Platforms and experiments AI Scenarios – M6

D2.2

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Deliverable N.:	D2.2
Work Package N.:	WP2
Date:	3/11/2023
Project N.:	101092069
Classification:	PU
File name:	"Platforms and experiments AI Scenarios – M6"
Number of pages:	115

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Status of deliverable

Action	By	Date (dd.mm.yyyy)
Submitted (author(s))	Elisabetta Toschi Alina Bisag	3.11.2023
Responsible (WP Leader)	ART-ER	3.11.2023
Approved by Peer reviewer	N. Stojanovic (NISSA)	1.11.2023

Revision History

Date (dd.mm.yyyy)	Revision version	Author	Comments
13.04.2023	V0.1	Elisabetta Toschi (ART.ER)	ToC – initial version
3.11.2023	V1.0	Elisabetta Toschi (ART.ER)	Final version
3.11.2023	V1.1	G.Monteleone (POLIMI)	Quality Check

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Abbreviations and Acronyms:	
AI	Artificial Intelligence
Cobot	Collaborative Robot
CNC	Computerised Numerical Control
CVS	Contextualised Visual System
DF	Didactic Factory
DIH	Digital Innovation Hubs
ERP	Enterprise Resource Planning
HMI	Human Machine Interface
HTTP	Hyper Text Transfer Protocol
IIoT	Industriallinternet of Things
KPI	Key Performance Indicator
MES	Manufacturing Execution System
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
OPC UA	Open Platform Communications (OPC) UA (Unified Architecture)
PLC	Programmable Logical Controller
SME	Small and Medium Enterprise
TCP	Transmission Control Protocol
TERESA	Technical and Regulatory Sandbox
WISE	Well-being, inclusion, safety, ergonomics
WP	Workpackage

Executive summary

The **goal of AI REDGIO 5.0** project is to **move artificial intelligence (AI) and machine learning (ML) to the "edge"** which means closer to the source of manufacturing information. This "local cloud" depicts the possibility to have an efficient computing infrastructure locally, which can be of a big importance for manufacturing small and medium-sized enterprises (SMEs). AI REDGIO 5.0 will lower the complexity and cost barriers for manufacturing enterprises (notably SMEs) to develop, deploy and fully leverage the cloud/edge computing paradigm for the implementation of applications like predictive maintenance, quality management, Zero Defect Manufacturing, Lifecycle Assessment, Intelligent Asset Management, Human Robot Collaboration and Digital Twins, through providing:

- **free open source**, and **user friendly tools** for developing end-to-end **pipeline for edge ML/AI applications**;
- **cloud/edge AI deployment patterns and blueprints** for different manufacturing applications.

During the project implementation **7 SMEs** are monitored and supported in their experiments deployment and **14 Didactic Factories** around Europe are involved for the implementation of didactic experiments addressed to SMEs.

In this framework, WP2 is in charge of developing methodologies and tools to collect needs, requirements, and to evaluate the experiments; in particular T2.2 "*Platform and Experiments Scenarios & Expectations*" deals with the analysis of the 21 experiments, to depict **AS-IS and TO-BE Industry 5.0 scenarios** enabled by AI-at-the- edge technologies.

The deliverable D2.2 "*Platforms and experiments AI scenarios"* reports an in-depth overview of the present (AS-IS) and future (TO-BE) scenarios of the first pillar of AI REDGIO 5.0 project, *i.e.*, the EXPERIMENTS.

The 7 SMEs-driven and the 14 Didactic Factories (DF) experiments involved in the project have been analyzed, following the "*Requirements Engineering Methodology*" developed in T2.1 and reported in D2.1. For each SME-driven /DF experiment, after a short description of the organization the AS-IS and TO-BE industrial scenarios are presented.

The AS-IS scenario represents the starting point of the experiment, while the TO-BE scenario represents the expected scenario, Industry 5.0 compliant, that will be reached thanks to the implementation of the experiment.

Being the experiments just started, the D2.2 provides only a sketch of the TO-BE scenarios, while the deliverable D2.5, to be submitted in month 24, will go in depth on the technologies applied, obstacles met in the deployment, and on the results obtained.

The deliverable includes the following chapters:

- **§ 1 "D2.2 in the AI REDGIO 5.0 workplan"** introduces the deliverable and explains its aim, connection with other WPs, tasks and deliverables of the AI REDGIO 5.0 project.
- **§ 2 "Approach and methodology":** introduces the 3 axis that have been used to map the need of experiments, i.e. The Technological Platform, the DIH Services (based on the D-BEST methodology developed in WP3), and the Business Indicators.
- **§ 3 "Industrial Scenarios from SMEs driven Experiments"** describes the AS-IS scenario, the status of deployment, and TO-BE scenarios of the 7 SMEs –driven experiments.
- **§ 4 "Industrial Scenarios from DF Experiments"** describes the AS-IS scenario, status of deployment, and TO-BE scenarios of the 14 Didactic Factories.

- **§ 5** is dedicated to **"Conclusions"**.

1. D2.2 in the AI REDGIO 5.0 workplan

The deliverable 2.2 is a result of the work performed in T2.2, and is strictly related to the task T2.1, and to WP4 "*Industry 5.0 Data4AI Platform & Data Spaces*", WP5 "*Industry 5.0 EDGE AI Toolkit & AI-On-demand Platform"* and WP6 "*AI REDGIO 5.0 Application Experiments*".

In T2.1 the Requirements Engineering Methodology (see D2.1) and the Trial Handbook - a structured 'logbook' with which experiments are monitored and evaluated - have been developed, while WP4 and WP5 deal with the development of the platforms where the experiments will be integrated, and finally WP6 is in charge of the coordination of the experiments. The figure below - Figure 1 - shows the WP6 synoptic diagram.

