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AI-Based Edge Acquisition, Processing and Analytics for Industrial Food Production

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Abstract. This article presents a novel approach to the acquisition, processing, and analytics of industrial food production by employing state-of-the-art artificial intelligence (AI) at the edge. Intelligent Industrial Internet of Things (IIoT) devices are used to gather relevant production parameters of industrial equipment and motors, such as vibration, temperature and current using built-in and external sensors. Machine learning (ML) is applied to measurements of the key parameters of motors and equipment. It runs on edge devices that aggregate sensor data using Bluetooth, LoRaWAN, and Wi-Fi communication protocols. ML is embedded across the edge continuum, powering IIoT devices with anomaly detectors, classifiers, predictors, and neural networks. The ML workflows are automated, allowing them to be easily integrated with more complex production flows for predictive maintenance (PdM). The approach proposes a decentralized ML solution for industrial applications, reducing bandwidth consumption and latency while increasing privacy and data security. The system allows for the continuous monitoring of parameters and is designed to identify potential breakdown situations and alert users to prevent damage, reduce maintenance costs and increase productivity.

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, Adaptive alerts

1. Introduction

Intelligent sensors, industrial process modelling and simulations, IIoT technologies, AI-based autonomous systems, additive manufacturing, and edge computing systems are expected to affect food-processing industrial processes by enabling integration of AI-based methods and techniques.

Systems of connected IIoT devices, AI-based algorithms and data analytics support industrial food-production facilities in improving efficiency, quality and safety while reducing costs and time to market. The food industry is gradually implementing Industry 4.0 concepts and exploring progression into Industry 5.0.

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Industry 5.0 is the fifth industrial paradigm, where technology is created and developed for more intelligent, productive, sustainable, resilient, and energy-efficient manufacturing systems. Food processing operations have benefitted from Industry 4.0 concepts by improving traceability and monitoring; controlling food quality; improving safety, manufacturing automation and preventive maintenance, while reducing loss and waste. To accelerate the green and sustainable industrial transformation, Industry 5.0 concepts build on these developments to further advance intelligent autonomous systems, robotics, IIoT, connectivity and AI-based processes, methods, and techniques.

Implementing intelligent edge IIoT networks and data analytics tools to improve business productivity and manufacturing sustainability is part of digital transformation in food production facilities. AI can enable further optimisation, automation, rapid industrial processes, and decision-making in all these implementations.

PdM in the food processing industry benefits from advances in the integration of real-time edge IIoT, AI-based models and edge-based training, which enhances maintenance operations. Predicting specific equipment issues and downtimes with increasingly higher success rates enables maintenance personnel to replace fixed maintenance intervals with data-based predictions obtained from IIoT devices placed on industrial equipment/motors for measuring vibration, temperature, and electric current profiles.

When implementing AI-based industrial systems, data-driven AI models require extensive data training and validation. ML and AI models' data requirements involve consideration for scalability, multimodality, interoperability, and standardisation, which require qualified professionals engaged in food industrial processes.

Edge IoT devices and their functions cover edge computing, communication, and data analytics capabilities. An edge IoT device is designed around the computing units (CPUs, GPUs, FPGAs, ASICs platforms, AI accelerators/processing, etc.), communication network, storage infrastructure and the applications or workloads that run on it.

The edge IoT devices can be optimized based on different aspects, like processing, memory, energy, connectivity, size, cost, and their capabilities are constrained by these parameters. AI capabilities integrated into IoT devices or AI on edge significantly enhances their capabilities (e.g., functionality, performances, low latency, low power consumption, high processing power). The shift to processing data at the edge and the edge extended granularity covering micro-, deep- and meta-edge advances the use of AI-based techniques across the edge processing continuum.

Automated AI inspection processes in industrial production facilities use real-time information to divide decisions at the edge and transfer relevant data to on-premises meta-edge systems or the cloud for post-processing, analytics and new model development that extends IIoT edge-based decisions.

