A Systematic Review of Predictive Maintenance and Production Scheduling Methodologies with PRISMA Approach

***Salma Maataoui[†], Ghita Bencheikh[††] and Ghizlane Bencheikh[†]**
salma.maataoui@edu.umi.ac.ma , gbencheikh@cesi.fr and g.bencheikh@umi.ac.ma
[†]Moulay Ismail University of Meknes, Morocco
[††] Laboratoire Lineact, Cesi école d'ingénieurs, Assat Nouvelle-Aquitaine, France

Abstract
Predictive maintenance has been considered fundamental in industrial applications over the last few years. It contributes to improving reliability, availability, and maintainability of the systems and decreasing production efficiency in manufacturing plants. This article aims to explore the integration of predictive maintenance into production scheduling through a systematic review of literature. The review includes 165 research articles published in international journals indexed in the Scopus database. Press articles, conference papers, and non-English papers are not considered in this study. After carefully evaluating each study for its purpose and scope, 50 research articles are selected for this review, following the 2020 Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA) statement. Benchmarking of predictive maintenance methods was used to understand the parameters contributing to improved production scheduling. The results of our comparative analysis, which assessed various methods for prediction, underscore the promising potential of artificial intelligence in anticipating breakdowns. An additional insight from this study is that each equipment has its own parameters that must be collected, monitored, and analyzed.

Keywords:
Predictive Maintenance; Production Scheduling; Systematic Review; PRISMA; Artificial Intelligence.

1. Introduction

In contemporary times, the primary goal of every production plant is to achieve and sustain prosperity and success. The maintenance department, an integral component of any thriving business enterprise, plays a pivotal role in the overall operation. While it may not directly contribute to the productive output, its significance cannot be overstated. It stands as one of the most vital departments within the production plant, responsible for maximizing equipment and machinery availability and operational efficiency.

The maintenance department's primary objective is to ensure continuous machine and equipment operation, minimizing failures and production interruptions. Achieving this goal necessitates the department's prompt resolution of problems to minimize losses due to equipment shutdowns and prevent future occurrences.

Fundamentally, maintenance aims to uphold optimal equipment and machinery condition throughout their operational cycles, ensuring functionality. Properly defining, meticulously planning, and gaining acceptance for maintenance activities are key principles. These activities encompass aspects such as product quality, equipment usability, cost reduction, safety, and environmental protection. Adhering to these activities guarantees that machines and equipment remain in optimal condition, facilitating safe, efficient, and reliable operation.

This research aims to explore the benefits of predictive maintenance in the context of production scheduling. The systematic literature review conducted for this research identifies, evaluates, and synthesizes existing knowledge and evidence on predictive maintenance's application in production scheduling.

This paper is organized into five sections, starting with an introduction. In section 2, the paper explores foundational aspects of production scheduling and predictive maintenance. The third section outlines the materials and methods employed in this research. Section 4 presents the findings and outcomes of the systematic literature review. Finally, section 5 concludes the study by summarizing key findings and suggesting future research directions.

2. Fundamentals of production scheduling and predictive maintenance

Industrial systems have experienced significant transformations in recent years, necessitating a corresponding evolution in maintenance strategies toward increased efficiency and sophistication. These advancements, however, come with challenges,

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particularly in managing the usage time of increasingly expensive machines. The extensive utilization of resources can accelerate their health deterioration, ultimately resulting in breakdowns. Consequently, there is a pressing need to develop decision support tools that facilitate the optimized management of machine usage. In this section, we provide clear definitions of production scheduling and predictive maintenance, elucidating the potential impact of predictive maintenance on production scheduling.

2.1 Production Scheduling

Production scheduling is a crucial decision-making process that facilitates the efficient organization of production resources within a company. Positioned as a key step in the planning process, it integrates essential factors in the production system, including customer demands, production planning, and resource allocation (refer to Figure 1). Scheduling, widely applicable in various industries, particularly in manufacturing and services, involves allocating existing production resources, such as machines, to execute a sequence of tasks or jobs within a specified timeframe. The primary objective is to meet performance criteria, encompassing both customer satisfaction and production efficiency [2].

