Bridging Predictive and Prescriptive Maintenance in Equipment Leasing: A Review and Research Roadmap

K.F.Rémi Djoumato[1,2], Ayoub Chakroun[1], Faicel Hnaien[1], Adekunlé Akim Salami[2]

***Abstract*— One of economical solutions for industries is equipment leasing, which allows them to meet customer demands on time. However, without a good maintenance strategy, this proves difficult. Maintenance strategies have also evolved and now moved from corrective maintenance to proactive maintenance, such as predictive maintenance and prescriptive maintenance. Predictive maintenance (PdM) and prescriptive maintenance (PsM) are increasingly seen as complementary pillars of Industry 4.0. The literature remains fragmented between anomaly detection using artificial intelligence, reliability engineering, and operational research, and the operational translation of prognoses such as Remaining Useful Life (RUL) and failure probability into decisions, planning, resource allocation, and optimized policies, where several areas remain to be explored. This paper offers a comprehensive review on maintenance policies particularly PdM and PsM and also taking into account the different maintenance strategies used for leased equipment.Based on the insights gained from reviewing recent publications on these three strands of literature, we then engage in a discussion and outline possible directions for the future.**

Keywords: Prescriptive maintenance; Predictive maintenance; Industry 4.0; Leased equipment; Anomaly detection; Fault probability; Optimization.

I. INTRODUCTION

In the fiercely competitive landscape of modern manufacturing, companies are increasingly adopting advanced technologies to maintain their market share. With smart technology, processes and production methods are being refined to meet evolving manufacturer requirements. Industry 4.0 fosters the transformation of conventional factories through digitization and enhanced connectivity[1]. Often subject to budgetary constraints, the purchase of heavy equipment represents a significant initial investment for the manufacturing industries. However, in order to maintain their capacity for innovation while remaining competitive, industries need access to high-performance equipment without tying up significant capital. Equipment leasing is becoming a strategic solution to meet the challenges of competitiveness and reduce the costs associated with maintenance and asset management. Indeed, effective maintenance operations are essential to maintaining the productivity of production sites and, consequently, the competitiveness of manufacturing companies[2]. To be more competitive, operators are adopting maintenance policies such as predictive and prescriptive maintenance, which have become central pillars of Industry 4.0, reducing unplanned downtime, improving asset utilization, and supporting data-driven decision-making in increasingly complex and connected production systems. While PdM focuses on predicting equipment degradation and failures and, PsM extends this paradigm by recommending or optimizing concrete actions, resources, and schedules to achieve objectives such as cost, availability, and sustainability[3]. After extensively reviewing the literature, we identified reviews devoted to predictive maintenance[4],[5] and others devoted to prescriptive maintenance[6], as well as articles that have addressed the maintenance of leased equipment[7],[8].The main contribution of this paper is not limited to providing a general review of PdM and PsM. Rather, it aims to connect three research streams that are still largely fragmented: PdM, PsM, and maintenance strategies for leased equipment. The specific contributions are fourfold. First, the paper proposes a structured classification of recent maintenance approaches in Industry 4.0. Second, it provides a comparative analysis of PsM approaches. Third, it identifies specific research gaps related to the integration of predictive outputs into prescriptive decision-making in leasing systems. Fourth, it outlines a conceptual roadmap for a framework that combines PdM and PsM for leased equipment. The remainder of this paper is organized as follows, Section II provides an overview based on PdM; PsM and maintenance for leased equipment, and Section III gives a discussion and future research direction, and finally by the conclusion Section IV.

II. METHODOLOGY AND RELEVANT PUBLICATION

The literature corpus was collected primarily from Scopus and Dimensions, ensuring broad interdisciplinary coverage. A preliminary exploration phase allowed fine-tuning of the search string to capture the intersection between data-driven predictive models and prescriptive decision-making frameworks with keywords: ("predictive maintenance" OR "prognostics and health management") AND ("prescriptive maintenance" OR "maintenance optimization" OR "maintenance scheduling") AND ("Industry 4.0" OR "smart manufacturing" OR "cyber-physical production system") at first level and after we focused on the case of maintenance of leased equipment: ("equipment leasing" OR "asset leasing") AND ("maintenance" OR "repair") AND ("Industry 4.0" OR "smart manufacturing" OR "cyber-physical production system") on second level from 2020 to 2025. Over the period covered by our study, we identified 3,334 articles respectively 2,533 from the Dimension database and 801 from Scopus. We then selected 31 articles based on the selection criteria presented in Table I to conduct our analysis.