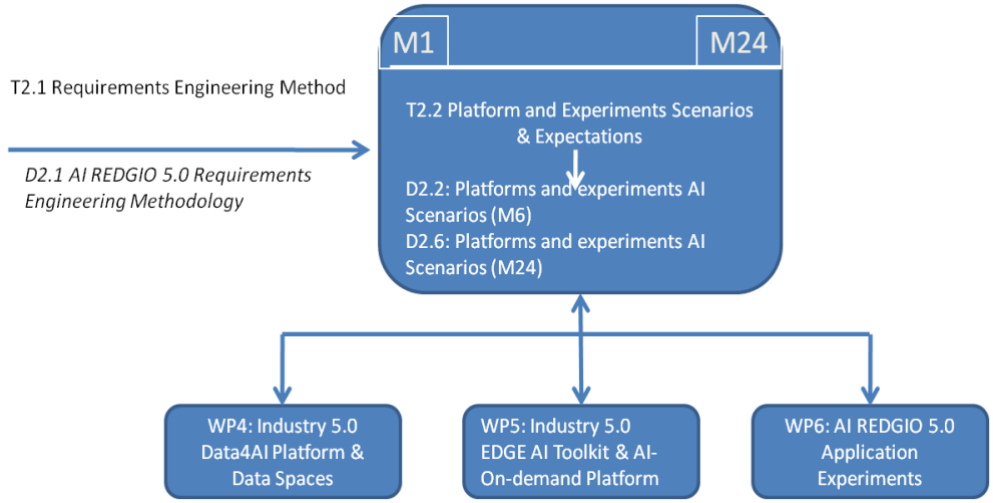

Figure 1. WP6 synoptic diagram

2. Approach and methodology

The monitoring of the experiments AI scenarios is made following some consolidated methodologies.

In WP2, as already mentioned, the REM – Requirements Engineering Methodology – has been developed together with the Trial Handbook.

In parallel, to monitor and support the experiments deployment, their needs have been mapped following 3 main axes:

The needs for integrating the experiments into the platforms (activities carried out in WP4 and WP5)

- The needs of services provided by the EDIHs, based on the D-BEST methodology developed in WP3
- The business indicators, identified in WP2

Here below a brief recap of the three axis and methodologies applied are presented.

2.2 TECHNOLOGICAL PLATFORMS

There is an ever-increasing demand for faster processing, lower latency and insights from the local data.

This is forcing the data processing (analytics) to move from the cloud to the edge. At the same time, all these devices connect using different protocols which may or may not be reliable and the type of devices

may at times generate noisy data. This noisy data which has been generated needs to be cleaned before being used by any Machine Learning models. The best way to clean the data is at the source itself and at devices closer to the source, namely the edge.

Main objective of technological platforms is to provide an efficient and easy for usage infrastructure, based on a secure computation continuum between edge and cloud, for enabling manufacturing SMEs to prepare own data for the usage in AI applications. The main objective is to include the domain expertise in the data preparation process, but in a convenient way for non-technical expert.

Main goal is a comprehensive end-to-end solution designed to ingest, process, analyze and present data generated by the systems and infrastructures of the modern digital enterprise or organization.

Data4AI platform, developed in AI REGIO project, is a new generation of platforms for ensuring data quality for AI applications.

The platform enables efficient collection, storage and analysis of process data, and allows the storage of manufacturing big data to optimize value chains, with detailed connections between product lifecycle business data and on-site IoT data.

One of main challenges is how to select an ideal dataset for learning (to avoid garbage in /out effect).

2.3 D-BEST

METHODIH methodology and DBEST framework, has evolved over time through different projects. Its initial version can be found in the MIDIH project, where a preliminary analysis of tools and methods to support DIHs for Smart Manufacturing was conducted. Later, the METHODIH methodology was also adopted in the AI-REGIO project, where its most updated version was consolidated and adopted also in AI REDGIO 5.0.

Briefly, the METHODIH methodology is an acronym derived from METHOdology for DIHs, specialized in AI for Manufacturing Industry, structured in four pillars that will be described in detail in this section of the deliverable.

The set of tools and techniques elaborated in these previous projects has been tweaked, developed, improved, and validated in collaboration with the AI REDGIO 5.0 ecosystem of 19 Digital Innovation Hubs, aiming at enhancing their service proposition both addressed to their customer base and to other DIHs in the network.

The methodology provides a common framework and a set of guidelines to describe and manage the four main pillars of the DIH's offer:

- **Service Portfolio Analysis**. A structured approach is proposed for DIHs to define their AS-IS and TO-BE service portfolio. Services are classified into five main top-level categories or service classes (D-BEST: Data, Business, Ecosystem, Skills, Technology), while a three level taxonomy with examples is provided to support DIHs in the definition and description of their AS-IS and TO-BE services. The first and wider level of the taxonomy is the service class. The second level is the service type, and the last and more detailed level is the service instance. The objective is twofold: on one side, DIHs are equipped with a standard Service Portfolio that allows them to interact with other European organizations, "speaking the same language"; on the other, it represents a stimulus to define new services to get a complete range of services to be offered to the constituency.
- **Customer Journeys** (CJ) and **Blocking Points** (BP). Customer analysis is proposed to understand usual needs, expectations, and interaction workflows by the various ecosystem stakeholders. Customizable templates for six different customer types (Technology Provider, Technology User, Student, Policy Maker, Start-up, and Experimenter) are provided. Customer Journeys are defined as step-by-step Digital Transformation evolutionary pathways that typically model the customer interaction with a

DIH. A third step in this analysis is the identification of Blocking Points, i.e. of factors preventing customers from evolving their Digital Transformation from one level to the subsequent one.

- **Digital Transformation Pipeline**. The third pillar of the methodology consists of populating the Customer Journeys with as-is and to-be Services to overcome the Blocking Points identified. The result is a bi-dimensional matrix where the different steps of the Customer Journeys are implemented by services, supporting the evolutionary pathways from one level to the subsequent one.
- **Business and Governance model**. The last pillar of the methodology is the definition of a business model that considers the complexity of a DIH customer base, which typically is a multi-stakeholder system, and the cross-regional activities that the hub will perform both inside the project and autonomously. The business and governance models pillar have been developed in previous projects, but in AI-REDGIO 5.0, the focus will be on the first three steps.

