

Hybrid Artificial Intelligence Model for the Transition from Predictive to Prescriptive Maintenance in Textile Manufacturing

N. Chambi Quiroz, Master¹ , S. Choque Quispe, Student²

^{1,2} Universidad Nacional de Ingeniería, Perú, nchambiq@uni.pe, sara.choque.q@uni.pe

Abstract— *This paper presents the development and validation of a hybrid artificial intelligence framework integrating predictive and prescriptive capabilities to optimize maintenance in the textile industry. The research addresses the high failure rate of critical textile machinery components—such as needles, feeders, guides, and tensioners—whose traditionally reactive management leads to unplanned downtime, increased operational costs, and deterioration of final product quality. The methodology comprises: historical data acquisition, preprocessing, feature engineering (MTBF, MTTR), development of predictive models (ARIMA, XGBoost), and a prescriptive module that transforms predictions into optimized decisions through multi-objective optimization subject to operational constraints. The results demonstrate significant improvements: reduced downtime from unexpected breakages, near-total elimination of fabric waste due to defective seams, decreased sudden failures, increased specific MTBF, and reduction of non-conforming products. It is concluded that the value of predictive maintenance is enhanced when complemented by a prescriptive module that translates predictions into contextualized decisions, bridging the gap between theory and its practical application in real production environments. The framework provides a replicable roadmap for extending the benefits of prescriptive maintenance to the textile sector.*

Keywords— *Prescriptive maintenance, artificial intelligence, textile industry, operational reliability.*

I. INTRODUCTION

The textile manufacturing industry constitutes one of the most economically significant production sectors globally, characterized by continuous flow production processes and a high dependence on the operational reliability of its machinery. In this environment, the continuity of the production flow and final product quality are intrinsically linked to the performance of critical components subject to progressive wear and sudden failures. However, particularly in companies with limited investment in asset management technologies, a predominant reliance on reactive maintenance (RM) persists—a practice that triggers corrective interventions only after the occurrence of a breakdown [1]. This situation generates unplanned downtime that significantly increases operational costs due to personnel overtime, productivity losses, and accelerated reduction in equipment service life, thereby compromising the sector's competitiveness.

The central problem addressed by this study lies in the high incidence of mechanical failures in specific components

of textile machinery—such as needles, shuttles, rollers, and tensioning systems—and the absence of effective strategies to anticipate them. The root cause of this issue resides in the insufficient application of advanced predictive analytics techniques, combined with deficiencies in strategic planning and the execution of maintenance interventions [2]. Although conventional strategies—fixed-interval preventive maintenance (PM) and basic predictive maintenance (PdM)—have demonstrated effectiveness in other industrial sectors [3], their implementation in the textile sector is hindered by specific structural limitations: absence of real-time monitoring systems, lack of reliable historical records, and the lack of integrated maintenance management systems [4]. These deficiencies lead to a progressive deterioration of operational conditions, resulting in recurrent interruptions, increased corrective overtime hours, and ultimately, a significant rise in the operational costs of the final product.

Predictive maintenance (PdM) is distinguished by its ability to anticipate failures through early anomaly detection based on actual equipment condition, overcoming the limitations of preventive and reactive approaches [5]. In recent decades, various industrial sectors have reported significant advances in this direction. Studies confirm that, for critical equipment, PdM techniques based on advanced algorithms are required to optimize maintenance cycles [6], with hybrid models incorporating metaheuristics being particularly effective for predicting time-to-failure [7]. Likewise, data mining techniques have improved the diagnosis of critical failures and the estimation of Remaining Useful Life (RUL) in large-scale equipment in sectors such as energy and advanced manufacturing [8].

Concurrently, the integration of Industry 4.0 enabling technologies has enhanced these predictive capabilities. Condition-Based Monitoring (CBM) through vibration analysis [9], the Internet of Things (IoT) [10], and Digital Twins [11] have demonstrated their effectiveness in optimizing operational efficiency and economic profitability in sectors such as mining, chemical industry, and construction [12]. A relevant milestone is observed in hybrid PdM models integrating Machine Learning (ML) techniques, achieving accuracies exceeding 92% alongside significant reductions in costs (25%) and downtime (15%) [13].

Specifically, within the textile domain, although with more incipient development, promising applications of ML have been reported for predicting supply chain disruptions, employing algorithms such as Support Vector Machine (SVM), AdaBoost, and Naive Bayes with accuracies exceeding 91% [14]. However, a critical research gap persists: the application of these advanced techniques to the predictive maintenance of textile manufacturing machinery itself remains largely unexplored.

The motivation for this study emerges precisely from the identified gap between the demonstrated potential of advanced PdM techniques in other industrial sectors and their limited implementation in textile manufacturing. This technological disconnect generates tangible economic and operational consequences: avoidable unplanned downtime, oversized spare parts inventories, inefficient human resource allocation, and ultimately, reduced competitiveness of the sector. The urgency of addressing this problem is accentuated in a context of increasing pressure for operational efficiency and productive sustainability, where artificial intelligence emerges as a key enabler for the digital transformation of the maintenance function.

