# Machine Learning-Driven Preventive Maintenance for Fibreboard Production in Industry 4.0

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***Abstract*—The transition to Industry 4.0 has necessitated the adoption of intelligent maintenance strategies to enhance manufacturing efficiency and reduce operational disruptions. In fibreboard production, conventional preventive maintenance, reliant on fixed schedules, often leads to inefficient resource allocation and unexpected failures. This study proposes a machine learning-driven predictive maintenance (PdM) framework that utilises real-time sensor data and predictive analytics to optimise maintenance scheduling and improve system reliability. The proposed approach is validated using real-world industrial data, where Random Forest and Gradient Boosting regression models are applied to predict machine wear progression and estimate the remaining useful life (RUL) of critical components. Performance evaluation shows that Random Forest outperforms Gradient Boosting, achieving a lower Mean Squared Error (MSE) of 0.630, a lower Mean Absolute Error (MAE) of 0.613, and a higher R-squared score of 0.857. Feature importance analysis further identifies surface grade as a key determinant of equipment wear, suggesting that redistributing production across lower-impact grades can significantly reduce long-term wear and extend machine lifespan. These findings underscore the potential of artificial intelligence in predictive maintenance applications, contributing to the advancement of smart manufacturing in Industry 4.0. This research lays the foundation for further investigations into adaptive, real-time maintenance frameworks, supporting sustainable and efficient industrial operations.***

***Keywords*—Predictive maintenance; machine learning; fibreboard production; operational efficiency; Industry 4.0; smart manufacturing**

## I. Introduction

Predictive maintenance (PdM), often referred to as "on-line monitoring," "risk-based maintenance," or "condition-based maintenance," has been extensively studied due to its historical significance and increasing relevance in modern industrial settings [1]. PdM primarily focuses on assessing the operational health of machinery to proactively prevent unexpected failures. Over time, PdM methodologies have evolved from simple visual inspections to highly sophisticated, automated techniques that leverage advanced signal processing, pattern recognition, and machine learning approaches, including neural networks and fuzzy logic [2]. These automated approaches provide significant advantages across various industries, particularly in capturing and analysing critical operational data from equipment such as electric motors, where human perception alone is insufficient [3].

The integration of intelligent sensors within industrial systems facilitates predictive maintenance by enhancing machine performance, preventing unnecessary component replacements, reducing downtime, and identifying potential faults at an early stage [4]. By adopting this approach, organisations can significantly improve cost efficiency and operational reliability. While PdM shares similarities with preventive maintenance (PM) in proactively scheduling maintenance tasks ahead of failures, PdM uniquely relies on real-time sensor data and predictive analytics rather than predetermined maintenance intervals [5].

Among various failure mechanisms, bearing faults remain one of the most prevalent causes of motor breakdowns, necessitating effective monitoring and diagnostic techniques [6]. Consequently, PdM strategies are typically designed with two primary objectives: improving energy efficiency, which is critical for industrial energy conservation, and minimising unplanned operational disruptions. Various algorithms have been developed to address these aspects, broadly classified into the following categories:

- Energy efficiency assessment: Evaluating power consumption and optimising energy usage through multiple assessment methods and measurement tools.
- System condition monitoring: Diagnosing motor faults and detecting irregularities using advanced fault-detection techniques.

Recent research has also explored the development of intelligent decision-support systems for PdM, with various frameworks proposed to enhance industrial reliability and pro-

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ductivity. Algorithms play a crucial role in PdM implementation, particularly in its three core phases: data processing, fault diagnostics, and prognostics [7]. Three predominant methodological approaches in PdM research have been identified [8]:

*1) Data-driven approach:* Also known as the machine learning or data mining approach, this method involves training predictive models on historical operational data to identify trends and anomalies.

*2) Model-based approach:* This approach incorporates domain expertise by utilising physics-based analytical models to represent system behaviour and predict potential failures.

*3) Hybrid approach:* A combination of data-driven and model-based methods, designed to enhance predictive accuracy by integrating both empirical data and theoretical models.

With the increasing availability of industrial data, machine learning techniques have become a powerful tool in predictive maintenance, providing robust solutions such as cloud-based platforms and advanced predictive models [9].