2.4 BUSINESS INDICATORS

Within AI REDGIO 5.0 each of the experiment, uses the Trial Handbook, to define their own set of Business Objectives for each of the future scenarios expected as a consequence of the experiment implementation. For each of the Business Objectives defined, quantifiable indicators have been set including the initial value and the expected value at the end of the experiment. This will enable all the experiments to assess the impact and results of their experiment implementation.

Defining business indicators in the AI REDGIO 5.0 experiments is essential for setting clear objectives and goals which led to the creation of a framework to understand what the experiment is intended to achieve and provide a definition to what success is in each of the cases. Additionally, business indicators enable the measurement of the progress and effectiveness of the experiment through specific and objective metrics. The performance of this measurement allows the experiment managers to use relevant data for informed decision making, as well as to identify potential risks and challenges that may arise during the pilot experiment.

3. Industrial Scenarios from SMEs driven Experiments

In this chapter the 7 SME-driven experiments are presented:

- SCAMM: AI-based quality control of white goods components.
- PERNOUD: decision-making tool for the realization and organization of the manufacturing sequences in a shop floor.
- GPALMEC: autonomous driving for agricultural vehicle.
- POLYCOM: maximization of availability, production quality and efficiency of molding machines.
- QUESCREM: quality improvement of cheese products and reduction of wastes.
- CAP: Intelligent contextualized visual system for error reduction.
- KATTY FASHION: development of a product defect detection system for clothing items.

For each experiment AS-IS and TO-BE scenarios have been defined, and the current status of deployment has been described.

3.2 SME Pilot I SCAMM (Lombardy, Italy): AI-based quality control of white goods components

SME description

SCAMM in an Italian company born in 1975; since then, it operates in the industrial automation for cold metal sheet transformation process sector. Its technical knowledge in prefabrication and assembling technologies and continuous research allows the company to be a worldwide leader, offering an integrated service able of dealing with any specific automation requirement in appliances. The sector of operation is manufacturing of special equipment for automatic sheet metal forming and assembling, mainly for major home and professional appliances – in Figure 2 are reported some of SME facilities and an example of application.

Figure 2 SCAMM Plant and example of application

Motivation

In the frame of AIREDGIO 5.0, SCAMM leads an experiment dealing with the real time monitoring for control and detection of production non conformances in a reconfigurable pressing line. The aim of this experiment is the development of a physical model of the line that can predict variations in the quality of the final product starting from the process parameters. For this purpose there will be used real-time monitoring and predictive AI algorithms which allow to optimize both efficiency and product quality.

Objectives and benefits

There are expected several benefits from the activities carried out in the framework of AIREDGIO 5.0 project, both for SCAMM as end-user and as a provider of the technology; specifically:

- **SCAMM as END-USER**: since it provides the manufacturing capacity of the reconfigurable pressing line as a service, it is expected to achieve an increase in productivity and a reduction of operating costs as a consequence of the reduction of waste, reworking, and energy.
- **SCAMM as a PROVIDER**: since it is specialized in designing integrated solutions for sheet metal working automation according to the client objectives, it is expected to achieve an improvement of the value proposition through additional services such as monitoring and anomaly detection, process parameters optimization and predictive maintenance, therefore increasing market competitiveness.

Experiment team

The stakeholders that will be involved in this project are:

- **SCAMM**: is the leader SME of the project and aims to optimize a reconfigurable pressing line using real-time monitoring and predictive AI algorithms.
- **IMECH:** is a Consortium of 48 enterprises devoted to interdisciplinary research in Mechatronics. It will support SCAMM in the AI system development and integration and will ensure knowledge transfer towards other process industries and manufacturing companies within the IMECH consortium.
- **Politecnico di Milano (POLIMI):** is the most important technical university in Italy and one of the best in Europe. POLIMI is the AI REDGIO 5.0 coordinator and it will facilitate collaboration within the project team and provide scientific and technological support to improve the solution, ensuring the fulfillment of the project goals.
- **PORINI s.r.l.**: is specialized in strategic consultancy, design, development, integration, implementation and maintenance of complex solutions and infrastructures based on all the major technologies on the market. Porini offer covers the entire ICT value chain and it will support IMECH in the definition of the ICT architecture.
- **AFIL**: is an Italian private, non-profit legal entity representing the regional technological cluster for Advanced Manufacturing. AFIL will be responsible for dissemination and exploitation of AI REDGIO 5.0 results. Besides dissemination activities towards the Lombardy manufacturing context, AFIL will ensure alignment with the relevant European regulatory framework.

3.2.1 AS-IS scenario

The existing reconfigurable pressing line is installed at MOLLIS ANTONIO S.r.l. (Italy). It is an integrated solution for sheet metal working automation (forming, cutting, drawing, etc…) that allows to manufacture complex finished products such as large household appliances. An example of the current scenario is depicted in Figure 3; some of its features are given below:

- the process parameters are currently locally monitored and data is not historicized;
- concerning quality, the inspection of the most critical defects has been automatized through a machine vision system: images are processed by AI algorithms that extract synthetic indexes useful to assess the quality of the products and to predict quality trends in order to investigate in advance the reasons that might lead to an unacceptable reduction in the quality of the products;
- no correlation between process parameters and product quality has been investigated yet.

