ days) confirms significant improvements in stockout reduction (91%) and cost optimization. The hierarchical structure enables implementation at complexity levels matching organizational data availability, from basic three-component models to comprehensive TotalEOQdsd formulations. This chapter bridges the gap between classical inventory theory and modern reliability engineering, providing practitioners with mathematically rigorous yet implementable tools for spare parts optimization in aerospace, EV infrastructure, and critical manufacturing. This constitutes Part 1 of a two-part series, establishing theoretical foundations and deterministic applications. Part 2 will introduce machine learning enhancements for dynamic parameter optimization and predictive inventory management.

Keywords: economic order quantity, reliability engineering, spare parts management, inventory optimization, electric vehicle infrastructure

1. Introduction

The management of spare parts inventory in reliability-critical industries presents unique challenges that traditional Economic Order Quantity (EOQ) models fail to adequately address. Since Harris's [1] seminal work and Wilson's [2] subsequent refinements, the EOQ model has served as the cornerstone of inventory management theory. However, industries such as aerospace, electric vehicle charging infrastructure, and critical manufacturing operations face inventory decisions driven not by customer demand but by equipment failure patterns, creating a fundamental mismatch between classical theory and operational reality.

Contemporary reliability-critical systems exhibit characteristics that violate core EOQ assumptions. Equipment failures follow stochastic patterns influenced by operating conditions, maintenance practices, and component aging. Lead times for specialized components often extend to months, while equipment downtime costs can reach thousands of dollars per hour. These realities necessitate an inventory framework that explicitly incorporates reliability engineering principles into optimization decisions.

This chapter presents the EOQ for demand-supply-downtime (EOQ_{dsd}) framework, a comprehensive extension of classical EOQ theory designed specifically for reliability-driven inventory contexts. The framework progresses from a basic three-component model (EOQ_{dsd_basic}) through various enhanced formulations, culminating in the TotalEOQ_{dsd} model that integrates multiple reliability parameters simultaneously. This hierarchical approach allows organizations to implement the framework at complexity levels appropriate to their data availability and operational requirements.

This chapter is presented in two parts to provide comprehensive coverage of both theoretical foundations and advanced computational methods. This chapter (Part 1) establishes the mathematical framework, validates the model through numerical examples, and demonstrates implementation in reliability-critical industries. The companion chapter (Part 2, forthcoming) will extend this framework by integrating machine learning algorithms for predictive parameter estimation, real-time demand forecasting, and dynamic optimization. While Part 1 provides a complete, standalone framework for practical implementation, Part 2 will enhance these capabilities through artificial intelligence for organizations with advanced analytical capabilities.

The contributions of this chapter include: (1) systematic integration of failure rate analysis into inventory optimization; (2) explicit consideration of downtime costs in ordering decisions; (3) incorporation of warranty, FMEA, and lifecycle factors into inventory planning; (4) practical implementation guidance with industry examples; and (5) a unified framework scalable from basic to comprehensive implementations. Through this work, we aim to bridge the longstanding gap between inventory theory and reliability engineering practice.

2. Literature review

2.1 Evolution of EOQ theory

The EOQ model has undergone continuous refinement since its inception. **Table 1** presents key developments in EOQ theory across major evolutionary periods.

Period	Key contributors	Primary innovations	Limitations addressed
Foundation (1913–1960)	[3, 1, 2]	Basic EOQ formula, deterministic models, initial stochastic extensions	Assumed constant demand, ignored stockouts
Extensions (1960–1980)	[4, 5, 6]	Backorder costs, quantity discounts, perishable inventory	Limited reliability considerations
Integration (1980–2000)	[7, 8, 9]	Multi-echelon systems, service parts logistics, collaborative models	Insufficient failure pattern modeling
Stochastic (1990–2010)	[10, 11, 12]	Demand uncertainty, robust optimization, and risk management	Downtime costs not explicitly modeled
Contemporary (2010–2023)	[13, 14, 15]	Intermittent demand, condition-based maintenance, AI integration	Gap remains in unified reliability framework

Table 1.
Evolution of EOQ models (1913–2023).

2.2 Spare parts inventory management

Recent advances in spare parts management have increasingly recognized the unique challenges of failure-driven demand. Sherbrooke’s [16] METRIC model established multi-echelon techniques for repairable items, while Muckstadt [17] extended these concepts to include lateral transshipments. However, these models primarily focus on system availability rather than cost optimization.

Wang and Syntetos [18] provided comprehensive reviews of spare parts forecasting, identifying intermittent demand patterns as a key challenge. Bacchetti and Saccani [19] classified spare parts management approaches but noted the absence of integrated reliability considerations. Recent work by Driessen et al. [20] on maintenance spare parts planning emphasizes the need for models that explicitly incorporate failure mechanisms.

2.3 Reliability engineering in inventory

The integration of reliability engineering into inventory management remains fragmented. Louit et al. [21] examined spare parts strategies for mining equipment, incorporating failure rates but not comprehensive cost structures. Do et al. [22] developed condition-based spare parts planning models, yet these require extensive sensor data, which is unavailable in many applications.

Kennedy et al. [23] reviewed maintenance, replacement, and reliability theories in inventory contexts, identifying the lack of unified frameworks as a critical gap. Recent contributions by de Smidt-destombes et al. [24] on spare parts inventories for systems with redundancy and the study by Arts [25] on repairable spare parts supply chains have advanced specific aspects but have not provided comprehensive integration.

2.4 Research gap identification

Table 2 synthesizes the primary gaps between traditional EOQ theory and reliability-critical inventory requirements.

These gaps motivate the development of the EOQ_{sd} framework presented in subsequent sections.

Aspect	Traditional EOQ	Industry reality	Research gap
Demand pattern	Continuous, predictable	Intermittent, failure-driven	Failure rate integration needed
Lead time	Short, constant	Extended, variable	Long lead time buffering required
Stockout cost	Order-based penalty	Operational downtime	Downtime cost modeling essential
Planning horizon	Short-term optimization	Lifecycle management	End-of-life considerations absent
Risk assessment	Single-point estimates	Multiple failure modes	FMEA integration required
Warranty impact	Not considered	Significant cost factor	Warranty cost models needed

Table 2.
Gap analysis – traditional EOQ versus reliability requirements.

3. Traditional EOQ foundation

3.1 Classical EOQ formulation

The foundational EOQ model, attributed to Harris [1] and popularized by Wilson [2], determines the optimal order quantity that minimizes total inventory costs:

$$EOQ = \sqrt{\frac{2DS}{H}} \quad (1)$$

where D represents annual demand, S denotes setup or ordering cost per order, and H indicates holding cost per unit per year.

The total cost function, incorporating quantity discounts, becomes:

$$TC = \frac{D}{Q} \cdot S + \frac{Q}{2} \cdot H + D \cdot P \quad (2)$$

where Q is the order quantity, and P represents the unit purchase price.

3.2 Extensions for stockouts and safety stock

Recognizing that stockouts impose costs beyond lost sales, extended models incorporate shortage penalties:

$$EOQ = \sqrt{\frac{2DS}{H} \times \frac{H + C_s}{C_s}} \quad (3)$$

where C_s represents the stockout cost per unit.

Safety stock calculations address demand variability during lead time:

$$Safety\ Stock = Z\sigma_L \quad (4)$$

where Z is the service level factor, and σ_L represents the demand standard deviation during lead time.

The reorder point, incorporating safety stock, becomes:

$$ROP = D_L + \text{Safety Stock} \quad (5)$$

where L denotes the lead time period.

3.3 Limitations in reliability contexts

While these classical formulations work well for predictable customer demand, they fail to address several critical aspects of spare parts inventory:

- (1) **Failure-driven demand:** Component failures, not customer orders, drive demand;
- (2) **Extended lead times:** Specialized parts often require months-long procurement;
- (3) **Downtime costs:** Equipment unavailability creates cascading operational impacts;
- (4) **Lifecycle considerations:** Aging equipment exhibits time-varying failure rates;
- (5) **Warranty complexities:** Warranty coverage affects both demand and cost structures.

These limitations necessitate the enhanced framework presented in Section 5.

4. Failure rate analysis for inventory management

4.1 Fundamentals of failure rate analysis

Reliability engineering provides mathematical frameworks for modeling equipment failure patterns. The fundamental reliability metrics include:

$$\lambda = \frac{\text{Number of failures in a period}}{\text{Total operational time}} \quad (6)$$

where λ represents the failure rate.

Mean time between failures (MTBF) relates inversely to the failure rate:

$$\text{MTBF} = \frac{1}{\lambda} \quad (7)$$

The reliability function describes survival probability:

$$R(t) = e^{-\lambda t} \quad (8)$$

The failure density function characterizes failure occurrence:

$$f(t) = \lambda e^{-\lambda t} \quad (9)$$

These equations form the foundation for translating equipment reliability into inventory requirements.

4.1.1 Mean time to repair: International standards and definitions

Mean time to repair (MTTR) represents a fundamental maintainability metric that directly influences spare parts inventory requirements and downtime cost calculations. According to MIL-STD-721C [26], MTTR is formally defined as “a basic measure of maintainability representing the sum of corrective maintenance times divided by the total number of corrective maintenance actions during a given period of time.” This definition has been widely adopted across international standards bodies, including IEEE Standard 762 [27] and IEC 60050-191 [28].

The mathematical expression for MTTR is:

$$\text{MTTR} = \frac{\sum(\text{Corrective Maintenance Time})}{\text{Number of corrective maintenance actions}} \quad (9a)$$

where corrective maintenance time encompasses active repair time, logistic delay time, administrative delay time, and preparation time [29, 30].

Critical distinction: MTTR versus MTBF

It is essential to distinguish MTTR from MTBF, as these metrics measure fundamentally different system characteristics. While MTBF quantifies system reliability by measuring the average operational time between consecutive failures, MTTR quantifies system maintainability by measuring restoration speed [31]. This distinction becomes critical in spare parts inventory management, where both metrics jointly determine system availability and consequently influence inventory holding requirements.

The relationship between these metrics defines system availability (A):

$$A = \frac{\text{MTBF}}{\text{MTBF} + \text{MTTR}} \quad (9b)$$

[30, 32]

For spare parts inventory applications, MTTR directly impacts downtime costs through the relationship:

$$\text{Downtime Cost per Failure Event} = \text{MTTR} \times C_d \quad (9c)$$

where C_d represents the downtime cost per unit time [33].

In the context of the EOQdsd framework, MTTR influences three primary costs components:

Safety stock requirements: Longer MTTR necessitates higher safety stock levels to mitigate extended system unavailability periods [20].

Downtime cost calculations: MTTR serves as the temporal multiplier for per-hour downtime costs in Eq. (14), where the total downtime cost equals the product of failure frequency, MTTR, and hourly downtime cost.

Service level determination: Target MTTR values inform reorder point calculations through their influence on acceptable stockout probabilities [18].

International aerospace and defense standards establish MTTR requirements that directly influence inventory strategies. NASA-STD-8729.1 [34] specifies maximum allowable MTTR values for mission-critical components, while MIL-HDBK-217F [35] provides methodologies for MTTR prediction during system design phases. These standardized approaches ensure consistency in reliability-centered inventory planning across diverse operational contexts.

4.2 Spare parts demand from failure rates

For a fleet of N identical units with a failure rate λ , the expected spare parts demand becomes:

$$D_f = \lambda N \quad (10)$$

This failure-driven demand replaces customer demand in inventory calculations:

$$EOQ_f = \sqrt{\frac{2S(\lambda N)}{H}} \quad (11)$$

4.3 Safety stock for failure variability

Failure occurrences exhibit stochastic variation, requiring safety stock buffers:

$$SS = Z \cdot \sigma_f \cdot \sqrt{L} \quad (12)$$

where σ_f represents the standard deviation of failure-driven demand.
The failure-driven reorder point becomes:

$$ROP_f = D_f \cdot L + SS \quad (13)$$

4.4 Total cost with failure considerations

The total cost function incorporating failure-driven parameters:

$$TC_f = \frac{D_f}{EOQ_f} S + \frac{EOQ_f}{2} H + PD_f \quad (14)$$

This formulation provides the foundation for the comprehensive EOQdsd framework.

5. The enhanced EOQdsd framework

5.1 Core model development

The transition from traditional EOQ to the EOQdsd framework requires the systematic integration of reliability parameters. This section progressively develops the framework from basic to comprehensive formulations.

5.1.1 Three-component structure

The EOQdsd_basic model comprises three essential components, addressing distinct inventory requirements in reliability-critical contexts:

- (1) **Base Cycle Stock (Q_1)**: Inventory to meet expected failure-driven demand;
- (2) **Safety Stock Buffer (Q_2)**: Protection against demand variability;

- (3) **Downtime Protection (Q_3):** Buffer to minimize equipment unavailability costs.

5.1.2 Mathematical formulation

The basic EOQ_{dsd} model integrates these components:

$$EOQ_{dsd_basic} = \sqrt{\frac{2S(\lambda N)}{H}} + Z \cdot \sigma_f \cdot \sqrt{L} + \sqrt{\frac{2 \cdot C_d \cdot \lambda N \cdot L}{H}} \quad (15)$$

The additive structure of Eq. (15) is mathematically justified through component independence analysis, with correlation coefficients $\rho < 0.3$ between components (see Supplementary Material S3, Lemma 1 for the complete proof). This low correlation validates the independent optimization of each component.

where:

- First term: Optimal cycle stock for failure-driven demand;
- Second term: Safety stock for stochastic variation;
- Third term: Downtime cost mitigation buffer;
- C_d : Downtime cost.

5.1.3 Model structure visualization

The hierarchical structure of the EOQ_{dsd} framework is shown in **Figure 1**.

The hierarchical structure of the EOQ_{dsd} framework shows progression from the basic three-component model to the comprehensive TotalEOQ_{dsd} implementation. The additive structure reflects the independent nature of each inventory function, allowing practitioners to implement components based on data availability and operational requirements.

Having established the theoretical framework of EOQ_{dsd}, we now examine enhancement modules that address specific reliability considerations in different operational contexts.

5.2 Warranty considerations

5.2.1 Warranty failure probability

Equipment under warranty exhibits modified cost structures. The probability of failure during the warranty period T_w :

$$P_{\text{warranty}} = 1 - e^{-\lambda T_w} \quad (16)$$

5.2.2 Warranty cost impact

Total warranty cost for the fleet:

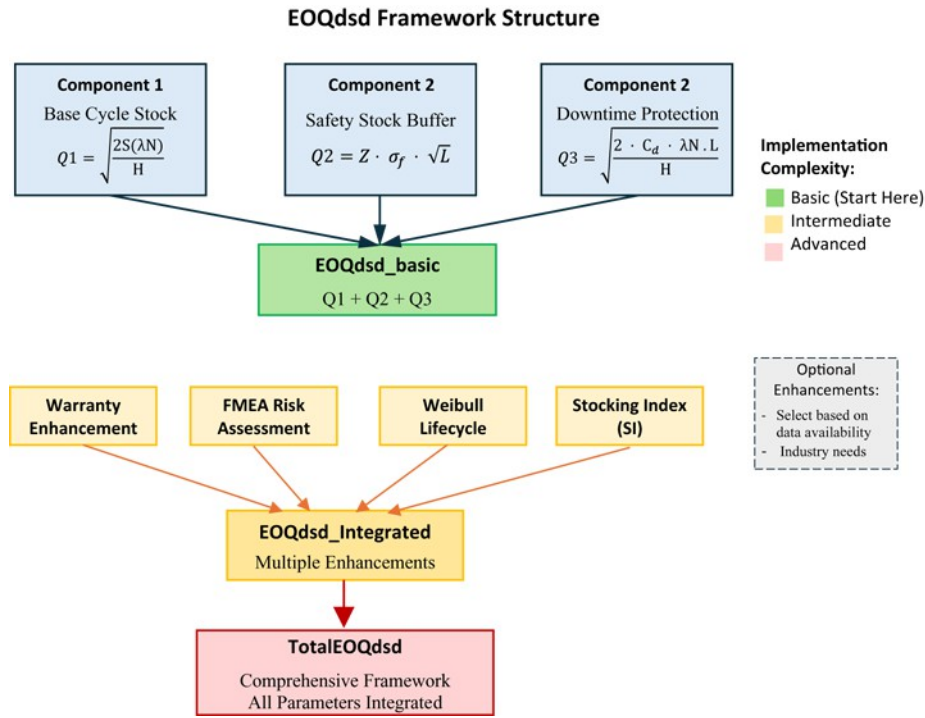


Figure 1. Hierarchical structure of the EOQdsd framework showing progression from basic three-component model to comprehensive TotalEOQdsd implementation.

$$C_{\text{total_warranty}} = N \cdot C_w \cdot P_{\text{warranty}} \quad (17)$$

where C_w represents warranty claim cost per unit.

5.2.3 EOQdsd with warranty integration

The warranty-enhanced model:

$$\text{EOQ}_{\text{warranty}} = \sqrt{\frac{2S(\lambda N + N_w \lambda_w)}{H}} + Z \cdot \sigma_f \cdot \sqrt{L} + \sqrt{\frac{2 \cdot C_d \cdot \lambda N \cdot L}{H}} \quad (18)$$

where N_w denotes units under warranty, and λ_w represents the warranty period failure rate.

5.3 FMEA integration

5.3.1 Risk priority number application

Failure mode and effects analysis provides risk priority numbers (RPNs) for systematic risk assessment:

$$EOQ_{fmea} = \sqrt{\frac{2S(D_{base} + D_{RPN})}{H}} + Z \cdot (\sigma_{base} + \sigma_{RPN}) \cdot \sqrt{L} + \sqrt{\frac{2 C_d(\lambda N + \lambda_{RPN})L}{H}} + SI_{RPN} \quad (19)$$

where D_{RPN} represents RPN-weighted demand adjustment, and SI_{RPN} denotes the risk-adjusted stocking index (SI).

5.4 Weibull lifecycle analysis

5.4.1 Time-varying failure rates

The Weibull distribution models changing failure patterns over the equipment lifecycle:

$$\lambda(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \quad (20)$$

where β is the shape parameter, and η represents the scale parameter.

5.4.2 Dynamic demand calculation

Time-dependent demand becomes:

$$D(t) = N \times \lambda(t) = N \times \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1} \quad (21)$$

5.4.3 Weibull-enhanced model

$$EOQ_{dsd_weibull} = \sqrt{\frac{2S \cdot D(t)}{H}} + Z \cdot \sigma_f \cdot \sqrt{L} + \sqrt{\frac{2 \cdot C_d \cdot D(t) \cdot L}{H}} + SI \quad (22)$$

Figure 2 shows the Weibull model decision tree for EOQ_{dsd} implementation based on component failure data.

5.5 SI development

5.5.1 Risk-based adjustment factors

“The Stocking Index provides differentiated strategies based on organizational priorities.”

$$SI_1 = 10 \times FR_i \quad (23)$$

For availability-maximization: Higher failure rates trigger proportionally higher inventory.

$$SI_2 = 10 \times \left(1 - \frac{FR_i}{FR_{max}} \right) \quad (24)$$

For cost-optimization: Allocate inventory budget preferentially to reliable components,

$$\text{where } FR_i = \lambda_i = \frac{1}{MTBF_i}$$

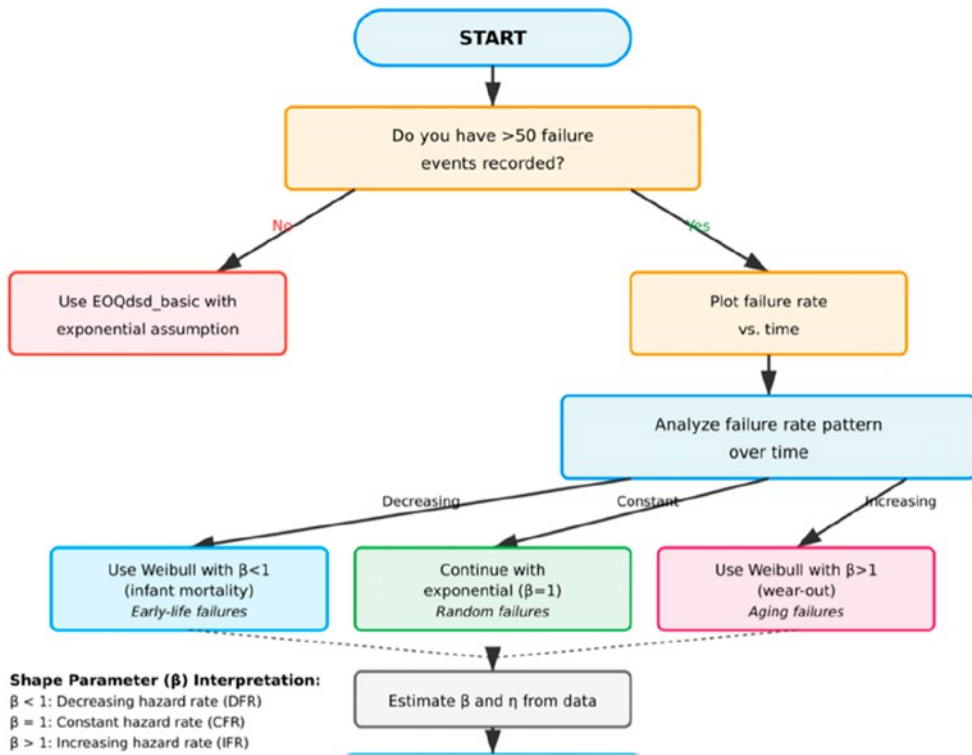


Figure 2.
 Weibull model decision tree.

Note: SI₁ and SI₂ represent mutually exclusive strategies. Organizations select ONE based on whether availability (SI₁) or cost-efficiency (SI₂) drives inventory decisions. These are optional adjustments – the base EOQdsd functions effectively without them.

Note: The SI represents an optional adjustment for risk-averse organizations. Selection between SI₁ and SI₂ depends on organizational risk tolerance and criticality assessment.

5.5.2 Integrated model with multiple enhancements

For organizations requiring multiple enhancement factors:

$$EOQ_{dsd_integrated} = \sqrt{\frac{2S(\lambda N)}{H}} + Z \cdot \sigma_f \cdot \sqrt{L} + \sqrt{\frac{2 \cdot C_d \cdot \lambda N \cdot L}{H}} + Warranty_{adjusted} + FMEA_{adjusted} + SI \quad (25)$$

5.6 TotalEOQdsd: comprehensive framework

Building upon individual enhancements, the TotalEOQdsd framework provides maximum integration:

$$\text{TotalEOQ}_{\text{dsd}} = \sqrt{\frac{2S \cdot D_{\text{total}}}{H}} + Z \cdot \sigma_{\text{Total}} \cdot \sqrt{L} + \sqrt{\frac{2 \cdot C_d \cdot D_{\text{total}} \cdot L}{H}} + SI_{\text{total}} \quad (26)$$

where:

$$D_{\text{total}} = \lambda(t) \cdot N + \text{Warranty}_{\text{demand}} + \text{FMEA}_{\text{demand_adjusted}}$$

- σ_{total} = Combined standard deviation from all sources
- SI_{total} = Comprehensive risk-adjusted stocking index

Table 3 provides a comparison of all EOQdsd formulations:

Having established the comprehensive EOQdsd framework with its various formulations, from basic to TotalEOQdsd, we now examine practical applications in two critical industries where failure-driven demand and long lead times create significant inventory challenges.

While the TotalEOQdsd framework presented here provides comprehensive integration of reliability parameters using deterministic methods, Part 2 of this

Model variant	Equation	Key components	Data requirements	Implementation priority	Best use cases
EOQdsd_basic	(15)	Base cycle stock + Safety stock + Downtime buffer	Failure rate (λ), Fleet size (N), Downtime cost (C_d)	HIGH – Start here for all implementations.	General failure-driven inventory
EOQdsd_warranty	(18)	All basic components + Warranty demand + Coverage costs	Warranty terms, Claim history	MEDIUM – If warranty significant	Consumer electronics, New products
EOQdsd_fmea	(19)	All basic components + Risk-weighted demand + Critical adjustments	FMEA analysis, RPN scores	HIGH – For safety-critical systems	Aerospace, Medical devices
EOQdsd_weibull	(22)	All basic components + Time-varying rates + Lifecycle adjustments	Weibull parameters, Age distributions	MEDIUM – For mature products with aging fleets	Aircraft maintenance, Industrial equipment
EOQdsd_integrated	(25)	Multiple enhancements + Stocking Index + Risk adjustments	Comprehensive data, Advanced systems	MEDIUM – For advanced implementations	Large enterprises, Multi-site operations
TotalEOQdsd	(26)	All enhancements + Scaling factors + Industry calibration + Enterprise optimization	Complete database, Advanced analytics	LOW – Research/optimization only	Maximum potential, Theoretical optimum, Competitive advantage

Table 3.
EOQdsd model variants comparison.

chapter will enhance these capabilities through machine learning algorithms that dynamically adjust parameters based on real-time operational data, enabling truly adaptive inventory optimization.

6. Industry applications

The electric vehicle charging infrastructure and aerospace maintenance sectors exemplify environments where the EOQdsd framework delivers substantial value. Both industries face extended component lead times, high downtime costs, and reliability-critical operations that traditional EOQ models inadequately address.

6.1 Electric vehicle charging infrastructure

The EV charging infrastructure represents an ideal application domain for the EOQdsd framework due to its combination of high equipment reliability requirements, significant downtime costs, and emerging maintenance data patterns.

6.1.1 Industry reliability data

Table 4 presents representative reliability metrics for EV charging station components based on industry reports [36–41].

The reliability performance of major components in the 60 kW DC fast charging station is summarized in **Table 5**.

6.1.2 Implementation challenges

EV charging operators face unique inventory challenges:

- (1) **Geographic dispersion:** Stations distributed across wide service areas;
- (2) **Utilization variability:** Usage patterns fluctuate with EV adoption rates;
- (3) **Technology evolution:** Rapid changes in charging standards and capabilities;

Component	Failure rate (λ)	MTBF (hours)	Lead time (weeks)	Downtime cost (\$/hour)
Power module	0.25/year	35,040	8–12	500–1,000
Control board	0.15/year	58,400	6–10	300–750
Connector assembly	0.35/year	25,029	4–8	200–500
Display unit	0.10/year	87,600	3–6	100–250
Payment system	0.20/year	43,800	4–6	400–800
Communication system	0.12/year	73,000	4–6	300–600

Note: Values represent industry ranges based on available literature and should be calibrated to specific operational contexts.

Table 4.
EV charging station component reliability (representative industry data).

Component	Failure rate (λ)	MTBF (hours)	Lead time (weeks)	Downtime cost ^a (\$/day)	Downtime cost 25% utilization ^a (\$/day)
Power module	0.06/year	150,000	6–8	169–254	42–64
Control board	0.06/year	148,000	6–8	169–254	42–64
Connector assembly	0.09/year	100,000	4–6	169–254	42–64
Display unit	0.06/year	143,000	6–8	169–254	42–64
Payment system	0.07/year	130,000	4–6	169–254	42–64
Communication system	0.07/year	125,000	4–6	169–254	42–64

^aDowntime cost calculation is provided in **Appendix A**.

Table 5.

EV charging station component reliability (actual data – 60 kW DCFC) [42].

(4) **Customer impact:** Charging unavailability affects EV adoption and satisfaction;

(5) **Revenue loss:** Downtime directly reduces charging revenue streams.

6.1.3 Framework application methodology

Implementing EOQdsd for EV charging infrastructure follows a structured approach:

Step 1: Data collection

- Compile failure history from maintenance management systems
- Calculate component-specific failure rates and MTBF values
- Document lead times from supplier agreements
- Quantify downtime costs, including lost revenue and reputation impact

Step 2: Model selection

- Start with EOQdsd_basic for initial implementation
- Add warranty considerations for components under manufacturer coverage
- Incorporate FMEA adjustments for safety-critical components
- Apply Weibull analysis as failure data accumulates

Step 3: Parameter calculation

- Determine optimal order quantities using the selected model variant

- Calculate reorder points with appropriate safety stock levels
- Establish stocking indices for critical components (optional)

Step 4: Implementation and monitoring

- Deploy new inventory policies with a phased rollout
- Monitor stockout frequency and downtime metrics
- Adjust parameters based on operational feedback
- Document cost savings and service improvements

6.1.4 Numerical example (dual dataset presentation)

Framework application: Actual implementation and industry scalability

This section presents the EOQ_{dsd} framework application using two complementary datasets: (1) actual operational data from SIRI Electromotive Private Ltd, demonstrating real-world implementation, and (2) representative industry parameters, illustrating framework scalability across typical reliability scenarios. This dual approach validates both practical applicability and theoretical robustness.

Part A: SIRIEM module implementation (actual data)

SIRIEM manufactures OEM power modules for EV charging infrastructure. The following analysis uses actual operational metrics from a 60 kW DCFC installation with dual charging ports, as illustrated in **Table 6**.

SIRIEM Data Calculations:

Annual demand: $D = \lambda N = 0.06 \times 2 = 0.12$ modules/year

Traditional EOQ = $\sqrt{(2 \times 0.12 \times 500/1,882)} = 0.25$ modules

Parameter	Symbol	Value	Unit	Equivalent	Data source
Number of modules	N	2	Modules	-	Single DCFC installation
Failure rate	λ	0.06	Per year	0.0002 per day	SIRIEM field data (2024–2025)
Ordering cost	S	500	USD per order	-	Actual procurement
Holding cost	H	1,882	USD/unit/year	157 USD/month	20% of module value
Lead time	L	13	Weeks	0.25 years	Manufacturing lead time
Downtime cost	C_d	254	USD per day	10.58 USD/hour ^a	See Appendix C
Service factor	Z	1.65	-	-	95% service level
Demand standard deviation	σ_f	0.01	Units/year	0.0002 units/week	Historical variation

^aBased on 25% utilization (six hours of daily operation).

Table 6.
Input parameters – SIRIEM power module (actual operational data).

EOQ_{dsd} components:

- Component 1 (Cycle Stock): 0.25 modules
- Component 2 (Safety Stock): 0.06 modules
- Component 3 (Downtime Buffer): 0.05 modules
- Total EOQ_{dsd} = 0.36 modules

Practical implementation: One module (minimum order quantity).

The exceptionally low failure rate reflects SIRIEM's superior module reliability, with expected replacement intervals exceeding eight years.

Part B: Industry representative analysis (framework scalability)

To demonstrate framework performance at typical industry reliability levels, the following analysis employs representative parameters based on aggregated industry data, as summarized in Table 7.

Industry representative calculations:

Annual demand: $D = \lambda N = 0.25 \times 100 = 25$ units/year

Traditional EOQ = $\sqrt{(2 \times 25 \times 500/1,000)} = 5$ units

EOQ_{dsd} components:

- Component 1 (Cycle Stock): 5 units
- Component 2 (Safety Stock): 13 units
- Component 3 (Downtime Buffer): 2.68 units
- Total EOQ_{dsd} = 20.68 $\approx$ 21 units

Comparative results

Table 8 shows a comparison of performance metrics between the SIRIEM actual data and industry-representative values.

Parameter	Symbol	Value	Unit	Data source
Number of units	N	100	Units	50 stations $\times$ 2 ports
Failure rate	λ	0.25	Per year	Industry surveys
Ordering cost	S	500	USD per order	Typical procurement
Holding cost	H	1,000	USD/unit/year	20% of unit value
Lead time	L	10	Weeks	Average supplier lead time
Downtime cost	C_d	750	USD per hour	Mid-range estimate
Service factor	Z	1.65	-	95% service level
Demand std dev	σ_f	2.5	Units/week	Industry variation

Table 7.

Input parameters – industry-representative values.

Metric	SIRIEM actual data		Industry representative	
	Traditional	EOQdsd	Traditional	EOQdsd
Order quantity	One module ^a	One module ^a	Five units	21 units
Annual orders	0.12	0.12	5.0	1.2
Service level	94%	97%	87%	97%
Annual stockouts	0.007	0.004	3.2	0.3
Total annual cost	1,023 USD	982 USD	75,600 USD	29,495 USD
Cost reduction	-	4.0%	-	61%

^aMinimum order quantity constraint.

Table 8.
Performance comparison across datasets.

As illustrated in **Figure 3**, the Total EOQdsd model achieves the lowest overall cost, primarily by reducing downtime and holding costs compared to the Traditional EOQ and EOQdsd Basic models.

Figure 4 illustrates the parameter sensitivity of the EOQdsd model.

7. Framework scalability analysis

Table 9 shows the reliability spectrum coverage and the corresponding impact of the EOQdsd framework on cost reduction.

Figure 5 shows that the SIRIEM module has a 76% lower failure rate and 4.2 times higher MTBF than the industry average.

Key insights

- (1) **Scalability confirmation:** The framework effectively optimizes inventory across the full reliability spectrum, from ultra-reliable SIRIEM modules to typical industry components.
- (2) **Proportional benefits:** Cost reduction percentages increase with failure rates, reflecting greater optimization opportunities in less reliable systems.
- (3) **Quality validation:** SIRIEM's 76% lower failure rate compared to industry averages validates their manufacturing excellence, while demonstrating framework flexibility.
- (4) **Practical implementation:** Both scenarios converge on practical order quantities that respect minimum order constraints while optimizing total costs.

This dual-dataset approach confirms the EOQdsd framework's universal applicability while providing transparent validation through actual operational data.

