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Original Article

AI-Based Predictive Maintenance Models in Smart Manufacturing Environments

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***Abstract** - Equipment downtime incurs direct financial losses, reduced end-customer service levels, and negative environmental impact. Downtimes often result from equipment failures that could be prevented through proper maintenance planning. Predictive maintenance promises to minimize unplanned downtimes by exploiting the data generated by Industrial IoT devices. While these types of data are usually plentiful, their quality is sometimes unsatisfactory, making machine learning models difficult to develop. Available datasets for predictive maintenance build upon condition monitoring, and usually cover conditions that are rarely met in real workloads. Therefore, finding approaches for handling rare events is essential for training reliable failure prediction models. Observing the factors that impact these paradigms, several predictive-maintenance models can be proposed. Supervised learning methods can be applied for predicting future failures based on labelled data, while anomaly-detection models can be explored to identify abnormal use conditions. Unsupervised clustering techniques can help identify outliers in usage patterns, and self-supervised setups exploit the rich information available in sensors, but do not require predictions of rare failures. The proposed methods cover the full predictive-maintenance lifecycle, from identifying, collecting, and preprocessing data, to context-based training-validation-testing pipelines, to interpretation and hints on integration with maintenance management systems.*

***Keywords** - Predictive Maintenance, Industrial IoT (IIoT), Equipment Failure Prediction, Rare Event Modeling, Machine Learning For Maintenance, Condition Monitoring Data, Anomaly Detection Techniques, Supervised Learning Models, Unsupervised Clustering Methods, Self-Supervised Learning Approaches, Data Quality In IoT Systems, Failure Risk Assessment, Context-Aware Model Validation, Maintenance Lifecycle Analytics, Intelligent Maintenance Management Systems.*

1. Introduction

Manufacturers strive to minimize equipment downtime and maintenance costs due to their dramatic impact on the bottom line. Smart manufacturing concepts advocate for a data-driven approach capable of supporting predictive maintenance models for handling production and automation resources. Predictive maintenance refers to a set of data-driven models monitoring the health conditions of devices in order to predict near-future failures or remaining useful life. Its implementation in smart factories relies on the adoption of sensors and on the ability to collect, store, clean, and analyze data coming from those sensors and from other sources, such as enterprise resource planning (ERP) and manufacturing execution systems (MES), Programmable Logic Controllers (PLCs), and maintenance documentation.

The growing training datasets allow predictive maintenance models to explore supervised, unsupervised, and semi-supervised setups. Supervised models predict the approaching failure of a unit, while the other two paradigms detect anomalous behavior and examine clusters of similar operating conditions for detecting rare faults without a historical failure record. Machine-learning techniques strive to parallel what humans would accomplish: analyzing all data and detecting emerging patterns. The goal of data-driven predictive maintenance is to guarantee the availability of Industrial Internet of Things (IIoT) devices and minimize costs associated with their failure. The fundamental underlying question is, “What is the probability of failure in a specified time span?” the question asked by a reliability engineer.

1.1. Rationale for Predictive Maintenance in Smart Manufacturing

Unscheduled machinery downtime is a major issue in many business domains, bringing about large inefficiencies and financial losses. Apart from the abrupt interruption of production, the equipment unavailability can cause violation of delivery times or even a stop of the entire production process, with large associated costs. Moreover, the maintenance and spare part inventory represent major running expenses, and the failure to notice maintenance needs can result in even larger repair works and costs. Predictive maintenance can solve those issues, analyzing the condition of the equipment and predicting about required maintenance actions. Modern Smart Manufacturing environments are particularly advantageous for predictive maintenance since they provide a large amount of low-cost data. Multiple paradigms of predictive maintenance exist, with the most well-known being Condition-Based Maintenance and Predictive Maintenance. For the purposes of this work, the term predictive maintenance is used in a wide sense and encompasses any data-based prediction of machinery failure from history data. For manufacturing scenarios, the automation and data collection system, such as a Manufacturing Execution System (MES), are very beneficial. In MES architectures, real-time data can be used for monitoring machines and easily label past failure events for model training. Moreover, the historical data from the MES store maintenance orders and associated reasons.

Data-driven modeling is a modeling paradigm in which the model is determined from data without the use of physics. The model can be a black box (e.g., Machine Learning) or can use some physics-based interpretation (e.g., System Identification). Data-driven modeling can also be used for predictive maintenance, as it uses the behavior of the equipment prior to failure to correctly label it and can potentially require less domain knowledge than other methods. Processing of the data, such as Feature Engineering, plays an important role as the predictive maintenance model captures the condition of the equipment during usage prior to failure. Finally, it should be noted that, in an industrial context, data-driven models are more commonly called statistical than machine learning models; this terminology is maintained throughout the work for clarity of meaning.