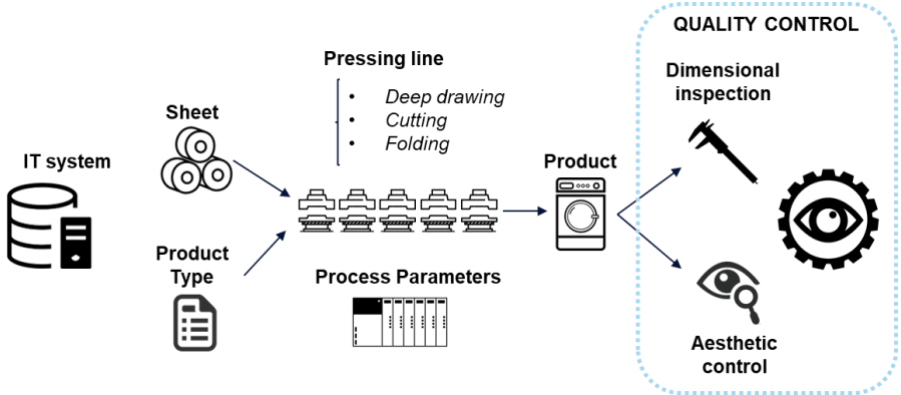

Figure 3 SCAMM AS-IS process flow diagram

3.2.2 Technical Implementation

Currently, a proprietary software enables the operators to set process parameters, such as presses cylinders forces, and provides direct and indirect measures such as the temperature of the hydraulic oil or the torque of the servomotors. Additionally, a machine vision system collects images of finished products, that are processed by AI algorithms and the results are stored in a dedicated SQL database. The collected images and quality control measurements are accessible through Rest API.

The technical solutions that will be adopted to **predict the variations in the quality** of the final product starting from the process parameters are:

Hardware

- Fully automatic transfer lines installed at MOLLIS ANTONIO S.r.l.
- Sensors (industrial cameras) for quality control.

Software

- Tool to monitor and configure process parameters and to communicate with MES (User Interface, MES Integration, Machine Communication)
- Tool for quality data acquisition and evaluation (Data acquisition, Data analysis, User interface, Visualization)

Communication channel/s

- OPC-UA, TCP, Rest API, HTTP Request

3.2.3 TO-BE scenario

Given the difficulty of developing a physical model of the line that can predict variations in the quality of the final product, an AI model is necessary to discover the nonlinear relationships between the two, starting from the collected data. Indeed, real-time monitoring enables the creation of self-adaptive production processes, which allow continuous adaptation of the operating conditions of production systems to optimize both efficiency and product quality - Figure 4.

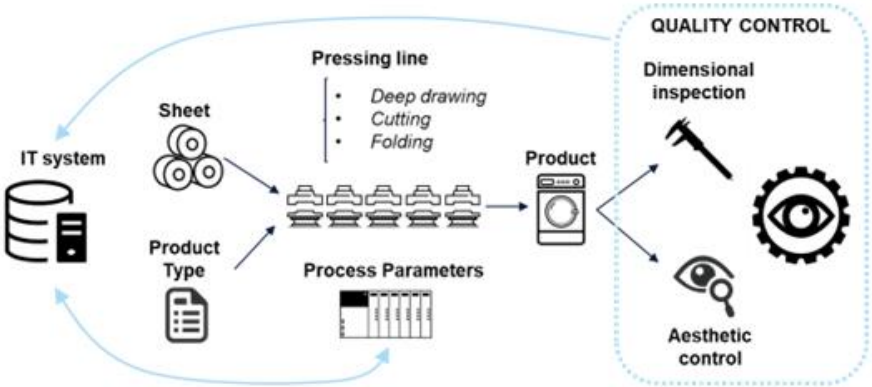

Figure 4 SCAMM TO-BE process flow diagram

Scenario 1

SCAMM as END-USER: since it provides the manufacturing capacity of the reconfigurable pressing line as a service, it is expected to achieve an increase in productivity and a reduction of operating costs as a consequence of the reduction of waste production and an overall reduction in the variability of the quality of the products.

Scenario 2

SCAMM as a **PROVIDER**: since it is specialized in designing integrated solutions for sheet metal working automation according to the client objectives, it is expected to achieve an improvement of the value proposition through additional services such as monitoring and anomaly detection, process parameters optimization and predictive maintenance, therefore increasing market competitiveness.

3.3 SME Pilot II PERNOUD (Rhône Alps, France): decision-making tool for the realization and organization of the manufacturing sequences in a shop floor

SME description

The **PERNOUD** Group is an international toolmaker company, created in 1971 and located in France and USA. It is specialized in molds for plastic parts injection, composites and die casting tools. Pernoud has 65 collaborators and exhibits a turnover of 10 M€. It works for different activities such as automotive, packaging, building, aeronautics and defense sectors. Moreover, ilts various activities are organized around four business units, namely:

- R&D: is dedicated to feasibility studies, product process / innovation, and parts co-design.
- Tool & Mold: designs and manufactures complex tools with high kinematics.
- Services: is dedicated to the repair and maintenance activities of used tools from all sources.
- Pernoud Machining: is specialized in the realization of complex prototypes and parts from micro to mini-series (from 1 up to 10 parts).

The Pernoud Group emphasizes personalized customer services through molding process improvement & increased productivity. It is ISO 9001 version 2015 certified and received the research centre accreditation status from the French government.

Motivation

Pernoud designs, manufactures, modifies, or repairs moulds composed of several hundred pieces and each piece can require more than ten different operations (in a precise order) to be manufactured. The common practice is to realize a manufacturing sequence and then to plan it manually in the ERP system for each piece, but this method is very time-consuming and creates latency in the organization. In the framework of AIREDGIO 5.0, AI will be used as a decision-making tool for the realization and organization of the manufacturing sequences in a shop floor where resources are shared for different kinds of business units. It will be linked to the PERNOUD MES system to analyze the current status of every task and predict if some delays (or advance) is expected. In case of delays (or advances), alerts will be launched to inform the users, and advice to improve the planning will be sent to the users. Advice will be defined to limit the impact according to PERNOUD decision rules. The final call will always be done by the user, a human, with the ability to not follow the tool's advice.

Objectives and benefits

The objective of this experiment is to **keep control of the time** by anticipating sooner as possible. When time is out of control, the actions to be focused are:

- Retrieve the shop floor efficiency with an optimized planning to increase the annual volume of production (+10%).
- Reduced the latency to take decisions by automatic prescriptions (planning and methods) to keep control of time.