### A. Application in Fibreboard Manufacturing

This study introduces a machine learning-driven preventive maintenance (PM) framework specifically tailored for fibreboard production within the Industry 4.0 paradigm. Given the rising demand for operational efficiency and cost reduction, the proposed approach seeks to minimise unplanned downtime, optimise maintenance scheduling, and improve manufacturing system reliability. By leveraging advanced predictive analytics and near real-time data monitoring, this framework enables proactive fault detection and data-driven maintenance decision-making.

The methodology has been implemented and validated in an experimental setting using real-world industrial data collected from fibreboard manufacturing processes. The empirical results demonstrate the framework's effectiveness in reducing maintenance-related disruptions and enhancing overall production efficiency. The following sections provide an in-depth exploration of its design, implementation, and implications for smart manufacturing in Industry 4.0.

### B. Fibreboard: A Critical Manufacturing Material

Fibreboard is an engineered wood product manufactured by compressing wood fibres with synthetic adhesives under heat and pressure to form rigid panels. Due to its cost-effectiveness, uniformity, and structural stability, fibreboard is widely used in construction and furniture industries [10].

Fibreboard is classified into different types based on density and manufacturing processes:

*1) Low-Density Fibreboard (LDF):* Also known as particle board, LDF is lightweight and primarily used for insulation and soundproofing applications.

*2) Medium-Density Fibreboard (MDF):* MDF is denser than LDF and is widely utilised in furniture, cabinetry, and interior paneling due to its smooth surface and machining ease [11].

*3) High-Density Fibreboard (HDF):* Also referred to as hardboard, HDF is characterised by its high density and strength, making it suitable for flooring, door skins, and high-load applications.

The manufacturing process of fibreboard involves breaking down hardwood or softwood residuals into wood fibres, mixing them with wax and resin binders, and compressing them under high temperature and pressure. This results in a stable, uniform material that lacks the natural defects (e.g., knots) commonly found in solid wood. However, moisture resistance and formaldehyde emissions from certain resins remain critical factors to consider in fibreboard production. Recent advancements have introduced eco-friendly alternatives that utilise formaldehyde-free adhesives, enhancing both environmental sustainability and human health considerations [12].

In summary, fibreboard is a cost-efficient and adaptable material crucial for modern construction and furniture manufacturing. Ongoing innovations continue to improve its mechanical properties, environmental sustainability, and application potential.

### C. Paper Structure

The remainder of this paper is structured as follows: Section II presents a comprehensive review of prior research on preventive maintenance strategies, particularly focusing on machine learning applications in industrial settings and the role of Industry 4.0 in maintenance optimisation. Section III details the proposed machine learning-driven preventive maintenance framework, outlining the data-driven approach, predictive modelling techniques, and integration into fibreboard production systems. Section IV discusses the experimental setup, performance analysis, and validation of the proposed methodology using real-world industrial data. Finally, Section V summarises the key findings, highlights this study's contributions to smart manufacturing, and identifies future research directions for advancing predictive and preventive maintenance in Industry 4.0 environments.

## II. Related Work

The rapid evolution of manufacturing technologies has led to the widespread adoption of Industry 4.0, a transformative paradigm that leverages automation, data-driven decision-making, and smart technologies to optimise industrial processes[13]. Traditional maintenance strategies, such as corrective and preventive maintenance (PM), are often inefficient in preventing unexpected equipment failures and production downtime. In response, predictive maintenance (PdM) has emerged as a data-driven approach that utilises real-time monitoring and machine learning algorithms to detect anomalies, estimate equipment degradation, and improve maintenance scheduling. By integrating PdM into industrial systems, manufacturers can enhance operational efficiency, reduce maintenance costs, and ensure higher production reliability[14].

The following sections explore the role of Industry 4.0 and predictive maintenance in modern industrial settings. The discussion begins by outlining the key characteristics of Industry 4.0 and its impact on manufacturing efficiency. Subsequently, we examine preventive and predictive maintenance approaches, their significance in optimising production systems, and the application of machine learning-driven methodologies. The final sections address the challenges of implementing PdM in Industry 4.0 environments and highlight potential future research directions.

### A. The Role of Industry 4.0 and Predictive Maintenance in Enhancing Industrial Efficiency

In today's highly competitive and globalised economy, industries must continuously innovate to optimise their production processes, improve resource efficiency, and maintain a competitive edge in the marketplace. The rapid advancements in automation, data-driven decision-making, and artificial intelligence (AI) have led to the emergence of Industry 4.0, which integrates smart technologies to enhance manufacturing operations. Industry 4.0 relies on real-time data exchange, cyber-physical systems, machine learning, and interconnected industrial networks to drive operational efficiency and predictive capabilities[15]. This digital transformation is underpinned by three primary innovations distinguishing traditional manufacturing from the Industry 4.0 paradigm:

*1) Intelligent machines:* Capable of self-awareness, self-diagnosis, and self-optimisation, reducing the need for manual intervention.

