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AI and IIoT-based Predictive Maintenance System for Soybean Processing

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Abstract

This article presents an industrial predictive maintenance (PdM) system used in soybean processing based on artificial intelligence (AI) and Industrial Internet of Things (IIoT) technologies. The PdM system allows for the continuous monitoring of relevant production equipment/motor parameters, such as vibration, sound/noise, temperature, and current/voltage. It is designed to identify abnormalities and potentially break down situations to prevent damage, reduce maintenance costs and increase productivity. Condition monitoring is combined with AI-based methods and edge processing to identify the parameter changes and unusual patterns that occur before a failure and predict impending failure modes well before they occur. The PdM demonstrator currently under evaluation is planned to integrate intelligent IIoT-based sensors to measure parameters, convolutional neural network and Wi-Fi, LoRaWAN, Bluetooth low energy (BLE) technologies for intelligent communication.

Keywords: predictive maintenance, artificial intelligence, smart sensors systems, edge computing, industrial internet of things, industrial internet of intelligent things, soybeans manufacturing, vibration analysis, condition monitoring, machine learning, deep learning.

4.5.1 Introduction

Artificial intelligence (AI), Industrial Internet of Things (IIoT) and edge computing combined with intelligent sensors and actuators are enablers for digitising industry and driving the development of new technologies for the Industrial Internet of Intelligent Things (IIoIT). The advancement in these technologies brings additional intelligence at the edge that empowers IIoIT devices with more intelligent decision making, high performance, low power processing and built-in security to create more intelligent and adaptive industrial applications.

As the intelligent capabilities of the IIoT devices expand, industrial systems become more efficient, interactions become more seamless and IIoT devices become capable of detecting anomalies and potential failures sooner.

The manufacturing infrastructure, equipment and industrial products integrate novel components (e.g., CPUs, GPUs, AI accelerators, neuromorphic processors) that support AI operations and capabilities, allowing intelligence to be moved to the edge. Integrating edge distributed intelligent sensors/actuators and AI methods and techniques into industrial process flows accelerates the digitising of industry and improves manufacturing processes (i.e., lower cost, less energy consumption, higher yield, and quality).

Furthermore, the progress in equipment monitoring accelerates the transition of maintenance operations from preventive maintenance (PvM) towards predictive maintenance (PdM). These developments further advance cost reduction, machine fault reduction, repair stop reduction, spare parts inventory reduction, spare part life increasing, increased production, operator safety, repair verification and overall profit.

Soy is a predominant ingredient in the food industry. Soybean production and the maintenance of equipment in the soybean production line can be improved through optimisations and reductions in downtime, repair costs and additional labour costs and requirements.

Predictive quality analytics using AI is helping soybean production facilities gain control over the equipment. Predictive analytics substantially helps to:

- Detect production equipment/motor anomalies and failures.
- Predict abnormalities and faults.
- Redefine and define error classes.
- Find factors that hamper productivity.

IIoT and intelligent sensors/actuators integrated with different AI techniques offer benefits to PdM solutions in soybean processing and manufacturing. These benefits include detecting faults early and accurately, predicting the remaining useful lifetime of an equipment/motor given an operational context or even prescribing guidance on work scope for the field service team with recommendations regarding the parts and personnel skills desired to service them.

The equipment and motors of the soybean production facility have little or no communication with the SCADA control system. As a result, it is challenging to determine the actual fault that causes a stop to the equipment without remote monitoring. Combined with AI-based techniques, placing various sensors and IIoT devices on the equipment to monitor critical parameters help identify abnormalities and potentially break down situations that reduce the production's unforeseen downtime. Some of the typical parameters to monitor are vibration, sound/noise, temperature/thermography, and current/voltage. In addition to the real-time measurements of these parameters, an analysis of the rate of change of the machine condition can provide valuable information for estimating warning levels and absolute limits before failure. Sensor data collection can be carried out in parallel for similar machines by building an AI/ML/DL model that can predict how much the mechanical machine components have deteriorated. The model can also determine which sensors should get the most attention to increase the sampling frequency and/or length of sampling interval. Several measurement technologies also reduce the possibility of false positives and false negatives (i.e. an indication for machinery when it is not deteriorated and no indication when a warning should have been received from the inference).

The article is organised as follows. The next sections present the elements describing the maintenance foundations in industrial production facilities and principles of PdM. Soybean production process and maintenance policies are described in the next section, followed by the description of the AI-based PdM framework methodology. Afterwards, the section on integrated industrial system for the maintenance of soybean production equipment describes the current approaches and elements. The experimental set-up section depicts the overall architecture, the specific experiments performed and results. Finally, the last section concludes and highlights the next steps.

4.5.2 Maintenance Foundations

Maintenance is defined by the standard European Standard EN 13306 as “the combination of all technical, administrative and managerial actions performed during the life cycle of an item intended to retain it in or restore it to, a state in which it can perform a required function” [1]. A maintenance management plan is required to perform the maintenance operation.

Maintenance management is defined as the sum of all the management activities that determine the maintenance objectives, strategies and responsibilities, and implementation through maintenance planning, maintenance control, and improvement of maintenance activities. Regular maintenance is critical to keep the equipment/motors and the work environment safe and reliable. Several types of maintenance are defined by the EN 13306 standard and illustrated in Figure 4.5.1.

The classification includes the following maintenance types [1]:

Reactive Maintenance (RM) is a run-to-failure maintenance management method, offering maximum production output of the equipment by using it to its limits. The maintenance action for repairing equipment is performed only when the equipment has broken down or been run to the point of failure. The cost of repairing or replacing a component would potentially be more than the production value received by running it to failure.

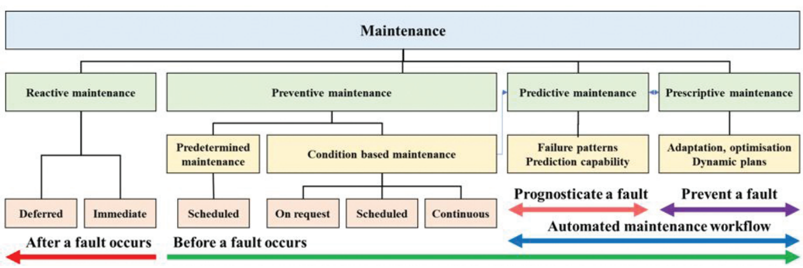

Figure 4.5.1 Maintenance types. Adapted from EN 13306 Standard [1].