In today's production systems, the pursuit of increased productivity and optimized average costs requires the development of flexible scheduling systems capable of adapting to changes and minimizing downtime. Production systems encounter challenges such as unpredictable customer demands, machine breakdowns, and delivery delays, imposing significant constraints. As a result, production management extends beyond its core objective of goods production to address secondary objectives, categorized as external objectives related to customer satisfaction and internal objectives linked to optimizing the production system's use.

Effective scheduling plays a pivotal role in improving both external and internal objectives, positioning production scheduling as a extensively researched topic in operations research, management science, and artificial intelligence, all aimed at enhancing production efficiency.

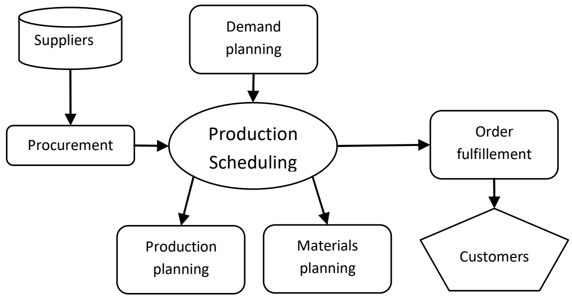

Fig. 1. A summary of production planning and control activities in a company [1].

There are various types of production scheduling, each suited to different manufacturing scenarios. These include production within a single machine, parallel machines, and job production scheduling, further categorized into flow shop, open shop, and job shop [3]. In flow shop scheduling, jobs follow a predetermined sequence of operations, ideal for highly standardized assembly line production [1]. Open shop scheduling is similar, but with no specific ordering constraints on operations. Job shop scheduling (JSS) deals with jobs having ordered lists of operations, and it's a challenging problem in combinatorial optimization, often considered NP-hard [4]. Job shops, prevalent in businesses with complete customization, pose complexity due to varied production processes for each job, resulting in unique finished products [1]. JSS can be classified based on job information availability, distinguishing between static (classical) JSS and dynamic JSS [5]. Additionally, depending on whether a job can be processed on more than one machine, JSS is categorized into flexible JSS and non-flexible JSS [6].

2.2 Predictive Maintenance

Predictive Maintenance (PdM) employs advanced tools to determine the optimal timing for maintenance actions [7]. This approach relies on continuous monitoring of machine or process integrity, allowing for maintenance only when necessary [8]. It also facilitates early failure detection through predictive tools utilizing historical data (e.g., machine learning techniques), integrity factors (e.g., visual aspects, wear, discoloration differing from the original), statistical inference methods, and engineering approaches [8].

PdM revolves around real-time monitoring and diagnosis of system components, processes, and production chains [9]. The core strategy involves taking action when items or parts display behaviors indicative of potential machine failure, degraded performance, or a decline in product quality. Initially driven by system checks at predetermined intervals, preventive maintenance focused on analyzing the health of equipment, machines, or components within machinery [10]. In recent years, PdM has found applications in various domains, including (cyber) security issues, infrastructure management, energy fabrication, power plants, maritime systems, exploitation facilities, as well as in production chains or in future factories [11].

Essentially, predictive maintenance is a philosophy that optimizes total plant operation by utilizing the actual operating condition of plant equipment and systems. A comprehensive predictive maintenance management program utilizes cost-effective tools (e.g., vibration monitoring, thermography, tribology) to acquire real-time data and schedules maintenance activities based on actual needs [12]. The integration of predictive maintenance in a comprehensive maintenance management program optimizes process machinery availability, significantly reduces maintenance costs, and enhances product quality, productivity, and profitability in manufacturing and production plants [12].

