

Field LAB

*Where Ideas Meet
the Factory of the Future*

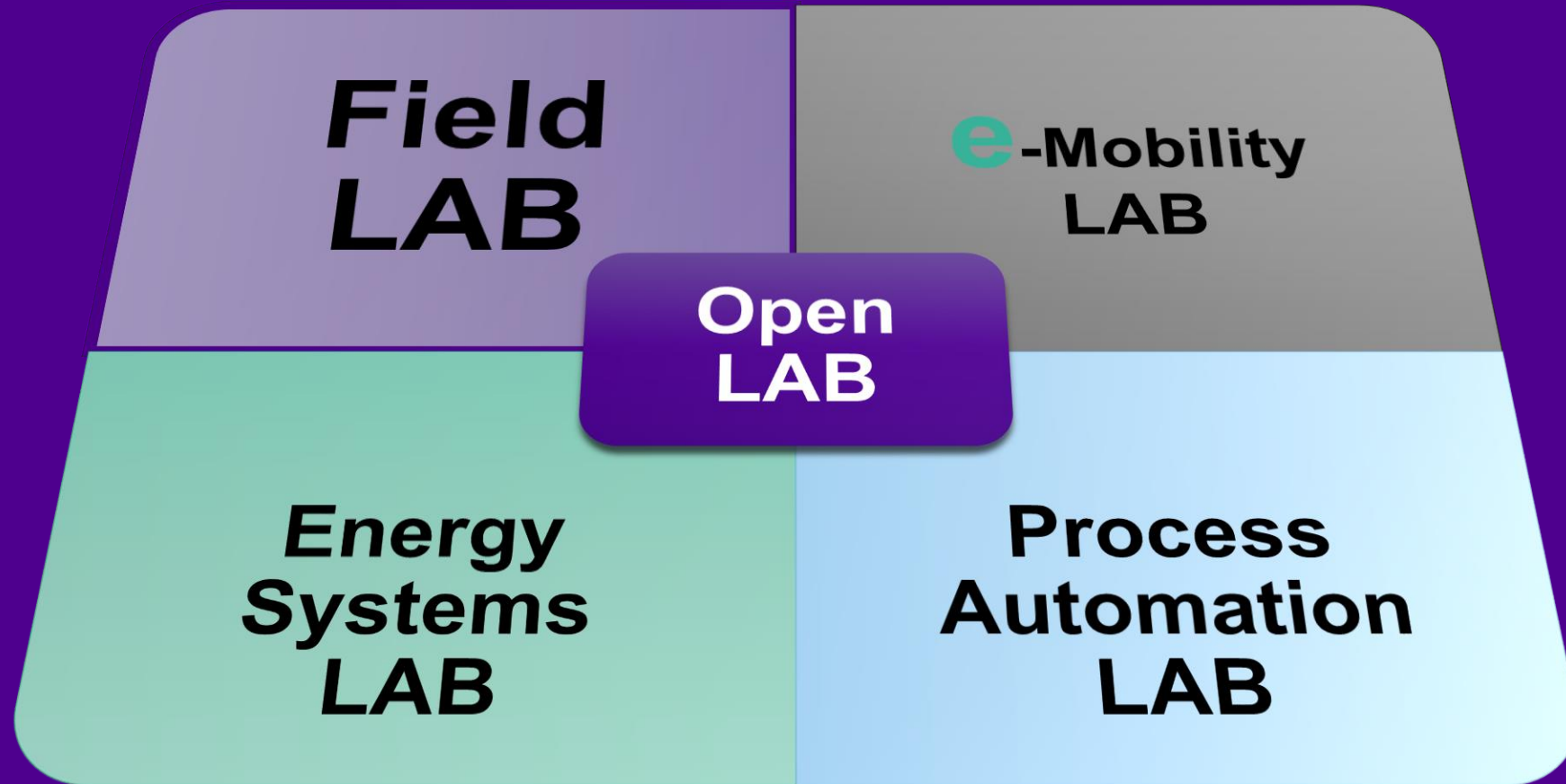
2024

Unleashing the Engineering Potential with New Skills

FieldLAB provides an innovative space and equipment for companies and other actors to try, develop and test Industry 4.0 practices, aiming to elevate technology and competence in Intelligent Machines and Equipment.

Open LAB

*RDI services and expertise for
companies and communities*





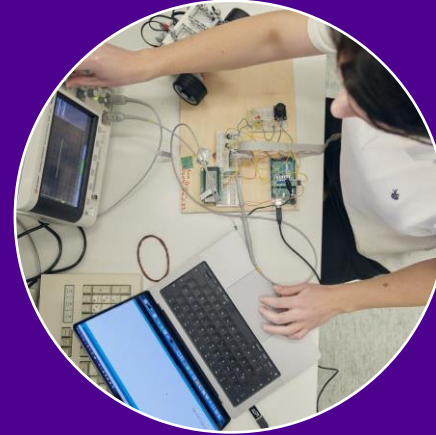
**Additive
Manufacturing**



Robotics



**Industrial
Engineering**



Industrial Data



**Virtual &
Human
Centric
FieldLAB**

Capabilities

Introduction to Predictive Maintenance

- Predictive Maintenance is a proactive approach that uses **data analysis and machine learning** to predict equipment failures before they occur. This method helps in reducing downtime, optimizing maintenance schedules, and improving overall operational efficiency.



<https://maintainly.com/articles/the-power-of-predictive-maintenance-a-comprehensive-guide>

Predictive Maintenance

What is Predictive Maintenance?

- Predictive Maintenance is a proactive strategy that leverages data analysis and machine learning to foresee equipment failures before they happen. By [analyzing historical and real-time data](#), this approach identifies patterns and anomalies that indicate potential issues. This foresight allows maintenance teams [to address problems before they escalate](#), reducing unplanned downtime and extending the lifespan of equipment. Predictive Maintenance not only enhances operational efficiency but also optimizes [maintenance schedules, ensuring that resources are used effectively](#). This method is particularly valuable in industries where [equipment reliability is critical](#), such as manufacturing, energy, and transportation

Predictive Maintenance

Benefits of Predictive Maintenance

- Predictive Maintenance offers numerous benefits, including **reduced downtime, cost savings, and improved asset reliability**. By predicting failures before they occur, organizations can schedule maintenance activities during planned downtimes, minimizing disruptions to operations. This proactive approach also reduces the need for **emergency repairs**, which are often more costly and time-consuming. Additionally, Predictive Maintenance helps **extend the lifespan of equipment** by addressing issues early, preventing further damage. Improved asset reliability leads to increased productivity and customer satisfaction. Overall, Predictive Maintenance enhances operational efficiency, reduces maintenance costs, and contributes to a **safer working environment**.

Predictive Maintenance

types of system maintenance: corrective, preventative, and predetermined:

- **Corrective maintenance** is a type of maintenance that occurs when a breakdown has already happened. This type is often used for low-value equipment that can be quickly fixed or changed (e.g., light bulbs). Corrective maintenance can be applied for systems that don't have a significant impact on business operations if they malfunction.
- **Preventative maintenance** focuses on pre-scheduled checking of a system's performance to prevent any unexpected failure. Businesses usually leverage this type of maintenance for moderately valued equipment. Preventive maintenance occurs outside of production hours.
- **Predetermined maintenance** revolves around predicting potential failures without relying on any prescheduled maintenance. Predetermined maintenance allows businesses to estimate how long the equipment will run. This type of maintenance helps to take care of expensive equipment.

<https://lebergssolutions.com/blog/machine-learning-predictive-maintenance-how-implement-it>

Predictive Maintenance

Key Components of Predictive Maintenance

- Predictive Maintenance relies on several key components: [data collection](#), [data analysis](#), and [machine learning algorithms](#), [predictive Models](#).
- [Data collection](#) involves gathering information from various sensors and monitoring devices installed on equipment. This data includes parameters such as [temperature](#), [vibration](#), [pressure](#), and more.
- [Data analysis](#) is the process of examining this information to identify patterns and trends that indicate potential issues.
- [Machine learning algorithms](#) play a crucial role in Predictive Maintenance by analyzing large datasets and making accurate predictions about equipment failures. These components work together to provide actionable insights that help maintenance teams make informed decisions.

Predictive Maintenance

Key Components of Predictive Maintenance

- Predictive Models

Organizations develop predictive models based on historical data, equipment specifications, and real-time monitoring. These models predict the remaining useful life of assets and anticipate when maintenance activities should be performed. Predictive models are continuously refined and improved as more data becomes available, enhancing their accuracy.

Predictive Maintenance

Data Collection in Predictive Maintenance

- Data collection is a fundamental aspect of Predictive Maintenance. It involves the use of sensors and monitoring devices **to gather real-time information about equipment performance**. These sensors measure various parameters, such as temperature, vibration, pressure, and humidity, providing a comprehensive view of the equipment's condition. The collected data is then transmitted to a **central system for analysis**. Effective data collection requires the integration of advanced technologies, such as the Internet of Things (IoT), which enables seamless communication between devices. Accurate and reliable data collection is essential for making **precise predictions** and ensuring the success of Predictive Maintenance initiatives.

Predictive Maintenance

Data Analysis in Predictive Maintenance

- Data analysis is a critical step in the Predictive Maintenance process. It involves examining the collected data to **identify patterns, trends, and anomalies** that may indicate potential equipment failures. Advanced analytical techniques, such as statistical analysis, machine learning, and artificial intelligence, are used to process and interpret the data. These techniques help in detecting early warning signs of issues, allowing maintenance teams to take proactive measures. Data analysis also provides valuable insights into the overall health and performance of equipment, enabling organizations to optimize maintenance schedules and improve operational efficiency.

Predictive Maintenance

Machine Learning in Predictive Maintenance

- Machine learning is a key technology in Predictive Maintenance.
- It involves the use of algorithms that can [learn from historical and real-time data](#) to make accurate predictions about equipment failures.
- These algorithms analyze large datasets to identify patterns and correlations that may not be apparent through traditional analysis methods.
- Machine learning models can [continuously improve their accuracy over time as they are exposed to more data](#). By leveraging machine learning, organizations can enhance their Predictive Maintenance capabilities, making more informed decisions and reducing the risk of unexpected equipment failures.

Predictive Maintenance

What types of data are required for effective ML-based predictive maintenance?

- ML-based predictive maintenance relies on various types of data to train accurate models. Commonly used data includes sensor data, historical maintenance records, and environmental conditions. Integrating data from diverse sources helps ML models understand normal operating conditions and detect deviations that may indicate potential failures. Additionally, real-time data enhances the accuracy of predictions and enables timely interventions to prevent equipment failures.

Predictive Maintenance

Implementing Predictive Maintenance

- Implementing Predictive Maintenance involves several steps: assessing [current maintenance practices](#), selecting [appropriate technologies](#), and [integrating them into existing systems](#).
- The first step is to evaluate the current maintenance strategy and identify areas for improvement.
- Next, organizations need to choose the right sensors, monitoring devices, and analytical tools that align with their specific needs. Integration is crucial, as the new technologies must work seamlessly with existing systems and processes.
- Training and support are also essential to ensure that maintenance [teams can effectively](#) use the new tools. Successful implementation requires careful planning, collaboration, and ongoing evaluation.

Predictive Maintenance

Challenges in Predictive Maintenance

- While Predictive Maintenance offers significant benefits, it also presents several challenges. One of the main challenges is [the initial investment in sensors, monitoring devices, and analytical tools](#). Additionally, integrating these technologies into existing systems can be complex and time-consuming.
- [Data quality and accuracy are critical](#), as inaccurate data can lead to incorrect predictions and ineffective maintenance actions.
- Another challenge is the need for skilled personnel who can interpret the data and make informed decisions. Despite these challenges, the long-term benefits of Predictive Maintenance, such as reduced downtime and cost savings, make it a worthwhile investment for many organizations.

Predictive Maintenance

Predictive Maintenance models

- Predictive Maintenance models leverage **both historical and real-time data to accurately predict** the remaining useful life (RUL) of equipment.
- By analyzing **patterns and trends**, these models can forecast when a machine is likely to fail, allowing maintenance to be scheduled at the most opportune time. This proactive approach helps in preventing unexpected breakdowns, reducing downtime, and optimizing maintenance schedules. Consequently, the lifespan of machinery is extended, and overall operational efficiency is improved.
- Predictive Maintenance models are essential tools in modern industrial settings, where equipment reliability and performance are critical to maintaining productivity and minimizing costs.