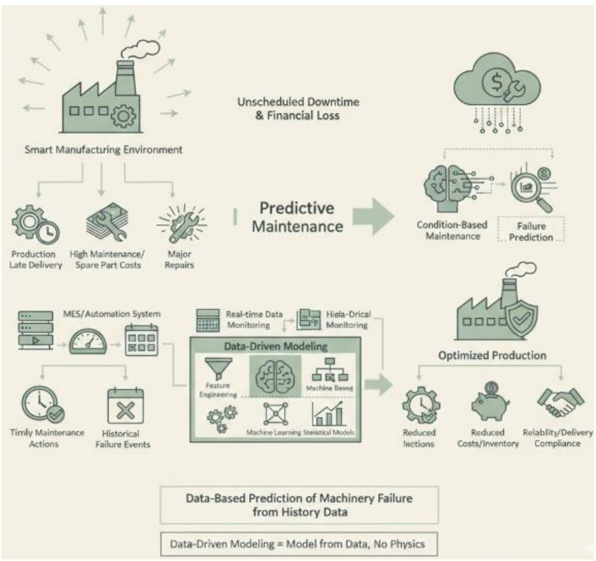

Fig 1: Data-Driven Predictive Maintenance in Smart Manufacturing: A Statistical Modeling Framework for Optimizing MES-Integrated Production Reliability

1.2. Scope and Objectives

Equipment performance degradation is a well-known cause of incidents and blackouts in manufacturing. Like in many other industries, highly expensive equipment must be repaired or replaced mainly because predictions and repairs were not optimized; therefore, too much was spent on equipment replacement and repair because of not predicting incidents and stop buying expensive equipment. Prediction of incidents avoiding such costs is what all of these algorithms try to achieve. Smarter factories enhanced by smart monitoring and intelligent analytics have been proposed to overcome common issues in manufacturing. Monitoring of failure and degraded states is achieved by sensors attached to the equipment, enabling the definition of innovative diagnostic algorithms based on the sensor streams.

Predictive maintenance supports a more efficient allocation of maintenance resources and, thus, avoids unnecessary factory downtime. Predictive maintenance is enabled by estimating the remaining useful life of the equipment or by predicting the time until the next failure occurs. Such predictions can be obtained by data-driven models that rely on historical data. Data-driven predictive maintenance models can be categorized into supervised, unsupervised, or semi-supervised approaches. The traditional category comprises supervised methods in which failures are used as labels for the learning process; however, when historical failures are rare, the models might fail. In these cases, anomaly detection and clustering can be applied. The unsupervised models detect and identify anomalies or rare degraded states during the life of equipment without the need of previous incidents at the same level.

2. Theoretical Foundations

Constantly rising demands for productivity require manufacturers to continuously improve their processes and reduce costs. Manufacturing equipment is complex and suffers random failures that reduce production efficiency. Indeed, equipment downtime represents one of the highest costs a manufacturing company incurs. These costs can be reduced by accurately predicting when equipment or components are going to fail, and taking proper action before the failure occurs.

Predictive maintenance in smart manufacturing relies on the data produced by the manufacturing process itself and data from normal operation of historical equipment assets of similar type. Smart factories provide suitable infrastructures for setting up and applying predictive maintenance. They provide support in collecting the required information and data in a structured way and creating predictive models with analysis capabilities. In the context of smart factories, predictive maintenance paradigms can be classified into five categories: reactive, preventive, condition-based, predictive and prescriptive maintenance.

This classification emphasizes the evolution of maintenance actions and associated costs as the timing of the maintenance decision moves from an external cognition (after failure) to an internal cognition (before failure). Smart factories lend themselves well to the analysis of predictive and prescriptive maintenance paradigms, since they provide the means, know-how and digital twin of the asset to accomplish such tasks. Predictive maintenance in smart manufacturing environments should thus rely on data-driven modeling methodologies for failure prediction.

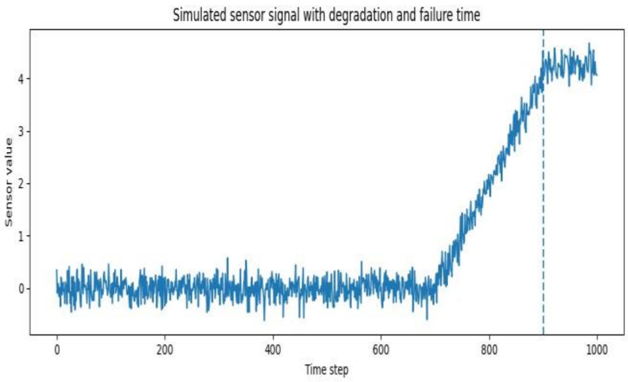

Fig 2: Detection of Anomalous Drift and Failure Thresholds

Equation 1) Core reliability target: "failure in a specified time span"

Let **T** be the random time-to-failure of an asset (from "now", time 0).