*2) Autonomous components:* Components with embedded sensors that facilitate self-monitoring and predictive fault detection.

*3) Smart production systems:* Designed for dynamic self-configuration, self-maintenance, and decentralised decision-making, enhancing production flexibility and operational resilience.

As manufacturing environments become increasingly automated, the collaboration between human operators and intelligent systems has become essential. Real-time customisation, mass production adaptability, and large-scale data processing play a pivotal role in achieving Industry 4.0's objectives, enabling proactive decision-making and reducing inefficiencies in industrial workflows[16].

One of the most transformative aspects of Industry 4.0 is predictive maintenance (PdM), which leverages AI-driven analytics and machine learning techniques to predict equipment failures before they occur. Traditional maintenance strategies, such as corrective and preventive maintenance (PM), rely on scheduled inspections and reactive repairs, often leading to excessive downtime, increased operational costs, and suboptimal resource utilisation[15]. In contrast, PdM offers a proactive approach by analysing sensor data, identifying failure patterns, and optimising maintenance schedules, thereby minimising production disruptions and improving system reliability.

### B. Preventive and Predictive Maintenance: A Data-Driven Approach

Within maintenance engineering, a diverse set of analytical models and decision-support methodologies is employed to enhance maintenance effectiveness[17]. Preventive maintenance (PM) has historically been a crucial method for mitigating unplanned machine failures by conducting routine inspections and replacing deteriorating components before critical breakdowns occur. However, the inherent complexity and unpredictability of industrial systems pose challenges in determining optimal PM schedules. An extensive study on the adaptation of Total Productive Maintenance (TPM) methodologies has concluded that implementing preventive maintenance in modern production environments remains a multifaceted challenge due to fluctuating operational conditions and machine variability[18]. The research highlights several critical obstacles, including the integration of TPM processes into existing manufacturing systems, compatibility issues with legacy equipment and workflows, and the necessity of comprehensive training programs. Additionally, the study emphasises the importance of management commitment and resource allocation in ensuring the successful deployment of TPM initiatives.

To address these challenges, a validated preventive maintenance strategy has been successfully deployed in real-world manufacturing settings. For instance, ITT (Czech Republic) has implemented an innovative PM framework that integrates digital diagnostics, condition monitoring, and real-time sensor data to transition from theoretical maintenance planning to practical, data-driven solutions. Empirical studies have substantiated the effectiveness of this approach, demonstrating measurable improvements in production uptime, machine longevity, and cost efficiency across industrial sectors.

A maintenance scheduling framework has been developed utilising Mixed Integer Linear Programming (MILP) to optimise maintenance intervals through dynamic time windows. This approach is designed to minimise operational downtime while ensuring high equipment reliability. Experimental results have demonstrated that implementing flexible preventive maintenance scheduling can significantly reduce the frequency of downtimes, enhance overall system efficiency, and extend the life cycles of assets[19]. By adjusting maintenance schedules dynamically, the framework accommodates varying operational demands and equipment conditions, promoting more effective resource utilisation and improved maintenance planning.

### C. Predictive Maintenance and Intelligent Decision-Making

Predictive maintenance (PdM) represents an advanced evolution of traditional maintenance frameworks, integrating AI-powered analytics, statistical modelling, and real-time machine learning applications to proactively forecast failures. Unlike preventive maintenance, which follows predefined schedules, PdM continuously monitors machine conditions to detect early signs of wear, degradation, and potential breakdowns[16]. By leveraging historical operational data, PdM enables industries to transition from reactive to predictive decision-making, thereby reducing maintenance costs and improving overall equipment effectiveness.

A key application of PdM is real-time machine health monitoring, with a strong emphasis on estimating the Remaining Useful Life (RUL) of critical components[20]. A novel mathematical model was introduced that optimises maintenance costs by incorporating RUL and Mean Time Between Failures (MTBF) data. Empirical validation was performed using real-world industrial datasets, demonstrating the model's ability to enhance maintenance scheduling, reduce failure-related downtime, and improve production efficiency in high-demand manufacturing environments[21].