Experiment team

The stakeholders that will be involved in this project are:

- ***PERNOUD***: is the leader SME of the experiment that aims to improve the organization of the manufacturing sequences on its shop floor.
- ***POLYMERIS*** is the French cluster of plastics, composites and rubber industry. It will support PERNOUD in its experimentation, planning, preparation, monitoring, evaluation and collection of feedback on the impact of integrating AI solutions in mould-making processes. Moreover, Polymeris will support PERNOUD in the search for partners and expertise which the company currently lacks, in particular around the integration of AI, or the training associated with these new technologies.
- ***POLYTRONICS:*** support companies in plastics, composites, rubbers and textile industries in their digital transformation thanks to artificial intelligence (AI). As an EDIH, Polytronics gathers a group of experts in digital and polymer manufacturing processes, whose aim is to constitute a single entry point for SMEs which want to implement AI technologies in their activities. The EDIH is based on a service offer dedicated to testing before investing (by providing technologies, prototyping, testing and validation), skills and training, the support of SMEs for funding, and the animation of an ecosystem.

3.3.1 AS-IS scenario

The organization of the company is mainly done with the MES system WORKPLAN from Hexagon software. Every action related to a project is stored on this software, from the quotation to the delivery. More specifically, every project is available and composed of different pieces called “REP”. Each “REP” owns its manufacturing sequences and every manufacturing sequence (MS) is composed of different tasks (T) that need to be scheduled. As a resume: REP > MS > T.

As an example, Figure 5 reports an example showing the “M1773” project containing different REP (in orange), “100 – PB Empreinte” is a REP from the project M1773 and composed of a manufacturing sequences (in green) and finally “#2205628 “ Is a task from the manufacturing sequences of REP 100.

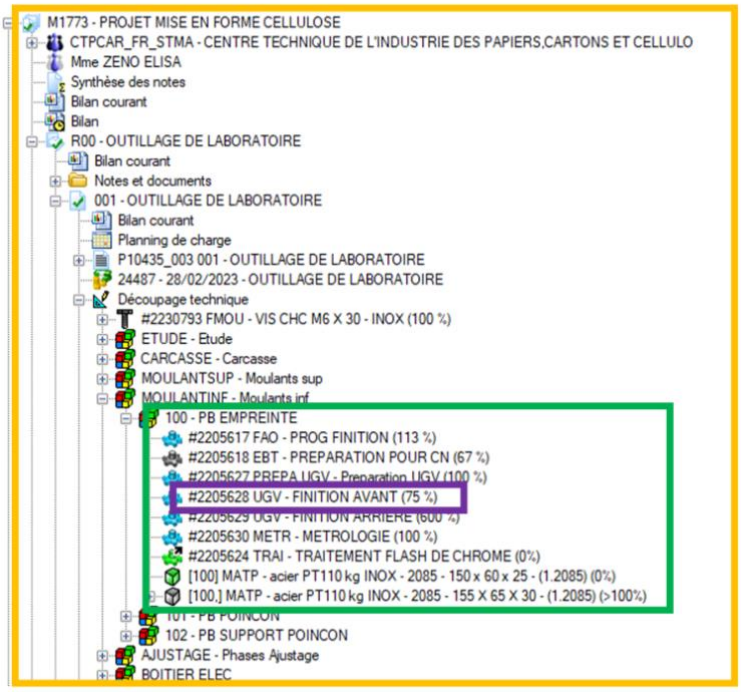

Figure 5 PERNOUD AS-IS example of tree diagram in WORKPALN

Currently, to complete a manufacturing sequence, all the tasks have to be completed in the right order and to complete a project every REP (and manufacturing sequences) have to be completed as well. The planning of those tasks is made by the scheduler on an Excel file (see Figure 6) during the planning meeting on Monday and update during the "top 5" every day.

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PLANNING DETAILLE USINAGE HELLER Semaine 15 2023

Date	N° MOULE	REP - Pièce	Nb Pièces	Tps alloué	Infos / pièces	montage	N°OP	Flux
début soirée								
Nuit								
MARDI	U00557	Emps	1	1	reprise nc			
	M1776	2	1	1	prepa			
début soirée								
	U00579	3e Noyau	1	5	eb 2e sens			
Nuit	M1774	30303	1	7	fi 2e sens			
	M1774	20154	1	4	fi ar			
MERCREDI	M1776	2	1	3	fi ar			
	M1767	5	1	1	prepa			
début soirée								
	M1767	5	1	3	eb ar			
Nuit	M1774	20165	1	8	fi ar			
	M1699	96		4	eb ar			
JEUDI	M1774	20151	2	2	Reprise			
	M1776	2	1	2	fi av			
début soirée								
Nuit	M1774	10151	1	8	fi av			
	M1774	20165	1	5	fi av			
VENDREDI								
début soirée								
	U00579	4e Noyau	1	5	eb 2e sens			
Nuit	U00579	5e Noyau	1	14	eb 1er sens			
	U00580	Emp fixe KV	2	32	eb 2e sens			
				105				

Figure 6 Example of planning for resource "HELLER"

On the MES system, tasks are characterized (resources, duration) without any timing or date. So during the planning meeting, all the information needed to be prioritized is gathered to set the planning for the two following weeks. Information comes from many sources, such as sales meetings, the real status of ongoing projects or even from the strategic point of view of the general management – Figure 7. Every morning, a "top 5" meeting is organized to update the daily planning according to new information (new projects, issues, delays, or emergencies) and a "to-do" list is printed for each resource. For the 24 following hours, no "official" changes are done. If some modifications are requested, the information is transmitted directly by the industrial manager to the required person.