Step 1 Survival and CDF

- Define the CDF of failure time: $F(t) = P(T \leq t)$
- Define the survival function (probability it survives past time t): $S(t) = P(T > t) = 1 - F(t)$

Step 2 "Probability of failure within a horizon H"

The paper's question "probability of failure in a specified time span" corresponds to:

$$P(T \leq H) = F(H) = 1 - S(H)$$

Step 3 Conditional probability given it survived until now

In predictive maintenance we often want:

$$P(T \leq t + H \mid T > t)$$

Use conditional probability:

$$P(T \leq t + H \mid T > t) = \frac{P(t < T \leq t + H)}{P(T > t)}$$

Now rewrite numerator using F:

$$P(t < T \leq t + H) = F(t + H) - F(t)$$

Denominator is $S(t) = 1 - F(t)$. So:

$$P(T \leq t + H \mid T > t) = \frac{F(t + H) - F(t)}{S(t)}$$

2.1. Predictive Maintenance Paradigms

Random hardware failures cause unscheduled stoppages of production equipment and machines. This unavailability leads to production delays, dissatisfied customers, and financial loss. These issues can be reduced through the application of predictive maintenance (PdM) techniques, which allow operations and maintenance managers to apply their maintenance resources more effectively. All predictive maintenance paradigms follow the principle of condition-based maintenance but differ in their failure prediction mechanisms. The PM-Models group recognizes four predictive maintenance paradigms: reactive, preventive, condition-based, and prescriptive maintenance. Predictive maintenance uses data from machine learning, statistical methods, or reliability models to detect impending failures. These failure predictions can support maintenance management systems by creating an alarm for upcoming failures and warranty logistics.

Predictive maintenance techniques that apply machine learning or statistical methods to determine when an equipment part will fail within a predefined time period are referred to as supervised predictive maintenance techniques. Predictive maintenance methods that do not require failure labels but provide valuable information about the possible loss of system health are categorized as unsupervised predictive maintenance techniques. The PM-Models group includes a third subclass, semi-supervised predictive maintenance techniques, which use limited supervision or partial failure labels. Such techniques play a key role when labelled failure data are rare.

2.2. Data-Driven Modelling Techniques

Data-driven modelling methods encompassing machine learning, statistical analysis, and reliability-engineering metrics capture different aspects of equipment reliability. These provide complementary insights and enable convergence of predictive models. Nevertheless, each technique has specific strengths and challenges that suit particular use cases for data collection and population. Although these approaches can be integrated in various ways, the decision ultimately depends on available data and the frequency of failure occurrences.

Machine learning excels at learning complex, nonlinear relationships from real-world data because of its rich feature-extraction capabilities. Nevertheless, it often requires substantial amounts of high-quality labelled data and can become a black box; therefore, it is typically applied to problems with a wealth of labelled data. Statistical analysis directly captures the effects of small sample sizes and the associated uncertainty in inference and prediction. Whereas patterns or anomalies can be learned from good examples, caution is needed with unexpected situations, especially in rare-failure scenarios. Reliability-engineering metrics, models, and testing validate traditional physical models through empirical data, thus enhancing predictive capacity beyond the data. They rely on relatively little data, which can often be simulated by digital twins.

3. Data Architecture and Governance

Three primary categories of data underpin the predictive maintenance models for smart factories. First are data streams from sensors incorporated into machines and equipment; second are data generated by the MES or ERP systems; and third are maintenance records maintained by the CMMS responsible for planning maintenance activities and keeping logs of repairs. These sources provide a rich array of data to feed AI models aimed at predicting rare failure events, enhancing model generalization capabilities and improving accuracy metrics.

The modelling architectures and approaches adopted fully leverage these three sources of data. Sensor failure prediction relies primarily on labelled features and failure labels derived from the streaming data and event logs recorded, while prediction of failure-related anomalies (semi-supervised) and predictive maintenance clustering demand a greater mix of data sources. As supervision is not tightly restrained, the three converging data sources help increase sample size, build reliability metrics, and consider historical context for anomalies and other signal patterns detected. Data Management Data Governance and Data Quality sections should be referenced for a more in-depth discussion of these data sources and requirements for supporting the development, deployment, and production of the AI models envisaged.

Equation 2) Hazard rate: converting "instantaneous risk" to "risk in a window"

Step 1 Define hazard

Hazard (instantaneous failure rate) is:

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t \mid T \ge t)}{\Delta t}$$

Step 2 Relationship between hazard and survival

A key identity:

$$h(t) = \frac{f(t)}{S(t)}$$

where $f(t) = F'(t)$ is the density.

Step 3 Derive S(t) from h(t)

Start with:

$$f(t) = h(t)S(t)$$

But also:

$$S'(t) = \frac{d}{dt}\big(1 - F(t)\big) = -f(t)$$

So:

$$S'(t) = -h(t)S(t)$$

Separate variables:

$$\frac{S'(t)}{S(t)} = -h(t)$$

Integrate $0 \to t$:

$$\int_0^t \frac{S'(u)}{S(u)}\, du = -\int_0^t h(u)\, du$$

Left side becomes $\ln S(t) - \ln S(0)$. Since $S(0) = 1$, $\ln S(0) = 0$:

$$\ln S(t) = -\int_0^t h(u)\, du$$

Exponentiate:

$$S(t) = \exp\left(-\int_0^t h(u)\, du\right)$$

Then failure probability within horizon H is:

$$P(T \le H) = 1 - S(H) = 1 - \exp\left(-\int_0^H h(u)\, du\right)$$

3.1. Data Sources in Smart Factories

Data ownership and accessibility represent severe obstacles for machine learning-based predictive maintenance models. Indeed, the vast majority of proposed models do not provide practical implementations, and only a handful of solutions are deployed in production environments. A clear mapping of available data sources is a prerequisite to effective model development in a smart factory context. Relevant sources of structured and unstructured data include.

