

Implementing Big Data Analytics and Machine Learning for Predictive Maintenance in Manufacturing Facilities in South Korea

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Abstract

Predictive maintenance utilizing big data analytics and machine learning has emerged as a promising approach to optimize maintenance strategies and reduce unplanned downtime in manufacturing facilities. This paper provides a comprehensive overview of implementing predictive maintenance solutions in manufacturing plants in South Korea. It begins by highlighting the challenges of traditional preventive and reactive maintenance approaches. The paper then introduces big data analytics and machine learning as enablers for transitioning to predictive maintenance. Current applications, benefits, and challenges of implementing predictive maintenance in manufacturing are discussed. The core sections provide practical guidelines for collecting and integrating data from industrial assets, applying machine learning algorithms, and deploying predictive maintenance systems. Factors unique to manufacturing facilities in South Korea, such as high automation rates and nationwide 5G coverage, are considered. Detailed examples of using sensor data and machine learning algorithms like classification, regression, and deep learning for equipment maintenance are presented. The paper concludes by proposing a roadmap for manufacturing plants in South Korea to leverage big data and analytics to optimize maintenance strategies, minimize downtime, reduce costs, and improve overall equipment effectiveness.

Keywords: predictive maintenance, big data analytics, machine learning, manufacturing, South Korea

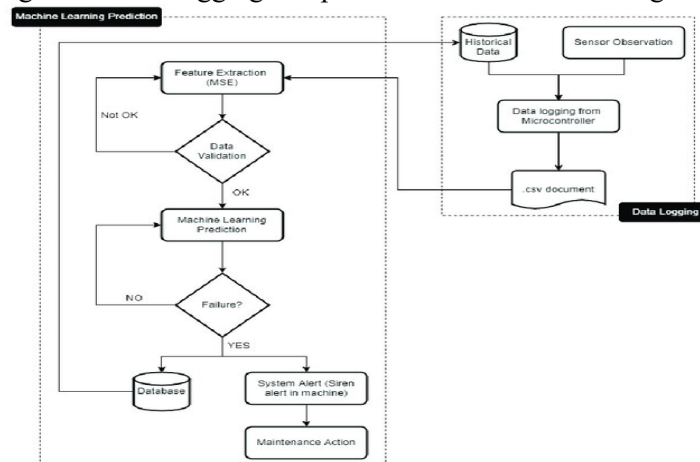
Introduction

Effective maintenance is crucial for ensuring high productivity and efficiency in manufacturing facilities. However, traditional preventive and reactive maintenance approaches face several limitations in today's complex and automated manufacturing environments. Preventive maintenance based on predetermined time intervals can result in unnecessary maintenance actions and disruptions. Reactive maintenance after faults occurs leads to unplanned downtime and loss of production [1]. A paradigm shift towards predictive maintenance has emerged as a solution to overcome these challenges. Predictive maintenance utilizes advanced analytics and machine learning methods to predict failures before they occur and schedule proactive maintenance[2]. Several industry reports highlight the transformational potential of predictive maintenance in manufacturing. A survey by Deloitte in 2016 found that predictive maintenance could reduce downtime by 30-50% and maintenance costs by 10-40%. McKinsey estimates that effective predictive maintenance adoption could yield a 10-40% increase in equipment uptime and 25-35% reduction in maintenance costs. These benefits make a compelling case for manufacturers to transition from traditional maintenance strategies to predictive maintenance powered by data analytics and machine learning.

This paper aims to provide comprehensive practical guidelines for implementing predictive maintenance solutions in manufacturing facilities in South Korea. An overview of the limitations of current maintenance approaches and the capabilities of predictive maintenance systems is first presented. The paper then discusses best practices for collecting and preparing data, applying machine learning algorithms, and deploying predictive maintenance systems tailored for the

manufacturing industry in South Korea. Detailed case studies and examples focused on the South Korean manufacturing sector are provided. Finally, a roadmap summarizing the key steps and recommendations for implementing predictive maintenance is proposed.

Figure 1. Flow diagram of data logging and predictive maintenance using machine learning [3].



2. Limitations of Traditional Maintenance Approaches

Preventive and reactive maintenance have been the most commonly adopted strategies in manufacturing plants in South Korea. However, several drawbacks to these approaches have become more prominent with increased automation and complexity of modern production assets and processes.

2.1 Preventive Maintenance

Preventive maintenance, as a strategy in manufacturing plants, is aimed at averting equipment failures by conducting routine inspections, cleaning, lubrication, or component replacements at predetermined intervals, as highlighted by Mobley (2002). However, the conventional approach of time-based or usage-based scheduling recommended by equipment manufacturers presents several shortcomings [4]. Firstly, it often leads to unnecessary maintenance activities, contributing to increased downtime and costs, as indicated by Deloitte (2016) who suggested that up to 70% of preventive maintenance actions may be unnecessary. Secondly, fixed intervals fail to consider variations in asset deterioration rates influenced by operating conditions and part variability, resulting in maintenance being either premature or delayed. Additionally, despite adhering to scheduled maintenance, functional failures still occur unexpectedly, with studies such as Moubray (1997) finding that scheduled replacements alone would prevent less than 20% of equipment breakdowns. These limitations underscore the need for more adaptive and data-driven maintenance strategies in manufacturing settings [5].

2.2 Reactive Maintenance

Reactive maintenance, prevalent in South Korean manufacturing plants particularly for non-critical equipment and unplanned failures, involves repairing or replacing equipment only after failure occurs. However, this approach entails significant drawbacks. Firstly, it leads to unplanned downtime and disrupts production when equipment fails unexpectedly. Secondly, it results in increased maintenance costs due to the need for expediting repair parts, labor, and overtime. Thirdly, there is a risk of secondary equipment failures and safety hazards arising from the reactive nature of maintenance actions. Lastly, the inability to schedule maintenance activities optimally further compounds these challenges. In essence, both preventive and reactive maintenance strategies fall short in addressing the growing complexity and integration of modern manufacturing assets and processes [6]. Therefore, there is a pressing need for a new predictive maintenance approach leveraging technological advancements to enhance maintenance effectiveness and efficiency in manufacturing operations.