[1]LIST3N, Université de Technologie de Troyes, (remi.djoumato,ayoub.chakroun,faicel.hnaien).@utt.fr
[2]LARSI, Université de Lomé akim_salami@yahoo.fr

TABLE I: Exclusion criteria (EC) and inclusion criteria (IC)

EC and IC	Description
EC1	The full text of the article is not accessible.
EC2	The paper is not written in English or is less than four pages long.
EC3	The document is a book, editorial, thesis, dissertation, technical report, or non-peer-reviewed source.
EC4	The article is outside the selected publication period, i.e., 2020-2025.
EC5	The article is not directly related to predictive maintenance, prescriptive maintenance, maintenance optimization, or equipment leasing.
IC	The articles used for the paper review are published in Q1 and Q2 journals.

A. Predictive Maintenance

1) Models based on Artificial Intelligence methods: Predictive maintenance is a data-driven maintenance strategy that continuously monitors the actual condition of assets and leverages historical and real-time data typically collected via IoT sensors and machine learning models to predict when a component is likely to degrade to a critical level or fail, so maintenance can be scheduled just before the breakdown.[9]. Machine Learning(ML) framework for real-time predictive maintenance presented in [10] for early fault decting. The IoT sensor data was collected and then principal component analysis (PCA) was applied to reduce the dimensionality and train supervised classifiers (Decision Tree(DT), Random Forest(RF), Gradient Boosting(GB), Support Vector Machine(SVM) to detect normal and critical bearing conditions. The digital Twin driven PdM framework that fuses IoT sensor networks , multiple ML models for prediction and anomaly detection was implemented in [11]. The digital twin is further strengthened with physics-based simulations for more accurate behavior representation, and they add reinforcement learning as an asset management layer to optimize maintenance timing by balancing maintenance and downtime cost. Classification model was built in [12] using a combination of time-series imaging and Convolutional Neural Network (CNN) for better accuracy to classify fault severity. Hybrid deep learning framework based on CNN-LSTM [13] combines the advantages of convolutional neural networks (CNN), which extract the effective features and patterns among multi-variate input variables, and LSTM, which captures the complex long-term dependencies and automatically selects the mode best suited for relevant time-series data. The hybrid CNN-LSTM model is designed to make the optimization easier by extracting the effective features using CNNs and then incorporating LSTM in parallel to predict machine failures. In [14], an existing deep model, named Attention-based Equitable Segmentation Gated Recurrent Unit Networks (AESGRU), the specific model structure is depicted in, which is composed of a bidirectional Gated Recurrent Unit (GRU) network and enhanced with the attention mechanism is used to overcome the same issue. The explainable PdM pipeline is implemented in [15] with four stages: multi-fault data acquisition, extraction of statistical features in the frequency domain from Fast Fourrier Transform (FFT) signals, training and use multiple ML classifiers (SVM, DT, RF), and integration tools to provide local and global explanations of predictions. PdM also lay on failure rate prediction challenges. A model based on ML and Artificial Intelligence named Discrete Bayes Filter(DBF) was developed in [16] to estimate and foresee the gradual deterioration of robots' power transmitters in a Cyber-Physical Production System workshop.

2) Models based on probabilistic methods: In [17], a sensorless PdM solution based on survival analysis was proposed, where historical maintenance logs are transformed into series of time-between-failures and then modeled with a two-parameter Weibull distribution to estimate the probability of failure. The failure probability tied to the next scheduled job model is built in [18] on the acquisition of sensor signal from the Cyber-Physical System; health assessment using logistic regression to map multi-sensor inputs into a unified failure probability indicator; using a feed-forward neural network from time series to forecast future failure probabilities. Another model is used in [19] the use of the Cross Industry Standard Process for Data Mining (CRISP-DM) model based on the Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR) and analysis of past failures in the industrial sector guaranty the prediction accuracy of machine failures.