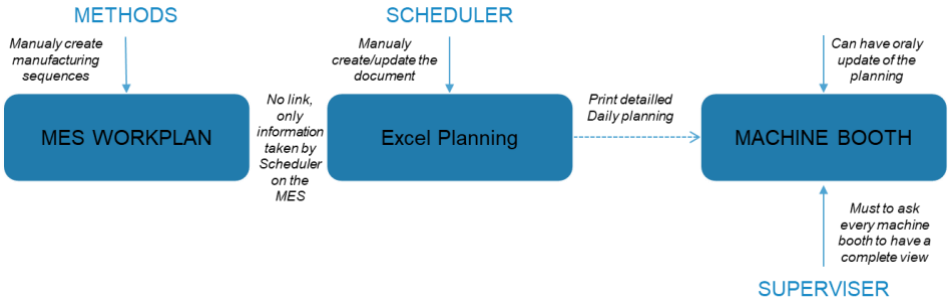


Figure 7 PERNOUD AS-IS PERNOUD flow diagram

What makes the planification in the Pernoud shop floor complicated is the presence of automatic machine tools able to work 24/7. The working hours are divided into three different categories and each category is characterized by its own specification:

- Day (7 AM – 6 PM): is dedicated to complex or very precise tasks
- Night (6 PM – 7 AM)
- Weekend: is mainly dedicated to long task

Nevertheless, some tasks can be completed in different types of working hours. If there is availability, a task previously planned on the weekend could be moved to day or night, but a task planned during the day (because of its complexity) should never be rescheduled on the weekend or night.

3.3.2 Technical Implementation

Currently Pernoud works together with Polytronics to find the right technology provider for its project; an example of this flow diagram is reported in Figure 8.

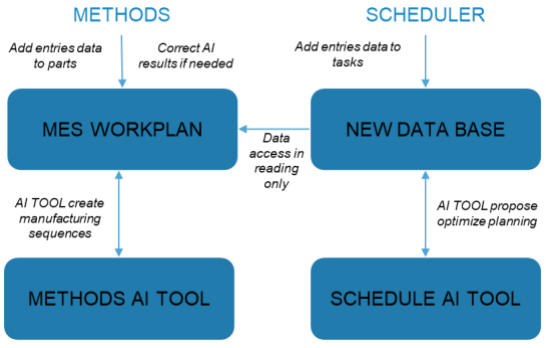


Figure 8 PERNOUD current action in progress

3.3.3 TO-BE scenario

In the TO-BE scenario of Figure 9, the planning will be automatically or manually generated on the MES tool and no longer on an Excel file. The "to-do" list will be accessible from a numeric support such as a tablet or a TV. This dashboard would allow seeing the upcoming tasks and their status (in which step of their

manufacturing sequences they are). Moreover, if they are not on time some advice will be sent to the user; its appearance will be similar to a departure/landing schedule of an airport with the upcoming flights and their gates. In this example, the flights are the tasks while the gates are the resources.

The advice to adapt the planning would be generated by Artificial Intelligence, taking into account the whole project's information to prioritize and find the best solution.

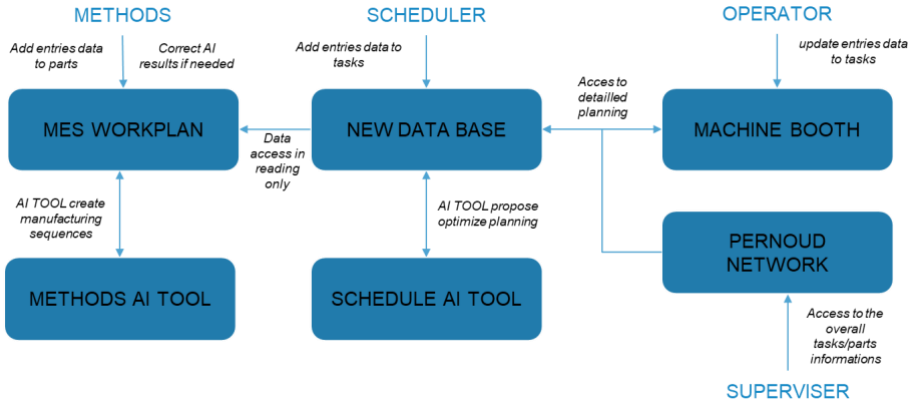


Figure 9 PERNOUD TO-BE flow diagram

3.4 SME Pilot III GPALMEC (Trentino, Italy): autonomous driving for agricultural vehicle

SME description

GPALMECH is an Italian company based in Rovereto (TN) and known at a national level as a leader in the distribution of industrial supplies for hydraulics, pneumatics, instrumentation, linear motion, transmission and fittings, technical and ferrous materials with over 100,000 products always in stock and supplied by the best international brands on the market.

Motivation

In the frame of AIREDGIO 5.0, GPALMEC leads an experiment dealing with **autonomous driving for agricultural vehicle** by implementing the Industry 5.0 paradigm to the agriculture with the use of AI at the Edge. The experiment is aimed at minimizing the risk of vehicle rollover, severe impact and loss of control. Indeed, according to the ANSA press release – June, 10th 2022 – from 2010 and 2020 there have been more than 2.000 fatal accident involving tractors only in Italy. Autonomous machines will increase the operator safety because they don't need the driver to be on board.

Objectives and benefits

After discussing the matter with the machine's OEM, implementing the autonomous drive to his vehicle might have a huge impact on the market. Autonomous driving, even with the operator on board, could have a positive benefit on safety: driving a machine for a long time is a repetitive job that could lead to distraction or tiredness and, therefore, to an accident. The electronic autonomous drive system, instead, will not get tired and will not lose the focus on the task, improving the safety by keeping the machine on the right track and avoiding obstacles.

Moreover, the project could have a follow up, *i.e.* giving not only the tractor the "smart" capability, but implementing the logic on the tool that is installed on the vehicle. Taking an atomizer as example, the sensors could detect if a tree is diseased and spray only in this case, contributing to save fuel, treatment and money by not continuously spraying.