### D. Bridging the Gap: Machine Learning-Driven Preventive Maintenance for Fibreboard Production

The application of predictive maintenance in traditional manufacturing industries has been extensively studied, yet its implementation in fibreboard production remains underexplored. Fibreboard manufacturing processes involve complex machinery, high-temperature operations, and precise material compositions, making it an ideal candidate for machine learning-driven preventive maintenance solutions.

This research aims to develop a Machine Learning-Driven Preventive Maintenance Framework tailored specifically for fibreboard production within Industry 4.0. By leveraging AI-driven analytics, IoT-enabled sensor monitoring, and historical maintenance data, this study seeks to enhance system reliability, optimise maintenance scheduling, and reduce unexpected production downtime.

The subsequent sections of this paper will detail the proposed framework, its integration into fibreboard manufacturing systems, and empirical validation through real-world industrial case studies. This research contributes to the growing field of smart manufacturing by demonstrating how machine learning-based PdM can be effectively implemented in the fibreboard industry.

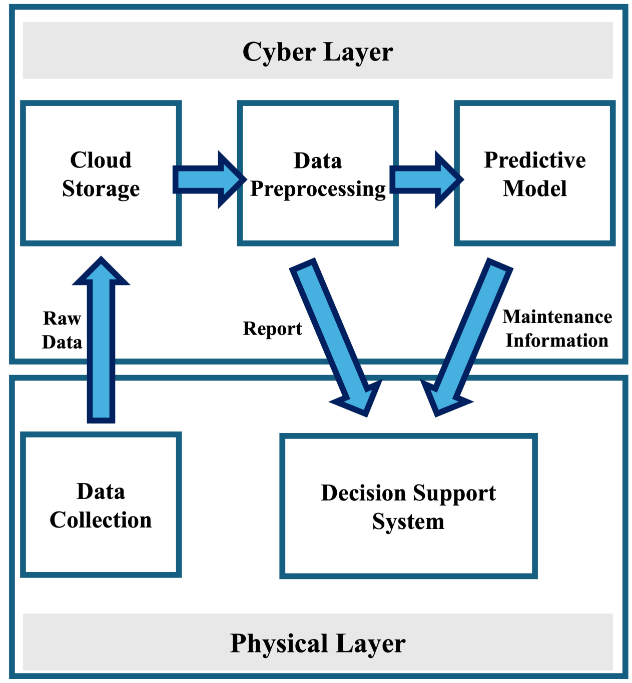


Fig. 1. Cyber-physical system architecture for a PdM-based decision support system.

## III. Methodology

### A. Cyber-Physical System Architecture

The cyber-physical system architecture, depicted in Figure 1, is designed to incorporate predictive maintenance (PdM) as a core component of a decision support system for the fibreboard production case study. The structured approach follows a sequential process, beginning with data collection and storage, followed by preprocessing, predictive modelling, and integration into the decision support system. The proposed architecture is composed of two primary layers:

*1) Physical layer:* This layer consists of sensors that continuously monitor the operational behaviour of machines and individual components, collecting real-time data. The acquired data is transmitted via a communication network and securely stored within the Cyber Layer for further analysis.

*2) Cyber layer:* The Cyber Layer serves as a central repository for raw data before it undergoes preprocessing. The preprocessing phase refines and structures the data, generating reports that facilitate decision support while simultaneously providing input for machine learning-based predictive models.

The Physical Layer is responsible for continuously collecting and transmitting real-time data on the operational conditions of machines and individual components. This includes a wide range of diagnostic and prognostic parameters, such as temperature fluctuations, vibration analysis, and estimates of the remaining useful life (RUL) of critical components. By leveraging advanced sensor networks and industrial Internet of Things (IIoT) technologies, this layer ensures that all relevant maintenance-related data is accurately recorded and transmitted for further analysis.

In parallel, the Cyber Layer employs sophisticated machine learning-based predictive models to process the acquired data, identifying patterns and potential failure points before they escalate into critical issues. These models not only enhance predictive maintenance capabilities but also facilitate the generation of optimised maintenance schedules tailored to specific operational demands. Furthermore, they assist in determining the most effective maintenance routes, taking into account factors such as resource availability, system load, and overall production efficiency. The integration of these layers significantly enhances the decision-making process within predictive maintenance systems, enabling a transition from reactive maintenance strategies to a fully data-driven, proactive approach that minimises unplanned downtime and maximises asset longevity.