B. Prescriptive Maintenance

Prescriptive maintenance is a maintenance strategy that goes one step beyond prediction maintenance by not only estimating when and how an asset will fail, but also recommending or optimizing what actions should be taken, when, and with which resources to reduce downtime cost and increase availability.

1) Optimization-based methods: In [20] a Degradation-aware Model Predictive Control (D-MPC) is proposed with a two-level architecture first for RUL forecasting and secondary a Mixed Integer Linear Programming (MILP) that co-optimizes job sequencing and maintenance intervention. As a contribution, a holistic and scaleable Smart predictive (HSSP) Optimization framework is developed in [21] to integrate operation; maintenance decision; maintenance resources and uncertainties into a single prescriptive decision layer, implemented as a MILP to recommend an optimal course of action that maximizes system level performance. In [22], authors proposed a separate chance-constrained stochastic programming model for predictive maintenance planning in which degradation levels are treated as random variables, and reliability is enforced via probabilistic constraints. SVM is implemented in [23] to predict failure probabilities; then MILP was used to plan maintenance tasks based on the predictions provided by SVM. In [24] an integrated cost minimization framework based on the metaheuristic Jaya algorithm that jointly plans the production sequence, Preventive maintenance (PM) intervals , and selection of a group of components for PM.

2) Simulation-based method: A maintenance process of the existing machines in the gear-manufacturing workshop is modeled in [25]. It is a dual simulation model for an optimal assignment of human resources to properly manage the maintenance of assets taking into account the availability of maintenance operators and the types of breakdowns encountered. For long-term preventive maintenance scheduling problem (LTPMSP) faced by large industrial companies(for example scheduling for a year), a simheuristic approach called SIM-ILS [26], combining an Iterated Local Search (ILS) with Monte Carlo Simulation is used to capture duration uncertainty and optimize maintenance schedules.

3) Learning-based methods: In [27] a joint production and preventive maintenance schedule is modeled for a single-machine system as a Markov Decision Process (MDP) and then solved with Reinforcement Learning (RL) and improved heuristic RL algorithms. In [28] a Deep Q-Network (DQN) is modeled In the for maintenance scheduling for a semi conductor front-end wafer fabrication. The Tran-DRL model in [29] is used to predict machine RUL using the Transformer model, the predictions are used as input for the Proximal Policy Optimization (PPO), DQN and Soft Actor Critic (SAC) models to recommend maintenance actions. The authors in [30] addressed the preventive maintenance scheduling issue and proposed a DQN approach for load balancing and makespan reduction. To provide a more analytical perspective, a comparative synthesis of the main prescriptive maintenance approaches is presented in Table II.

C. Maintenance strategy for leased equipment

1) Maintenance-oriented models for leased equipment: In [7] an opportunistic maintenance framework is introduced for serial–parallel leased systems that explicitly couples maintenance decisions with leasing profit and capacity balancing. To better reflect realistic operating regimes, the authors in [31] propose a multi-phase PM strategy where the maintenance plan adapts to variation in usage-rates throughout the lease term. Moving from time-based PM to condition-driven decisions, a condition-based optimal maintenance is developed in [32] policy that combines hybrid preventive maintenance with periodic inspection to control risk and cost under partially observed deterioration. From a multi-objective perspective in [33], an optimization model was built and solved that jointly considers degradation, maintenance choices, and residual value of equipment using NSGA-II to generate Pareto-optimal maintenance plans. In [34], authors introduced a framework assuming that the lessor handles preventive maintenance (PM) and covers all maintenance expenses during the warranty period, although they are not liable for corrective maintenance (CM) once this period ends.