Experiment team

The stakeholders that will be involved in this project are:

- ***GPALMEC Srl:*** is the leader SME that aims to develop a control for making an agricultural machine autonomous.
- ***HIT – Hub Innovation Trentino*** will participate as DIH regional representative for Trentino – Alto Adige area.
- ***FBK – Fondazione Bruno Kessler*** will participate as a research foundation linked to HIT that will help GPALMEC to develop machine on-field routing functions.
- ***Geier Srl*** is the end-user and the test-machine provider that aims to improve the functionalities of its agricultural vehicles.

3.4.1 AS-IS scenario

The existing vehicle is property of Geier srl, a test-machine provider with the aim to improve the functionalities of its agricultural vehicles. Actually the vehicle is fully controlled and piloted by the driver who must simultaneously looking for:

- the driving process:
  - keeping the machine within the rows of trees
  - detecting and avoiding obstacles and dangerous driving conditions
- the working process.

3.4.2 Technical Implementation

The technical solutions that will be adopted to make the agricultural vehicle autonomous consists in implementing the following technologies:

Hardware

- **3D camera:** it is provided with an array of photoelectric sensors measuring the distance between each sensor and the nearest surface by calculating the time of flight (TOF) of the light emitted by an illuminator installed next to the camera. The processed data is used to describe three-dimensionally the captured scene and the internal AI allows to detect the rows of trees and obstacles. The data is transferred to the mobile control unit via CAN interface.
- **Mobile control unit:** control unit specifically designed for mobile applications withstanding wide operating temperature range and high vibrations. The control unit communicates via CAN-bus with sensors, the camera and the vehicle control unit.
- **Mobile GPS with accelerometer and Wi-Fi/Bluetooth (BT):** unit containing GPS, accelerometer, Wi-Fi and BT for mobile applications. Wi-Fi and BT are used to communicate with tags installed on the field and combined with the GPS give a precise localization even in case of poor GPS coverage. Wi-Fi and BT are also needed to receive remotely the target area. Position, target area and accelerometer are sent to the control unit.
- **Inclinometer:** sensor for steepness measurement.

Software

- Proprietary for 3D camera configuration.
- Software for configuring accelerometer and inclinometer.
- Programming environment for control unit configuration according to standard IEC 61131-3.

3.4.3 TO-BE scenario

Once the vehicle will be equipped with the above mentioned technologies and a second PLC will be installed, the interface PLC will collect all the information from the sensors, run the analyses and gives the

master PLC the commands to move the machine. To transfer the commands to the master PLC and to retrieve from it the machine status, a data exchange between the two PLCs will be set-up. Figure 10 shows a schematic representation of the interaction between transmitter and receiver.

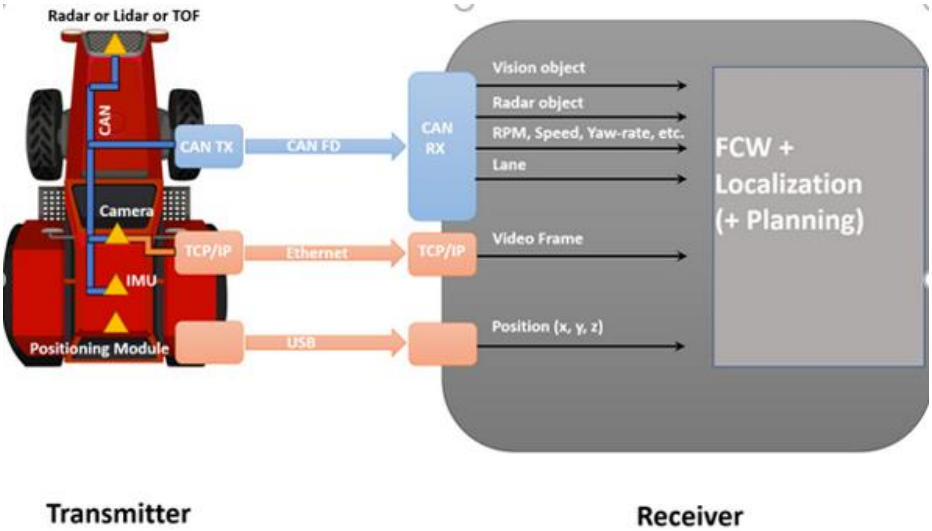


Figure 10 GIPALMECH schematic representation of the interaction between transmitter and receiver

At this point, the machine will:

- stop in case of obstacles that might damage the vehicle or injure the driver
- warn the driver in case the vehicle is crossing its operational limits
- follow the path within the rows of trees, freeing the driver from this task
- intrinsically lower repair costs and down-time.

3.5 SME Pilot IV POLYCOM (Slovenia): maximization of availability, production quality and efficiency of molding machines

SME description

POLYCOM is a midcap company located in Slovenia and it is an innovative quality provider of integrated development solutions for the automotive sector and other industries. The company's activity is the processing of thermoplastics and tool making. POLYCOM, as a specialist in moulding processes, has a manufacturing floor that consists of more than 110 moulding machines along with a range of moulding tools. To maximize their availability and hence production quality and efficiency, these highly distributed assets need to be continuously supervised.

Motivation

POLYCOM, as a specialist in moulding processes, has a manufacturing floor that consists of more than 110 moulding machines along with a range of moulding tools. To maximize their availability and hence production quality and efficiency, these highly distributed assets need to be continuously supervised. Today, data needed to manage the maintenance actions is already collected manually, but all these actions are highly labour intensive. To support these business objectives through the increased utilization of production data, this experiment will explore the possibilities to integrate the data using interoperability standards, exploit the data for predictive maintenance while employing novel AI and local edge processing solutions. The experiment is aimed at adoption of **smart production monitoring** solutions for the injection moulding process. The aim is to utilize continuous assets supervision to maximize process availability through improved monitoring capability.

It is a big challenge to manually monitor the performance of a high number of moulding machines and moulding tools in the company. A systematic approach is needed in order to utilize the process data for high-level monitoring. The long-term goal is to develop data-based predictive maintenance solutions for machines and tools.