Preventive Maintenance (PvM), time-based, or scheduled is a maintenance procedure conducted periodically with a planned schedule in time or process iterations to anticipate process/equipment/motors failures. The main aim is to improve the efficiency of the equipment/motors by minimising the failures in production preventive maintenance works usually under a pre-existing maintenance schedule provided by the equipment's manufacturer The procedure is used in many different industrial processes to avoid failures. However, the method requires several corrective actions that can lead to increased operating costs.

Condition-based Maintenance (CBM) is defined as a method based on constant equipment/motors monitoring or their behavioural health that can be performed when they are necessary and not planned. The maintenance actions can be performed when the actions on the process are taken after one or more conditions of degradation of the equipment/motors.

Predictive Maintenance (PdM) is based on the continuous monitoring of the equipment/motors to detect trends in the health of a machine and using prediction tools, models, and algorithms to predict when failure occur and estimate when such maintenance actions are required, and maintenance scheduled.

Prescriptive Maintenance (PsM) uses sensors, data, and advanced analytics to determine the root cause of a potential failure so specific corrective action can be prescribed. A fully proactive/prescriptive maintenance implements the following tasks. The workflow starts with *detection* – measuring machine vibrations and making comparisons to the baseline or previously measured data to determine changes in condition. If significant changes occur, the data are analysed to identify problems and prepare maintenance timelines. *Analysis* involves evaluating the relationship between phase, frequency and amplitude in the data collected from various sensors to deduce the symptoms that identify the root problem. If necessary, maintenance or corrective repairs are scheduled. Additional measurements are taken to *Verify* that the problem has been fixed. Finally, data history is studied to determine the *Root Cause* so that it can be avoided if the problem is recurrent. PsM solutions are in the first stages of evaluation and the implementations still require increased complexity and costs.

The solution presented in this article focusses on a PdM system approach that does not involve the prescriptive part, which is envisaged in the next development steps. Figure 4.5.2 illustrates the comparison between PdM,

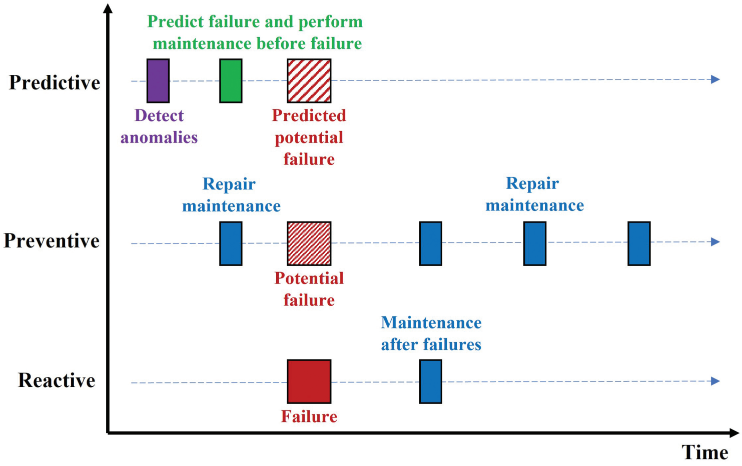

Figure 4.5.2 Failure and maintenance timing. Adapted from [8].

PvM and RM types in terms of maintenance plans and intervention timing and Figure 4.5.3 shows the comparison in terms of cost.

The maintenance types display different trade-offs between repair cost and prevention cost. PvM has the lowest repair cost – due to well-scheduled downtime – but has the highest prevention cost, while RM has the lowest

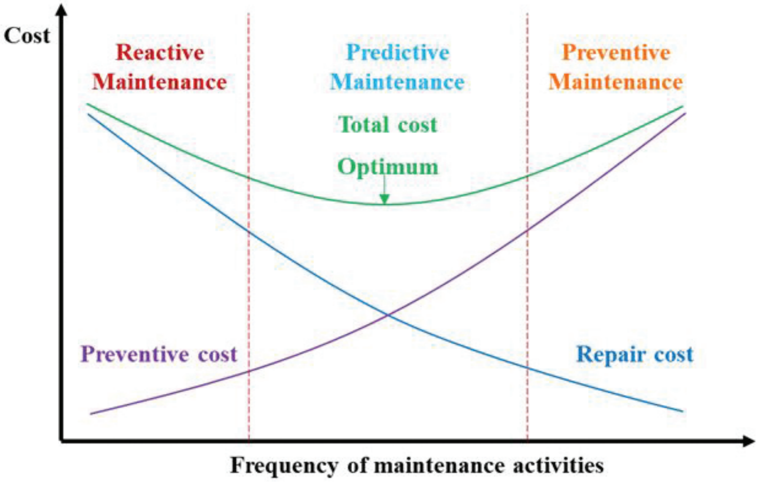

Figure 4.5.3 Comparison of maintenance cost and frequency of maintenance. Adapted from [3].

prevention cost – due to using run-to-failure management – but has the highest repair cost. PdM's goal is to predict when the equipment is likely to fail and to decide which maintenance activity should be performed. Therefore, PdM can achieve the optimal trade-off.

Although PdM supersedes both PvM and RM, the total cost of its condition monitoring devices (e.g., sensors, IIoT devices) is often higher. PdM systems become increasingly complex to detect failures in early stages, using real-time IIoT data, historical data, prediction tools such as AI, machine learning (ML) methods, feature extraction from sensor and monitoring analysis, model-based condition analysis, statistical inference approaches and engineering techniques.

For the soybean production the focus is on predictive maintenance using condition-based monitoring and AI-based techniques for the prediction algorithms.

4.5.3 Principles of Predictive Maintenance

PdM collects data from IIoT sensors and devices connected to machines and processes the data through predictive algorithms to discover trends and identify when the equipment needs to be repaired or retired.

The principle of PdM is to use the actual operating condition of systems and components to optimise operation and maintenance – neither running the equipment to failure, nor replacing it when it still functions. Maintenance is conducted only when necessary. The motors requiring maintenance are identified in time and are shut down only just before imminent failure occurs, a decision that reduces the time and money spent on maintenance, minimising the production hours lost to maintenance as well as the cost of spare parts and supplies. Maintenance is scheduled when specific conditions are met and before the equipment/motors break down.

