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Enhancing the Reliability of Materials Handling Equipment in the Cement Industry through Predictive Maintenance Strategies

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Abstract: Predictive maintenance (PdM) has emerged as a crucial element of contemporary asset management, allowing businesses to transition from usage- or calendar-based maintenance to condition-driven interventions that maximize dependability and cost effectiveness. In the cement industry, materials handling devices like bucket elevators, rotary feeders, and conveyors work under constant high load and abrasive conditions. So, unforeseen breakdowns could seriously impair safety, raise maintenance costs, and disrupt production. To reduce the effect of unforeseen breakdowns, predictive maintenance is encouraged. Using sensor-based methods, oil analysis tracks lubricant deterioration and particulate contamination before they cause mechanical failure, and vibration analysis identify bearing flaws and misalignment early. In motors and gearboxes, thermal imaging detects electrical and friction-related hotspots, while ultrasonic sensors identify lubrication irregularities and air or fluid leaks. Beyond these, data-driven PdM, emphasizes machine learning algorithms that support vector machines, neural networks, and anomaly detection models that use real-time telemetry and historical maintenance records to anticipate remaining useful life and precise schedule interventions. To implement data driven PdM strong data infrastructure, cross-functional cooperation between the IT and maintenance teams, and employee training to decipher diagnostic results are required. Important issues to look at include managing upfront expenditure, integrating with current plant-wide management systems, and calibrating sensors in dusty conditions. Peer cement operations' case studies show an average return on investment, which includes a 15-20% decrease in downtime, a 15-20% reduction in maintenance costs, and an extended equipment lifespan. This review paper summarizes the main PdM approaches, investigates how they apply specifically to materials handling systems, and outlines best practices for Cement companies.

Key words: Predictive Maintenance Strategies, Cement Industry, Material handling Equipment, Reliability

1. Introduction

The construction of buildings, roads, bridges, dams, and other vital structures depends heavily on the cement industry, which is a vital part of the global infrastructure sector. The most common building material in the world, concrete, contains cement as a binding agent. The cement industry is considered a crucial indication of economic progress and urban development due to its widespread use in both residential and industrial developments. Most cement industries' current maintenance strategies are more preventive in nature, with routinely planned inspections and fixes meant to minimize possible failures. Although preventive maintenance is a fundamental component of effective asset management, the persistence of unscheduled malfunctions indicates that it may not be able to adequately handle all possible failure modes. This suggests that in order to improve equipment uptime and lessen the effect of unplanned breakdowns, the company has to investigate and maybe implement more dynamic and responsive maintenance approaches (Kumar et al. 2013; Raeyatinezhad 2023; Shaheen and Németh 2022). It could be advantageous to implement condition monitoring, predictive maintenance strategies, and a more proactive approach to spotting and resolving possible problems (Ahmed Murtaza et al. 2024). Additionally, enhancing the effectiveness of overall maintenance may be possible by planning and carrying out preventative chores more efficiently based on equipment criticality and past failure data (Achouch et al. 2022; Ahmed Murtaza et al. 2024).

Predictive maintenance (PdM) has become an indispensable component of modern asset management, enabling organizations to shift from calendar or usage-based upkeep toward condition driven interventions that optimize reliability and cost-efficiency. In the cement industry where materials handling equipment such as conveyors, bucket elevators, and rotary feeders operate under continuous high load and abrasive conditions unplanned failures can severely disrupt production, inflate maintenance budgets, and compromise safety (Adeodu et al. 2014). The sector's reliance on aging machinery, harsh operational environments, and remote plant locations further amplifies the urgency for robust PdM strategies. Recent advancements in Industrial Internet of Things (IIoT) sensors and machine learning (ML) have revolutionized PdM, allowing real-time monitoring of equipment health through vibration, temperature, and noise analysis (Rahman et al. 2023). AI-driven systems, for instance, can anticipate kiln imbalances or bearing failures in crushers days in advance, sometimes cutting down on unscheduled downtime by up to 82% (Mohapatra 2024).