Predictive Maintenance

Predictive Maintenance – Digital twins

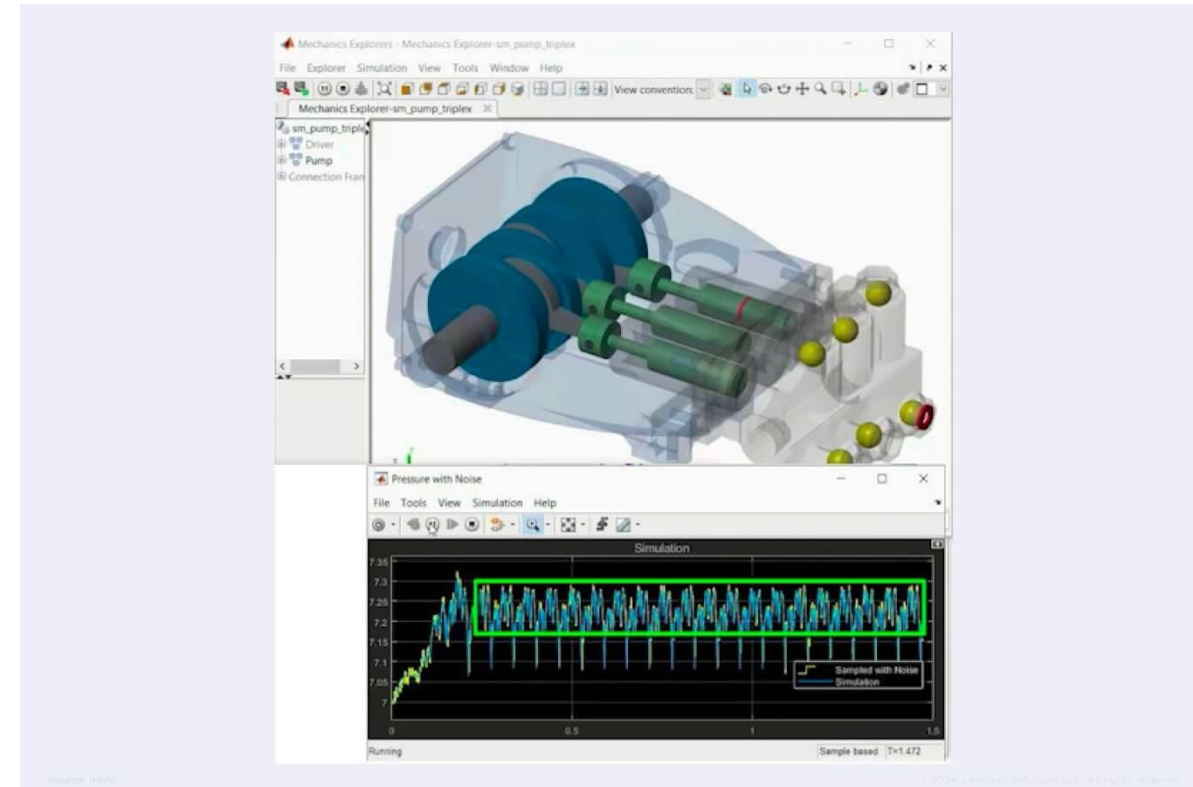
- In some cases, manufacturers cannot collect data from physical equipment during its breakdown. To cause failure on purpose for data collection may lead to permanent damage and money losses. That's when digital twins come in handy. A digital twin is a piece of needed physical equipment recreated in a digital environment. A digital twin can mimic the reaction of real equipment during its breakdown. Manufacturers can collect the needed data from a digital twin to understand what issues to prevent in the future.

<https://lebergssolutions.com/blog/machine-learning-predictive-maintenance-how-implement-it>

Predictive Maintenance

Predictive Maintenance – Digital twins

In the image, you can see a digital twin pump created with the help of Simscape, MATLAB, and Simulink. When the needed data is collected, data science engineers train an ML algorithm on simulation data to predict similar failures.



<https://leberg solutions.com/blog/machine-learning-predictive-maintenance-how-implement-it>

Predictive Maintenance

Predictive Maintenance models, example: Industrial Pumps

- Scenario:
 - A manufacturing plant uses several industrial pumps to maintain fluid flow in its production process. These pumps are critical to the operation, and any unexpected failure can cause significant downtime and financial loss.

Predictive Maintenance

Predictive Maintenance models, example: Industrial Pumps

- Data Collection:
 - Historical Data: Historical maintenance records, failure logs, and performance data of the pumps.
 - Real-Time Data: Sensors installed on the pumps collect real-time data such as vibration levels, temperature, pressure, and flow rate.

Predictive Maintenance

Predictive Maintenance models, example: Industrial Pumps

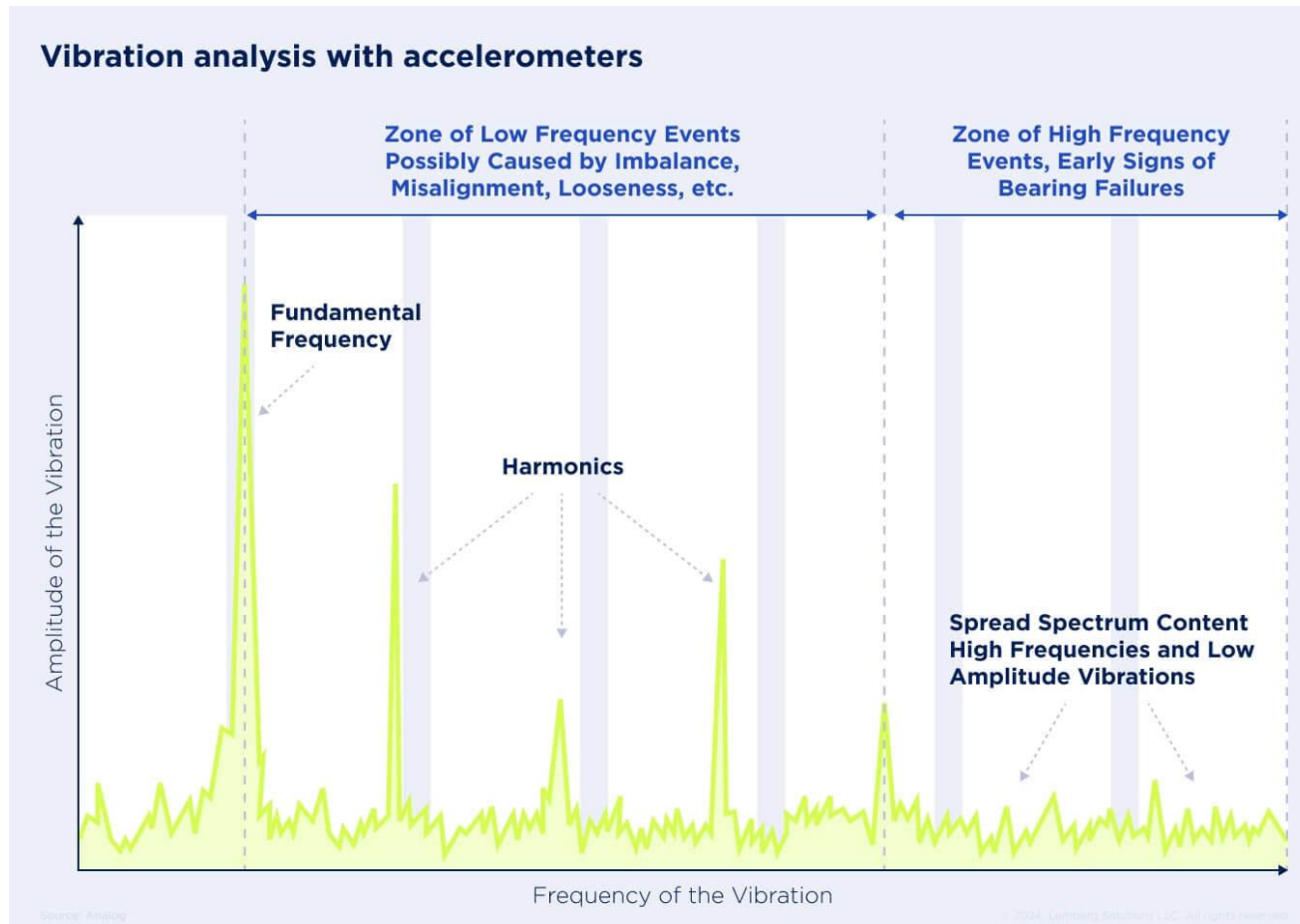
Model Development:

- 1.Data Preprocessing:** Clean and preprocess the collected data to handle missing values, outliers, and noise.
- 2.Feature Engineering:** Extract relevant features from the data, such as average vibration levels, temperature trends, and pressure fluctuations.
- 3.Model Training:** Use machine learning algorithms (e.g., Random Forest, Gradient Boosting, or Neural Networks) to train a model on the historical data. The model learns to identify patterns and correlations between the sensor data and past failures.

Prediction: The trained model continuously analyzes the real-time data from the sensors. It predicts the Remaining Useful Life (RUL) of each pump by identifying patterns that indicate potential failures.

Predictive Maintenance

Vibration analysis with accelerometers



<https://lebergolutions.com/blog/machine-learning-predictive-maintenance-how-implement-it>

Predictive Maintenance

Predictive Maintenance models, example: Industrial Pumps

Actionable Insights:

- 1.Maintenance Scheduling:** The model provides alerts when a pump is predicted to fail within a certain timeframe. Maintenance can be scheduled proactively to replace or repair the pump before it fails.
- 2.Resource Optimization:** Maintenance resources and spare parts can be managed more efficiently, reducing inventory costs and ensuring that critical components are available when needed.
- 3.Downtime Reduction:** By preventing unexpected failures, the plant minimizes downtime and maintains continuous production.

Predictive Maintenance

Predictive Maintenance models, example: Industrial Pumps

Outcome: The implementation of the Predictive Maintenance model leads to improved equipment reliability, extended machinery lifespan, and optimized maintenance schedules. This results in increased operational efficiency and reduced maintenance costs.

Predictive Maintenance

Data that is used for analysis:

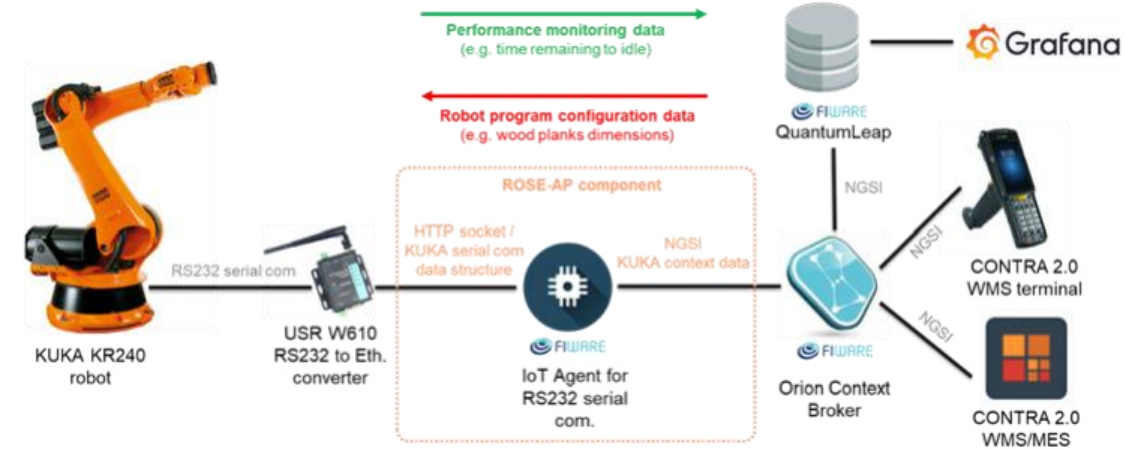
- 1.Vibration Analysis:** Monitoring vibrations can help detect imbalances, misalignments, and bearing failures.
- 2.Temperature Monitoring:** Abnormal temperature changes can indicate issues like overheating or insufficient lubrication.
- 3.Oil Analysis:** Checking oil quality and contamination levels can reveal wear and tear in machinery.
- 4.Acoustic Emissions:** Listening for unusual sounds can help identify cracks, leaks, or other structural issues.
- 5.Infrared Thermography:** Using thermal imaging to detect hot spots that indicate electrical or mechanical problems.
- 6.Pressure Monitoring:** Variations in pressure can signal blockages, leaks, or pump failures.
- 7.Current and Voltage Analysis:** Electrical measurements can detect motor issues, insulation failures, and other electrical problems.
- 8.Humidity and Moisture Levels:** High moisture levels can lead to corrosion and electrical failures.
- 9.Speed and Rotation Measurements:** Monitoring the speed and rotation of components can help identify performance issues.
- 10.Visual Inspections:** Regular visual checks can catch signs of wear, corrosion, or other physical damage

Data Collection and Integration

- The first step in Predictive Maintenance is **collecting data** from various sources such as sensors, equipment logs, and operational records. This data is then integrated into a centralized system for analysis. Effective data collection and integration are crucial for accurate predictions and decision-making.

