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Engineering Predictive Industrial Systems Through IoT-Driven Asset Monitoring and Machine Learning Prognostics

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ABSTRACT: Predictive operation of industrial assets and systems helps improve their efficiency and overall productivity. An Internet of Things (IoT)-driven monitoring system reformulates such a system from being reactive to being predictive, connecting operational physics to address long-standing operational issues affecting efficiency and productivity through predictive maintenance and a data-centric approach to risk management. Data-driven methods and machine learning, and in particular machine-learning prognostics, are at the core of enabling this transition, while the IoT-driven system is the data producer. Prognostics are defined as the prediction of future asset health states based on historical data and operational history, and they assess the remaining useful life (RUL) of an asset, the time until failure, or the asset or system health index at time To.

Prognostics can be applied during the use phase of the asset-life cycle, which encompasses the period between the last overhaul and the next, and therefore evaluates the effect of maintenance decisions on availability, reliability, and total cost of ownership of the asset or system undergoing such an analysis. Such a predictive capability changes the way a company reacts to deteriorating asset health, and it needs no longer rely on time-based models, resulting in lower-risk and risk-based maintenance strategies — predictive maintenance strategies — that consequently improve the company's competitiveness. The concept of prognostics is clarified, and its specificities in relation to related concepts are highlighted. Moreover, the typical performance evaluation metrics used in the literature are summarized, and the different classes of prognostic models are established, thus paving the way for the application of machine-learning methods within an IoT-based monitoring system for predictive maintenance and risk management.

KEYWORDS: Industrial Internet of Things (IIoT), Asset Condition Monitoring, Predictive Maintenance Machine Learning Prognostics, Remaining Useful Life (RUL) Prediction, Industrial Asset Management, Sensor Data Analytics, Fault Detection and Diagnosis, Digital Twin Technology, Smart Manufacturing Systems.

I. INTRODUCTION

Industrial systems safety typically requires a strong deal of engineering effort and money to keep equipment and machinery running without trouble. Nevertheless, unexpected breakdowns with serious consequences happen regularly in most industrial plants due to poor maintenance, ageing assets, sudden loads, and so on, which result in heavy additional maintenance costs, manufacturing delays, or even accidents with injury or fatalities. The condition of each asset must be constantly measured and assessed to warn of harmful conditions and predict future failures, so that maintenance or replacement can be executed at the right moment, thereby preventing production downtime, accident risk, and huge repairs costs. This concept is known as predictive maintenance; today, with the advent of the Internet of Things (IoT), predictive monitoring is substituting predictive maintenance, focusing on earlier monitoring actions aimed at failure prevention, mainly by improving failure timing, increasing availability, and decreasing the total cost of ownership.

The Internet of Things is an evolution of the internet where not only humans but also physical assets, such as machines, cars or pumps, exchange information among themselves. These assets are drove by several integrated sensors that generate large amounts of data, which are processed by suitable algorithms and software, thus allowing a number of new business models and services. The main market application areas for the IoT today are security, logistics, e-health, smart cities and home automation, energy efficiency and management. From an audio-visual perspective, Google

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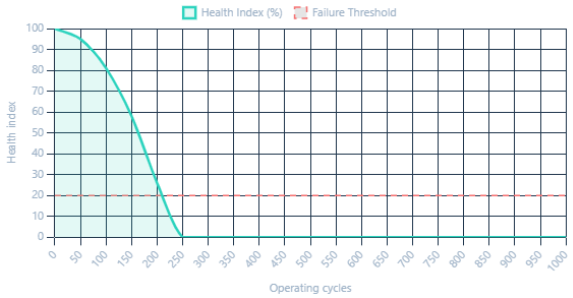
combines the word “smart” with every day objects and services currently augmented with computers and data analytics. In the analysis and simulation field, it is predicted that within five years the traffic generated by sensors and cameras will exceed the traffic produced by humans.



Asset Health Degradation & RUL (§3) — health index decaying over operating cycles against a failure threshold, the core prognostics concept.