When PdM is used in industrial processes, such as soybean production, maintenance is performed by observing specific parameters or components (e.g., equipment, motors) of the system or production line. The advantage of this procedure is that the system is controlled in real time based on the monitored parameters. The equipment/motors in the production systems have an operating curve that is well defined by the manufacturer.

PdM has the possibility of detecting potentially critical situations with the equipment/motors that lead to serious consequences situations before they arise. A cost-benefit analysis is conducted before deciding if PdM is profitable and preferred for a specific motor.

The performance of a PdM system – deciding which machines to keep running and which to schedule for maintenance – depends on the accuracy of the information gathered from various sensors, IIoT devices and the algorithms' ability to interpret that information i.e., the system's intelligence. CBM enables real-time evaluation of machine health and triggers alarms (e.g., by indicating excess vibration or temperature) so that immediate corrective action can be taken to avert failure.

There is a dependency between PdM and CBM and PsM. CBM can be standalone without a PdM in place, but PdM relies on CBM in collecting, comparing, and storing measurements that determine a machine's health. Also, PdM is part of a proactive (prescriptive) maintenance approach but is not necessarily a fully proactive/prescriptive system: it does not guarantee that the root causes of problems and failures are eliminated.

4.5.4 Soybean Production Process and Maintenance Policies

The predictive maintenance policies for soybean production are centred on improving the efficiency of the equipment/motors utilisation, reducing the down time, estimating the remaining useful lifetime of the equipment/motors, and reducing the overall maintenance costs.

The approach used for the soybean production process is based on condition-based monitoring implemented using various sensors, IIoT devices that allow a continuous monitoring process of relevant equipment/motors sensor parameters. Condition based monitoring is combined with AI-based methods and edge processing to identify the parameter changes that occur before a failure and predict a future period in which the parameter changes appear, and thus the failure might happen.

The policies adopted are based on the production manufacturing goals, the selected category for conditioning monitoring, the maintenance scope, fault detection categories, manufacturing system size, predictive AI-based techniques, data handling and the evaluation approach. A short description of these different categories selected for the soybean production process and maintenance policies is presented in the following paragraphs.

The predictive maintenance system combining CBM, and AI is aimed to minimise the downtime of the soybean production line as it allows to plan maintenance actions and group-specific maintenance actions to reduce the number of production stops for single maintenance actions.

Minimising downtime helps reducing costs and increase productivity. The goals are aligned with the non-functional requirements (NFRs) for the implementation, such as reliability, compatibility, and maintainability according to the standard ISO/IEC 25010 (SQuaRE - Systems and software Quality Requirements and Evaluation) [4].

The selection of NFRs such as maintainability and reliability emphasises the importance of preserving the system's capabilities over the operational lifetime. The reliability aims in improving individual components and providing redundancy. Maintainability enhances the maintenance measures to implement and improve preventive maintenance, apply predictive maintenance measures, and increase repair capability and speed.

The soybean production PdM system aims to evolve from inspection-based monitoring to sensor-based continuous online monitoring in real-time. With sensor-based monitoring, various IIoT sensors and devices monitor vibration, temperature/thermography, sound/noise, current/voltage parameters and collect the relevant data. Continuous collection of relevant monitoring data is used to identify the running state and estimate the useful life of the equipment/motors.

Figure 4.5.4 shows the operative curve slope of the machine condition dependency on the life cycle of the equipment that is typical for industrial motors and hence applicable in our case. At the failure inception point, the machine's condition starts to deteriorate, and various sensor modalities (such as vibration, temperature, sound and current) can reveal conditions that indicate the machine's potential for failure. The combinations of parameter measurements associated with specific failure modes, such as motor imbalance, misalignment, loose coupling and degraded bearings, are valuable data. These data sets are used as input to supervised learning algorithms (such as decision trees or neural-network models) to later predict those failure modes from real-time sensor data collected from motors.

As illustrated in Figure 4.5.4, a vibration analysis is typically an indicator of machine health. It enables the early detection of a sudden failure and helps to eliminate downtime due to such a failure. A well-designed PdM system uses a combination of several sensor modalities to determine the time elapsed from the detection of deterioration symptoms to the failure of the equipment. For example, increased current consumption, noise or heat typically suggests a shorter potential to failure time interval for most motors.

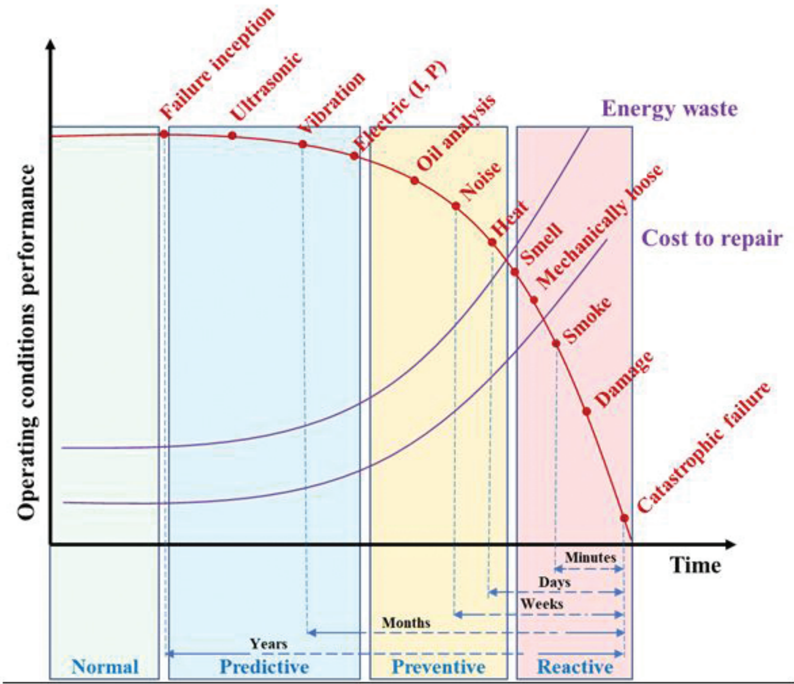

Figure 4.5.4 Parameters monitored during equipment life-time operation. Adapted from STMicroelectronics.

In the case of soybean production, vibration, sound, temperature, and current modalities, are monitored as part of the CBM and integrated into the PdM system.