Through the analysis of historical and current data from cement production lines, the integration of machine learning models, such as CatBoost and LightGBM, improved the accuracy of fault prediction and made proactive maintenance scheduling possible (Kausik et al. 2025). These solutions tackle important issues such as gear wear, conveyor belt obstructions, and motor damage that led to low Overall Equipment Effectiveness (OEE), a statistic that is frequently less than 70% in conventional cement plants (Anon n.d.-d; Mustakim and Asih 2022). PdM's ability to lower energy losses and increase operational agility is demonstrated by case studies like Cimpor Global's installation of 10,500 sensors across 25 facilities (Anon n.d.-g). Additionally, plant managers may now access dashboards from edge computing platforms that promote data-driven decision-making by assigning machine health scores, highlighting anomalies, and suggesting remedial measures. Furthermore, to promote data-driven decision making, edge computing systems now give plant managers dashboards that assign machine health scores, highlight anomalies, and suggest corrective actions. This paper aims to summarize the main PdM approaches, investigates how they apply specifically to materials handling systems, and outlines best practices for Cement companies.

2. Overview of Maintenance Strategies

2.1 Reactive Maintenance

Reactive maintenance, also referred to as "run-to-failure," is fixing equipment problems only after a breakdown has taken place. This method reduces the initial cost of maintenance, but it frequently results in high repair costs, considerable unscheduled downtime, and possible safety risks. Because cement machinery works in severe environments, depending only on reactive maintenance can lead to frequent disruptions and higher operating expenses. Unplanned downtime in cement plants can result in significant financial losses since it makes it impossible to satisfy production goals and client orders (Chukwunweike et al. 2024).

2.2 Preventive Maintenance

The goal of preventive maintenance is to lower the chance of equipment failure by scheduling interventions according to time or usage data. When compared to reactive maintenance, this approach improves equipment reliability. However, in complex systems where wear and tears do not follow expected patterns, it may result in needless maintenance or fail to identify impending breakdowns. Preventive maintenance programs are essential for cement plants because they proactively repair vital machinery, such as rotary kilns and crushers, reduce downtime, increasing equipment life, and improving performance (Au-Yong, Ali, and Ahmad 2014; Castro 2009)

2.3 Predictive Maintenance

Predictive maintenance (PdM) anticipates equipment breakdowns before they happen by using real-time data and sophisticated analytics. PdM makes it possible to continuously monitor the health of equipment by leveraging technologies like the Internet of Things (IoT), artificial intelligence (AI), and machine learning (ML) (Mohapatra 2024; Singgih, Zakiyyah, and Andrew 2024; Vijayakumar et al. 2023). Maintenance teams can improve equipment reliability, minimize downtime, and optimize maintenance costs by using a proactive approach that enables them to rapidly address possible concerns. By gathering intricate machine data and evaluating it to give maintenance and reliability specialists insightful information, predictive maintenance has demonstrated remarkable efficacy in minimizing unscheduled downtime at multiple cement manufacturing facilities (Anon n.d.-f; Rani et al. 2024).

Table 2.1: Comparative Perspectives

Strategy	Cost Impact	Downtime	Technology Dependency
Reactive	High (emergency repairs)	Severe (unplanned)	Low
Preventive	Moderate (planned intervals)	Reduced (scheduled)	Moderate
Predictive	Low (targeted interventions)	Minimal (proactive)	High (IoT, AL, analytics)

3. Predictive Maintenance Technologies

A variety of nondestructive assessment techniques and data-driven approaches are included in predictive maintenance, which aims to evaluate the condition of equipment and anticipate breakdowns before they happen. These technologies are essential to the cement industry because they guarantee the dependability of materials handling machinery including bucket elevators, rotary feeders, and conveyors that operate in harsh environments and with constant high loads (Anh, Dąbrowski, and Skrzypek 2018; Park et al. n.d.).

3.1 Vibration Analysis

To identify imbalances, misalignments, and bearing problems in rotating machinery such as conveyor motors and gearboxes, vibration analysis measures mechanical oscillations (Adeodu et al. 2014). Recent studies have greatly increased the accuracy of defect prediction in kiln process fans by adding machine learning models like random forest and k-nearest neighbors to vibration data (Asif et al. 2022). According to a thorough analysis, contemporary vibration monitoring systems now incorporate AI-based diagnostics and sophisticated signal processing, allowing for the early identification of emerging issues and minimizing unscheduled downtime in heavy sectors (Sperandio Nascimento et al. 2022).