The novelty of this work resides in the conception and application of a hybrid Artificial Intelligence framework that transcends purely predictive capabilities to venture into the domain of prescriptive maintenance (PxM). This emerging paradigm not only predicts when a failure will occur but, through advanced optimization techniques and constraint-based reasoning, recommends or automatically executes the most appropriate maintenance action (what to do, when, and why), considering operational constraints, resource availability, and associated costs [15, 16]. The novelty materializes, therefore, in the synergistic integration of: (i) high-precision predictive models for RUL estimation in critical textile components, and (ii) an AI-based prescriptive module that transforms these predictions into optimized intervention recommendations, tailored to the particularities of the textile production environment.

Consequently, the central purpose of this study is to develop and validate a hybrid Artificial Intelligence framework integrating predictive and prescriptive capabilities, specifically designed to optimize maintenance management in textile manufacturing. The study seeks to demonstrate that the strategic combination of ML algorithms for failure prediction and optimization techniques for action prescription constitutes an effective pathway to overcome the sector's current limitations and advance toward proactive and intelligent management of production assets.

The main contribution of this article to the literature and industrial practice is threefold. First, it addresses the research gap through the pioneering application of a prescriptive approach to textile machinery maintenance, an area scarcely

explored in the specialized literature. Second, it provides a replicable methodological framework integrating RUL estimation with maintenance decision optimization, constituting a guide for future implementations in the sector and other manufacturing domains with analogous characteristics. Third, it empirically validates the benefits of this hybrid approach in terms of improved predictive accuracy, reduced unplanned downtime, optimized resource allocation, and increased overall operational availability of the textile production system.

The remainder of this article is structured as follows. Section 2 presents the theoretical framework and fundamentals of predictive and prescriptive maintenance, as well as the AI algorithms employed. Section 3 describes the proposed methodology in detail, including the hybrid model architecture, development phases, and validation criteria. Section 4 presents the results obtained from implementing the proposed framework in a textile industry case study. Finally, Section 5 presents the conclusions and future research directions derived from this investigation.

2. REVIEW

Prescriptive maintenance (PxM) emerges as an advanced paradigm that transcends conventional predictive capabilities by incorporating intervention recommendation and optimization mechanisms. Unlike predictive maintenance, which is limited to forecasting failure occurrence, the prescriptive approach addresses the fundamental questions of what action to take, when to execute it, and why it is optimal under specific operating conditions [15, 16]. In this regard, conducted a meta-synthesis revealing the still-fragmented nature of the concept, identifying artificial intelligence, digital twins, and real-time data integration as key enablers. The authors conclude that PxM, supported by these enablers, enables the transition toward autonomous decisions through optimal intervention recommendations, laying the theoretical foundations for subsequent developments in various industrial sectors [17].

The consolidation of prescriptive maintenance requires robust architectures that integrate monitoring, prediction, and optimization capabilities. Proposed a five-layer framework for AI-powered digital twins in the manufacturing sector, which prescribes data-driven mitigation strategies to optimize operational efficiency and reliability [18]. Complementarily, developed a Smart Maintenance framework integrating Big Data and AI to reduce potential losses and improve the resilience of industrial plants against disruptions. The authors demonstrate that the capacity to restore operability is significantly strengthened when the system not only predicts failures but also prescribes corrective actions tailored to special causes of failure, traditionally ignored by conventional approaches [19].

In the sustainability domain, presented a digital twin prototype integrating machine learning with environmental impact assessments, enabling prescriptive maintenance execution aligned with economic, environmental, and social goals. This multidimensional approach addresses a critical limitation of traditional maintenance: the inability to integrate sustainability dimensions into intervention planning [20]. Likewise, addressed the coordination gap between production and maintenance through a normative framework integrating PxM with production planning, facilitating the self-configuration of operational plans and paving the way toward defect-free manufacturing with autonomous control processes [21].

Various industrial sectors have begun implementing prescriptive approaches with promising results. In the railway sector, developed a prescriptive analytics framework based on Graph Convolutional Networks and geometric measurements to optimize intervention schedules and predict rail failures before their occurrence, significantly improving safety margins [22]. Extending this line of research, through the DAYDREAMS project, implemented prescriptive analytics based on multi-objective optimization for railway asset management, demonstrating that prescribing optimal decisions classified according to risk and uncertainty improves network reliability and availability, overcoming the limitations of isolated asset management [23].

In intensive sectors such as mining, proposed a causal discovery framework based on deep learning and sensor data. This approach identifies specific failure triggers, enabling proactive and precise operational interventions that surpass the limitations of previous strategies incapable of interpreting underlying degradation mechanisms [24]. Furthermore, in the electrical sector, developed a prescriptive operation and maintenance model driven by reinforcement learning, optimizing battery usage to minimize electricity costs and grid alarms, thereby protecting aging assets against stochastic loads [25].

The effectiveness of prescriptive maintenance rests on the robustness of the underlying models that translate predictions into optimized decisions. In this context, proposed a variable-order Markov decision model fed with historical operational data, which advises when to advance preventive interventions to minimize total contractual costs in manufacturing environments. This approach outperforms fixed periodic policies, demonstrating that adaptive prescription based on equipment condition generates substantial savings [26]. Complementarily, developed a system integrating LSTM networks with stochastic optimization, incorporating "chance constraints" to schedule interventions that effectively balance failure probability and operational costs in complex facilities [27]. In motorized systems, the combination of motor current signature analysis with LSTM networks has enabled the incorporation of a prescriptive layer that translates diagnoses

into specific action guidelines according to the detected risk level. This approach demonstrates that contextualized prescription, based on degradation severity, enables intervention prioritization and resource allocation more efficiently than conventional predictive systems, which merely alert about expected failure occurrence [28].