The soybean production predictive maintenance system focuses on the prediction of the future conditional state of equipment/motors to schedule maintenance activities in an appropriate way and scope, and provide fault detection, attempting to predict the remaining life of the equipment/motors and in the future to identify the root cause of the failure based on the collected data.

The future activities are targeting the processing of acquired monitoring data to reveal the reasons for future failure. The feasibility and accuracy of a fault detection approach depend on the monitoring activity level, which means that the more equipment/motors parts and components are monitored separately, the better can be identified where the root cause for a future failure is.

Manufacturing system size for the soybean production PdM is applied to single-component equipment/motors. Further work could focus on multi-component systems. The implementation of PdM system for these multi-component systems requires increasing the number of monitoring devices and processing data and dependencies between the equipment/motors' components.

PdM incorporates a combination of monitoring techniques such as ultrasonic, vibration, noise/sound, temperature/thermography, and motor parameters (e.g., current, voltage, load).

The selection of the sensors is important as the sensors can detect certain faults and failures. Several types of parameters and transducer types are considered for monitoring the equipment/motors:

- Vibration is measured using accelerometers based on piezo transducers with low noise measuring frequencies up to 30kHz to identify bearing conditions, gear meshing, misalignment, imbalance, and load conditions. MEMS accelerometers offer low cost/power/size solutions for vibration measurements up to 20kHz.
- Sound pressure is measured using low cost/power/size microphones detecting sound with frequencies up to 20kHz for identifying bearing conditions, gear meshing, pump cavitation, misalignment, imbalance, load conditions or ultrasonic microphones detecting sound with frequencies up to 30kHz.
- Currents up to 150 A are measured using a clamp-on transformer with wireless capabilities (e.g., LoRaWAN).
- Temperature is measured using thermocouple or thermistor sensors (e.g., temperature range from 0 to 85℃. An infrared camera is considered for taking thermographic images of the motors.

4.5.4.1 Vibration Analysis

Predictive maintenance incorporates a combination of monitoring techniques, such as vibration, noise/sound, temperature/thermography, and motor parameters (e.g., current, voltage and load). Vibration analysis stands out due to the multitude of problems that can be discovered and rectified through it.

Vibration is adaptable to various machines and indicates overall machine condition and problem severity, and analysis provides information on specific faults.

A vibration analysis is the best indicator of the condition of motors with rotating parts. It is considered a direct measurement for detecting and monitoring imbalance, misalignment, and looseness of a rotating part. Machines/motors vibrate regularly when operated, and a low vibration level normally indicates that the equipment is running correctly. When vibration begins to increase, the machine may be about to fail.

Vibration amplitude can be expressed in units of displacement, velocity or acceleration. Displacement is a measurement of the linear movement in the signal as the machine oscillates back and forth. Velocity is the speed of the signal as the machine oscillates back and forth. Acceleration is usually compared to the gravitational acceleration in the signal at the instant the oscillation changes direction. In summary, displacement is the peak-to-peak movement of the vibrating part. The velocity is the speed at which displacement occurs, and acceleration is the rate of velocity change.

Vibration is the motion of machine components caused by dynamic forces. It refers to the mechanical oscillations around an equilibrium point. The oscillations may be periodic, random, or transient. Transient vibration appears, for example, when pump cavitations occur due to an improper system line-up.

Vibration is described by amplitude (typically velocity), time, frequency, and phase. Vibration is measured by transducers that convert vibration motion (e.g., an accelerometer to measure g-force on a 3-axis and then convert speed and frequency into an electrical signal for processing), vibration meters that detect only amplitude (no frequency components) and vibration analysers that convert amplitude versus time to amplitude versus frequency (spectrum analysis).

Faults can be detected early using a full signature (spectrum) analysis, frequency analysis parameter sets and overall vibration levels (no specific faults can be detected via this method). Types of faults that can be detected include misalignment, looseness, bearing defects or wear, unbalance, internal component rubbing and resonant structural conditions.

Different vibration sensors are under evaluation for the implementation including two high-performance accelerometer-based sensors with very low noise operation (45 μg/$\sqrt{}$Hz $\pm$2g, and $\pm$10g), 3D accelerometer + 3D Gyro inertial measurement sensor, and an ultra-wide bandwidth (up to 6 kHz) low-noise 3-axis digital vibration sensor.

4.5.5 AI-based Predictive Maintenance Framework Methodology

The AI-based predictive maintenance framework includes the design and development of an intelligent multi-sensors wireless system that comprise the following steps:

- Define the system architecture.
- Find sensors that measure and collect the required physical parameters with the correct accuracy and stability at the right price and availability.
- Determine the required processing microcontroller specifications, including computational power, memory, interfaces, and AI-based capabilities.
- Choose the connectivity and communication protocols technologies.
- Design the power management, form factor and integration into the industrial system.
- Outline the edge integration strategy and the overall collection of information flow.
- Develop the AI-based models and algorithms.
- Implement the required analytics and characterise the system.
- Validate the AI-based system in the real application scenario.

The AI-based algorithms are fed with data gathered to monitor the motors/equipment parameters and train models to identify possible anomalies.

The architecture used for predictive maintenance allows the implementation of edge machine learning, using intelligent capabilities of IIoT devices, which can be deployed to run AI models directly on the motors/equipment.

The IIoT devices collect the information from sensors in the edge node in real-time, allowing continuous monitoring of the motors/equipment operations. Data is processed in the cloud and locally at the edge from machine learning predictive models, detecting anomalies.

The overall AI-based predictive maintenance framework used for the soybean production is illustrated in Figure 4.5.5. The AI-based models can be deployed at different micro, deep and meta-edge levels as illustrated in Figure 4.5.6. The work described in this article consider the case of the deployment of the AI-based models at the meta-edge level.

AI-based PdM refers to the ability of a PdM system to use knowledge and sensor data to anticipate and address potential issues before they lead to breakdowns in operations, processes, services, or systems. In the context of the soybean production demonstrator, three AI-based techniques have been

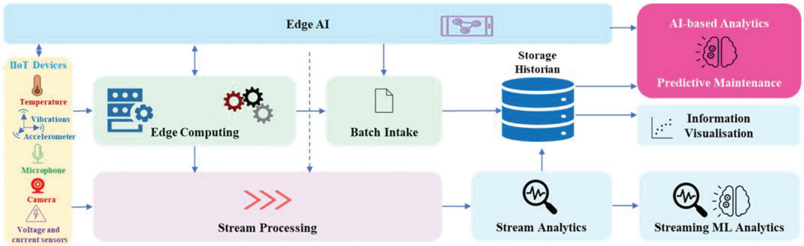

Figure 4.5.5 AI-based predictive maintenance framework.

explored: knowledge-based, ML-based and DL-based approaches. A more comprehensive survey of current AI approaches for PdM can be found in [9].