- real-time sensor streams collected through a SCADA (Supervisory Control And Data Acquisition) system;
- data generated by a Manufacturing Execution System (MES) and an Enterprise Resource Planning (ERP) system;
- information reactive and preventive maintenance logs;
- data emitted by Programmable Logic Controllers (PLCs);
- control and fault signals generated by the equipment itself; and
- Information provided by suppliers regarding parts and components.

Implementing a data architecture that integrates these and other sources of information allows manufacturing companies to gain deeper insights into the health of their production interfaces and process assets. Such insights enrich the decision-making process and enable the application of more resource-efficient maintenance strategies throughout the supply chain. Data governance and quality play a fundamental role in the development and application of any predictive maintenance model or system.

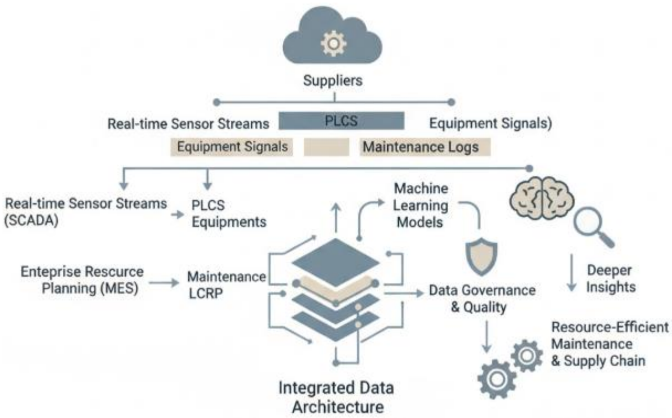

Fig 3: Integrated Data Governance: A Multi-Source Architecture for Scalable Predictive Maintenance In Smart Manufacturing

3.2. Data Quality, Preprocessing, and Integration

Predictive maintenance models in smart manufacturing rely on quality data from diverse sources: sensor streams, stacks of manufacturing execution and enterprise resource planning data, maintenance logs, programmable logic controllers events, and time series from any data source. Raw data often contain noise, missing, inconsistent, or duplicated values. Data quality fulfills specific requirements depending on the use case, including placeholders for missing data treatments, generation time coherence, distribution shape, and value range. As detailed below, tailored preprocessing and integration strategies are necessary to create a reliable data asset.

Several challenges arise in predictive maintenance use case data. Data streams from fake sensors or Industry 4.0 real ones can contain noise. Maintenance event logs can be subject to user inaccuracies, as people may improperly enter data or skip fields. Meanwhile, time series data from distinct data sources may experience misalignment or lack observability when faults conditions are infrequent exciting work resources. Integrating different datasets is also a challenge when they come from distinct verticals of a smart factory, such as the enterprise resource planning layer and manufacturing execution layer. Nevertheless, properly integrated data streams can still affect several predictive maintenance models becauseas expert systems or physics-based modelsthe scores of any output space are also correlated and shouldn't be overlapping for similar fault scenarios.

Such methods can include unsupervised techniques like clustering that require a reduced number of labels, with models trained to classify the situation as normal or not when faults are infrequent. Missing data cases may be treated using generative adversarial networks or deep learning, or even directly solved in the shadow of the original data, preserving the distribution shape. Data streams that provide value for the solution but cannot be shared because of confidentiality issues can be treated through transfer learning. Synchronization problems may be addressed through dynamic time warping or parallel adaptive sliding windows, while low-cost, time-consuming solutions may be adopted to monitor the reliability of fake sensors and other noncritical devices.

4. Modelling Methodologies

Either supervised or unsupervised techniques can be employed for predictive maintenance model development. Supervised learning requires the generation of labels determining failure events, whereas unsupervised techniques identify anomalous patterns or utilize methods such as clustering to signal upcoming faults. Rare failure events, presenting significant classification imbalance, can also be addressed with semi-supervised setups where normal conditions are characterized to support anomaly detection.

In supervised setups, feature candidates for failure forecasting are defined, selected, and engineered, and the choice of representation dimensioning also considered. Finally, automatic machine learning frameworks can support algorithm selection and hyperparameter tuning, yielding models that simplify predictive maintenance operationalization. Business logic established in the predictive maintenance use case informs deployment in a maintenance management system (CMMS or ERP), facilitate alert activation and composing supporting information, and contribute to the creation of decision-support material. Continuous monitoring services enable active surveillance of model predictive power, retraining opportunity identification, and versioning control.