Predictive Maintenance

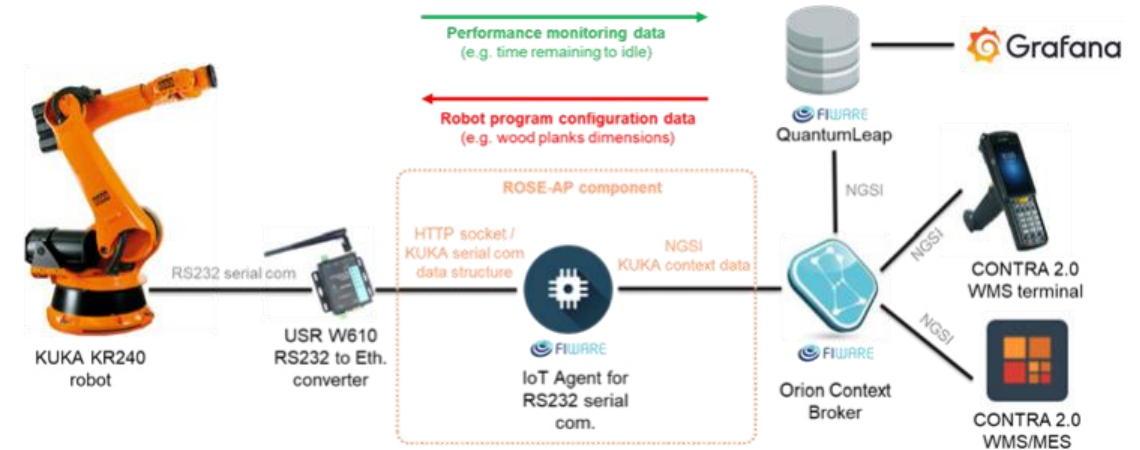
Implementing Predictive Maintenance with FIWARE



- **FIWARE Overview:** Open-source platform that provides a set of APIs and tools for building smart applications.
- **Key Components:**
 - **Context Broker:** Manages context information in real-time.
 - **IoT Agents:** Connects IoT devices to the FIWARE ecosystem.
 - **Data Models:** Standardized models for representing data.

Predictive Maintenance

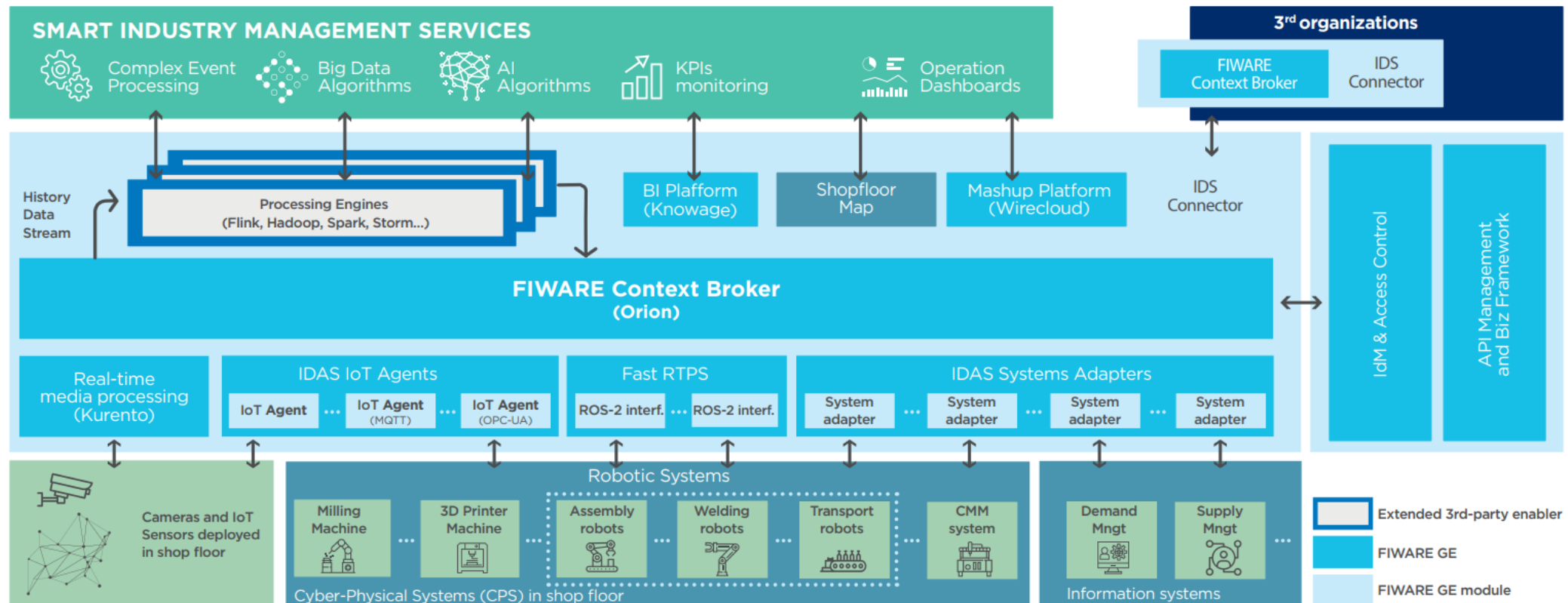
Implementing Predictive Maintenance with FIWARE



- **Data Collection:** Use IoT sensors to gather data on equipment performance.
- **Data Integration:** Connect sensors to FIWARE using IoT Agents.
- **Real-time Monitoring:** Use the Context Broker to monitor data in real-time.
- **Data Analysis:** Apply machine learning algorithms to predict failures.
- **Actionable Insights:** Generate alerts and maintenance schedules based on predictions.

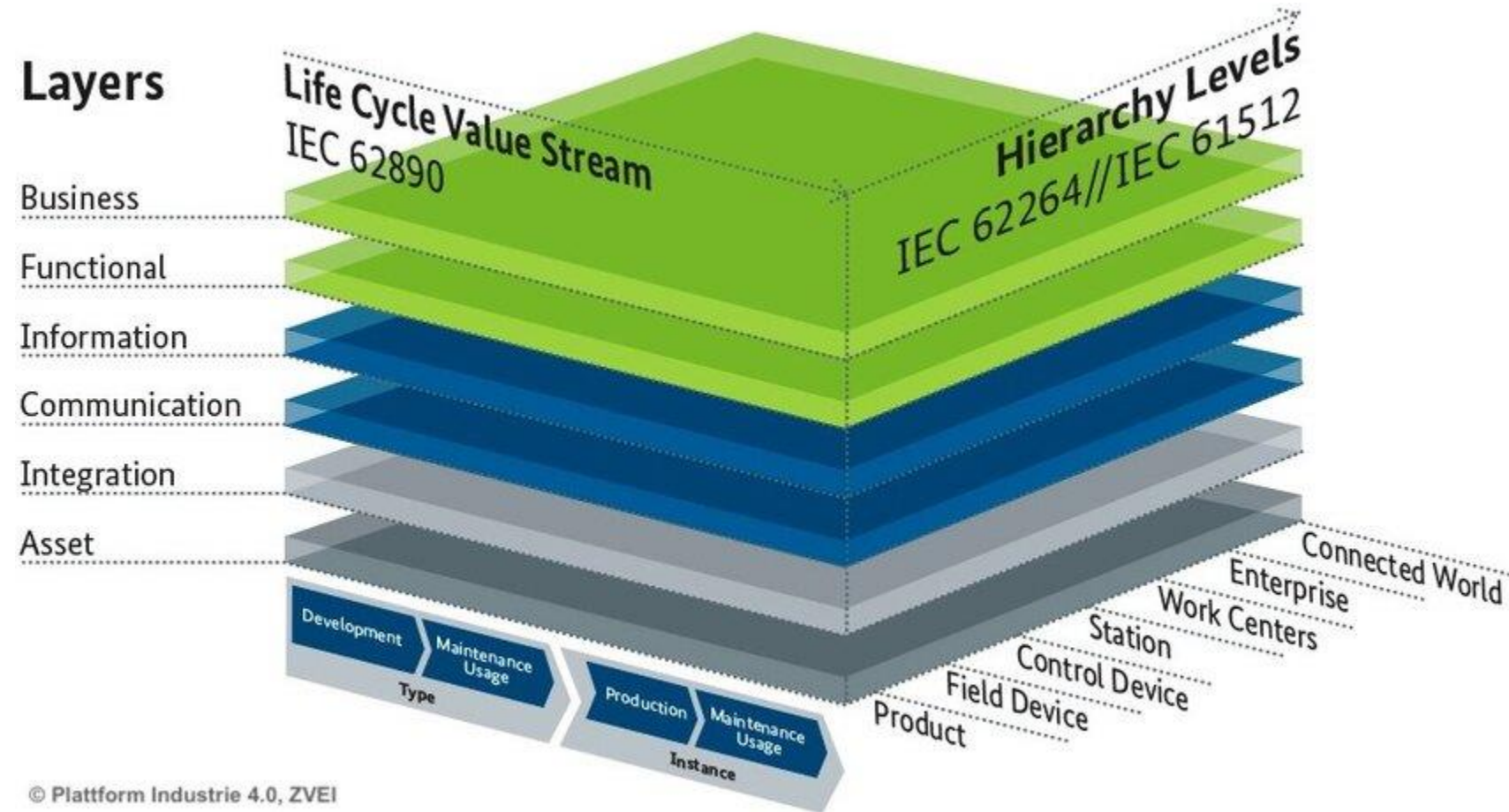
Predictive Maintenance

Implementing Predictive Maintenance with FIWARE



Predictive Maintenance

Industry 4.0 Models

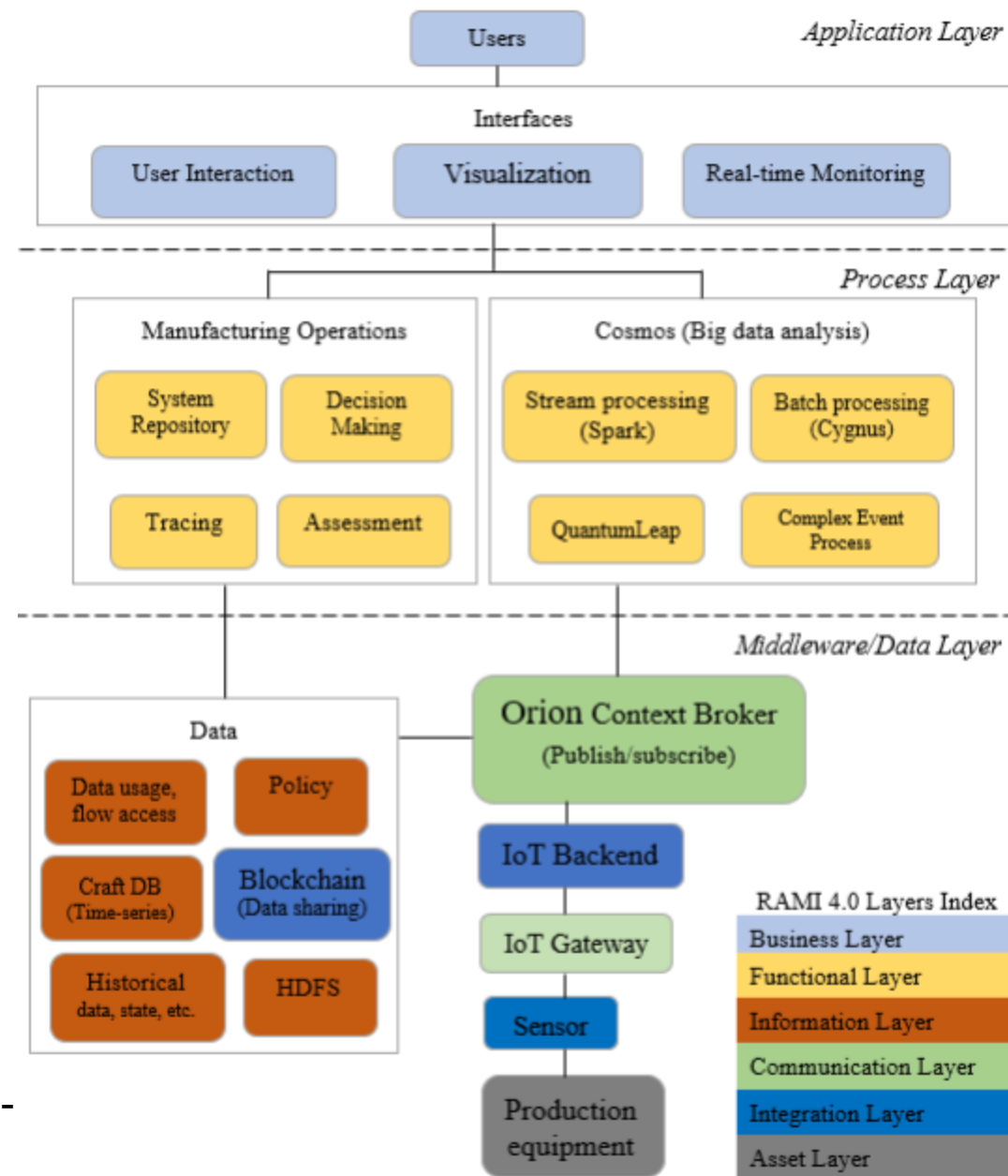


Reference Architectural Model Industry 4.0

https://www.researchgate.net/figure/Reference-Architectural-Model-Industry-40-2_fig1_350132076