Knowledge-based approaches make use of domain expert knowledge and deductive reasoning, of which expert systems and model-based reasoning are two representative examples.

Expert systems typically consist of a knowledge database and an inference engine. The knowledge database contains the human domain expert knowledge represented in a form that can be processed by machines. For example, rules are structured in an “if A, then B” format. The inference engine consists of algorithms, which, via step-by-step inferences, draw deductions based on the knowledge rules.

Model-based approaches are applicable in cases where physical processes that have an impact on the health of the equipment can be simulated using mathematical models. The advantage of these approaches is that they are effective and accurate, and models can be reused. However, complex systems cannot always be approximated precisely using explicit mathematical models.

Knowledge-based approaches are feasible when there is a lot of human expert knowledge and experience that can be modelled but not enough data. On the downside, knowledge bases take time to acquire and represent on computers, and if some knowledge is missing or incomplete, a less reliable result will be produced.

Machine learning (ML)-based approaches are useful when domain knowledge and experience is scarce, but vast amounts of data are available, allowing ML algorithms to search for large patterns and extract useful knowledge. ML algorithms developed for the context of PdM include Artificial Neural Network (ANN), decision tree (DT), Support Vector Machine (SVM), k-Nearest Neighbours (k-NN).

These approaches typically involve feeding a neural network with data (images, vibration, audio, etc.), and the network thus trained would then be able to accurately guess the motor diagnosis when fed with real-time sensor data.

The advantage of ML-based approaches is that they do not rely on a domain expert's knowledge and are able to handle large amounts of real-time sensor data, thus allowing for automation. ML-based approaches also have limitations depending on the use case application of the PdM. A survey of ML methods applied to PdM, their challenges and opportunities can be found in [2].

Deep learning (DL)-based approaches have been proven to be superior to ML-based approaches in the field of PdM. For example, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) are widely applied.

It is technologically possible to combine the above approaches to obtain the best trade-offs. For the demonstrator, a combination of regression methods and statistical techniques, along with CNN or RNN, is under evaluation.

The choice of DL algorithms for the demonstrator is justified by their abilities in feature learning and prediction involving multilayer nonlinear transformations. CNN can extract local features of the input data and combine them layer by layer to generate high-level features. The CNN structure consists mainly of input layer, convolution layer, pooling layer, and fully connected layer [9][7][10]. The steps involved are data collection, the data pre-processing, the data transformation [6], and the CNN model creation [5].

Preparation of the training data requires analysing the following information sources: real-time data from the IIoT monitoring devices, the motors/equipment fault history, including the description of the error events, the failure scheme that contains a sufficient number of failure cases, motors/equipment maintenance/repair history including information about replaced components, predictive maintenance tasks performed, and the motors/equipment conditions to estimate the life-time. The data collected should contain time-varying functions that acquire ageing patterns or any anomaly that could cause performance reduction.

For training/learning the data pre-processing requires to create/construct the datasets, create the features, and the anomalies and normalise the data sets that they can be used for training. For supervised anomaly detection ML models, creation of data sets for training and testing are both needed.

The DL models can identify an anomaly, and the edge device sends a notification to signal that was recognised a different function pattern (e.g., different current consumption, increased operating temperature, alternative operational state, different vibration, and sound patterns, etc.).

Whereas model training is primarily done in cloud, model inference is performed at the edge and on the devices to allow for information to be captured and analysed without transferring across network communication protocols or storing in cloud infrastructure.

4.5.6 Industrial Integrated System for Soybean Production Equipment Maintenance

The architecture proposed takes into consideration that the IIoT sub-systems are connected to different edge gateways, and then the information is aggregated to an on-premises edge server as presented in Figure 4.5.6. The edge computing solution proposed is to improve the performance, security, operating cost, and reliability of IIoT and AI-based platform, applications, and services.

The system design is based on a heterogeneous wireless sensor network that consists of sensor nodes and IIoT devices with different communication interfaces (e.g., BLE, LoRaWAN, Wi-Fi), computing power, sensing range and AI-based processing capabilities.

The system implements an architecture integrated at micro, deep and meta-edge levels, allowing heterogeneous wireless sensor networks to communicate with the various gateways while integrating the information

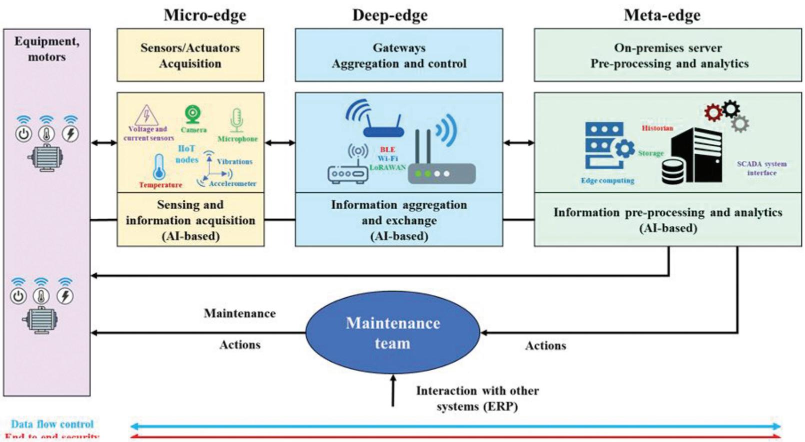

Figure 4.5.6 Industrial integrated system for equipment maintenance.

from heterogeneous nodes in a shared on-premises edge server application and a shared database. The network architecture allows for interfacing with the existing SCADA system and providing a secure link to external cloud applications.

The micro-edge implementation increases the information acquisition from the intelligent edge sensors placed on equipment/motors and allows end-users to build predictive maintenance solutions based on advanced anomaly detection algorithms.