2.3 Predictive Maintenance Integrated into Production Scheduling

In the management of production and maintenance during disturbance conditions, three distinct approaches are employed: predictive, proactive, and reactive (refer to Figure 2) [13]. The goal of the predictive approach is to formulate a schedule capable of absorbing disturbances without affecting planned external activities, all while maintaining heightened system efficiency.

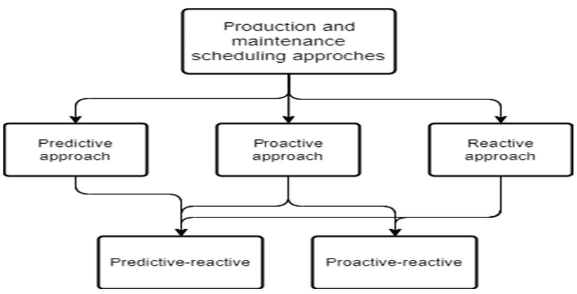

Fig. 2. Classification of Production and Maintenance Scheduling Approaches [13].

By foreseeing future machine conditions and assessing the health states of machines before executing a production schedule, plant decision-makers can proactively prevent failures attributed to machine degradation, subsequently enhancing the overall cost-effectiveness of the manufacturing system [14]. The joint optimization of job operations and Predictive Maintenance (PdM) actions results in improved planning and increased efficiency.

3. Literature Review of Predictive Maintenance Integrated into Production Scheduling

The Systematic Literature Review (SLR) is a well-acknowledged approach utilized to discover, evaluate, and interpret pertinent research on a particular subject, domain, or phenomenon [15]. Functioning as a supplementary examination, SLR strives to review studies with comparable objectives, rigorously assess methodologies, and consolidate results for statistical or meta-analysis when applicable [8]. In order to improve reporting transparency and consistency, the Quality Of Reporting Of Meta-analyses (QUOROM) guidelines were initially created and subsequently refined through the PRISMA statement [16].

3.1 Literature Review According to PRISMA Guidelines

The PRISMA 2020 statement is primarily crafted for systematic reviews examining the effects of health interventions, regardless of study design [17]. Despite its health focus, the checklist items are versatile and can be applied to systematic reviews evaluating various interventions like social or educational interventions. These guidelines are relevant not only for reviews centered on intervention assessment but also for those with broader objectives, such as examining prevalence or prognosis [16]. PRISMA 2020 is suitable for systematic reviews with or without synthesis, encompassing mixed-methods reviews that integrate both quantitative and qualitative studies. While it emphasizes original and updated systematic reviews, PRISMA 2020 is also pertinent to continuously updated ("living") systematic reviews [17].

This updated statement empowers academic authors to efficiently construct comprehensive systematic reviews with significant relevance to the research community. It ensures a thorough understanding of the research topic and facilitates the identification of new questions for future investigation [16, 17, 19].

3.2 Literature Review Planning Protocol

This paper follows a systematic planning protocol for the review, offering a comprehensive framework that serves as a valuable guide for researchers to gain a deeper understanding of the research topic, recognize limitations, and explore future directions for integrating maintenance methods into production scheduling.

Research Questions: The paper addresses two main questions: (1) How are predictive maintenance methods utilized in production scheduling? and (2) In which fields is predictive maintenance widely applied? The selection of papers discussed in this work is based on these key questions.

Databases for Literature Searching: The study utilized Scopus, a reputable scientific literature database. All chosen papers are scientific articles from international journals indexed by Scopus, published in English between 2011 and 2023.

Execution: For the execution of the Systematic Literature Review (SLR), keywords for constructing search strings were selected based on terms commonly found in the literature and terms specific to this review (i.e., Predictive maintenance applied to production scheduling).