3. The Emergence of Predictive Maintenance

Predictive maintenance has emerged as an opportunity to overcome the limitations of traditional maintenance practices. The core concept of predictive maintenance is using analytics and machine

learning to predict precisely when maintenance should be performed to avoid operational disruptions and unexpected equipment failures. Enabled by the Industrial Internet of Things (IIoT), predictive maintenance allows maintenance to be scheduled based on actual equipment condition and probability of future failures.

3.1 Technological Enablers

The transition from time or usage-based to condition-based predictive maintenance has been facilitated by several key technological advancements. Firstly, the development of inexpensive yet reliable industrial sensors capable of measuring various parameters such as vibration, temperature, pressure, and current has been instrumental. These sensors enable continuous monitoring of equipment health and condition. Secondly, increased connectivity and the integration of cyber-physical systems allow for real-time monitoring of equipment performance and health status. Thirdly, advancements in data storage and transmission capabilities have made it possible to collect and store large volumes of equipment data efficiently. Fourthly, the growth in computing power has enabled real-time analysis of high-velocity data streams, facilitating timely decision-making [7]. Lastly, progress in analytics and machine learning algorithms has empowered organizations to detect patterns and trends within equipment data, thereby predicting potential failures and determining optimal maintenance timing. Collectively, these technological advancements provide the foundation for implementing predictive maintenance strategies, enabling organizations to proactively manage their assets and optimize maintenance schedules based on actual equipment condition.

3.2 Predictive Maintenance Process

A typical predictive maintenance system follows a structured process outlined in Figure 1. Initially, data acquisition involves strategically placing sensors on industrial equipment to gather a range of condition monitoring data, including vibration, temperature, pressure, voltage, current, and acoustics, over time. Following this, data transmission securely transfers the collected sensor data to a central location for storage and analysis, employing both wired and wireless networking technologies for efficient data transfer. Once stored, the high-velocity streaming data from sensors resides in a centralized data lake or cloud platform, ensuring accessibility and scalability for subsequent processing steps. Data processing is then undertaken to preprocess and clean the raw sensor data, enhancing its quality, with feature engineering techniques potentially applied to extract informative signals for analysis.

Subsequently, analytics and machine learning algorithms are deployed to analyze the processed data, aiming to detect anomalies, uncover failure patterns, and predict future failures using leading indicators. This step encompasses both supervised and unsupervised machine learning methods, leveraging the power of advanced algorithms to derive actionable insights from the data [8]. These insights, along with notifications and recommended actions, are visualized through dashboards and mobile applications, providing maintenance teams with decision support to facilitate timely interventions.

The predictive maintenance system utilizes the predictions derived from analytics to plan maintenance activities proactively, moving away from traditional time-based schedules to more precise condition-based scheduling. By scheduling maintenance based on equipment condition rather than fixed intervals, organizations can optimize asset performance and minimize downtime effectively [9]. Finally, the closed-loop optimization aspect ensures the continuous improvement of the predictive maintenance system over time by updating models and algorithms based on new data, thereby enhancing accuracy and reliability in the long term.

4. Applications and Benefits of Predictive Maintenance in Manufacturing

When implemented effectively, predictive maintenance powered by data analytics can transform maintenance practices in manufacturing facilities. Predictive maintenance allows for optimal scheduling of maintenance activities based on actual need. Unnecessary maintenance actions and unplanned reactive repairs are minimized. The main applications and benefits are highlighted below:

4.1 Reduced Downtime

Predictive maintenance is a proactive approach aimed at maximizing equipment availability and minimizing unexpected failures by employing prescriptive maintenance strategies. By leveraging data analytics and machine learning algorithms, predictive maintenance enables organizations to anticipate potential issues and address them before they escalate into costly disruptions. Research by Deloitte in 2016 indicated that unplanned reactive downtime can be significantly reduced by up to 50% through the implementation of predictive maintenance practices. This reduction in downtime not only enhances operational efficiency but also optimizes production schedules, as downtime becomes more predictable and can be strategically managed to minimize its impact on overall productivity. Consequently, businesses can achieve higher levels of reliability, improve resource utilization, and ultimately enhance their competitive edge in the market [10].

4.2 Improved Maintenance Planning

Maintenance planning undergoes a transformative enhancement with the integration of predictive insights into component condition, departing from traditional time-based schedules. By harnessing real-time data and advanced analytics, organizations can accurately assess the health and performance of critical equipment, enabling maintenance activities to be precisely aligned with actual need rather than predetermined intervals. This optimization of maintenance frequency and timing ensures that resources are allocated efficiently, minimizing unnecessary downtime while effectively addressing emerging issues before they escalate [11]. Additionally, predictive maintenance facilitates improvements in inventory and parts management by providing insights into the specific components requiring replacement or servicing. This targeted approach enhances inventory accuracy, reduces excess stockpiling, and streamlines procurement processes, thereby optimizing asset utilization and operational efficiency across the maintenance lifecycle.

4.3 Lower Maintenance Costs

According to estimates provided by McKinsey in 2017, the implementation of predictive maintenance strategies can result in substantial reductions of total maintenance costs, ranging from 10% to 40%. These cost savings stem from various factors, including the elimination of unnecessary maintenance tasks, reduced overtime labor charges, and more efficient management of spare parts inventory. Predictive maintenance enables organizations to focus their resources on critical maintenance activities by accurately identifying maintenance needs based on equipment condition, thereby eliminating unnecessary or premature servicing. This targeted approach not only minimizes downtime but also reduces labor costs associated with overtime and emergency repairs. Furthermore, by optimizing spare parts inventory through predictive insights, organizations can avoid overstocking or understocking, leading to significant cost savings in procurement and storage. Additionally, the extended equipment lifetime resulting from proactive maintenance practices contributes to further cost reductions by deferring capital expenditures on replacements and upgrades. Overall, predictive maintenance offers a comprehensive approach to cost optimization, driving efficiency improvements and enhancing the long-term financial sustainability of maintenance operations.