1.1. Edge versus Cloud Computing Architectures

The deployment of Internet of Things (IoT) technology for task execution in remote and uncontrolled environments challenges traditional cloud computing solutions. Specifically, in asset monitoring scenarios where nanosecond latencies are required, communication resources are limited, and requirements are dynamic or unknown, edge management of devices is an advantageous alternative. More specifically, service delivery from the cloud at the service level agreement (SLA) required in the monitoring scenario is not guaranteed, leading to failure in hidden layer tasks such as feature extraction, machine learning (ML) prognostics, and decision support. Although SLAs can be met by treating some monitoring requirements with an edge service, a strictly edge-based architecture only partially overcomes the problem of resource contention—computer network bandwidth and system computing resources are not unlimited. The ideal situation is to have a hybrid topology where intensive computing tasks that require data from different sources and locations are performed on the cloud and latency-critical tasks are handled through edge computing.

A hybrid topology was therefore designed with a proprietary architecture capable of fluidly switching between edge, cloud, and partially cloud configurations based on the current state of the monitoring implementation. Events of interest are handled locally by edge components, keeping latency low when the time difference between the incident and its immediate consequences is small. Noncontemporaneous feature extraction and prognostic model deployment are delegated to the cloud when data requirements exceed the edge statement limitations. The processes of model training and definition, risk detection, and scaling of the governing edge layer are not time-sensitive, so they are also optimally done on the cloud.

Table 1. IoT Sensor Types and Monitored Asset Parameters

Sensor Type	Monitored Parameter	Typical Industrial Asset	Purpose
Vibration Sensor	Vibration Amplitude	Motors, Bearings, Gearboxes	Detect wear, imbalance, misalignment
Temperature Sensor	Surface/Internal Temperature	Motors, Transformers	Detect overheating conditions
Pressure Sensor	Pressure Variations	Compressors, Pumps	Monitor operational efficiency
Acoustic Sensor	Sound Emissions	Rotating Machinery	Detect abnormal mechanical

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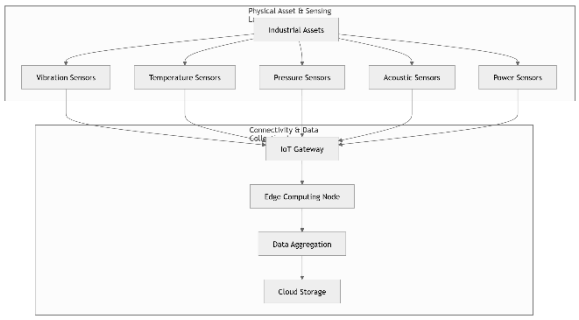
Sensor Type	Monitored Parameter	Typical Industrial Asset	Purpose
			behavior
Power Sensor	Energy Consumption	Manufacturing Equipment	Identify efficiency degradation
Thermal Imager	Heat Distribution	Production Lines	Detect hotspots and insulation faults



IoT Asset Monitoring and Data Acquisition Layer

II. FOUNDATIONS OF IOT-DRIVEN ASSET MONITORING

The Internet of Things (IoT) comprises intelligent and connected objects that gather information through an array of sensors, communicate with one another by means of a reusable network infrastructure, and produce valuable knowledge for data consumers, who use it to improve processes, products, and services. In an industrial context, an asset is any piece of equipment that contributes to the delivery of products and services to customers (e.g., a machine tool, an injection mold, a motor, a compressor, a transformer) throughout its lifecycle. Equipment manufacturers, operators, and maintainers produce, consume, or utilize information in various forms and for different purposes, including monitoring, diagnosis, and predictive maintenance. IoT-based asset-monitoring systems represent one of the steps toward a predictive industrial system where smart asset systems, such as predictive equipment, and their supporting ecosystems work together to improve efficiency, reduce costs, and increase customer satisfaction.

The goal of an asset-monitoring system is to offer a continuous, automated assessment of an asset's health condition in order to support proactive decision-making. The useful service lifetime of an asset can be monitored by assessing key health indicators and their associated failure modes, namely the underlying physical reasons for deterioration leading to a failure. A thorough discussion of the service lifecycle and the corresponding prognostic targets—both remaining useful life and time-to-failure estimation—is beyond the scope of this paper, although it should be borne in mind that the targets drive the overall design of the asset-monitoring system. The monitoring process is subject to a number of constraints, which may stem from adoption feasibility and cost, data governance and security requirements, and technology limitations.