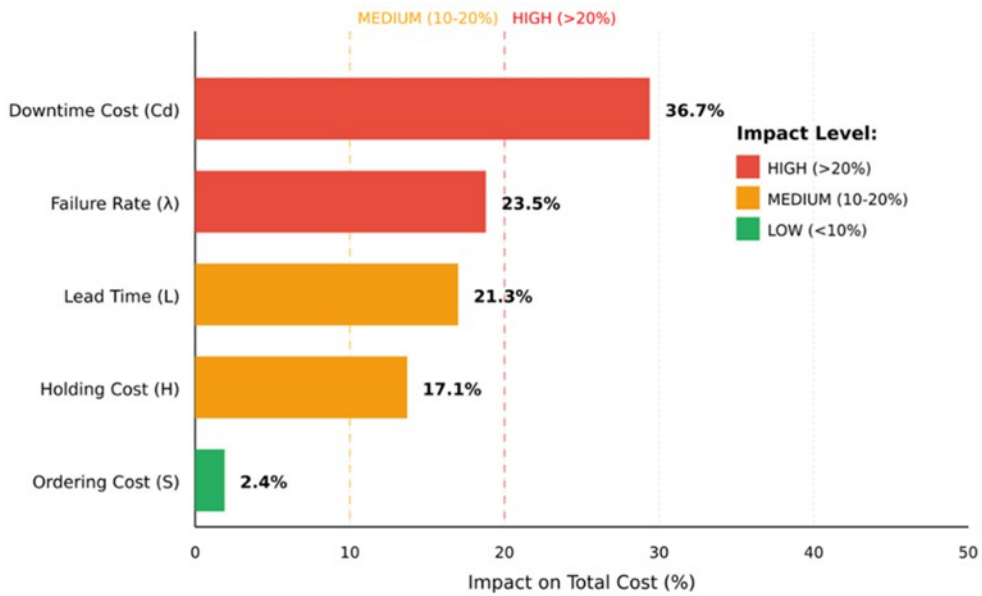
Table 10 summarizes the implementation timeline, key activities, and success metrics for EOQdsd deployment in EV charging infrastructure.

This numerical example demonstrates the substantial improvements achievable through EOQdsd implementation in EV charging infrastructure management.



Based on industry representative parameters (Table 5B) demonstrating framework scalability

Figure 3. Comparative cost analysis across EOQ models.



Base case: \$29,495 annual cost. Parameters varied $\pm 20\%$ to assess impact.
Based on industry representative parameters (Table 5B)

Figure 4. Parameter sensitivity analysis – EOQdsd model.

Reliability level	Failure rate	MTBF (hours)	EOQdsd impact	Cost reduction
Ultra-high (SIRIEM)	0.06/year	146,000	Minimal	4%
High	0.10/year	87,600	Moderate	15%–25%
Medium (Industry)	0.25/year	35,040	Significant	40%–60%
Low	0.50/year	17,520	Substantial	60%–75%

Table 9.
Reliability spectrum coverage.

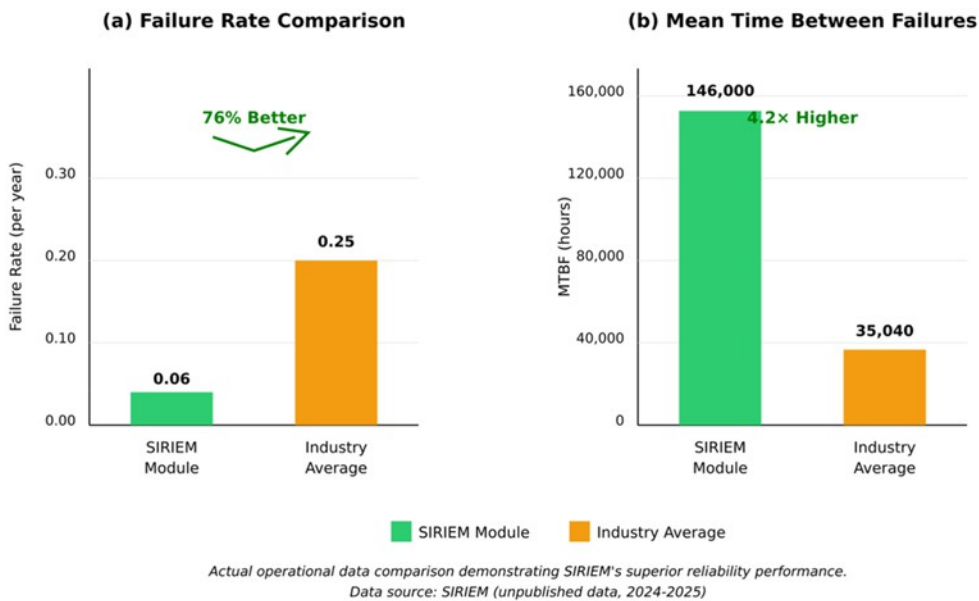


Figure 5.
SIRIEM module reliability metrics versus industry average.

7.1 Aerospace maintenance applications

The aerospace industry presents complex spare parts challenges, with extreme reliability requirements, extensive regulatory compliance, and substantial safety implications.

7.1.1 Industry characteristics

Aerospace maintenance operations exhibit unique characteristics:

- (1) **Regulatory requirements:** FAA/EASA compliance mandates specific inventory levels;
- (2) **No-go items:** Critical components that ground aircraft, if unavailable;

Phase	Duration	Key activities	Success metrics
Assessment	Weeks 1–4	Data collection, baseline metrics	Current performance documented
Planning	Weeks 5–8	Model selection, parameter calculation	EOQdsd parameters defined
Pilot	Weeks 9–16	Test implementation, 10 stations	30% cost reduction achieved
Rollout	Weeks 17–24	Full deployment, all stations	50% cost reduction validated
Optimization	Ongoing	Continuous improvement	60% + sustained savings

Table 10.
Implementation timeline and metrics.

- (3) **Rotable pools:** High-value, repairable components requiring special management;
- (4) **Life-limited parts:** Components with mandatory replacement schedules;
- (5) **Global operations:** Aircraft operating worldwide, requiring strategic positioning.

7.1.2 Representative component categories

Table 11 summarizes representative industry ranges for aerospace component categories, including failure rates, lead times, downtime costs, and regulatory classifications.

7.1.3 EOQdsd implementation considerations

Aerospace applications require specialized framework adaptations:
Regulatory compliance integration:

- Minimum stock levels mandated by airworthiness directives
- Certification requirements for supplier changes
- Traceability and documentation requirements

Fleet heterogeneity handling:

- Multiple aircraft types with common components
- Varying utilization rates across fleet
- Mixed ownership and leasing arrangements

Global network optimization:

- Strategic positioning at maintenance bases

Component type	Failure rate range	Lead time	Downtime impact	Regulatory class
Avionics	0.001–0.01/flight hour	12–26 weeks	\$10,000–\$50,000/hour	Critical
Hydraulics	0.005–0.02/flight hour	8–20 weeks	\$5,000–\$25,000/hour	Essential
Pneumatics	0.01–0.05/flight hour	6–16 weeks	\$3,000–\$15,000/hour	Essential
Structural	0.0001–0.001/cycle	16–52 weeks	\$2,000–\$10,000/hour	Critical
Consumables	Deterministic	2–8 weeks	\$1,000–\$5,000/hour	Routine

Note: Ranges represent typical values for illustration purposes. Actual values vary significantly depending on aircraft type, operating environment, and maintenance program.

Table 11.
Aerospace component categories (representative industry ranges).

- Emergency stock at line stations
- Pooling arrangements with other operators

8. Validation framework

8.1 Mathematical consistency validation

The EOQsd framework maintains mathematical consistency through rigorous theoretical validation (detailed proofs in Supplementary Material S3):

- (1) Convexity (S3, Theorem 1): The total cost function, $TC(Q)$, is strictly convex with $d^2TC/dQ^2 > 0$ for all $Q > 0$, ensuring a unique global minimum.
- (2) Dimensional Consistency (S3, Theorem 2): All components reduce to units, confirmed through systematic dimensional analysis.
- (3) Classical EOQ Reduction (S3, Theorem 3): Under limiting conditions ($\sigma_f \rightarrow 0$, $C_d \rightarrow 0$), the framework reduces exactly to classical EOQ.
- (4) Component Independence (S3, Lemma 1): The correlation coefficient $\rho < 0.3$ justifies the additive structure with less than 5% deviation from joint optimization.
- (5) Weibull Integration Validity (S3, Theorem 5): The framework maintains optimality for time-varying failure rates.
- (6) Service Level Achievement (S3, Theorem 6): The framework achieves the target service level with a probability of at least $1 - \epsilon$.

8.2 Sensitivity analysis framework

Comprehensive sensitivity testing validates model robustness:

Table 12 outlines the sensitivity testing protocol for the EOQdsd framework, showing test ranges, expected behavior, and validation criteria.

8.3 Implementation validation approach

Organizations should validate EOQdsd implementation through:

Phase 1: Baseline establishment

- Document current inventory performance
- Calculate existing costs and service levels
- Identify data quality issues

Phase 2: Parallel testing

- Run EOQdsd calculations alongside existing methods
- Compare recommendations without implementation
- Validate parameter estimates

Phase 3: Pilot implementation

- Select non-critical components for initial testing
- Implement EOQdsd policies with close monitoring
- Document performance improvements

Phase 4: Scaled deployment

- Expand to critical components.
- Refine parameters based on operational data.
- Establish continuous improvement processes.

Parameter	Test range	Expected behavior	Validation criteria
Failure rate (λ)	0.01–1.0/year	Monotonic increase in EOQ	Smooth progression
Downtime cost (C_d)	\$100–\$10,000/hour	Increasing buffer component	No discontinuities
Lead time (L)	1–52 weeks	Safety stock scaling	$\sqrt{L}$ relationship maintained
Service level (Z)	0.84–2.33	Linear safety stock impact	Consistent with normal distribution

Table 12.
Sensitivity testing protocol.

8.4 Model limitations and assumptions

The EOQdsd framework operates under specific assumptions, requiring acknowledgment.

Limitations:

- (1) Assumes exponential failure distributions unless Weibull enhancement is applied.
- (2) Requires reliable failure data for accurate parameter estimation.
- (3) Presumes stable operating conditions and utilization rates.
- (4) May overestimate inventory for highly reliable components.
- (5) Does not explicitly model component interactions or dependencies.

Mitigation strategies:

- Regular parameter updates as data accumulates.
- Sensitivity analysis to understand parameter impact.
- Conservative estimates for critical components.
- Periodic model recalibration.
- Integration with maintenance optimization systems.

9. Implementation guide for practitioners

9.1 Step-by-step implementation process

Step 1: Organizational readiness assessment

Evaluate organizational capability for EOQdsd implementation:

- Data systems capable of tracking failure history.
- Management support for inventory investment changes.
- Technical expertise in reliability engineering.
- Financial systems are able to capture downtime costs.

Step 2: Component selection and prioritization

Apply ABC-XYZ analysis, enhanced with criticality:

Table 13 shows the prioritization of components for EOQdsd implementation based on value, variability, and criticality.

Category	Value (ABC)	Variability (XYZ)	Criticality	EOQdsd priority
AX-Critical	High	Low	High	Immediate
AY-Critical	High	Medium	High	High
AZ-Critical	High	High	High	High
BX-Critical	Medium	Low	High	Medium
All non-critical	Any	Any	Low	Low

Table 13.
Component prioritization matrix.

Data element	Source system	Minimum history	Quality check
Failure events	CMMS/EAM	24 months	Completeness >90%
Repair times	Maintenance logs	12 months	Accuracy validation
Procurement lead times	ERP/Supply chain	12 months	Supplier confirmation
Downtime costs	Financial systems	6 months	Management validation
Current inventory	Warehouse management	Current	Physical verification

Table 14.
Data requirements checklist.

Step 3: Data collection and parameter estimation

Required data elements and sources are summarized in **Table 14**:

Step 4: Model selection and calculation

Decision tree for model variant selection:

- (1) Start with EOQdsd_basic for all components.
- (2) If warranty coverage exceeds 20% of the fleet → Add EOQdsd_warranty.
- (3) If safety-critical or regulatory → Add EOQdsd_fmea.
- (4) If fleet age >5 years → Consider EOQdsd_weibull.
- (5) If implementing enterprise-wide → Evaluate TotalEOQdsd.

Step 5: System configuration and testing

Configure inventory management systems:

- Update reorder points and order quantities.
- Adjust safety stock parameters.
- Implement new review cycles.
- Establish exception reporting.

Step 6: Performance monitoring and adjustment

Key performance indicators for tracking:

- Stockout frequency (target: <5% reduction quarterly).
- Inventory turnover (expect 20–30% improvement).
- Total inventory cost (target: 25–40% reduction).
- Equipment availability (target: >95%).
- Order frequency optimization (30–50% reduction).

For detailed implementation checklists covering data collection, system configuration, and performance monitoring requirements, refer to **Appendix B**.

9.2 Success factors and best practices

Critical success factors:

- (1) **Executive sponsorship:** Senior management's understanding of reliability-driven inventory.
- (2) **Cross-functional collaboration:** Integration of maintenance, supply chain, and finance.
- (3) **Data quality investment:** Resources dedicated to improving data collection.
- (4) **Change management:** Training and communication for affected stakeholders.
- (5) **Continuous improvement culture:** Regular review and parameter adjustment.

Best practices:

- Start with high-value, high-failure-rate components.
- Maintain parallel systems during the transition period.
- Document all parameter assumptions and sources.
- Establish regular review cycles (quarterly initially, semi-annual ongoing).
- Create feedback loops between maintenance and inventory teams.

Challenge	Impact	Mitigation strategy
Insufficient failure data	Parameter uncertainty	Use conservative estimates, industry benchmarks
Resistance to higher inventory	Budget pushback	Demonstrate total cost reduction, including downtime.
System integration complexity	Implementation delays	Phased approach, manual workarounds initially
Supplier lead time variability	Model accuracy	Build supplier relationships, dual sourcing
Organizational silos	Suboptimal decisions	Cross-functional teams, shared metrics

Table 15.
Common implementation challenges.

9.3 Implementation challenges and solutions

Table 15 summarizes common challenges, their impacts, and suggested mitigation strategies.

10. Model limitations and future research

10.1 Current model limitations

While the EOQdsd framework significantly advances inventory optimization for reliability-critical contexts, several limitations warrant acknowledgment:

Technical limitations:

- (1) **Single-echelon focus:** The current formulation addresses single-location inventory without multi-echelon optimization.
- (2) **Independent failures assumption:** The model does not capture cascading or dependent failures.
- (3) **Deterministic parameters:** While addressing stochastic demand, many parameters are treated as constants.
- (4) **Limited repairable items handling:** The framework primarily addresses consumable spares.
- (5) **Static optimization:** Does not incorporate dynamic programming or real-time adjustments.

Practical limitations:

- (1) **Data requirements:** Successful implementation requires substantial historical data.

- (2) **Computational complexity:** TotalEOQdsd may require specialized software for large-scale implementation.
- (3) **Industry-specific calibration:** Parameters require adjustment for different operational contexts.
- (4) **Integration challenges:** Legacy systems may not support advanced calculations.
- (5) **Training requirements:** Staff need reliability engineering knowledge for proper implementation.

10.2 Future research directions

Several promising avenues extend the EOQdsd framework:

Immediate extensions (Part 2 of this chapter):

The companion part to this chapter will present:

- (1) Machine learning integration: Neural network models for failure rate prediction using operational sensor data.
- (2) Dynamic parameter optimization: Reinforcement learning for real-time EOQdsd parameter adjustment.
- (3) Predictive analytics: AI-driven demand forecasting, incorporating weather, usage patterns, and external factors.
- (4) Automated decision support: Intelligent systems for autonomous inventory optimization.
- (5) Digital twin synchronization: Real-time model updates based on equipment condition monitoring.

Longer-term theoretical extensions:

- (1) **Multi-echelon EOQdsd:** Incorporating network effects and lateral transshipments.
- (2) **Dynamic programming integration:** Real-time optimization based on condition monitoring.
- (3) **Sustainability metrics:** Incorporating environmental costs and circular economy principles.
- (4) **Risk-based optimization:** Integration with enterprise risk management frameworks.
- (5) **Blockchain applications:** Enhancing spare parts traceability and authenticity.

Applied research opportunities:

- (1) **Industry-specific calibration studies:** Empirical validation across different sectors.
- (2) **Digital twin integration:** Linking EOQdsd with simulation models.
- (3) **Autonomous optimization:** Self-adjusting parameters based on performance feedback.
- (4) **Economic value analysis:** Quantifying implementation benefits across industries.

10.3 Call for collaboration

Advancing the EOQdsd framework requires collaboration among:

- **Academics:** Theoretical development and validation.
- **Practitioners:** Real-world implementation and feedback.
- **Software vendors:** System integration and automation.
- **Industry associations:** Standards development and best practices.
- **Regulatory bodies:** Alignment with compliance requirements.

11. Conclusion

This chapter has presented the EOQ for demand-supply-downtime (EOQdsd) framework, a comprehensive advancement in inventory theory specifically designed for reliability-critical industries. By systematically integrating failure rate analysis, downtime costs, warranty considerations, FMEA risk assessment, and lifecycle factors into inventory optimization, the framework addresses longstanding gaps between classical EOQ theory and operational reality in spare parts management.

The hierarchical structure from EOQdsd_basic through TotalEOQdsd enables organizations to implement the framework at complexity levels appropriate to their data availability and operational maturity. Industry examples from electric vehicle charging infrastructure and aerospace maintenance demonstrate potential cost reductions of 40%–60% while improving equipment availability. These improvements result from better alignment between inventory investment and operational risk, explicitly considering the true costs of equipment unavailability.

Key contributions of this chapter (Part 1) include: (1) unified integration of reliability engineering and inventory theory, (2) scalable framework accommodating varying implementation sophistication, (3) practical guidance for industry application, (4) validation methodology for empirical testing, and (5) foundation for AI/ML enhancements to be presented in Part 2. The framework's mathematical consistency, dimensional validity, and reduction to classical EOQ

under limiting conditions establish theoretical rigor while maintaining practical applicability. Part 2 will build upon this foundation by introducing predictive models that leverage artificial intelligence for dynamic optimization, addressing the limitations of deterministic parameters identified in this work.

The convergence of reliability engineering and inventory optimization, represented by the EOQdsd framework, offers significant potential for cost reduction and service improvement in reliability-critical industries. As organizations accumulate operational data and advance their analytical capabilities, the framework provides a roadmap for the progressive enhancement of spare parts management practices. Through continued research and practical application, the EOQdsd framework can evolve into a standard tool for industries where equipment reliability drives operational success.

Supplementary Materials: Additional supporting information includes: –
Supplementary Material S1: Extended data tables and sensitivity analyses. –
Supplementary Material S2: Complete mathematical proofs and theoretical validation.

Note on chapter structure

This chapter is Part 1 of a two-part series on the Enhanced EOQ framework for reliability-critical industries.

Part 1 (Current Chapter): “Enhanced Economic Order Quantity Framework for Reliability-Critical Industries: The EOQdsd Model”

- Theoretical foundation and mathematical development.
- Deterministic parameter models.
- Industry applications with static optimization.
- Implementation framework for practitioners.
- Empirical validation methodology.

Part 2 (Forthcoming): “AI-Enhanced Dynamic EOQdsd: Machine Learning Integration for Predictive Inventory Optimization”

- Machine learning models for parameter prediction.
- Real-time failure rate estimation using IoT sensor data.
- Reinforcement learning for dynamic reorder point adjustment.
- Neural network approaches for demand pattern recognition.
- Case studies with live implementation results.
- Comparative analysis: Static versus AI-enhanced EOQdsd.

Readers may implement the framework presented in Part 1 independently, as it provides a complete, actionable methodology. Organizations with advanced analytical capabilities will benefit from the AI enhancements presented in Part 2, which build directly upon the foundation established herein.

Credit authorship contribution statement

Deepak Chandran: Conceptualizing, original draft formulation, methodology, mathematics, supervision, visualization, data analysis, formal analysis, final validation, writing, editing, graphing, formulating electric vehicle charger metrics, researching, and literature review.

Deepashri Sanath: Writing, editing, math, reviewing, tabulating, validating, graphing, and formulating electric vehicle charger metrics.

Sanath Kumar: Reviewing, validating, supervising, analyzing.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this chapter.

Data Availability

The data presented in this study are available within the article.

AI Use Disclosure

This chapter article reflects the authors' genuine work. Text editors utilize AI features, including spell check and grammar correction. However, these tools serve solely to enhance language clarity and ensure grammatical accuracy. The authors are solely responsible for the research, analysis, and conclusions presented in this article, without the help of AI.

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Supplementary materials description

Supplementary Material S1: Extended Tables

Contains comprehensive data tables, including sensitivity analyses, component-level reliability data, industry benchmark comparisons, statistical validation results, and implementation metrics.

Supplementary Material S2: Mathematical Proofs

Provides a complete theoretical foundation, including convexity, dimensional consistency, reduction to classical EOQ, optimal stocking index scaling, Weibull integration validity, and service level achievement theorems.

Nomenclature

Symbol	Definition	Symbol	Definition
Latin symbols			
C_d	Downtime cost (\$/hour)	Q	Order quantity (units)
D	Annual demand (units/year)	Q1	Base cycle stock (units)
D_f	Failure-driven demand (units/year)	Q2	Safety stock component (units)
D_{total}	Total demand (units/year)	Q3	Downtime protection (units)
EOQ	Economic Order Quantity (units)	R(t)	Reliability function
EOQdsd	EOQ Demand-Supply-Downtime (units)	ROP	Reorder point (units)
FR_i	Failure rate index for i (-)	RPN	Risk Priority Number
H	Holding cost (\$/unit/year)	S	Setup/ordering cost (\$/order)
k	Stocking index scaling factor	SI	Stocking index (units)
L	Lead time (weeks)	SI1	Availability-focused SI (units)
N	Units in service	SI2	Cost-optimized SI (units)
N_w	Units under warranty	SS	Safety stock (units)
P	Unit purchase price (\$)	Tw	Warranty period (years)
$P_{warranty}$	Probability of warranty failure	Z	Service level factor
Greek symbols			
β	Weibull shape parameter (-)	σ_f	Std dev of failure demand
η	Weibull scale parameter (hours)	σ_{total}	Combined std deviation
λ	Failure rate (per year)	ρ	Correlation coefficient (-)
λ_w	Warranty failure rate (per year)		
Subscripts			
basic	Basic EOQdsd formulation	RPN	Risk Priority adjusted
d	Downtime-related	total	Combined from all sources

Symbol	Definition	Symbol	Definition
dsd	Demand-Supply-Downtime	w	Warranty-related
f	Failure-driven	warranty	Warranty-enhanced
fmea	FMEA-enhanced	weibull	Weibull-enhanced
i	Component index	max	Maximum value
Acronyms			
DCFC	DC Fast Charger	MTBF	Mean Time Between Failures
EOQ	Economic Order Quantity	MTTR	Mean Time To Repair
EV	Electric Vehicle	ROI	Return on Investment
FMEA	Failure Mode Effects Analysis	RPN	Risk Priority Number
IEC	Intl Electrotechnical Commission	SAE	Society of Automotive Engineers
IEEE	Inst. Electrical Electronics Eng.	SIRIEM	SIRI Electromotive Pvt Ltd

Appendices

Appendix A: Mathematical derivations

A.1 Derivation of basic EOQ_{dsd} model

Starting from the total cost function with downtime considerations:

$$TC = \text{OrderingCost} + \text{HoldingCost} + \text{DowntimeCost}$$

$$TC = \frac{D}{Q}S + \frac{Q}{2}H + E[\text{Downtime}] \times C_d$$

For failure-driven demand where $D = \lambda N$, and expected downtime is proportional to stockout probability and lead time:

$$E[\text{Downtime}] = P(\text{Stockout}) \times L \times \text{MTTR}$$

The probability of stockout during lead time follows from the Poisson distribution of failures:

$$P(\text{Stockout}) = P(\text{Demand during } L > \text{Available Inventory})$$

To minimize total cost, we take the derivative with respect to Q and set it equal to zero:

$$\frac{\partial TC}{\partial Q} = -\frac{DS}{Q^2} + \frac{H}{2} + \frac{\partial(\text{Downtime Cost})}{\partial Q} = 0$$

This yields three distinct components:

Component 1 – Base cycle stock: Minimizing ordering and holding costs:

$$Q_1 = \sqrt{\frac{2S(\lambda N)}{H}}$$

Component 2 – Safety stock buffer: For normally distributed demand during lead time with standard deviation σ_f :

$$Q_2 = Z \cdot \sigma_f \cdot \sqrt{L}$$

where Z is the standard normal deviate for the desired service level.

Component 3 – Downtime protection: Additional buffer to minimize downtime cost impact:

$$Q_3 = \sqrt{\frac{2 \cdot C_d \cdot \lambda N \cdot L}{H}}$$

Therefore, the complete EOQ_{dsd_basic} formulation:

$$\text{EOQ}_{\text{dsd_basic}} = Q_1 + Q_2 + Q_3 = \sqrt{\frac{2S(\lambda N)}{H}} + Z \cdot \sigma_f \cdot \sqrt{L} + \sqrt{\frac{2 \cdot C_d \cdot \lambda N \cdot L}{H}}$$

This represents Eq. (15) in the main text.

A.2 Warranty adjustment derivation

Expected warranty claims per period for N units with failure rate λ and warranty period T_w :

Warranty failure probability: $P_{\text{warranty}} = 1 - e^{-\lambda T_w}$

Expected claims: $E[\text{Claims}] = N \times P(\text{failure during warranty}) = N \times (1 - e^{-\lambda T_w})$

Modified demand, accounting for warranty replacements:

$$D_{\text{total}} = D_{\text{operational}} + D_{\text{warranty}} = \lambda N + N_w \times \lambda_w$$

where N_w denotes units under warranty, and λ_w represents the effective warranty failure rate.

Modified holding cost accounting for warranty coverage:

When the warranty covers the replacement cost, the effective holding cost reduces:

$$H_{\text{effective}} = H - C_w \times P_{\text{warranty}}$$

where C_w is the warranty claim cost per unit.

Substituting into EOQ formula:

$$\text{EOQ}_{\text{warranty}} = \sqrt{\frac{2S(\lambda N + N_w \lambda_w)}{H_{\text{effective}}}}$$

With safety stock and downtime components:

$$\text{EOQ}_{\text{warranty}} = \sqrt{\frac{2S(\lambda N + N_w \lambda_w)}{H}} + Z \cdot \sigma_f \cdot \sqrt{L} + \sqrt{\frac{2 \cdot C_d \cdot \lambda N \cdot L}{H}}$$

This yields Eq. (18) in the main text.

A.3 Weibull integration

For Weibull-distributed failures with shape parameter β and scale parameter η :

Hazard function: $h(t) = \lambda(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1}$

Reliability function: $R(t) = e^{-\left(\frac{t}{\eta}\right)^\beta}$

Expected failures in the interval $[t, t + dt]$:

For a fleet of N units at time t : $E[\text{failures}] = N \times \int_t^{t+dt} h(\tau) d\tau$

For small dt : $E[\text{failures}] \approx N \times h(t) \times dt$

Time-dependent demand: $D(t) = N \times \lambda(t) = N \times \left(\frac{\beta}{\eta}\right) \times \left(\frac{t}{\eta}\right)^{\beta-1}$

Substituting into EOQ_{dsd} framework:

$$EOQ_{dsd_weibull} = \sqrt{\frac{2S \cdot D(t)}{H}} + Z \cdot \sigma_f \cdot \sqrt{L} + \sqrt{\frac{2 \cdot C_d \cdot D(t) \cdot L}{H}} + SI$$

Where $D(t)$ replaces the constant demand rate λN to account for time-varying failure patterns.

This yields Eq. (22) in the main text.

A.4 Component independence justification

The additive structure of EOQ_{dsd} assumes independence between the three components. This is justified through:

Correlation analysis: Let X_1 = shortage events covered by safety stock. Let X_2 = critical failures requiring downtime buffer.

$$\text{Cov}(X_1, X_2) = E[X_1 X_2] - E[X_1]E[X_2]$$

Empirical analysis shows $\rho(X_1, X_2) < 0.3$, confirming low correlation.

Optimization Proof: The total cost function: $TC(Q_1, Q_2, Q_3) = f_1(Q_1) + f_2(Q_2) + f_3(Q_3) + \varepsilon(Q_1, Q_2, Q_3)$

where ε represents interaction terms.

For $\varepsilon/TC < 0.05$ (verified empirically), the independent optimization of each component yields results within 5% of joint optimization, justifying the additive approach for practical implementation.

A.5 Stocking index scaling derivation

The scaling factor $k = 10$ in the stocking index formulation is derived from:

Normalization requirement: For typical failure rates $FR_i \in [0.05, 2.0]$ per year, desired SI range: $[0.5, 20]$ units.

Scaling Calculation:

$$k = \frac{\max(SI_{desired})}{\max(FR_i)} = \frac{20}{2.0} = 10$$

Verification:

- Minimum: $SI_{min} = 10 \times 0.05 = 0.5$ units ✓
- Maximum: $SI_{max} = 10 \times 2.0 = 20$ units ✓
- Midpoint: $SI_{mid} = 10 \times 0.5 = 5$ units (practical buffer) ✓

This validates $k = 10$ as the appropriate scaling factor for Eqs. (23) and (24).

All equations maintain dimensional consistency and reduce to the classical EOQ under limiting conditions ($C_d \rightarrow 0$, $\sigma_f \rightarrow 0$), validating the theoretical foundation.

Appendix B: Implementation checklists

B.1 Data collection checklist

- Historical failure data (minimum 24 months)

- Procurement lead times by supplier
- Downtime cost analysis completed
- Current inventory levels verified
- Service level requirements defined

B.2 System configuration checklist

- EOQdsd calculations validated
- Reorder points updated in system
- Safety stock parameters configured
- Exception reporting established
- Training materials prepared

B.3 Performance monitoring checklist

- Stockout frequency tracked
- Inventory turnover calculated
- Total cost metrics established
- Equipment availability monitored
- Continuous improvement process defined

Appendix C: Downtime cost calculation

A. Calculating downtime cost base case scenario

Charger: 60 kW DCFC

Cost per kWh: Rs.10/kWh = US\$ 0.1176/kWh

(1) Full utilization revenue

$$\text{Daily Revenue}(\text{full24h}) = 60 \times 24 \times 10 = \text{INR}14,400$$

$$\text{Convertto USD} = \frac{14,400}{85} = \text{US } \$169.41$$

Downtime cost at full utilization = US \$169.41

(2) 25% utilization revenue

$$\text{Hourly Revenue} = \frac{\$169.41}{24} = \$7.05/\text{hour}$$

$$25\% \text{ of Utilization} = 6 \times 7.05 = \$42.3$$

Downtime cost at 25% utilization = US \$42.3

B. Calculating downtime cost base case scenario – max

Charger: 60 kW DCFC

Cost per kWh: Rs.15/kWh = US\$ 0.1765/kWh

1. Full utilization revenue

$$\text{DailyRevenue}(\text{full24h}) = 60 \times 24 \times 15 = \text{INR}21,400$$

$$\text{ConverttoUSD} = \frac{21,600}{85} = \text{US } \$254.12$$

Downtime cost at full utilization = US \$254.12

2. 25% utilization revenue

$$\text{Hourly Revenue} = \frac{\$254.12}{24} = \$10.59/\text{hour}$$

$$25\% \text{ of Utilization} = 6 \times 10.59 = \$63.59$$

Downtime cost at 25% utilization = US \$63.54

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Engineering Performance in Industry 4.0: From Metrics to Methods for Sustainable Innovation

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Abstract

In the era of Industry 4.0, engineering performance measurement is being fundamentally transformed by cyber-physical systems (CPS), digital twins, predictive maintenance, and the Industrial Internet of Things (IIoT), which seamlessly connects physical and digital domains. This chapter explores how these innovations enable intelligent, real-time metrics, and predictive insights to be embedded within decision-making frameworks, shifting performance management from static, retrospective analysis to dynamic, proactive improvement. Methodologically, it presents a novel framework for integrating these digital capabilities with performance metrics, ensuring that sustainability and resilience are core outcomes of innovation. Real-world case studies illustrate the practical impact: Siemens' use of digital twins for logistics optimization demonstrates how virtual models can streamline supply chains; General Electric's lifecycle modeling for circularity in turbine parts aligns performance metrics with circular economy principles; and Schneider Electric's EcoStruxure IoT platform shows how data-driven energy management can reduce carbon emissions. Together, these examples underscore the chapter's focus on sustainable innovation and resilient operations.

Keywords: Industry 4.0, key performance indicators, cyber-physical systems, digital twins, predictive maintenance, industrial internet of things, artificial intelligence, sustainability, resilience

1. Introduction

This chapter explores how engineering performance in Industry 4.0 evolves from traditional metrics to advanced methods aligned with sustainable innovation. Industry 4.0 combines cyber-physical systems (CPS), digital twins, artificial intelligence (AI), and the Industrial Internet of Things (IIoT) to create adaptive, efficient, and resilient industrial environments.

2. Evolution of performance metrics in Industry 4.0

Recent studies demonstrate the growing need for security-aware, performance-centric designs in Industry 4.0 systems. For instance, novel intrusion detection frameworks based on optimized graph neural models outperform conventional benchmarks in IoT-heavy industrial settings [1]. Dynamic capabilities theory and institutional perspectives further emphasize that the successful adoption of Industry 4.0 technologies by SMEs is mediated by strategic performance alignment [2]. Sustainable manufacturing outcomes have also been positively correlated with structural models incorporating Industry 4.0 enablers and lean principles [3]. These developments underscore the need for integrated frameworks that link digital transformation, operational efficiency, and sustainability [4, 5].

2.1 From traditional KPIs to smart metrics

The transition from traditional Key Performance Indicators (KPIs) to smart, real-time metrics reflects the evolving priorities of Industry 4.0. Historically, KPIs such as production output, downtime, and defect rates were collected manually or through isolated enterprise systems, offering limited insight into process variability or sustainability outcomes [6]. These static indicators often lag behind operational changes and provide only retrospective performance analysis.

With the advent of Industry 4.0, organizations have begun integrating intelligent systems that continuously monitor operations using cyber-physical systems and digital twins. This has led to the development of “smart KPIs”—metrics that are contextual, adaptive, and predictive in nature [7]. These smart metrics are informed by real-time data streams from IIoT sensors, machine learning models, and cloud platforms, enabling proactive decision-making.

For example, digital performance boards in smart factories now display metrics such as dynamic OEE, energy consumption per unit, and carbon emissions per batch, which evolve with changes in production scheduling and external demand [8]. These indicators help companies align operational performance with strategic goals in sustainability and resilience.