4.4 Increased Asset Utilization

The overall equipment effectiveness (OEE) experiences a notable increase as organizations implement predictive maintenance practices, leading to enhanced availability and efficiency of critical assets. By minimizing unplanned downtime and optimizing maintenance schedules, predictive maintenance allows manufacturers to push asset utilization closer to capacity levels without compromising reliability. This increased utilization translates into higher production output and improved productivity levels across operations. With reduced disruptions and enhanced equipment performance, organizations can maximize the potential of their assets, achieving higher OEE scores and driving greater operational efficiency. Moreover, the ability to operate machinery closer to its full capacity without reliability concerns enables manufacturers to meet production demands more effectively, capitalize on market opportunities, and ultimately enhance their competitive position [12]. As a result, predictive maintenance serves as a catalyst for improving overall equipment effectiveness, driving performance improvements, and facilitating sustainable growth in manufacturing operations.

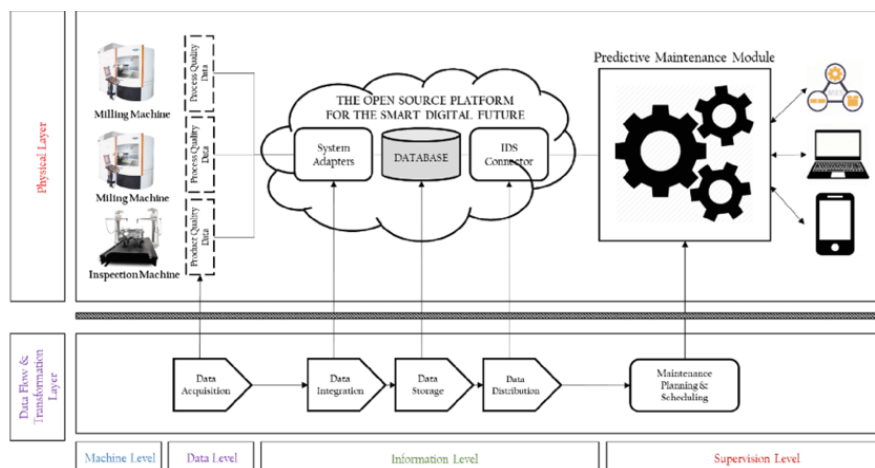
4.5 Enhanced Worker Safety

Predictive maintenance plays a crucial role in enhancing workplace safety by proactively identifying and addressing potential equipment failures before they escalate into dangerous breakdowns or accidents. By continuously monitoring equipment health and performance, organizations can detect early warning signs of impending failures and take preventive measures to mitigate risks. This proactive approach helps to prevent sudden equipment malfunctions that could pose safety hazards to workers, such as machinery malfunctions, structural failures, or hazardous chemical leaks. As a result, the occurrence of workplace injuries caused by unexpected equipment outages and emergency repairs is significantly reduced. Moreover, by minimizing unplanned downtime and optimizing maintenance activities, predictive maintenance reduces the need for workers to perform high-risk tasks under time pressure or in hazardous conditions, further enhancing workplace safety. Overall, the implementation of predictive maintenance not only improves operational efficiency and equipment reliability but also fosters a safer work environment, ultimately safeguarding the well-being of employees and promoting a culture of safety within the organization.

4.6 Sustainability Benefits

Unplanned downtime not only disrupts operations but also leads to the wasteful consumption of energy resources in manufacturing plants. However, through optimized maintenance scheduling facilitated by predictive maintenance strategies, organizations can significantly decrease this excess energy usage, thereby mitigating their carbon footprint. By proactively addressing equipment issues and minimizing downtime, predictive maintenance ensures that energy is utilized more efficiently, reducing unnecessary consumption during idle periods or emergency repairs. This optimization not only lowers operational costs but also contributes to environmental sustainability efforts by reducing greenhouse gas emissions associated with energy production and usage. Moreover, predictive maintenance offers additional sustainability benefits beyond energy conservation. By extending the lifespan of critical assets through proactive maintenance practices, organizations reduce the frequency of equipment replacements, thereby minimizing the environmental impact associated with manufacturing, transportation, and disposal of equipment. Additionally, predictive maintenance promotes resource efficiency by optimizing spare parts inventory management and reducing material waste generated from reactive maintenance activities. This streamlined approach to maintenance not only conserves resources but also enhances operational resilience and competitiveness in an increasingly resource-constrained world.

Figure 2.



5. Challenges and Considerations for Implementation

While predictive maintenance has demonstrated value, manufacturers need to be aware of challenges and critical factors for successful implementation. Careful planning and execution is required to overcome these barriers:

5.1 Data Infrastructure Requirements

In addition to the need for a robust data infrastructure to aggregate and analyze sensor data from connected equipment, it's imperative for manufacturers to recognize the necessity of ongoing investment in various facets of their technological ecosystem. This includes updating and implementing new data architectures tailored to handle the vast streams of data generated by interconnected devices efficiently. Moreover, establishing reliable networks capable of handling the continuous flow of data while ensuring minimal latency is essential [13]. Alongside these technological investments, stringent cybersecurity controls must be put in place to safeguard sensitive data and protect against potential cyber threats and breaches. Embracing cloud platforms or leveraging managed services can serve as viable solutions to bridge existing gaps in analytics and infrastructure. These platforms offer scalability, flexibility, and specialized expertise, enabling manufacturers to streamline their data operations while focusing on their core business objectives.

5.2 Technical Expertise Needs

The level of analytics and machine learning expertise required to effectively harness the potential of sensor data may not be readily available internally within manufacturing organizations. Consequently, forming strategic partnerships with predictive maintenance solution providers or machine learning specialists becomes essential. These partnerships can provide access to specialized knowledge and resources necessary for developing and deploying advanced analytics solutions tailored to the specific needs of the manufacturing environment [14]. Furthermore, investing in comprehensive training programs is crucial to upskill existing employees and empower them with the knowledge and skills required to work effectively with analytics tools and machine learning algorithms. By nurturing internal talent and fostering a culture of continuous learning and innovation, manufacturers can enhance their capabilities in leveraging data-driven insights to optimize operations and drive business growth.