2) Models based on contractual strategy for leased equipment: Leased equipment refers to industrial assets that are provided to a user (lessee) for a fixed contractual period in exchange for a payment system (rent, pay-per-use, or even “free leasing”[8] linked to consumables provided by the lessor in compensation) while ownership remains with the supplier. In parallel, authors in [35] broaden the leasing decision space by integrating operational and economic levers (pricing–inventory with lessee options) with maintenance-driven performance impacts. Interested on contract and supply-chain layer, authors in [36] incorporate learning effects (maintenance experience reducing PM intervention time and cost) and show that coordination mechanisms (e.g., cost-sharing and failure-limitation contracts) can outperform decentralized decisions. In [37] a customized leasing pricing model is developed that accounts for customer differences, incorporates a two-dimensional warranty strategy along with PM considerations, and offers three distinct rental services by categorizing customers into high, medium and low usage groups based on their utilization of leased equipment. In [38] a joint optimization approach of a maintenance strategy and an economical production plan is developed considering the influence of usage rates on machine degradation; addressing the issue of detecting the exact number of machines to be leased, the quantity to produce by each and subjecting to variable customer demand.

III. DISCUSSION AND FUTURE REASEARCH DIRECTIONS

A. Specific Research Gaps in PdM–PsM Integration for Equipment Leasing

Specific research gaps in PdM-PsM integration for equipment leasing can be summarized along three dimensions. First one, an integration gap remains between the transition from prediction results to prescription models. Many PdM models provide health indicators, RUL estimates, or failure probabilities, but these outputs are not systematically transformed into maintenance interventions schedules, resources allocation decisions, or cost-risk trade-offs. Second, leasing systems differ from conventional maintenance settings because the lessor and the lessee are distinct actors that will need to be taken into account. This creates specific constraints related to rental contracts, warranty periods, consumable supply, usage rate, residual value, equipment return, and maintenance responsibilities. Third, several existing models rely on assumptions that are difficult to maintain in practice, such as fixed usage rates, deterministic degradation, negligible spare-part constraints, or fixed maintenance duration. These limitations motivate the development of an integrated PdM-PsM framework capable of using real-time condition data to support maintenance planning decisions in equipment leasing systems.

B. Future Research Directions

Based on this literature review, significant progress has been achieved in PdM and PsM. However, critical gaps remain, particularly regarding stochastic degradation models, the management of prediction uncertainties, and the complex interdependencies within multi-component systems. Future research in PdM and PsM should prioritize the refinement of RUL estimation, the integration of component dependencies, and real-time model updates that account for diverse system operating modes. Regarding decision-making and planning, the development of stochastic and robust models is essential

TABLE II: Comparative synthesis of prescriptive maintenance approaches.

PsM approach	Main principle	Strengths	Limitations
MILP optimization	Optimizes maintenance and production decisions under explicit constraints	High interpretability, good for exact constraint modeling and suitable for planning	Difficult to solve when the problem keeps getting bigger
Stochastic optimization	Incorporates uncertainty in degradation or RUL estimation, or maintenance duration	Better uncertainty handling and more reliable decisions under variability	Requires probability distributions and can be computationally demanding
Reinforcement learning	Learns sequential maintenance policies from interaction with the environment	Adaptive and suitable for dynamic decision-making environments	Need huge amount of data, and is less interpretable

to effectively integrate predictive outputs while mitigating uncertainty. Let's shed the light in a such specific context of leased equipment, a field we are particularly interested in exploring existing frameworks often lack the integration of real-time operating data. Based on the existing works in this field, our interest lies in incorporating predictive models based on actual equipment usage to move beyond static virtual age assumptions. Future research must also explicitly model maintenance and repair times while considering resource constraints, such as technician availability and spare parts inventory, to better reflect the operational realities of the lessor.