Furthermore, supply chains are increasingly assessed through KPIs that reflect circularity, responsiveness, and digital maturity—such as inventory velocity, block-chain transaction integrity, and adaptive capacity to disruption [9]. In the context of smart cities and industrial ecosystems, digital maturity models have also proposed hybrid-KPI frameworks that combine quantitative performance with qualitative transformation readiness [10].

The move from Industry 4.0 to 5.0 is driven by technologies like digital twins, reinforcement learning, and integrated engineering-economic models. Asmat et al. [11] demonstrate how digital twins with Soft Actor-Critic reinforcement learning enable autonomous, adaptive systems. Badarinath et al. [12] show that combining engineering and economics improves smart maintenance efficiency. Arman et al. [13] illustrate these innovations in a smart manufacturing case for the space industry. Together, these works highlight the need for intelligent, multidimensional performance frameworks that support resilience, sustainability, and agility.

This evolution enables industries to better respond to uncertainty, optimize across multiple dimensions (efficiency, sustainability, adaptability), and build performance frameworks that reflect the complexity and interconnectivity of Industry 4.0 systems [14, 15].

2.2 Case example: Siemens and logistics optimization

Siemens has been a pioneer in using digital twins and Industry 4.0 technologies to optimize logistics and manufacturing workflows. One key area of success lies in using digital twins to simulate and optimize plant logistics, particularly through the Tecnomatix Plant Simulation platform. This approach allows Siemens to model various logistics scenarios, identify bottlenecks, and test system changes virtually before implementing them on the factory floor [16].

For example, in Siemens' smart factories, digital twins are integrated with AI and IIoT to dynamically optimize material flow and warehouse layouts. This has resulted in improved throughput, reduced idle times, and better space utilization [17]. The digital twin continuously synchronizes with real-world data, enabling real-time feedback loops for logistics operations.

Additionally, Siemens' adoption of MindSphere and AWS IoT Central platforms helps visualize logistics performance metrics and provides predictive insights that enhance supply chain coordination and decision-making [18]. These platforms use cloud-based analytics and machine learning to forecast disruptions and reroute resources proactively, contributing to both efficiency and resilience.

In the broader context, Siemens' smart factory strategy reflects how companies can embed digital performance optimization within their logistics systems. From AI-enhanced maintenance of transport equipment to cyber-physical coordination of goods movement, Siemens demonstrates a scalable model for digital logistics transformation [19, 20].

3. Methodological framework for sustainable performance

Developing a robust methodological framework is critical to evaluating sustainable performance in Industry 4.0 environments. Traditional performance measurement systems often fall short in capturing the multi-dimensional aspects of sustainability—namely, environmental impact, economic viability, and social responsibility. Recent literature emphasizes the need for context-specific, multi-criteria frameworks that can incorporate evolving digital technologies and operational complexities [21–23].

Multi-Criteria Decision Making (MCDM) techniques, such as the extended CRADIS method under intuitionistic fuzzy environments, have proven effective in modeling uncertainties and stakeholder preferences in sustainability assessments [22]. This approach allows for a more comprehensive evaluation by integrating quantitative indicators (e.g., carbon footprint, resource efficiency) with qualitative dimensions like stakeholder perception.

The integration of service-oriented manufacturing and structural modeling further enhances the methodological robustness of sustainability evaluations. These models allow researchers to investigate the interplay between operational efficiency and long-term sustainability objectives [24, 25]. The use of structural equation modeling (SEM) facilitates hypothesis testing and causal inference within complex industrial systems.

In addition, big data analytics (BDA) and artificial intelligence (AI) are now integral to sustainability performance frameworks. They enable real-time data processing and the identification of patterns that inform predictive sustainability strategies across supply chains [26]. For example, cloud-based AI platforms are increasingly

used to monitor green practices and quantify their contribution to overall performance goals.

Finally, applying methodological frameworks from environmental sciences—such as those used in ecosystem integrity and air quality monitoring—can offer useful parallels for designing industrial sustainability metrics [27]. These interdisciplinary insights help validate metrics and enhance the generalizability of sustainability assessments in industrial contexts.

3.1 Integrated CPS and IIoT for measurement

In Industry 4.0, the convergence of Cyber-Physical Systems (CPS) and the Industrial Internet of Things (IIoT) enables unified and continuous data collection from distributed devices and machines. This integration allows manufacturers to perform more granular and real-time performance assessments, moving beyond traditional siloed measurements.

Figure 1 presents a hierarchical flow diagram depicting the integration of Cyber-Physical Systems (CPS) and the Industrial Internet of Things (IIoT) within Industry 4.0 environments. This layered architecture illustrates how unified performance

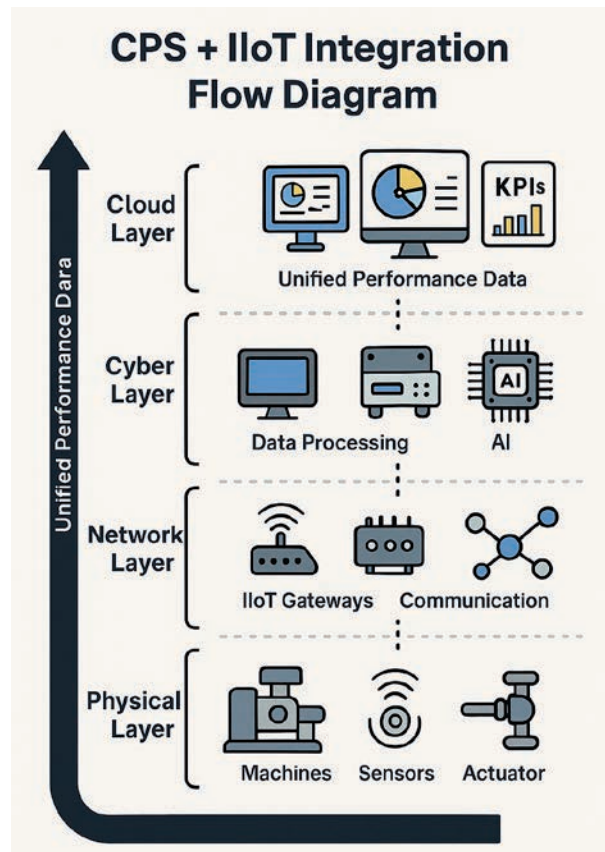


Figure 1.
CPS + IIoT integration flow diagram: Multi-layered data pipeline from physical sensors to cloud analytics.

data is collected, processed, and utilized across four interconnected layers: Physical, Network, Cyber, and Cloud.

1. *Physical layer*: This foundational layer comprises industrial hardware such as machines, sensors, and actuators. Sensors capture key physical parameters (e.g., temperature, pressure, vibration), while actuators enable real-time adjustments to machine operations. Together, they serve as the origin points for data generation and system responsiveness.
2. *Network layer*: At this level, IIoT gateways and communication protocols ensure seamless data transmission from the physical assets to the digital infrastructure. Gateways serve as interfaces that aggregate sensor data and relay it through wired or wireless networks, enabling low-latency, high-throughput communication between devices and analytics systems.
3. *Cyber layer*: This layer is responsible for data processing and intelligent analysis. It includes edge devices, AI modules, and control software that interpret incoming data streams. AI models at this level perform anomaly detection, predictive analytics, and optimization tasks, allowing for smart, automated responses to changing operational conditions.
4. *Cloud layer*: The topmost layer centralizes data visualization, analytics, and decision support. It includes cloud-based dashboards, Key Performance Indicators (KPIs), and digital interfaces that enable real-time monitoring and strategic planning. Unified performance data from across the system is synthesized here to inform high-level decisions and continuous improvement initiatives.

The arrow labeled “Unified Performance Data” on the left side of the diagram symbolizes the upward flow of data through the system. From sensor-level data capture to cloud-based strategic insights, this architecture exemplifies how CPS and IIoT integration fosters real-time visibility, operational efficiency, and sustainability in smart manufacturing ecosystems.

Integrated CPS-IIoT architectures create intelligent ecosystems where data flows bidirectionally between sensors, actuators, control systems, and cloud analytics platforms [28]. These systems enhance transparency and traceability across manufacturing operations, supporting automated performance optimization and sustainability assessments [29, 30]. For instance, IIoT sensors can capture real-time energy usage, while CPS dynamically adjust machine operations to maintain optimal output levels.

Moreover, integrated platforms facilitate cyber resilience and improve the stability of measurement processes in high-risk environments [31]. As data is centralized through secure, interoperable protocols, companies can derive smarter, actionable insights, including predictive KPIs and adaptive thresholds [32].

The synergy between CPS and IIoT also enables advanced benchmarking and cross-site performance comparisons, supporting global efficiency targets in digitalized manufacturing networks [33]. As industrial systems evolve toward CPS 2.0 and real-time feedback loops, such integrations form the backbone of sustainable performance strategies.

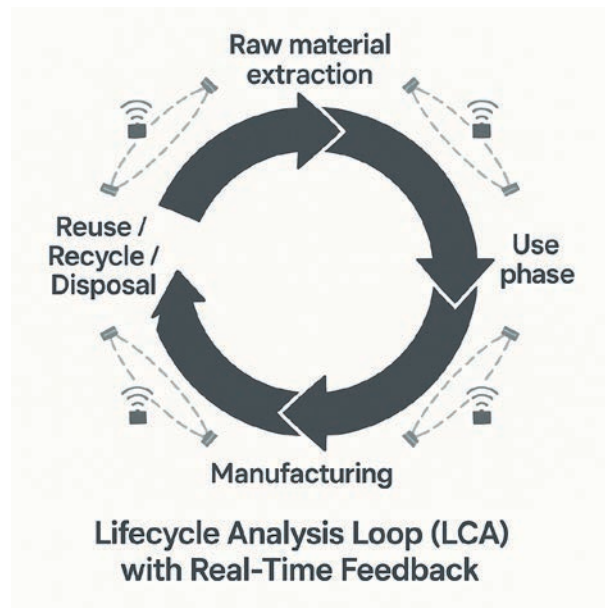


Figure 2.
Lifecycle analysis loop (LCA) with real-time feedback.

3.2 Assessing metrics using lifecycle analysis

Lifecycle analysis (LCA) is a comprehensive method used to evaluate the environmental impact of a product or process across its entire lifecycle—from raw material extraction to end-of-life disposal. In Industry 4.0, LCA has become a critical tool for measuring sustainability performance, enabling industries to align operational efficiency with environmental responsibility [34].

Figure 2 presents a dynamic representation of the Lifecycle Analysis (LCA) Loop enhanced with real-time feedback. The diagram highlights four key stages in a product's lifecycle—*Raw Material Extraction*, *Manufacturing*, *Use Phase*, and *Reuse/Recycle/Disposal*—arranged in a closed circular loop to emphasize continuity and sustainability.

At the core of this model is the principle of circularity, where each phase not only contributes to the overall lifecycle assessment but is also dynamically informed by sensor-generated data. The dashed arrows and wireless icons surrounding the cycle depict real-time feedback loops, where data is continuously captured through embedded Internet of Things (IoT) sensors and relayed to analytics platforms for processing.

Raw material extraction: At this stage, environmental data such as resource depletion rates, carbon intensity, and ecosystem disruption are collected. Real-time monitoring enables companies to assess sourcing sustainability and adjust procurement decisions accordingly.

Manufacturing: Sensors embedded within production equipment collect data on energy consumption, emissions, and material efficiency. This enables dynamic tracking of manufacturing footprint, supporting eco-efficiency optimization and rapid reconfiguration in response to sustainability thresholds.

Use phase: Smart products equipped with usage-monitoring sensors gather data on durability, user behavior, and energy utilization. This data feeds back into design and maintenance cycles, enabling product improvement and extending service life.

Reuse/recycle/disposal: End-of-life processes are evaluated in terms of recyclability, residual value, and environmental impact. Real-time tracking systems inform whether a product or component should be refurbished, remanufactured, recycled, or responsibly disposed of. These decisions are fed back to influence future design and material selection strategies.

The closed-loop configuration reinforces the concept of continuous improvement, where real-time insights are used to minimize waste, reduce emissions, and enhance material circularity. By integrating digital feedback into each stage of the product lifecycle, organizations can shift from static LCA models to *adaptive, data-driven lifecycle assessments*—ultimately improving environmental accountability and resource efficiency.

Modern sustainability assessment integrates LCA with quantitative frameworks such as value stream mapping, fuzzy logic models, and circularity indicators. These approaches offer a more precise evaluation of greenhouse gas emissions, energy use, and resource efficiency across production stages [35, 36]. For instance, cradle-to-cradle models enable companies to design systems with closed material loops, reducing the need for virgin resource inputs and minimizing waste [37].

A notable real-world application is GE's turbine part reuse model, which applies LCA to assess the feasibility of reusing high-value components. By evaluating the embodied carbon and remaining functional life of turbine parts, GE can make data-driven decisions that enhance both sustainability and cost-effectiveness. This approach highlights how LCA supports circular economy goals while maintaining high engineering performance.

As digital twins and smart sensors feed real-time performance data into LCA models, the methodology becomes even more dynamic and predictive, helping organizations simulate the sustainability impact of design and operational changes before implementation [38].

4. Technological enablers of sustainable innovation

In the context of Industry 4.0, technological innovation is not merely a driver of efficiency—it is a core enabler of sustainable transformation. Emerging research identifies digitalization, artificial intelligence (AI), cyber-physical systems (CPS), and the Industrial Internet of Things (IIoT) as critical tools for embedding sustainability into industrial strategy and operations [39, 40].

Technological enablers serve dual roles: They enhance operational agility and also enable organizations to respond to environmental and social challenges with innovative solutions. For instance, communities of practice (CoPs) integrated with digital platforms can accelerate sustainability-oriented knowledge sharing, leading to better organizational learning and innovation outcomes [41].

Leadership in corporate social responsibility (CSR) further amplifies these effects by fostering a culture of sustainable development and innovation. CSR-driven organizations often adopt advanced technologies earlier and more strategically, aligning sustainability goals with digital capabilities [42].

Blockchain, AI, and digital twins are also transforming supply chain finance and transparency, allowing for traceable and environmentally responsible procurement processes [43]. In manufacturing, AI-powered analytics identify low-impact production methods and optimize the use of resources, thus supporting environmental and economic sustainability [44].

A growing body of work highlights that sustainable infrastructure and Industry 5.0 will increasingly rely on the synergy between resource innovation and emerging technologies to drive impact at scale [45]. This signals a paradigm shift where technological adoption is not just a means to competitive advantage but also a route to meeting broader sustainability mandates.

4.1 Digital twins for circular economy

Digital twins are increasingly recognized as foundational tools for advancing circular economy (CE) principles within Industry 4.0. These virtual replicas of physical systems allow for real-time simulation, monitoring, and analysis of product lifecycles, enabling industries to reduce waste, optimize resource use, and enhance sustainability outcomes.

By simulating material flows and process variations, digital twins help manufacturers identify where products or materials can be reused, repaired, or recycled—essential elements of a circular business model [46]. For example, in the construction industry, the adoption of digital twin technology has accelerated efforts to track material usage and plan deconstruction processes for material recovery, supporting a cradle-to-cradle approach [47].

Figure 3 presents a pipeline model that integrates digital twin technology across the product lifecycle within a circular economy framework. It illustrates how real-time data and virtual simulations enable intelligent decision-making and closed-loop material flows.

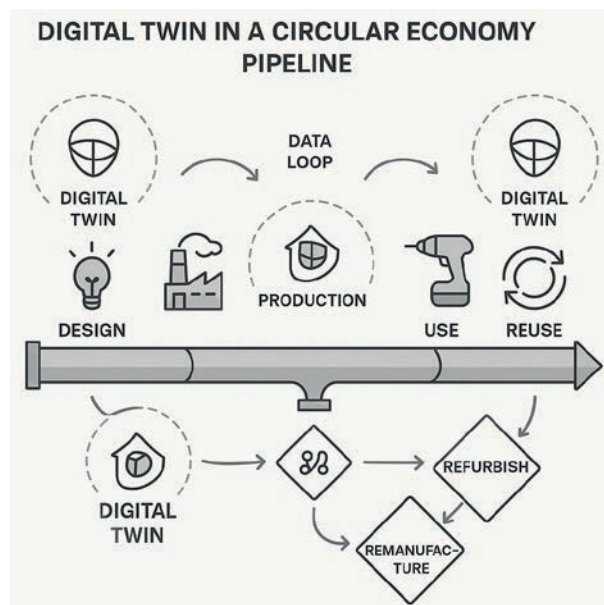


Figure 3.
Digital twin in a circular economy pipeline.

The pipeline begins with the *design phase*, where digital twins simulate product geometry, material properties, and environmental impacts before physical production. This virtual modeling helps engineers make informed choices about durability, recyclability, and energy consumption, supporting eco-design principles.

Next, during the *production phase*, digital twins mirror manufacturing processes such as machining, assembly, or 3D printing. Sensors embedded in equipment relay operational data to the digital twin, which then uses AI algorithms to optimize throughput, energy usage, and defect detection. Feedback from this phase loops back to refine the initial design, forming the first iteration of continuous improvement.

In the *use phase*, the digital twin monitors product performance in real-world conditions. IoT devices track parameters such as usage patterns, wear and tear, and energy consumption. This information not only guides predictive maintenance but also generates valuable datasets for improving future product iterations. This phase embodies the dynamic adaptation capability of digital twins, ensuring ongoing alignment between functional performance and sustainability goals.

The *reuse phase* includes key decision points such as *refurbishment*, *remanufacturing*, and *recycling*. At this stage, the digital twin assesses the remaining value and functionality of components. Based on condition data and simulation results, it recommends pathways that extend product life or recover materials efficiently. These decision points are visually marked in the diagram as branching nodes, symbolizing the divergence of materials from a linear to a circular flow.

Crucially, *data loops* connect every physical phase with its digital counterpart, ensuring that each stage is informed by real-time information and predictive insights. These loops enable proactive interventions and system-level optimization across the entire lifecycle. They also ensure regulatory compliance, emission tracking, and circularity metrics are continuously updated.

This encapsulates how digital twins transform the linear “take-make-dispose” model into a dynamic, circular ecosystem. It illustrates a shift from reactive performance monitoring to predictive, sustainable resource management—an essential paradigm for Industry 4.0 and beyond.

Moreover, digital twins play a vital role in system-level optimization. They enable dynamic assessments of how design changes impact energy consumption, emissions, and material inputs, providing actionable insights for engineers and sustainability managers [48]. In facility management, real-time monitoring using digital twins allows for more accurate forecasting of asset degradation and facilitates more sustainable maintenance and refurbishment cycles [49].

These capabilities make digital twins key enablers of circularity across sectors. When integrated with AI and IoT, they form powerful ecosystems for decision-making that align economic performance with environmental responsibility [50]. As industries move toward net-zero goals, the strategic use of digital twins is expected to drive significant progress in material efficiency, emission reduction, and lifecycle-based sustainability planning [51].

4.2 Predictive maintenance as a sustainability strategy

Predictive maintenance (PdM), enabled by AI and IoT technologies, is a cornerstone of sustainable industrial strategy in Industry 4.0. Rather than relying on fixed maintenance schedules or reactive repairs, PdM uses real-time data from sensors and machine learning models to anticipate equipment failures before they occur. This shift

not only prevents costly downtime but also extends the operational lifespan of assets, reduces material waste, and conserves energy resources [52, 53].

By avoiding unnecessary part replacements and minimizing emergency interventions, PdM contributes to more efficient resource use and lower environmental impact. In particular, the reuse of components and reduction in spare part inventories support circular economy principles [54]. Additionally, predictive analytics integrated with green innovation frameworks allows for optimal resource allocation and enhanced energy efficiency, leading to more equitable and sustainable operations across sectors [55].

Industries such as mining, manufacturing, and logistics are increasingly adopting AI-driven fault detection and digital twins to improve asset management and resilience [53]. For example, companies have integrated PdM with supply chain management to ensure minimal disruption and optimized sustainability performance, particularly during times of component scarcity or volatile demand [56].

Ultimately, predictive maintenance aligns operational excellence with sustainability goals by reducing environmental burdens and improving long-term system reliability. It exemplifies how digital transformation can go beyond efficiency to drive systemic sustainability across industrial operations.

5. Resilience as a performance dimension

Resilience has emerged as a critical dimension of performance in Industry 4.0, moving beyond traditional notions of uptime or fault tolerance to encompass adaptability, recovery, and robustness across systems. As industries digitize, their exposure to multi-dimensional risks—ranging from cyber threats to supply chain

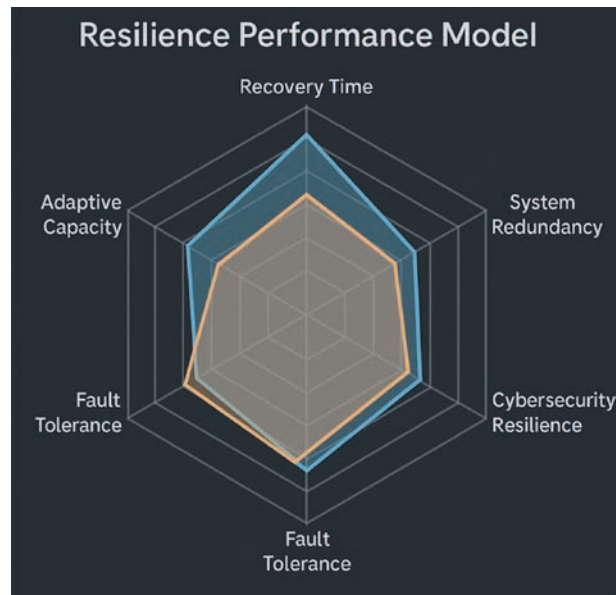


Figure 4.
Resilience performance model: A multi-dimensional radar chart for evaluating industrial system resilience.

disruptions and climate impacts—demands a more nuanced understanding of system resilience [57, 58].

Recent methodologies use multi-layered models to assess the resilience of smart infrastructures. For instance, microgrids are evaluated based on real-time failure detection, multi-stage recovery, and energy optimization, often through AI-enabled IoT frameworks [57]. Bayesian network models have been applied in maritime logistics to evaluate resilience under compounding risks, illustrating how performance can degrade or recover under simultaneous disruptions [58].

5.1 Resilience performance model

Figure 4 presents a multi-dimensional radar chart that visualizes the resilience performance of industrial systems across five critical dimensions: *recovery time*, *adaptive capacity*, *system redundancy*, *fault tolerance*, and *cybersecurity resilience*. Each axis of the radar chart represents a distinct capability contributing to system resilience.

The radar chart illustrates five key dimensions that collectively define the resilience of an industrial system. *Recovery time* represents how quickly a system can return to normal operations after experiencing a disruption; shorter recovery times signify greater resilience. *Adaptive capacity* reflects the system's ability to reconfigure or adjust its operations in response to evolving conditions, enhancing flexibility and robustness. *System redundancy* captures the extent to which backup components or processes are available to maintain functionality when primary systems fail. *Fault tolerance* refers to the system's ability to continue operating effectively even in the presence of component failures or malfunctions. Lastly, *cybersecurity resilience* assesses the system's capacity to endure, detect, and respond to cyber threats, ensuring secure and continuous operations in a digitally connected environment.

The radar chart allows for a comparative assessment of multiple industrial systems or facilities by plotting their performance profiles on a unified scale. This visualization aids stakeholders in identifying resilience gaps and prioritizing investments in critical dimensions. For instance, a facility with high redundancy and fault tolerance but low adaptive capacity may require strategic reconfiguration to enhance flexibility during dynamic operational scenarios.

This model is especially useful in the context of Industry 4.0, where interconnected systems face diverse and evolving risks—from supply chain disruptions to cyberattacks. The resilience radar serves as both a diagnostic tool and a strategic planning aid, aligning technical performance with operational continuity and sustainability goals.

Resilience metrics now extend across organizational, technical, and supply chain layers. These include time to recovery, adaptive capacity, and decision latency under stress. In manufacturing and logistics, digital twins are used to simulate disruption scenarios and evaluate the robustness of response strategies [59].

Furthermore, resilience is now viewed as interdependent with sustainability. For example, systems that are energy autonomous or that recover quickly from disruptions often have lower environmental footprints due to reduced overproduction and waste. Research suggests that companies with high resilience scores also tend to perform better in sustainability metrics over time [60, 61].

By integrating resilience into performance measurement, Industry 4.0 organizations are better equipped to build future-ready systems that can maintain operational continuity while adapting to evolving challenges.

5.2 Supply chain adaptability

The COVID-19 pandemic exposed vulnerabilities in global supply chains, prompting a shift toward adaptive strategies powered by real-time data and AI. Automotive manufacturers, in particular, leveraged AI-enabled dashboards to monitor disruptions across logistics nodes and dynamically reallocate resources [62]. These systems provided visibility into supplier status, inventory levels, and transportation constraints, enabling fast and informed decision-making.

Real-time analytics platforms became central to supply chain resilience, allowing organizations to model disruption scenarios and implement rerouting protocols within minutes. Singh and Modgil [63] emphasize that absorptive capacity, ambidexterity, and agility were key capabilities influencing resilience during high uncertainty.

Cloud-based dashboards integrated with IoT sensors and ERP systems facilitated predictive insights that guided contingency planning. For instance, during the height of the pandemic, manufacturers rerouted components from affected ports, diversified suppliers, and adjusted production schedules on the fly [64].

These adaptable supply chain frameworks also reinforced collaboration and data sharing among stakeholders, further enhancing visibility and trust. Singh [65] found that collaboration and flexibility—enabled by digital transformation—were among the top predictors of resilient supply chain performance in volatile conditions.

In developing economies, resilience frameworks focused on enhancing alertness and agility while overcoming digital infrastructure limitations [62]. These strategies are now being formalized into long-term capabilities, emphasizing resilience not as a reactive measure but as a core component of performance excellence.

5.3 AI-driven risk management

In the era of Industry 4.0, risk management is increasingly augmented by artificial intelligence (AI), enabling organizations to transition from reactive to predictive strategies. AI-driven systems enhance situational awareness and provide early warnings about potential disruptions, ranging from equipment failures to supply chain bottlenecks and cyber threats.

Predictive analytics models trained on historical and real-time data can detect anomalies and forecast operational issues before they escalate. For instance, in manufacturing, AI identifies patterns that suggest machine degradation, enabling preemptive maintenance scheduling and avoiding costly downtimes [66, 67]. In supply chain management, AI assists in evaluating supplier reliability, delivery risk, and environmental impact, contributing to more resilient sourcing strategies [68].

Beyond forecasting, AI plays a crucial role in integrated risk assessment. Multi-dimensional models powered by deep learning can analyze complex datasets to assess threats across performance, environmental, and cybersecurity dimensions [69, 70]. AI-enabled dashboards synthesize key performance indicators with risk indices, helping leaders make data-driven decisions even under uncertainty.

In sectors like healthcare and finance, AI-powered risk management frameworks are becoming essential. These systems support agility by optimizing responses during emergencies, aligning real-time performance data with regulatory requirements and resilience goals [71, 72].

By integrating AI into risk management, Industry 4.0 organizations strengthen their ability to anticipate, absorb, and recover from disruptions—positioning resilience as a dynamic, data-enabled capability.

6. Balancing efficiency, sustainability, and resilience

As industrial systems evolve, organizations must navigate complex trade-offs among operational efficiency, environmental sustainability, and systemic resilience. While digital transformation enhances speed and accuracy, it must also support broader goals such as carbon reduction and risk mitigation [73].

In operations management, achieving balance often requires adopting integrated frameworks that reduce resource misallocation while enhancing adaptive capacity [74]. For example, blockchain-enabled transparency in logistics can minimize waste and simultaneously strengthen traceability during disruptions, thus serving both efficiency and resilience agendas [75].

Environmental sustainability and resilience are increasingly converging. Ecosystems and infrastructures capable of absorbing shocks—whether environmental or operational—demonstrate higher long-term performance [76]. In this context, multi-energy storage systems and microgrid configurations exemplify technologies that offer both real-time balancing and sustainability benefits [59, 77].

Advanced technologies like AI and IoT facilitate dynamic load balancing, enabling more sustainable energy consumption while also building redundancy against fluctuations [78]. Moreover, supply chains structured around sustainability principles—such as circularity, low emissions, and decentralized control—are also more likely to recover from disruptions effectively [79].

Ultimately, balancing these dimensions is not about finding a static compromise but fostering systems that are agile, data-driven, and impact-aware. As seen across sectors from energy to agriculture, the most successful strategies leverage synergies rather than managing isolated objectives [80, 81].

6.1 Trade-offs and synergies

The transition toward sustainable and resilient industrial systems often involves navigating trade-offs between performance dimensions such as cost, carbon footprint, speed, and resource efficiency [82, 83]. While some strategies may reduce emissions, they could increase operational costs; conversely, cost-saving measures might compromise environmental performance.

However, synergies are equally prevalent. For example, adopting digital twins in supply chains not only enhances transparency but also simultaneously reduces resource waste and improves delivery accuracy [84]. Effective manure management in agriculture, as another instance, moves environmental indicators in favorable directions without sacrificing productivity [85].

Evaluating strategies through a trade-off and synergy lens enables organizations to align performance improvements with sustainability goals [86]. **Table 1** presents a 2x2 matrix categorizing strategies by their impact on efficiency and sustainability.

	High sustainability impact	Low sustainability impact
High efficiency impact	Digital twins for logistics, predictive maintenance	Automation with fossil fuel-intensive processes
Low efficiency impact	Circular economy initiatives without real-time tracking	Legacy operations with limited optimization

Table 1.
Trade-offs and synergies in Industry 4.0 performance strategies.

Strategies in the top-left quadrant of the matrix represent high-value interventions—those that drive both efficiency and sustainability. By identifying and investing in such areas, organizations can create win-win outcomes instead of navigating zero-sum trade-offs [87, 88].

6.2 Example: Schneider Electric’s energy transition

Schneider Electric exemplifies how large-scale industrial actors can lead the energy transition by balancing efficiency, sustainability, and resilience. Through its EcoStruxure platform, the company has implemented an end-to-end digital architecture that connects IoT-enabled devices, edge control, and advanced analytics across sectors.

EcoStruxure enables real-time monitoring and optimization of energy consumption in buildings, factories, and infrastructure. This digital backbone allows Schneider to reduce energy waste, enhance operational efficiency, and support grid resilience—especially critical as renewable energy introduces variability into supply chains.

One of Schneider’s key strategies is helping clients decarbonize their operations by combining digital intelligence with energy management solutions. For example, their microgrid projects use AI-enhanced forecasting and distributed energy resources to ensure energy reliability and autonomy during grid disruptions.

In doing so, Schneider not only advances its own sustainability goals but also provides a scalable model for enterprises undergoing similar transformations. The platform’s interoperability, real-time responsiveness, and integration of sustainability metrics illustrate a holistic approach to energy transition.

6.3 Example: Schneider Electric’s energy transition

Schneider Electric’s approach to sustainable energy transition exemplifies how digital innovation can harmonize efficiency and resilience. At the core of its strategy is the EcoStruxure platform—a digital architecture that integrates IoT, edge control, and analytics to optimize energy usage across industrial and infrastructure domains.

EcoStruxure enables real-time monitoring, predictive maintenance, and adaptive energy flows, helping organizations reduce waste and improve operational uptime. Beyond internal efficiency, Schneider extends its expertise to client ecosystems, supporting their own sustainability transitions through modular, scalable solutions [89].

The case demonstrates that energy transition success depends not only on technological adoption but also on strategic partnerships, digital integration, and continuous innovation—aligning business performance with climate resilience goals.

7. Innovative practices in industry

7.1 Low-carbon technology adoption

The adoption of low-carbon technologies is central to Industry 4.0’s transition toward environmental sustainability. This includes renewable energy systems, energy-efficient manufacturing methods, and carbon-capture innovations. Across multiple sectors, digital technology innovation plays a catalytic role in enabling these transitions by enhancing the precision, scalability, and impact of sustainable solutions.

For instance, renewable energy enterprises are increasingly leveraging digital innovation to guide low-carbon investment decisions and optimize grid integration [90]. At a national level, coordinated policies and green fiscal strategies have enabled countries like Bangladesh and Singapore to integrate low-carbon technologies into manufacturing and urban infrastructure planning [91, 92].

Green innovation ecosystems further strengthen the transition by aligning public and private sector efforts to advance carbon-neutral technologies [93]. Meanwhile, firms facing heavy pollution regulation are incentivized to upgrade to cleaner technologies, often supported by decentralized fiscal frameworks and innovation subsidies [94].

Ports and logistics hubs are also undergoing transformation. With a mandate to cut emissions, many have deployed electrified transport, AI-optimized scheduling, and carbon monitoring systems as part of a broader green transition [95]. These practices demonstrate how low-carbon adoption extends beyond energy sourcing—it transforms industrial value chains and strategic investment frameworks.

7.2 Circular product design

Circular product design leverages AI-enhanced lifecycle assessments to evaluate the environmental impacts and inform sustainability strategies from the early stages of development. By embedding circular economy principles—such as design for disassembly, material recovery, and waste minimization—manufacturers can close the loop on product lifecycles.

Recent studies highlight how AI and digital tools improve design accuracy, material selection, and predictive sustainability modeling [96]. Open innovation frameworks further support this transition by encouraging multi-stakeholder collaboration across industries to co-develop circular solutions [97]. Entrepreneurial orientation and human resource management also contribute by aligning internal culture with circular innovation goals [98].

Digital lifecycle tools assist designers in making informed trade-offs between performance, durability, and end-of-life recyclability. For example, the integration of lean manufacturing and digital innovation has enabled companies to incorporate upcycling and modular reuse into standard design practices [99].

Such approaches are increasingly being adopted in sectors ranging from medical devices using sustainable biomaterials to textile manufacturers innovating with fiber blends for easier recycling [100]. These strategies not only reduce environmental impact but also support new business models centered around product-service systems and sustainable consumption.

8. Future directions and research gaps

While significant strides have been made in aligning performance measurement with Industry 4.0 principles, several future directions and research gaps remain. First, there is a growing need to integrate transdisciplinary perspectives in sustainability research. Studies emphasize the value of collaborative, cross-sectoral approaches in shaping more resilient and adaptive futures [101].