A critical challenge in prescriptive maintenance adoption lies in the opacity of AI models, a phenomenon generating distrust among operators and decision-makers. To address this limitation, proposed a taxonomy of eXplainable Artificial Intelligence (XAI) applied to power systems, ensuring operational transparency by suggesting clear actions such as load adjustments or part replacement [29]. The ability to explain the reasoning behind each prescription emerges as a determining factor for industrial acceptance of the paradigm. In the biopharmaceutical industry, recent research indicates that stringent regulatory requirements demand not only accurate predictions but also traceability and justification of recommended actions, highlighting the need to integrate IoT sensor data with intelligent corporate systems ensuring regulatory compliance [30].

Collectively, the reviewed literature evidences a growing consensus on the potential of prescriptive maintenance to transform industrial asset management. However, significant gaps persist in specific sectors such as textile manufacturing, where the application of these advanced approaches remains unexplored. This finding reinforces the motivation of the present study, aimed at developing and validating a hybrid AI framework integrating predictive and prescriptive capabilities adapted to the particularities of textile machinery, thereby contributing to closing the identified gap and expanding the knowledge frontiers in this domain.

3. METHODOLOGY

This study utilizes historical data from textile processing equipment, as well as failure reports and maintenance records. Fig. 1 presents the adopted methodological framework, which integrates phases of data acquisition, preprocessing, feature engineering, predictive model development, and, as its central contribution, a prescription module for optimizing maintenance decisions.



Fig. 1 Methodological Framework for Predictive-Prescriptive Maintenance.

Data Acquisition

First, historical operation and maintenance records from critical equipment in a textile manufacturing plant will be compiled. The dataset will cover the period from November 2024 to August 2025 and will include: (i) equipment

downtime records, (ii) detailed failure reports classified by system and component, (iii) vibration analysis data, (iv) thickness measurements of components subject to wear, and (v) preventive and corrective maintenance work orders.

It should be noted that, in the current phase of the study, variable monitoring was performed sequentially and not continuously, using calibrated portable instruments. Specifically:

- **Vibration:** a portable piezoelectric accelerometer with a frequency range of 0.5 Hz to 10 kHz, magnetically attached to predetermined points on each piece of equipment during the monitoring routes.
- **Component thickness:** a digital flat-tip micrometer with a resolution of 0.001 mm, applied to needles and hooks during scheduled stops.
- **Electrical current:** a Hall-effect clamp meter (range 0-200 A AC/DC), measuring at motor terminals without interrupting operation.

While the current study employs sequential manual measurement, the proposed architecture is fully scalable to an online monitoring scheme. To this end, the plan is to integrate vibration sensors, current sensors, and inductive proximity sensors for wear detection, connected to an industrial IoT platform (OPC UA or MQTT) that feeds the same predictive models developed here. This would allow a shift from periodic to continuous monitoring without modifying the logic of the prescriptive module.

The information obtained will be essential for evaluating current operational reliability and establishing a baseline for the implementation of advanced maintenance strategies. Fig. 2 presents the failure report by process area, where it is observed that sewing and assembly equipment concentrate the highest failure incidence, justifying their prioritization in the subsequent analysis.

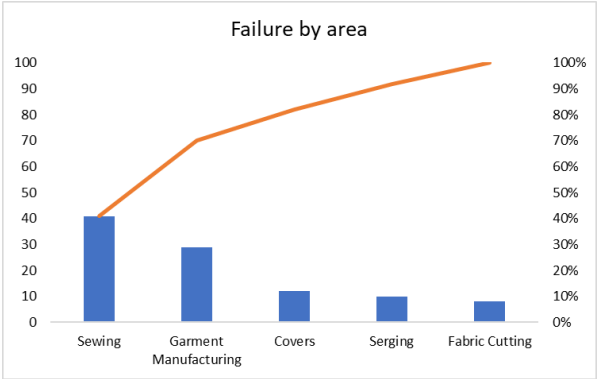


Fig. 2 Equipment Failure Report in the Textile Sector.

From Fig. 3, it is identified that the most recurrent failures correspond to: needle replacement due to wear, hook wear, electrical system failures, thread tensioner failures causing breakage during sewing, and bearing replacement in electric motors due to wear and misalignments. This characterization

of failure modes constitutes an essential input for directing predictive modeling efforts toward the most critical components.