### B. Dataset Collection

For a predictive maintenance solution to be effective, data must be sourced from three critical domains:

*1) Fault history:* Predictive maintenance applications frequently involve rare fault occurrences. However, to ensure predictive models accurately anticipate failures, they must be trained on data representing both normal and faulty operational conditions. Consequently, the training dataset must contain a sufficiently balanced representation of both categories to improve model reliability and robustness.

*2) Maintenance and repair records:* A comprehensive maintenance history is fundamental to the effectiveness of predictive maintenance. This includes detailed records of component replacements, preventive maintenance activities, and service logs, which provide essential insights into equipment reliability, wear patterns, and failure trends.

*3) Machine condition monitoring:* Estimating the remaining useful life (RUL) of machinery necessitates continuous monitoring of its operational health over time. Time-series data capturing ageing patterns, performance degradation, and operational anomalies is essential for accurate failure prediction and maintenance scheduling.

The dataset covers a 12-month period (from January to December 2023) and captures detailed records of fibreboard production performance and wear progression. It encompasses both normal operating conditions and fault events, ensuring that predictive models can effectively distinguish between different stages of wear and failure. The dataset is structured with 14 key features, incorporating a balanced mix of categorical and numerical variables to facilitate a comprehensive and robust analysis.

TABLE I. FEATURES OF THE COLLECTED DATASET FOR PREDICTIVE MODELLING IN FIBREBOARD PRODUCTION

| Feature (Raw Data) | Description |
|---|---|
| **Timestamp (time)** | Time at which the event was recorded in the system |
| **Specific Energy Consumption (SEC)** | Energy consumed per ton of fibreboard produced (kWh/ton) |
| **Adhesive Type (glue type)** | Type of adhesive used in the fibreboard manufacturing process |
| **Total Weight (tons)** | Total mass of raw wood material processed per batch |
| **Average Refiner Capacity (tons/hr)** | Mean throughput of the refiner, measuring processing capability per hour |
| **Surface Grades (material surface grade)** | Classification of board surface quality based on production parameters |
| AA, A1, A2, B, RG/ORG, RJ/ORJ | Specific grade labels assigned to fibreboard materials |
| **Wood Chip Type (chip type)** | Categorisation of wood chips based on size and quality |
| Fine Chips (15%) | Small-sized wood particles contributing to material consistency |
| High-Quality Chips (80%) | Preferred wood chips ensuring high-quality board formation |
| Oversized Chips (5%) | Large wood chips exceeding optimal processing size |

Table I presents a list of features extracted from the dataset, collected from the proposed system architecture and integrated within the fibreboard production environment. These features include key parameters from refining equipment records, such as:

1) Surface grades produced during the manufacturing process.
2) Types of adhesives and binding agents used in production.
3) Specific Energy Consumption (SEC) metrics.
4) The average operational capacity of the refiner.

This dataset serves as the foundation for predictive modelling, facilitating the development of machine learning models for failure prediction and maintenance optimisation. By leveraging these diverse data sources, the system enhances its ability to pre-emptively identify potential faults, thereby improving operational efficiency and minimising unplanned downtime.

### *C. Data Preparation*

Data preparation is a fundamental step in processing raw data for predictive modelling. The quality of the dataset directly influences the accuracy and reliability of machine learning models. This process involves data cleaning, transformation, and feature selection to ensure that the dataset is structured, standardised, and optimised for analysis. Effective preprocessing enhances model performance, reduces biases, and improves interpretability, ultimately enabling more robust predictive maintenance strategies. Properly prepared data leads to more generalisable models, reduces the risk of overfitting, and ensures that predictions remain consistent across different operational conditions.

*1) Data cleaning:* Data cleaning is a critical step in ensuring data quality and reliability for predictive modelling. Its primary objective is to remove inconsistencies, handle missing values, and standardise the dataset to improve the accuracy and performance of machine learning models. This process mitigates biases, reduces errors, and enhances the overall interpretability of the results.