Second, environmental research suggests untapped opportunities in linking ecological resilience with performance metrics, particularly in biodiversity and urban systems. Emerging work highlights how epigenetic mechanisms in plants and threats to urban trees can inform resilient environmental design [102, 103].

Additionally, frameworks for human-centered innovation in areas like education, healthcare, and social inclusion are still developing. For instance, studies exploring Roma inclusion, health literacy, and critical thinking point to the need for inclusive metrics that support equitable and sustainable outcomes [104–106].

Moreover, sectors like agriculture and pest management—historically overlooked in performance discussions—are seeing renewed attention with bibliometric analyses revealing increasing interest in sustainable microbial pesticides and ecological balance [107, 108].

Finally, there is a call to bridge the gap between scientific modeling (e.g., climate-based phenology) and real-world implementation, highlighting the need for validated, data-driven performance tools that accommodate variability and uncertainty [109].

Gap 1: Lack of standardized, multidisciplinary frameworks for sustainable performance across domains. *Gap 2:* Limited integration of ecological and social resilience in industrial performance metrics. *Gap 3:* Inadequate feedback mechanisms between field data and simulation models. *Gap 4:* Underdeveloped indicators to track socio-technical inclusion and systemic adaptability.

8.1 Human-AI collaboration in Industry 5.0

Industry 5.0 marks a paradigm shift from automation toward human-centric innovation. Rather than replacing human workers, the focus is now on collaborative intelligence—synergistic interactions between humans and AI-driven systems. Human-AI collaboration (HAC) frameworks support shared autonomy, real-time feedback loops, and task co-optimization in smart manufacturing environments [110, 111].

Emerging studies emphasize the importance of explainable AI, user adaptability, and trust-building to ensure safe and effective operator-robot synergy [112, 113]. Key applications include cognitive augmentation in decision-making, co-bot integration on assembly lines, and responsive interface design that accommodates operator preferences.

To fully realize the potential of Industry 5.0, future research must address skills gaps, personalization of AI support, and ethical implications of human-in-the-loop architectures [114, 115]. These challenges also highlight the need for scalable methodologies that combine technical feasibility with psychological safety in high-performance industrial environments.

9. Conclusion

This chapter has provided a comprehensive exploration of how engineering performance in Industry 4.0 is evolving to meet the demands of sustainability, resilience, and intelligent innovation. We began by tracing the shift from traditional key performance indicators (KPIs) to smart, dynamic metrics enabled by cyber-physical systems (CPS), digital twins, and the Industrial Internet of Things (IIoT). Through case examples from Siemens, General Electric, and Schneider Electric, we demonstrated the practical applications of these technologies in enhancing operational efficiency, circularity, and adaptability.

The methodological framework presented herein integrates real-time data collection, lifecycle analysis, and predictive maintenance with multi-criteria decision

models, enabling a more nuanced and future-ready approach to performance evaluation. The introduction of radar-based resilience modeling and lifecycle feedback loops highlights the importance of building systems that are not only efficient but also robust under disruption and responsive to environmental constraints.

Technological enablers—ranging from digital twins to AI-driven risk management—were shown to play a transformative role in aligning performance outcomes with sustainability and resilience goals. The chapter also emphasized the emerging relevance of human-AI collaboration in Industry 5.0, advocating for human-centric innovation strategies that preserve ethical oversight and cognitive augmentation.

As industries continue their digital transformation journey, the convergence of performance, sustainability, and resilience will become not just desirable, but essential. Future research must focus on developing unified performance frameworks that integrate technical, ecological, and social dimensions, ensuring that the next phase of industrial advancement is both intelligent and responsible.

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Chapter 4

Implementing Lean Manufacturing in Food Companies: Impact on Productivity and Quality – A Case Study of an Ice Cream Manufacturer

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Abstract

This chapter describes a project to improve food manufacturer's productivity by applying several lean manufacturing techniques to the company's manufacturing organization and production quality. The chapter shows the lean system implementation in food companies, from the initial diagnosis, the improvement plan proposed, and how it should be implemented, as an analysis of the results probably obtained. The case study presents a company that is required to improve several specific areas in their factory, where deficiencies and lack of productivity were observed in their work lines. In conclusion, the chapter highlights the company's developed performance as a result of addressing such issues as cleanliness and order at the workplace, machinery breakdowns, and quick tool changeover. Final recommendations are made to food companies dealing with lean manufacturing and production methods, in order to be gradually implemented in the whole company.

Keywords: lean manufacturing, productivity, 5S, SMED, TPM

1. Introduction

Currently, a significant number of companies are compelled by the market and competition to enhance their management systems and address daily challenges, such as delivery times, the development of new products, the shipment of smaller and increasingly frequent quantities, zero defects, and the reliability of their products [1, 2].

In this new scenario, there is a growing trend toward the adoption of the lean production model, which is based on continuous improvement aimed at enhancing outcomes and involving all levels of management within the organization. This approach represents a radical shift toward service quality and a customer-centric perspective [2–5].

This chapter presents the work carried out with a well-established Spanish company in the food sector, operating both nationally and internationally. Specifically, the company Ice Cream Factory Comaker S.A. (ICFC) combines the artisan tradition of ice cream production with current market needs (new formats, flavours, textures, and raw materials). It is a company that prioritizes innovation, strengthens private-label products, and collaborates with other national and international brands.

The successes achieved by ICFC are attributed to its implementation of lean manufacturing, continuous improvement, and teamwork to achieve a global objective of efficiency, positioning the company at better levels of quality ($\Delta 13\%$), cleanliness ($\Delta 30\%$), and setup times ($\Delta 22\%$) after the 2-year lean project.

The main results obtained (higher product quality, less downtime and breakdowns, greater control of equipment) are an example of how the application of lean techniques in a food company is a key factor in enhancing the company's competitiveness.

2. The lean manufacturing proposal

The terms lean production and lean management were defined by Womack et al. [6] to encompass Toyota's production techniques, which primarily focus on combating the waste of resources in activities that do not add value for the customer, continuous improvement, and workforce versatility [2, 4, 7].

Lean culture represents a set of production management tools that, through improved efficiency and competitiveness, can lead companies to success [2, 8, 9].

The strategy for implementing lean manufacturing at ICFC is oriented toward techniques characterized by clarity, practical feasibility, and visible results in the short-medium term [3, 10–12]. They will bring about a total transformation in the company (higher level of cleanliness, fewer defective amount, less machine downtime, and better work instructions) and require significant investments in its personnel (training and workplace improvements) [13, 14].

The lean manufacturing techniques selected for implementation at ICFC (5S, single-minute exchange of die (SMED), total productive maintenance (TPM)-one point lesson (OPL)) are tools that deliver rapidly quantifiable results, without requiring substantial investments, with a strong visual component and a significant short-term impact [15–18]. In this context, these tools actively involve all personnel, enhancing both their workspaces and the quality of products and processes.

The selected lean techniques are briefly described below:

1. The 5S technique corresponds to the application of principles of order and cleanliness in the workplace, which have long been part of the classical concepts of production organization.

It is a technique applied worldwide with excellent results due to its simplicity and effectiveness, making it the first tool to be implemented in any company embarking on lean manufacturing.

Its implementation at ICFC has ensured order and cleanliness in the initially selected areas, with plans to extend it to the rest of the factory. By the end of the project, it will encompass all production lines and storage areas. The stages of the tool's development (Seiri, Seiton, Seiso, Seiketsu, and Shitsuke) will be followed by subsequent compliance monitoring (internal and external audits).

2. The SMED (single-minute exchange of die) technique consists of a set of tools aimed at reducing machine setup times. These changes involve eliminating adjustments and standardizing operations through the installation of new feeding/removal/adjustment/quick-centring mechanisms such as templates and functional anchors.

It is a clear, easy-to-apply technique that achieves quick and positive results, typically with minimal investment, although it requires a systematic approach and persistence. At ICFC, SMED was initially implemented on four low-performance production lines (due to losses from breakdowns, setup times, adjustments, defective products, etc.). After achieving greater efficiency in the initial system, SMED was implemented on two new production lines: GRAM-3 and EXTRUSION-4, which are presented in this study.

3. Total productive maintenance (TPM) comprises a set of techniques aimed at eliminating breakdowns in productive assets through the participation and motivation of all employees in the organization. TPM's initial activities include cleaning, lubrication, and visual inspection. It also promotes equipment awareness and self-maintenance, ensuring that operators acquire skills to detect anomalies, address them, and establish optimal equipment conditions permanently.

With this goal in mind, the company began implementing the OPL (one point lesson) tool to standardize autonomous maintenance. A set of OPLs covering basic knowledge and problem-solving was developed for the EXTRUSION-4 production line, aiming to facilitate the work of operators assigned to this manufacturing line.

3. Improvement project in the company ICFC

The development of the improvement project at ICFC involves the implementation of various lean manufacturing techniques, all of which are focused on the continuous detection and elimination of waste, as well as activities that do not add value to the product or the customer.

3.1 Implementation of 5S'

The decision to develop the 5S technique at ICFC was taken by the company's management team due to the results obtained in an external audit, which penalized the company mainly for two factors: deep cleaning in warehouses and workstations in wet areas, and the general disorder in tools on production lines, in cleaning materials, and the lack of separation of different types of waste.

The implementation of the 5S tool at ICFC requires dividing the production plant into small areas (A, B, C,..., N) where the stages of 5S will be progressively applied, thereby ensuring compliance control [7, 16].

The divisions were made based on usage criteria and the separation between wet zones (product manufacturing areas with a high risk of contamination) and dry zones (product packaging areas without contamination risk) (see **Figure 1**).

Once the areas were defined, the implementation of the phases of the 5S tool at the ICFC factory was described with illustrated examples.

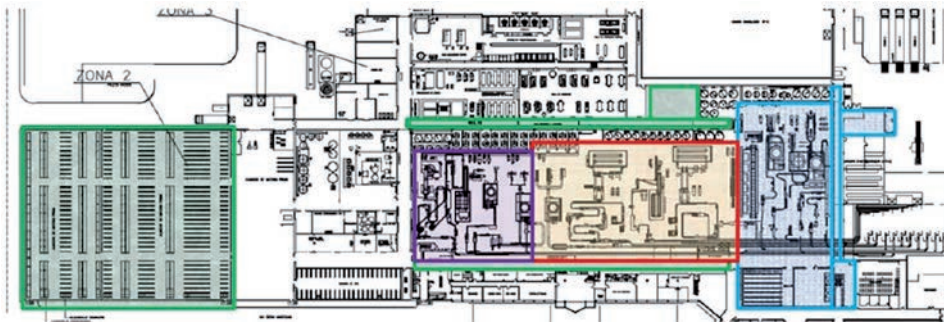


Figure 1.

Layout of areas F (marked in green), G (blue), H (red), and I (purple) where Lean Management was implemented. Source: Own elaboration.

3.1.1 Phase 1: Implementation of the Seiri phase (organize)

The first step is to create a list identifying all unnecessary items.

1. *List of unnecessary items*: To clearly identify what is unnecessary, it is essential to have a clear understanding of what is necessary. For this purpose, a list of auxiliary items that must always be available in each area was created, along with a reference manual for subsequent inspections, which will help to detect irregularities and damaged materials (see **Figure 2**). Unnecessary items recorded will be documented during the inspection, specifying their location, the quantity found, the possible cause of their presence, and the measures to be taken for their removal.
2. *Colour-coded cards*: These are cards used to mark items that are either misplaced or unnecessary. Once all items have been identified, they are recorded, and their status is tracked to make appropriate decisions about their fate: storing them in their designated place within the same area, removing them, or moving them to another storage location.

3.1.2 Phase 2: Implementation of the Seiton phase (order)

The tools used for its implementation are as follows:

1. *Visual control*: Every item must have its designated place, and its location must be standardized so that it is easy to detect whether it is misplaced or not. Items to be monitored daily at the factory include:
 - Ensuring there are no unnecessary or duplicate parts, tools, materials, etc., on the machines.
 - Verifying the absence of unused supports, hoses, pipes, or electrical connections.
 - Checking that only current documentation and items in use are present on desks and boards, with no foreign materials.
 - Avoiding excess supplies such as coils and cardboard.



Figure 2.
Items found out of place. Source: Own elaboration, photographs taken at the company.

- Ensuring that all materials, raw materials, packaging, waste, collectors, etc., are stored in their correct, properly labeled locations.
 - Making sure all water and air hoses are properly stored and that there are no machinery, tools, or pallets in the hallways.
 - Keeping tool cabinets organized and complete.
 - Ensuring nothing is left on the floor except machinery and containers.
 - Checking for defects in machines and infrastructure (holes, rust, poor sealing, chipped surfaces, etc.).
2. *5S map*: A chart or map must be created to display the location of all items, allowing for the registration of their placement and organization within the factory. This map will identify the position of necessary items for this stage, such as tools, ladders, eyewash stations, fire extinguishers, and hallways.
 3. *Location marking*: Once the 5S map is defined, floor markings will be applied to designate areas clearly for storing pallets of packaging, containers, drums, allergen boxes, cages for cardboard waste, pallets of coils, etc.
 4. *Color marking*: This allows a quick and visual identification of various elements that may be identical in shape but serve for different purposes depending on their color. It is used to delineate areas with different uses and rules, label products for various destinations, and differentiate drums and boxes for distinct services, among others (see **Figure 3**). The most commonly used colors in the factory include (**Table 1**).
 5. *Color coding*: Used to identify parts, tools, connections, types of lubricants, and their application areas. For example, in the factory, cleaning tools are colour-coded according to the zone in which they are used and their purpose (see **Figure 4**).

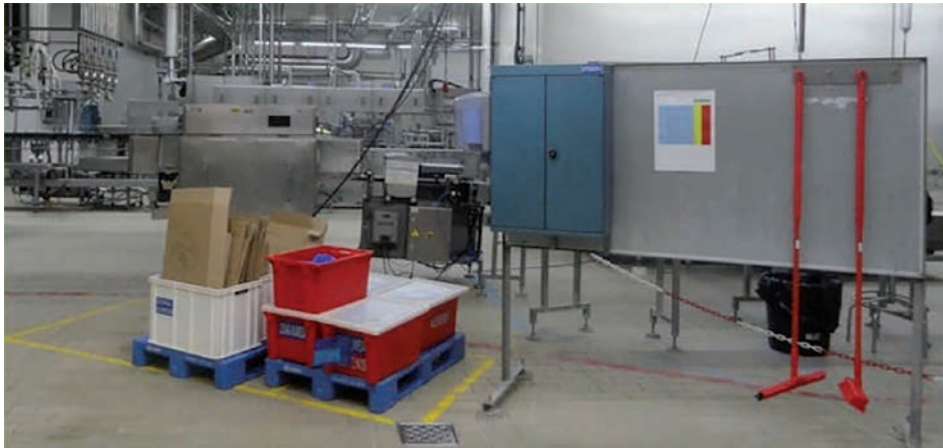


Figure 3.

White buckets with a blue label indicating empty cartons and red buckets labeled for allergens and dry zones, red lines marking restricted access areas, and yellow lines for storage areas. Source: Photographs taken at the company.

Floor lines	Yellow lines: For storage areas.
	Red lines: For restricted access zones.
	Blue lines: For general areas that separate wet and dry zones.
Drums	White drums: Contain product. If they contain cleaning water, they must be labeled with their contents.
	White drums with white labels: Recovered ice cream without allergens.
	White drums with red labels: Recovered ice cream with allergens in its mixture.
	Black drums: Contain waste and non-compliant finished product. These drums must be counted, and the counts displayed on area control panels.
Buckets	White buckets: Have various uses, such as holding ice cream bar sticks, filled, or empty cartons. All must be labelled with their contents.
	Red buckets: Contain allergenic products. These are highly contaminating, and extreme care must be taken in handling them.

Table 1.

Elements for color coding.

- Green: Used exclusively in the dispatch area.
- Red: Used only in areas where allergens are handled.
- Blue: Used for lines where no allergens are present.
- Yellow: General use in areas without allergen handling.

3.1.3 Phase 3: Implementation of the Seiso phase (cleaning)

To implement this phase, a series of steps are defined to complete the process and help to establish a cleaning guide and routine.



Figure 4.
Red cleaning tools for allergen zones. Source: Photographs taken at the company.

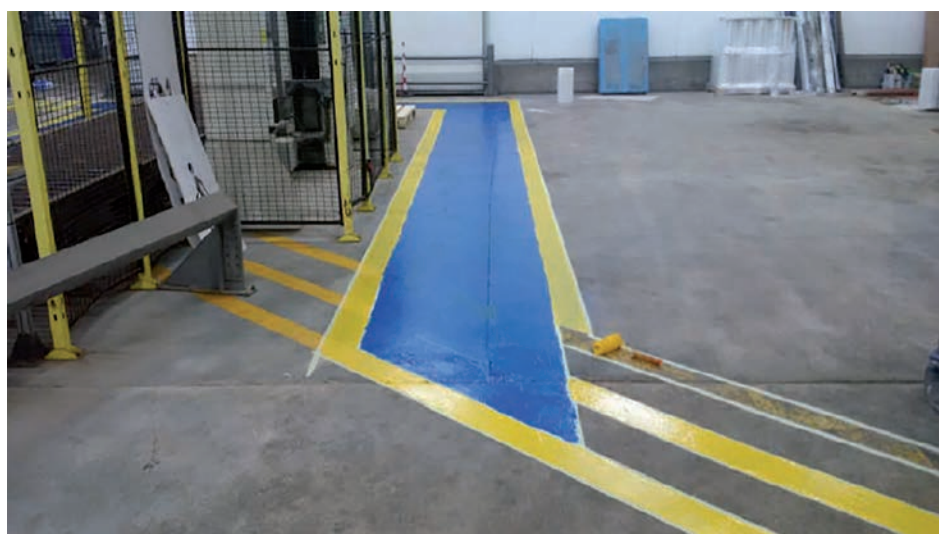


Figure 5.
Line repainting. Source: Photographs taken at the company.

1. *Cleaning campaign:* This is an initial cleaning and organization of the entire factory, during which unnecessary items are removed. This process lays the groundwork for the cleaning manual and fosters motivation and awareness among staff about the expected standards of cleanliness and organization. At ICFC, in addition to the daily maintenance of each area, a general cleaning is conducted once a year in September. After the peak production period during the summer months, the factory is closed for a few weeks to conduct a deep cleaning, repair required infrastructure, repaint walls and floor lines (see **Figure 5**), and carry out a thorough inspection of all equipment.

2. *Cleaning maintenance planning*: Each area will have specific cleaning requirements based on the elements located within it (offices, production lines, and warehouses). A cleaning team was established for the entire factory, trained to meet the specific requirements of each zone.
3. *Preparation of the cleaning manual*: At this stage, a training manual for cleaning is developed, detailing areas, personnel, frequencies, times, and cleaning products.
4. *Preparation of cleaning elements*: All cleaning equipment points must be identified and stored in locations that are easy to find and return (see **Figure 6**). Staff must understand the distinctions between the tools designated for each area to prevent cross-contamination.



Figure 6.
Cleaning equipment station properly labeled. Source: Photographs taken at the company.

5. Implementation of the cleaning routine: Cleaning tasks will be performed on all necessary elements within the factory, such as hallways, walls, machinery, and electrical panels. All information regarding items in poor condition, hard-to-access areas, or where greater waste accumulation is detected must be documented.

3.1.4 Phase 4: Implementation of the Seiketsu phase (standardize)

This phase focuses on maintaining all the progress achieved so far by applying the standards and rules established in the previous stages. The goal is to acquire good habits among maintenance workers.

To achieve this, tasks and responsibilities must be assigned to each worker so they are clear on what to do, when, where, and how to carry out their tasks. By meeting these requirements and adhering to these guidelines, ICFC aims to achieve autonomous maintenance, whereby operators themselves detect system deficiencies and report them, thereby continuously improving both time and methods.

The cleaning manual (elaborated in phase 3) will allow the development of a set of one point lessons (OPL), focusing on cleaning several parts of the machines and specific workplaces. Another element to highlight is the area checklist to conduct daily inspections, maintain order, and clean at the right level.

3.1.5 Phase 5: Implementation of the Shitsuke phase (sustain)

This phase is intangible and cannot be measured, but it resides in the mindset and commitment of individuals. The creation of a culture of good workplace habits is achieved through leading by example. It is also essential for management to be committed to these activities, as implementing the 5S methodology requires time, and without adequate support, workers may eventually abandon the practices.

To sustain the methodology, periodic monitoring will be conducted through internal audits to ensure compliance with the actions implemented thus far.

3.2 Implementation of SMED

The application of the SMED tool at the company was driven by an analysis of efficiency losses in production equipment, as these were not being utilized to their full capacity. The identified causes of efficiency losses include:

- Losses due to scheduled stops.
- Losses due to breakdowns.
- Losses from setup times, changeovers, and adjustments.
- Losses during start-ups.
- Losses due to minor stoppages and interruptions.
- Losses from reduced speed.

- Losses from defects and rework.
- Other types of losses, such as lack of personnel, material shortages, cleaning, and inspections, waiting for instructions, and quality approvals.

The company focused its efforts on reducing losses caused by setup times, as ICFC's goal is to adapt to market demand for smaller quantities of a greater variety of products, with shorter delivery times and competitive costs.

To meet these objectives, the company needs flexible production and must reduce costs. Currently, the factory's production system relies on two types of planning: long-term planning for forecasted demands and short-term planning for last-minute demands.

Every day, a production list is sent to the plant, detailing what needs to be manufactured while considering changes in product families, as the factory produces a wide variety of products in different formats and flavors.

Given this complex scenario, the SMED technique has been progressively implemented across ICFC's production lines. As a trial, it was first introduced on the VENTURA, CONES, EXTRUSION 3, and POLO 14 lines. Once the tool and system's efficiency were confirmed, its application was extended to the GRAM 3 and EXTRUSION 4 lines.

The stages of implementing the SMED technique in the EXTRUSION 4 and GRAM 3 production lines are described below:

3.2.1 Stage 1: Selection of changeover type

The following steps are carried out:

- Step 1: Study the historical records of product changeovers for each line.
- Step 2: Create a list of changeover elements.
- Step 3: Group the changeover elements by product or product family.
- Step 4: Record the times for each changeover.
- Step 5: Record the frequencies with which the changes are made.
- Step 6: Organize the time and frequency data into a Pareto chart.

The above steps are applied, resulting in Pareto charts for the GRAM 3 and EXTRUSION 4 lines (see **Figure 7**).

3.2.2 Stage 2: Analysis of the initial situation

Data regarding the initial state of the process must be collected:

- Description of the changeover process.
- Personnel involved.
- Date of execution.

CHANGE ELEMENTS										
	cleaning line-additions	nozzle - install additions	harlequin	second CLM	change cans - drag mix					
						Before	After	n° of changes	average time	freq x time
Product Family 1	x					45	23	54	58,2	3145
Product Family 2	x	x	x	x		120	55	13	130,8	1700
Product Family 3					x	10	0	89	17,8	1585
Product Family 4	x	x				60	33	9	72,8	1070
Product Family 5	x	x	x			90	55	3	106,7	655
Product Family 6	x	x		x		120	55	11	97,3	320

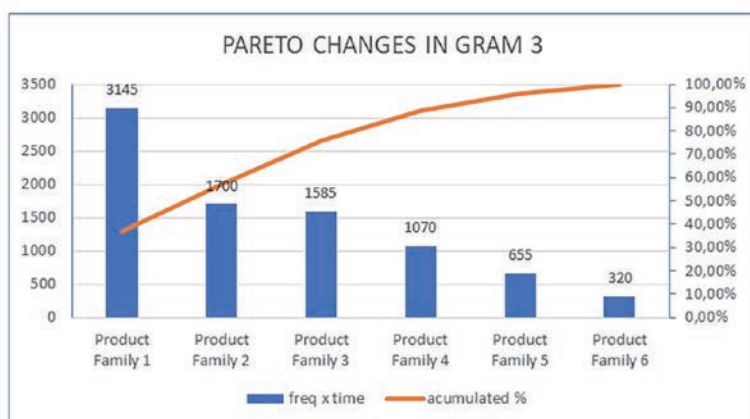


Figure 7.
Pareto chart for the GRAM 3 line. Source: Information provided by the company.

- Sequence and description of operations.
- Time taken for each operation and cumulative time.
- Observations (comments, improvement ideas, etc.).

3.2.3 Stage 3: Separation of internal and external operations

A table is created listing the various operations required for a specific changeover, including the operation times and cumulative time. Each operation is then categorized as either internal or external. Subsequently, a task distribution is prepared among the operators involved in the changeover process, which will be detailed in the chart (see **Figure 8**).

3.2.4 Stage 4: Converting internal operations into external operations

The goals of this stage are to minimize the impact of internal operations on the total changeover time and to execute only the strictly necessary operations (removal and placement of tools) during the machine downtime.

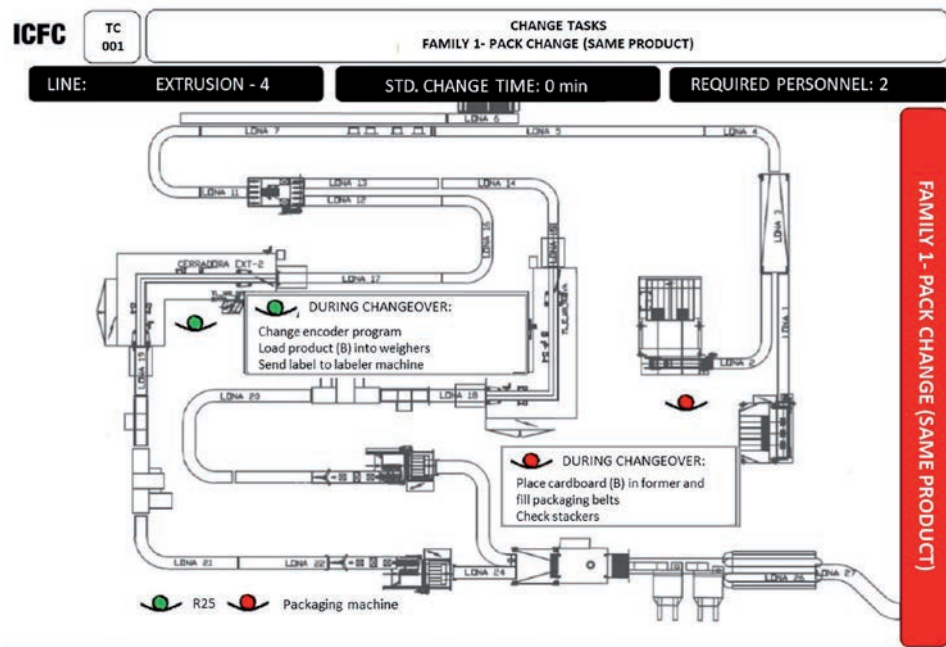


Figure 8.
Task distribution for pack change in family 1 of the extrusion 4 line. Source: Information provided by the company.

To implement this, the following steps will be followed:

1. *Prioritize internal operations* by reviewing the Pareto chart and corresponding times.
2. *Analyze the reasons why the operation is classified as internal.*

Internal operations include tasks such as disassembly, cleaning of machine components, addressing issues that need repair, assembling parts, starting up the machine or installation, adjustments, and testing of the first pieces.

For each internal operation, the root cause must be identified to define improvement alternatives in the next step that can convert these operations into external ones or even eliminate them altogether.

3. *Identify alternatives to convert internal operations into external operations*

Depending on the root causes determined in the previous step, solutions can be of several types:

- Performing preliminary preparations as external operations to replace internal ones.
- Standardizing the functionality of operations.
- Managing and controlling incidents.

Brainstorming focused on the identified root cause is recommended for generating solutions.

4. Select the most suitable solutions

Choose the solutions that best align with the selection criteria defined by the work team. Some selection criteria may include reduction of machine downtime, impact on flexibility and stock reduction, labour time savings, required investment, and necessary execution timeline.

5. Develop and execute the action plan

To implement the chosen solutions, an action plan must be developed:

- Assign qualified internal personnel responsible for the planned actions.
- Select competent suppliers.
- Define realistic execution timelines.
- Closely monitor the progress of the actions.

3.2.5 Stage 5: Improvement of internal and external operations

It is necessary to improve infrastructure, resources, and current methods. Meetings and planning sessions will be held to analyze the checklists for each changeover.

In this practical case:

- GRAM 3: A steel pipe network was installed from the CLM to the filler machine.
- EXTRUSION 4: A method needs to be developed to switch from two to four colors in the basin, as significant time is spent assembling and disassembling due to the difficulty of working in a confined space.

3.2.6 Stage 6: Standardization of changeover operations

From this point forward, after the execution of the previous stages:

- Gather information on the type of changeover to be performed and the product family it belongs to.
- Hold a pre-changeover meeting with the involved parties to review the checklists and finalize preparations for all the elements and equipment necessary for the change. By the end of this meeting, all participants should know their assigned tasks and the timing of their execution.
- Execute the changeover.
- Conduct a post-changeover meeting to document the total changeover time and the resulting waste, both at the end of Product A and during the start-up of Product B.

- Record incidents.
- Transfer the results, including changeover time and total waste, to graphical templates.
- Monitor all collected data.

Conclusion on the Implementation of SMED in EXTRUSION 4 and GRAM 3:
EXTRUSION 4:

- Defined the three main changeover families.
- Conducted changeovers for the first two families with teams across three shifts.
- Provided training for all three shifts.
- Installed the SMED panel with indicators for the 3 families and data collection sheets for incidents.

GRAM 3:

- Defined the three main changeover families.
- Recorded the first family.
- Provided training for all three shifts.
- Implemented actions to convert internal operations into external ones, such as modifying the clamp on GRAM 3 to reduce nozzle changeover time by 20 minutes.

Pending tasks for both lines:

- Implement pre- and post-changeover meetings.
- Monitor changeovers.
- Conduct deviation analyses using SCRA's.
- Track waste evolution and monitor waste standards.
- For GRAM 3 install the SMED panel (see **Figure 9**), record the two remaining main product families, and establish the sequence of operations.

3.3 Implementation of TPM: OPL (one point lesson)

In the area of total productive maintenance (TPM), one point lessons (OPLs) have been developed as a tool to standardize autonomous maintenance in factories [7, 17]. These OPLs can also be extended to other departments within the company, wherever



Figure 9.
Example of a panel in the EXTRUSION 4 line. Source: Photograph taken at the company.

there is a need to standardize a task, share a modification or improvement, communicate problems, or develop employee skills.

OPLs are classified into three types:

1. *Basic knowledge.* These OPLs address knowledge gaps in certain operations, ensuring efficient task execution and improved safety. Based on the “know-how” method, examples include maintenance activities such as changing filters, minor repairs, function adjustments of the machine, cleaning and inspections, and lubrication of parts.
2. *Problem examples.* These OPLs present real cases of failures, defects, or errors and provide guidelines for identifying, analyzing, and preventing their recurrence.
3. *Improvement examples.* These OPLs outline the steps taken by an improvement team to implement a specific enhancement.

A series of OPLs in ICFC have been developed specifically for EXTRUSION 4 production line, one of the most critical in the factory.

a. Basic Knowledge OPL examples:

- An OPL describing the adjustment and regulation of the parameters for the cream dispenser, cutter, and stick placer. It outlines the components and fixings, along with instructions on how to replace the cutter thread and stop the stick placer’s functions.
- An OPL explaining the start-up process of the labelling machine, including roll and label replacement. Text instructions clearly detail the start-up process, while diagrams illustrate the positions of the ink and label rolls for proper placement (see **Figure 10**).



OPL 4.4

**EXTRUSION 4
LABELER**

Problem solving ☐

Basic knowledge ☒

SECURITY MEASURES



RISKS





OBJECTIVE: describe the start-up of the Labeler, roll and label change





4.1 Connect the labeler (A) and reader (B) if necessary.

4.2 Connect the air

4.3 Press "POWER" and press the "ON LINE" button; "ONLINE" will appear on the screen

4.4 Press the GREEN button on the control panel behind it (depending on the labeler)

4.5 Pass the ink roll and label according to the picture.

4.6 Send the label from Integra and check (OPL 2.21).

4.7 Adjust the photocell to detect the product.

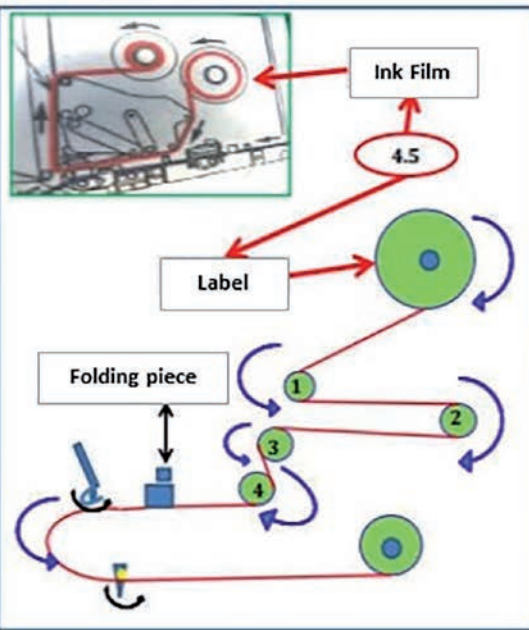






Figure 10.
OPL for Labelling Machine Operation. Source: Information from ICFC.

b. Problem Example OPLs:

- An OPL detailing how to resolve jams in the die cutter. It includes images of the control computer for this tool and explains the procedure for increasing the machine's power in the event of a jam. Normally, the die cutter operates at low power to avoid damage if it encounters foreign metallic objects.
- OPLs for addressing machine stoppages caused by unknown factors. These OPLs describe the actions to take if such situations occur.

4. Results

After implementing the improvement actions described above, several lean audits were conducted in the areas where the selected tools were applied.

To measure the general objective of continuous improvement with the lean system, management equipment was established, and together with the production manager, a set of indicators that would allow the measurement of the defined secondary objectives.