3.2 Thermal Imaging

By mapping temperature differences on equipment surfaces using high-performance infrared sensors, infrared thermography (also known as thermal imaging) enables the identification of hot spots in mechanical and electrical systems prior to failure (Fox et al. 2014; Sperandio Nascimento et al. 2022). Real-time heat mapping of kiln shells in cement plants enables operators to proactively

schedule maintenance interventions and detect coating loss or tire misalignment (Anon n.d.-e). Thermal cameras are now more affordable thanks to developments in uncooled microbolometer technology, which enables continuous monitoring of kilns, fans, and other vital assets for early defect diagnosis and energy optimization (Grujić 2023).

3.3 Ultrasonic Testing

High frequency acoustic waves are used in ultrasonic testing to find wear, friction, leaks, and other early signs of equipment deterioration. These sensors are able to detect internal bearing and gear assembly flaws that vibration analysis alone is unable to detect (Hassani and Dackermann 2023). IoT connectivity and machine learning techniques enable ultrasonic inspection devices to reliably predict failures, automatically identify anomalous patterns, and continually monitor acoustic emissions (Arockiasamy et al. 2023; Chevtchenko et al. 2023).

3.4 Oil Analysis

To forecast wear and upcoming failures in gearboxes and hydraulic systems, oil analysis assesses lubricant characteristics such as viscosity, impurity levels, and wear-particle concentration. Maintenance teams can identify metal debris and chemical degradation far in advance of mechanical breakdowns by conducting routine spectrometric and particle count investigations (Wakiru et al. n.d.-a). In order to prolong equipment life and save maintenance costs, integrated oil analysis services that integrate lab testing with online sensor data provide turnkey solutions for lubricant health monitoring and condition-based oil change scheduling (Wakiru et al. n.d.-b). Professional oil analysis programs can enhance data-driven maintenance decision making, minimize unscheduled downtime, and save repair costs (Benhanifia et al. 2025; Roosefert Mohan et al. 2021).

3.5 Machine Learning and AI

Machine learning (ML) and artificial intelligence (AI) are being used more and more in advanced predictive maintenance strategies to evaluate massive information from numerous sensors and more accurately forecast equipment breakdowns. To detect intricate failure signals that would be challenging to detect manually, AI systems can combine vibration, temperature, ultrasonic, and oil analysis data streams (Aminzadeh et al. 2025; Benhanifia et al. 2025; Roosefert Mohan et al. 2021). In the cement industry, machine learning models analyze real-time sensor data, historical maintenance records, and environmental factors to predict malfunctions and improve maintenance plans, resulting in a notable decrease in unscheduled downtime (Hector and Panjanathan 2024; Rojek et al. 2023; Theissler et al. 2021). Algorithm based predictive maintenance solutions ranging from simple threshold-based alerts to sophisticated deep-learning networks enable continuous improvement of fault-detection accuracy and operational efficiency in cement plants (Asif et al. 2022; Habyarimana and Adebiyi 2025; Rojek et al. 2023).

Table 3.1: Summary for Condition Monitoring technologies in the Cement Company

Technology	Key Features	Applications in Cement Industry	Advantages	Limitations	Data Sources & Tools
Vibration Analysis	Measures mechanical oscillations to detect imbalances, misalignments, and bearing wear.	Rotating equipment (motors, gearboxes, kiln fans).	High accuracy in detecting early-stage faults. Integrates with AI/ML for pattern recognition.	Limited to rotating machinery; requires baseline data for comparison.	Accelerometers, IoT sensors, ML models (random forest, k-NN), and signal processing tools.
Thermal Imaging	Uses infrared sensors to detect temperature anomalies (hot spots).	Kiln shells, electrical panels, bearings, motors.	Non-invasive; detects overheating issues early. Cost-effective with modern microbolometer.	Affected by environmental factors (dust, moisture); surface-only diagnostics.	Infrared cameras, thermal mapping software, IoT platforms (e.g., Uptime AI).
Ultrasonic Testing	Employ high-frequency sound waves to detect friction, leaks, and internal defects.	Bearings, gear assemblies, compressed air systems.	Identifies issues missed by vibration analysis (e.g., internal wear). Works in noisy environments.	Requires skilled technicians; limited to localized inspections.	Ultrasonic sensors, IoT-enabled acoustic detectors, ML-based anomaly detection systems.