Predictive Maintenance

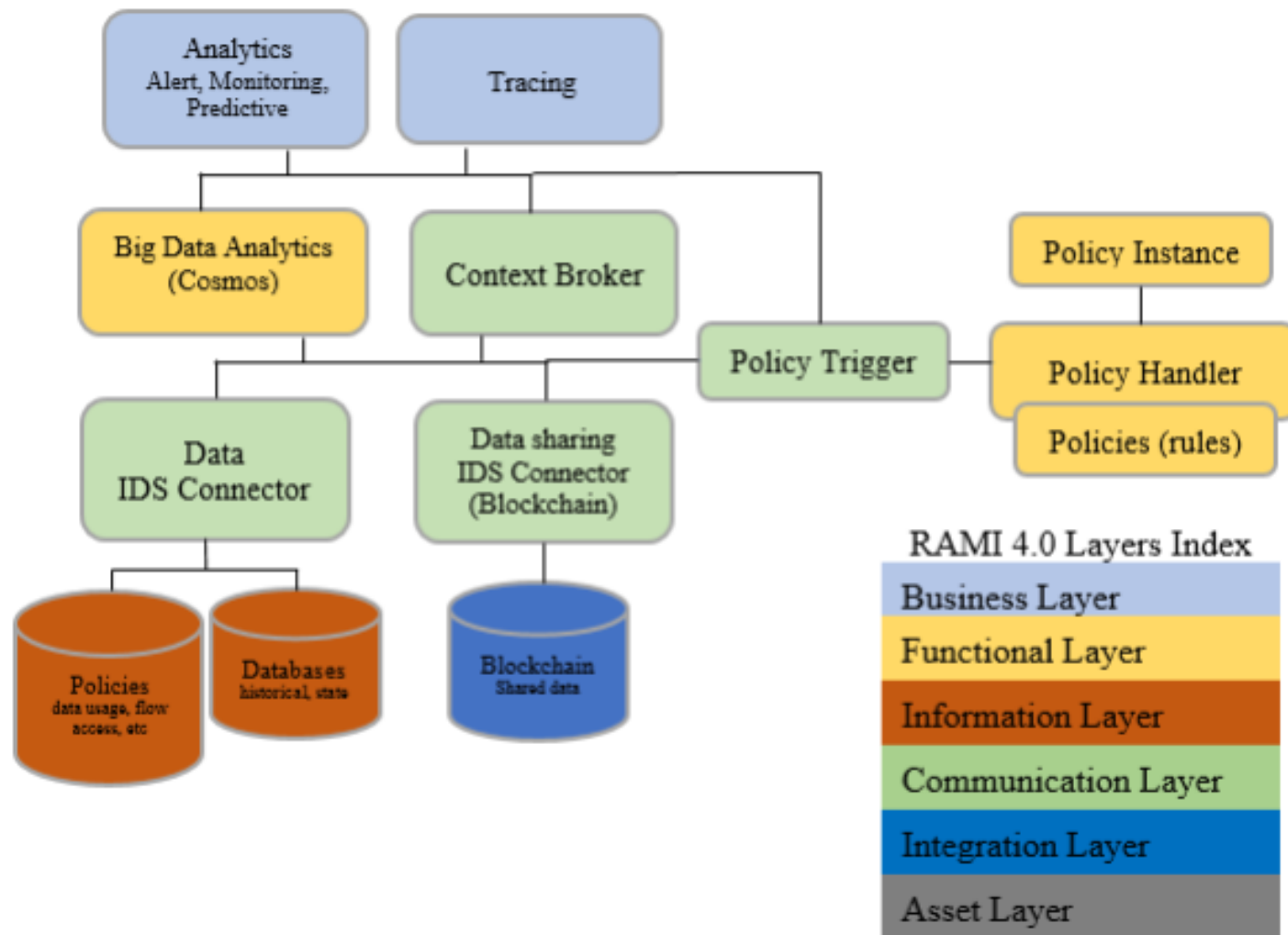
Implementing Predictive Maintenance with FIWARE



<https://www.semanticscholar.org/paper/Predictive-Maintenance-in-Industry-4.0-Sang-Xu/45a20535fb293828c34347192e9fbf4d764f33e3>

Predictive Maintenance

Implementing Predictive Maintenance with FIWARE



A RAMI 4.0 View **Monitoring and Tracing Analytics based on FIWARE**

<https://www.semanticscholar.org/paper/Predictive-Maintenance-in-Industry-4.0-Sang-Xu/45a20535fb293828c34347192e9fbf4d764f33e3>

Predictive Maintenance – FLAB DEMO

acoustic data - Predictive Maintenance Using Sound

Traditional methods of predictive maintenance are categorized into three sections:

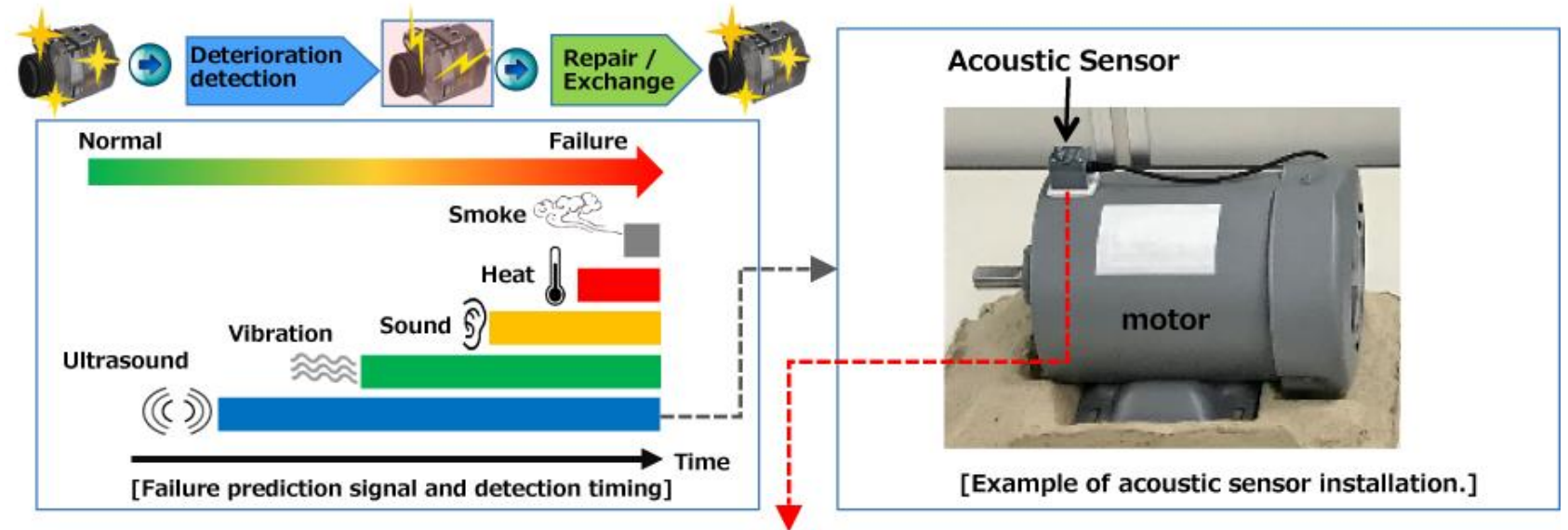
- 1) Recognizing abnormal sounds using conventional hardware tools like a ultrasonic microphone before machines start to fail.
- 2) Detection of discharge or leakage detection using infrared cameras
- 3) Using sensors that can recognize pressure, temperature or vibration changes. Recent advances in Artificial Intelligence (AI) has changed the landscape in how predictive maintenance would be optimized.

<https://growthbotics.medium.com/a-primer-predictive-maintenance-using-sound-afe2e169cc40>

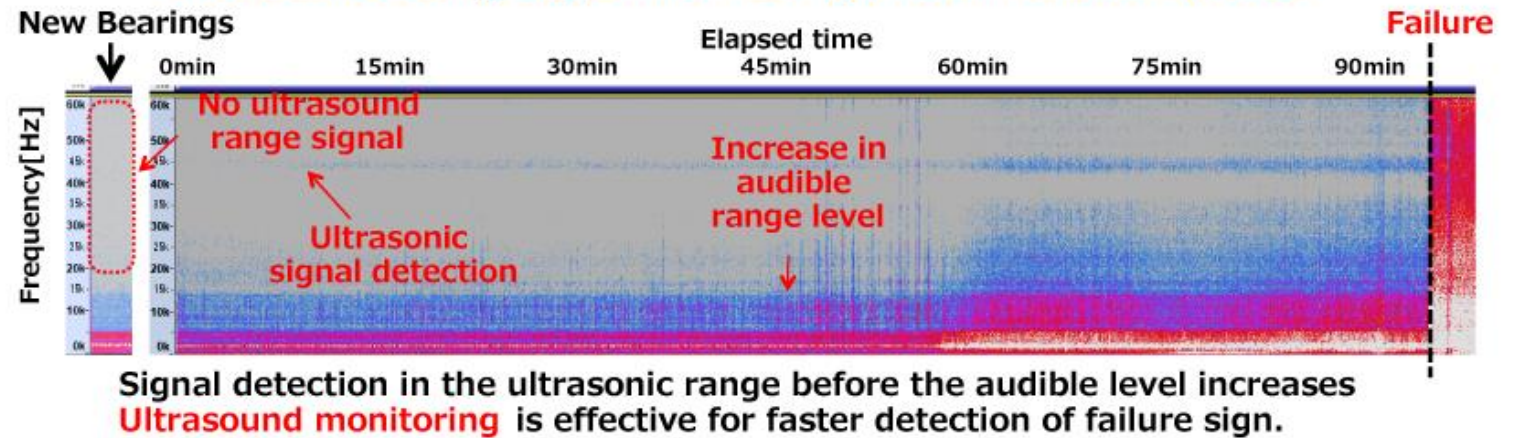
<https://lebergersolutions.com/case-study/ai-based-ultrasonic-device-rolling-bearing-condition-monitoring>