5.3 Monitoring of Critical Assets

A phased approach that prioritizes the monitoring of the most critical assets is highly recommended over attempting to monitor all equipment simultaneously. By focusing initially on the most critical assets, manufacturers can efficiently allocate resources and attention to areas where potential failures or downtime pose the greatest risk to operations and safety. This targeted approach allows for the implementation of comprehensive monitoring and predictive maintenance strategies tailored to the specific needs and characteristics of critical equipment. Once the monitoring systems and processes have been successfully implemented and optimized for critical assets, expansion can then be gradually extended to cover non-critical assets. This phased approach enables manufacturers to prioritize their efforts effectively, ensuring that limited resources are utilized where they can deliver the most significant impact on operational efficiency, reliability, and overall performance. Additionally, it allows organizations to incrementally scale their monitoring capabilities in alignment with evolving business priorities and technological advancements.

5.4 Algorithm Development and Optimization

Developing and optimizing predictive algorithms tailored to each equipment use case is fundamental for achieving accurate predictions in predictive maintenance strategies. This process begins with a comprehensive understanding of the specific failure modes and patterns associated with each piece of equipment. By analyzing historical data, conducting failure mode analysis, and leveraging domain expertise, manufacturers can identify key indicators and variables that signal potential equipment failures. These insights serve as the foundation for building predictive models that can effectively forecast impending issues before they escalate into costly downtime or safety hazards. Moreover, the development of predictive algorithms is an iterative process that requires continuous improvement over time. As new data is gathered from ongoing operations and maintenance activities, these data points are incorporated into the predictive models to enhance their accuracy and reliability [15]. This iterative process enables manufacturers to adapt their predictive algorithms to changing operating conditions, evolving equipment behaviors, and emerging failure patterns. Additionally, leveraging advanced techniques such as machine learning and artificial intelligence allows for the automatic refinement and optimization of predictive models based on real-time data inputs.

Table 1. Key performance metrics for evaluating predictive maintenance.

Metric	Description
Unplanned downtime	Time equipment is stopped due to unexpected failure.
Maintenance cost	Total labor, parts, contractors, and other costs.
Number of breakdowns	Quantity of equipment failures.
MTTR	Mean time to repair after failure.
OEE	Overall equipment effectiveness based on availability, performance, quality.
MTTF	Mean time to failure for equipment or components.
Service intervals	Average time between maintenance tasks.

By continuously refining and improving predictive algorithms, manufacturers can achieve higher levels of accuracy and reliability in predicting equipment failures, thereby minimizing unplanned downtime, reducing maintenance costs, and optimizing overall asset performance. This iterative approach also ensures that predictive maintenance strategies remain effective and responsive to the dynamic nature of industrial operations.

5.5 Change Management Challenges

Transitioning maintenance workflows, mindsets, and corporate culture to embrace predictive maintenance represents a significant organizational change challenge for manufacturing companies. This transformation entails shifting from a reactive or time-based maintenance approach to a proactive and data-driven model. To facilitate successful adoption, it's crucial to prioritize education and communication efforts aimed at all levels of the organization. Providing comprehensive training programs and workshops that highlight the benefits of predictive maintenance and introduce employees to new processes and technologies is essential. This educational approach helps employees understand the rationale behind the transition and empowers them to effectively utilize new tools and methodologies in their daily workflows.

Moreover, fostering a culture of continuous learning and improvement is imperative for long-term success. Encouraging open dialogue, soliciting feedback, and recognizing and rewarding innovative behaviors can help instill a mindset of adaptability and experimentation within the organization. By emphasizing the positive impact of predictive maintenance on operational efficiency, equipment reliability, and overall business performance, manufacturers can garner buy-in and enthusiasm from employees at all levels. Additionally, effective change management strategies should be employed to address potential resistance to change and mitigate any associated risks. This may involve appointing change champions or ambassadors to advocate for the benefits of predictive maintenance, providing ongoing support and resources for employees navigating the transition, and establishing clear metrics and milestones to track progress and celebrate successes.

6. Manufacturing Environment in South Korea

South Korea provides a favorable environment for manufacturing firms to adopt predictive maintenance practices, but also has unique characteristics that need to be considered. These key aspects are highlighted below:

6.1 Automation Levels

South Korea's manufacturing sector boasts an impressive degree of automation, evident in its remarkable density of industrial robots, which stands at over 700 per 10,000 employees, according to the International Federation of Robotics (IFR) report of 2021. This statistic underscores South Korea's position as a global leader in industrial automation. However, alongside the benefits of increased automation come new challenges, particularly in terms of equipment maintenance and failure prediction. While automation facilitates the generation of vast amounts of equipment data ripe for analysis, it also necessitates a nuanced understanding of the various failure modes specific to robots. Incorporating these diverse failure modes into predictive maintenance strategies is crucial for ensuring uninterrupted operations and maximizing the efficiency of automated manufacturing processes [16]. Thus, as South Korea's manufacturing sector continues to embrace automation, there is a growing imperative to refine predictive maintenance techniques to address the unique challenges posed by robotic systems.

6.2 Government Initiatives

In alignment with its Manufacturing Innovation 3.0 strategy, the South Korean government has placed a strategic emphasis on the development of "smart factories" and the implementation of predictive maintenance practices. Recognizing the transformative potential of Industry 4.0 technologies, such as artificial intelligence, Internet of Things (IoT), and big data analytics, the government has fostered public-private partnerships and provided financial incentives to drive forward these initiatives. By promoting collaboration between industry stakeholders and facilitating investment in advanced technologies, South Korea aims to accelerate the adoption of smart manufacturing processes and enhance the competitiveness of its industrial sector on the global stage. This concerted effort underscores the government's commitment to leveraging cutting-edge technologies to drive innovation, improve operational efficiency, and sustain long-term economic growth.

6.3 5G Leadership

South Korea, as one of the pioneers in deploying 5G networks, stands at the forefront of high-speed and low-latency connectivity, crucial for facilitating Industrial Internet of Things (IIoT) applications such as predictive maintenance. The rollout of 5G infrastructure has significantly enhanced the country's digital ecosystem, enabling seamless communication and real-time data exchange between interconnected devices in industrial settings. This ultra-fast and reliable connectivity is instrumental in supporting advanced predictive maintenance systems, allowing for timely data collection, analysis, and decision-making. With its robust 5G infrastructure in place, South Korea is well-positioned to harness the full potential of IIoT technologies, driving efficiency gains, reducing downtime, and optimizing asset management across various industrial sectors. This strategic advantage underscores South Korea's commitment to fostering innovation and maintaining its leadership in the global digital economy.