4. Applications of PdM in the Cement Industry

Cement plants all over the world have embraced predictive maintenance, which has shown notable improvements in equipment reliability, decreased unscheduled downtime, and maintenance cost savings. Many technologies and implementation strategies that propel these advantages are demonstrated by case studies from South Africa, Germany, India, North America, and international operators. Within the first year of implementation, a top factory in India reduced unexpected downtime by more than 250 hours by utilizing a PdM as a service solution that leveraged IoT sensors and machine learning diagnostics (Asif et al. 2022; Habyarimana and Adebiyi 2025). One cement factory in North America was able to achieve nearly "low touch" plant operations with just one operator by outfitting it with 5,000 sensors and 50 edge computing nodes (Azhari 2008; Biernacki et al. 2017).

In order to prevent failure modes and preserve product quality, multinational manufacturers like Holcim have implemented AI-driven PdM at several locations, focusing on extractors, crushers, grinders, kilns, and conveyors (Peicic n.d.). In his talk at the 2023

Global CemProducer Conference, Schaeffler described how predictive analytics and smart lubrication increased plant availability and decreased bearing failures in kiln and conveyor drive trains. By using SKF's "three-barrier" sealing and monitoring method on clinker pan conveyor bearings, South African operations were able to increase the mean time between failures from four to more than twelve months (Anon n.d.-c). When AI Reliability was implemented in a cement plant worldwide, false positive alarms were reduced by 96%, and vertical roller mill failures with seven-day advance warnings were 100% precise (Anon 2023). Further shown the scalability of PdM systems by deploying 10 to 500 sensors for real-time machine-health monitoring throughout its global footprint (Janocha and Czarnecki 2016; Rao et al. 2022; Wong et al. 2021). Ultimately, a vibration-based system specifically designed for high-temperature rotary kilns was developed by FLSmidth and Brüel & Kjaer Vibro as a result of their online kiln condition monitoring study, improving fault identification under harsh process conditions (Anon n.d.-a; Sinha 2020). At Cement industries, installing vibration sensors on bucket elevators and conveyors provides a first step toward PdM. These sensors make it possible to continuously monitor rotating parts like pulleys, gearboxes, and motors in order to identify early-stage issues like imbalance, misalignment, or bearing degradation (Diaz et al. 2017; Xu et al. 2023). It has been demonstrated that vibration-based analytics can cut unplanned material handling system malfunctions by as much as 60% (Chukwunweike et al. 2024). Before problems arise, infrared thermography is a real-time, non-invasive technique that can detect hotspots, faulty connections, or overloaded circuits. Preventing expensive unplanned downtime caused by electrical problems in cement plants has been made possible by frequent thermal imaging of motor control centers (MCCs) and drives (Futra Zamsyah Bin 2020). By integrating automated thermal scanning systems, inspection labor is decreased, and fault detection is improved. Machine learning algorithms can identify trends before failures occur by combining sensor outputs into centralized platforms. PdM platforms powered by AI can anticipate problems days or weeks ahead of time, allowing for prompt treatments (Rojas, Peña, and Garcia 2025). Similar AI-driven initiatives have been implemented by Holcim worldwide, showcasing how intelligent algorithms enhance asset health visibility and decision-making (LO CONTE 2025; Rani et al. 2024).

Table 4.1: Performance Comparison of Predictive Maintenance Models

Model Type	**Parameters Used**	**Dataset Size**	**Accuracy**	**Time Used**	**Recall**	**Precision**	**Source**
Boosted Decision Tree	Vibration, temperature, speed, current	400,000+ records	98%	Not specified	90%	93%	(Colabianchi S et al. n.d.)
Logistic Regression	Vibration, temperature, speed, current	400,000+ records	97%	Not specified	100%	80%	(Colabianchi S et al. n.d.)
Random Forest	Mining sensor data	Varies	90–96%	Medium	88–95%	-	(Rojas et al. 2025)
SVM	Mining sensor data	Varies	88–93%	Low	85–92%	-	(Rojas et al. 2025)
XGBoost	Mining sensor data	Varies	92–97%	Medium	90–96%	-	(Rojas et al. 2025)
CNN	Acoustic, thermal, vibration data	Varies	93–98%	High	92–97%	-	(Rojas et al. 2025)
RNN/LSTM	Time-series mining data	Varies	90–95%	High	88–94%	-	(Rojas et al. 2025)
TPM and 5S Implementation	OEE tracking in mills, conveyors	Not specified	OEE improved from 65.6% to 68%	Not specified	-	-	(Hossen Irfan, Rafiquzzaman, and Manik 2025)
CNN	Vibration, temperature, pressure (IoT sensors)	Not specified	92%	Real-time	-	-	(Alshahrani n.d.)
LSTM + ARIMA	Vibration, temperature, pressure (IoT sensors)	Not specified	87%	Real-time	-	-	(Alshahrani n.d.)
Isolation Forest	Vibration, temperature, pressure (IoT sensors)	Not specified	-	Real-time	88%	93%	(Alshahrani n.d.)
Deep Learning	BCF Machine (vibration, energy, temp.)	Industrial data via IoT	96%	Real-time	-	0.86	(Alshahrani n.d.)