Key data cleaning procedures include:

- Handling Missing Values: Missing values in numerical attributes were imputed using mean values to maintain the overall distribution of data. For categorical attributes, the most frequent category (mode) was used as an imputation strategy to prevent loss of categorical information.
- Duplicate Record Removal: Redundant data entries were identified and removed to prevent skewed model performance due to over-represented instances.
- Standardisation of Units: Measurements and attributes recorded in different units were converted to a common scale to ensure uniformity, thereby improving model interpretability and preventing potential errors during analysis.
- Outlier Detection and Handling: Extreme values in numerical features were identified using statistical techniques such as the interquartile range (IQR) method, and appropriate handling mechanisms, such as capping or transformation, were applied.

*2) Data transformation:* Data transformation is an essential preprocessing step that ensures data consistency and compatibility for machine learning models. This process involves converting raw data into a structured format that enhances analytical accuracy. Standardising categorical and numerical data formats improves model interpretability, comparability, and overall predictive performance.

The main transformation techniques applied include:

- Encoding Categorical Variables: Categorical attributes, such as glue types and surface grades, were converted into numerical representations through encoding techniques. One-hot encoding was used for nominal variables, while ordinal encoding was applied where categorical attributes had an inherent order.
- Feature Scaling: Numerical attributes, including SEC (Specific Energy Consumption) and the average capacity of the refiner, were normalised using min-max scaling to bring all features to a common range. This process improves the stability and convergence of gradient-based optimisation algorithms in machine learning models.

- Feature Engineering: Additional features were derived from existing attributes to enhance model performance. For example, interaction terms between key process parameters were introduced to capture non-linear dependencies.

## D. Predictive Modelling

Predictive modelling is a crucial component of predictive maintenance (PdM), enabling the estimation of machine wear and the identification of potential failures before they occur. By leveraging advanced machine learning techniques such as Random Forest and Gradient Boosting, predictive maintenance strategies enhance equipment reliability, reduce unexpected downtimes, and optimise maintenance scheduling. Machine learning-based PdM can generally be categorised into two main approaches:

*1) Supervised learning:* Supervised learning relies on labelled data where failure occurrences are explicitly recorded. The model learns from historical failure instances to predict future wear levels and estimate the remaining useful life (RUL) of a machine or component. The two most common applications of supervised learning in PdM are:

*a) Classification models:* These models categorise machine states into discrete conditions, such as "healthy" or "faulty." Algorithms such as Support Vector Machines (SVMs), Decision Trees, and Deep Neural Networks are widely used in this context.

*b) Regression models:* These models predict continuous values, such as the remaining useful life (RUL) of a component. Common regression-based techniques include Linear Regression, Random Forest Regression, and Gradient Boosting Machines (GBMs).

Supervised learning models require a well-labelled dataset with accurately recorded failure instances and associated operational parameters. Feature selection and engineering play a critical role in improving model robustness and generalisation.

*2) Unsupervised learning:* In scenarios where failure records are unavailable or incomplete, unsupervised learning models are employed to identify patterns and anomalies within operational data. These models detect deviations from normal operating conditions, which may indicate potential failure events. The most widely used unsupervised learning approaches include:

*a) Clustering techniques:* Methods such as K-Means and DBSCAN (Density-Based Spatial Clustering of Applications with Noise) group similar operational states and help differentiate between normal and abnormal machine behaviour.

*b) Anomaly detection algorithms:* Techniques such as Isolation Forests, Principal Component Analysis (PCA)-based anomaly detection, and Autoencoders (a type of neural network) are utilised to identify deviations from normal operational conditions, serving as early warning indicators of potential failures.

Unlike supervised learning, unsupervised models do not require predefined labels, making them particularly useful in real-world industrial settings where failure data may be scarce or inconsistent.

*3) Hybrid approaches:* In practical applications, a combination of supervised and unsupervised learning methods is often used to improve predictive maintenance performance. Hybrid approaches integrate anomaly detection with classification or regression models to enhance predictive accuracy. Additionally, reinforcement learning-based models are emerging as a promising technique for optimising maintenance strategies based on dynamic system feedback.

By leveraging both historical failure data and real-time operational metrics, predictive maintenance strategies can significantly enhance asset reliability, reduce maintenance costs, and improve overall operational efficiency.

# IV. RESULTS AND DISCUSSION

## A. Results

*1) Regression-based wear prediction:* In predictive maintenance (PdM) applications, regression-based models are used to estimate the remaining useful life (RUL) of an asset. This study evaluates the performance of Random Forest and Gradient Boosting regression models in predicting wear progression in fiberboard production.

Table II presents the results of the models based on three key evaluation metrics: Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared ($R^2$).