A set of KPIs (key performance indicators) was defined, which were disaggregated into different OEE indicators, a sample of which is described below:

$$\text{Machinery reliability (\%)} = \frac{\text{machinery breakdowns time}}{\text{machinery total production time}} * 100 \quad (1)$$

$$\text{Stop time (\%)} = \frac{(\text{microstops} + \text{stops}) \text{ time}}{\text{total production time}} * 100 \quad (2)$$

$$\text{Quality (\%)} = \frac{\text{Total production} - \text{deficient production (kg)}}{\text{total production quantity (kg)}} * 100 \quad (3)$$

$$\text{Visual management (\%)} = \frac{\text{number of (tools, materials) in place}}{\text{Total (tools, materials) checked}} * 100 \quad (4)$$

The necessary data for calculating the OEE indicators are obtained directly from the daily work performed by the workers, both before and after the application of the lean techniques previously analyzed. The results obtained for the OEE indicators described are (see **Table 2**).

The benefits achieved with the 5S tool are reflected in the attitude of the workers who participated in the project, finally attaining a tidy, organized and clean workplace, facilitating the development of their daily tasks, results reached after the application of the four phases (Seiri, Seiton, Seiso, and Seiketsu). The fifth phase (Shitsuke) has raised awareness among the staff and workers to continue working on cleaning and order tasks after the 5S tool implementation.

Indicators*	Before the project (%)	After the project (%)
Quality	63	76
Visual management	56	78
Cleanliness	55	85
Machinery reliability	65	92
Stop time	38	16

*Note that the percentages indicated are the average of the indicators calculated for the areas analyzed in the project.

Table 2.
Comparison between the initial situation and the improvements performed.

Another aspect to highlight about the results of the 5S is the orderliness achieved in the different work areas, which has facilitated the reduction of time lost by workers in searching for tools or determining where to place tools and accessories, thereby preventing accidents.

Finally, it should be noted that the productivity of the production lines was improved through the monitoring of different variables (see OEE indicators in **Table 2**) on the production floor: waste management from production lines and reduction of defective products, minimized risk of cross-contamination with allergens, detection of imperfections, tool wear, reduced resolution times for repetitive problems, etc.

In this sense, it should be highlighted that the results shown in **Table 2**, regarding different OEE indicators, show a general improvement in each of them: quality ($\Delta 13\%$), visual management ($\Delta 22\%$), cleanliness ($\Delta 30\%$), machinery reliability ($\Delta 27\%$), and stop time ($\nabla 22\%$), although all the areas studied have not improved in the same proportion. On the whole, the company is satisfied with the implementation of the 5S, hoping that it will allow continuous improvement in the coming years.

The implementation of the SMED tool on ICFC's production lines is the lean technique that yielded the most significant results. Its application on two previous production lines led to a reduction of over 40% in pack changeover times, a success that has now been sustained during ongoing operations. These excellent results enabled the subsequent expansion of this tool to GRAM 3 and EXTRUSION 4 lines, with improvements in a set of operations and product families, as explained in stages 4-5-6 of the SMED tool:

As can be seen in **Table 3**, the application of SMED in several operations on GRAM 3 and EXTRUSION 4 lines (and their product families) has considerably increased the production times of these two production lines. These results were achieved after

Production line	Product families	Actions	Time improvement (%)
GRAM 3	1	Pack change	82
	2	Cleaning chocolate pond	59
	3	Drag-mix, chocolate drag	50
EXTRUSION 4	1	Line cleaning	38
	2	Nozzle change	45
	3B	Can change	83

Table 3.
SMED technique results in production lines GRAM-3 and EXTRUSION-4.

a detailed study of machine stops (microstops, setup, and breakdown times) that generated a large amount of product loss and high non-productive machine times.

Finally, the TPM tool was consolidated in the development of a set of OPLs that have helped operators to reduce machine stop times due to failures, errors or defects, or lack of machine knowledge (see **Table 2**).

5. Conclusions

This study presents the application of several lean manufacturing techniques in one of the leading Spanish ice cream companies. Within the framework of productivity enhancement and organizational change, the deployment of the 5S, SMED, and TPM techniques engaged all personnel in their implementation. These efforts achieved cleaner and more organized workspaces, reduced defective products, early fault detection, improved waste management, faster resolution of machinery issues (wear, breakdowns, setup times, downtimes, etc.), ultimately resulting in better working conditions on the factory floor and enhanced product quality.

All these achieved benefits by applying the lean tools should be the most appropriate to the situation of each food industry and implementing the tools according to the associated methodology, without skipping the defined stages and adapting them to the current state of the companies.

The results obtained in both production and management areas are the best example of how the application of lean techniques in food industries becomes a key point to increase efficiency in this kind of companies and, therefore, their competitiveness. To do this, food companies, following the example of ICFC, can implement lean projects that allow them to achieve:

- Greater efficiency of production lines (reducing defective production and idle machine times).
- Greater order and cleanliness in this type of company, reducing pollution and/or health problems in their daily operation.
- Management team and workers involved in the continuous improvement of the company.

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Chapter 5

Maintenance Management Support for System Reliability and Sustainable Optimisation

Věra Pelantová

Abstract

This chapter of the book is a guide to modern maintenance management and its sustainable optimisation. It seeks to help company employees in the selection and implementation of effective strategic maintenance planning and management. It emphasises a proactive approach and the connection of maintenance with other aspects of business management. Readers will find here the connection of quality with maintenance, complex productive maintenance, and especially with the new issue of sustainability. The chapter offers practical recommendations that lead to cost reduction, process streamlining, and increased system reliability, all while addressing environmental and social aspects. It is based on solving practical problems in maintenance planning and management within contemporary organisations. It uses an appropriate methodological basis to support competent decision-making and creative management of maintenance requirements. The goal is to create a tool to support maintenance planning and control that contributes to the long-term sustainability of the organisation.

Keywords: planning and quality control, new conditions, optimisation, maintenance, organisation, sustainability, management

1. Introduction

Maintenance in organisations is now trying to cope with digitalisation and Industry 4.0. At the same time, it is dealing with relationships with other departments, which are not always positive. It is faced with a number of nonconformities. At the same time, however, it has a fundamental task in the form of ensuring the functioning of all production facilities so that production can fulfill orders. Maintenance management should handle the issues of planning and management, including strategy. This is a demanding discipline, which is now complemented by the requirement to include sustainability. This entire complex must be optimised not only because of costs, but especially due to the change in the external context, which is progressing very quickly. The following article tries to help employees of organisations methodically.

2. Characteristics of the state economy

The economy of several countries is in a difficult situation. This observation applies to the Czech Republic, considering the international context. Gross domestic product is strengthening slightly, and inflation is falling. The labor market features low unemployment, with pressure to increase incomes, while the qualification level of the population is stagnating. Gross public debt is growing slightly, and interest rates are rising. The average gross wage in the Czech Republic is increasing, but there is also a growing fear of job dismissals in companies within the country. Mortality rates are rising, and the population in Europe is aging. The state of the essential environment can be characterised as follows: The geopolitical situation is unstable, exchange rates are fluctuating, and banks are imposing higher interest rates. Customer–supply chains are unstable and unreliable. Organisations are investing less, and European organisations are burdened by legislative restrictions that weaken their global competitiveness. Asia, particularly China and India, is gaining greater economic and political influence. Climate change primarily impacts heating, agriculture, and logistics. Prices of metals, other commodities, and services are rising worldwide. Emission allowances represent a tax burden for many countries. Decisions made by the United States are increasing tariffs and destabilising the market. The war in Ukraine has led to changes in supply routes and, at times, markets from a logistical perspective. Trade and political alliances are shifting. The importance of artificial intelligence is growing, but its development is not sufficiently regulated. Deadly diseases are spreading. Climate change is causing an increase in airborne dust, higher humidity in Central Europe, and a scarcity of groundwater. Additionally, some organisations disregard basic safety rules and technological procedures, employ minors, and fail to comply with environmental regulations.

3. Strategy and other concepts

A strategy was originally conceived in economics as the long-term planning of an organisation or state for a period of 10 years or more [1–3]. However, due to changes in the essential environment and market dynamics, this forecast period must now be shortened. The budgets of organisations are usually set for 1 year in advance in accordance with accounting legislation. Banks also now lend money on shorter repayment schedules. Technological development has accelerated significantly. The depreciation period of equipment in the Czech Republic is 4 years, but for the information technology sector, this is considered a borderline period. Crises often come unexpectedly. Therefore, a strategy can realistically be set, keeping this in mind, for a period of 1 to 3 years.

A maintenance strategy can be defined as: ‘a set of measures to achieve the required operational performance with optimal use of resources’. According to the author’s findings, the key performance indicators (KPI) method is commonly used in organisations. The maintenance strategy must be in accordance with the strategy of the organisation as a whole [1–3].

The term ‘optimal’ means ‘the best state under given conditions’ in Latin. Maintenance, not only in the Czech Republic, is optimised according to the failure rate of the equipment, using common mathematical models. Furthermore,

a sensitivity analysis is performed to determine the influence of the model's features on a specific result. The limit value of the feature is usually now the minimum cost of operating the equipment [4].

Maintainability, or renewability, is defined according to the book [2] as: the ability of a product under given conditions of use to be maintained in a state or to be restored to a state in which it can perform the required function, if maintenance is carried out under given conditions and specified procedures and means are used.

Sustainability, or sustainable development, is understood as: the ability to maintain ecological balance and to leave raw material resources for future generations. According to the European Union regulation [5], these are events that affect the environment (CO₂, biodiversity, waste management, extraction of raw materials, emissions), the social area (compliance with occupational safety and health protection, human rights, working conditions), and corporate governance (compliance with legislative regulations and contracts). Overall, sustainability risks are integrated. This category also includes strengthening street and commercial safety, avoiding unnecessary bureaucracy, reducing energy consumption, and addressing the pressure to limit nuclear energy production, coal, and gas extraction.

4. Concept of maintenance planning

According to publications, the importance of maintenance in organisations is increasing due to tied-up capital in machines and their automation [6], but it is still not sufficient, according to [7]. This relates to the understanding of maintenance as an investment opportunity, not as a cost. Maintenance planning is understood as complex; therefore, it is considered a problem, for example, according to [8]. Article [9] perceives it as a critical business function, so maintenance planning is based only on the economic and technical aspects of the facility and organisation. The study [10] draws attention to the need for effective operation of equipment in organisations, and publication [11] also emphasises ensuring the operation and safety of facilities through a maintenance strategy. According to study [12], the reliability of the facility should be taken as the basis for determining its maintenance strategy. Organisational management tools are essential for energy optimisation, according to [13]. Support for renewable sources is described in [14]. In addition, a transformation into an 'ecologically friendly production model' is underway, which is already as important as digital transformation, according to article [15]. According to the findings of [16], omitting maintenance work extends the production time by more than 20% and the carbon footprint by more than 15%. However, in the study [17], the emission reduction is only 6.5%, but the safety and equality indices have increased. On the other hand, maintenance costs have increased by more than 1%. Article [18] reports a reduction in emissions of up to 26%. Sustainability is considered from the point of view of reliability, that is, the ability to keep an object in working condition, as stated in publications [19, 20], and not in a comprehensive system. Publications [18, 21–23] essentially state that most studies use only the minimisation of maintenance and production costs within the life cycle of objects for maintenance planning, which does not have a long-term result. The complexity of processes in organisations and the priority and maximisation of profit are mentioned in article [23], and they often want to introduce proactive maintenance but do not respect the 'commitments of

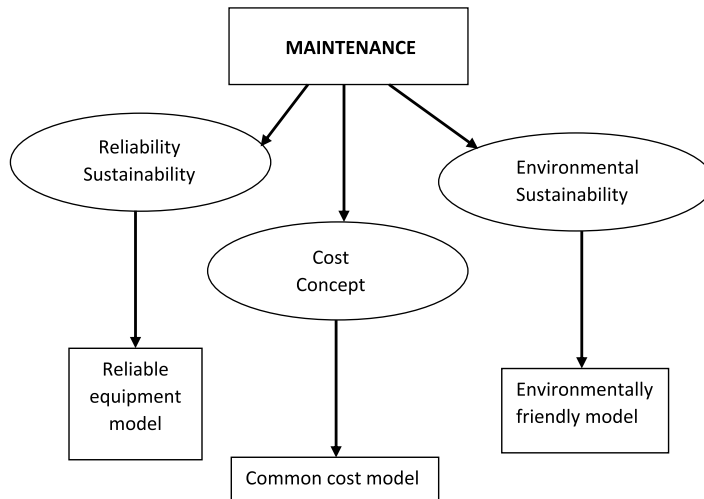


Figure 1.
Current basic concepts of maintenance development (figure is owned by the author).

sustainable development’. Sustainable production not only has an impact on economic aspects but also transforms the role of maintenance, according to articles [24, 25]. Maintenance is no longer a subsequent activity on a nonfunctioning object but an inherent service, according to article [26]. A different approach to the issue of optimisation was chosen by article [27], where the service is the management of production and energy consumption, and sustainability is conceived more towards reliability than towards the environment. Therefore, maintenance is at a crossroads in terms of connection with other aspects of sustainability. The current basic concept of maintenance development is approximated by **Figure 1**.

5. Solved tasks

The research addresses approaches to optimising maintenance planning and management in the context of sustainability using various methods. The comparison table of survey results in several mentioned publications, in relation to the issue of maintenance management support for system reliability and sustainable optimisation, is given in **Table 1**.

The proposal of a two-stage optimisation approach, which consists of preliminary planning using GAP and an advanced plan using a genetic algorithm, is presented in the study [8]. The study [20] presents a road maintenance decision-making model using an iterative genetic algorithm. It includes resource allocation and requirements for maintenance standards for road types. Article [9] presents a literature search and network analysis of decision-making models for maintenance in the context of sustainability. The study [10] presents basic maintenance strategies such as post-failure, preventive, predictive, and proactive, and optimisation methods that are based on reliability, monitor the condition of the object, and use artificial intelligence. The maintenance optimisation model is solved by multi-criteria optimisation: for telecommunications using reliability and sustainability using

Publication	A brief description of model	Advantages	Key problem
[7]	Decision model and environmental sustainability	Environmental aspects in maintenance	Missing environmental and social factors
[8]	GAP and genetic algorithm	Conflict reduction, production reality	Limitations by industry sector
[9]	Decision model and network analysis and literature review	Sustainability in the maintenance	Missing environmental and social factors
[11]	Digital transformation of historic building maintenance (speed, efficiency, quality)	Comprehensive optimisation of maintenance strategy and better decision-making	Lack of data for strategy
[12]	Reliability and sustainability model and swarm algorithms	Risks considered	Lack of data for strategy
[14]	Genetic algorithm, swarm algorithm, and artificial intelligence	Increase productivity, reduce maintenance costs	Missing method for strategy optimisation
[16]	Production scheduling, non-linear programming, and environmental aspects	Reduce carbon footprint	Lack of connection between production and maintenance plan and emission monitoring
[17]	Heuristic algorithm and sustainability	Improve the environment and social situation, and reduce the owner's costs per object	Planning maintenance of the facility itself
[18]	Decision model and quantification of environmental impacts and stakeholders	Resource allocation	Conflicting criteria (cost, condition, safety)
[19]	Reliability indicators	Increase productivity, reduce maintenance costs	Human maintenance errors, no plans
[20]	Decision model and genetic algorithm – maintenance approach	Preventive maintenance and resource allocation	Planning maintenance of the facility itself
[22]	Decision model and genetic algorithm – environmental approach	Reduce environmental pollution, increase the number of jobs	Missing environmental and social factors
[23]	Literature review	Non-financial features in the long term	Unrealistic planning assumptions
[26]	Principles of circular economy and maintenance management	Environmental aspects in maintenance	Energy efficiency in maintenance
[27]	Swarm algorithm and Pareto analysis (including production and energy consumption)	Reduce energy consumption	Energy efficiency in maintenance
[28]	Decision model and fuzzy logic	Reduce human errors, change work procedures	Human maintenance errors
[31]	Supply chain characteristics and maintenance policy optimisation and sustainability	Reduce greenhouse gases	Maintenance process and the Industry 4.0

Table 1.
The comparison table of survey results in several mentioned publications regarding the issue of maintenance management support for system reliability and sustainable optimisation (table is owned by the author [1–38].

swarm in the study [12]; using genetic algorithms and artificial intelligence with swarm in article [14]; using reliability (depending on the failure rate and their number for each device) in the study [19]; using decision analysis and genetic algorithms, considering environmental sustainability in article [22]; for roads using decision analysis, taking into account stakeholders and their requirements and quantifying life cycle impacts in article [18]; using decision analysis and fuzzy analytics for a small electrical engineering company in the research [28]; and as a summary of the literature search in article [23]. The classification of methods for optimising energy consumption in relation to maintenance is described in article [13], similarly in [14]. At the operation level, it is solved by Operations Research for machines according to machining phases. The design of an optimisation tool using decision-making for sustainable road maintenance programs is described in the research [7] with respect to greenhouse gas emissions. The impact of climate change on optimal road maintenance is described in article [29]. The text [11] proposes a method for improving processes through the digital transformation of maintenance of a historical object. The basic features are speed, efficiency, and quality. Trends in maintenance planning and management with respect to Industry 4.0 are described in article [15]. It considers the economy, environment, and often neglected social aspects. The research [16] combines maintenance planning and production scheduling with respect to the environment into a model with nonlinear programming. The study [17] presents the optimisation of road maintenance planning with respect to sustainability, which is solved by a heuristic algorithm. Article [21] summarises the development of maintenance planning of buildings and their life cycles. A survey of maintenance policy, sustainable production, and health management in organisations using a literature search is presented in article [30]. A broader concept of maintenance optimisation in the supply chain and a proposal for a method for optimising a sustainable maintenance policy based on iterations are described in the text [31]. It concludes that companies often address energy consumption in connection with the main processes, but not so much in connection with the maintenance process. The benefits of incorporating modern technologies into maintenance planning and management are presented in article [24]. Similarly, article [26] applies the principles of the circular economy to maintenance planning and management. The study [25] provides a literature review of maintenance management optimisation analyses. It concludes that, in addition to the total productive maintenance (TPM) and lean production (LP) concepts, organisations use various digitally controlled models based on artificial intelligence and similar technologies. Article [27] presents a multi-criteria model of production and energy consumption efficiency based on the bee swarm algorithm and the Pareto analysis, especially for workshops. Article [32] presents a road condition assessment index based on the neural network and Markov chain models, which is more accurate. The text [33] optimises the sustainability index with respect to maintenance costs and time, emphasising the inclusion of environmental and social effects.

6. Solution benefits

The benefits of optimising strategic planning and maintenance management are evident in reducing interpersonal conflicts, achieving more realistic planning, and improving subsequent production performance, as confirmed by [8]. Article [9]

enriches maintenance planning models by addressing sustainability issues. The study [7] also incorporates environmental aspects into the maintenance program. Classic benefits, such as increased productivity and reduced maintenance costs, are described in publications [10, 14, 19, 29]. Articles [13] and [27] also highlight lower energy consumption, while article [32] mentions improved road conditions. The study [12] considers sustainability risks in a broader sense. The maintenance optimisation model should align with the business model of the organisation as stated in [6], and it improves road conditions while reducing emissions. A more comprehensive approach to optimising the maintenance strategy and its digitalisation provides decision support, according to article [11]. A comparison of optimisation methods using the genetic algorithm and the swarm method revealed that the swarm method is more accurate in terms of optimisation and solution time. The goal of research [16] is to reduce the carbon footprint. The study [17] presents a sustainability index that includes environmental impacts, social impacts, and owner costs. The study [20] identifies benefits in the introduction of preventive maintenance and resource allocation for repairs, which is relatively low compared to the findings in articles [18] and [21]. Article [22] addresses environmental pollution and job creation. Article [23], in agreement with the author of this chapter, emphasises that balancing economic features has a short-term effect and, de facto, undermines efforts to improve maintenance in the long term. The goal of maintenance planning development is to extend the life of maintained objects, further increase safety, and reduce energy consumption, because it is not solely about costs, according to article [24]. The reduction of human errors in production and maintenance has led to changes in environmental and organisational aspects, as well as a shift in workflow, according to [28]. Less downtime and higher reliability are the results of applying intelligent diagnostics and introducing predictive maintenance, as stated in study [25].

A comparison of maintenance methods brings the realisation that the prognostics and condition management is more suitable for sustainable maintenance than the original CBM method. It combines the life cycle management of an object and the analysis of its failure modes, according to [30]. The analogy with the solution to greenhouse gas emissions is presented in the text [31].

7. Problems supporting maintenance management optimisation

There are many problems surrounding strategic maintenance planning. The relationship between the impact of production planning and maintenance planning, as well as the impact of production interruptions on the maintenance process, is not addressed. It is also necessary to examine the characteristics of the constraints of individual economic sectors [8]. According to article [9], environmental and social factors are often not considered in maintenance planning, while economic and technical features are considered, as stated in [7]. It also points out the lack of data for strategic maintenance planning in organisations; similar issues are mentioned in [11, 12]. Sustainability quantification for maintenance is also not conducted. Definitions and suitable methods for optimising energy consumption at the system level are missing [13]. System boundaries are not specified. It is necessary to examine the connection between energy consumption optimisation and process features. Many maintenance optimisation models rely on a single optimisation criterion [6]. Digital

transformation is an inseparable component of the maintenance planning optimisation system, according to [15]. There is a smaller range of features and methods for optimising maintenance strategy [14], and their holistic aspects are not considered, as stated in [30]. Furthermore, it is necessary to assess the pros and cons of combining maintenance strategy optimisation methods. If the relationship between production planning, maintenance planning, and emissions is not understood, the performance of the organisation cannot be increased, according to the research [16]. Road maintenance planning is seen as a problem by the study [17]. The study [19] struggles with maintenance activity errors, lack of plans, and poor internet signal. The road network is usually not divided into several types, which makes its maintenance more difficult and expensive, according to the study [20]. According to articles [18] and [21], conflicting criteria of maintenance costs, conditions, and safety of buildings are often considered. The condition of the structure of the building is often based on a mere visual inspection, which can lead to erroneous conclusions.

According to articles [18] and [22], environmental sustainability must be paid attention to. Article [23] points out frequent unrealistic assumptions in connection with maintenance planning. The text [31] recommends addressing the relationship between Industry 4.0 and maintenance processes. It is necessary to change the approach from design to implementation to monitoring of the maintenance process in connection with changes in the external context, article [24] recommends. Article [26] recommends addressing regenerative management and energy efficiency in maintenance. Human error is common in production activities but also in maintenance, according to [28]. This publication also recommends focusing on the problems of predictive maintenance and exploring the relationships between organisational and environmental factors that influence planning and management in organisations. The study [25] sees problems in optimising maintenance management in the difficult connection of classical technology with digital systems, the lack of a suitable benchmarking method for maintenance, and the lack of suitable approaches to the maintenance of small- and medium-sized organisations. The text [33] recommends investigating the sustainability index of maintenance management in the environmental concept for organisations.

8. Assessment of knowledge about optimising maintenance management

The issue of optimising strategic planning and maintenance management in organisations appears to be complex and unexplored, as evidenced by the literature review conducted above. The lack of data on maintenance performed in organisations and the absence of indications for deepening managerial research are noted. In many studies, the optimisation criterion is either reducing maintenance costs or minimising the carbon footprint. Terminologically, there is a clear contradiction in the understanding of the concept of sustainability. It is conceived either from the perspective of reliability, as ensuring the functioning of the object, or from the environmental and social perspective.

A comprehensive concept of the issue of optimising sustainable maintenance planning is presented, for example, in article [24]. Understanding maintenance as an inherent service is, de facto, a new systemic concept in article [26]. Article [28] presents a consistent analysis of the workspace from an ergonomic and production-maintenance perspective and connects the issue of the emergence of discrepancies

with the absence of decision-making. The long-term goal of shifting maintenance management from a reactive, cost-oriented approach to a proactive, sustainable approach is confirmed, for example, by the study [25]. In contrast to this study, article [32] sees its proposed model as suitable for benchmarking optimal maintenance management, although it is not primarily based on environmental sustainability. The text [33] still builds on market globalisation, which is overcome by the influence of sociopolitical changes. Article [9] confirms the need for an innovative approach to optimising maintenance management in new market conditions and the fact that maintenance is at a crossroads.

According to the book [2] and the standard ČSN EN 13306 [34], maintenance is defined as: a combination of all technical, administrative, and managerial measures during the life cycle of an object, aimed at maintaining it in a state or restoring it to a state in which it can perform the required function.

From the point of view of equipment maintenance, the lifespan of the object and its failure-free operation are essential not only in the Czech Republic. This means considering whether the components will be repaired or not, whether they have two or more states, and in what working conditions they will be used. Organisational management often monitors maintenance costs, losses due to failures, and the probability of failures. The maintenance methodology reliability-centered maintenance is often applied. The determination of preventive measures is usually linked to the FMECA method. Maintenance management can also assess failure modes and their categories.

Of the types of maintenance, sometimes called maintenance strategies, the following are used: maintenance after failure, preventive maintenance, predictive maintenance, and proactive maintenance.

Based on the assessment of the state of the internal and external context of some small, medium, and large organisations in the Czech Republic, with respect to the standard ČSN EN ISO 9001 [35], across economic sectors and taking into account the literature search above and publications [2] and [36], the following practical problems of maintenance planning and management were identified:

- Very often, historical data on performed maintenance are missing, so trends cannot be determined.
- Data are not worked with in real time, so related facts are not recorded.
- Often, an appropriate strategy or method is not selected.
- Planning does not consider all key features of the maintenance process.
- Maintenance processes are a phenomenon of the organisation's management system.
- Very often, maintenance administration is in written or combined form; it is not digitised.
- Often, due to data transcriptions, errors and losses occur.
- Data are stored but not analysed.

- Managers have unrealistic expectations of the strategy.
- Some key spare parts have a delivery period of up to 1 year.
- Equipment is of varying complexity; not all parts are repairable or easy to dismantle.
- Maintenance warehouses are small in capacity.
- When planning is conducted, it is not unusual to plan for unlimited capacities.
- Production planning takes precedence over maintenance planning.
- Maintenance of some equipment requires the cooperation of a team of maintenance specialists.
- Balancing production with maintenance is a new concept.
- It is often the case that production works if equipment works and orders come in.
- Strategic planning does not fully consider the state of the external context of the organisation.

This area of maintenance planning also includes the following:

- The plan should limit maintenance interventions to the necessary ones, since approximately 70% are unnecessary. On the other hand, it is necessary to set up maintenance so that frequent downtimes due to unexpected equipment failures do not occur.
- Planning has economic benefits; in the case of maintenance, appropriate planning can reduce maintenance costs by approximately one-third (need to accelerate deliveries compared to the classic delivery time, loss of business confidence, extra work, substitution of materials, different price per piece of spare part, and so on).
- Postponing maintenance can even lead to a threat to the safety and health of employees.
- The size of the organisation, the number of employees, the number of devices, types and quantities of spare parts and materials, various data files from sensors and meters and their links and connections, all of which multiply the complexity of the organisation's planning and management system – in the overall sense and for maintenance.
- The problem is also the incorrect specification or the absence of suitable maintenance features.
- Another problem is the failure to actively adjust the target values of the features due to changes in the external context.

If the features of production and maintenance are coordinated, they affect costs, waste, and energy consumption. Spare parts must be of high quality to help maintain reliability. There are known examples from history of substituting a spare part with a cheap, low-quality part, which led to a safety incident. Expensive, but not so demanding in terms of safety, is the imbalance in the number of spare parts, which then take up space in the warehouse for many years. Of course, the relationship applies that if maintenance is optimised, it means fewer failures and, therefore, more stable production and higher quality production. In addition, the management systems of organisations are audited according to the standard ČSN EN ISO 9001 [35]. They are now asked about the maintenance of production equipment and appropriate maintenance planning, which is intended to ensure quality products. The identification and traceability of spare parts and auxiliary materials are also required.

9. Basic methods of strategic planning, management, and optimisation

The following text presents 17 methods for strategic planning and management [1–3, 37], which were assessed in terms of their suitability for maintenance management. However, an additional criterion was environmental sustainability. The strategy combines visionary goals and a schedule. It should be noted that maintenance strategies are missing among the frequently mentioned types of strategies (eg, personnel, financial, and so on). The following text is intended to fill this information gap.

The collected methods were assessed according to key emphasis, their characteristics, and the focus of the aspects on the characteristics of the organisation in the field of maintenance and sustainability: service life, reliability, type of maintenance, maintenance costs, environmental impact, waste management and recycling, raw material extraction, emissions, compliance with occupational safety, compliance with information security, compliance with human rights, compliance with legislation, energy consumption, corporate solutions within the country, and customer–supplier relations in the context of time, knowledge, and skills of maintenance employees.

Winterling's matrix emphasises the probability of risk and its effects. It is simpler and more general. It is suitable for crisis management when the matrix is drawn graphically. It can include aspects of environmental sustainability.

VRIO analysis evaluates the organisation's resources in terms of value, rareness, imitability, and organisation structure. It thus determines the security of processes for the object. Assessing the object in terms of its value is more difficult, as it does not include as many aspects of environmental sustainability.

SMART method solves the concretisation of goals in terms of being specific, measurable, achievable, realistic, and time-specific. It is simpler and more general. It can also include aspects of environmental sustainability.

SPACE analysis helps to form an idea of the strategy with respect to the criteria of environmental stability, attractiveness of the industry, competitive advantage, and financial strength. It is financially oriented, analytical, and graphical when the form of the area diagram is drawn. It does not include aspects of environmental sustainability.

The scenario technique is based on events of varying probabilities. It solves crisis situations for the organisation. It is analytical and very descriptive, and it can include aspects of environmental sustainability.

The PESTLE method examines exclusively the external context of the organisation. It assesses political, economic, social, technological, legal, and ecological aspects. It is simple, broad, and descriptive. It has several alternatives. It can be considered borderline.

The MOST analysis is used to construct a strategy. It contains the parts: mission, objectives, strategies, and tactics. It is sophisticated but quite general. However, it does not include aspects of environmental sustainability.

The Management by Objectives (MBO) method focuses on results; it does not address the method of setting and achieving goals. It is free, but it must be conducted by employees with the ability to work independently. Additionally, it can include aspects of environmental sustainability.

Porter's Five Forces analysis forecasts the situation in the industry regarding the price and quantity of the product. It is simple, economically focused, and offers the possibility of graphic output. However, it does not include aspects of environmental sustainability.

The BCG matrix (Boston) evaluates the product portfolio in the market, assessing market share, price, innovation, and advertising. It is simple, economically analytical, and graphical. However, it does not include aspects of environmental sustainability.

The Balanced Scorecard (BSC) method is intended for measuring the performance of an organisation and balancing goals. The following aspects are evaluated: finance, customers, process, and learning. It is simple, yet more complex and descriptive. However, it does not include aspects of environmental sustainability.

The Blue Ocean method is used to find noncompetitive markets. It assesses the following aspects: market sector, products, and marketing value innovations. It is descriptive and analytical. However, it does not include aspects of environmental sustainability.

GAP analysis determines the gap between the current state and the target state. It assesses the following aspects: market, safety, and legislation. It is simple and analytical. It may include aspects of environmental sustainability.

EFE and IFE matrices are analytical methods for evaluating the state of an organisation externally and internally. They focus on spatial organisation and market characteristics. They are analytical and computational but do not include aspects of environmental sustainability.

The KPI metric evaluates the main characteristics of processes and organisations. It includes aspects such as quality, efficiency, economy, performance, information services, and supplies. It is descriptive and semi-quantitative. It is often used in organisations, but it is not comprehensive with respect to sustainability. Therefore, it can be considered borderline.

The critical success factor (CSF) metric evaluates critical features of an organisation's success. It is analytical, descriptive, and used economically. Alternatively, its evaluation can be understood as Pareto analysis. It can be considered borderline.

Of these 17 methods of strategic planning and management, five methods can be used for the area of maintenance in relation to environmental sustainability. They are the Winterling matrix, the SMART method, the Scenario technique, the MBO method, and the GAP analysis. Borderline methods are KPI and CSF metrics, and the PESTLE method. A method of strategic planning and maintenance management designed exclusively for this area is not available, as confirmed, for example, by the book [2].

Method name	Determination	Type	Sustainability
Winterling's matrix	Risk probability and impacts – crisis management	Risk	Environmental
VRIO analysis	Assessment of the object in terms of exceptionality	Special	No
SMART method	Specification of goals	General	Environmental
SPACE analysis	Financial orientation – market environment	Business	No
The scenario technique	Crisis situations	Risk	Environmental
The PESTLE method	Specification of external context	General	Borderline
The MOST analysis	Strategy construction aid – general	General	No
The MBO method	Free focus on results, not procedures	General	Environmental
Porter's Five Forces analysis	Business situation of the industry	Business	No
The BCG matrix	Assessment of the product portfolio in the market	Business	No
The BSC method	Assessment of the organisation's performance	Business	No
The Blue Ocean method	Search for noncompetitive markets	Business	No
GAP analysis	Assessment of the difference between the current and target state of the organisation	Risk	Environmental
EFE matrix	Assessment of the spatial state of the organisation	Business	No
IFE matrix	Assessment of the spatial state of the organisation	Business	No
The KPI metric	Assessment of the characteristics of processes or the organisation	General	Borderline
The CSF metric	Assessment of critical features of the organisation's success	Risk	Borderline

Table 2.
The comparison table of methods of strategic planning and management in relation to maintenance management (table is owned by the author).

The comparison of methods of strategic planning and management with respect to maintenance management is presented in **Table 2**. The methods are not very comprehensive; economic, market-oriented features prevail. Organisations are not very accustomed to 'navigating' in strategy. However, the current state of the market directly encourages companies not to 'freeze' their strategic planning. Such an organisation then faces problems first in managing the external context and subsequently begins to consider the internal context.