2. Predictive Maintenance

This article presents a real-time intelligent system for PdM for edge acquisition, processing and analytics for industrial food production based on the IIoT and AI methods.

The norm EN 13306 [1] defines maintenance as the combination of all technical, administrative, and managerial actions during the lifecycle of an item intended to retain it in or restore it to a state in which it can perform the required function, and identifies several types of maintenance, including PdM.

PdM is based on the continuous monitoring of equipment/motors using IIoT devices and prediction tools to detect trends in the health of a machine and identify when maintenance actions are needed to schedule maintenance activities. PdM uses ML methods, integrity factors, statistical inference approaches and engineering techniques to predict when failure occurs based on historical data. Equipment/motor conditions are monitored using multiple IIoT devices with multi-sensing capabilities, and real-time raw data are pre-processed for further analysis.

IIoT, AI and edge-processing technologies enable new PdM functions to analyse various processes and related data based on condition monitoring. PdM can provide cost-optimal maintenance solutions to achieve overall equipment effectiveness (OEE) [2] higher than 90% [3] by anticipating maintenance requirements and providing a high level of return on investment. Maintenance optimisation is a priority for soybean production, given that effective maintenance can significantly reduce costs by correcting failures of equipment/motors and manufacturing systems. Implementing PdM solutions increases an asset's longevity, reduces maintenance costs and unnecessary inventory, and decreases a company's overall downtime [5].

The technologies that drive PdM fall into different categories, such as IIoT devices, networks, integration, extended intelligent processing and analytics and enhanced intelligent behaviour. Intelligent IIoT devices are used to gather industrial motors/equipment parameters using built-in sensors in IIoT devices or environmental information with the implementation of external sensors. The network transfers data using Bluetooth, LoRaWAN, and Wi-Fi communication protocols. Technology integration allows for data management and data aggregation via the IIoT and intelligent gateways. Extended intelligence assists with data processing and data analytics. In addition, enhanced behaviour allows virtualisation, edge computing processing and services to assist maintenance personnel.

The real-time intelligent system for PdM for edge acquisition, processing and analytics is used to monitor electric motors such as ABB HXR 315 4 B3/HXUR 638G2 B3 (preparation/conditioning) with the following characteristics: 200 kW power, 380/220 V, 360/624 A, 50 Hz, and ~1500 rpm.

The vibration measurements in the range of 10 Hz - 1 kHz are performed using a smart sensor device connected via a Bluetooth IEEE 802.15.1-gateway operating in ISM band, 2.402-2.480 GHz. The sensor measures the radial, tangential and axial vibration and the motor skin temperature that is used for calculating other relevant statistical parameters to evaluate the state of health and detect abnormal patterns.

3. Machine Learning with time-series

ML is an AI-based method whose outcomes can be forecasted based on a model built and trained on past or historical input data and its output behaviour. ML uses computer science and statistical techniques to support learning on different processing units. The learning process can be supervised or unsupervised and depends on the data being used to provide inputs to the ML algorithms and thus can be categorized into several different types such as supervised, unsupervised and reinforcement learning (RL). ML categories are defined as classification, regression, and clustering. In unsupervised ML, there is no feedback from an external trainer or expert – rather, the algorithm identifies the clusters based on the existing data. Clustering, self-organizing maps, and association rules are the three main types of unsupervised learning. Supervised learning determines the unknown classes of items by clustering and then classification. Data utilized by ML algorithms can be categorized into:

- Real data collected from real industrial equipment/motors.
- Simulated and synthetic data generated to meet specific needs (e.g., model validation in ML).

In terms of PdM and manufacturing applications, ML algorithms have their advantages and limitations. Selecting the most appropriate and suitable ML algorithm can be a significant challenge for the requirements of the PdM problem. ML must be applied on different datasets, as each situation requires other data preparation and modelling methods. Datasets can be classified as univariate, multivariate, time-series, sequential, text, and domain-theory. The datasets used in this article are real datasets obtained from real motors and industrial production processes.