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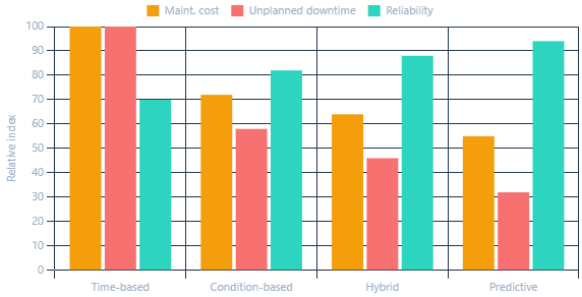

Maintenance Strategy Comparison (§4) — time-based vs condition-based vs hybrid vs predictive, across cost, downtime, and reliability.

2.1. Sensor Networks and Connectivity

A suitable IoT platform supports both the sensing layer—networking and Internet connectivity for data producers—and the data-driven services. The types of sensors typically integrated in asset-monitoring activities include vibration, temperature, pressure, acoustic, and power, supplemented by additional devices for machine vision and sensing large moving areas. The choice of monitored quantity depends on the type of asset, its operating conditions, and the potential failure modes to be predicted.

The correct choice of the sensor network topology depends on the number of monitored assets and their joint behavior. For a big number of sensors cluttered in a small area, a star topology is preferred for efficiency and simplicity, while a mesh topology becomes more appropriate in a less dense setup. In addition, both the communication protocol and power-management policy need to be selected with care to optimize battery life, minimize radio traffic and reduce the number of dropouts during data transmission.

Table 2. Edge vs Cloud Computing in Predictive Monitoring

Feature	Edge Computing	Cloud Computing
Latency	Very Low	Moderate to High
Processing Location	Near Asset	Remote Data Center
Bandwidth Usage	Reduced	Higher
Real-Time Decision Support	Excellent	Limited
Model Training	Limited	Highly Suitable
Scalability	Moderate	High
Resource Availability	Constrained	Extensive

III. MACHINE LEARNING PROGNOSTICS IN INDUSTRIAL SYSTEMS

Machine learning introduces predictive capabilities by recognizing complex nonlinear patterns in data and training predictive ML models on historical, labelled datasets that link system conditions with RUL values. The objective of prognostics is to estimate the remaining useful life or time to failure of monitored assets in order to support predictive maintenance policies that outperform traditional preventive maintenance practices. Adopting a predictive maintenance strategy based on RUL information supports a Predictive Maintenance Policy by rapidly addressing the most severe risk in terms of lost production opportunity costs.

The estimated remaining useful life for equipment drives decision support. Therefore, when available datasets do not support the direct estimation of RUL for a particular equipment type, the system explores the feasibility of collapse time prediction or the ratio of the time to the expected collapse time. Time-to-failure scenarios correspond to unsupervised models, which are fundamentally different from the supervised models used for RUL estimation.

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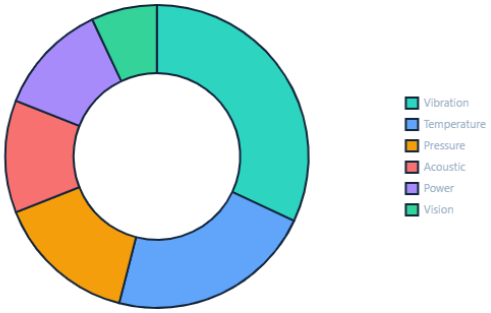

Sensor Modalities (§2.1) — deployment share of vibration, temperature, pressure, acoustic, power, and vision sensors.

Mathematical Formulas:

Eq. (1) Asset Health Index

$$HI = \frac{S_c}{S_n}$$

Eq. (2) Remaining Useful Life

$$RUL = T_f - T_c$$

Eq. (3) Time-to-Failure

$$TTF = t_f - t$$

Eq. (4) Failure Probability

$$P_f = \frac{N_f}{N}$$

Eq. (5) Machine Availability

$$A = \frac{Uptime}{TotalTime}$$

Eq. (6) Reliability Function

$$R(t) = e^{-\lambda t}$$

Eq. (7) Sensor Data Average

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

Eq. (8) Predictive Risk Score

$$Risk = P_f \times Impact$$

Eq. (9) Maintenance Cost Index

$$MCI = \frac{C_m}{C_t}$$

Eq. (10) Data Transmission Efficiency

$$DTE = \frac{D_r}{D_s}$$

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Eq. (11) Vibration Severity

$$VS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} v_i^2}$$

Eq. (12) Temperature Deviation

$$TD = T_c - T_n$$

Eq. (13) Fault Detection Rate

$$FDR = \frac{TP}{TP + FN}$$

Eq. (14) False Alarm Rate

$$FAR = \frac{FP}{FP + TN}$$

Eq. (15) Prediction Accuracy

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

Eq. (16) Asset Utilization

$$AU = \frac{OperatingTime}{AvailableTime}$$

Eq. (17) Data Fusion Score

$$DFS = \sum_{i=1}^{m} w_i\, d_i$$

Eq. (18) Prognostic Error

$$PE = | RUL_{actual} - RUL_{pred} |$$

Eq. (19) Health Degradation Rate

$$HDR = \frac{\Delta HI}{\Delta t}$$

Eq. (20) Maintenance Priority Index

$$MPI = \frac{Risk}{RUL}$$

3.1. Failure Modes and Prognostic Targets

Common failure mechanisms can be identified across various asset classes within specific domains, such as manufacturing, transportation, and power generation, and these comprise failing bearings, external mechanical component wear, cavitation, imbalances and misalignments, and insulation degradation. While models and approaches can vary significantly between asset classes, the failure modes remain, and consequently, the underlying measurable health indicators are similar. The detection of these failure mechanisms can be achieved through one or more measurable indicators and, eventually, deployment of an appropriate model. Predictive targets that can be directly computed or affected by model prediction are remaining useful life or time-to-failure estimates that can be computed along the asset operation and provide guidance on the status of the monitored component.

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Table 3. Failure Modes and Prognostic Indicators

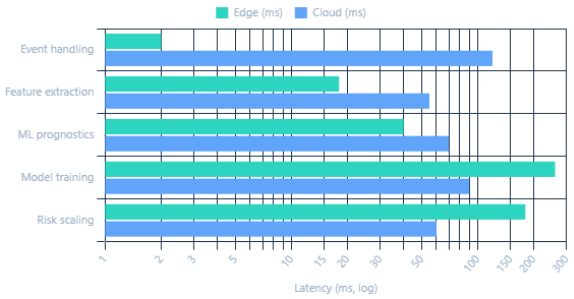
Failure Mode	Health Indicator	Sensor Used	Prognostic Target
Bearing Wear	Vibration Trend	Vibration Sensor	RUL Estimation
Cavitation	Pressure Fluctuation	Pressure Sensor	Time-to-Failure
Shaft Misalignment	Vibration Spectrum	Vibration Sensor	Health Index
Mechanical Imbalance	Frequency Deviation	Vibration Sensor	Failure Probability
Insulation Degradation	Temperature Rise	Thermal Sensor	Remaining Life
Component Fatigue	Acoustic Changes	Acoustic Sensor	Risk Assessment

IV. PREDICTIVE MAINTENANCE STRATEGIES

Operating a system to predict the time to failure of its assets is not sufficient for making maintenance decisions. The selected approach must consider the corresponding maintenance strategy. The traditional time-based strategy produces consecutive inspections that yield the same level of performed maintenance. The condition-based paradigm executes maintenance actions only when the health status of the asset is close to its failure threshold. However, this strategy introduces uncertainty, since it executes an inspection only when the system is above a predefined risk threshold. Conversely, the hybrid procedure commits to an inspection at regular intervals and applies maintenance actions when the health status indicates an imminent failure. Therefore, combining the information delivered by the condition-based approach for maintenance decision making when needed with time-based maintenance inspections can help reduce the total maintenance cost while ensuring a desired reliability level.

From a decision-making perspective, the influence of the chosen maintenance policy is twofold: it determines the impact of the maintenance actions on the considered asset availability and reliability and it affects the associated total cost of ownership. Consequently, the selection of the most convenient strategy is a critical task in every phase of the asset life cycle. Three sets of condition-based maintenance decision criteria are usually followed: i) the time-to-failure estimation predicted by the method must not exceed the time-to-maintenance inspection; ii) the probability of false alarm associated with the method must be kept below a specified risk threshold; iii) the cost of delay in executing a maintenance action associated with the method needs to be considered.