The heterogeneous architecture provides the ability to retrieve data from LoRaWAN and Wi-Fi wireless sensor nodes using for example the MQTT protocol. The architecture has several advantages related to integrating data from heterogeneous sensor nodes and providing a mechanism for their transmission to an on-premises edge computing server and creating geographically distributed wireless sensor nodes over the production facility.

LoRaWAN network is deployed in a star topology, where the end nodes communicate with the LoRA gateways. Information received by LoRa gateways is sent to the LoRA network server and the application server using an IP-based backhaul network. The components integrated into meta-edge are detailed in Figure 4.5.7.

AI models can run on the edge server, considering the ability to use the Kubernetes platform on-premises.

Two or three nodes (servers/processing units) can be connected to the master node running the "brain" of the Kubernetes. A cluster of nodes/resources need to be created virtually by sharing the available CPUs and RAMs using the on-premises edge server.

The edge server interfaces include protocols such as MQTT, HTTPS using RESTful API, OPC UA, etc.

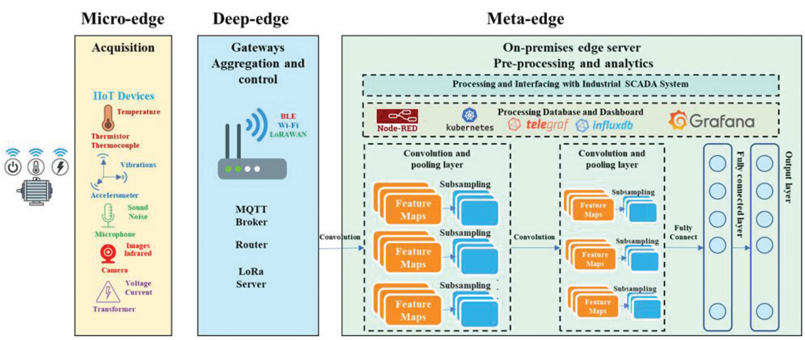

Figure 4.5.7 Soybean production predictive maintenance system demonstrator.

The soybean manufacturing facility produces soy oil, lecithin, and meal. In the soybean production line, the hammer mill located in the crushing area of the plant is defined as one of the most critical equipment to monitor and prioritised in the predictive maintenance use case.

The lumps in the soybean meal are crushed in two parallel hammer mills, and the meal is transported to the soybean meal storage. The hammer mills are only inspected visually by operators two times a day and have no communication back to the control system. The hammers and shafts get worn repeatedly, and trained operators can sometimes hear the weariness before a breakdown. The hammer mills sound picture is an important characteristic that can indicate an imminent accident.

The experimental set-up comprises of the physical/field part that includes the equipment/motors and the IIoT sensors and actuators. The control layer includes different types of network and domain controllers, PLCs, communication IIoT gateways, etc. The operation and information layers include backbone network, clients (e.g., OPC), edge server(s), and data storage.

Predictive maintenance demonstrator performs maintenance based on the motors/equipment health status indicators. The IIoT-based sensors are used to measure unusual patterns of motors parameters, such as motor's vibration level, temperature, current consumption, and, based on experience, failures are preceded by an unusual pattern of these parameters. A convolutional neural network (CNN) DL technique capable of extracting data representation is planned for the demonstrator that is integrated in the AI-based model and the algorithms developed.

CNN deep learning is proposed due to its shared weights and the ability of local field representation to extract the input sensors/IIoT data features and combine them layer by layer to generate high-level features. The CNN structure consists of the input layer, convolution layer, pooling layer, and fully connected layer.

CNN can extract valuable and robust features from IIoT and sensor monitoring data such as raw vibration signals to identify fault types. For example, the vibration signals can be converted to discrete frequency spectrum via Fast Fourier Transform (FFT) and use CNN to analyse the spectrum-principal-energy-vector and obtains a series of eigenvectors. Next, a CNN model can be used for regression prediction. RNN deep learning is another method evaluated in the project that includes feedback connections in ANN architecture, accounting for past input state influence to the current network output. Compared with the simple feedforward architectures, the training of the RNN architecture is a much more complex task.

The edge computing approach is integrated and interfaced with industrial SCADA infrastructure and linked through the historian component.

Consolidating the historian, SCADA, and HMI applications alongside new containerised functions for PdM using AI-based models and algorithms alongside an IIoT stack supports the processing at the edge and the AI deployment.

4.5.7 Experimental Set-up and Implementation

The overall architecture and role of the different components, technologies and protocols that constitute the PdM system is depicted in Figure 4.5.8. The evaluation approach for the soybean production PdM system is based on specific experiments conducted to validate the approach. The experiments are limited to test setups suitable to demonstrate the concept. The aim is to scale up the system as the experiments validate the different solutions.

As vibration analysis is the most common technique of PdM programs in the industry, this section focuses on experimentation related to the vibration parameter. The deployed HW/SW predictive maintenance solution measure and analyse vibrations to detect abnormal behaviours of the motors/equipment, with AI-based techniques for detecting operating anomalies before a failure occurs.

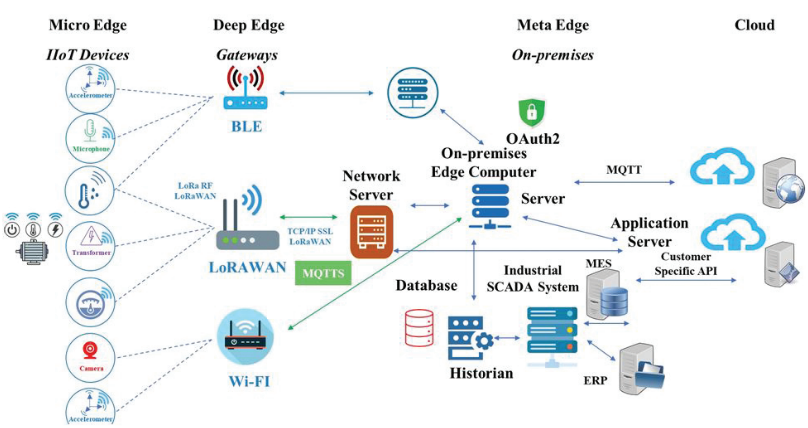

Figure 4.5.8 Overall architecture.

The inference is applied as well to a class of devices based on microcontrollers (e.g., STMicroelectronics microcontrollers) that have AI-based components and can implement semi-supervised learning engine that aggregates data from sensors, identify and create a reference behavioural profile of the motor/equipment, then detects and acts upon anomalous/abnormal behaviour.