The search on Scopus used the formula:
TITLE-ABS-KEY(("predictive maintenance" OR "PdM") AND ("production schedu*" OR "production plan*"))

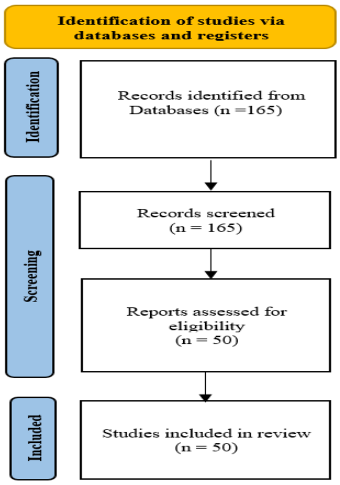

Fig. 3. Literature review according to PRISMA guidelines

A total of 165 papers were initially found. After completing the PRISMA process (Figure 3), 50 papers were identified as relevant to this literature review and selected for subsequent analysis. These papers offer insights into predictive maintenance within the context of production scheduling.

4. Results and Discussions

Adhering to the PRISMA guidelines, 50 research papers were identified during the literature review, primarily sourced from journals with an engineering and manufacturing focus.

4.1 Distribution of publications over the year

In Figure 4, the publication trend from 2011 to 2023, complete with a trend line, is evident. This analysis reveals that the incorporation of predictive maintenance into production scheduling has gained attention relatively recently in research. Up until 2017, only four papers were published, indicating a growing interest in this concept. However, there has been a noticeable upswing in research activity post-2017. Specifically, the average number of papers rose from 0.8 articles per year in the period of 2011–2016 to 7.6 articles per year in 2017–2023.

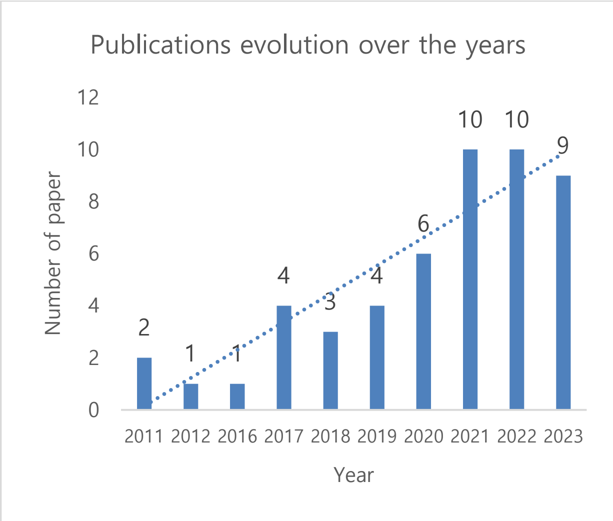

Fig. 4. Publications evolution from 2011 to 2023.

The authors in [20] argue that the limited number of works in the PdM domain is attributed to the intricacy of implementing effective PdM strategies in production settings.

4.2 Journal-wise Publication Distribution

The chosen papers, focusing on PDM applied to production scheduling, are dispersed across a diverse set of journals, encompassing a total of 28 journals. Notably, the International Journal of Advanced Manufacturing Technology holds the top position with 3 publications, followed by the Robotics and Computer-Integrated Manufacturing journal with 2 publications. The remaining journals each feature 1 publication (See Figure 5).

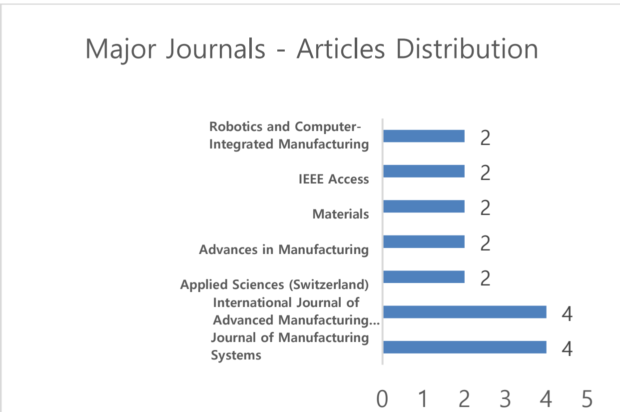

Fig. 5. Journal-wise Article Distribution.