6.4 Chaebol Presence

The presence of major chaebols like Samsung and Hyundai, operating extensive manufacturing facilities in South Korea, presents a significant opportunity for driving nationwide scale-up of predictive maintenance efforts. By focusing on implementing predictive maintenance strategies within the plants operated by these conglomerates, the country can leverage their considerable resources, expertise, and influence to catalyze broader adoption across the industrial landscape [17]. These large-scale manufacturing facilities serve as showcases for innovative technologies and best practices, setting industry standards and influencing the practices of smaller enterprises within their supply chains. Furthermore, collaboration with major chaebols can facilitate knowledge sharing, technology transfer, and capacity building initiatives, enhancing the overall readiness of the manufacturing sector to embrace predictive maintenance solutions. Therefore, by strategically targeting plants operated by prominent conglomerates like Samsung and Hyundai, South Korea can accelerate the proliferation of predictive maintenance practices, driving efficiency improvements and competitiveness on a nationwide scale.

Table 2. Overview of sensors for condition monitoring.

Sensor	Typical Measurements	Failure Modes Detected
Vibration	Acceleration, velocity, displacement	Imbalance, looseness, bearing faults, gear defects
Acoustic emission	Sound waves and ultrasonic noise	Leaks, cracks, cavitation, impacting
Temperature	Thermal patterns and gradients	Overheating, chemical leaks, seal issues
Pressure	Force per unit area	Blockages, relief valve faults, tank leaks
Current	Electrical load profiles	Motor faults, insulation breakdown, short circuits
Voltage	Potential difference	Power quality issues, insulation problems

6.5 Energy Dependence

South Korea's reliance on imported energy sources underscores the importance of optimizing predictive maintenance practices in the manufacturing sector, as it offers significant potential for enhancing energy efficiency and realizing cost savings. By implementing predictive maintenance solutions, manufacturers can proactively identify and address equipment issues before they escalate into costly failures, thereby minimizing unplanned downtime and reducing energy consumption. This proactive approach not only improves operational efficiency but also helps mitigate the risk of production disruptions, which can have cascading effects on energy usage and costs [18]. Additionally, by optimizing equipment performance and extending asset lifespan through predictive maintenance, manufacturers can reduce the need for frequent replacements and repairs, further contributing to cost savings and sustainability efforts. Given the economic implications of energy imports and the imperative to mitigate environmental impact, the prospect of achieving greater energy efficiency and cost savings serves as a compelling motivator for manufacturers in South Korea to adopt predictive maintenance practices as part of their operational strategies.

7. Data Collection and Preparation

The first steps in implementing predictive maintenance are installing sensors on equipment to collect condition monitoring data and preparing that data for analytics applications. This section provides an overview of best practices to ensure high-quality data pipelines.

7.1 Sensor Selection and Installation

In addition to selecting appropriate sensor types, it is also essential to consider the overall sensor network architecture and data integration strategies. The integration of sensors into a cohesive monitoring system requires careful planning to ensure compatibility, scalability, and interoperability. This includes designing data acquisition systems, establishing communication protocols, and implementing data processing algorithms to extract meaningful insights from the collected sensor data [19]. Furthermore, the deployment of sensors often involves considerations such as power supply requirements, communication range, and data transmission rates, which can influence the overall system design and implementation. Therefore, a comprehensive approach to sensor deployment encompasses not only sensor selection and installation but also the broader aspects of system architecture and data management. By addressing these factors holistically, organizations can build robust and effective sensor-based monitoring systems that support their operational objectives and enable data-driven decision-making.

7.2 Data Acquisition Infrastructure

A reliable and secure network infrastructure with sufficient bandwidth is indispensable for aggregating and transmitting sensor data effectively. In factory environments, where stability and low latency are paramount, wired solutions such as industrial Ethernet are commonly employed. Industrial Ethernet offers the stability and bandwidth necessary to support real-time monitoring and control applications within the factory setting. By leveraging wired connections, organizations can ensure consistent data transmission and minimize the risk of interference or signal degradation. However, for outdoor assets that are more dispersed and may be located in remote or challenging environments, wireless networking options become essential. These options include WiFi, private LTE/5G, satellite communications, and LPWAN (Low-Power Wide-Area Network) technologies. Each of these wireless technologies has its own strengths and suitability depending on factors such as range, bandwidth requirements, power consumption, and coverage area. For instance, WiFi may be suitable for short-range communication within a limited area, while satellite communication can provide connectivity in remote or geographically isolated locations where other options are not feasible [20]–[22].

Edge devices, such as industrial gateways, play a crucial role in managing connections between sensors and the network infrastructure. These devices serve as intermediaries between the sensors and the central data processing systems, handling tasks such as data aggregation, protocol conversion, security enforcement, and local data processing. By deploying edge devices strategically, organizations can optimize network performance, reduce latency, and enhance data security by processing sensitive information locally before transmitting it to the central servers or cloud-based platforms.

7.3 Data Storage and Management

Managing the high-velocity data streams generated by potentially thousands of sensors necessitates the utilization of specialized time-series databases capable of efficiently storing and managing such data. Time-series databases like InfluxDB, Snowflake, or data lakes offer features tailored to handle the unique requirements of time-stamped data, such as fast ingestion rates, efficient storage compression, and optimized querying capabilities. These databases enable organizations to store vast amounts of sensor data while maintaining high performance and scalability, essential for real-time monitoring and historical analysis.

Furthermore, the choice between on-premise servers and cloud platforms for hosting these databases is a critical consideration. Cloud platforms offer several advantages, including scalability, flexibility, and ease of deployment. By leveraging cloud services, organizations can dynamically scale their storage and computing resources to accommodate fluctuating data volumes and processing demands without the need for significant upfront investment in hardware infrastructure. Additionally, cloud platforms often provide built-in features for data replication, backup, and disaster recovery, enhancing data resilience and reliability. However, regardless of whether data storage and processing occur on-premise or in the cloud, it is imperative to design a robust data architecture that can adapt to evolving analytics needs. This entails establishing clear data governance policies, defining data ingestion pipelines, and implementing data processing workflows that support both real-time analytics and batch processing. Moreover, integrating data from disparate sources, such as sensor networks, operational systems, and external data sources, requires careful consideration of data integration techniques and standards to ensure data consistency and accuracy.