Every machine component produces a specific type of vibration signal, which, when displayed in the vibration spectrum, often forms characteristic patterns. Pattern recognition is a key part of vibration analysis, but significant training and experience are necessary to read patterns.

The experimental setup uses a four item software stack: Node-RED [15] and MQTT [16] to collect vibration measurements from two IIoT devices placed on an AC test motor; and InfluxDB [11] and Grafana [13] to store the data into a database and query the database to build dashboards and create visualisations of the data in the form of charts, graphs and more.

Node-RED implements various automation logic, while InfluxDB is preferred over other databases (such as MySQL); a timestamp is automatically added when data are pushed into the database. The experimental setup is detailed in Figure 4.5.9.

An MQTT broker (e.g., Mosquitto [12]) is installed on a separate server. The IIoT devices are connected to the broker using a 2.4 GHz band Wi-Fi connectivity protocol. An analysis of the load on different channels was conducted before selecting the channel for the IIoT sensor node. As illustrated in Figure 4.5.10, some channels are loaded more than others depending on the

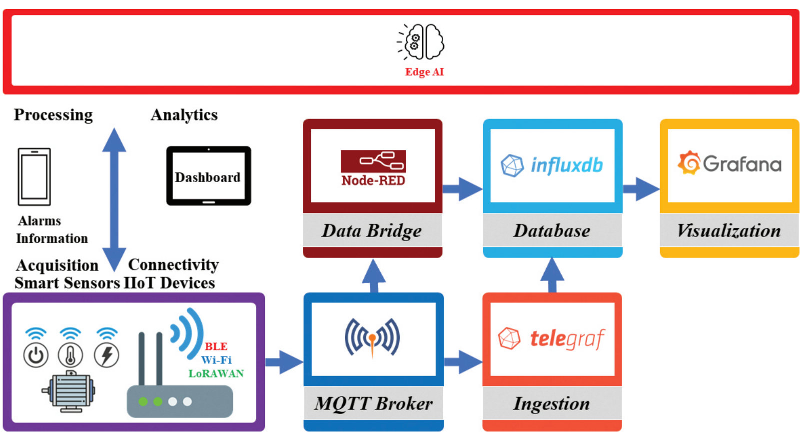

Figure 4.5.9 Experimental set-up detailed.

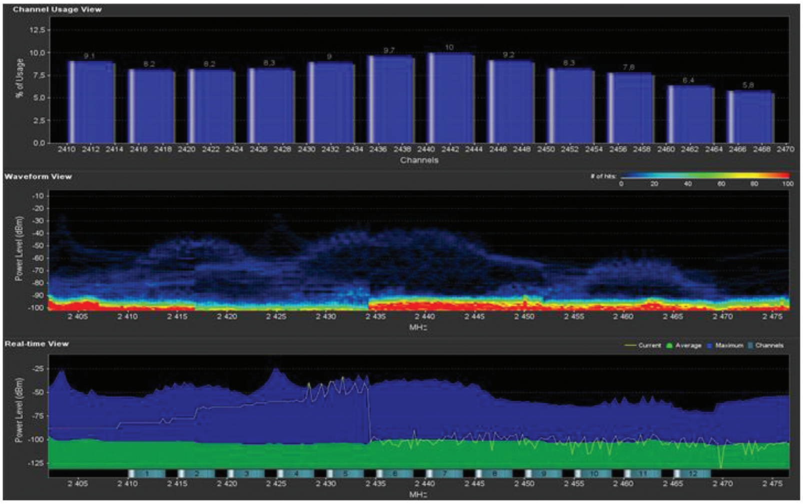

Figure 4.5.10 Spectrum analysis Wi-Fi 2.4GHz.

Wi-Fi devices operating in the area where the sensors are installed. For the setup the channel with the lower load was selected (channel 12).

The IIoT devices are set up to use MQTT and have five channels (three for the accelerometer and two for inclinometer) that are active and enabled for static or streaming mode. During the former, measurements are published to separate topics, while during the latter all measurements are published to a single topic.

The data is parsed on the Node-RED. The Node-RED flow connects to the MQTT broker and subscribes to each sensor's measurement topic, waits for the payloads, checks the acquisition mode, parses the payload, extracts measurements, displays the data on live dashboards, stores data into the database and displays in Grafana. A Node-RED flow is visualised in Figure 4.5.11 and a Node-RED dashboard in Figure 4.5.12.

The Payload Parsing node function receives as input the payload sent from the IIoT device and captured by the MQTT broker nodes. The payload is sliced into sections, each section will hold only the payload of each field of the MQTT frame content and return them in array object.

The Measurement Threshold Alarm function listens to measurement values and send notification if a defined threshold is reached. SMTP or SMS to mobile are used for notifications. Other functions nodes are preparing the data for the database and for the Node-RED live dashboard.

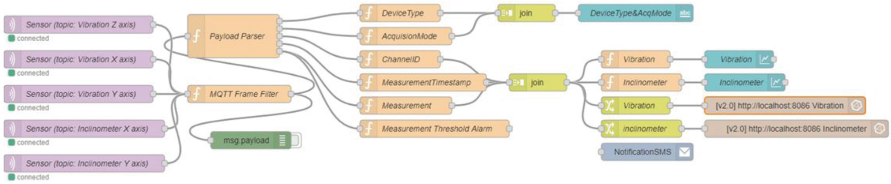

Figure 4.5.11 MQTT subscriber with Node-RED flow (vibration sensor per topic).

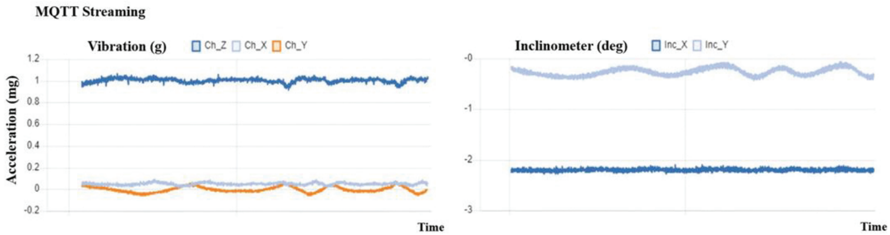

Figure 4.5.12 MQTT subscriber with Node-RED results (vibration data streaming).