Table 4.2: Comparison of Regression-Based Predictive Maintenance Models

Model Type	Parameters Used	Dataset Size	Accuracy	Time Used	Recall	Precision	Source
Decision Forest Regression	Vibration, temperature, speed, current	400,000+ records	$R^2 = 0.95$	Not specified	-	-	(Colabianchi S et al. n.d.)
ARIMA + Regression	Sensor data (equipment faults)	Industrial historical data	R^2 qualitative (trend accuracy	Real-time	-	-	(Shaikh et al. 2024)
Random Forest Regression	15 machine features (vibration, PLC, sensor data)	530,731 data points	$R^2 = 0.95$	Real-time (Azure)	-	-	(Alshahrani n.d.)
Two-class Logistic Regression	IoT + Fog data from manufacturing systems	Real-time operational data	Training $R^2 = 0.951$, Testing $R^2 = 0.945$	Real-time	-	-	(Teoh, Gill, and Parlikad 2023)
Linear Regression	Vibration, temperature, speed, current	400,000+ records	$R^2 = 0.93$	Not specified	-	-	(Colabianchi S et al. n.d.)
Linear Regression (IIoT)	Sensor data (equipment health status)	Real-time industrial data	R^2 not reported	Real-time	-	-	(Shaikh et al. 2024)
Regression Model (Soft Sensor)	Raw meal quality and kiln variables	Not specified	$R^2 = 0.9999$, MSE = 8.96e-7	Real-time estimation	-	-	(Ambaye 2013)

5. Challenges and Limitations

5.1 High Initial Cost

Predictive maintenance (PdM) system implementation requires large upfront investments in analytics platforms, cloud infrastructure, edge devices, and sensors. Without a definite return on investment, these capital expenditures may be unaffordable for mid-sized cement facilities such as Cement industries. However, upgrading older equipment with predictive maintenance (PdM) technology can end up costing more, especially when retrofitting existing systems (Anon n.d.-b).

5.2 Data Management Complexity

Predictive maintenance (PdM) systems collect large amounts of real-time data from different sources like vibration sensors, thermal cameras, and sound monitors. Handling all this information isn't simple. It takes powerful analytics tools, fast processing, and reliable storage. On top of that, maintenance teams often struggle with pulling together such a wide variety of data and making sure it's accurate and dependable. Predictive maintenance (PdM) systems produce a lot of real-time data from different sources like sound monitors, thermal cameras, and vibration sensors. To handle all this data, you need fast processing, strong storage, and smart tools to analyze it. For maintenance teams, it can be quite challenging to bring all these different data together and make sure it's accurate and reliable (Fawzy et al. 2025; Gudivada, Apon, and Ding n.d.).

5.3 Skill Gap and Training Needs

Employees with expertise in data analysis, machine learning, and condition monitoring methods are essential to the effective implementation of PdM. However, the cement sector frequently lacks such knowledge, especially in areas like developing countries. Time and resources are needed for extensive training programs and ongoing professional development in order to close this skill gap (Arthur-Mensah 2020; Wazihul et al. n.d.). Therefore, the readiness of the workforce is critical to the success of PdM projects. It is imperative that maintenance staff at cement industries receive upskills in condition monitoring methods, data interpretation, and digital technologies. Training courses that follow ISO 17359 PdM standards can enable local technicians to efficiently run and debug PdM systems (Gonzalez Nava 2019). Integrating PdM into everyday operations will require cross-functional cooperation and digital literacy.