In addition to these decision criteria, an uncertainty analysis allows for the derivation of more general condition-based maintenance–related decision criteria, which take into account the evolution of both the remaining useful life and time-to-failure predictions in an explicit form. Moreover, the incorporated risk threshold enables maintenance decisions to be continuous functions of the risk index considered. Since maintenance operations are neither free nor predictable, the inspection intervals constitute a vital dimension on which to focus. Finally, because dedicated resources are limited, it should also be possible to enforce resource constraints during implementation.



Edge vs Cloud Task Placement (§1.1) — latency per task type, showing why latency-critical work stays at the edge while training/scaling goes to the cloud.

4.1. Maintenance Policy Formulation

Formulation of maintenance policies often relies on risk management principles, allowing the specification of a risk threshold that, if met, triggers an inspection of the critical component(s). This inspection is usually counted since it is

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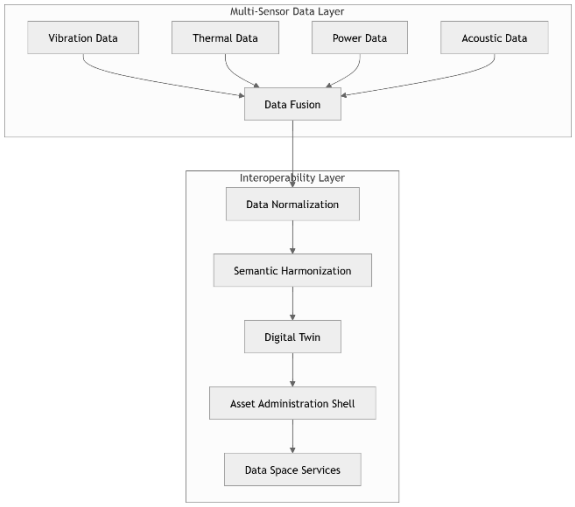
known ex ante that a replacement will be needed. If not, the probability of the component being in the dangerous state has to be estimated, which could lead to a replacement decision even for a moderate operational cost. When the condition of the system is assessed, the risk source with the highest cumulative risk is prioritized. Furthermore, maintenance policies defined based on inspection costs or technical resources available to the company can also be easily integrated into this framework. These elements are shaped by αinspection and investigatordistrust, indicating how much importance is given to the inspections and how much trust is put into the investigative nodes.

These aspects can be naturally embedded into the scoping of the maintenance policy. Inspection intervals for condition-based maintenance within the predictive control loop constitute another element that can be formulated for this family of maintenance policies by specifying γconditionbased. Subsequent extensions can seamlessly incorporate other uncertainties, such as the presence of measurement noise, by resorting to probabilistic maps across the detection, warning, and administration phases of the predictive approach.

The proposed formulation has been applied to the two-case study setup, and it has been shown that resources, either in terms of costs or of technical decision capacity, can be assigned expressly considering risk measures and risk thresholds. As a consequence, the overall lifestyle and perception of the system are altered, bringing the functionality toward a more preventative direction.



Data Fusion and Interoperability Architecture

Table 4. Machine Learning Techniques for Prognostics

ML Technique	Learning Type	Application	Output
Linear Regression	Supervised	RUL Prediction	Continuous Value
Random Forest	Supervised	Failure Prediction	Classification
Support Vector Machine	Supervised	Fault Detection	Class Label
Neural Networks	Supervised	Health Assessment	Health Score
Autoencoders	Unsupervised	Anomaly Detection	Anomaly Score
LSTM Networks	Deep Learning	Time-Series Prognostics	RUL Forecast

V. SYSTEM INTEGRATION AND ARCHITECTURE

Enabling implementation of predictive capabilities requires the integration of services, communicating through formalized interfaces. A comprehensive architecture describes the whole ecosystem, its components, data governance, and security aspects—together ensuring data privacy, confidentiality, and management of sensitive information along the entire data life cycle. Scalability is supported through a distributed, multi-layered structure that accommodates

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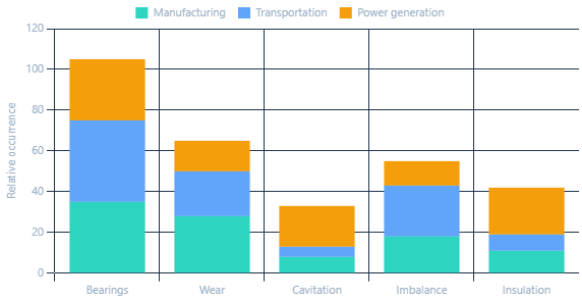
services running in the edge, on the premises, or migrated in the cloud. Interoperability throughout the architecture meets requirements imposed by requirements highlighted in Section 2; adherence to relevant standards guarantees compatibility with other services, encouraging the reuse of existing resources.