Deep learning (DL) uses a complex structure of algorithms modelled on neural networks. DL algorithms are seen as the mathematically complex evolution of ML algorithms. DL describes algorithms that analyse data with a logic structure through supervised and unsupervised learning using a layered topology of artificial neural networks. DL requires large amounts of data and computing power. The development of transfer learning techniques – for example, using pre-trained models – can reduce the amount of data that are required. Feature extraction and classification in the DL algorithm are done in the same phase because the features are extracted automatically, and the algorithm learns from the errors.

Processing the real-time data from IIoT devices connected to industrial equipment using ML algorithms that extract phenomena such as trends (long-term perspective) and seasonality (short-term perspective), as well as noise and anomalies, is extremely useful. Such algorithms can be used for forecasting of operational and health parameters and anomaly detection and thus for increasing the efficiency of PdM industrial applications.

In this article, the proposed solution is that data via several IIoT devices are collected for PdM, referred to here as multivariate time-series data, and ML is applied to key parameters; it runs the model inference on the edge devices that aggregate the data. The approach applies a decentralized ML solution for industrial applications, reducing bandwidth consumption and end-to-end latency. ML is combined with pre-processing techniques, such as fast Fourier transform (FFT), denoising and dimensionality reduction. FFT relies on variations in the frequency to isolate faulty conditions and the successful combination of FFT and ML for fault detection and diagnosis of induction motors has been reported in [21].

There are several approaches to finding anomalies in data and forecasting by using the time-series IIoT device data.

DL algorithms such as Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) have been widely used for time-series analysis and forecasting and PdM in particular [23], due to several advantages over statistical approaches (such as less pre-processing needed). When combined with long short-term memory (LSTM) as hybrid solutions, the benefits of using DL for time-series are even more tangible. Nevertheless, the recently developed ML model Prophet [19] attracts attention due to the motivation behind its development – namely to facilitate accurate and realistic forecasting– and its robustness to outliers, missing values and sudden changes in the time-series forecasting. Successful applications of Prophet have been reported in the literature, either as a single model or as a hybrid model, for example, combined with LSTM [22], yielding better performance and prediction accuracy.

Several implementations of the Prophet ML models for time-series forecasting have been employed for motor vibration analysis and forecasting, which are reported in this article. Experiments have also been performed with NeuralProphet [20], which is the successor of Prophet, retaining all of Prophet's advantages while improving its accuracy and scalability by including neural network modules. In future research to be conducted, the intention is to fuse the latest advances in DL into the Prophet time-series components that have been developed, thus contributing to forecasting with an eye to improving PdM beyond its state-of-the-art functionality.

4. Architecture of the experimental setup and workflows

Food processing requires extensive resources for motors/equipment monitoring, which results in many time-series measurements of relevant parameters. These measurements may exhibit occasionally anomalous behaviour indicating the presence of issues or problems that are difficult to detect manually or prior to failure. To address this issue, we propose an AI-based approach for training ML models on these measurements to predict and alert the anomalous behaviour. The approach is based on time-series predictions about the future and the identification of impending events. That information is subsequently used for planning maintenance and other actions. Based on those predictions, adaptable alerts can be defined. In contrast to static alerts, adaptable alerts can self-adjust to the context and changes in the context in the future.

The ML model can be scheduled to retrain periodically to automate the whole monitoring and alerting process. These intelligent and adaptable alerts reduce the need to have an operator continuously watching dashboards or to maintain static thresholds. In addition, the more advanced alerting capabilities allow for a wide range of intelligent alerts to be configured and set for various scenarios and use cases.

The employment of ML in the prediction equips the model to detect false alerts by effectively grasping new ways to understand the measurements being produced, thus improving continuously on the notion of what constitutes anomalous behaviour. The learning and inference process is transparent, which permits human validation and eventual correction.

Since ensuring that models remain trained and up to date with the latest actual data may be a resource-consuming endeavour, not all measurements need to be used for prediction.