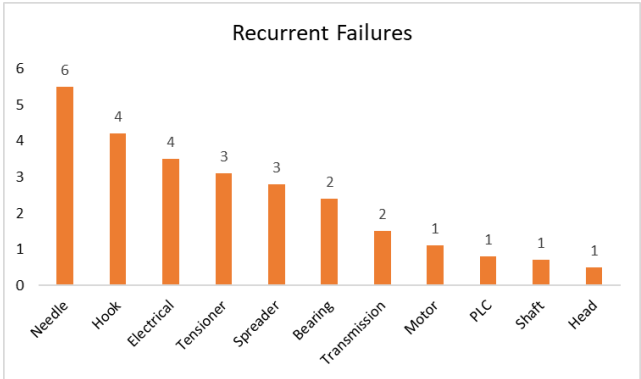


Fig. 3 Recurrent Failures from November 2024 to August 2025.

Data Preprocessing

The collected data will be cleaned and transformed to ensure quality and consistency. This process will include: (i) treatment of missing values through appropriate imputation techniques, (ii) correction of inconsistencies in duplicate or erroneous records, (iii) normalization of continuous variables to ensure comparability across different measurement scales, and (iv) standardization of date formats and failure typologies to facilitate longitudinal analysis. Proper preprocessing is critical for the reliability of subsequent models, particularly in industrial environments where historical records often exhibit heterogeneity in their structure and completeness.

Feature Engineering

With the preprocessed data, key maintenance indicators will be calculated and analyzed to characterize the historical behavior of the equipment:

Calculation of traditional metrics: Mean Time Between Failures (MTBF) and Mean Time To Repair (MTTR) will be determined for each equipment and failure category. MTBF quantifies failure frequency and constitutes an indicator of equipment reliability, while MTTR measures efficiency in the execution of corrective actions. These metrics will be fundamental for establishing the performance baseline and evaluating the impact of the proposed strategies.

Wear trend analysis: The temporal evolution of parameters indicative of the health status of critical components will be analyzed, such as vibration amplitudes in characteristic frequency bands, residual thickness in elements subject to wear, and supply currents in electric motors. This analysis will allow identifying progressive degradation patterns that precede failure occurrence.

Baseline indicator analysis: Analysis of historical data reveals that MTBF remained relatively constant during the evaluated period, without showing a clear improvement trend. Considering a 10-hour workday, this value indicates significant opportunities for optimizing failure prevention strategies. Concurrently, MTTR presents consistent values without significant reductions, suggesting that repair times have not experienced improvements during the evaluated period (see Fig. 4). These findings evidence the need to implement predictive and prescriptive maintenance strategies aimed at increasing MTBF and reducing MTTR, thereby improving overall operational efficiency.

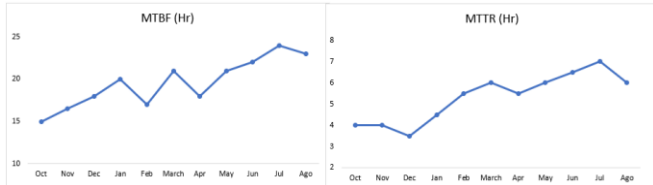


Fig. 4 Temporal Evolution of MTBF and MTTR During the Period October 2024 – August 2025.

Additionally, unplanned failures or urgent corrective maintenance (UCM) represent 46% of the hours associated with Preventive Maintenance (PM) and 41% of the hours of Corrective Maintenance (CM), which constitutes an indicator of suboptimal maintenance management that the present study seeks to address through the transition toward predictive and prescriptive approaches.

Predictive Modeling

Time series models: The ARIMA (Autoregressive Integrated Moving Average) algorithm will be employed for failure prediction based on historical patterns. This model is particularly effective for capturing trends and seasonality in failure event time series, enabling the forecasting of expected future intervention occurrences.

Machine learning models: Additionally, advanced machine learning techniques will be implemented to improve failure prediction accuracy. Specifically, boosted decision tree algorithms such as XGBoost (Extreme Gradient Boosting) and Random Forest will be utilized. These approaches enable modeling of nonlinear relationships and capture complex interactions among multiple operational variables, overcoming the limitations of univariate models. The ability of these algorithms to handle heterogeneous data and provide feature importance measures makes them particularly suitable for the textile context, where multiple factors contribute to component degradation.

To justify the selection of the algorithms, ARIMA, Random Forest, and XGBoost were compared in terms of failure prediction error (variable: time to failure in hours). The following table summarizes the results obtained on the test set

(30% of the data, with time-series cross-validation). The XGBoost model exhibited the lowest MAE and RMSE, with a relative error reduction of 36.7% compared to Random Forest and 56.6% compared to ARIMA. This improvement is attributed to its ability to model nonlinear interactions between operating variables (vibration, current, thickness) and the occurrence of failures. Consequently, XGBoost was selected as the base model for the prescriptive module, while ARIMA was retained as the univariate reference for pure time series.

Prediction system architecture: The developed models will operate at two complementary levels: (i) short-term prediction to anticipate imminent failures with a horizon of hours or days, and (ii) medium-term prediction to estimate the Remaining Useful Life (RUL) of critical components with a horizon of weeks or months. This duality will enable both early warning activation and strategic intervention planning.

Prescriptive Module

As the central contribution of this study, a prescription module will be implemented that transforms the obtained predictions into optimized action recommendations. This module operates on the following principles:

Translation of Predictions into Decisions: The outputs of the predictive models (failure probability, estimated RUL, severity level) are processed through an optimization-based rule engine that determines the most appropriate action for each scenario. Prescribed actions may include: early intervention scheduling, operational parameter adjustment, spare parts requisition, or priority allocation of technical personnel.