4.3 Overview of Highly Referenced Articles

Examining the topic in question, the most referenced articles (refer to Figure 6) are succinctly summarized. Leading the citation count is the research paper titled "Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison," boasting an impressive 939 citations. Close behind is the article on "A Deep Learning Model for Smart Manufacturing Using Convolutional LSTM Neural Network Auto encoders" which has garnered 145 citations. Additionally, "Machine learning for predictive scheduling and resource allocation in large scale manufacturing systems" follows suit with 104 citations, while the remaining articles have each accrued fewer than 100 citations. This analysis highlights the prominence and impact of key contributions within the realm of smart manufacturing and Industry 4.0.

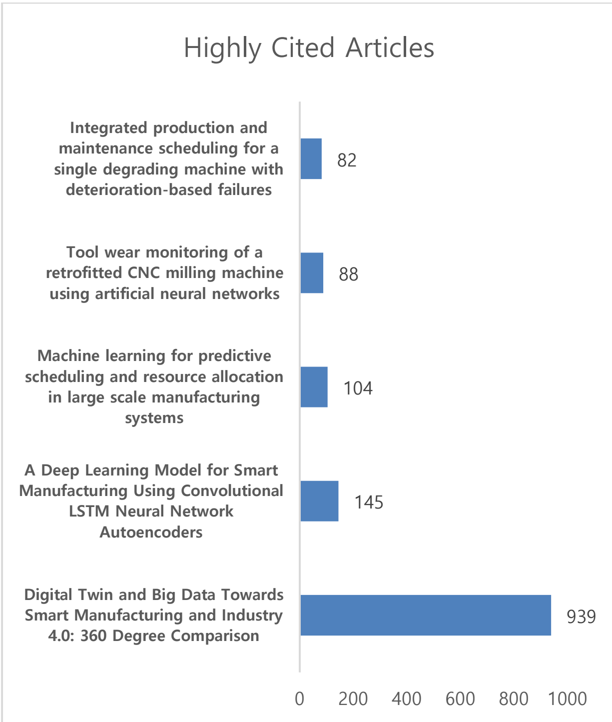

Fig. 6. Highly Cited Articles

4.4 Analysis of Research Methods

Table 1 presents our analyses of eligible articles, offering an insight into the most recent papers on PdM and production scheduling. Each line corresponds to a specific paper, with the first three columns detailing its reference, method employed, and equipment used. The fourth column provides a description of the data applied for prediction, while the fifth column, labeled "Data type," indicates whether Real Data (RD) or Synthetic Data (SD) was used in the study case. "N/A" denotes not applicable.

TABLE I. ANALYSIS OF RESEARCH ARTICLES

Reference	Used Methods	Equipment	Description of the data applied for predictive maintenance	Data type
[21]	Machine Learning	Wear on a brake system	Braking force Brake pads thickness	RD
[22]	Ant colony optimization	FDM (Fused Deposition Molding)	Data on the environment FDM machine generated data	RD
[23]	Artificial Intelligence	Photovoltaic cells	Electrical signals	RD
[24]	Mathematical Model	Micro Gas Turbines	Sensors measurement	SD
[25]	Hybrid metaheuristic	Industrial equipment	Prognostics and Health management (PHM) Signals	SD
[26]	Artificial Intelligence	Production chains	Key Indicator Performance Results	RD
[13]	Ant colony optimization	-	Reliability characteristics	SD
[27]	Mathematical Model	Electric steering gears	Reliability characteristics	RD
[28]	Deep learning model	Machine Speed Direction	Historical data	RD
[29]	Big data and Machine learning	-	Manufacturing Execution System & Signals data	SD
[30]	Online measuring device	5axis CNC milling machine	Sensor's data	RD
[31]	Genetic Algorithm	-	Design parameters	SD
[32]	Mathematical model	Gas compression system	Historical maintenance data Sensor's data	RD
[33]	Agglomerative hierarchical clustering algorithm	CNC Computer Numerical Control	Electrical power	SD
[34]	A predictive association rule-based maintenance policy	Oil refinery	Input parameters	RD
[35]	Genetic Algorithm	Hydraulic Pump Wear	Health state transition probability Production parameters	RD
[36]	Artificial neural networks	Retrofitted CNC milling machine	Sensor Signal: Vibration data	RD
[37]	Monitoring Model	Bearings	Lubricating oil samples analysis	RD
[38]	Big data	Smart manufacturing	-	NA
[39]	Deep digital maintenance	Oil cooler	Enterprise Resource Planning (ERP) Manufacturing Execution System (MES)	RD
[40]	Nonlinear optimization	Boring tool	Parameters setting	RD
[50]	-Deep learning and mathematical programming -A long short-term memory model	-	Sensor's data	RD
[51]	Maintenance driven scheduling cockpit	-	-	N/A
[52]	- Deep neural networks (DNN) and recurrent neural networks (RNN) models - Regression random forest (RRF) - Job Shop algorithms from Google's OR-Tools	-	Sensor telemetry and operating information	RD
[53]	Production-inventory model	-	-	RD