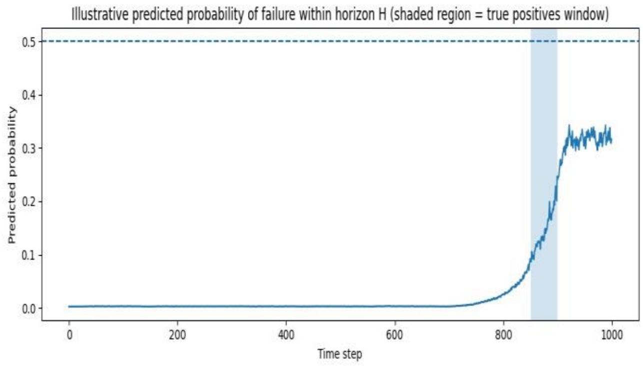

Fig 4: Simulated Sensor Signal Degradation and Failure Point

Equation 3) Supervised failure prediction (classification)

Label construction for "failure within horizon H"

Let time index be t. Define label:

$$y_t = \begin{cases} 1, & \text{if a failure occurs in } (t, t+H] \\ 0, & \text{otherwise} \end{cases}$$

Logistic regression model (probability output)

Let feature vector at time t be $x_t \in \mathbb{R}^d$. Logistic model:

1. Linear score:
$$z_t = w^\top x_t + b$$
2. Convert score to probability via sigmoid:
$$p_t = P(y_t = 1 \mid x_t) = \sigma(z_t) = \frac{1}{1 + e^{-z_t}}$$

Training objective (cross-entropy)

Given dataset $\{(x_t, y_t)\}$:

1. Likelihood for one sample:
$$P(y_t|x_t) = p_t^{y_t}(1 - p_t)^{(1-y_t)}$$
2. Log-likelihood:
$$\log P(y_t|x_t) = y_t \log p_t + (1 - y_t)\log(1 - p_t)$$
3. Negative log-likelihood (loss) summed:
$$\mathcal{L} = -\sum_t [y_t \log p_t + (1 - y_t)\log(1 - p_t)]$$

Rare events ⇒ you often use **class-weighted loss** (common PdM practice):

$$\mathcal{L}_w = -\sum_t [\alpha\, y_t \log p_t + \beta\, (1 - y_t)\log(1 - p_t)]$$

4.1. Supervised Learning for Failure Prediction

Despite the different sources of data available from the smart manufacturing ecosystem, PD models are often based on supervised machine learning methods using historical labeled data. This type of model requires a prior definition of what is meant by a failure and the construction of corresponding labels. The majority of labels corresponding to equipment failures in a manufacturing context are created from maintenance logs. These logs summarize the maintenance tasks performed on the equipment, indicating where and when they occurred, as well as the failure reasons. After the failure events are identified, labeling continues with feature engineering to extract indicators from the data streams that can provide useful information for the prediction.

Common indicators include simple time-series statistics that can be calculated for the time windows prior to the event: the last time the indicator took a value in the "normal" regime (with "normal" being determined by whatever expert knowledge or historical analysis is available), or the difference at the time of the prediction between different indicators of physical quantities with a known evolution pattern in preventive maintenance. Models trained on this type of labeled data typically treat the label as an event, with all-time points at which the failure occurred or at which the equipment was in a failure condition being classified as positive-predictive points. Consequently, the model is trained to classify the state of the equipment rather than the future occurrence of a failure event. A typical evaluation approach consists of time-based cross-validation, where training is performed in data windows preceding a test window in order to reasonably ensure that future events have been unseen at the training time. Moreover, the last maintenance date is usually considered when evaluating future performance.

The deployed model is then used to classify time windows on a near real-time basis in production, providing alerts on the predicted equipment condition. Its output can be integrated within the factory's CMMS or preventive maintenance decision system processes as an additional information source. Other machine-learning models, such as regression problems predicting remaining useful life or future condition of key features, may also be trained, considering both historical data and the status of the equipment at the prediction time. Because failures are rarely encountered (at least in data containing several machines), methods such as anomaly detection, clustering, or self-supervised setups based on contrastive or generative learning can also be applied.

4.2. Unsupervised and Semi-Supervised Approaches

The fact that most failures are extremely rare presents a considerable challenge for supervised approaches. It is thus important to investigate the applicability of unsupervised or semi-supervised setups. Anomaly detection techniques learn an operational profile (e.g. using one-class classifiers or autoencoders) and are then able to identify deviations in normal behaviour that are indicative of a forthcoming failure. They can often be used in combination with a secondary supervised model that refines classification during periods with a sufficient number of labels. Anomalies can also be detected when the predictive distribution from a generative model, such as a Gaussian Mixture Model, is low, or derived from unsupervised clustering methods.

Clustering techniques, in particular, have gained increasing popularity in the community. The clustering approach is conceptually simple, directly addressing the issue that the failure is extremely rare. Within the data preparation for clustering, measures of proximity/dissimilarity between the given data points that are representative of normal behaviour and the data point to be evaluated can be obtained using distances. Several studies have also highlighted the potential of self-supervised setups, where different modalities are jointly learned (e.g. representations from sensor data and images) or a collaborative learning task is added to the model (e.g. reconstructing different views of the same scene).