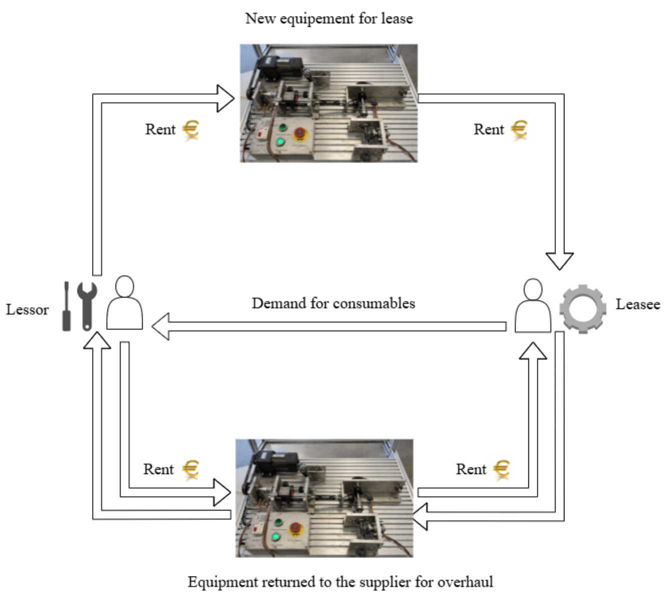

Fig. 1: Leasing supply chain

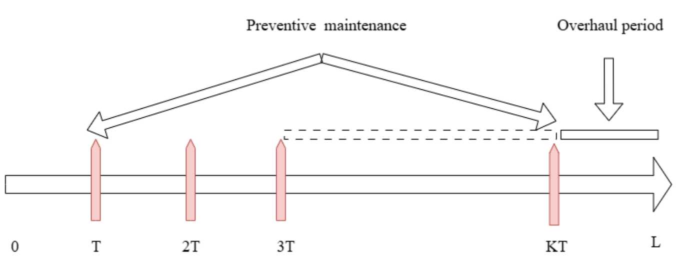

Fig. 2: Timeline of activities related to lessor

C. Research Roadmap

The supply chain of our leasing model is presented in Figure 1, and shows that the machine to be leased is the ZM1101T Movement Transmission and Transformation System of Université de Technologie de Troyes (UTT) CapSec Platform presented in Figure 4, which consists of subsystems such as belt, gear, and chain modules connected to each other by transmission bearings. The Figure 4 shows that the lessor leases the machine to the lessee at a fixed rent and is responsible for preventive maintenance to be carried out at the customer's premises at specific intervals T over rental period L as presented in Figure 2. After reviewing the literature for the period from 2020 to 2025, specifically for maintenance strategies for leased equipment, to the best of our knowledge, no author has developed a strategy that integrates predictive and prescriptive maintenance into their leasing model. In this study, our objective for roadmap presented in Figure 3 is to develop a hierarchical model that uses the leasing model and a PdM model to estimate the state of deterioration of leased equipment and predict the equivalent RUL of all equipment subsystems. We will then develop a prescription model that incorporates the prediction results in order to plan preventive maintenance interventions at the lessee's side. In return, the lessee must pay the lessor a fixed rent and must purchase consumables from the lessor according to a demand to be formulated. At the end of the lease period, the customer may lease the equipment again after it has been reconditioned by the lessor, or activate a purchase option to acquire the equipment outright.

IV. CONCLUSION

This article examines the evolution of maintenance policies in the context of Industry 4.0, with a particular focus on the growing complementarity between PdM and PsM, as well as the different maintenance strategies employed in the context of equipment leasing. By reviewing recent studies, we have highlighted avenues for exploring a more robust connection between the two maintenance policies. Particularly in the context of equipment leasing, the gap is felt in the sense that there is still no framework model that integrates PdM and PsM strategies, as well as uncertainties about the provision of consumables to the customer and maintenance plans that take into account the different modes of use of the leased equipment. Based on a summary of