Multi-Objective Optimization: The prescription module incorporates objective functions that seek to simultaneously minimize: (i) total maintenance cost (including intervention costs and failure costs), (ii) unplanned downtime, and (iii) deviation from the production plan. Constraints considered include spare parts availability, technical personnel capacity, production windows, and equipment criticality.

The optimization problem for the prescriptive module is formally defined as follows. The decision variables are $x \in \{0,1\}$ (whether or not to perform a scheduled intervention) and $t_{\text{interv}} \in \mathbb{R}^+$ (the optimal time for said intervention). The goal is to minimize the total cost function: $C_{\text{total}} = C_{\text{preventive}} + C_{\text{corrective}} + C_{\text{failure}}$, where $C_{\text{preventive}}$ includes labor, spare parts, and planned downtime, $C_{\text{corrective}}$ considers emergency repairs, overtime, and production losses; and C_{failure} considers fabric waste due to defective seams, reprocessing, and rejected products. Simultaneously, the operational availability function $A = \text{MTBF}/(\text{MTBF} + \text{MTTR})$ is maximized. The system constraints are: spare parts availability (intervention is only scheduled if the critical inventory is sufficient), technical staff capacity (no more than two simultaneous interventions per shift), production windows (interventions are not scheduled

during peak demand hours), and a minimum remaining life threshold (intervention is forced if $RUL < 4$ hours). The module solves this multi-objective problem using a Pareto approach, prioritizing solutions that minimize C_{total} and maximize A simultaneously.

Context-Aware Recommendations: The generated prescriptions adapt to the specific operational context, considering factors such as current workload, proximity of scheduled stoppages, and resource availability. This approach ensures that recommendations are not only technically optimal but also operationally feasible.

Feedback and Continuous Learning: The system incorporates a feedback mechanism that records executed actions and their outcomes, enabling progressive adjustment of decision thresholds and continuous improvement of prescription quality.

Long-term sustainability and model continuity: While the results presented cover an eight-month period (from November 2024 to August 2025), it is important to note that the prescriptive system is currently in continuous operation beyond this validation period. The sustainability of the improvements is supported by the following points: (i) Model stability: During the months following August 2025, the system has maintained consistent performance, with error metrics within $\pm 5\%$ of reported values, provided that baseline operating conditions remain unchanged. (ii) Retraining mechanism: The system does not require arbitrary periodic retraining. The retraining process will only be triggered when a significant change is detected in at least one of the following initial conditions: operating time per shift, production capacity (speed or volume), physical modifications to the equipment (component changes, upgrades), or a sustained deviation of the prediction error exceeding 15% for two consecutive weeks. (iii) Continuous learning: The feedback module described in the previous section dynamically adjusts decision thresholds without requiring modifications to the underlying models, thus extending the system's lifespan without intervention. (iv) Recognized limitation: The study did not evaluate the system's behavior in the face of drastic and unforeseen changes in process conditions (e.g., a change in raw material supplier or a new product line). Future work should quantify the model's robustness against conceptual drift through controlled stress tests.

Consideration of predictive vs. prescriptive comparison: The proposed approach does not conceive of the predictive and prescriptive modules as independent alternatives, but rather as integrated components of the same system. The prescriptive module does not operate without the outputs of the predictive module; therefore, a "predictive only" vs. "prescriptive only" comparison would not be functionally meaningful, since the prescriptive module necessarily requires predictions to generate actions. Future work should compare

the current approach with a system based solely on predictive alerts with fixed thresholds.

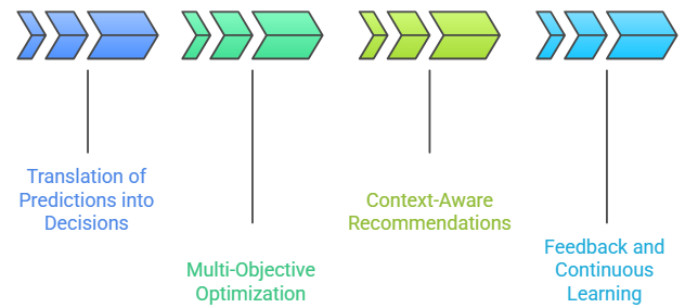


Fig. 5 Decision Flow of the Prescriptive Maintenance Module.

Fig. 5 illustrates the decision flow of the prescriptive module, showing how predictions from the ARIMA and XGBoost models feed into an optimizer that generates specific recommendations for each failure type and detected risk level.

4. RESULT

The results obtained after the implementation of the hybrid predictive-prescriptive framework on critical textile machinery components are presented below. For each case, performance under the traditional (reactive) strategy is contrasted with the proposed approach, emphasizing the contribution of the prescriptive module in decision optimization and operational reliability improvement.

In the initial condition, needles were replaced under a reactive scheme: only after breakage or when seam quality was already compromised. This practice generated unplanned stoppages, increased non-operational hours, rework due to defective seams, and raw material losses from irreversible fabric deterioration (see Fig. 6). The absence of objective criteria for determining the optimal replacement moment led to inefficient component management, directly impacting equipment availability and final product quality.