Table 1: Confusion Matrix for Failure Prediction Model

	Pred 0	Pred 1
Actual 0 (no imminent failure)	950	0
Actual 1 (failure within H)	50	0

5. Sensor Technologies and Edge Computing

Selecting the appropriate sensor technologies is a critical first step for successful implementation of data-driven predictive maintenance in smart manufacturing. Essential sensor selection criteria include: (i) Data Accuracy data from selected sensor technologies need to deliver relevant information without putting a burden on the data tagging effort. Sensor technologies with sufficient accuracy should therefore be selected; (ii) Data Utilization As with any ML-based approach, the value of any collected data will only be realized if the data is utilized by the trained models. Thus, sensors or sensor fusion that enhances prediction quality or reliability (lowers uncertainty) should be considered; (iii) Data Availability To enable model predictions on a continuous basis, the condition of the monitored component should be determined at a sufficient frequency and reliability; (iv) Data Drift Sensors are failure prone. For most systems the reliability of the sensing information is critical. Therefore, a model evaluating sensor health status is often recommended.

Recent developments in edge computing address the challenge of providing time-sensitive inference with low latency. Logic at the edge can enable processing of selected data from sensors and deliver quasi real-time predictions. This can reduce the burden for upstream data processing resources and avoid situations where time-sensitive requirements are ignored or unsupported due to network bandwidth constraints. Edge analytics can include real-time model inference, where an ML model is hosted by an edge device and performs inferences on data continuously streamed by connected sensors. This can cover situations that require low-latency predictions (leading to automatic alarms, etc.) or where latency-sensitive information should be transmitted to a central unit while less critical information is processed closer to the data source. Considerations for a suitable edge framework include: (i) Device Selection The target analytics workload serves as a starting point for the selection of the edge devices; (ii) Deployment The deployment of commercial edge devices along with the use of ML model development frameworks should simplify deployment procedures. Model deployment may also utilize specialized scheduling, model compression or reduction techniques; (iii) Security Security of data and devices often imposes an additional layer of complexity in any deployed analytics architecture. Care should be taken to harden security and present frequent automatic audits in order to limit the attack surface of the deployed system.

Equation 4) Feature engineering from sensor streams

Let raw sensor signal be $s(t)$. Choose a window length W (samples).

Rolling mean

$$\mu_t = \frac{1}{W}\sum_{i=0}^{W-1} s\,(t-i)$$

Rolling variance / standard deviation

$$\sigma_t^2 = \frac{1}{W-1}\sum_{i=0}^{W-1}(s(t-i)-\mu_t)^2\,, \quad \sigma_t = \sqrt{\sigma_t^2}$$

Simple trend / slope feature

A basic discrete trend indicator:

$$\text{slope}_t = \frac{s(t)-s(t-W+1)}{W-1}$$

5.1. Sensor Selection and Characterization

Sensor technology is now ubiquitous in manufacturing, with smart factories relying on a multitude of sensors for operation, safety, and quality assurance. Their introduction has contributed to many advances in manufacturing, such as intelligent fault-tolerant control systems, demystifying the underlying mechanisms of machining processes, machine tools with increased resilience, and enhanced workplace safety. However, the failure of a single sensor can lead to considerable losses and even accidents. Sensor failures have caused large-scale blackouts and fires. Therefore, an assessment of sensor reliability and a strategy for sensor selection and placement should precede the deployment of a smart factory. Once the sensors are selected, their performance needs to be constantly monitored to ensure a sustainable smart factory.

Sensor selection for failure prediction requires consideration of network topology, apparent reliability, capability to capture essential information concerning failure events, redundancy in cases of inconsistency, data transmission rates, and areas with little redundancy. Sensor fusion is also important, especially when the available information is limited. All sensors should be calibrated before deployment, and a health-monitoring mechanism should be established. Reliability analysis of individual sensors should be performed periodically. Edge-computing-based sensor-data analytics should be developed to allow real-time analytical inference directly on the edge devices. The deployment and updates of such analytical models can be challenging on devices with restricted resources. Therefore, an appropriate model-update strategy is crucial.

Fig 5: Resilient Sensor Architectures for Smart Manufacturing: A Framework for Strategic Selection, Edge-Analytics, and Life-Cycle Reliability In Intelligent Factories

5.2. Edge Analytics and Real-Time Inference

A comprehensive predictive maintenance pipeline must encompass deployment in the target environment to be genuinely applicable. All lifecycles from data collection, harvesting, and integration to feature definition, model training, monitoring, and versioning are to be envisioned. Ideally, such models will subsequently be linked with a CMMS (Computerized Maintenance Management System) or ERP (Enterprise Resource Planning) software solution, enabling call creation or even dispatching orders autonomously when pre-defined conditions arose.

Well-defined feedback loops are necessary to guarantee continuous improvement of the AI-powered models. All aspects need to be carefully organized in the smart factory data architecture and tested against risks, with sensible mitigation actions developed. The mitigation measures should be focused on data quality, model governance, and management integration. The development and deployment of a model supporting maintenance management should guarantee performance across these dimensions enabling integration in the real-world environment of smart manufacturing.