Predictive Maintenance – FLAB DEMO

acoustic data



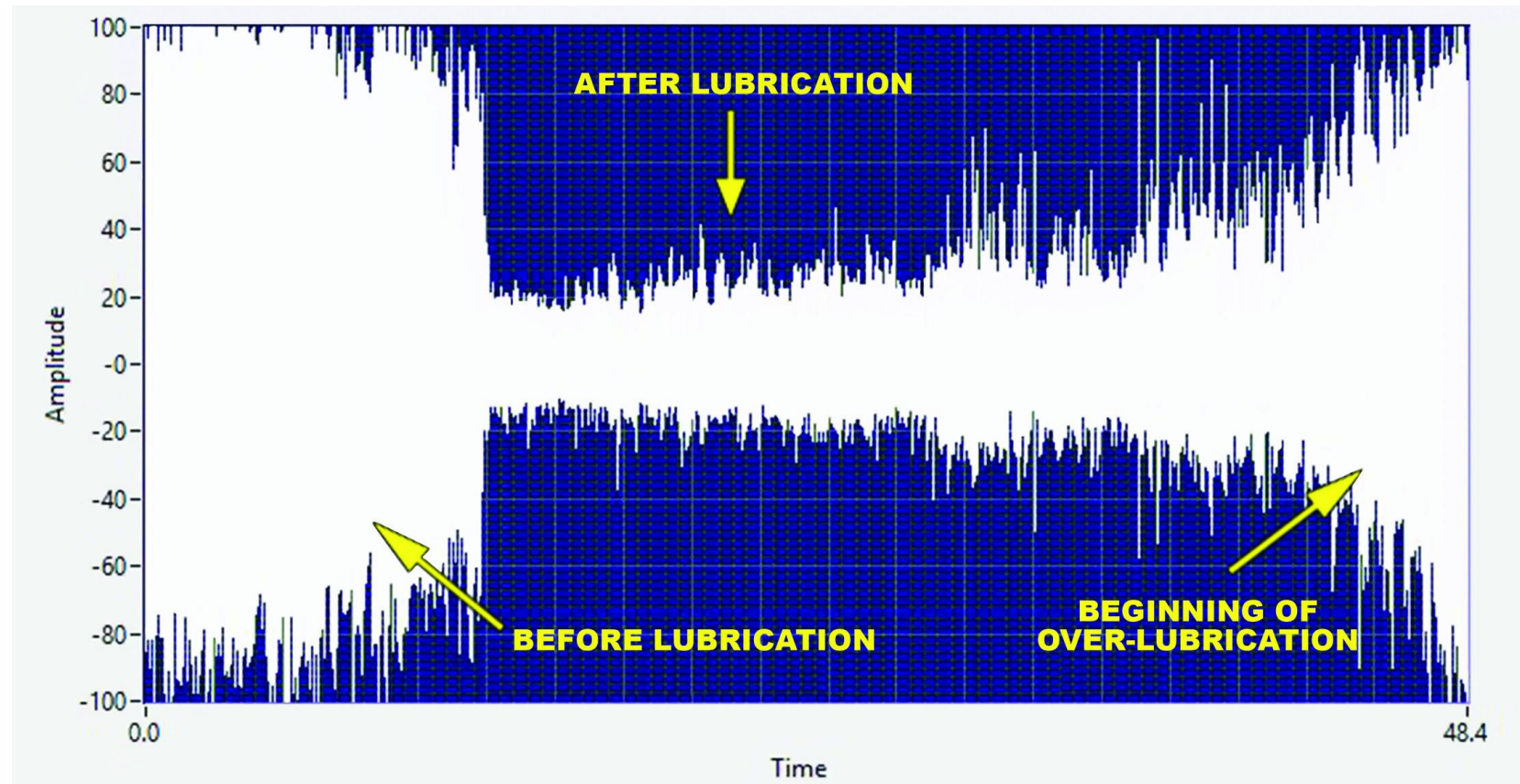
Accelerated Bearing Degradation Test Spectrum Transition Results



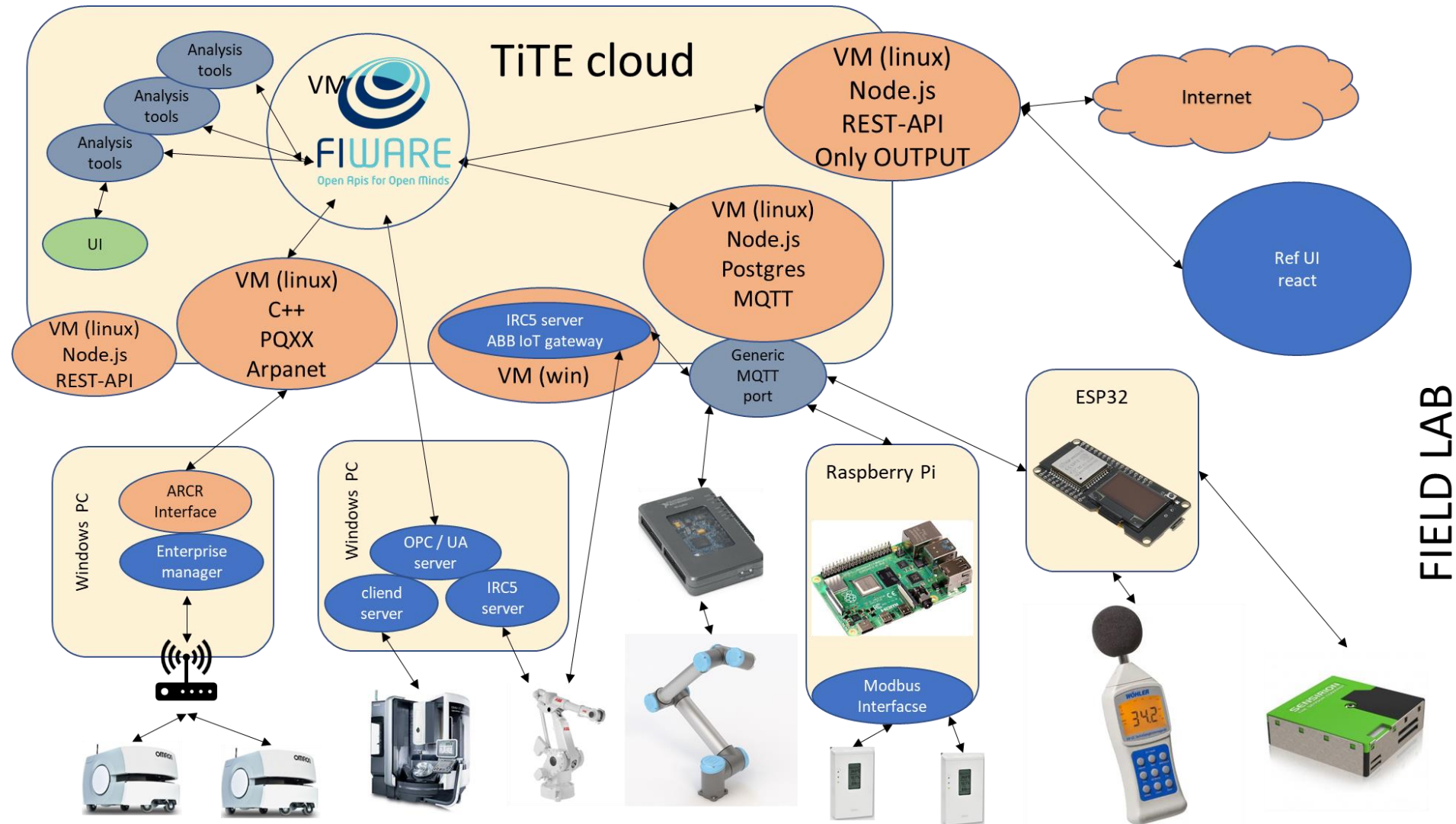
<https://www.nisshinbo-microdevices.co.jp/en/products/featured-products/nm2101.html>

Predictive Maintenance – FLAB DEMO

acoustic data



TAMK FLAB DATA ACQUISITION SYSTEM



TAMK FLAB FIWARE SETUP

Device API:s

MQTT

OPC /UA

DB:s

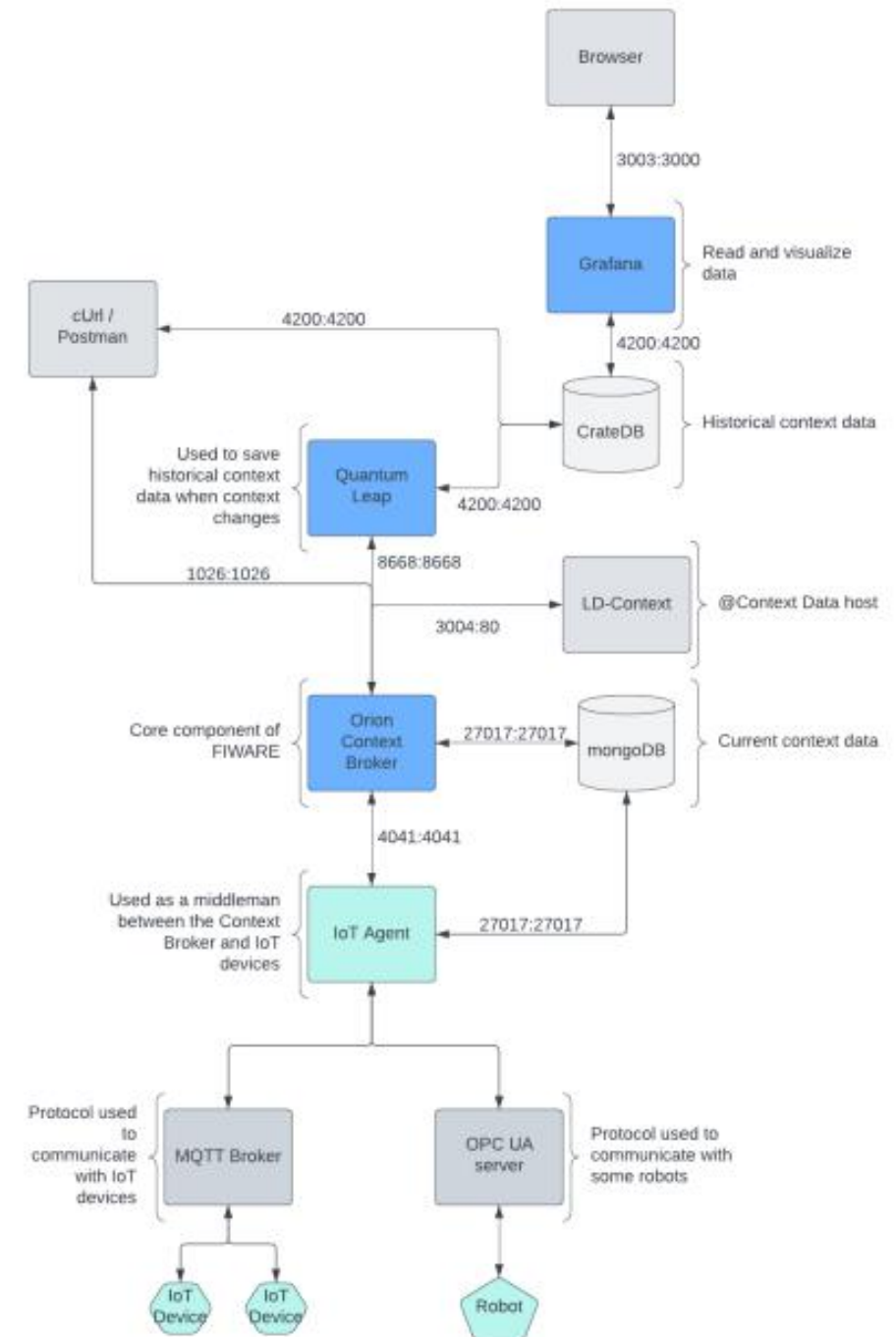
Crate DB

MongoDB

Common API:s

Quantum Leap

Orion



TAMK FieldLab

Data model

fieldlabCamelCase.yaml

createEntities.py



Create a
template for
entity

Datamodel
concept

```
Robot:
  type: object
  required:
    - ownedBy
    - entityType
  description: >
    An autonomous robot in TAMK
    FieldLab`.
  properties:
    robotType:
      type: array
    robotManufacturer:
      type: object
    robotModel:
      type: object
    robotMaximumLoad:
      type: object
    robotMaximumSpeed:
      type: object
    robotKitType:
      type: object
    robotSafety:
      type: array
    robotStandards:
```

Filling the data
model with data
and creating an
entity with it via
Orion API

Datamodel
in use

```
{
  "id": "urn:ngsi-Id:Robot:001",
  "type": "Robot",
  "robotType": [{
    "type": "Property",
    "value": "Mobile robot"
  }],
  "robotManufacturer": {
    "type": "Property",
    "value": "LD-90"
  },
  "robotModel": {
    "type": "Property",
    "value": "LD-90"
  },
  "robotMaximumLoad": {
    "type": "Property",
    "value": "60",
    "unitCode": "kg"
  },
}
```

TAMK FieldLab

Data model example: OMRON -LD90

```
{  
  "id": "urn:ngsi-ld:Robot:001"  
  "type": "Robot",  
  "robotType": [{  
    "type": "Property",  
    "value": "Mobile robot"  
  }, {  
    "type": "Property",  
    "value": "LD-90"  
  }],  
  "robotManufacturer": {  
    "type": "Property",  
    "value": "Omron"  
  },  
  "robotModel": {  
    "type": "Property",  
    "value": "LD-90"  
  },  
  "robotMaximumLoad": {  
    "type": "Property",  
    "value": "60",  
    "unitCode": "kg"  
  },  
}
```

```
"robotConnections": [{  
  "type": "Property",  
  "value": "WLAN OFF"  
}, {  
  "type": "Property",  
  "value": "RJ45 ON"  
}],
```

```
"robotDatasheet": {  
  "type": "Property",  
  "value": "https://industrial.omron.fi/fi/products/ld-60-90",  
  "unitCode": "url"  
},
```

```
"ownedBy": [{  
  "type": "Relationship",  
  "object": "urn:ngsi-ld:FieldLab:001"  
}],
```

```
"ownerOf": [{  
  "type": "Relationship",  
  "object": "urn:ngsi-ld:Microphone:001"  
}, {  
  "type": "Relationship",  
  "object": "urn:ngsi-ld:Camera:001"  
}]
```

TAMK FieldLab - Data model visualization UI

Flab digital Twin

TAMK, Field lab F0-29



Some nice and descriptive text regarding the selected entity.
(This content should be available via Fiware.)