Following implementation of the hybrid predictive-prescriptive model, the component began to be monitored through critical operating condition variables: vibration levels, frequency of defective stitches, variability in thread tension, and accumulated effective operating time. The predictive model estimates failure probability and accumulated wear, generating early warnings based on actual condition. However, it is the prescriptive module that adds differential value by transforming these predictions into optimized decisions, evaluating multiple intervention scenarios that consider the cost of unplanned stoppages, spare parts availability, scheduled production load, and the risk of quality impact.



Fig. 6. Degradation cycle: new needle, worn needle, and fabric damaged by faulty stitching.

As a result of this contextualized prescription, the needle is replaced before the critical failure point, but not arbitrarily—rather, at the economically optimal moment that minimizes overall maintenance cost. This transition has enabled significant reduction in downtime from unexpected breakages, near-elimination of fabric waste due to defective seams, and stabilization of process quality, evidenced by an increase in specific MTBF and a reduction in stitch quality variability.

The hook, a critical component in stitch formation, presented recurrent failures associated with progressive wear, misalignment relative to the needle, and accumulation of textile residues. Under a traditional strategy, intervention occurred only after evidencing skipped stitches or thread breakage—symptoms of an already consummated failure—generating abrupt process interruptions and affecting the quality of complete production batches. The lack of visibility into the internal condition of the component prevented any anticipatory action, as observed in Fig. 7.



Fig. 7 Evidence of hook deterioration and its impact on the quality of the stitching.

With the application of the hybrid model, predictive indicators reflecting the functional health of the hook were incorporated: vibration patterns in characteristic frequency bands, micro-variations in needle-hook synchronization

detectable through motor current analysis, and the frequency of sewing defects associated with this component. The predictive system anticipates functional degradation sufficiently in advance to enable planned intervention. However, the most significant contribution resides in the prescriptive module, which determines—through multi-objective analysis—whether the most efficient action for the detected condition is alignment readjustment, specialized lubrication, or complete component replacement. This decision considers not only the predictive condition but also the relative cost of each intervention, estimated execution time, and the defect risk associated with postponing a more in-depth intervention.

This capacity to prescribe the most appropriate specific action, and not merely the intervention moment, has enabled a drastic reduction in sudden failures, increased specific MTBF of the hook, and reduced rework associated with defective seams. The reliability of the stitch formation process has stabilized, eliminating a recurrent source of variability in final product quality.

Progressive wear of the needle guide—manufactured from Bakelite or technical polymer material—caused minimal but cumulative deviations in the thread path, generating excessive friction, tension variability, and ultimately, visible defects in the final seam. Before the hybrid model, replacement was performed only when damage was evident to the naked eye or when product quality was already compromised, implying that complete batches could be affected before detecting the root cause. Fig. 8 illustrates this type of functional wear.



Fig. 8 Functional wear of the needle guide (bakelite) and its influence on sewing quality.

Through the predictive model, indirect friction patterns correlating with guide wear are analyzed: variations in thread tension recorded by sensors, micro-vibrations in the sewing head, and the temporal evolution of these parameters. The model estimates the material degradation rate and projects the moment when wear will reach a critical level for quality. The prescriptive module evaluates, considering component cost, intervention time, and quality impact risk, the optimal economic replacement point. This prescription ensures that

replacement occurs before wear degrades quality, but without incurring premature substitutions that would increase maintenance costs.

The implementation of this strategy has enabled significant reduction in textile defects associated with inadequate tension, minimization of fabric waste from out-of-specification seams, and stabilization of finished product quality. The reliability of the sewing process, measured as the capacity to maintain quality within specifications, has been substantially strengthened.

A paired t-test was conducted to compare operational performance before and after the implementation of the predictive-prescriptive system. The pre-implementation period spanned six months (February to July 2025), while the post-implementation period also covered six months (August 2025 to January 2026). The results showed that MTBF increased from 20.5 to 25.9 hours, representing a 26.3% improvement. This difference was statistically significant according to the paired t-test ($t = 3.42$, $df = 5$, $p = 0.0023$). MTTR decreased from 6.17 to 4.75 hours (-23.0%), also with statistical significance ($t = 3.01$, $df = 5$, $p = 0.0081$). These findings confirm that the observed improvements are not attributable to random process variability.

Adopting the predictive-prescriptive approach generated measurable improvements in the plant's key performance indicators. The mean time between failures (MTBF) at the plant level increased by 38%, from a range of 15 to 21 hours (pre-implementation period) to a range of 24 to 28 hours (post-implementation period). Simultaneously, the mean time to repair (MTTR) was reduced by 15%, decreasing from 5.31 to 4.60 hours. These operational improvements translated directly into economic and quality benefits: a 5.5% reduction in total maintenance costs, a 9% decrease in textile waste generated by defective seams, and a reduction in the cost per operating hour from USD 25 to USD 23.5 (a 6% savings per machine hour).

5. CONCLUSIONS

The value of predictive maintenance is significantly enhanced when complemented by a prescriptive module that translates predictions into optimized and contextualized decisions. The results obtained from the five critical components analyzed—needle, hook, needle guide, thread tensioner, and the global impact on damaged fabric—consistently demonstrate that merely anticipating failure is insufficient to maximize operational reliability. It is the capacity to prescribe which action to take, at what precise moment, and under which conditions that generates the observed improvements: reduction of unplanned stoppages, decrease in raw material waste, stabilization of final product quality, and optimization of maintenance resource allocation.