7.4 Data Cleansing and Preprocessing

The challenges posed by real-world data are multifaceted. Real-world sensor data often encompasses a plethora of noise, gaps, and irregularities, stemming from various sources such as sensor malfunctions, environmental factors, or transmission errors. Addressing these issues is paramount to ensure the accuracy and reliability of the models built upon such data. Data cleansing and preprocessing techniques serve as the cornerstone in this endeavor. These techniques encompass a spectrum of methodologies aimed at detecting and filtering out erroneous or irrelevant data points, thereby enhancing the quality of the dataset. One commonly employed technique is data smoothing, which involves the application of filters to attenuate noise and mitigate signal irregularities [23]. Additionally, methods such as interpolation can be utilized to fill in gaps in the data caused by sensor failures or communication issues. Furthermore, normalization and scaling techniques may be applied to standardize the range and distribution of the data, facilitating more effective model training and inference. Feature engineering constitutes another pivotal aspect of data preprocessing, wherein meaningful representations are extracted from the raw sensor data to serve as input features for machine learning models. Techniques such as time-domain and frequency-domain analysis can reveal insightful patterns and characteristics embedded within the time-series data, enriching the feature space and enabling more robust model performance. In essence, data cleansing and preprocessing serve as indispensable steps in the data analytics pipeline, enabling practitioners to harness the full potential of sensor data and derive actionable insights for decision-making and predictive maintenance strategies.

7.5 Data Labelling

Labeling, a fundamental aspect of supervised machine learning, plays a pivotal role in training predictive models for component failure prediction and degradation state analysis in industrial settings. However, in the context of sensor data analytics, data labeling presents unique challenges and complexities. Unlike conventional datasets where labels may be readily available, such as in image classification tasks, labeling sensor data often requires domain-specific knowledge and expertise. Historical maintenance records serve as a valuable source of labels, providing insights into past instances of component failures or performance degradation [24]. Nevertheless, reliance solely on historical records may present limitations, especially in scenarios where data may be sparse or incomplete. Consequently, the expertise of subject matter experts becomes indispensable, as they possess the nuanced understanding and domain knowledge required to interpret sensor data and discern anomalous behavior indicative of impending failures or degradation. Manual labeling of sensor data by subject matter experts thus becomes imperative, albeit labor-intensive and time-

consuming. Moreover, as industrial systems evolve and new failure modes emerge, the task of continuously updating and refining the labeling process becomes an ongoing endeavor. Consequently, the development of automated or semi-automated labeling methodologies, leveraging techniques such as clustering and anomaly detection, represents a promising avenue for alleviating the labeling burden while ensuring the accuracy and relevance of the labeled data. In summary, data labeling constitutes a critical phase in the machine learning pipeline for sensor data analytics, necessitating a judicious blend of historical records, domain expertise, and emerging technologies to facilitate effective model training and predictive maintenance in industrial environments.

Algorithm	Description	Advantages
Random forest	Ensemble of decision trees	Handles nonlinearity, prevents overfitting
SVM	Maximize margin between classes	Effective with high-dimensional data
Neural network	Deep learning model	Learns complex relationships
CNN	Neural network for 2D data	Useful for image-based monitoring
LSTM	Recurrent neural network	Predicts temporal sequences
Autoencoder	Reconstruction-based deep learning	Good for anomaly detection
Regression	Predicts continuous outputs	Estimates remaining useful life
k-NN	Non-parametric classification	Simple and fast prediction

8. Analytics and Machine Learning Methods

Properly processed equipment data can be used to train machine learning models to detect anomalies, classify degradation states, predict future failures, and guide intelligent maintenance planning. This section outlines predictive maintenance algorithms and training approaches tailored for manufacturing.

8.1 Failure Modes and Model Selection

The process of identifying and addressing failure modes in critical equipment components represents a foundational step in the development of effective predictive maintenance strategies. Techniques such as Failure Modes and Effects Analysis (FMEA), as articulated by Stamatis (2003), provide structured methodologies for systematically identifying potential failure modes and their associated effects on equipment performance. By comprehensively cataloging failure types and patterns, organizations can gain valuable insights into the underlying mechanisms driving equipment degradation, thereby facilitating informed decisions regarding machine learning model selection and training. Different types of machine learning models serve distinct purposes in predictive maintenance applications, each tailored to address specific predictive tasks [25]–[27]. Classification models, for instance, are adept at categorizing equipment degradation into discrete states, such as normal, warning, or alarm conditions. For example, a Random Forest classifier may be employed to classify gearbox faults based on vibration signatures. Regression models, on the other hand, excel at predicting continuous response variables, such as Remaining Useful Life (RUL). Recurrent Neural Networks (RNNs) are often utilized for RUL prediction tasks, leveraging their ability to capture temporal dependencies in time-series data. Additionally, anomaly detection models play a crucial role in identifying deviations from normal equipment behavior, signaling potential impending failures. For instance, an autoencoder model trained on vibration data can effectively detect anomalies indicative of equipment malfunction. By carefully aligning model selection with the specific predictive tasks and failure modes prevalent in the equipment under consideration, organizations can enhance the efficacy and accuracy of their predictive maintenance frameworks, ultimately reducing downtime and improving operational efficiency.

8.2 Training Approaches

The efficacy of predictive maintenance models hinges on the quality and diversity of the training data used to train them. In scenarios where failure data is limited or imbalanced, employing appropriate training approaches becomes imperative to ensure model robustness and generalizability. An effective strategy to address data scarcity and class imbalance involves augmenting the training dataset through techniques such as data augmentation and synthetic minority oversampling (SMOTE). These methods artificially generate additional instances of minority class samples, thereby rebalancing the dataset and preventing the model from being biased towards the majority class. Furthermore, leveraging transfer learning techniques allows organizations to transfer knowledge from pre-trained models on related tasks to enhance the performance of predictive maintenance models. Online sequential learning represents another innovative approach to model training, enabling adaptive learning and continuous model refinement in response to new incoming data streams. By embracing a diverse array of training approaches and methodologies, organizations can overcome data-related challenges and build predictive maintenance models that exhibit robustness, accuracy, and scalability in real-world deployment scenarios.