For the soybean production PdM use case, the axial, radial and tangential vibrations are key measurements for the health status of the motors and are therefore continuously monitored and used for prediction. Experimental results confirm that the prediction is even more accurate when using conglomerated and aggregated data. Thus, the overall vibration velocity (e.g., RMS) is also monitored and used for prediction.

The vibration root-mean-square velocity (RMS velocity) technique determines the vibration signal trend over time. As machines wear, their vibration velocity increases, and monitoring RMS velocity trends provides an indicator of wear that is compared to pre-determined thresholds to identify a need for maintenance. Acceleration is compared to pre-determined thresholds to detect bending or breakage in mechanisms for motors.

As a rule, the measurements to be used for prediction are those of parameters with service level objectives that are of key relevance for the soybean production process.

Such parameters also tend to exhibit predictable patterns and are thus particularly suited to prediction.

The architecture of the experimental setup is depicted in Figure 1.

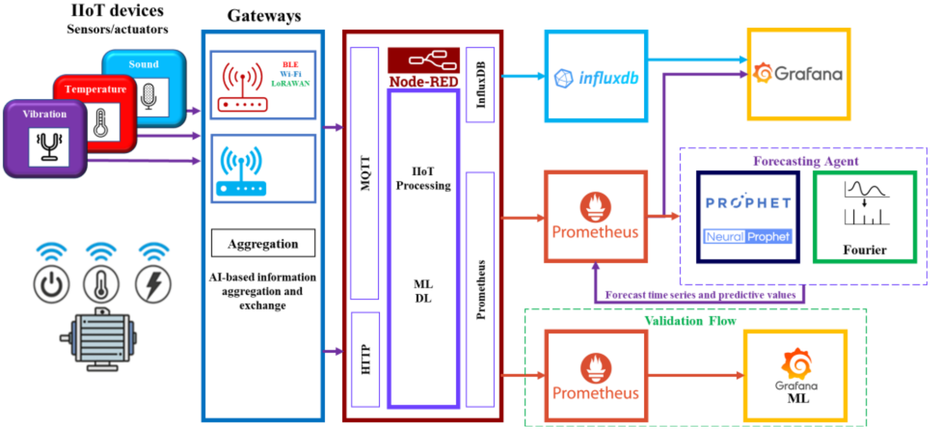


Figure 1. Architecture of the experimental setup

The architecture uses a five-item software stack: Node-RED [16] to collect measurements from IIoT devices and provide a development environment with ML functionalities, InfluxDB [10] and Prometheus [14] for storage, monitoring and alerting, Python [15] framework for forecasting and Grafana [13] to create visualisations of actual and predicted data in the form of charts, graphs and more. Additionally, the implementation uses a Grafana ML to run in validation mode.

The Node-RED collects all data in real time from various sensors, wiring together IIoT devices, APIs, and services. It has the flexibility to connect to a broad range of existing IIoT sensors and devices, supporting standard-based protocols such as MQTT [16][11], HTTP and telemetry protocols such as OPC-UA [12]. It also actively pushes the data into the InfluxDB server and exposes the data to a Prometheus server.

InfluxDB is an essential component in the IIoT data architecture, with capabilities to acquire, store, enrich and analyse a large amount of time series from IIoT devices at the edge. While both InfluxDB and Prometheus are time-series which can store data, InfluxDB is mainly utilised for managing, analytically pre-processing, and storing IIoT data from sensors in real time, while Prometheus is used predominantly for monitoring and alerting.

Prometheus uses a pull model and a scheduler to scrap metrics from all systems being monitored, each running an exporter to expose sensor data in an HTTP endpoint. It has an advanced alerting system, allowing to track metrics at all edge levels. Visualizations and alerting are powered by PromQL queries.

The forecasting agent is performing predictions with various time-series forecasting models (e.g., linear regression, Prophet, FFT, etc.). The agent is a clustered system of components equipped with query and storage capabilities as well as statistical algorithms and ML techniques to generate predictions based on historical data.