6. Deployment Strategies in Smart Factories

The deployment of predictive maintenance solutions enables intelligent use of predictive models for equipment management throughout their lifecycle in the manufacturing processes. The deployment steps can be summarized as a sequence of operations: covering data collection for training, model training and validation, and operationalization, including monitoring, versioning, and re-training mechanisms when required. During the operational phase, the actual prediction capability moves into real-time inference on an edge device, integrating with a Computerized Maintenance Management System (CMMS) to provide alerts to maintenance teams based on multiple prediction strategic decisions. Within the deployment context, integration into decision-making workflows is facilitated. Consequently, feedback from maintenance actions can provide a closed-loop effect for continuous improvement of any deployed prediction model. In particular, the feedback from the maintenance teams can initiate the process for the training data version.

During the operational stage of predictive models, a maintenance management system (CMMS) provides the three basic layers of data retention for a smart factory and allows the integration of decision trees for predictive models. Long- and short-term predictions for failure events of any factory equipment or machinery/components can be communicated to maintenance handlers and team leaders. Alerts, generated through either a centralized or distributed approach, guide maintenance teams in scheduling maintenance activities based on predictive alarms, N-1 predictive models, anomaly detection results, and CMMS historical information of previous irregular behavior and other relevant factors (e.g., special occasion, maintenance quality, etc.) contributing to its reliability. Predictive maintenance models are used primarily to advise the maintenance team rest status. However, the alerts can also be activated through any combination of alerts from predictive models under a centralized alert flags structure.

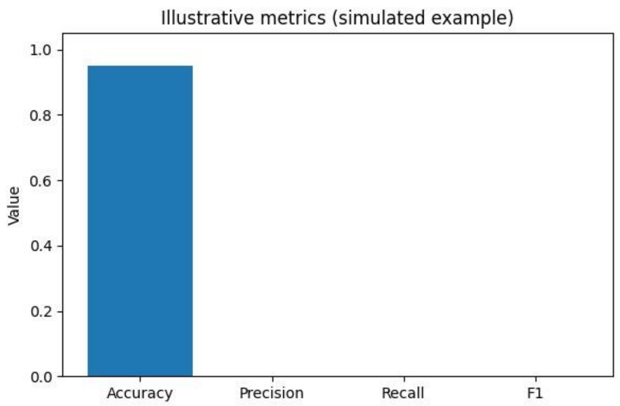

Fig 6: Time-Series Sensor Degradation and Failure Point Analysis

Equation 5) Unsupervised / semi-supervised anomaly detection and clustering

Autoencoder anomaly score (semi-supervised/unsupervised)
Given input x, autoencoder outputs reconstruction $\hat{x}$.

1.Reconstruction error:

$$e(x) = \| x - \hat{x} \|_2^2$$

2.Flag anomaly if:

$$e(x) > \tau$$

where τ is chosen from normal-data quantiles (common in PdM).

Gaussian Mixture Model (GMM) "low likelihood = anomaly"
If:

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k)$$

then anomaly score:

$$a(x) = -\log p(x)$$

K-means clustering objective (distance-based outliers)
Given clusters $C_1, \ldots, C_K$ with centroids μ_k, minimize:

$$J = \sum_{k=1}^{K} \sum_{x \in C_k} \| x - \mu_k \|_2^2$$

Outlier score can be distance to nearest centroid:

$$d(x) = \min_k \| x - \mu_k \|$$

6.1. Lifecycle from Model Development to Operationalization

The lifecycle of predictive maintenance models spans multiple phases: data collection, training, validation, monitoring, versioning, retraining triggers, and ultimately, operationalization. A concise description of each phase highlights key activities and decisions, catering specifically to researchers and practitioners without delving into theoretical details. Adhering to a standard model-development governance framework facilitates risk management throughout the lifecycle.

The transition from workshop to operational environment necessitates integration with Maintenance Management Systems (CMMS), such as Computerized Maintenance Management Systems (CMMS)/Enterprise Resource Planning (ERP) solutions. Integration encompasses automated alert generation, operational feedback cycles, or human-in-the-loop decision-support systems that capitalize on model predictions. To ensure continual learning, processes for performance monitoring, versioning, and retraining trigger definition must also be established.

By outlining the complete lifecycle from data collection to operationalization empirical research contributes to the predictive maintenance knowledge base. The practical framework facilitates comprehension of the development and operationalization process, empowering companies to configure maintenance model governance for specific workshop contexts.

6.2. Integration with Maintenance Management Systems

The operationalization stage of predictive maintenance models bridges the development of methods and models with their deployment at smart factories. The operationalization steps cover the prerequisites for the models to work properly and continuously, data coverage across the entire lifecycle, and integration into the factory's organizational and IT ecosystems.

Once predictive models have been deployed, they are put into steady-state operation. Information from sensor data and/or monitored systems is processed and the models provide failure predictions. Periodically, models are retrained. New data are gathered, enabling the models to be improved or updated to account for changes in context that affect the alerts' reliability.

Model outputs must trigger alerts in maintenance management software (CMMS, ERP, etc.) that integrate any warnings into the daily maintenance decision workflow.