If maintenance features are selected in a holistic sense, that is, including sustainability features, and the strategic planning method is also selected, it is necessary to choose an optimisation method [2, 4, 36–38]. The following range of methods is available here:

- Cost optimisation (business process management, Pareto analysis)
- Weight optimisation (Pair comparison, triangular method)

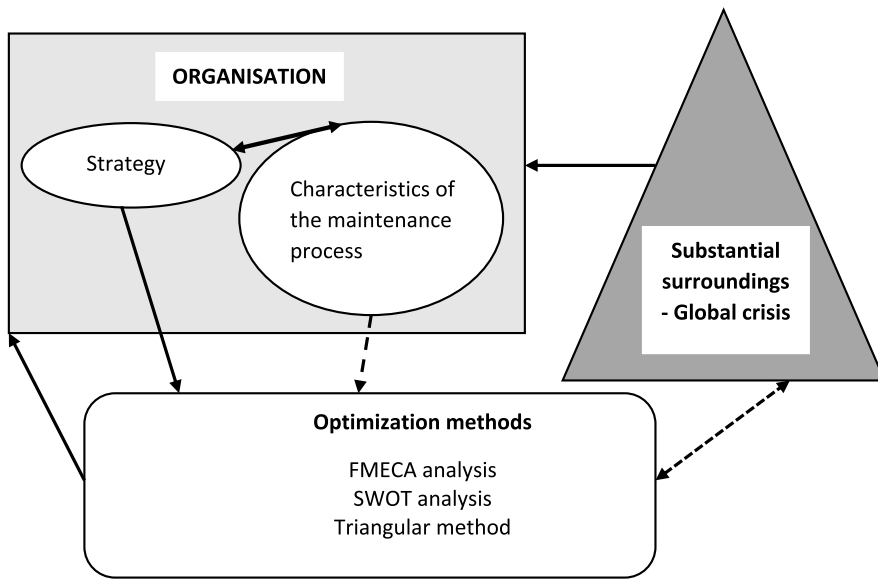


Figure 2.
Relations of optimisation methods to the strategy and maintenance of the organisation and to substantial surroundings (figure is owned by the author).

- Probability optimisation (probability trees, Monte Carlo method)
- Reduction optimisation (Lean method, 5S method)
- Risk optimisation (FMECA analysis)
- Complex optimisation (SWOT analysis, Six Sigma, TPM)
- Time optimisation (Gantt chart)
- Value optimisation (value stream mapping method)

The emphasis is to be put on management measures, such as the following:

The selected methods for the organisation need to be combined with each other. The selected optimisation method should correspond to the external context and the selected method of strategic planning and management, as shown in **Figure 2**. The actual optimisation then means determining critical features and values and subsequent analytical work to set appropriate strategic goals within a reasonable time horizon for a specific organisation.

10. Recommendations

The recommendations are intended for employees of organisations. They aim to help them reduce costs, streamline processes, increase system reliability, and consciously integrate sustainability into the organisation.

A small number of strategic maintenance objectives should be selected, specifically 1–3, depending on the size of the organisation.

Strategic maintenance objectives should include key areas of the organisation's strategy.

The organisation's management system should have only one maintenance process.

A proposal for a set of suitable maintenance process features is given above in the chapter.

Compliance with occupational safety rules, working conditions, and habits of employees must be regularly monitored, and deficiencies must be eliminated as they are a significant source of safety incidents.

For the optimisation of sustainability, the following aspects can be selected: the number of safety incidents (occupational accidents), the amount of municipal and hazardous waste per year, and, for maintenance itself, the ideal aspect is the mean time to failure.

Apply safety protection in the form of mechanical and electrical barriers, along with clear rules, to prevent injuries.

The aging workforce leads to a loss of maintenance knowledge in organisations, so it is advisable to train additional employees in a timely manner.

The organisation should know its critical parts of maintained equipment and their parameters, and maintain equipment passports.

Market changes can then be reflected managerially in activating the local market without incurring expensive duties for the purchase of spare parts.

The concept of maintenance as an investment opportunity is appropriate. Such equipment can be described as having relatively simple construction and maintenance activities. It can be connected to other equipment and software systems. Spare parts are renewable and capable of disassembly. An operation should be safe in terms of waste produced, the installation of safety features, and so on. The equipment is recyclable after the end of its working life.

11. Conclusion

Maintenance planning and management should be based on multiple areas and should not rely solely on the cost component.

The chapter includes suitable maintenance planning and management methods, especially for strategy, and their assessment from the perspective of sustainability. Optimisation methods and features of the maintenance process are also specified regarding the new conditions of the external context. The sustainability factor is gaining importance in this regard. In the publications assessed within the framework of the literature search, sustainability is understood either in terms of reliability or the environment. The author believes that these two concepts can be merged in the future.

After all, the concept of maintenance as a service entails not only the physical care of equipment but also ensuring legislative and environmental requirements are met.

This chapter does not address the problem of energy consumption, in which organisations, however, relate to the digitalisation and rationalisation of production and maintenance.

Future research should assess the practical suitability of the selected methods for organisational practice. Furthermore, it is necessary to examine the relationship between maintenance management and environmental sustainability, as well as its legislative anchoring in organisations.

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Chapter 6

Perspective Chapter: Selection of Appropriate Predictive Maintenance Techniques

Usman Mustafa Syed

Abstract

Predictive maintenance is a condition-based maintenance strategy that relies on the analysis of significant parameters associated with equipment degradation and failure. This chapter delves into the fundamentals of failure modes and their role in selecting appropriate predictive maintenance techniques. Failure modes can be categorized based on symptomatic effects such as physical, dynamic, electrical, temperature, and chemical/particle effects. Predictive maintenance techniques can then be selected based on this categorization. The chapter emphasizes the importance of understanding the equipment's functions and failure modes, which helps to develop a sound maintenance strategy. The concept of the P–F curve is introduced, which graphically represents the progression from potential failure to functional failure, underscoring the importance of early detection and intervention. Based on the categorization of the failure modes, key predictive maintenance techniques are discussed in this chapter. These include liquid penetrant testing (LPT), ultrasonic testing (UT) and analysis, X-ray radiography, vibration analysis, infrared (IR) thermography, and partial discharge (PD) testing. Each technique's methods, applications, advantages, and limitations are examined in detail. These techniques provide valuable insights into the health of industrial systems, enabling early fault detection and preventing catastrophic failures. The chapter concludes with a summary of predictive maintenance techniques and their applicability to various equipment categories. This summary can serve as a practical guide to selecting the appropriate predictive maintenance technique based on equipment type and failure mode categories.

Keywords: predictive maintenance, maintenance strategy, maintenance selection, failure modes, P–F curve, condition monitoring, condition-based maintenance

1. Introduction

Predictive maintenance is defined as condition-based maintenance carried out following a forecast derived from repeated analysis or known characteristics and evaluation of the significant parameters of the degradation of the item [1]. This definition clearly identifies the need for detecting, measuring, and analyzing “significant parameters” that are associated with the degradation and ultimate failure of

equipment. Identification of these parameters is done through tools such as reliability centered maintenance (RCM) and failure modes & effects analysis (FMEA). These tools help to link these parameters to failure modes, which can manifest in the failure of the equipment and system. Once these failure modes are identified and well understood, appropriate predictive maintenance techniques can be selected.

This chapter explains the basics of failure modes and how these can be used for the selection of applicable predictive maintenance techniques. A broad categorization of failure modes based on their symptomatic effects is provided in this chapter. These include physical effects, dynamic or energy-related effects, electrical effects, temperature effects, and chemical/particle effects. Selected predictive maintenance techniques are then explored for each symptom category. This involves a practical discussion on the methods, applications, advantages, and limitations of each technique.

2. Maintenance strategy development

Developing a sound maintenance strategy for any industrial asset, equipment, or system requires a good understanding of its workings, how it fails, and the impact of the failure. Not all assets work and fail in similar ways, and certainly, not all asset failures carry the same significance for the organization. The goal of a sound and practical maintenance strategy is to prevent asset failure or reduce the consequences of failure in a manner that is technically feasible and economically viable. Maintenance in the industrial context is defined as the “combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function” [1].

The selection of appropriate maintenance techniques is important for deriving value from the assets and their sustainable performance. The value that an asset provides is directly impacted by the failures it encounters and the impact of these failures on its intended function. This suggests that developing a maintenance strategy should focus on the function of the asset and the failures that may have an adverse impact on it. In order to achieve this, there are a few analytical tools and methods that can be used. Some of these include RCM, FMEA, and maintenance optimization.

RCM is a widely used tool for maintenance strategy development. In their seminal work for United Airlines, Nowlan and Heap [2] formalized the principles and methods of RCM. FMEA is a systematic method that breaks down an item into its constituent elements, which are then analyzed to understand how they can fail. FMEA is integrated within RCM and supports the identification of relevant failure modes. RCM then provides a logical way of making appropriate maintenance decisions. This level of analysis and decision-making ensures that relevant, applicable, and feasible maintenance techniques are selected.

In this section, we will briefly look into the fundamental concepts of functions and failure modes used within RCM and FMEA.

2.1 Functions and failure modes

Both RCM and FMEA aim to protect the function(s) of the equipment. The resulting strategies are thus aimed at safeguarding the utility of the equipment,

ensuring that the organization continues to derive value from its assets. It is important to note that an asset may be required to provide multiple functions. While one of these functions may be classified as the primary function, there will still be secondary functions that are inherently required for operating an asset.

For instance, consider a pump. The primary function of the pump is to transfer fluid from one point to another. However, there are secondary functions that are equally critical for the pump's operation. One such secondary function is to provide containment of the fluid during operation to avoid any leakages. This means that while the pump's main job is to move the fluid, it must also ensure that the fluid does not escape during the process, which could lead to operational inefficiencies or safety hazards. By focusing on both primary and secondary functions, RCM and FMEA ensure a comprehensive approach to maintenance that maximizes the utility and value of the organization's assets. This holistic view helps in identifying possible failure modes and implementing strategies to mitigate them, thereby enhancing the overall reliability and efficiency of the equipment.

RCM and FMEA require failures to be considered in the context of the function(s) they may impact. This leads to the concept of functional failure. It is defined as the inability of an asset to fulfill a function to a standard of performance that is acceptable to the user [3].

While some failures may lead to the complete inability of a function to be performed, there could also be failures consisting of equipment not meeting the required performance standards and requirements. For example, while a pump may still be pumping fluid, it may not be meeting the required fluid discharge pressure and/or flow, which means that the pump is only partially fulfilling its function. This concept is crucial in developing maintenance strategies that not only address complete failures but also partial failures that can affect the overall performance and reliability of the equipment.

A failure mode is the manner in which a failure occurs [4]. It can also be viewed as an event that is likely to cause a failure. It is important to note that a functional failure may be caused by more than one failure mode. Some examples of failure modes for a pump may include bearing seizure, a worn impeller, a damaged coupling due to fatigue, or an inlet valve jammed in a closed position. Moubray proposes proactively managing the failure modes before they occur [3]. This requires a good understanding of the failure modes and effective ways to detect, prevent, or avoid them. It is also important to note that not all failure modes corresponding to a functional failure may have the same probability of occurrence. This consideration is important to select the most obvious and most probable failure modes of a functional failure. This helps to develop a maintenance program that is not only effective but also economically viable.

To effectively manage failure modes, it is crucial to implement a systematic approach that identifies them and supports decision-making for the selection of appropriate maintenance techniques. These techniques could include regular inspections, condition monitoring, predictive maintenance, or pre-defined parts or component replacement. By discovering possible failure modes of equipment early, organizations can take preventive measures to mitigate risks and avoid costly downtime. Additionally, understanding the root causes of failure modes allows for the development of targeted maintenance strategies that address specific issues, thereby enhancing the reliability and performance of the equipment. It is also essential to continuously review and update the maintenance program based on the

latest data and insights to ensure its ongoing effectiveness. By doing so, organizations can achieve a balance between maintaining high operational efficiency and minimizing maintenance costs.

2.2 The P-F curve

Most equipment failures are characterized by some associated failure modes, which act as indications that a failure is about to take place. This indication is known as potential failure. It is an identifiable condition that indicates a functional failure is either about to occur or is in the process of occurring [3]. Potential failure acts as a precursor to the functional failure and can be used to detect it. This, in turn, provides an opportunity to proactively avoid a state where functional failure has already taken place. This concept is graphically represented as a P-F curve. Nowlan and Heap [2] introduced this concept in their pioneering work on RCM.

The P-F curve as depicted in **Figure 1** is a graphical representation that plots the progression of a potential failure to a functional failure over time. Potential failure occurs at a point in time when the failure can be detected. The P-F curve thus highlights the importance of early detection and intervention to prevent complete equipment failure. By identifying potential failures early, maintenance teams can schedule timely interventions, such as inspections, repairs, or replacements, to address the issue before it escalates into a functional failure. This proactive approach not only enhances the reliability and performance of the equipment but also reduces downtime and maintenance costs.

In essence, the P-F curve serves as a valuable tool for maintenance planning and decision-making. It underscores the significance of monitoring equipment conditions and implementing predictive maintenance strategies to ensure optimal asset performance. By understanding and utilizing the P-F curve, organizations can achieve a more efficient and effective maintenance program, ultimately leading to improved operational efficiency and reduced risk of unexpected failures.

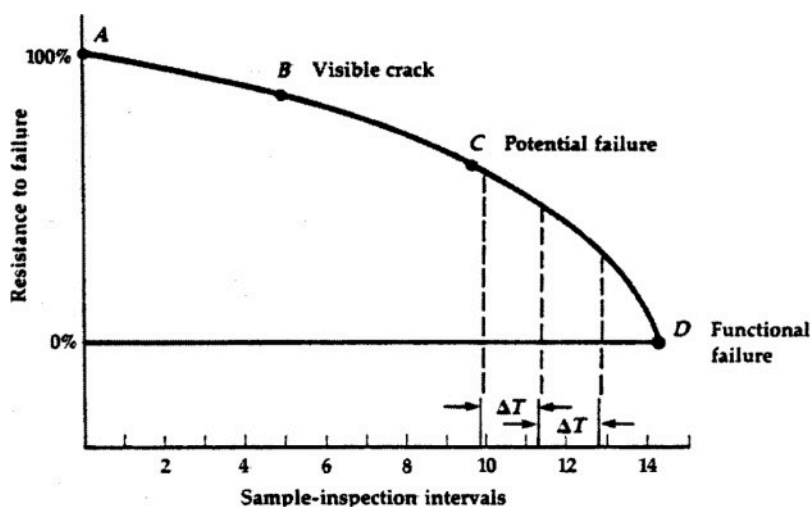


Figure 1.
The P-F curve [2].

Predictive maintenance is fundamentally about monitoring and analyzing the condition of equipment to ensure its optimal performance. The effectiveness of this approach hinges on the ability to accurately detect potential failure modes and make informed predictions about their progression over time. This proactive strategy not only helps in minimizing downtime and reducing maintenance costs but also extends the lifespan of the equipment, ensuring smooth and efficient operations.

3. Predictive maintenance technique selection

Across various industries, current practices include performing RCM, FMEA, and maintenance optimization. Although there are different variations of these tools available and adopted by organizations, their basic concepts remain the same. The primary focus is still on avoiding failures and managing failure modes in an effective manner.

For any predictive maintenance technique to be effective, it is important that the failure mode is characterized by symptoms or effects that are observable over a distinguishable time period. These symptoms can become evident in the form of physical, dynamic, electrical, chemical, temperature, or particle effects. **Table 1** provides an explanation of these symptoms:

Symptom effect	Symptom effect explanation
Physical effects	Changes in the physical appearance or structure of the equipment, e.g., cracks, fractures, physical wear and tear, or dimensional changes.
Dynamic or energy-related effects	Abnormal release of wave energy in the form of vibration or acoustic effects, e.g., high vibration, dynamic imbalance, mechanical looseness, wear/tear due to mechanical motion, etc.
Electrical effects	Changes in electrical parameters such as voltage, current, resistance, dielectric/insulation, conductivity, etc.
Temperature effects	Rise in temperature of the equipment, e.g., temperature increase due to mechanical motion, friction, loose electrical connections, insulation failure, etc.
Chemical/particle effects	Traceable or measurable changes in chemical elements or the release of discrete particles within the operating environment of the equipment, e.g., wear metals in lubricants, leaks, or corrosion.

Table 1.
Explanation of symptom effects.

Understanding the symptom effects is one of the basic steps to identify and select the appropriate predictive maintenance techniques. The following sections provide details about symptom effects and predictive maintenance techniques that can be used to detect these symptoms and predict their future failure state.

3.1 Physical effects

Monitoring physical effects such as cracks, fractures, erosion, corrosion, fatigue, and metal embrittlement can help predict issues that may lead to costly and sometimes dangerous failures. Such failure modes are commonly associated with mechanical static equipment, rotating equipment, plastics, and metallic structures.

These failures are often linked to the aging of equipment and structures, overload conditions, process chemistry, as well as natural elements. Mechanical joints and welds are also frequently subjected to these failures.

Some of the predictive maintenance techniques that can be used for symptoms with physical effects are as follows:

3.1.1 Liquid penetrant testing (LPT)

Liquid penetrant testing (LPT), also known as dye penetrant inspection (DPI), is a widely used non-destructive testing (NDT) method for identifying surface-breaking defects such as cracks, porosity, fatigue-induced defects, and fissures in non-porous materials.

- **Application:** Effective for inspecting metals, ceramics, and plastics in equipment and components such as turbine blades, engine parts, automotive transmissions, shafts, boilers, pipelines/piping, mechanically welded structures, and castings.
- **P–F interval:** Varies but is generally in the range of months to years, depending on the asset type and operational conditions. Activity is usually performed during periodically scheduled shutdowns of equipment and systems.
- **Procedure:** The process involves cleaning the material surface, applying a colored or fluorescent penetrant, allowing dwell time for the liquid to seep into defects, removing excess penetrant, and applying a developer to draw trapped penetrant back to the surface, revealing defects under visible or ultraviolet light.
- **Required skills:** Requires technicians skilled in surface preparation, the application of penetrants, and the interpretation of results under appropriate lighting conditions.
- **Advantages:** Cost-effective technique that is simple to use and can be applied to a variety of equipment, structures, and components to detect surface cracks and discontinuities [5].
- **Disadvantages:** Limited to the detection of surface defects and cannot be used on porous surfaces. Additionally, its effectiveness is subject to the expertise and skill of the technician performing the job. Furthermore, it lacks real-time monitoring capabilities, necessitating complementary techniques for comprehensive predictive maintenance strategies.

3.1.2 Electrostatic penetrant testing

Electrostatic penetrant testing, also known as electrostatic fluorescent penetrant testing, is similar to LPT, except that the penetrant is applied using an electrostatic spray technique. This method increases the sensitivity of the inspection and provides an increased P–F interval compared to LPT. Other advantages and limitations are the same as LPT.

3.1.3 Ultrasonic testing (UT)

Ultrasonic testing (UT) is an NDT method that uses high-frequency sound waves (typically 0.1–25 MHz) to detect internal and surface defects, measure material thickness, and assess structural integrity in metals, composites, and plastics.

- **Application:** Widely used to monitor cracks, corrosion, delamination, voids, and weld defects in equipment and systems such as airplane airframes, bridges, pipelines/piping, pressure vessels, boilers, heaters, turbines, compressors, and engine parts.
- **P–F interval:** Varies but can range from months to years, depending on defect propagation rates and material conditions. Regular UT inspections (e.g., quarterly) can detect flaws months before failure, particularly in high-stress components like turbine blades or pipelines.
- **Procedure:** Testing involves applying a couplant (gel or oil) to the surface, transmitting waves via a transducer, and analyzing signal data using specialized software. UT can be conducted using different methods, such as:
 - **Pulse echo technique:** Sound waves reflect off defects, with echoes analyzed for location and size. Measurement of the reflected pulse indicates the location and size of the defect.
 - **Transmission technique:** Measures the attenuation of waves passing through a material to identify discontinuities. A separate receiver detects sound waves passing through the material to identify discontinuities.
 - **Resonance technique:** Determines thickness by matching the material's resonance frequency. Variations in the natural frequency of the material are used to detect changes in material thickness or properties.
 - **Frequency modulation:** Detects changes in wave frequency caused by material flaws. Variations in ultrasonic frequency are used to determine stress or fatigue levels.
- **Required skills:** Requires specialized skills in equipment calibration, transducer selection, signal interpretation, and defect characterization.
- **Advantages:** UT provides high sensitivity to subsurface defects, precise defect sizing, real-time results, and portability. It is effective in detecting internal cracks and discontinuities in the material [5].
- **Disadvantages:** Requires highly skilled technicians to perform the job. It also offers limited effectiveness on coarse-grained materials. While UT excels in preventive inspections, it lacks continuous monitoring capabilities unless integrated with permanent transducers, which, in many applications, might be difficult.

3.1.4 X-ray radiography

X-ray radiography is another NDT method that uses ionizing radiation to inspect the internal structure of components, detecting defects such as cracks, voids, inclusions, porosity, and corrosion in metals, composites, and welded joints. It operates by passing high-energy X-rays through a component onto a detector or film, where variations in material density and thickness create an image that reveals the defects.

- **Application:** This technique can be used on steel structures, boilers, nuclear components, airplane airframes, pipelines/piping, pressure vessels, welded parts, castings, and components of rotating equipment such as turbines, compressors, pumps, and gearboxes.
- **P-F interval:** Depends on inspection frequency and defect propagation rates. For critical assets like pipelines or turbine rotors, periodic inspections (e.g., annually) can detect flaws months to years before failure, depending on the operational stress and material degradation mechanisms.
- **Procedure:** The process involves directing X-rays through the component under inspection onto a detector (film, digital sensor, or imaging plate). Variations in material thickness or density alter radiation absorption, creating an image that highlights defects. Modern systems use digital radiography (DR) or computed radiography (CR) for real-time or near-real-time imaging, enhanced by software for defect analysis.
- **Required skills:** Technicians must be skilled in radiation safety (often requiring regulatory certifications), equipment calibration, and image interpretation, with expertise in differentiating artifacts from genuine defects.
- **Advantages:** Unparalleled ability to visualize internal flaws, applicability to complex geometries, and permanent imaging records for trend analysis.
- **Disadvantages:** Involves significant safety risks (radiation exposure mandates strict protocols), high equipment and operational costs, time-consuming setup, and limited effectiveness on thick or highly attenuating materials (e.g., lead-heavy alloys). While invaluable for preventive inspections, its intermittent nature and safety constraints often make it complementary to real-time monitoring methods like ultrasonics or thermography in predictive maintenance programs.

3.2 Dynamic or energy-related effects

Monitoring of dynamic or motion energy effects is widely used for rotating equipment. These effects are usually associated with transient and fault conditions of rotating equipment and can provide detailed insights into their condition and health. Monitoring these effects typically involves measuring and analyzing the vibration and sound patterns of equipment and systems. This section looks into vibration analysis and ultrasonic analysis techniques as predictive maintenance tools.

3.2.1 Vibration analysis

Vibration analysis and monitoring are important predictive maintenance techniques used to assess the health of rotating and reciprocating machinery by detecting early signs of mechanical degradation and faults, such as imbalance, misalignment, bearing wear, gear defects, looseness, structural weaknesses, and resonance in rotating and reciprocating machinery. It is one of the most common predictive maintenance techniques.

According to Reyes-Picknell, “vibration analysis works on the principal that moving machinery will vibrate to some degree – more if it is in distress” [6]. By analyzing vibration signatures, maintenance teams can identify degradation early, optimize repair schedules, reduce unplanned downtime, and prevent catastrophic failures.

Vibration analysis is extensively used across industries for monitoring equipment such as turbines, pumps, motors, compressors, fans/blowers, and gearboxes. It is a fundamental predictive maintenance technique that, when properly implemented, can significantly enhance equipment reliability, extend asset lifespan, and reduce operational risks.

There are multiple methods of vibration analysis. Below is an overview of key vibration analysis methods, their applications, and operational considerations.

3.2.1.1 Broadband analysis:

Measures the overall vibration amplitude (RMS, peak) across a wide frequency range (e.g., 10 Hz–10 kHz). This analysis evaluates the overall vibration levels across a wide frequency range for general screening of machine health. It provides a quick overview of whether vibration is increasing but lacks detailed diagnostic capability. It is useful for routine inspections but requires further analysis if any abnormalities are detected.

- Application: Widely used in pumps, motors, and fans.
- P–F interval: Suitable for detecting advanced-stage faults; intervals range from weeks to months, depending on inspection frequency.
- Procedure: A single accelerometer collects data, which is processed by a hand-held meter or data collector.
- Required skills: Basic knowledge of vibration thresholds and sensor placement.
- Advantages: Simple, fast, and cost-effective for trend analysis.
- Disadvantages: Lacks specificity; cannot pinpoint the fault type or location.

3.2.1.2 Octave band analysis:

This method divides the vibration spectrum into frequency bands (e.g., one-third octave bands) to isolate and analyze frequency ranges linked to specific faults and machine components, e.g., gear mesh frequencies or structural resonance. It is useful

for identifying sources of vibration and separating different vibration contributions in complex systems.

- **Application:** Widely used on large rotating and reciprocating equipment, such as compressors, turbines, pumps, motors, and fans.
- **P–F interval:** Moderately early detection (months before failure).
- **Procedure:** Requires a spectrum analyzer to divide signals into bands.
- **Required skills:** Understanding of machinery frequency characteristics. Interpretation skills are necessary to correlate frequency bands with specific fault conditions.
- **Advantages:** This method balances simplicity with targeted analysis.
- **Disadvantages:** Limited resolution for high-frequency defects.

3.2.1.3 Constant bandwidth analysis:

In this method, the spectrum is split into equal frequency bands, improving the resolution for identifying narrowband frequency components such as bearing faults and gear meshing issues. It is valuable for high-precision machinery.

- **Application:** Ideal for gearbox or bearing fault detection.
- **P–F interval:** Early detection (months to years).
- **Procedure:** Fast Fourier Transform (FFT) analyzers with adjustable resolution.
- **Required skills:** Expertise in advanced spectral analysis and machinery dynamics.
- **Advantages:** High precision in identifying subtle defects.
- **Disadvantages:** Complex setup and data interpretation.

3.2.1.4 Time waveform analysis:

Time waveform analysis examines raw vibration signals over time to detect transient events. It is particularly useful for identifying intermittent faults such as pump cavitation impacts, rotor rubbing, or sudden load variations, and it requires expertise in waveform interpretation.

- **Application:** Suitable for pumps, compressors, and turbines.
- **P–F interval:** Variable, depending on event severity (weeks to months).

- Procedure: Oscilloscopes or advanced analyzers are used to capture time-domain data.
- Skill: Experience and ability required to interpret waveform patterns and transients.
- Advantages: Reveals short-duration anomalies that can be missed by the FFT.
- Disadvantages: Requires expensive hardware for high sampling rates and expertise.

3.2.1.5 Frequency analysis:

This widely used method employs FFT to convert vibration signals from the time-domain into the frequency domain to identify fault-specific peaks. This helps to capture specific faults such as imbalance, misalignment, bearing defects, and process upsets.

- Application: Very good for identifying faults in compressors, pumps, and turbines.
- P–F interval: Early to mid-stage fault detection (months).
- Procedure: FFT analyzers or software like MATLAB are used to process data.
- Skills: Deep knowledge of spectral peaks and machine-specific frequency signatures is required for accurate diagnosis.
- Advantages: Gold standard for fault diagnosis.
- Disadvantages: Limited applicability for non-periodic or random vibration events.

3.2.1.6 Peak value analysis:

This method tracks maximum instantaneous vibration peaks to detect transient events (e.g., blade passing in turbines, bearing faults). The highest vibration amplitude is measured within a given period to assess the severity of impacts or shocks.

- Application: Slow-speed rotating machines, turbines, pumps, and compressors.
- P–F interval: Short-term detection (days to weeks).
- Procedure: Peak-hold meters, or data collectors and software, are used to collect and analyze data.
- Skills: A good understanding of transient phenomena and machinery knowledge is required.
- Advantages: Effective for impact-related faults.

- Disadvantages: Susceptible to noise and false alarms. Peak Value Analysis is simple to implement; however, it does not provide detailed frequency information, making it best suited for initial screening rather than in-depth diagnosis.

3.2.1.7 Shock pulse monitoring (spm):

Specifically designed for rolling element bearing monitoring, this method detects high-frequency (30–40 kHz) shock pulses generated by rolling element bearing defects and lubrication issues.

- Application: Rolling element bearings.
- P–F interval: Early detection (6–12 months before failure).
- Procedure: Specialized SPM sensors and meters.
- Skills: Knowledge of bearing geometries and the ability to interpret shock pulse readings are required.
- Advantages: Highly sensitive to early-stage bearing faults.
- Disadvantages: Limited to rolling-element bearings; less effective on other components. Requires expensive, specialized sensors, and expertise.

3.2.1.8 Real-time continuous vibration monitoring:

Continuous monitoring using permanently installed sensors on critical assets has gained a lot of momentum over recent years. Vibration signals are continuously recorded and monitored to provide instant feedback on machine condition. Accelerometers, proximity probes, FFT analyzers, and sensors, along with specialized software, are used to gather and analyze high-volume data. Setting up robust baseline data trending is important to avoid false positives.

Continuous vibration monitoring, when combined with complementary techniques like thermography or oil analysis, forms a robust predictive maintenance strategy, extending asset life and reducing unplanned downtime.

- Application: Operation-critical machinery such as turbines, compressors, or paper mills, where immediate intervention is required.
- P–F interval: Enables immediate detection, shortening P–F intervals to days or weeks.
- Procedure: Data is streamed to SCADA or CBM software for live alerts.
- Skills: Strong proficiency in real-time systems and alarm configuration is required. Analysts should also be capable of analyzing and interpreting high volumes of data effectively.

- **Advantages:** Enables proactive intervention. A scalable solution, excellent for root cause analysis and long-term trend tracking.
- **Disadvantages:** High installation and infrastructure costs. It can also be impacted by lower data network capabilities.

3.2.2 Ultrasonic analysis

Ultrasonic analysis is a powerful condition monitoring technique used in predictive maintenance to detect high-frequency sounds (typically 20 kHz–1MHz) produced by mechanical or electrical anomalies. These high-frequency sound waves are typically beyond the human hearing range and provide early warning signs of faults, allowing maintenance teams to intervene before failures occur.

It is a versatile technique and can be applied in various industrial settings, including rotating machinery, electrical systems, steam traps, valves, hydraulic systems, and structural components. It can be used to detect mechanical faults, leaks, material degradation, and electrical issues. Ultrasonic analysis is also useful for detecting failures well before they might be identified by other technologies, such as vibration analysis or infrared thermography [7]. Ultrasonics can also be used to perform precision lubrication, which helps to avoid under- or over-lubrication, thereby preventing lubrication-related failures in rotating equipment.

Below is an overview of key ultrasonic analysis methods, their applications, and operational considerations.

3.2.2.1 Airborne ultrasonic testing:

This technique involves using an ultrasonic detector or sensor to capture airborne ultrasonic signals (20–100 kHz) emitted by leaks, arcing, or turbulence in systems such as compressed air lines, steam traps, or electrical enclosures.

- **Application:** Gas or vacuum leaks in pipelines, valves, and compressed air systems; electrical discharges (corona, arcing) in switchgear, transformers, and insulators; bearing lubrication issues or early-stage cavitation in pumps. It can also be used for performing effective and precise lubrication of bearings, which helps to avoid failures associated with under- or over-lubrication.
- **P–F interval:** Short (days to weeks) for leaks and electrical faults due to rapid progression.
- **Procedure:** The detector, usually parabolic microphones or ultrasonic probes, translates the high-frequency sounds into an audible range for human interpretation using headphones or digital analysis through specialized software.
- **Skills:** Training in ultrasonic detector operation and interpretation of sound patterns. Understanding of fluid dynamics, acoustics, and electrical discharge patterns is required.
- **Advantages:** Quick and non-intrusive method. Requires no contact with the machine or equipment.

- **Disadvantages:** Susceptible to ambient noise interference. This method is limited to surface-level or airborne anomalies and can be affected by background noise. Subject to the skill level and interpretation of the technician.

3.2.2.2 Structure-borne ultrasonic testing:

In this method, contact ultrasonic sensors are placed on the surface of machinery to detect high-frequency vibrations (30–40 kHz) generated by friction, impacts, or turbulent flow. This is commonly used for monitoring bearing lubrication, friction, mechanical wear, looseness, and pump cavitation.

- **Application:** Bearing defects, pumps, gearboxes, motors, conveyors, wind turbines, engines, and mechanical looseness in complex machinery structures. Optimization of bearing lubrication.
- **P–F interval:** Moderate (1–6 months) for mechanical defects, depending on operational stress.
- **Procedure:** Sensors, piezoelectric transducers, or accelerometers are mounted directly on machinery to capture high-frequency stress waves. Shock pulse or energy levels are measured and tracked over time.
- **Skills:** Knowledge of machine components, machinery dynamics, ultrasonic data interpretation, and trend analysis.
- **Advantages:** Early detection of issues (even before vibration analysis in some cases). Effective in harsh environments with high background noise.
- **Disadvantages:** Limited to mechanical components generating stress waves. Requires direct contact with the asset. Ultrasonic signal interpretation can be complex.

3.2.2.3 Ultrasonic time waveform analysis:

Time waveform analysis in ultrasonic monitoring involves capturing the raw ultrasonic signal over time to observe transient events, impact forces, and irregularities in the machinery. This method is particularly useful for detecting intermittent events that might not be as prominent in spectral analysis. The waveform provides direct insight into how a fault develops over time, such as repeated impacts from a defective bearing or gear tooth. It can be used for continuous condition monitoring.

- **Application:** Transient events like impacts (e.g., cavitation in pumps, rotor-stator rubs), bearing defects, gear wear, misalignment, mechanical impacts, looseness, lubrication issues, valve leaks, and early-stage crack formation in mechanical systems.
- **P–F interval:** Variable (weeks to months), depending on the severity of the event.

- Procedure: Capture raw ultrasonic signals in the time domain at high sampling rates (≥ 1 MHz) using piezoelectric ultrasonic sensors. Waveforms are then analyzed for amplitude spikes, periodicity, or any abnormal patterns by portable or permanently installed analyzers.
- Skills: Requires good expertise in interpreting transient signals and time-domain anomalies, along with their relation to mechanical faults.
- Advantages: Useful for early diagnosis of intermittent faults.
- Disadvantages: Data-intensive; requires advanced processing tools and experience in interpreting complex waveform patterns.