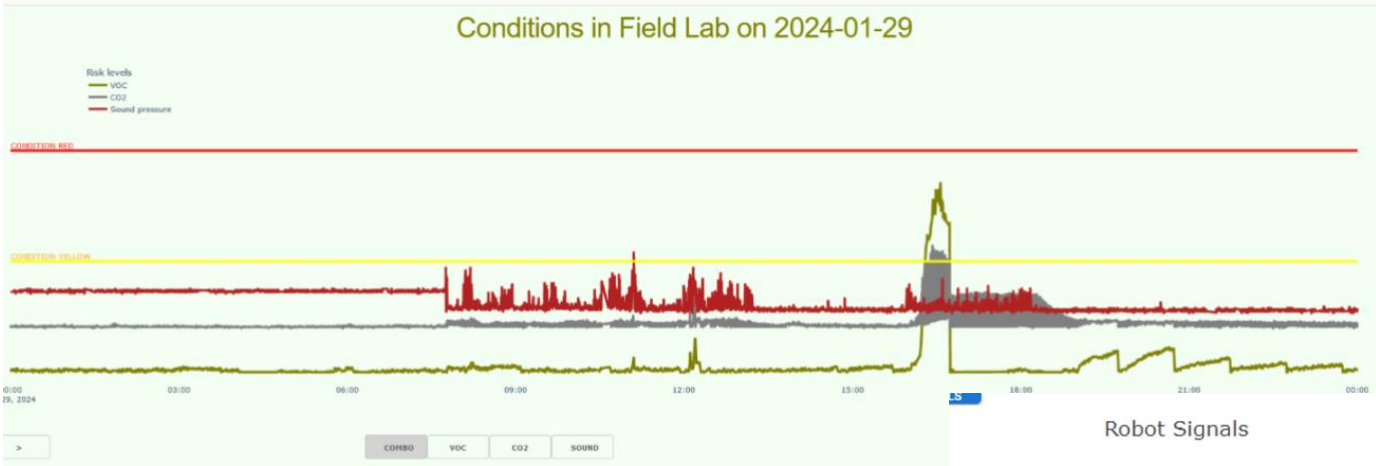
<< TOP LEVEL

Subentities:

URN:NGSI-LD:MICROPHONE:002

URN:NGSI-LD:ROBOT:001

URN:NGSI-LD:AIRQUALITYSENSOR:003



Mobile Robot 1. Omron LD90



Some nice and descriptive text regarding the selected entity.
(This content should be available via Fiware.)

<< TOP LEVEL

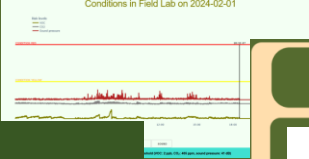
Subentities:

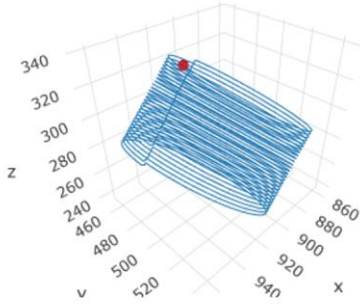
URN:NGSI-LD:MICROPHONE:002

URN:NGSI-LD:ROBOT:001

URN:NGSI-LD:AIRQUALITYSENSOR:003

Conditions in Field Lab on 2024-02-01





Entity: urn:ngsi-ld:FieldLab:001



Some nice and descriptive text regarding the selected entity.
(This content should be available via Fiware.)

<< TOP LEVEL

Subentities:

URN:NGSI-LD:MICROPHONE:002

URN:NGSI-LD:ROBOT:001

URN:NGSI-LD:AIRQUALITYSENSOR:003

Conditions in Field Lab on 2024-02-01



Sound level meter, SP22



Some nice and descriptive text regarding the selected entity.
(This content should be available via Fiware.)

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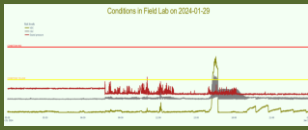
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URN:NGSI-LD:MICROPHONE:002

URN:NGSI-LD:ROBOT:001

URN:NGSI-LD:AIRQUALITYSENSOR:003

Conditions in Field Lab on 2024-01-29



Predictive Maintenance – FLAB DEMO

FieldLab:001



id

umngsi:IdFieldLab:001

type

FieldLab

Location

F029

EntityType

Building

image

http://172.16.101.198:9000/nuusku.vah/EDA_kuvat/PICTURE_IN_USE/FieldLab.jpg

Child entities

Nuusku

AirQ

ABB_3D

RYB

Individual_dev

Nuusku:001



id

umngsi:IdNuusku:001

type

Nuusku

EntityType

Device Group

image

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Child entities

SP22

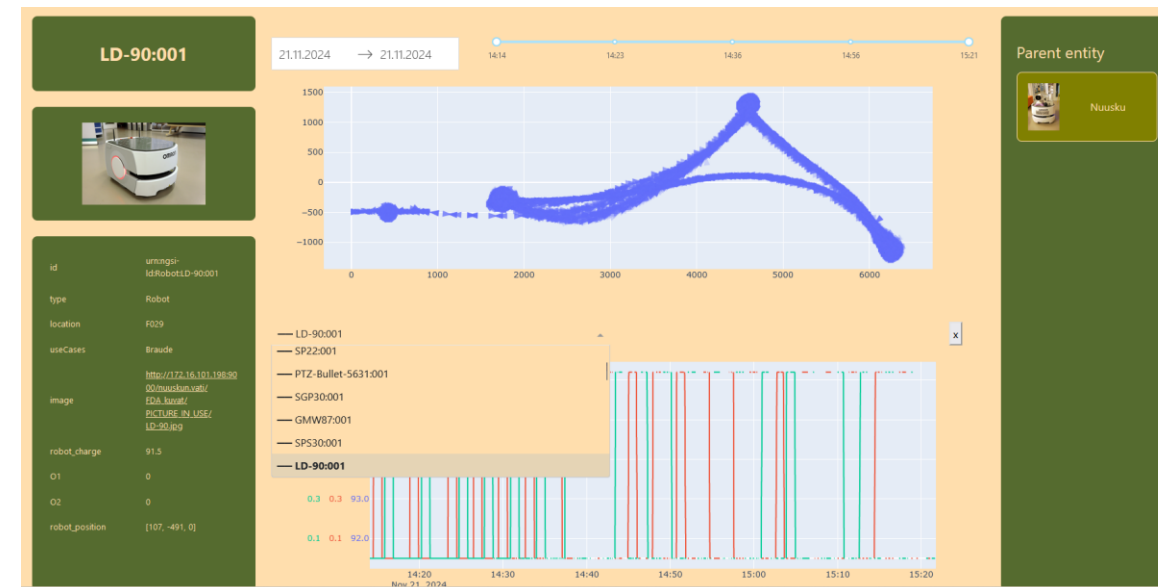
PTZ-Bullet-5631

SGP30

GMW87

SPS30

LD-90



Predictive Maintenance – FLAB DEMO

Raspberry-pi:001



urn:ngsi-Id:Camera:Raspberry-pi:001

type

Camera

location

F029

entityType

Device

image

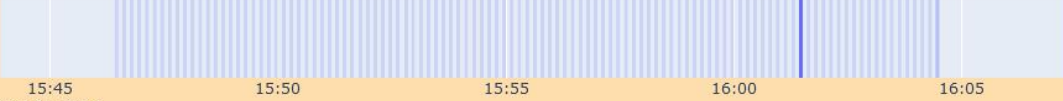
http://172.16.101.198:9000/nuuskun.vati/FDA_kuvat/PICTURE_IN_USE/Raspberry-pi.jpg

still_image

http://172.16.101.198:9000/raspberry/still/20241121_140427_609567.jpg

21.11.2024 → 21.11.2024

×
still_image



15:45
Nov 21, 2024
15:50
15:55
16:00
16:05

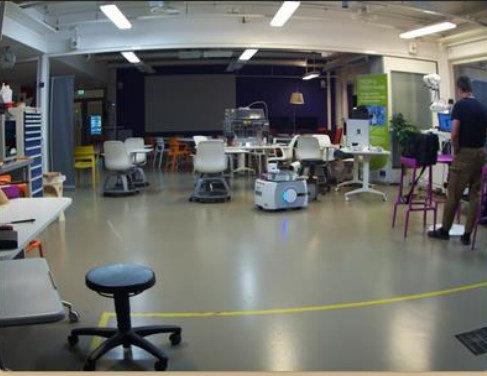
Add signal

20241121_135917_634960.jpg (JPEG Image,...)

×

http://172.16.101.198:9000/raspberry/still/

☆



20241121_124324_235162.jpg (JPEG Image,...)

×

http://172.16.101.198:9000/raspberry/still/

☆



20241121_140007_651144.jpg (JPEG Image,...)

×

http://172.16.101.198:9000/raspberry/still/

☆



Parent entity



ABB_3D

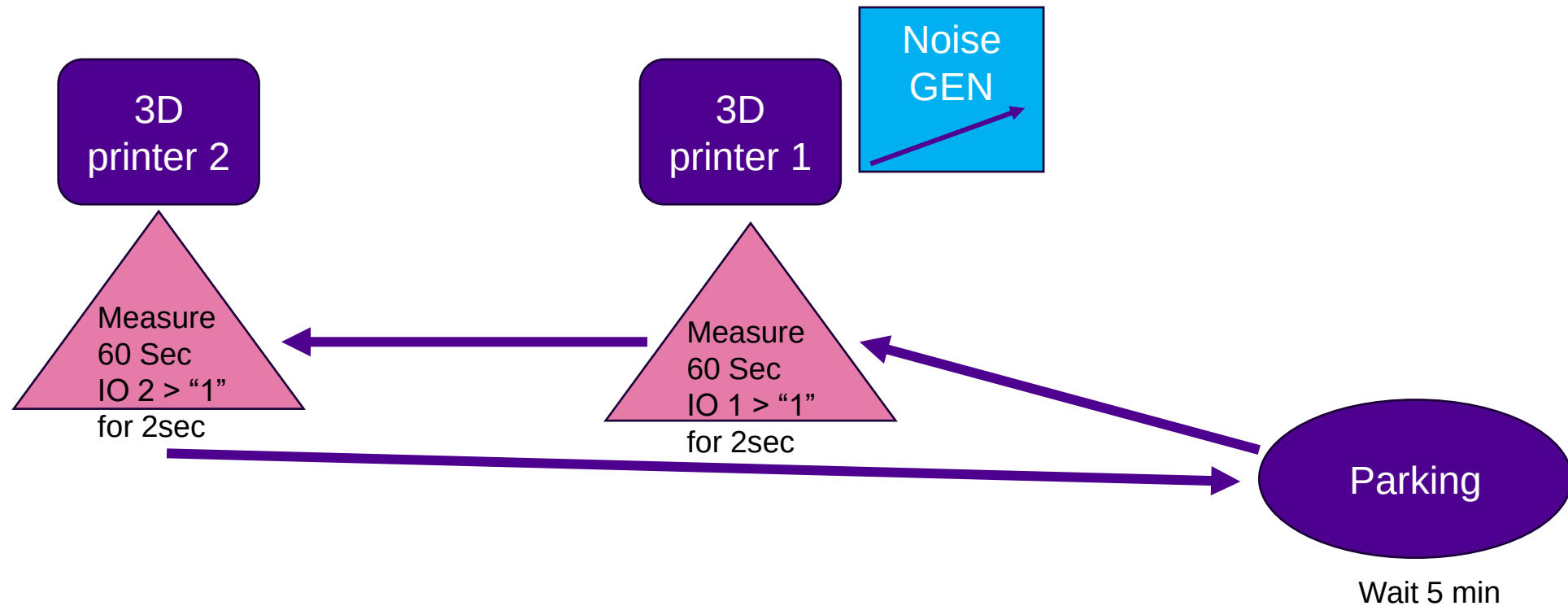
Predictive Maintenance – FLAB DEMO

Use case:

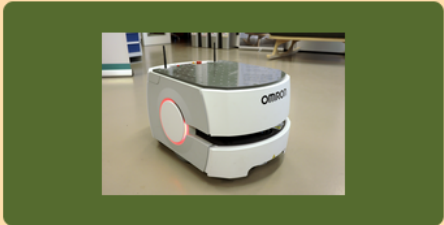
- 3D printer condition monitoring with acoustic noise level
- Mobile robot to carry dB meter to measure level
- Fiware framework for IoT / Data storage / DIY UI
- Visual data analysis

Predictive Maintenance – FLAB DEMO

Predictive Maintenance models, example: dB meter as sensor

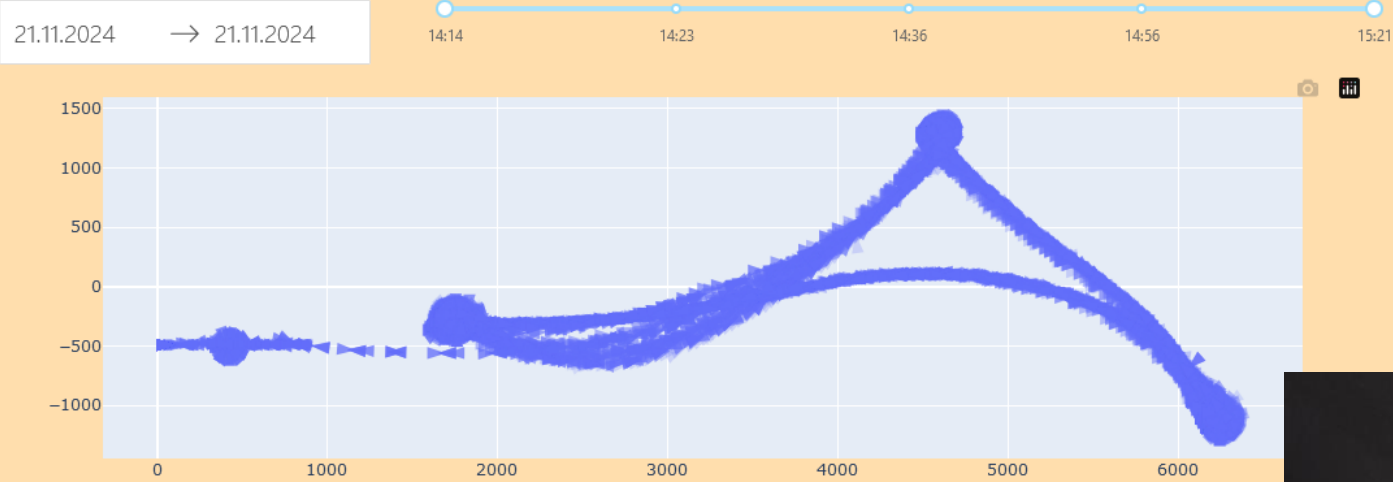


LD-90:001



id	urn:ngsi-ld:Robot:LD-90:001
type	Robot
location	F029
useCases	Braude
	http://172.16.101.198:9000/nuuskun.vati/FDA_kuvat/
image	

21.11.2024 → 21.11.2024

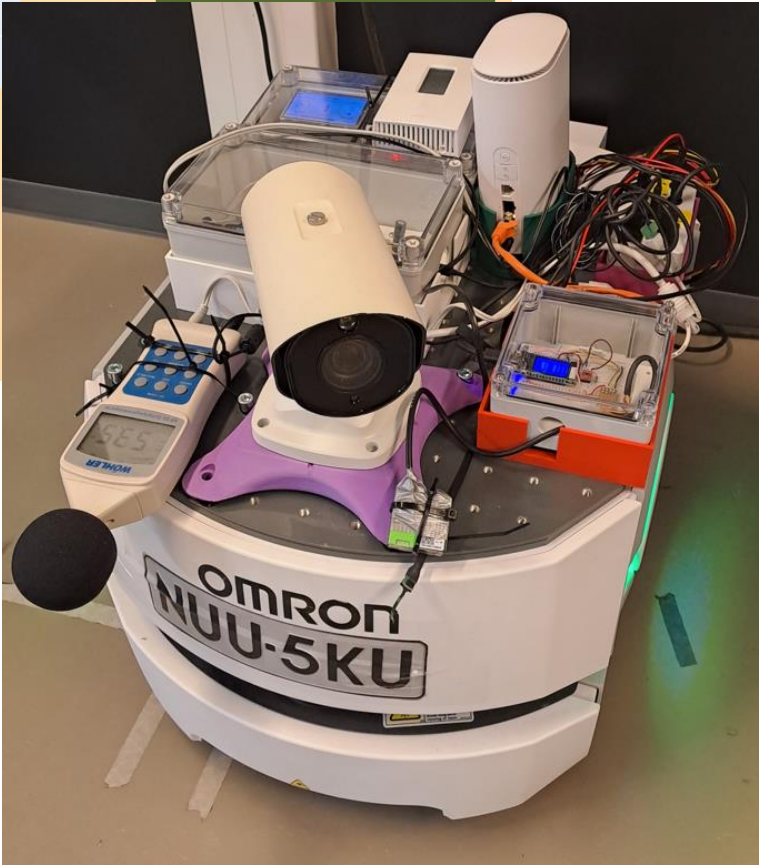


Add signal

Parent entity

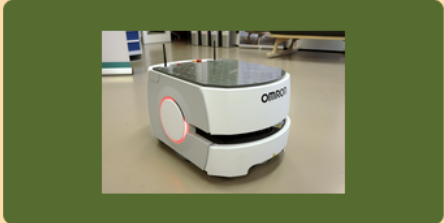


Nuusku



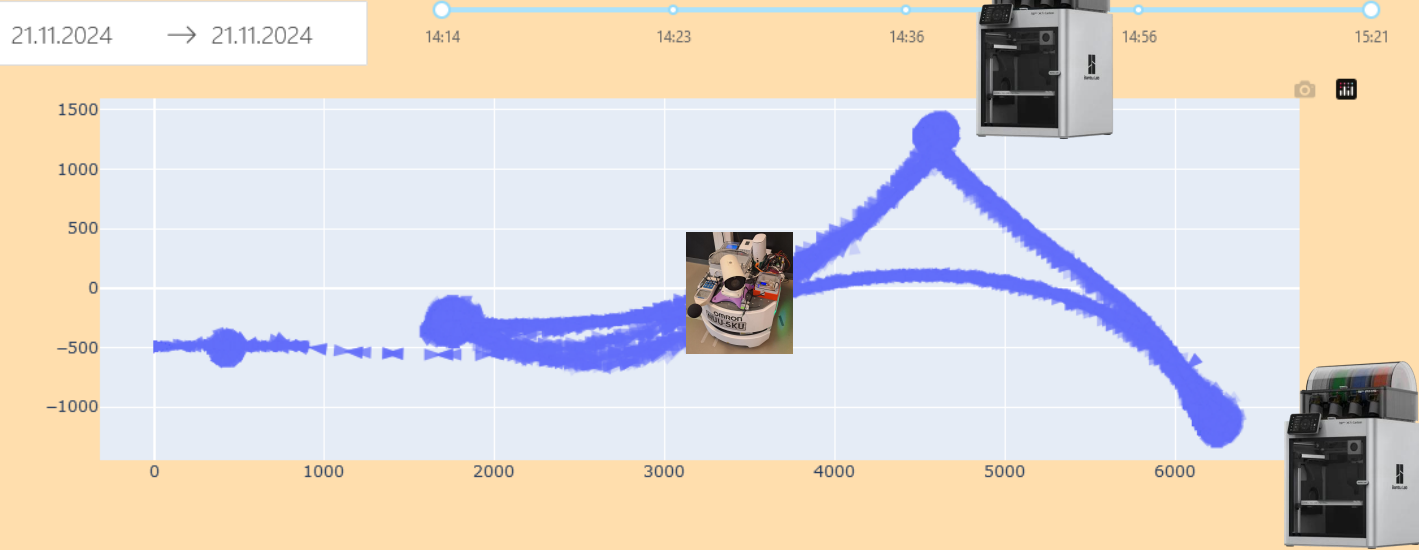
Bambu Lab P1S
Left_13

LD-90:001



id	urn:ngsi-Id:Robot:LD-90:001
type	Robot
location	F029
useCases	Braude
image	http://172.16.101.198:9000/nuuskun.vati/FDA_kuvat/