8.3 Model Optimization and Feature Selection

Optimizing predictive maintenance models involves fine-tuning various aspects of the model architecture and training process to enhance their performance, generalizability, and interpretability. Hyperparameter tuning, a critical component of model optimization, involves systematically searching through a range of hyperparameter values to identify the configuration that maximizes model performance metrics. Techniques such as grid search and randomized search are commonly employed to efficiently explore the hyperparameter space and identify optimal configurations. Cross-validation is another essential technique used to evaluate model performance and assess its robustness across different subsets of the training data. By partitioning the data into multiple folds and iteratively training and validating the model on different combinations of folds, cross-validation provides insights into the model's ability to generalize to unseen data.

Feature selection plays a pivotal role in enhancing model interpretability and reducing computational complexity by identifying the most informative and discriminative features from the input data. Techniques such as principal component analysis (PCA) can be used to reduce the dimensionality of the feature space while preserving the most significant variation in the data. Additionally, statistical metrics such as mutual information can help quantify the relevance of individual features to the target variable, guiding the selection of informative features for model training.

Regularization techniques, such as L1 and L2 regularization, are employed to prevent overfitting and improve model generalizability by penalizing overly complex models. These techniques constrain the magnitude of model parameters, thereby reducing the risk of overfitting to the training data. By incorporating model optimization and feature selection methodologies into the training pipeline, organizations can develop predictive maintenance models that strike a balance between accuracy, interpretability, and computational efficiency, enabling actionable insights to drive proactive maintenance strategies.

8.4 Handling Imbalanced Data

Imbalanced datasets, where the number of examples belonging to different classes is heavily skewed, present significant challenges during model development and evaluation. In the context of predictive maintenance, maintenance data typically contains far more examples of normal operating conditions compared to failure states, resulting in imbalanced classes. To address this imbalance, specialized techniques are employed to ensure that the predictive model does not exhibit bias towards the majority class while effectively capturing patterns associated with the minority class. Synthetic Minority Oversampling Technique (SMOTE) is a popular approach used to address class imbalance by artificially generating synthetic samples for the minority class, thereby balancing the class distribution. By introducing synthetic examples that lie along the line segments connecting existing minority class instances, SMOTE effectively increases the representation of the minority class in the training dataset, thereby mitigating the imbalance.

Additionally, cost-sensitive training methods adjust the misclassification costs associated with different classes to reflect their relative importance, thereby incentivizing the model to prioritize

the correct classification of minority class instances. By assigning higher misclassification costs to the minority class, these methods encourage the model to allocate more resources towards correctly identifying instances of failure or degradation.

By employing specialized techniques such as SMOTE and cost-sensitive training, organizations can develop predictive maintenance models that effectively address class imbalance, enabling accurate detection of equipment failures and degradation states in real-world scenarios.

8.5 Edge vs Cloud Analytics

The choice between edge and cloud analytics represents a fundamental consideration in the deployment of predictive maintenance solutions, with implications for latency, reliability, scalability, and data privacy. Edge analytics involves performing data processing and analysis directly on the edge devices, such as sensors or gateways, located in close proximity to the equipment being monitored. This approach offers several advantages, including reduced latency, as data processing occurs in near real-time without the need to transmit data to remote servers for analysis [28]. Additionally, edge analytics enhances data privacy and security by minimizing the exposure of sensitive information to external networks. However, edge analytics is constrained by limited computational resources and may struggle to handle complex analytical tasks or large volumes of data. In contrast, cloud analytics leverage the vast computational resources and scalability offered by cloud platforms to perform sophisticated data analysis and modeling. By offloading data processing and analysis to the cloud, organizations can benefit from enhanced scalability, allowing them to handle large volumes of data and accommodate fluctuations in computational demand.

A hybrid edge-cloud architecture represents a middle ground between edge and cloud analytics, combining the benefits of both approaches to optimize latency, reliability, and scalability. In this architecture, lightweight anomaly detection models are deployed locally on edge devices to perform real-time analysis and alerting, while more complex analytics tasks and model training are offloaded to the cloud for scalability and resource-intensive processing. Federated learning, an emerging paradigm in machine learning, enables collaborative model training across distributed edge devices while preserving data privacy and security. By carefully weighing the trade-offs between edge and cloud analytics and adopting a hybrid architecture tailored to the specific requirements of the application, organizations can effectively leverage predictive maintenance solutions to enhance equipment reliability, reduce downtime, and optimize maintenance operations.

9. Deployment Architecture and Integration

Once predictive models have been developed, deployment into production environments requires standardized architectures, workflow integration, and computing infrastructure. Cybersecurity is also critical.

9.1 Platforms and Standards

In contemporary industrial environments, the facilitation of connectivity among diverse sensors, machines, and software is imperative for seamless operations. Open platforms such as PLCOpen and MTConnect play a pivotal role in enabling this connectivity by adhering to standard APIs (Application Programming Interfaces). Additionally, organizations can benefit from the guidance provided by entities like the Industrial Internet Consortium, which offers frameworks and best practices for effective integration strategies across various industrial systems [29], [30].

9.2 Cloud Infrastructure

The advent of cloud computing has revolutionized data management practices within industrial settings. Cloud platforms offer unparalleled storage capacity, robust computing power, and the scalability necessary to handle vast amounts of industrial big data and facilitate machine learning model training. Furthermore, the deployment of private or hybrid cloud infrastructures ensures both security and low-latency access, crucial for maintaining operational integrity and efficiency.

9.3 OT/IT Integration

Achieving synergy between operational technology (OT) systems deployed within production facilities and corporate information technology (IT) systems is paramount in harnessing the full potential of data aggregation and digital transformation initiatives. However, this integration process often encounters cultural barriers between traditionally distinct OT and IT teams,

necessitating concerted efforts to overcome these challenges through collaboration and mutual understanding.