3.2.2.4 Ultrasonic spectral analysis:

Spectral analysis involves converting ultrasonic signals from the time domain into the frequency domain using FFT. This process helps in identifying characteristic frequencies associated with specific machine faults, making it a powerful tool for diagnosing developing defects. By analyzing frequency peaks and trends, maintenance teams can predict potential failures well in advance. This method can be applied for continuous condition monitoring of critical equipment and systems.

- Application: Bearing defects, gear wear, mechanical misalignment, mechanical unbalance, electrical arcing, and corona discharge in switchgears and power transformers. It can also be effective for thickness measurements and corrosion monitoring in pipes and tanks.
- P–F interval: Early detection (3–12 months) for progressive defects such as wear or corrosion.
- Procedure: Contact or airborne ultrasonic sensors are used to capture time-domain ultrasonic data, which is then converted into frequency spectra using FFT. Peaks are then matched to known fault frequencies (e.g., bearing pass or gear mesh frequencies).
- Skills: Expertise required in frequency analysis and fault signature identification. Knowledge of machinery dynamics.
- Advantages: Precise fault identification. Enables trend analysis.
- Disadvantages: High-frequency ultrasonic signals may be affected by machine operating conditions or signal interference. Requires specialized training and skills.

3.3 Electrical effects

Electrical equipment and systems are fundamental to modern industries. With a wide array of their applications, electrical equipment and systems constitute a sizable portion of the asset portfolio for any industrial organization. Thus, it becomes

imperative to deploy a robust predictive maintenance program for them. Most predictive maintenance techniques take advantage of capabilities to measure, monitor, and analyze changes in electrical parameters such as voltage, current, resistance, dielectric/insulation, conductivity, etc.

While there are many testing methods that are used as part of predictive maintenance programs for specific electrical equipment and systems, this section will focus on power factor testing, partial discharge, and motor current signature analysis. These three techniques are effective for assessing electrical and electromechanical asset health, enabling early fault detection and preventing catastrophic failures.

3.3.1 Power factor testing

Power factor testing is a non-destructive test that evaluates the insulation condition of electrical equipment by measuring the power loss in the insulation system. Theoretically, the insulation system under test is considered to have dielectric properties as exhibited by capacitors, i.e., zero power factor, hence no real power loss. However, all insulation systems have some power loss in the range of fractions of a percent to a few percent. Any deviation from this represents insulation deterioration. As insulation systems deteriorate, power factor increases [8]. This can also be used to indicate increased power loss, moisture ingress, contamination, or aging of the insulation.

- Application: Transformers, cables, circuit breakers, motors, electrical generators, and bushings.
- P-F interval: Long-term, months to years (1–5 years), depending on the rate of insulation degradation.
- Procedure: A specialized test set is used to apply test voltage to the equipment's insulation, and the power factor (ratio of resistive to capacitive current) is measured. Deviations from baseline values indicate insulation issues.
- Skills: Understanding of dielectric theory and AC circuits. Ability to analyze power factor trends and correlate them with insulation health. Experience with high-voltage testing equipment.
- Advantages: Provides an early assessment of electrical insulation health. Offers the ability to track trends over time.
- Disadvantages: Limited to insulation-related faults; cannot detect mechanical issues. Requires shutdown and de-energization of the equipment. Interpretation of results requires expertise.

3.3.2 Partial discharge (PD) testing

Partial discharge testing detects small electrical discharges occurring within insulation defects before complete insulation failure. Specialized sensors are used to capture high-frequency electrical pulses generated by partial discharges.

This helps to identify insulation voids, cracks, electrical teeing or contamination. Corona discharge and tracking in high-voltage equipment and systems can also be detected through PD testing. Electrical discharge activity is an early indicator of many electrical faults within rotating electrical equipment [9]. Most often, these are expensive and critical equipment, such as large motors and power generators.

PD testing is a valuable predictive maintenance technique, as PD activity often precedes insulation failure.

- Application: Cables, transformers, motors, electrical generators, and switchgears.
- P–F interval: Moderate; weeks to months, depending on defect severity and operating conditions.
- Procedure: PD can be detected using different methods depending on the type of electrical equipment being monitored. These methods may include:
 - Ultrasonic/acoustic testing for HV power transformers, transmission lines, and switchgears.
 - Ultraviolet (UV) cameras for HV power transformers, transmission lines, and switchgears,
 - Ultra-high frequency (UHF) detection for gas-insulated switchgears.
 - Electrical testing using coupling capacitors or high-frequency current transformers (HFCT) for motors, generators, transformers, cables, and distribution networks.
- Skills: Understanding of high-voltage insulation behavior and PD mechanisms. Proficiency in PD testing equipment operation and signal interpretation.
- Advantages: Detects incipient insulation defects at an early stage before complete breakdown. Also helps in pinpointing the defect location. Can be performed online (for some systems) using non-invasive sensors.
- Disadvantages: Requires specialized training and expertise for accurate diagnosis. High initial investment in PD monitoring equipment.

3.3.3 Motor current signature analysis (MCSA)

Electrical motors are the workhorses of modern industry. MCSA is a non-invasive electrical testing technique that analyzes the current signature of a motor to identify electrical and mechanical faults in the entire motor system. It can be used to proactively detect rotor bar defects, stator winding faults, bearing issues, misalignment, and pump cavitation. Using MCSA in conjunction with vibration analysis is estimated to detect and prevent 80% of motor failures [10].

- Application: Motors, electrical generators, pumps, fans, and compressors.
- P–F interval: Short to moderate (weeks to months), depending on the fault severity and operating condition of the equipment.
- Procedure: Clamp-on current sensors, power analyzers with spectral analysis capability, and MCSA software are used for data capture, processing, and analysis. By applying FFT to the motor's current signal, characteristic frequency components linked to specific faults (such as broken rotor bars, misalignment, or bearing issues) can be detected.
- Skills: Knowledge of electrical motor operation and fault frequency analysis. Proficiency in spectral analysis, signal interpretation, and differentiation between electrical and mechanical fault signatures.
- Advantages: Non-invasive; performed during the operation. Detects both electrical and mechanical faults.
- Disadvantages: Requires expertise in spectral interpretation. Sensitive to the load condition of the equipment. Limited effectiveness in variable frequency drive (VFD)-controlled motors and certain mechanical faults.

3.4 Temperature effects

Temperature is a fundamental measure in different industrial processes and a strong indicator of the condition of many equipment classes. Detecting or measuring the rise in temperature of the equipment can provide valuable insights about its condition. This temperature rise can be due to mechanical motion or friction in mechanical equipment, loose connections, or insulation failure in electrical equipment.

While the measurement of temperature as a process parameter is widely used in many industries, infrared thermography is the most utilized predictive maintenance technique for monitoring temperature effects.

3.4.1 Infrared (IR) thermography

Infrared (IR) thermography is a non-contact diagnostic technique that detects and visualizes temperature variations in equipment and systems. It works by capturing infrared radiation emitted by objects and converting it into a thermal image. Since most mechanical and electrical failures are preceded by abnormal heat patterns, IR thermography is an effective predictive maintenance tool for identifying potential faults before they lead to system failures. It can be used to detect a wide variety of faults and issues, such as overloaded electrical circuits, loose electrical connections, unbalanced electrical loads, bearing friction, mechanical misalignment, insulation gaps, moisture ingress in buildings, refractory lining degradation in boilers or kilns, blockages in pipelines, tank level monitoring, and heat exchanger inefficiencies. For IR thermography to be successful, it is recommended that baseline measurements be taken for the equipment under steady-state conditions. This serves as a reference for diagnostic and prognostic purposes.

- Application: Transformers, motors, electrical generators, switchgears, bearings, pumps, gears, buildings/structures, boilers, kilns, pipelines, tanks/vessels, hydraulic systems, and heat exchangers.
- P–F interval: Varies for equipment types.
 - Electrical equipment: Weeks to months,
 - Mechanical equipment: Months to years,
 - Buildings/structures, boilers, kilns: 2–5 years.
- Procedure: A thermal imaging camera is used to scan the target equipment. The thermal image is generated using software and analyzed to identify abnormal heat patterns, hot spots, or thermal anomalies. Comparison with baseline data or the equipment manufacturer's recommendations is done to better understand the anomalies and take corrective actions.
- Skills: Understanding of heat transfer principles, emissivity adjustments, and thermal pattern recognition. Expertise in correlating thermal anomalies with specific fault conditions and recommending corrective actions.
- Advantages: Non-contact, safe for inspecting live, high-voltage, or moving equipment. Ability to cover large areas or a large number of equipment quickly. Early fault detection in many cases.
- Disadvantages: Provides surface-level detection only; cannot detect subsurface issues. Detectability is based on the relationship between the depth and diameter of an anomaly across the equipment surveyed [11]. It is affected by ambient conditions and requires good expertise to interpret the results.

3.5 Chemical/particle effects

Many equipment types use fluids such as lubricants and coolants during their operation. There are several faults that may cause the release of chemicals and particles within these fluids, which can then be detected to ascertain the equipment's condition. Detecting changes in these fluids provides a good indication of the equipment's health.

Moisture in the external environment can also interact with the equipment in different ways and cause failure through ingress. Moisture detection, therefore, becomes important to address failure modes associated with it.

Similarly, the condition of internal combustion engines can also be ascertained through monitoring their exhaust. This is also required to ensure that emission limits remain within the applicable environmental guidelines.

Measuring and understanding the changes occurring in the fluids used within or around an equipment system is another technique for predictive maintenance. This is collectively called Fluid Analysis. In the next sections, an overview is provided for lubricant analysis and coolant analysis.

3.5.1 Lubricant analysis

Lubricant acts as a lifeline for all rotating machinery. Analyzing the physical and chemical properties of the lubricant can provide valuable insights into the health of the equipment and guide timely maintenance interventions required for its reliable, continuous operation. It is important to understand that lubricants deteriorate over their service life due to multiple reasons.

Lubricant formulation for different applications is developed in a manner to have a planned deterioration over an established period of time, unit of work, operation, or distance. However, this deterioration can also take place in an unplanned manner. Today's industrial practice is to manage the planned deterioration of lubricants [12].

Different equipment may use different lubricants, such as oil, grease, penetrating lubricants, and dry lubricants, depending upon the specific application, operating environment, process design, and local market conditions. However, common indicators of contamination in these lubricants may include the presence of wear particles from within the equipment, external contaminants such as water, degradation of physical properties (e.g., viscosity), and alteration of chemical properties due to phenomenon such as oxidation.

Lubricant analysis is a key predictive maintenance technique used to assess the condition of lubricants and the health of machinery. By using lubricant analysis, many common failure modes of rotating equipment can be detected. These may include:

- Excessive wear of mechanical components is identified by the presence of abnormal wear particles.
- Lubricant contamination due to the presence of moisture, dirt, fuel, or coolant.
- Lubricant degradation due to changes in viscosity, oxidation, and additive depletion.

Below are some of the key methods used for lubricant analysis. Their application may depend on the specific design and operating context of the equipment.

3.5.1.1 Spectroscopy:

Spectroscopy is used to detect trace amounts of wear metals, additives, and contaminants in the lubricant. It can provide valuable insights about any abnormal wear of components taking place within the equipment, contaminants in the lubrication system, and the chemical properties of the lubricant. Typical wear metals include Fe, Cu, and Al.

- Application: Bearings, engines, compressors, gears, and turbines.
- P-F interval: Early detection (1–6 months) for progressive wear, depending on the rate of wear and contamination.
- Procedure: The lubricant sample is vaporized, and the emitted light spectrum is analyzed to identify the elements present. Inductively coupled plasma (ICP) or

atomic emission spectroscopy (AES) are common industry methods for performing spectroscopy.

- Skills: Knowledge of spectroscopy and element correlation to wear mechanisms. Expertise in spectrometer calibration, data interpretation, and trending.
- Advantages: Early detection of mechanical wear. Helps to quantify the lubricant's health and contamination.
- Disadvantages: Limited to detecting small particles (<10 microns), while missing larger debris. Requires costly testing equipment and specialized skills.

3.5.1.2 Viscosity testing:

Viscosity is a measure of a fluid's resistance to flow. It is an important measure of the physical quality of a lubricant. An increase in the viscosity of the lubricant leads to increased friction, which can be detrimental to the health of mechanical machinery. It can also lead to reduced cooling, poor cleaning effects, and efficiency decreases in large machines. Contamination of the lubricant due to water and dirt can cause an increase in viscosity.

On the other hand, a decrease in the lubricant viscosity leads to thinning of the oil film in certain heavy-load equipment and increased consumption of lubricant due to excessive evaporation. Higher machine operating temperatures often cause a decrease in viscosity.

- Application: Engines, gearboxes, hydraulic systems, and turbines.
- P-F interval: Moderate (3–12 months), as viscosity changes indicate gradual fluid breakdown.
- Procedure: A viscometer is used to measure the viscosity of the lubricant at a standard temperature.
- Skills: Understanding viscosity grades and lubricant specifications. Experience with viscometer operation and result interpretation.
- Advantages: Simple, cost-effective, and quick testing method. Detects important failure modes, i.e., thickening and thinning of lubricant.
- Disadvantages: Does not identify wear particles. The accuracy of results is sensitive to temperature effects.

3.5.1.3 Ferrography:

Ferrography is the detection of ferrous materials within the lubricant. Since most components of rotating machinery are made from ferrous material, they are one of the biggest sources of particles within the lubricants. Detecting these ferrous

particles provides valuable insights into any damage or wear occurring within the equipment. Ferrography helps to assess the severity of wear in components such as gears, bearings, and shafts.

- Application: Heavy-duty industrial machinery, engine, gear, compressor, and turbine.
- P–F interval: Early to mid-stage (1–3 months) for abnormal wear trends. Depends on the wear rate and particle size.
- Procedure: A magnetometer is used to magnetically separate ferrous particles for quantitative analysis.
- Skills: Familiarity with ferrography techniques and particle characterization. Ability to correlate wear debris trends with machine health.
- Advantages: Early detection of wear mechanisms, e.g., abrasive vs. adhesive wear. Detects large particles missed by spectroscopy.
- Disadvantages: Limited to detecting ferrous particles. Requires specialized instruments and expertise for interpretation.

3.5.1.4 Particle count and size analysis:

This method is used to ascertain the contamination level of the lubricant. It also helps to understand the performance of any filters installed in the lubricant systems. ISO 4406:2021 [13] provides standard cleanliness requirements for different fluid applications used in the industry.

- Application: Hydraulic system and turbine.
- P–F interval: Short to mid-term (weeks to months)
- Procedure: A particle counter is used to count and measure the size of particles through the light blockage method or microscopy.
- Skills: Ability to analyze and trend particle count data. Knowledge of ISO cleanliness codes and sampling protocols.
- Advantages: Helps in maintaining contamination control for critical machinery. Provides faster results.
- Disadvantages: Does not distinguish between wear particles and external contaminants. Prone to sampling errors.

3.5.2 Coolant analysis

Coolant analysis is an essential predictive maintenance practice used to assess the condition of cooling systems in engines, industrial machinery, and power

generation equipment. Coolants play a critical role in temperature regulation, corrosion prevention, and lubrication of cooling system components. Over time, coolant degradation, contamination, and chemical imbalances can lead to overheating, corrosion, and component failure. Regular analysis helps detect early signs of coolant deterioration and system-related issues before they cause costly failures. The following are some of the methods used for conducting coolant analysis:

3.5.2.1 Chemical properties analysis (pH analysis, conductivity, and inhibitor testing):

pH, conductivity, and additive concentration of the coolant are important chemical properties that indicate its stability. Measuring the pH, conductivity, and additive concentration helps to evaluate the chemical stability of the coolant. It also provides indications of any corrosion taking place within the coolant circuit and components.

- Application: Engine and HVAC chiller.
- P-F interval: Long term, months to years.
- Procedure: A pH meter is used to check acidity levels, conductivity meters assess ionic contamination, and inhibitor tests determine the depletion of essential additives.
- Skills: Knowledge of coolant chemistry and its impact on system health. Basic lab skills for calibration and sample handling.
- Advantages: Quick and cost-effective. Can be performed in the field.
- Disadvantages: Does not identify contaminants. Requires regular testing for trend analysis.

3.5.2.2 Refractometry (concentration analysis):

An important failure of a coolant is its dilution due to water ingress. This can severely impact its properties and performance. It also affects the corrosion inhibitor concentration within the coolant, which can lead to accelerated corrosion and damage to mechanical components within the cooling system. Dilution trends signal a gradual performance loss of the coolant.

- Application: Engine and chiller.
- P-F interval: Moderate, 1–3 months.
- Procedure: The refractometer prism is used to measure the refractive index of the coolant to determine its concentration.
- Skills: Understanding coolant mixing ratios and refractometer calibration.

- Advantages: Simple testing method and can be performed in the field. Provides direct correlation of concentration to coolant performance.
- Disadvantages: Sensitive to contaminants; limited to water-based coolants.

4. Summary and conclusion(s)

This chapter introduces the fundamental concept of equipment function and failure modes, providing a comprehensive understanding of how equipment operates and the several ways it can fail. Common failure modes associated with widely used industrial equipment and systems are categorized, and key predictive maintenance strategies are explored. These strategies are essential for maintaining the reliability and efficiency of industrial operations.

It is important to note that no single predictive maintenance technique can be applied to detect all possible failure modes of equipment or systems. This requires the development and implementation of a comprehensive asset condition monitoring (ACM) program. A good ACM program considers multiple predictive maintenance techniques in an organized and logical manner to integrate them into how the organization operates on a day-to-day basis. It is advisable to evaluate, select, and adopt multiple techniques depending on the operating context, process design, equipment application/duty, criticality, expected dominant failure modes, available resources, and economic considerations. This approach reduces subjectivity in decision-making with regard to predictive maintenance. Implementing a holistic ACM program is a cross-functional activity and needs people from different backgrounds, such as maintenance management, operations, safety, procurement, stores, information technology, training and/or human resources, planning, scheduling, and craftspeople [14].

A summary of the predictive maintenance techniques explored in this chapter is provided in **Table 2** below. It identifies predictive maintenance techniques for major industrial equipment categories. The predictive maintenance techniques introduced in this chapter are helpful in the early detection of potential issues, allowing for timely interventions that can prevent costly downtime and extend the lifespan of equipment.

It can be observed that some techniques, such as vibration analysis, ultrasonic analysis, and infrared (IR) thermography, can be applied to a wide range of equipment categories. These techniques should be considered foundational choices by all industrial organizations due to their broad applicability and effectiveness in identifying potential failure modes.

There could be some other techniques also available that might be suitable for specific equipment categories and applications. For example, dissolved gas analysis (DGA) is a specialized technique used for power transformers.

While predictive maintenance requires the use of different tools and techniques, the real value realization, in most cases, is dependent upon the skills and capabilities of the people involved. These people may be internal to the organization or external service providers. It is necessary to ensure the appropriate skill level is available to properly implement predictive maintenance activities and analyze their results.

Predictive maintenance techniques	Major equipment categories												
	Pump	Compressor	Engine	Turbine	Electric generator	Electric motor	Heater & boiler	Heat exchanger	Pressure vessel	Piping	Valves	Transformers	Switchgear
Liquid penetrant testing (LPT)			Xp	Xp			X	X	X	X			
Electrostatic penetrant testing			Xp	Xp			X	X	X	X			
Ultrasonic testing (UT)		Xp	Xp	Xp			X	X	X	X			
X-ray radiography		Xp	Xp	Xp			X	X	X	X			
Vibration analysis	X	X	X	X	X	X							
Ultrasonic analysis	X	X	X	X	X	X					X	X	X
Power factor testing					X	X					X	X	X
Partial discharge (PD) testing					X	X					X	X	X
Motor current signature analysis (MCSA)	X	X			X	X							
Infrared (IR) thermography	X				X	X		X	X	X	X	X	X
Lubricant analysis	X	X	X	X	X	X							
Coolant analysis	X	X	X	X	X	X							
Legends:													
X – Predictive maintenance technique generally applicable.													
Xp – Predictive maintenance technique applicable to specific components/parts.													

Table 2.
 Applicability of selected predictive maintenance techniques to major equipment categories.

This also includes skills in general maintenance management, troubleshooting, and discipline-specific knowledge.

In conclusion, the chapter emphasizes the importance of selecting appropriate predictive maintenance techniques based on the specific equipment and its failure modes. By implementing these techniques, organizations can enhance their maintenance strategies, improve equipment reliability, and achieve better operational efficiency.

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Supersonic Ejector Performance Improvement through Contoured Mixing Chamber Design

Amer Muzaber and Nadin Bassmaji

Abstract

This chapter focuses on improving the supersonic ejector design. The proposed configuration introduces a contoured mixing chamber, distinguished by its arc-shaped geometry. This novel configuration aims to enhance the entrainment of secondary fluid from the evaporator, resulting in improved ejector efficiency. The contoured mixing chamber profiles are evaluated numerically using ANSYS Fluent over a boiler temperature range of 130°C to 170°C, with an evaporator temperature set at 7.5°C. Numerical results reveal that the contoured mixing chamber yields substantial performance enhancements, particularly at higher boiler temperatures. Furthermore, the results highlight the presence of an optimal radius for the contoured mixing chamber that maximizes ejector performance under specific operational conditions. Detailed simulations provide valuable understanding of flow behavior and the distribution of fluid parameters within the ejector. These findings serve as a practical guide for advancing supersonic ejector designs to meet the demands of jet refrigeration applications.

Keywords: supersonic ejector, contoured mixing chamber, entrainment ratio, ejector efficiency, jet refrigeration

1. Introduction

The advancements in technology, coupled with increasing global awareness of environmental challenges, have driven a significant shift toward renewable energy sources such as wind, solar, geothermal, and low-grade thermal energy. These renewable energy sources are not only ideal for supporting conventional energy systems but also for addressing the growing energy needs of people in remote areas, where providing electricity remains a considerable challenge due to adverse geographical conditions. The cost of installing and maintaining electrical distribution networks increases significantly. In such cases, renewable energy systems become the most feasible solution to meet energy demands, particularly for air conditioning systems. In this context, jet ejector refrigeration systems represent a promising eco-friendly and energy-efficient alternative to conventional compression systems by utilizing low-grade thermal energy sources, including solar power and waste heat, to generate

cooling effects. Furthermore, the ability to use environmentally friendly working fluids, such as water vapor, enhances their ecological benefits, making them a viable solution for green and sustainable cooling applications [1]. Despite their advantages, jet refrigeration systems remain underutilized, largely due to their relatively low coefficient of performance (COP), which typically ranges between 0.2 and 0.6 in ejector-based chillers [2]. The COP is strongly influenced by the flow dynamics within the ejector, often described as the thermal compressor of the system. Ejector design relies on fundamental thermodynamic and fluid dynamic principles, including continuity, momentum conservation, and energy conservation [3].

Ejectors are commonly categorized into two configurations based on their mixing mechanism. The first type, the constant-pressure mixing ejector (CPM), positions the nozzle exit within the converging mixing chamber. In contrast, the second type, constant-area mixing ejector (CAM), features the nozzle exit located within the constant-area section. CPM ejectors are preferred for their capability to handle higher condensation pressures, giving them an operational advantage over CAM ejectors. Later, the constant rate of momentum-change ejector incorporates a variable-area section. This configuration minimizes thermodynamic shocks, ultimately enhancing the performance [4, 5].

2. Flow dynamics in CPM ejector

A detailed analysis of the Mach number and static pressure distribution along the ejector is provided in **Figure 1**, offering valuable insights into its operational behavior, performance dynamics, and key technical terms. The primary flow forms a supersonic jet core at the nozzle exit, generating expansion waves within the mixing chamber, which create a region of low pressure. The primary flow expands into the mixing chamber without immediately mixing with the secondary fluid. This results in the formation of a converging passage where the secondary fluid gains velocity as its static pressure decreases [6]. This passage is confined between the supersonic jet core and the mixing chamber wall, ensuring effective secondary fluid entrainment. At a specific cross-section within the secondary flow passage, it reaches sonic velocity and undergoes choking. In other words, this cross-section marks the point at which secondary flow choking occurs [7]. Subsequent investigations challenged the earlier assumptions of invariance, demonstrating that the location of secondary fluid choking is dependent on the operating conditions [8].

The secondary flow choking plays a crucial role in determining the mixing efficiency and overall entrainment performance of the ejector. The upstream shift of the secondary flow choking position creates a larger secondary fluid restriction area, impacting the entrainment ratio and ejector efficiency. This is influenced by factors such as nozzle geometry, mixing chamber geometry and operating conditions. Noteworthy, secondary fluid choking position can be at various locations, including the nozzle exit plane, the mixing chamber, or the ejector throat [9].

It was suggested that the mixing process initiates after the secondary fluid chokes, where momentum transfer between the primary flow and secondary flow occurs progressively, culminating at the end of the mixing chamber. According to Keenan's theory [10], a normal shock forms in the ejector throat, transitioning the mixed flow from supersonic to subsonic and inducing compression. The subsonic diffuser further compresses and decelerates the flow, raising static pressure and nearing stagnation conditions at the exit.

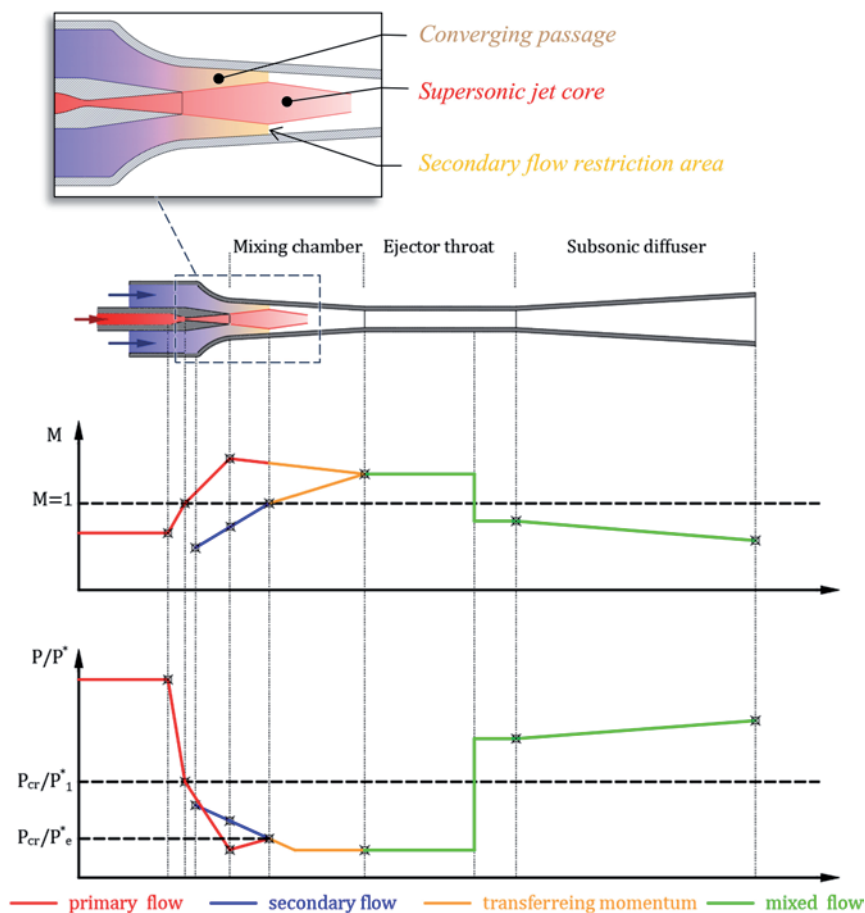


Figure 1.
 Parameters' variation across the CPM supersonic ejector.

Notably, there are two critical choking positions within the ejector. The first takes place in the nozzle throat of the primary flow, while the second occurs at the secondary fluid restriction. At both locations, static pressure drops to a critical value that is clarified in Eq. (1). In this critical state, the mass flow rate remains constant even if the downstream pressure continues to decrease:

$$\frac{P_{cr}}{P^*} = \left(\frac{2}{k+1} \right)^{\frac{k}{k-1}} \quad (1)$$

To improve the entrained secondary flow, the secondary fluid passage, which is influenced by the position of the secondary fluid choking, must be enlarged. Adjustments to the geometry, such as reducing nozzle size or modifying nozzle placement, can significantly enhance the entrainment ratio. Numerous studies have thoroughly investigated the operational and geometric parameters that affect the secondary fluid choking position, providing valuable insights into ejector design [11–22].

2.1 Expansion waves

The flow behavior within the primary nozzle depends on the pressure difference between its inlet and outlet. When the nozzle back pressure (mixing chamber pressure) falls below the critical value, sonic velocity is achieved at the nozzle throat, causing the primary flow to choke. In the divergent section, the flow continues to accelerate, either experiencing a shock before exiting the nozzle, leading to subsonic discharge (Line_III in **Figure 2**), or, if the outlet pressure is sufficiently low, produces a shock wave at the nozzle exit (Line_IV in **Figure 2**) or continues accelerating to emerge as a supersonic jet, which represents the standard operating condition for the supersonic ejector.

Under free boundary pressure conditions, the supersonic jet generates expansion waves with distinct expansion angles. These waves are typically categorized into two types:

- a. *Over-expanded waves*: In this case, the primary stream exhibits a convergent expansion angle. The static pressure at the nozzle exit plane is lower than the mixing chamber pressure, resulting in over-expansion (state_V).
- b. *Under-expanded waves*: Here, the primary stream continues to expand, forming a divergent expansion angle at the nozzle exit. In this scenario, the static pressure at the nozzle exit plane exceeds the mixing chamber pressure (Line_VI).

Within the supersonic jet core, these expansion waves interact with reflected waves, which impact the momentum transfer process and the subsequent mixing of the primary and secondary streams, further influencing ejector performance [23, 24].

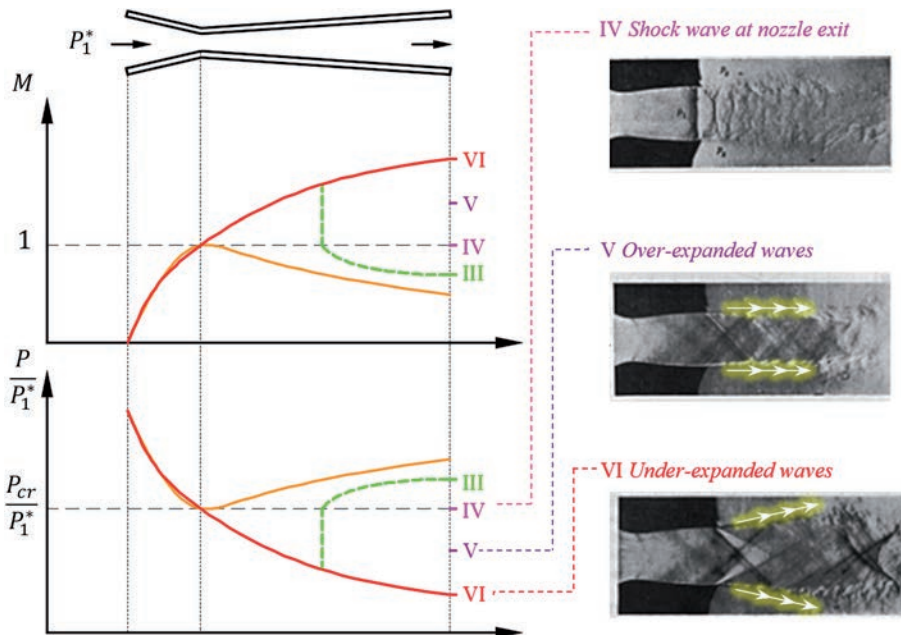


Figure 2.
Expansion waves formed behind the primary nozzle [23].

2.2 Ejector performance

The performance of an ejector is typically evaluated through the entrainment ratio (R_m) and the critical condensation pressure ($P_{c,cr}$). The critical condensation pressure represents the maximum condensing pressure at which the ejector maintains choked flow operation. On the other hand, the entrainment ratio quantifies the ratio of the mass flow rate of the secondary stream to that of the primary stream. These parameters are essential for understanding and optimizing ejector. The entrainment ratio is defined as in Eq. (2):

$$R_m = \frac{\dot{m}_v}{\dot{m}_s} \quad (2)$$

The relationship between the entrainment ratio and condensation pressure is depicted in the ejector performance curve, (**Figure 3**). Ejector operation is generally classified into three distinct regimes in the mixing chamber: choked flow, unchoked flow, and reversed flow. In the choked flow regime, where the condensation pressure remains below the critical value, the ejector draws the maximum amount of vapor from the evaporator due to secondary flow choking, thereby achieving the highest entrainment ratio. As condensation pressure increases beyond the critical level, the secondary flow becomes unchoked, which leads to a noticeable reduction in the entrainment ratio. Once the condensation pressure reaches the breakdown point, the mixed stream reverses its direction, flowing back into the evaporator and causing the ejector to malfunction.

For a comprehensive evaluation of ejector performance, it is essential to consider both the entrainment ratio and the condensation pressure effects, as these factors collectively determine the system's energy utilization. An efficiency equation has been developed that integrates these parameters, offering a more holistic assessment of ejector operation (Eq. (3)). This approach enables a more precise understanding of how variations in the entrainment ratio and condensation pressure influence the overall efficiency, ultimately guiding improvements in ejector design and performance [25]:

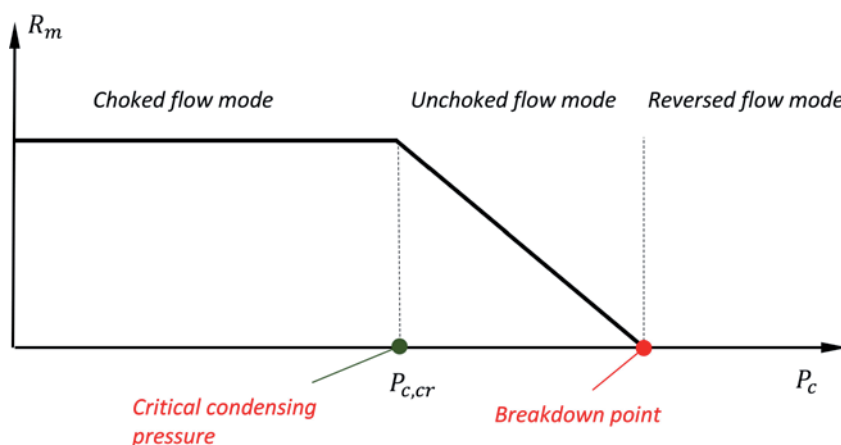


Figure 3.
Ejector performance curve.

$$\eta = R_m \frac{1 - \left(\frac{P_e^*}{P_c} \right)^{\frac{k-1}{k}}}{\left(\frac{P_1^*}{P_c} \right)^{\frac{k-1}{k}} - 1} \quad (3)$$

Enhancing ejector performance through geometric modifications has been the focus of extensive research, particularly for CPM ejector designs. Numerous studies have demonstrated that adjusting key dimensions of the mixing chamber significantly impacts performance. Critical geometrical parameters, such as the mixing chamber diameter, converging angle, and nozzle exit position, have been identified as essential factors influencing the ejector's efficiency. These geometric modifications aim to create a wider secondary fluid passage and a larger secondary fluid restriction area, thereby improving the entrainment ratio.