Alerts are monitored by maintenance personnel, who determine the next steps for each type of warning and decide whether to consult the models' prediction at the maintenance management software or through decision-support tools connected to the predictive service.

The final step involves a feedback loop that closes the PDCA circle for predictive maintenance models. Alerts generated by the models are used to build labelled data that help evaluate the models' reliability in production. Through this process, the predictions been used to direct maintenance resources towards the most critical failures in the near future, minimizing the operational issues and negative effects of these malfunctions. Lessons learnt from the alerts help further improve all data-driven predictive maintenance-related processes.

Table 2: Comparative Framework for Predictive Maintenance ML Paradigms

Paradigm	Needs	Typical Output	Main Risk
Supervised (classification)	Failure labels from logs	Direct failure risk in horizon	Label scarcity, class imbalance
Unsupervised (anomaly)	Normal operation data	Detect deviation from normal	False alarms; mapping anomalies to maintenance action
Semi-supervised	Mostly normal + few labels	Combine anomaly + limited labels	Model selection / calibration complexity
Self-supervised representation	Unlabeled sensor streams	Useful embeddings for downstream tasks	Needs careful pretext-task design

7. Conclusion

Equipment downtime and maintenance expenses are crucial problems for manufacturing companies. AI methods for predictive maintenance, now generally accepted, help mitigate these issues. Despite the mature state of predictive maintenance research, practical industrial applications remain rare; consequently, the operationalization of predictive maintenance models is a valuable topic. This section synthesizes the approach, covering the entire model lifecycle from development to deployment and describing how predictive maintenance models can be integrated into a smart factory environment.

Machine manufacturers and maintenance companies are typically bombarded with a multitude of alarms. To filter these alarms and act proactively, it is essential for factory owners to understand how the equipment behaves across different operational conditions. This understanding can then guide, for example, what alarms require preventive action and what alarms can be ignored. The findings boil down to deploying predictive maintenance models into a manufacturing environment, a task that encompasses the whole methodological cycle: from preprocessing the data to creating the model, from monitoring its performance to deploying it into an existing maintenance management system. The contribution lies in helping factories close the gap between model development (usually an academic exercise) and operationalization support, working with maintenance managers and decision-makers.

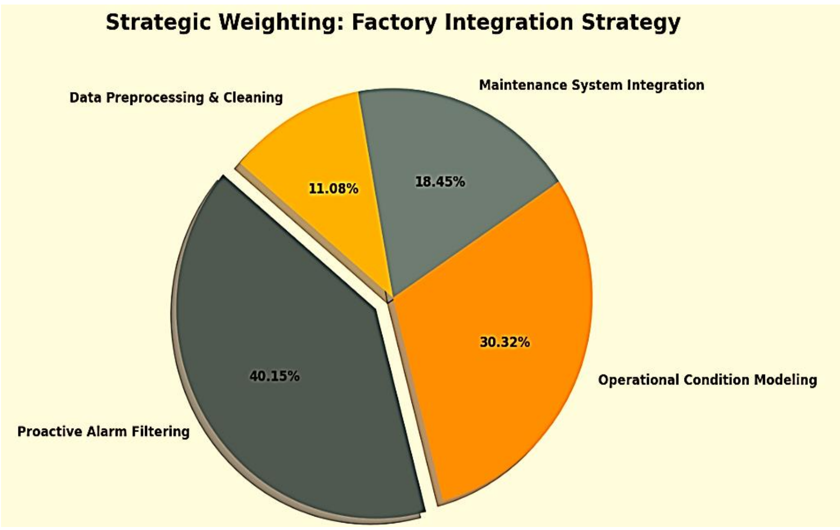

Fig 7: Strategic Weighting: Factory Integration Strategy

7.1. Final Thoughts and Future Directions

Guidelines to the successful deployment of AI-based models for predictive maintenance in smart factories were derived and discussed. Though no a priori constraints on data flow, storage architecture, quality, or completion were imposed, a data-centric view was adopted. The sensor data streams, in conjunction with production data stored in production and enterprise resource planning systems, and historical maintenance logs, are to be the main sources of data for training the models. A mixture of supervised, unsupervised, and self-supervised learning methods is thus suitable.

Supervised methods can be used to predict rare failure modes, where condition monitoring or warning thresholds have not yet been breached. Anomaly detection methods employing one-class classifiers can be used to detect accelerated degradation stages from “normal” operating conditions, while clustering methods can cluster sensor data into condition groups that differ in risk of failure during that operating cycle. Continuous model monitoring, versioning, and retraining minimize divergence of model predictions from reality.

Alert workflows to notify the maintenance department, response level definitions depending on the process criticality, and decision-support systems to refine maintenance actions based on model predictions are also important, as is integration with a computer maintenance management system or ERP. Finally, regular communication with production to enrich training datasets with additional operational situations is crucial for continuous learning and improvement.

While useful, these guidelines are not exhaustive, nor do they guarantee success. Each factory is a unique ecosystem, with its own constraints and opportunities. Supporting operational teams in their day-to-day work, explaining the benefits of AI-based models, and facilitating their development are important for increasing their adoption in predictive maintenance applications.

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