One such component, a Python client, is interacting with both InfluxDB, and Prometheus. It generates Flux queries to extract data from InfluxDB, sends the data to ML algorithms and FFT, and then generates a PromQL query to expose the predictions to the Prometheus instance for create/update the alerts.

The predicted measurements are scraped by the Prometheus instance and used to configure intelligent and adaptable alerts.

Both actual and predicted measurements can be visualised on a Grafana standalone server installed on the meta-edge.

The Grafana dashboards are connected to both InfluxDB and Prometheus and can be used interactively to visualize the health and operational status of the motors.

Figure 2. Grafana dashboard powered by Flux queries over real-time sensor data.

Figure 2, Figure 3, Figure 4, and Figure 5 show various snapshots from dashboards designed to display partial or overall health of soybean production motors/equipment.

Figure 2 shows a Grafana dashboard powered by Flux queries over real-time sensor data. The dashboard can be used interactively, by selecting the motor being monitored as regard to operational and health parameters.

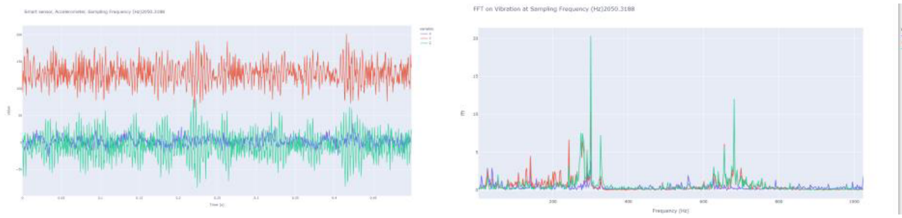
Figure 3 shows a Prometheus dashboard powered by PromQL queries over scrapped key measurements, visualizing in a graph. Prometheus user interface does not offer all the features necessary to display the overall health of the motors/equipment, so that Grafana is mostly used for this purpose.

a) Skin temperature from two motors.

b) Vibration (Axial, Radial, Tangential) from one motor.

Figure 3. Prometheus dashboard powered by PromQL queries over scrapped key measurements.

Figure 4 shows the vibration measurements along X, Y, Z axis at sampling frequency (Hz); 2050.3188 and their FFT values. Frequency-domain parameters offer additional information for health conditioning [4]. The vibration signals are transformed by applying the FFT, decomposing the signal into its different frequencies.



a) Vibration measurements along X, Y, Z axis at 2050 Hz sampling frequency, input to FFT.

b) FFT on vibration measurements along X, Y, Z axis at 2050 Hz sampling frequency.

Figure 4. Vibration measurements and FFT.

Figure 5 shows vibration measurements, actual and predicted, from the Prophet workflow, part of the forecasting agent.

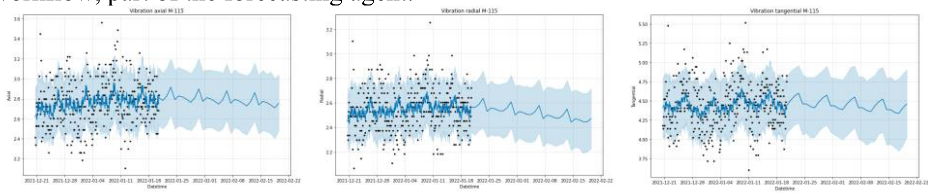


Figure 5. Actual and predicted values for Axial (left), Radial (middle), Tangential (right) Vibration from the Prophet workflow.

The above components are part of the development flow. The experimental architecture allows for an additional flow in which real-time data are processed in Node-RED by an exporter and scraped by another Prometheus instance. This instance is configured to push real-time measurements to Grafana ML for forecasting and configuring alerts. Grafana ML allows for the creation of forecasts based on the Prophet algorithm. The ML models are trained on real-time data to perform time-series forecasting. This flow is mainly used for validation purposes. Both actual and predicted measurements can be queried with PromQL, and the query results can be visualised in Grafana. This is shown in Figure 6.