TABLE II. PERFORMANCE COMPARISON OF RANDOM FOREST AND GRADIENT BOOSTING MODELS

| Model | MSE | MAE | $R^2$ Score |
|---|---|---|---|
| Gradient Boosting | 5.41 | 1.94 | -0.224 |
| Random Forest | 5.15 | 1.88 | -0.163 |

Random Forest achieved a lower MSE of 5.15 and a lower MAE of 1.88 compared to Gradient Boosting, which had an MSE of 5.41 and an MAE of 1.94. The $R^2$ scores for both models were negative, indicating limited predictive accuracy under the given conditions.

*2) Feature importance analysis:* Feature importance scores were computed to determine which variables have the most influence on wear progression. The feature importance rankings for Random Forest and Gradient Boosting are shown in Figure 2.

Surface grade was identified as the most significant factor affecting machine wear, with A1 and RG/ORG showing the highest contribution to wear progression. Other factors, including glue type and Specific Energy Consumption (SEC), had comparatively lower influence.

## B. Discussion

*1) Performance of regression models:* The results indicate that Random Forest slightly outperforms Gradient Boosting in terms of predictive accuracy. The lower MSE and MAE values suggest that Random Forest produces fewer large errors when estimating wear progression. However, the negative $R^2$ scores indicate that neither model generalizes well to the given dataset. This suggests that additional feature engineering or the inclusion of external environmental variables, such as temperature and vibration, may be necessary to improve predictive performance.

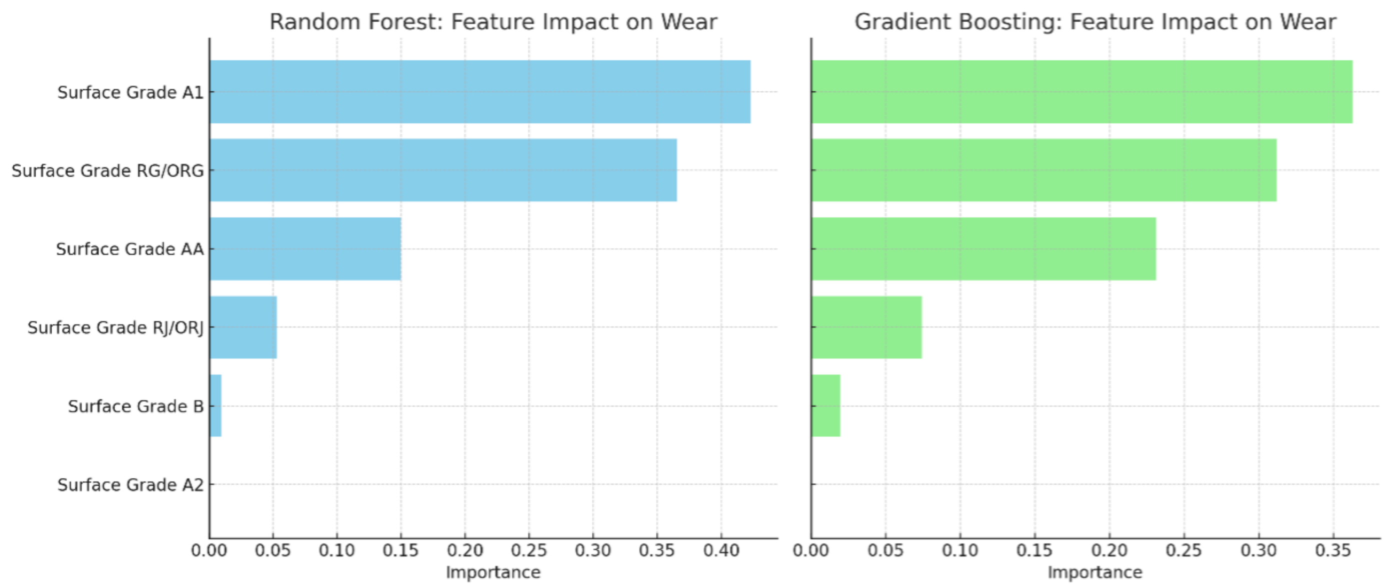


Fig. 2. Relationship between surface grade and wear in the production process.

Gradient Boosting, while effective in many machine learning applications, may have suffered from overfitting due to its iterative nature, which places higher emphasis on hard-to-predict samples. Further hyperparameter tuning could be explored to enhance its performance.