During the preliminary vibration analysis, techniques, such as K-means clustering to organise the measurements into useful clusters and non-linear regression to make predictions inside and outside of the training sets area, have been employed. The sensor data were also processed visually as 3D points and inputted to a K-means clustering and non-linear regression together with data to test against the learning data.

This configuration is implemented on meta-edge server, where MQTT, Node-RED, InfluxDB and Grafana are setup to work together. This workflow can also be implemented on deep edge. Furthermore, Node-RED and possibly also MQTT can be replaced with Telegraf [14] in case of simpler flows with less automation logic, thus reducing the software stack.

In addition to the above flow, a second flow has been deployed using the STWIN SensorTile Wireless Industrial Node [17], which is a complete sensor-to-edge and cloud ecosystem with environmental sensing, vibration monitoring and sound/ultrasound detection. It also features a debugger, embedded signal processing libraries running on an ARM Cortex-M4 microcontroller and an ultra–low-power accelerometer to preserve battery life during monitoring. As shown in Figure 4.5.13, it has digital and analogue microphones, inertial sensors and temperature and pressure sensors connected through wired or wireless options.

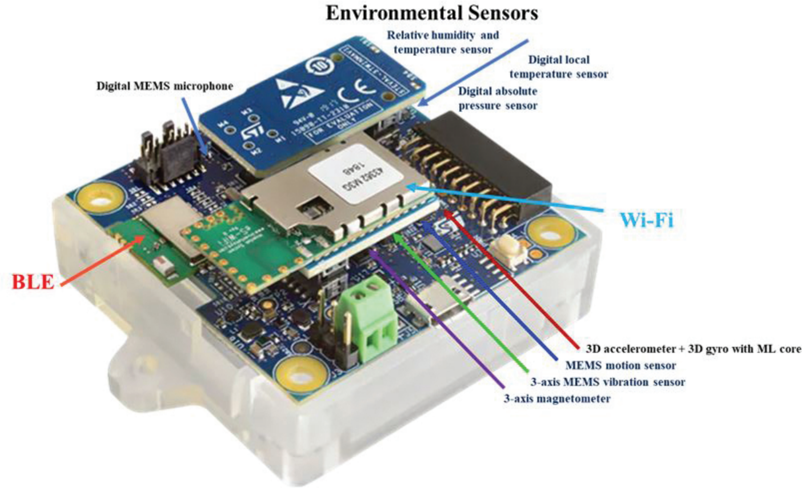

Figure 4.5.13 STWIN SensorTile wireless industrial node.

Data from all the sensors are sent to a USB at the maximum data rate for analysis by the computer; it can also be stored on an SD card or transmitted using BLE or Wi-Fi capabilities.

The device can be connected directly to the cloud through a secure connection using certificates. On the cloud side, it is also possible to collect data from various devices that are located at disparate places and/or from devices using different connectivity. AI methods can be employed to collect data at the edge and in the cloud.

The test setup includes several IIoT devices that take various measurements using BLE, Wi-Fi or LoRaWAN communication protocols and an AC low power e-motor installed on a lab test bench.

The data collection flow was also tested by IIoT devices connected directly to the cloud through the Wi-Fi expansion to verify the STWIN device's capabilities and fitness to the purpose. The end-to-end solution includes access to a dashboard for the predictive maintenance application that allows data from the IIoT devices to be collected and visualised. The sensor parameters have thresholds that trigger alarms and warnings.

Another IIoT device was connected via Bluetooth to an Android tablet with the BLE app installed. The app recognised the board after the board with the preloaded software was powered up. The data collected from the sensors are illustrated in Figure 4.5.14.

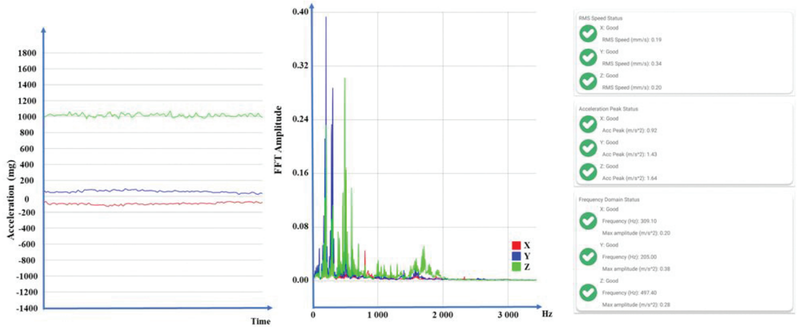

Figure 4.5.14 Real-time data from the three-axis MEMS vibration sensor.

The various graphs show the live data coming from the three-axis MEMS vibration sensor and the FFT applied to the signal received from the vibration sensor that indicates the main frequencies in the spectrum.

As illustrated in Figure 4.5.14, thresholds have been added to the sensors, and unbalanced situations were purposely created to trigger the alarms and warnings associated with the vibration parameters. The data logs were downloaded for further analysis and processing.

4.5.8 Summary and Future Work

This article presented an AI- and IIoT-based PdM for soybean processing and its implementation approaches. The PdM foundations described in the article are followed to develop a PdM concept that fits the process requirements of soybean manufacturing. The maintenance scope assumes that every maintenance action conducted at the equipment/motors restores functionality and durability to their original level. The PdM solution for the soybean production system targets individual equipment. Future activities could address the possibility of grouping maintenance actions that may lead to an overall cost reduction for maintenance activities.

The proposed edge computing solution improves the performance, security, operating cost and reliability of IIoT and AI-based platform, applications and services.

The system design is based on a heterogeneous wireless sensor network consisting of sensor nodes and IIoT devices with different communication interfaces (e.g., BLE, LoRaWAN, Wi-Fi), computing power, sensing range and AI-based processing capabilities. The network architecture allows for interfacing with the existing SCADA system and providing a secure link to external cloud applications.

Future work will focus on data fusion and filtering to integrate multiple sensor data and generate data that are more reliable than individual sensor data. The proposed convolutional neural network DL technique to extract data representation will be further evaluated to integrate the AI-based model and the algorithms developed. The vibration signals collected will be converted to a discrete frequency spectrum via Fast Fourier Transform and further analysed to improve the PdM model.

The AI- and IIoT-based PdM concept will be further developed for edge processing at different levels by combining micro, deep and meta-edge with local data access and storage.

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