9.4 Cybersecurity

As industrial environments become increasingly interconnected through sensor data transmission, cloud services, and interconnected equipment, cybersecurity emerges as a critical concern. To mitigate potential cyber risks effectively, organizations must adopt a comprehensive defense-in-depth strategy. This strategy typically encompasses measures such as network segregation, robust access controls, and enhanced device-level security protocols, as highlighted by Fereidunian et al. in their research.

9.5 Application Deployment

Industrial analytics applications play a pivotal role in enabling real-time monitoring, predictive analytics, alerts, and prescriptive recommendations to enhance operational efficiency. These applications can be developed utilizing industrial app platforms, offering organizations the capability to tailor solutions to their specific operational requirements. Moreover, user-centric applications serve to improve human-machine interactions, fostering a more intuitive and efficient working environment.

9.6 Workflow Integration

To fully capitalize on predictive maintenance recommendations and minimize operational disruptions, it is essential to integrate these insights seamlessly into existing maintenance workflows. This integration involves updating and optimizing work order management systems, maintenance history databases, and inventory management processes to align with the outputs generated by predictive analytics models. By streamlining workflow integration, organizations can realize significant improvements in maintenance efficiency and overall operational performance.

10. Use Cases and Examples

This section provides real-world examples demonstrating how machine learning and big data analytics have been applied for predictive maintenance in manufacturing facilities in South Korea.

10.1 Electronic Components Manufacturer

An electronic components plant installed sensors to monitor the condition of manufacturing equipment like SMT mounting machines and die bonders. Vibration, acoustics emission, humidity, and temperature data was collected. A LSTM neural network built using TensorFlow detected anomalies in vibration data and classified degradation severity, achieving over 90% accuracy in predicting failures an average of 5 days before occurrence. Unplanned downtime was reduced by over 8% in the first year, and maintenance costs decreased by \$120,000.

10.2 Automotive Manufacturer

A major automotive OEM applied data-driven predictive maintenance for stamping presses. Monitoring 150 presses in a single facility required an IoT platform to manage over 50TB of data per day from plethora of sensors. A distributed computing architecture enabled real-time anomaly detection using LSTM models to detect abnormalities in press vibrations and acoustic signals. Predictive insights were delivered via dashboards and mobile alerts. Implementing this system increased uptime by 43 hours per press on average annually.

10.3 Semiconductor Fab

Machine learning models were developed to predict failures for equipment in a semiconductor manufacturing fab based in South Korea. The Applied Materials E3 fault detection and classification solution uses supervised learning to classify errors and predict yield excursions. This provided up to 4 hours of early warning to avoid disruptions in the complex, high-mix fab. Across 20 process tools, unscheduled downtime was reduced by about 30 hours per month, increasing output.

11. Roadmap for Implementation

The roadmap presented in this paper delineates a comprehensive strategy for the implementation of predictive maintenance in manufacturing facilities situated in South Korea. Comprising six distinct steps, this roadmap offers a systematic approach to navigating the transition towards data-driven maintenance practices. Firstly, facilities are advised to conduct a thorough assessment of their readiness by scrutinizing existing assets, maintenance data, policies, and available resources.

This evaluation helps determine the organization's preparedness for embracing predictive maintenance and lays the groundwork for subsequent steps. Additionally, the identification of a cross-functional team to spearhead the initiative ensures effective coordination and collaboration across different departments and disciplines within the organization.

Furthermore, the roadmap underscores the importance of identifying critical assets as a crucial second step. By prioritizing mission-critical equipment and components with high downtime, manufacturing facilities can strategically allocate resources and efforts towards areas that promise the greatest potential for business impact. This targeted approach facilitates a focused and efficient implementation process, maximizing the benefits of predictive maintenance initiatives. Aligning asset prioritization with potential business impact ensures that resources are directed towards areas where they can deliver the most significant returns, thereby optimizing the overall effectiveness of the maintenance strategy [31]. Moreover, the subsequent steps of deploying sensors and infrastructure, developing an analytics foundation, building and validating models, and operationalization and change management are pivotal in laying the groundwork for a successful predictive maintenance program. From installing sensors on priority assets to integrating predictive insights into maintenance workflows and updating policies, each step contributes to the evolution of maintenance strategies in a phased manner. As capabilities mature and organizations gain experience with predictive maintenance, the transformative potential of data-driven intelligent maintenance becomes increasingly evident. Ultimately, the roadmap serves as a guiding framework for manufacturers to leverage predictive maintenance as a foundation for achieving higher levels of optimization, automation, and integration in their operations, thereby driving sustained improvements in efficiency and performance over time [32].

12. Conclusion

Predictive maintenance, fueled by the integration of Industrial IoT sensors, big data analytics, and machine learning, represents a paradigm shift in maintenance strategies within the manufacturing landscape of South Korea. While traditional approaches continue to dominate, the adoption of predictive maintenance offers a transformative path forward, mitigating the limitations associated with preventive and reactive models. By harnessing the power of advanced analytics, South Korean manufacturing facilities can realize significant improvements in uptime, cost savings, asset utilization, safety, and sustainability [33].

The transition to predictive maintenance necessitates meticulous planning and adept change management to ensure successful implementation [34]. This requires a holistic approach that encompasses technological integration, organizational restructuring, and workforce upskilling [35]. By aligning strategic objectives with operational capabilities, companies can navigate the complexities of adopting predictive maintenance effectively, leveraging it as a catalyst for operational excellence and competitive advantage.

This paper has provided invaluable insights and actionable guidelines tailored specifically to the South Korean manufacturing sector, offering practical strategies for industry adoption. By drawing upon real-world examples and best practices, manufacturers can glean insights into the challenges and opportunities inherent in transitioning to predictive maintenance. Moreover, the roadmap outlined in this paper serves as a comprehensive framework, delineating the step-by-step process for implementing predictive maintenance systems within South Korean manufacturing environments.

With the implementation of the right strategy and adherence to the guidelines presented herein, South Korean manufacturers stand poised to revolutionize their maintenance practices [36]. By embracing data-driven intelligent paradigms, they can optimize production efficiency, enhance equipment reliability, and drive sustainable growth in an increasingly competitive global marketplace. As such, the journey towards predictive maintenance represents not only a technological evolution but also a strategic imperative for South Korean manufacturers seeking to thrive in the digital age.

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