The shaded area between the upper and lower bounds represents the confidence interval for the prediction. The alerts are set to detect when the time-series is outside of the confidence interval. The criteria for alerting can be based on a percentage or an absolute difference from the predicted values rather than using static thresholds.

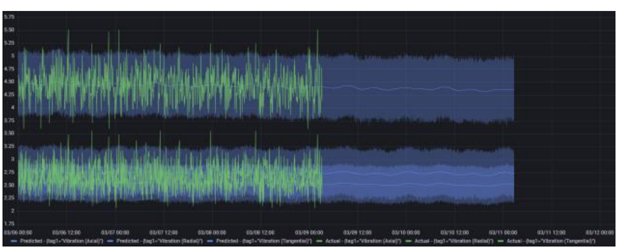


Figure 6. Actual and predicted values from Grafana ML for Vibration (Axial, Radial, Tangential) powered by PromQL.

An important feature of the proposed architecture is that it can incorporate all three micro-, deep- and meta-edges, allowing the full range of functionality (storage, analysis, ML, analytics, dashboard, and alerting) to be embedded where needed. Anomaly detection, classification and forecasting can be deployed not only on the meta-edge on historical data, but also on the deep-edge on real-time data.

For instance, Node-RED can be deployed at deep-edge, i.e., gateway, or at meta-edge, i.e., on premises edge server. While it collects data in real time from various sensors, incorporating ML into the flow is another key component. The Node-RED ML nodes can be used to perform classification and outlier detection and can be programmed to retrain the models periodically based on new measurements. Several flows have been implemented that employ ML algorithms based on decision trees, K-nearest-neighbour, support vector machines, random forest, and neural networks.

A sub-flow is dedicated to vibration analysis using FFT, while another sub-flow uses OPC-UA to control communication between the SCADA software and OPC server.

ML workflows are automated, allowing them to be easily integrated into more complex flows that implement the full range of functionalities mentioned above.

5. Summary

The article presents a new AI-based edge acquisition, processing, and analytics for industrial food production. This framework first extracts the time-series signal from the tri-axial IIoT device. Then, the acquired signal is processed using statistical methods and ML techniques to generate the condition motor indicators. As demonstrated in the experiments, vibration feature extraction techniques play a critical role in the fault diagnosis of industrial motors.

Time-domain techniques include raw signals, filter-based signals, and stochastic and model-based methods. The statistical values such as RMS, mean, kurtosis and crest factor are compared with a threshold value for fault detection in industrial motors. Frequency domain features are used effectively to detect faults through the utilization of FFT techniques on real-time vibration signals.

This article describes the real-time intelligent system for PdM for edge acquisition, processing and analytics for industrial food production based on the IIoT and AI methods. The approach uses a decentralised ML solution for industrial applications that reduces bandwidth consumption and end-to-end latency. The datasets used in this article are real datasets obtained from real motors and industrial production processes.

When edge devices communicate with each other, they may run into several known connectivity issues, such as bandwidth consumption and latency; thus, adding AI capabilities to these devices may pose further challenges. Traditional approaches involve sending the data from the devices to a server to perform ML calculations and sending the results back to the devices for appropriate action. The decentralized approach proposed in this article differs substantially from traditional approaches as it entails incorporating ML into devices across the edge continuum and powering them with predictors, classifiers, anomaly detectors and neural networks, considering the capabilities/limitations of each type of device. The solution developed implies that ML is applied to vibration signals; it runs the model inference on the edge devices that aggregate the data.

For the soybean production PdM use case, the axial, radial and tangential accelerations are key measurements for the health status of the motors and are therefore continuously monitored and used for prediction. The experimental results confirm that the forecast is even more accurate when using conglomerated and aggregated data.

The soybean production is implemented as a linear process, and the motors and equipment are part of the critical elements, as there are no redundant motors and equipment that may take over their functions in case of malfunction or failure. This increases the need for advanced PdM solutions to prevent motor failures and reduce unplanned or accidental downtime, thus avoiding any overall system failures that may be caused by single points of failure.

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