5.4 Organizational Resistance to Change

There must be a substantial organizational shift in order to switch from traditional maintenance methods to predictive ones (Park et al. n.d.). Lack of knowledge about the advantages of PdM, anxiety about losing one's career, or mistrust of new technology can all be causes of resistance. Stakeholder participation, clear communication, and efficient management techniques are necessary to overcome this reluctance (Anh et al. 2018; Park et al. n.d.).

5.5 Cyber security Concerns

Potential cyber security risks are introduced when PdM systems are integrated with current IT infrastructure. Two crucial issues are maintaining the integrity of PdM systems and safeguarding sensitive operational data. To reduce these risks, strong cyber security measures must be put in place, and best practices must be followed (Ledmaoui et al. 2025; Pansara et al. 2024).

6. Recommendations and Conclusions

6.1 Recommendations

Conduct a Feasibility Study to Assess ROI of PdM Implementation: To assess the possible return on investment (ROI), Cement industries should conduct a thorough feasibility assessment prior to putting Predictive Maintenance (PdM) tactics into practice. Current maintenance expenses, equipment downtime, and the possible advantages of PdM such as fewer unscheduled outages and longer equipment life should all be examined in this study. It will be easier to prioritize PdM projects and allocate resources wisely if these characteristics are quantified.

Start with Pilot Projects on Critical Equipment to Demonstrate Value: PdM effectiveness can be evaluated in a controlled setting by starting pilot projects on crucial machinery, such as kilns, mills, or conveyors. These pilots can give Cement industries important information about the advantages and practical difficulties of PdM, allowing them to improve their tactics before expanding. Additionally, successful pilot projects can act as proof of concept, encouraging organizational support.

Partner with Technology Providers for Installation and Staff Training: The smooth integration of PdM systems can be facilitated by working with knowledgeable technology vendors. These collaborations can give access to cutting-edge resources like IoT sensors and AI-driven analytics, as well as crucial staff training. Putting money into staff training guarantees that workers are prepared to use and maintain new technologies efficiently.

Establish a Centralized Maintenance Data System for Analytics and Reporting: Efficient data collection, analysis, and reporting are made possible by the implementation of a centralized maintenance data system, such as a Computerized Maintenance Management System (CMMS). By combining data from multiple sources, these systems can offer a comprehensive picture of the condition of the equipment and maintenance procedures. Proactive decision-making and ongoing enhancement of maintenance procedures are supported by this centralized approach.

Focus on Workforce Development and ISO-Aligned Training: Train technical staff in line with ISO 17359 standards for PdM, ensuring they are equipped to manage, analyze, and act on diagnostic insights efficiently.

6.2 Conclusions

With predictive maintenance (PdM), cement companies can improve operating efficiency, reduce unscheduled downtime, and increase the dependability of materials handling equipment. Early failure identification and more effective resource allocation are made possible by PdM, which makes use of technologies including IoT sensors, vibration analysis, thermal imaging, ultrasonic testing, and AI-driven data analytics. Maintenance teams are now able to make prompt decisions that minimize interruptions and prolong the life of vital machinery by switching from reactive or time-based maintenance to a condition-based, data-informed approach. Despite obstacles like a large upfront cost, complicated data integration, a lack of qualified staff, and internal change aversion, the long-term advantages like lower maintenance expenses, more accessible equipment, enhanced safety, and higher plant output far exceed the implementation hurdles. Additionally, PdM eases the reliance on reactive repair cycles and manual inspections, enabling more consistent cement production quality and throughput. The key to success is a gradual implementation strategy. Beginning with high-impact equipment pilot projects enables firms to evaluate performance, develop internal expertise, and support future growth. To increase digital maturity throughout the company, these early accomplishments should be bolstered by focused training programs, change management projects, and cooperation with knowledgeable technology partners. Additionally, by integrating easily with digital twins, cloud-based analytics platforms, and smart production systems, PdM helps cement industries align with the larger objectives of Industry 4.0. This shift improves operational agility and responsiveness by enabling automated decision-making, real-time monitoring, and predictive insights. From an environmental perspective, PdM contributes to sustainable manufacturing by optimizing energy consumption, reducing waste from equipment failure, and lowering the carbon footprint associated with emergency repairs and excessive inventory use. This aligns with global efforts to decarbonize heavy industries and meet Environmental, Social, and Governance (ESG) objectives.

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