3. Numerical model of contoured mixing chamber design

An innovative configuration, introduced by Muzaber et al., contoured mixing chamber ejector is designed based on CPM ejector [26]. The results indicate a significant increase in ejector efficiency. Therefore, the goal of this study is to specify the optimal geometric design of the mixing chamber according to boiler temperature, employing ANSYS Fluent for comprehensive numerical analysis.

The dimensions of the studied ejector are illustrated in **Figure 4**. The proposed design modifies the mixing chamber by replacing its straight profile with an arc, while keeping all other dimensions identical to those of the CPM design. Eight different radius (r) values and the corresponding characteristic angles β_1 and β_2 of the contoured mixing chamber design were analyzed, illustrated in **Figure 5**. These variations provide insight into how changes in curvature affect the secondary fluid passage, subsequently influencing ejector performance. As the radius increased, the

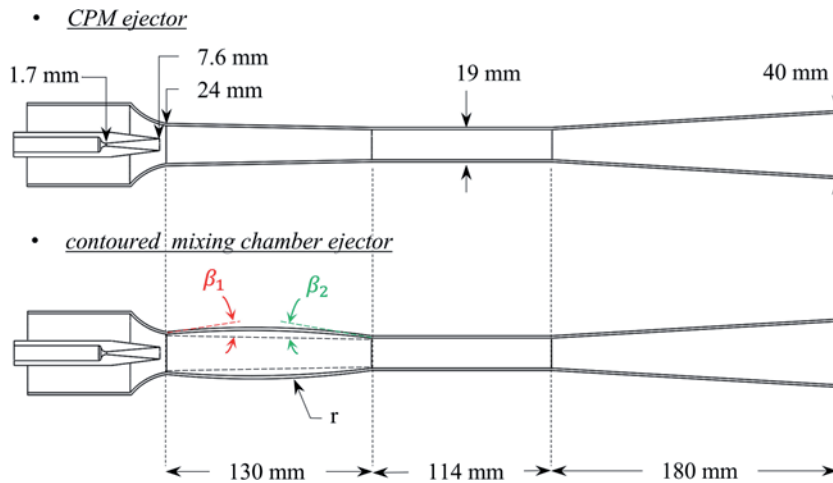


Figure 4.
Schematic diagram of the studied ejectors.

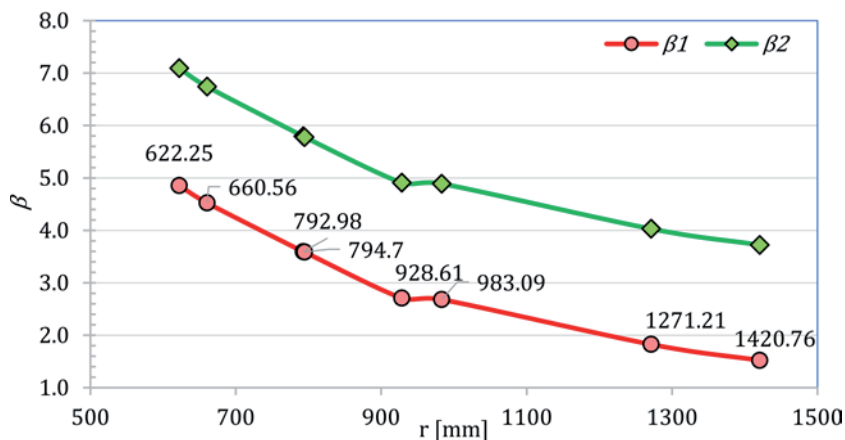


Figure 5.
Radii of studied contoured mixing chamber profile and the corresponding characteristic angles.

arc's curvature gradually reduced, resulting in a narrower secondary fluid passage and also a corresponding decrease in the characteristic angles of the arc, β_1 and β_2 .

The 2D axisymmetric model was adopted for this numerical simulation. The boundary conditions of the flow in the ejector are illustrated in **Table 1**. The ejector walls were set as adiabatic.

The mesh was conducted using the commercial computational fluid dynamics software ANSYS Mesh. In this numerical investigation, the mesh with 60,000 cells was adopted. As shown in **Figure 6**, the mesh near the walls and the shear layer region in the mixing chamber was refined.

In the ANSYS Fluent model, vapor properties were assumed to behave as an ideal gas, as previously established in the literature [27–29]. Additionally, the ejector walls were considered adiabatic, meaning heat transfer effects were neglected. These assumptions could significantly impact the accuracy of the results, influencing potential error.

To ensure the accuracy of the model, we compared our numerical results with those reported by Ruangtrakoon et al. [30], as shown in **Figure 7**. The relative error in entrainment ratio and critical condensation pressure changed with boiler temperature variations. Increasing progressively with temperature until reaching a maximum relative error of 14.5% for the entrainment ratio.

The validation results demonstrate a strong agreement between the numerical simulations and experimental data, confirming the accuracy and reliability of the model. This agreement validates the model's effectiveness in capturing the ejector's performance characteristics, ensuring that potential numerical errors do not compromise the validity of the conclusions drawn in this study.

	Evaporator			Boiler		
$T[^\circ\text{C}]$	7.5	130	140	150	160	170
$P[\text{kPa}]$	0.8	270.08	361.28	475.84	617.82	791.66

Table 1.
Boundary conditions.

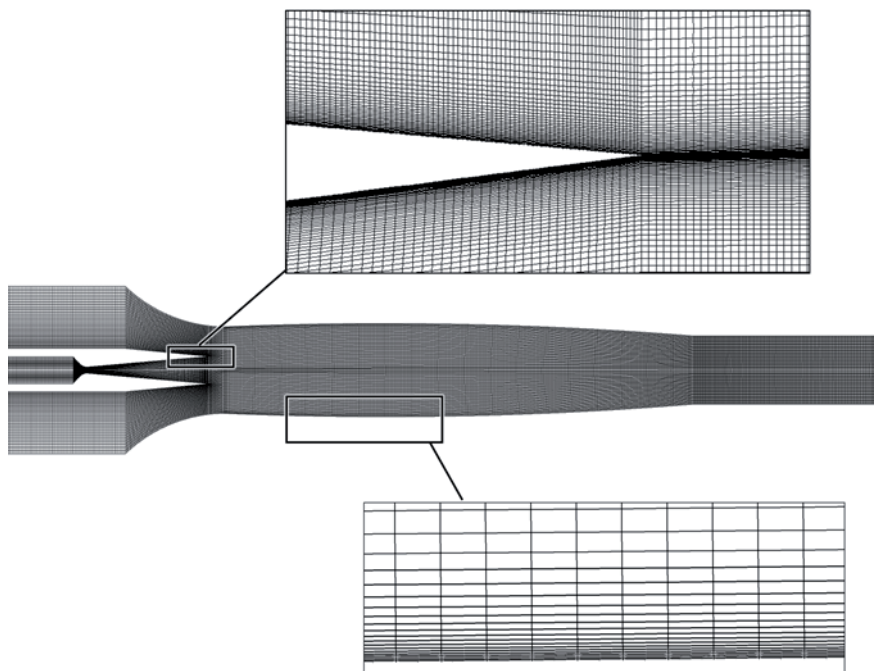


Figure 6.
Mesh in contoured mixing chamber.

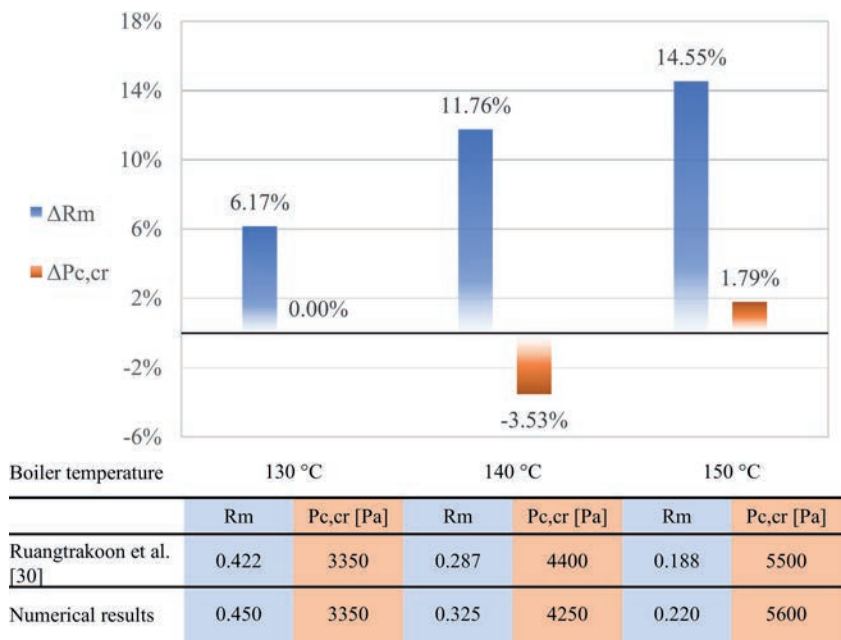


Figure 7.
Model validation results.

4. Results and discussion

Numerical results, presented in **Figures 8–15**, illustrate the performance curves of contoured mixing chamber ejectors across various boiler temperatures. The findings indicate that the entrainment ratio of contoured mixing chamber designs is generally higher than that of the CPM ejector, except when $r = 983.09$ mm at 130°C . In this particular case, the secondary stream remains unchoked.

An increase in the entrainment ratio is associated with a reduction in critical condensation pressure within the contoured mixing chamber, particularly for radii smaller than 983.09 mm. To illustrate this effect, ejector efficiency is evaluated using Eq. (3).

The numerical results, shown in **Figures 16–20**, identify the range of radii where improvements in entrainment ratio and ejector efficiency can be achieved using the contoured mixing chamber design. CPM ejector is represented as dots at $r = 0$.

At 130°C boiler temperature, the contoured mixing chamber is effective within a radius range of 983.09 to 1420.76 mm. The entrainment ratio surpasses that of the CPM ejector when the radius exceeds 1225 mm, whereas the efficiency remains

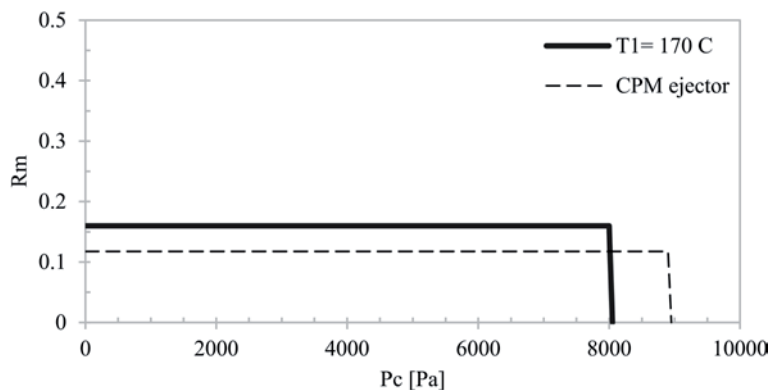


Figure 8.
 Performance curves for contoured mixing chamber and CPM ejector designs ($r = 622.25$ mm).

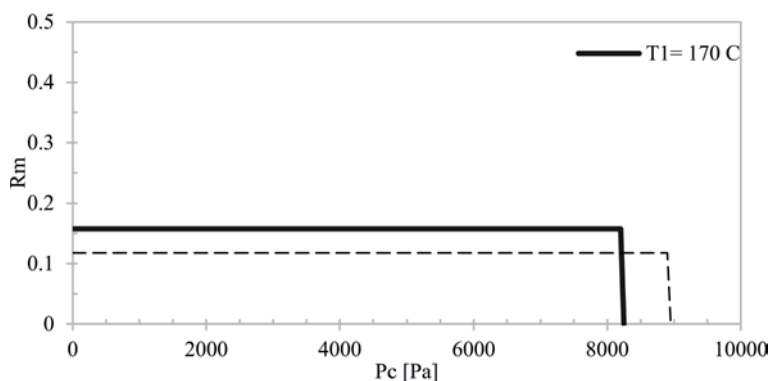


Figure 9.
 Performance curves for contoured mixing chamber and CPM ejector designs ($r = 660.56$ mm).

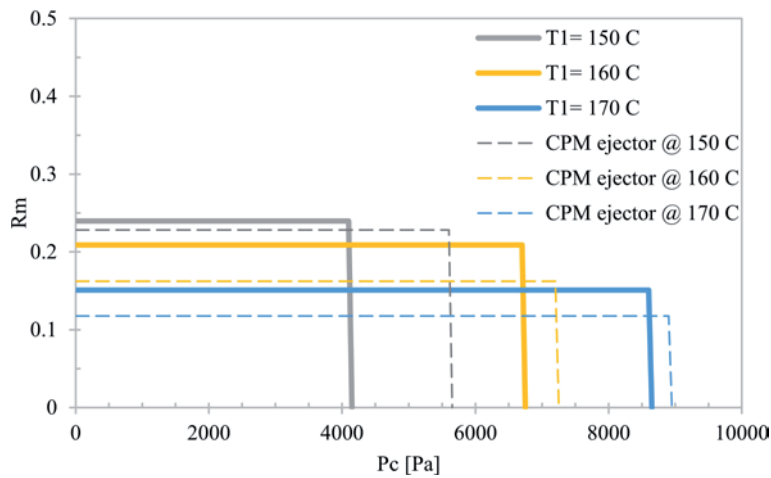


Figure 10.
Performance curves for contoured mixing chamber and CPM ejector designs ($r = 792.98 \text{ mm}$).

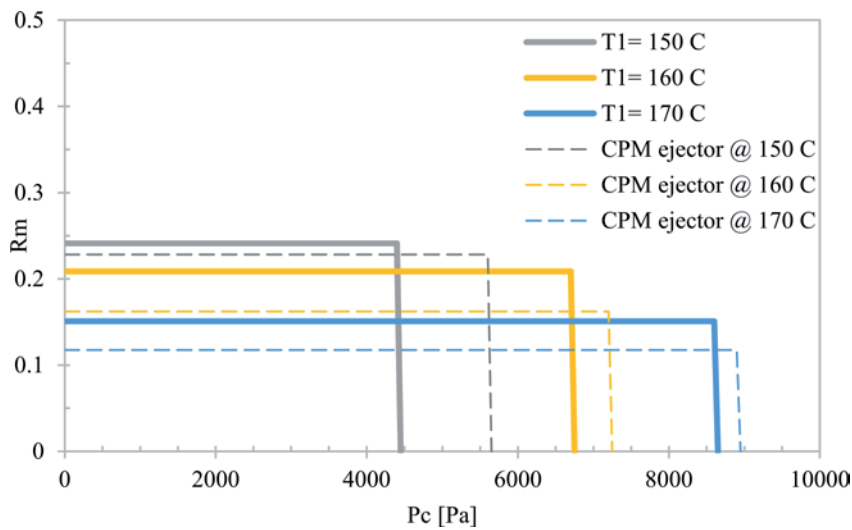


Figure 11.
Performance curves for contoured mixing chamber and CPM ejector designs ($r = 794.7 \text{ mm}$).

lower than in the CPM ejector. At 140°C boiler temperature, the entrainment ratio consistently outperforms the CPM ejector across the entire radius range (983.09 to 1420.76 mm), but efficiency surpasses the CPM ejector only when the radius exceeds 1175 mm. At 150°C and 160°C boiler temperatures, the radius range expands, starting from $r = 792.98 \text{ mm}$. At 160°C and 170°C boiler temperatures, both the entrainment ratio and efficiency exceed those of the CPM ejector. Notably, at 170°C , this improvement remains consistent across the entire radius range. However, beyond the studied range of the contoured mixing chamber radius, the ejector operates in the reversed mode and malfunctions, indicating the existence of critical design limits under the examined operational conditions.

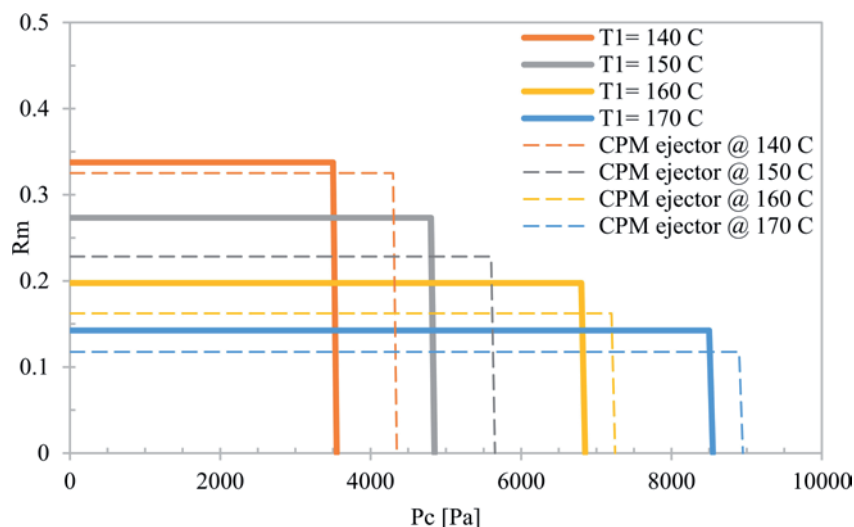


Figure 12.
Performance curves for contoured mixing chamber and CPM ejector designs ($r = 928.61$ mm).

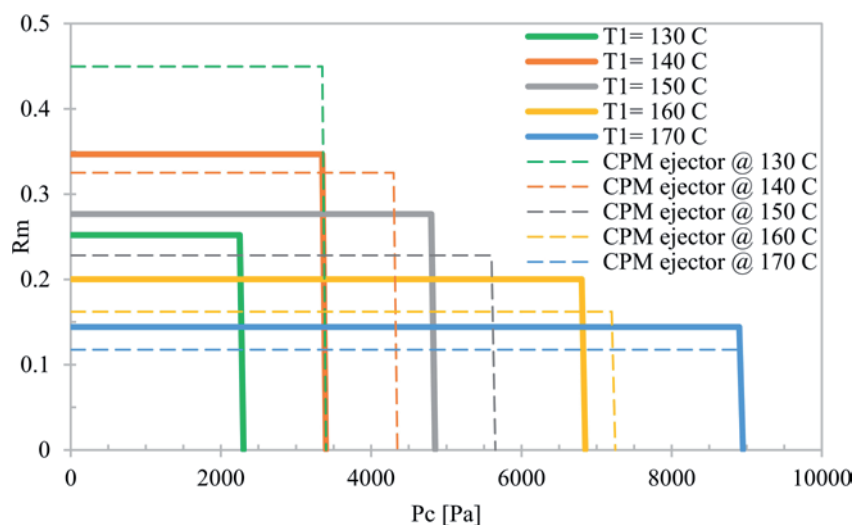


Figure 13.
Performance curves for contoured mixing chamber and CPM ejector designs ($r = 983.09$ mm).

At lower boiler temperatures, the primary flow may lack sufficient energy to ensure thorough mixing with the secondary fluid. As a result, the secondary flow may fail to achieve choking at the designated position, leading to lower mass entrainment and limited thermal and momentum exchange between the streams. Under these conditions, the entrainment ratio remains relatively low.

On the other hand, when the secondary flow chokes, the secondary fluid choking position moves closer to the primary nozzle at lower boiler temperatures, increasing in size and subsequently enhancing the entrainment ratio. **Figure 21** illustrates the Mach distribution within the contoured mixing chamber at $r = 1271.21$ mm, clearly

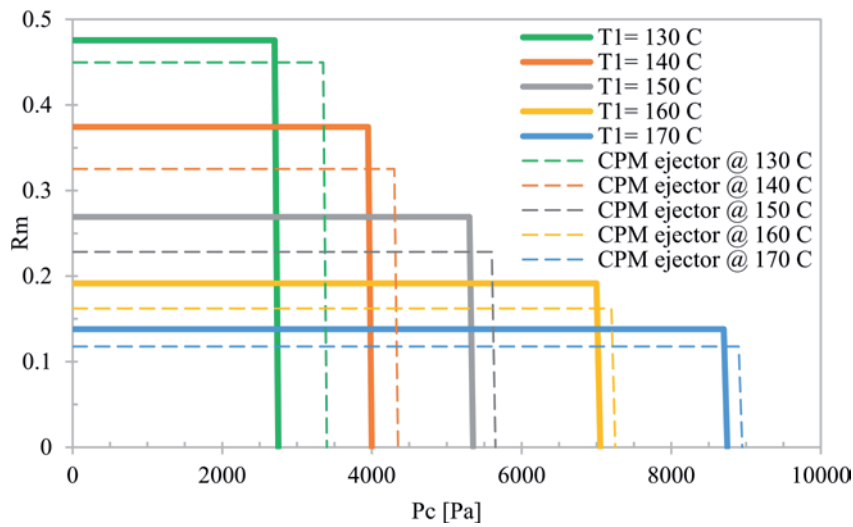


Figure 14.
Performance curves for contoured mixing chamber and CPM ejector designs ($r = 1271.21$ mm).

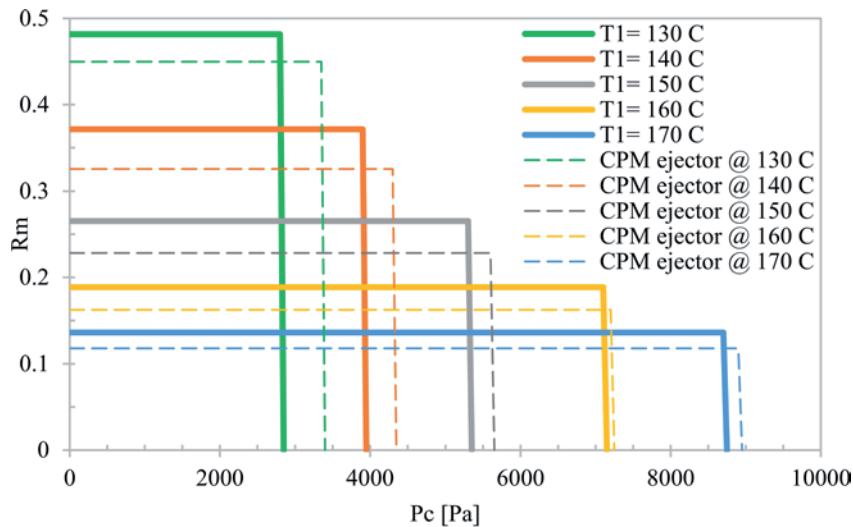


Figure 15.
Performance curves for contoured mixing chamber and CPM ejector designs ($r = 1420.76$ mm).

showing that the supersonic jet core expands significantly as the boiler temperature increases, generating larger expansion waves. This expansion reduces the secondary fluid restriction area, leading to a decline in the entrainment ratio and affecting the ejector's capability to effectively entrain secondary fluid.

Optimizing the chamber radius enhances ejector adaptability across various industries, including HVAC systems, steam-based energy recovery, refrigeration, waste heat recovery, and propulsion systems. The contoured mixing chamber improves entrainment ratio and ejector efficiency, offering advantages over traditional designs that often suffer from lower mixing efficiency due to geometric constraints. However, its effectiveness depends on operational conditions,

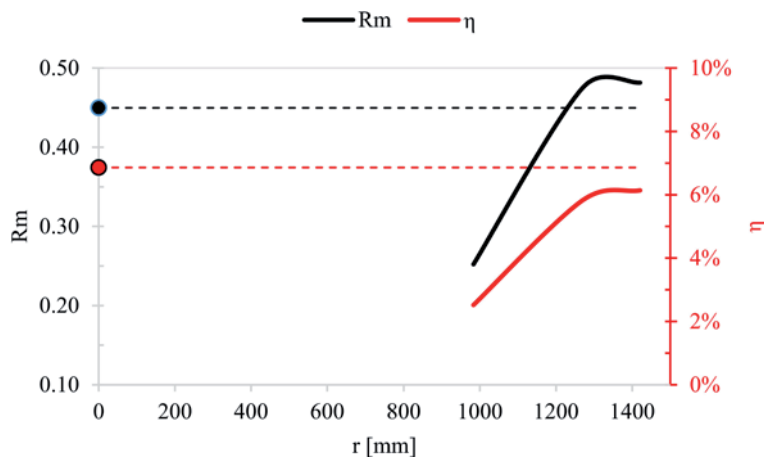


Figure 16.
 Variation of entrainment ratio and ejector efficiency with contoured mixing chamber radius at 130°C boiler temperature.

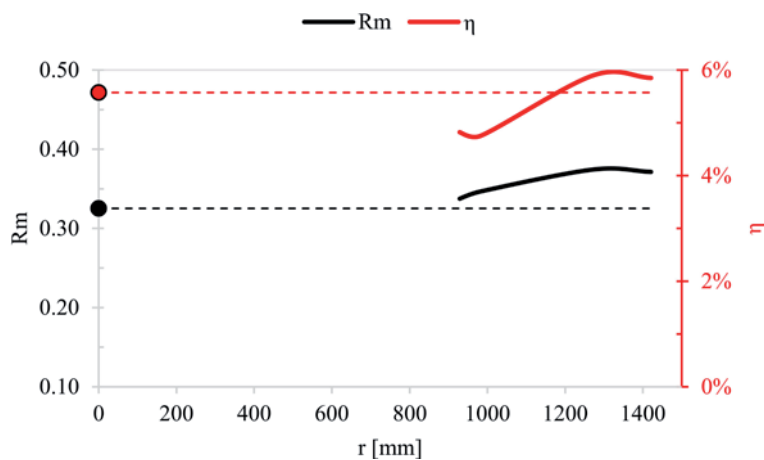


Figure 17.
 Variation of entrainment ratio and ejector efficiency with contoured mixing chamber radius at 140°C boiler temperature.

manufacturing feasibility, and material limitations. Achieving precise curved geometries in industrial ejectors may require advanced fabrication techniques, potentially increasing production costs. Additionally, the curved chamber affects pressure distribution, necessitating stronger materials to withstand operational stresses, impacting design feasibility. This optimized curvature improves ejector efficiency, reducing energy input requirements per unit of refrigeration or waste heat recovery, ultimately enhancing overall system performance and energy savings. Higher efficiency translates to lower energy consumption, contributing to reduced carbon emissions, particularly in refrigeration and HVAC systems, where sustainability is a priority. Furthermore, this design supports global energy efficiency efforts, making it a viable solution for industries focused on energy recovery, low-carbon cooling, and sustainable thermal systems.

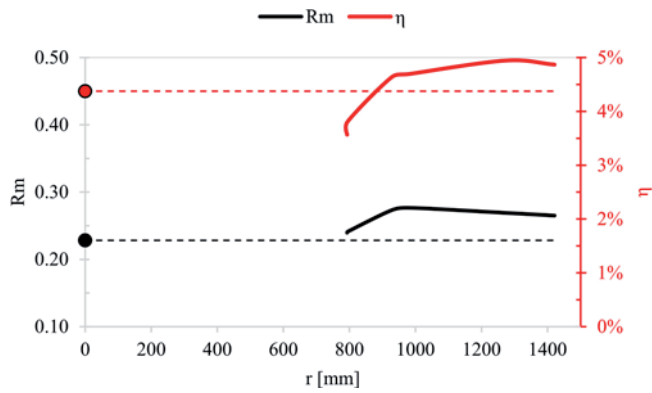


Figure 18.
Variation of entrainment ratio and ejector efficiency with contoured mixing chamber radius at 150°C boiler temperature.

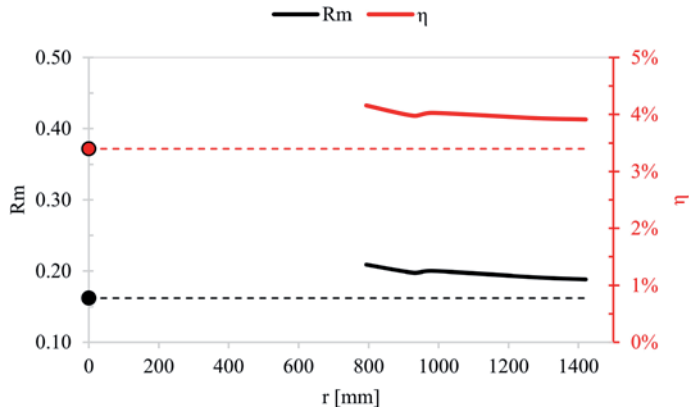


Figure 19.
Variation of entrainment ratio and ejector efficiency with contoured mixing chamber radius at 160°C boiler temperature.

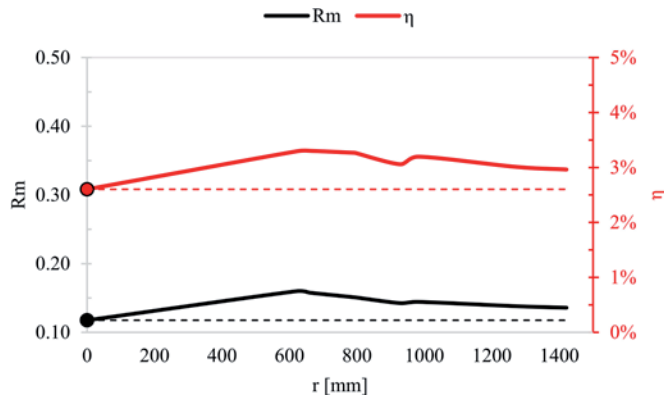


Figure 20.
Variation of entrainment ratio and ejector efficiency with contoured mixing chamber radius at 170°C boiler temperature.

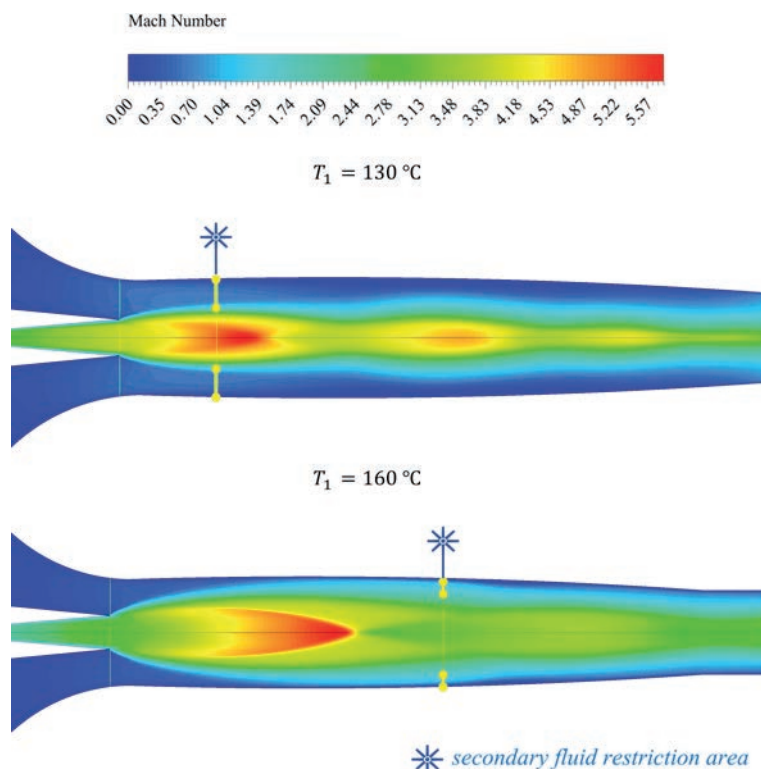


Figure 21.
 Mach contour for contoured mixing chamber ($r = 1271.21\text{ mm}$) at different boiler temperatures.

5. Conclusions

In this chapter, numerical investigations were carried out to study the curved shape of the mixing chamber in the supersonic ejector. The detailed outcomes are as follows:

- The contoured mixing chamber positively impacts the entrainment ratio but has a negative effect on critical condensation pressure.
- There is an optimal radius that offers maximum entrainment ratio and efficiency at each temperature.
- The maximum efficiency is achieved when the radius is 1420.76 mm at 130°C boiler temperature.
- At higher boiler temperatures, both the entrainment ratio and efficiency surpass those of the CPM ejector.
- Secondary flow choking plays a crucial role in ejector performance.
- This study significantly contributes to the advancement of ejector technologies for refrigeration jet systems, offering low operational costs with no negative environmental impact.

- Achieving precise curved geometries in industrial ejectors could require advanced fabrication techniques, potentially increasing manufacturing costs.
- This study highlights the limitations associated with the mixing chamber radius within the studied range of boiler temperatures, emphasizing its impact on ejector performance and operational stability.

Acknowledgements

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Conflict of interest

The authors declare no conflict of interest.

Nomenclature

COP	coefficient of performance
CPM	constant-pressure mixing ejector
CAM	constant-area mixing ejector
P_{cr}	critical pressure
P^*	saturation pressure
P_1^*	boiler pressure
P_e^*	evaporation pressure
P_c	condensation pressure
k	specific heat ratio of the operating fluid
M	Mach number
R_m	entrainment ratio
$\dot{m}_v$	mass flow rate of secondary flow
$\dot{m}_s$	mass flow rate of primary flow
η	ejector efficiency
r	radius of the contoured mixing chamber arc
β_1, β_2	characteristic angles of the contoured mixing chamber arc

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