*2) Impact of feature importance analysis:* Feature importance analysis reveals that surface grade is the dominant factor influencing machine wear. This finding aligns with industry knowledge, where harder or coarser materials accelerate equipment degradation. Specifically, the strong influence of A1 and RG/ORG materials suggests that redistributing production to lower-impact grades such as A2 and B could reduce wear rates and extend equipment lifespan.

Additionally, while glue type and Specific Energy Consumption (SEC) contribute to wear, their impact is less pronounced compared to surface grade. This indicates that adjusting glue composition may have minimal impact on maintenance optimization, whereas focusing on material selection could yield significant benefits.

*3) Implications for industrial application:* The findings highlight the practical benefits of integrating predictive maintenance strategies in fiberboard production. By leveraging machine learning to predict wear patterns, manufacturers can optimize maintenance schedules, reducing unplanned downtime and improving resource allocation. Moreover, the identification of high-impact wear factors enables more informed decision-making in material procurement and production planning.

To further enhance PdM implementation, future work should consider:

- Expanding the dataset to incorporate external variables, such as humidity and machine vibration, to improve model accuracy.
- Exploring deep learning approaches, such as Long Short-Term Memory (LSTM) networks, to better capture temporal wear progression patterns.
- Implementing real-time IoT-based monitoring systems to dynamically adjust maintenance schedules based on sensor data.

Overall, the integration of machine learning in predictive maintenance offers significant potential for enhancing efficiency in industrial operations.

## V. Conclusion and Future Work

This research explores the application of predictive maintenance (PdM) strategies in fiberboard production by leveraging machine learning techniques to analyze wear progression. The developed cyber-physical system architecture integrates real-time data collection, preprocessing, predictive modeling, and decision support, offering a robust approach for failure prediction and proactive maintenance scheduling. By enabling predictive insights into machine wear, the framework contributes to reducing downtime, improving equipment lifespan, and enhancing operational efficiency.

The study evaluates the performance of Random Forest and Gradient Boosting regression models in predicting wear progression. Results indicate that Random Forest achieves slightly better predictive accuracy, as reflected in its lower Mean Squared Error (MSE), lower Mean Absolute Error (MAE), and higher R-squared ($R^2$) score. Feature importance analysis further reveals that surface grade is the most influential factor affecting wear, suggesting that optimizing material usage could reduce degradation and improve equipment lifespan.

Beyond fiberboard production, these findings underscore the potential of machine learning-based PdM strategies across various industrial sectors. The ability to predict equipment failures and wear patterns with high accuracy can be instrumental in industries such as manufacturing, automotive, and energy, where unplanned downtime can lead to significant financial losses. By integrating predictive analytics into maintenance planning, companies can transition from traditional preventive maintenance approaches to data-driven, condition-based strategies that maximize asset utilization and operational efficiency.

Despite these contributions, the study acknowledges certain limitations. The current models rely on historical wear data, which, while useful, may not fully capture dynamic operational changes. Additionally, the absence of real-time sensor data in this evaluation highlights the need for further experimentation with IoT-enabled condition monitoring. Variability in production parameters, such as temperature fluctuations and mechanical stress, could further influence wear progression, suggesting that incorporating additional environmental variables may enhance model robustness.

Future research should explore adaptive PdM frameworks that incorporate reinforcement learning for real-time optimization of maintenance schedules. Additionally, integrating IoT-based monitoring systems would enable dynamic data collection, allowing for more precise failure predictions. The development of hybrid predictive models combining deep learning with traditional ensemble methods could also improve accuracy by capturing both sequential wear patterns and complex nonlinear relationships.

In conclusion, this research highlights the effectiveness of machine learning-driven predictive maintenance in fiberboard production, demonstrating how PdM can optimize maintenance planning and improve industrial sustainability. By identifying key wear factors and leveraging predictive analytics, manufacturers can make informed decisions that enhance resource allocation, operational reliability, and cost efficiency. With further advancements in real-time monitoring and adaptive learning, predictive maintenance has the potential to redefine industrial asset management, contributing to more resilient and intelligent manufacturing systems.

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## DISCLOSURE AND CONFLICTS OF INTEREST

The author declares that there are no conflicts of interest related to this research. Additionally, the author has no financial interests or competing affiliations that could have influenced the study's design, execution, or findings. This manuscript is the original work of the author and has not been previously published or submitted for review to any other journal or conference.

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