[54]	Multi-agent system called SCEMP (Supervisor, Customers, Environment, Maintainers and Producers)	-	-	SD
[55]	Markov decision model	-	IoT sensors	RD
[56]	- (Log)-location-scale (LLS) regression model - Multivariate functional principal component analysis (MFPCA) - Real-time prognosis updating framework	-	Monitoring data	RD
[57]	Advanced signal processing techniques	-Inertial vibrator -Sieving screen - Bearings -Vibrating screen - Accelerometers	Signals of vibration	RD
Reference	**Used Methods**	**Equipment**	**Description of the data applied for predictive maintenance**	**Data type**
[59]	-	-	-	N/A
[60]	Machine Learning	Production line of Cement plant	-	RD
[61]	-	-	-	N/A
[62]	-Multilayer bidirectional long short-term memory (Bi-LSTM) -Convolutional neural networks -Fusion network	-	C-MAPSS dataset	RD
[63]	Multi-perspective data-oriented services in Cyber-Physical Production Networks	-	Cyber Physical Production Network.	RD
[64]	- Multiple linear regression - GRU model	-	-	RD
[65]	Heuristic algorithm based on Tabu search.	Photolithography machines used by a red electronics manufacturer.	-	RD
[66]	- Prognostics and Health Management (PHM) module - Predictive maintenance integrated production scheduling (PdM-IPS) module - Two-stage Genetic Algorithm (TSGA)	-	-	N/A
[67]	Mathematical models	-	Reliability characteristics	N/A

The comprehensive review conducted underscores the widespread application of predictive maintenance across diverse equipment and fields. Notably, a significant observation is the predominant use of real data over synthetic data in the analyzed papers. This trend may stem from the specific characteristics inherent in each predictive maintenance application, where synthetic data might not effectively represent real-world scenarios [8].
Furthermore, table 1 highlights a clear preference for certain methods, with artificial intelligence, particularly machine learning, being the most frequently employed. Additionally, genetic algorithms and ant colony algorithms emerge as the preferred heuristic search algorithms.

The breakdown of PdM applications in Table 1 reveals a correlation between each application and specific equipment. This equipment spans various domains, including brake systems, molding machines, photovoltaic cells, turbines, electric steering gears, machine speed direction, CNC milling machines, gas compression systems, CNC (Computer Numerical Control), oil refineries, hydraulic pumps, bearings, and oil coolers.

An interesting trend identified in Table 1 is the prevalent use of sensor data to detect anomalies in equipment. Beyond the papers cited in Table 1, additional references [41–49] can be considered to further enrich the categorization by field (See Figure 7).