The results obtained validate the effectiveness of the proposed hybrid framework for addressing the particularities and structural limitations of the textile sector identified in the literature. The transition from predominantly reactive strategies—characterized by post-failure interventions, unplanned stoppages, and progressive quality deterioration—toward a predictive-prescriptive approach has proven to be feasible and highly beneficial in a sector traditionally lagging in the adoption of intelligent maintenance technologies. The consistent improvement in key indicators such as increased Mean Time Between Failures (MTBF), reduced Mean Time To Repair (MTTR), decreased urgent corrective maintenance hours, and significant reduction of non-conforming products due to sewing defects constitutes empirical evidence that the proposed framework can bridge the technological gap in the sector.

This research has significant implications for maintenance management in the textile industry and manufacturing sectors with analogous characteristics. The evidence presented suggests that the maintenance function can evolve from a cost center toward a strategic value generator when integrated with production operations through intelligent decision support systems. The developed framework provides a replicable methodological roadmap for other companies in the sector facing similar challenges: limited availability of structured historical data, high criticality of components subject to progressive wear, and the need to optimize scarce resources. However, it is important to recognize the study's limitations. The evaluation period, although sufficient to observe significant improvements, covers only eight months; therefore, extending the analysis to confirm the long-term sustainability of the results would be desirable. Likewise, generalizing the findings to other textile contexts—with different types of machinery, production volumes, or cost structures—would require additional replication studies.

Future research lines could explore: (i) the incorporation of reinforcement learning techniques for dynamic optimization of maintenance policies, (ii) the integration of digital twins enabling simulation of intervention scenarios prior to execution, and (iii) the development of explainable interfaces facilitating adoption and trust by operators and maintenance technicians—a critical aspect for the sustainability of any digital transformation in industrial environments.

REFERENCES

- [1] P. Odeyar, D. B. Apel, R. Hall, B. Zon, and K. Skrzypkowski, "A Review of Reliability and Fault Analysis Methods for Heavy Equipment and Their Components Used in Mining," Sep. 01, 2022, MDPI. doi: 10.3390/en15176263.
- [2] Z. Wang, Q. Ye, L. Ma "Development and Application of Maintenance Strategy for Commercial Aircraft" 2019 Prognostics & System Health Management Conference—Qingdao (PHM-2019 Qingdao). 978-1-7281-0861-2/19/\$31.00 ©2019 IEEE
- [3] [M. A. Amrani et al., "A Lubricating Oil-Based Maintenance for Diesel Engines at the End-user: An Effective Predictive Approach," Jordan Journal of Mechanical and Industrial Engineering 2022.