21.11.2024 → 21.11.2024



Parent entity



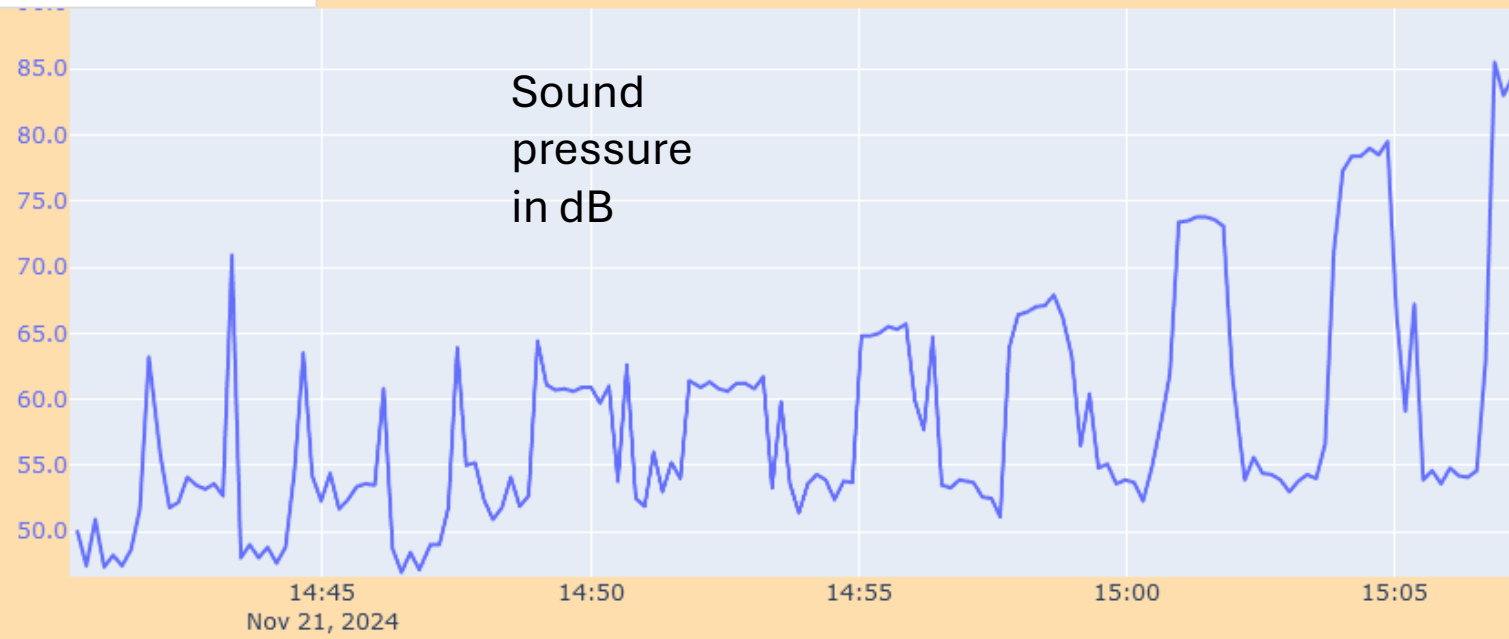
Nuusku

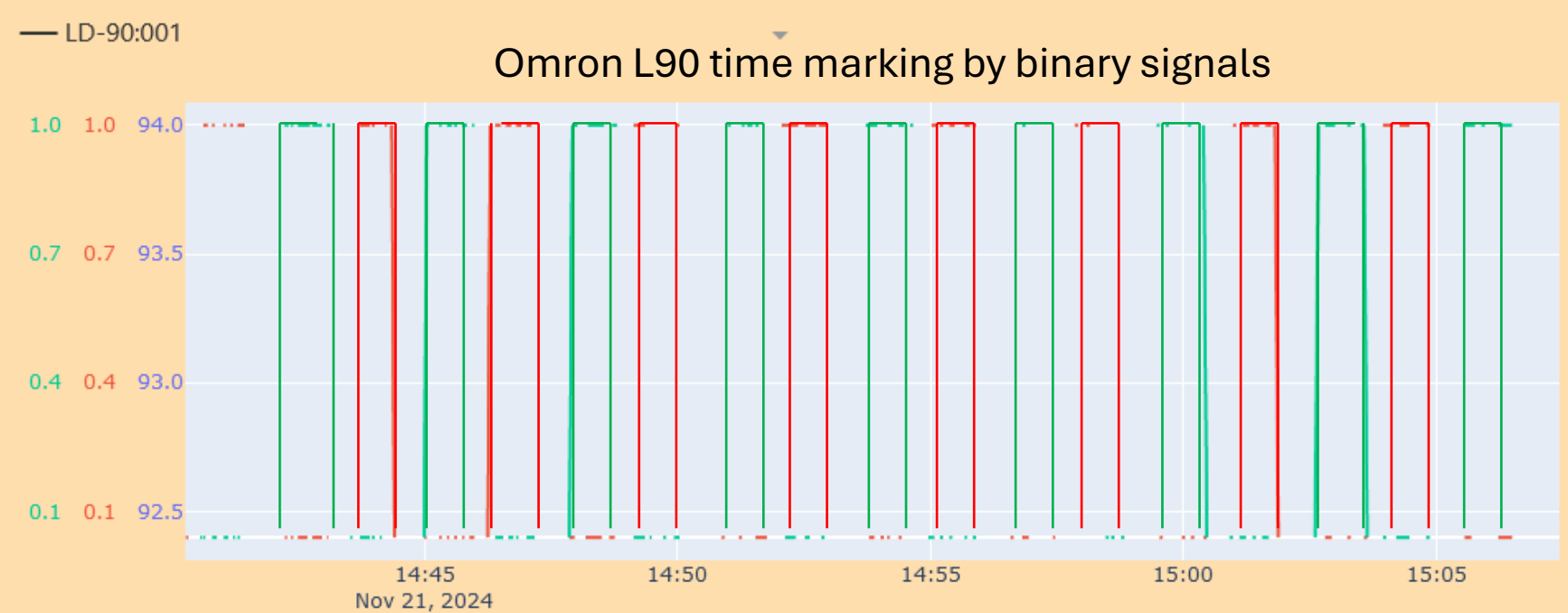
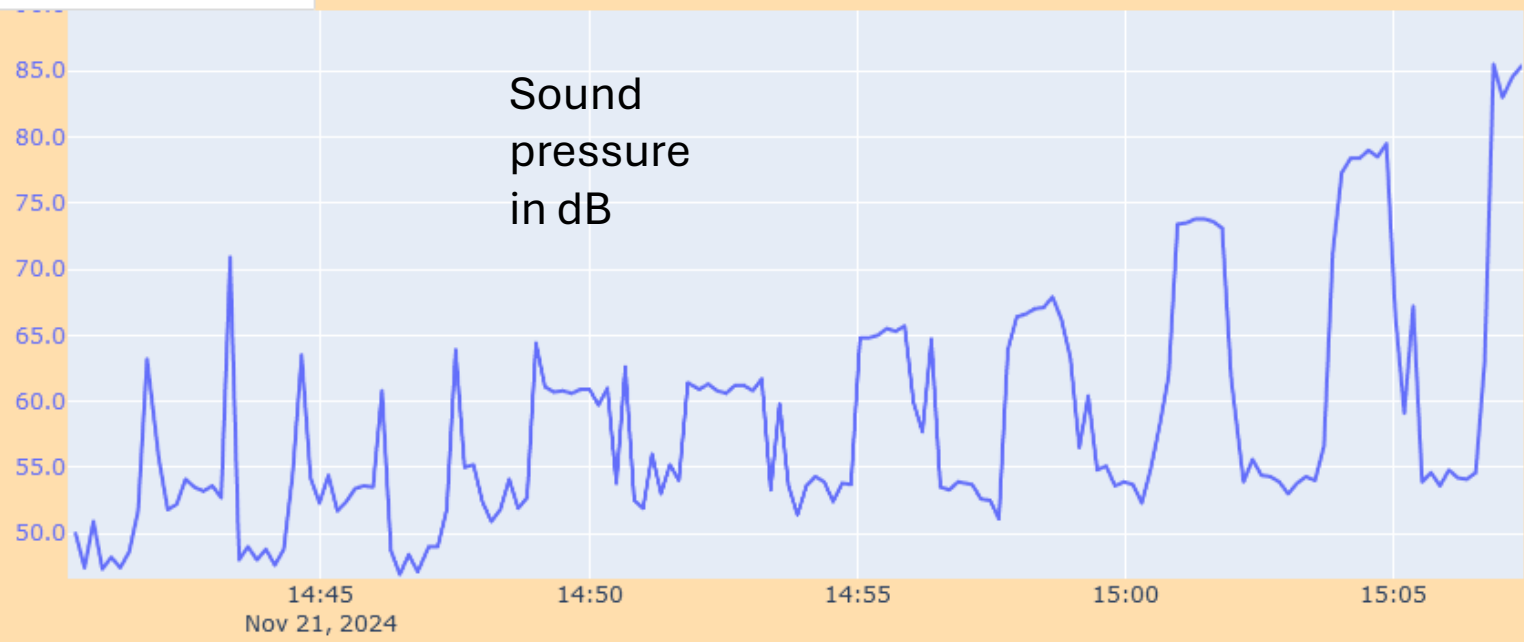
Bambu Lab P1S
Right_22

21.11.2024

→ 21.11.2024

× db_value





Bambu Lab P1S
Left_13

Bambu Lab P1S
Right_22

Raspberry-pi:001



id urn:ngsi-Id:Camera:Raspberry-pi:001

type Camera

location F029

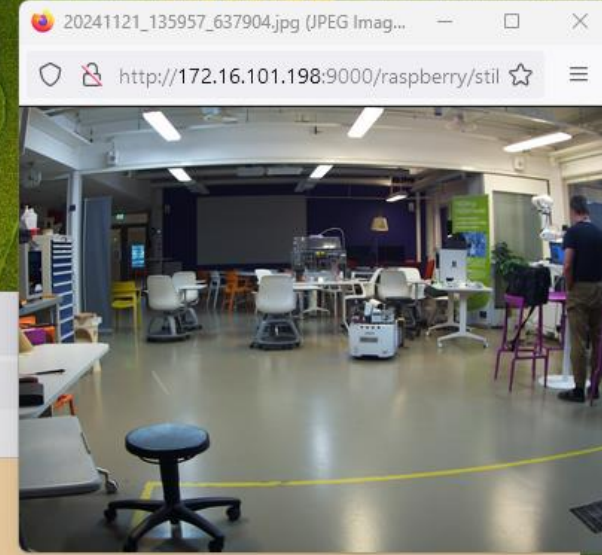
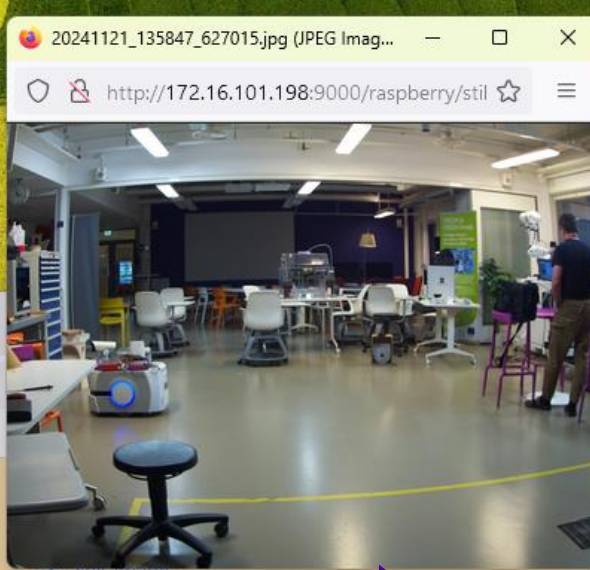
entityType Device

<http://172.16.101.198:9000/nuuskun.vati/>

21.11.2024 → 21.11.2024

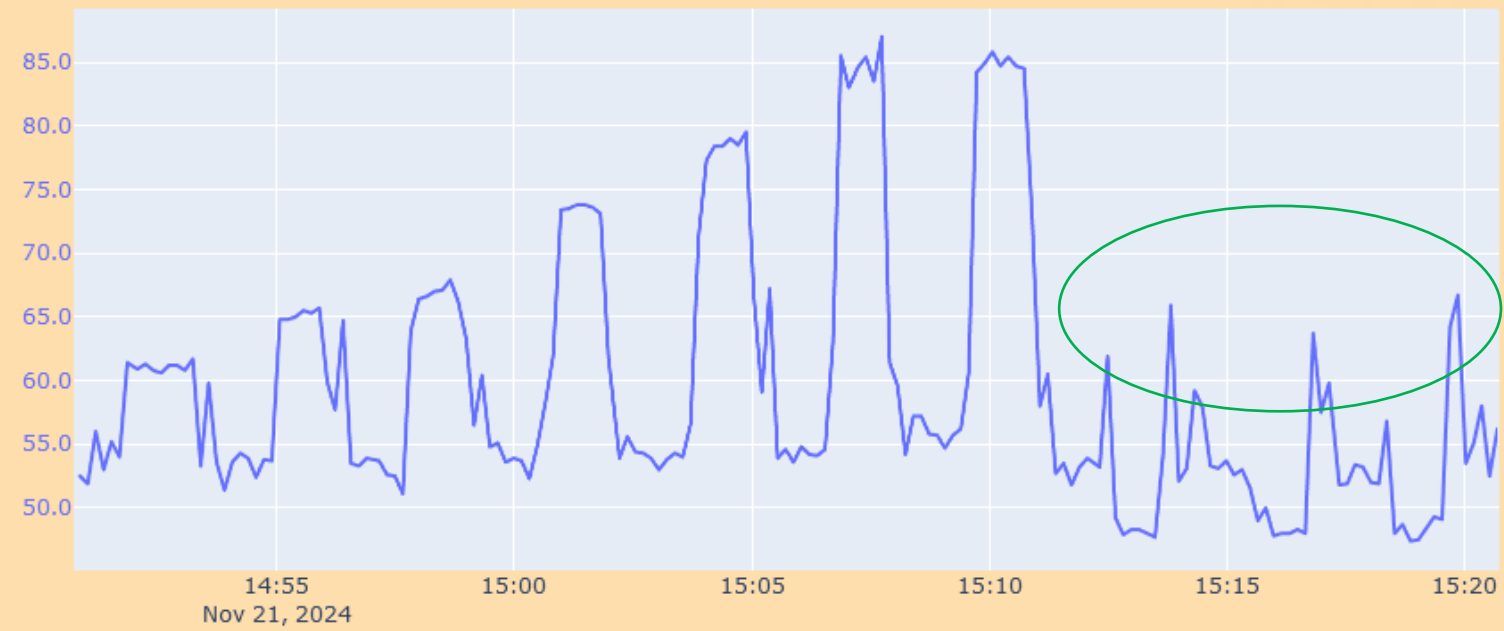


— SP22:001



21.11.2024 → 21.11.2024

db_value



LD-90:001



Flab – FIWARE – 5G : I4.0 testbed : IoT/ Data/ AI/ Data models

Why FIWARE ?

- all available IoT/AI system blocks available
- configurable for different kind of setups, scalable
- available API:s for OPC/UA, MQTT, Rest-API
- support for different DB:s like Mongo/Crate etc.
- Open Source (free)
- could be run in docker
- free support organization
- easy to replicate/clone

L2L

- tutorial examples mostly working as they are, implementing own features required studies/work
 - human support available from Fiware org
 - UI requires own development
 - Maintenance is big resource risk

Flab – FIWARE – what next:

- **SME Use cases**
- **Data models real case creation and verification**
- **Automated analysis**
- **Integration with machine vision camera (Zivid)**
- **3D printing (large scale) quality improvements studies**
- **UI development**
 - **Support for different signals**
 - **binary**
 - **3D**
 - **Easy signal compare**
 - **Video**
- **Data share co-operation**

**Questions ?
Comments ?
Thanks !**

kari.naakka@tuni.fi

+358 40 7294269

New skills
unleashing the
engineering
potential



<https://sites.tuni.fi/fieldlab-en/>