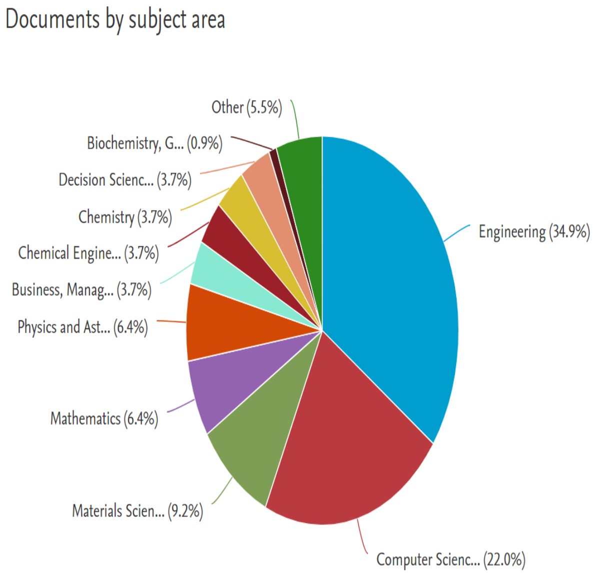

Fig. 7. Research Papers Addressing PDM and Production Scheduling by subject area.

The identified papers underwent additional scrutiny, considering their potential impact on specific field categories. On average, Engineering predominated, constituting the majority at 34.9% of the papers, followed by Computer Science at 22%. Papers centered on Material Science comprised 9.2% of the research, while Mathematics Sciences contributed 6.4%. The insights gleaned from the characteristics of the most recent papers on Predictive Maintenance (PdM) (refer to Table 1 and Figure 7) significantly contribute to addressing the research questions.

5. Conclusion

In conclusion, this paper thoroughly explored existing literature, delving into crucial research on Predictive Maintenance (PdM) and production scheduling, addressing outlined research questions following PRISMA 2020 guidelines. The findings emphasized the specificity of each proposed approach to particular equipment, making direct comparisons with other techniques challenging. Notably, PdM emerged as an innovative tool for effectively managing maintenance events, reflecting the evolving landscape within the industrial field.
Within this review, certain efforts utilized standard Machine Learning (ML) methodologies without parameter tuning, relying on sensor-derived data for predictive maintenance. This trend suggests the early stage of PdM exploration in the industrial domain.
A key point is the significance of prior implementation of PdM strategies within a facility's processes to gather essential data for effective modeling. This data-driven approach is crucial for designing and validating a successful PdM strategy, contributing to improved efficiency and reduced downtime.

However, acknowledging the study's limitations, future research directions were identified. These include the development of advanced sensing technologies, integration of deep learning and AI, holistic system optimization, quality impact assessments, alignment with Industry 4.0, benchmarking, human-machine collaboration, cost-benefit analyses, and cross-industry knowledge transfer. Pursuing these avenues aims to propel the ongoing evolution of predictive maintenance and production scheduling, fostering smarter, more resilient industrial processes.

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Salma MAATAOUI is a research scholar in Computer Science and Information Science at Moulay Ismail University of Meknes. She specializes in production scheduling, maintenance, quality, data science, and machine learning. As a Six Sigma Black Belt, she excels in process improvement and Core Tools, holding certifications as an internal auditor for IATF 16949:2016, ISO 9001:2015, ISO 14001:2015, and ISO 45001:2018. Salma's diverse expertise highlights her dedication to academic excellence, process optimization, and upholding global quality standards.

Dr. Ghita BENCHEIKH is teacher-researcher faculty member at the Lineact Laboratory within the Cesi School of Engineering in Pau. Her research focuses on optimization challenges within industrial systems and distribution in the urban logistics sector. Her research work has been centered around developing mathematical models and innovative computer techniques to optimize resource management, enhance operational efficiency, and reduce the environmental footprint of industrial activities in these intricate settings.

Ghizlane BENCHEIKH is a Professor of computer science at the Faculty of law, economics and socials of the university of Moulay Ismail of Meknes. Her research interests include Scheduling Problems, Transport, Combinatorial optimization and metaheuristics. She is a member of the laboratory of informatics and applications, and she is supervising a number of PhD students working on multi agent systems, production scheduling and maintenance.