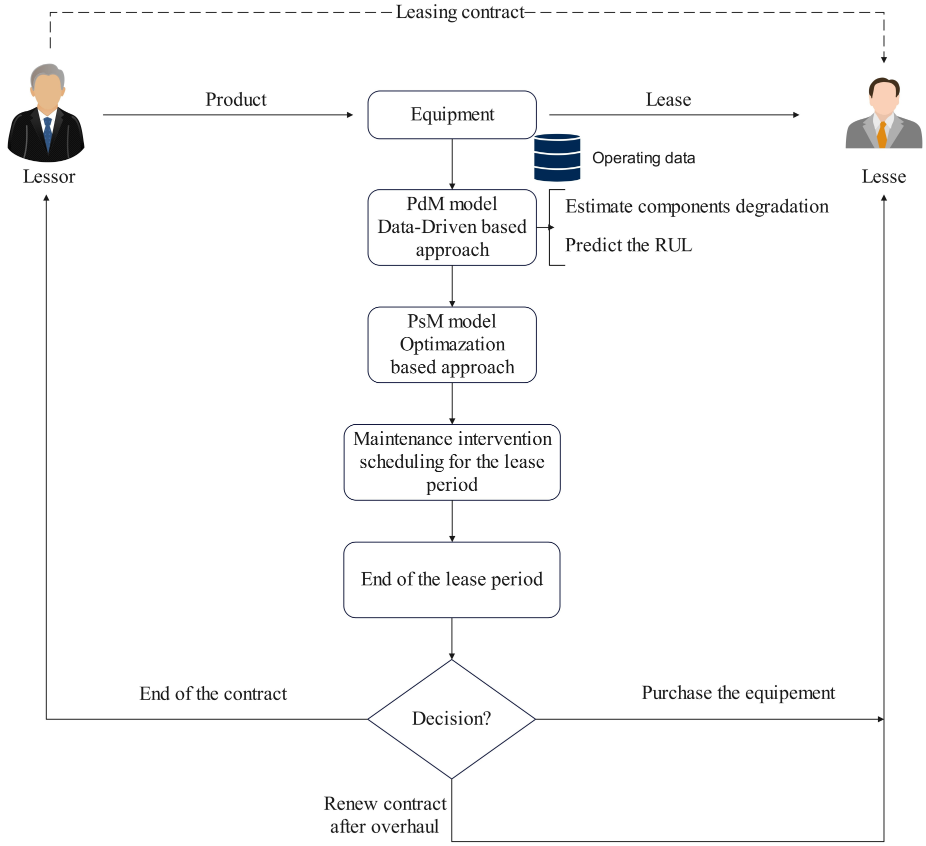

Fig. 3: Architectural overview of PdM and PsM strategies for leased equipment

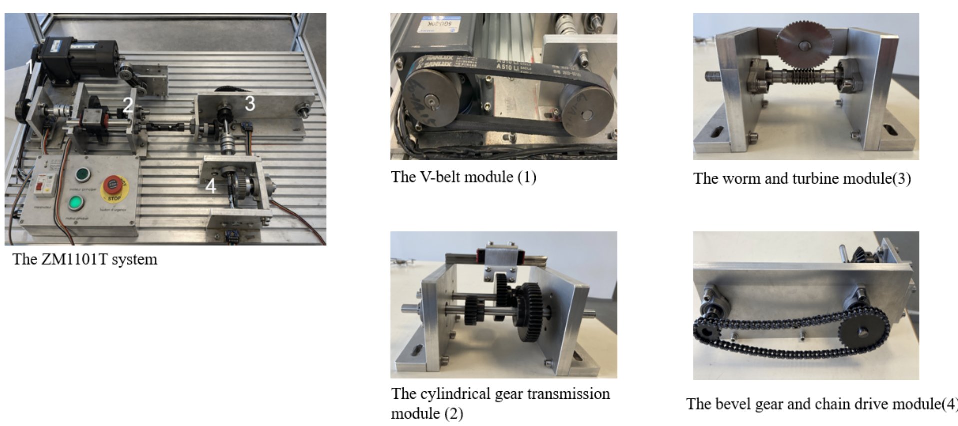

Fig. 4: ZM1101T Movement Transmission and Transformation System

work published between 2020 and 2025, we have outlined the main research directions for future studies of maintenance policies focused on equipment rental. Finally, we present our ongoing research that aims to establish a hierarchical framework that combines a rental model that incorporates a PdM strategy, based on vibration data, which will then be integrated into a prescriptive layer for planning preventive interventions at customer sites. This roadmap aims to contribute to the current literature on PdM and PsM and to move towards a maintenance strategy adapted to equipment leasing frameworks.

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