A predictive system is the composition of several services that sense asset operational conditions, apply ML algorithms to evaluate the predictive health state, and decide on the maintenance action to undertake. Integration of multiple sensors adds different information layers about the observed asset, increasing the amount of exploitable data for predictive maintenance applications. The approach adopted for data fusion must take into account not only the nature of the data coming from the different sensors but also their different sampling rate. Data normalization prior to fusion is needed, along with semantic harmonization to help the integration of heterogeneous data sources. Interoperability and communication between the involved services are assured through a shared API that manages data requests and communication. Data lineage, provenance, and versioning support data quality assessment, exposing possible anomalies detected in the monitoring stage.



Failure Mechanisms by Asset Class (§3.1) — bearings, wear, cavitation, imbalance, insulation degradation across manufacturing, transportation, and power generation.

5.1. Data Fusion and Interoperability

Inter-system or within-system data integration aims to narrow semantic gaps through fusion techniques or define joint information models. Multi-sensor data fusion extracts valuable insights by minimizing ambiguity and boosting reliability. Differences between observation modalities, sensor types, and manufacturers cause non-homogeneous data sets. Data normalization aligns observations, while semantic harmonization facilitates usage across different systems. Joint data specifications drive semantic interoperability. Provenance explains the origin of data, including creation, processing, integration, and potential use in hazard analysis and risk management. Versioning communicates the evolution of assets or models, including update frequency and effects on performance.

The accepted solution is the Industrial Internet Consortium's Asset Administration Shell (IAC), a digital twin that permits semantic interoperability with Data Spaces. A Data Space, defined by the European Commission, is a paradigm that emphasizes the importance and security of data-sharing ecosystems in which the ownership or trade of individual data remain with the original owner. Vertically, Data Spaces link data producers and consumers of a service or process inside an application domain; horizontally, they allow data sharing across different domains. The Data Space instance within the IAC framework enables Data Sharing Centers to streamline data flows, assure consistency, and guarantee balanced relationships among data producers, offering semantic-enhanced data services to data consumers. Data Sharing Centers, taken together, form national or regional Data Clouds that interconnect with other Data Clouds and also decompose into domain-specific and cross-domain Data Spaces. A trustworthy environment, as addressed in the previous section, lowers the costs of producing and using high-value data for training and validation.

Table 5. Maintenance Strategy Comparison

Strategy	Inspection Frequency	Maintenance Trigger	Cost Efficiency	Reliability
Corrective Maintenance	After Failure	Failure Occurrence	Low	Low
Preventive Maintenance	Scheduled	Time-Based	Moderate	Moderate
Condition-Based Maintenance	Variable	Asset Condition	High	High
Predictive Maintenance	Dynamic	ML Prognostics	Very High	Very High

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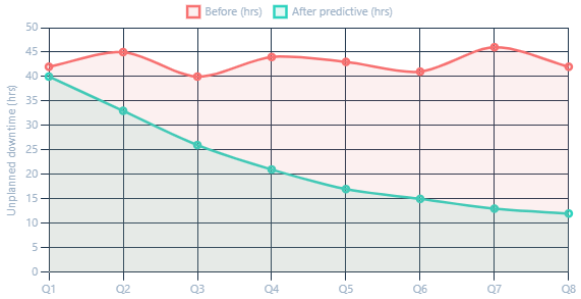
Strategy	Inspection Frequency	Maintenance Trigger	Cost Efficiency	Reliability
Hybrid Maintenance	Scheduled + Condition	Combined Approach	Highest	Highest

VI. CASE STUDIES AND APPLICATIONS

Indicative use cases are presented, depicting the complete system realization cascade—from IoT sensor deployment to decision support—within operational environments. The value add, difficulties encountered, and transferability concerns are also highlighted.