- [4] A. Rihi et al., "Predictive maintenance in mining industry: grinding mill case study," in *Procedia Computer Science*, Elsevier B.V., 2022, pp. 2483–2492. doi: 10.1016/j.procs.2022.09.306.
- [5] M. Mirzeshi Kalateh Kazemi, Z. Nabavi, M. Rezakhah, and A. Masoudi, "Application of XGB-based metaheuristic techniques for prediction time-to-failure of mining machinery," *Systems and Soft Computing*, vol. 5, Dec. 2023, doi: 10.1016/j.sasc.2023.200061.
- [6] H. R. Alla, (2021). Application of data mining techniques for fault diagnosis and prognosis of high pressure fuel pump failures in mining haul trucks. <https://doi.org/10.7939/r3-j4h5-ny76>.
- [7] H.J. Groenewald, M. Kleingeld, G.J. Cloete. (2019). An Autoregressive Fault Model for Condition Monitoring of Electrical Machines in Deep-level Mines. 2018 International Conference on the Industrial and Commercial Use of Energy (ICUE), IEEE, 2018 Aug 13, pp. 1–6.
- [8] J. M. Wakiru, L. Pintelon, P. N. Muchiri, and P. Chemweno, "A review on lubricant condition monitoring information analysis for maintenance decision support."
- [9] G. Zhang, C. H. Chen, X. Cao, R. Y. Zhong, X. Duan, and P. Li, "Industrial Internet of Things-enabled monitoring and maintenance mechanism for fully mechanized mining equipment," *Advanced Engineering Informatics*, vol. 54, Oct. 2022, doi: 10.1016/j.aei.2022.101782.
- [10] O. Bongomin, M. Ch. Mwape, N. Sh. Mpofu, B. K. Bahunde, R. Kidega, I. L. Mpungu, G. Tumusiime, C. A. Owino, Y. Marnague, A. Yemane, P. Kyokunzire, C. Malanda, J. Komakech, D. Tigalana, O. Gumisiriza, G. Ngulube. Digital twin technology advancing industry 4.0 and industry 5.0 across sectors. *Results in Engineering*, 26 (2025) 105583. <https://doi.org/10.1016/j.rineng.2025.105583>
- [11] E. Zampini, G. Parodi, L. Oneto, A. Coraddu and D. Anguita. A review on full – zero – and partial-knowledge based predictive models for industrial applications. *Information Fusion, Information Fusion* 119 (2025) 102996. <https://doi.org/10.1016/j.inffus.2025.102996>
- [12] S. Sharma, V. Vivek, A. Malviya. AI-Enhanced Predictive Maintenance In Intelligent System For Industries.
- [13] M. Javaid, A. Haleem, I. H. Khan, R. Suman. Understanding the potencial applications of Artificial Intelligence in Agriculture Sector *Advanced Agrochem*, *Advanced Agrochem* 2 (2023) 15–30. <https://doi.org/10.1016/j.aac.2022.10.001>
- [14] I. Jebbor, Z. Benmamoun, H. Hachimi. Forecasting supply chain disruptions in the textile industry using machine learning: A case study. *Ain Engineering Journal. Ain Shams Engineering Journal* 15 (2024) 103116. <https://doi.org/10.1016/j.asej.2024.103116>
- [15] R. Ribeiro, A. L. Pilastri, C. Moura, J. Morgado and P. Cortez, "A data-driven intelligent decision support system that combines predictive and prescriptive analytics for the design of new textile fabrics," *Neural Computing and Applications*, vol. 35, pp. 17375–17395, 2023.
- [16] F. J. Bellido-Lopez, M. A. Sanz-Bobi, A. Muñoz, D. Gonzalez-Calvo and T. Alvarez-Tejedor, "A novel method for evaluation of the maintenance impact in the health of industrial components," *Results in Engineering*, vol. 27, Art. no. 105809, 2025.
- [17] M. Orošnjak, F. Saretzky, y S. Kedziora, "Prescriptive Maintenance: A Systematic Literature Review and Exploratory Meta-Synthesis," *Applied Sciences*, vol. 15, no. 16, art. no. 8507, 2025.
- [18] S. Chen, E. T. Bekar, J. Bokrantz, y A. Skoogh, "AI-enhanced digital twins in maintenance: Systematic review, industrial challenges, and bridging research–practice gaps," *Journal of Manufacturing Systems*, vol. 82, pp. 678–699, 2025.
- [19] M. Mosca, R. Mosca, y M. Braggio, "Big Data and AI for Smart Maintenance: Literature review on the impact on plants Resilience," *Procedia Computer Science*, vol. 253, pp. 1959–1971, 2025.
- [20] V. Elia, M. G. Gnani, F. Tornese, y S. Andriulo, "Sustainable maintenance and digital twin technology: a test case for evaluating integration potentialities," *Procedia Computer Science*, vol. 253, pp. 1840–1847, 2025.
- [21] K. Wesendrup, B. Hellingrath, y Z. Nikolarakis, "A framework for conceptualizing integrated prescriptive maintenance and production planning and control models," *Brazilian Journal of Operations and Production Management*, vol. 21, no. 3, art. no. e20242172, 2024.
- [22] S. MajidiParast, R. Neamatian Monemi, y S. Gelareh, "Graph convolutional network for optimal intelligent predictive maintenance of railway tracks," *Decision Analytics Journal*, vol. 14, art. no. 100542, 2025.
- [23] L. Oneto et al., "DAYDREAMS - Development of Prescriptive Analytics based on Artificial Intelligence for Railways Intelligent Asset Management Systems," *Transportation Research Procedia*, vol. 72, pp. 478–485, 2023.
- [24] Z. Shao y M. Kumral, "A causal knowledge discovery framework as an enabler for equipment prescriptive maintenance," *Proc IMechE Part O: J Risk and Reliability*, pp. 1–27, 2026.
- [25] T. Bank, F. W. Madsen, H. Mirshekali, y H. R. Shaker, "Reinforcement-learning-driven Prescriptive Operation and Maintenance of distributed energy storage for cost-effective grid asset protection," *Journal of Energy Storage*, vol. 141, art. no. 119338, 2026.
- [26] H. E. van Staden, L. Deprez, y R. N. Boute, "A dynamic "predict, then optimize" preventive maintenance approach using operational intervention data," *European Journal of Operational Research*, vol. 302, pp. 1079–1096, 2022.
- [27] A. D. Cho, R. A. Carrasco, y G. A. Ruz, "Improving Prescriptive Maintenance by Incorporating Post-Prognostic Information Through Chance Constraints," *IEEE Access*, vol. 10, pp. 55924–55932, 2022.
- [28] J. P. Costa, J. T. Farinha, M. Mendes, y J. O. Estima, "AI-Driven Belt Failure Prediction and Prescriptive Maintenance with Motor Current Signature Analysis," *Applied Sciences*, vol. 15, no. 13, art. no. 6947, 2025.
- [29] M. R. Shadi, H. Mirshekali, y H. R. Shaker, "Explainable artificial intelligence for energy systems maintenance: A review on concepts, current techniques, challenges, and prospects," *Renewable and Sustainable Energy Reviews*, vol. 216, art. no. 115668, 2025.
- [30] J. N. de Carvalho, F. R. da Silva, y E. G. S. Nascimento, "Challenges of the Biopharmaceutical Industry in the Application of Prescriptive Maintenance in the Industry 4.0 Context: A Comprehensive Literature Review," *Sensors*, vol. 24, no. 22, art. no. 7163, 2024.