The first case focuses on the end-to-end predictive line-monitoring system of vibration, power, and overall temperature of an entire manufacturing line aiming to reduce unexpected failures and promote customer satisfaction. It illustrates the deployment of an asset-monitoring system, the feature extraction of the acquired data, the data-driven deployment of a machine-learning-based binary model for the detection of urgent maintenance inspection needs, and the definition of maintenance decisions. The achievement of an acceptable balance between false-positive and false-negative rates is emphasized. Over the monitored period, several maintenance interventions were produced by the algorithm, reducing the previous number of unexpected breakdowns.

The second, tailored toward manufacturing support systems, addresses the data-collection layer of an effective condition and performance-monitoring system. It presents a stand-alone setup for the collection of vibration signals, homing of the vibroacoustic signature for the extracted components, and local model prediction of vibration-feature excursion, remaining useful life, and time-to-failure quantities. Resources and data for a successful realization are detailed. The pitfalls encountered in an actual deployment for a predictive-monitoring operation are recounted, stressing the effects on model reliability and performance.



Downtime Before vs After Predictive (§6) — the downtime reduction the case studies and conclusion emphasize.

6.1. Predictive Monitoring in Manufacturing Lines

An end-to-end monitoring solution for a manufacturing line is described in a representative scenario. Sensor data from the line are processed to extract features suitable for the implementation of machine-learning models that estimate the health state of the monitored equipment and the remaining time to the next failure. The outputs of these models trigger the execution of predefined decision-support rules that indicate the criticality of each component and identify the need for maintenance actions. Real-life results show that the residual-life estimates correctly guide maintenance activities, providing information on which part of the line is experiencing trouble and should be inspected, and enabling repairs only when required. Finally, achieving transferability of the approach to other assembly stations, even if equipped with different brand components, is a relevant aspect of the examined case.

The predictive monitoring of a milk packaging line illustrates the monitoring lifecycle, from data acquisition to action coordination. The conditioning of the data before being forwarded to the decision-support layer is detailed, with a focus on the features extracted from the data streams. For two critical components, a vibration sensor and a thermal imager, machine-learning models predict the health state of the assembly and the time remaining before the next failure. Thanks to these estimates, a set of decision rules concludes whether the health status of any of the monitored elements calls for an inspection. Real-life results demonstrate the method's effectiveness, guiding maintenance actions and enabling repairs only when necessary. Transferability to different installations and brands is also examined.

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Table 6. Data Fusion Components in Predictive Systems

Component	Function	Benefit
Data Collection Layer	Acquire sensor data	Real-time visibility
Data Normalization	Standardize measurements	Improved consistency
Semantic Harmonization	Align heterogeneous data	Better interoperability
Data Fusion Engine	Combine multiple sources	Increased accuracy
ML Analytics Layer	Generate predictions	Prognostic insights
Decision Support Layer	Maintenance recommendations	Reduced downtime

VII. CONCLUSION

The presented results indicate a feasible approach to achieving predictive Industrial Systems Engineering through IoT-driven asset monitoring and machine learning-based prognostics. Operation-critical electrical and mechanical assets of an industrial facility were monitored under predictive maintenance principles, and the implemented framework allows for predictive decision-making models according to sensed signals. Time-to-failure requirements were considered, and remote predictive models can trigger corrective maintenance actions or internal visual inspections as-needed. Measured outcomes demonstrate a significant reduction in maintenance-related downtime. The proposed fully automatic data exploitation chain—from a sensor network to maintenance decision support—provides a low-cost, widely deployable solution for continuously monitoring and exploiting data during production and operation. Several research directions and recommendations for industry are outlined.

Recently, there has been considerable interest in integrating Artificial Intelligence with IoT and Cyber-Physical Systems, especially predictive maintenance in industrial environments. The presented predictive monitoring framework offers a step-by-step methodology to implement a predictive maintenance strategy for critical electric or mechanical assets of an industrial facility. Proposed timeliness thresholds indicate the required alert criteria for deploying remote predictive models or triggering internal visual inspections. The developed predictive monitoring chain provides a low-cost solution for continuously monitoring and exploiting production-generated data in a given asset. Experimental results indicate a significant reduction in average asset-related downtime when deploying the predictive maintenance decision-making. The detected research gap indicates a broad direction for future work.

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