Objectives and benefits

The experiment aims to validate and demonstrate the adoption of the smart production monitoring solution for injection moulding processes. The main objective of the experiment is to overview the already achievable data sources in the production and to identify the means of how these data can be employed to improve the insight into the production process. The main interest of the data analysis will be oriented towards providing the predictive maintenance solutions that will be able to scale over larger set of moulding machines that the company owns, and to obtain more detailed and faster insight into the current state of the process equipment and moulding tool as it is available at the moment.

With the analysis of the data and implementation of the AI powered tools it is expected that the following benefits could be addressed:

- Decrease unplanned stoppages
- Improve stability of products' quality
- Increase operational life-time of the production equipment
- Transfer of the concept to other machines in the company
- First step towards company-wide approach for predictive maintenance

Experiment team

Within the experiment, the participation of three partners is planned:

- ***POLYCOM**:* as experiment leader and end user, the company will host and coordinate the experiment. This means that the company will provide the data from the production, position the needs and requirements of the solution, provide the domain process knowledge and support the integration of the data sources and implementation of the demo solution.
- ***KCSV***: is a Competence center for advanced control technologies and a cluster connecting the research institutions, services providing engineering companies and industrial companies end-users of control technology. KCSTV was founded by the engineering companies providing services which are members of the Technology Network Process Control Technology consortium in order to promote collaboration among different partners in research and development projects. The role of the KCSTV in this experiment will be to coordinate the experiment and to provide administrative support to the POLYCOM. If needed additional experts from the cluster will be identified and included for the needs of the demo.
- ***JSI***: Jozef Stefan Institute is the leading scientific research and development organization in Slovenia. The role of the JSI institute within this demo will be to coordinate the development of solutions based on a priori analysis of the data, the domain problems and the existing solutions, to prepare the appropriate platform for the integration of the final solution and to integrate the testing solution.

3.5.1 AS-IS scenario

The company currently records a large number of process parameters, which are collected directly on the machine (87 basic parameters, some still have an additional 100 parameters). In addition, optical product quality control data is also collected in another system, where the control is carried out three times a day at the change of shift.

In the current practice the company already collects the data from the moulding machines. The data is being exported from the machines automatically and is being stored to the network hosted server. Then, the

data is being used by the domain specialists to resolve the acute problems in the production. These actions are not performed on-line, but only after the deviation is detected by operators or by end-product quality monitoring step. Moreover, such analysis is manual and highly labor intensive.

The large amount of data and information that this data may carry is not used, as the data is collected mostly for the subsequent review of critical situations. High number of moulding machines in the company demands a systematic approach. In order to truly monitor their performance and to automatically detect and alarm the abnormal behavior.

3.5.2 Technical Implementation

The technical solutions that will be adopted for the on-line monitoring of moulding machines are:

Hardware

- Raspberry Pi
- Orange Pi

Software

- Arrowhead platform
- NodeRed
- Grafana
- InfluxDB

Communication channel/s

- TCP/IP
- REST

Standard used

- OpenAPI/Swagger
- Euromap 63, Euromap 77

3.5.3 TO-BE scenario

The experiment will represent a validation of an approach where an additional local processing unit (edge device) will be connected to each moulding machine. The above cited local processing unit will be able to read data, perform calculations and forward results to the central unit.

The operating process data will be read on-line and according to the specifics of used tools and production requests the process operation data will be validated. Abnormal operation will be detected according to the normal process repeatability patterns and quality inspection feedback. For this purpose it will be used an open source software - python based analytics and communication channels TCP/IP. Figure 11 shows the future overview of the technical platform for integrating the final solution using Arrowhead platform.

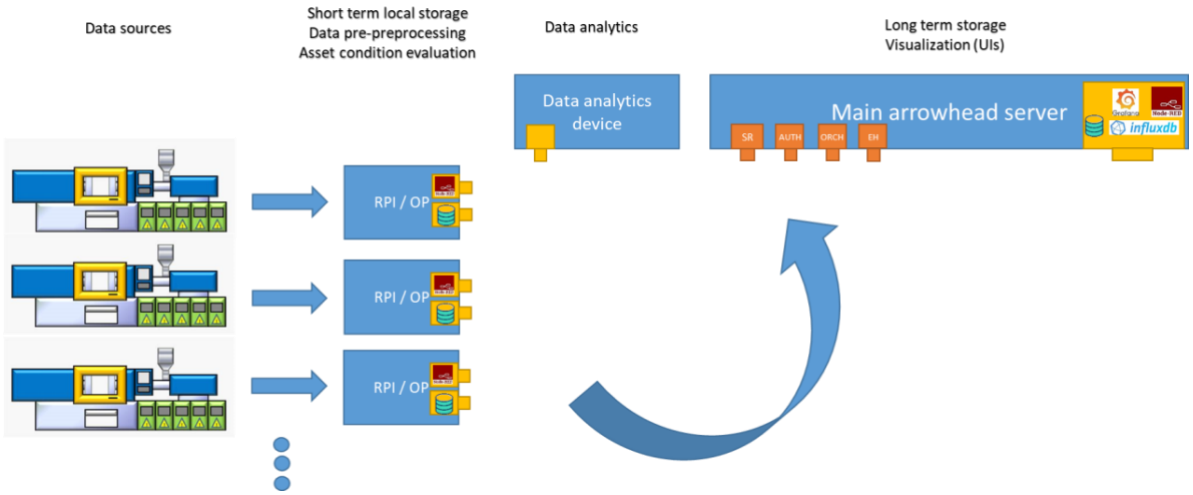


Figure 11 Overview of the technical platform for integration the final solution using Arrowhead

3.6 SME Pilot V QUESCREM (Galicia, Spain): quality improvement of cheese products and reduction of wastes

SME description

QUESCREM is an Innovative Spanish Dairy Company specialized in developing, manufacturing and commercializing different varieties of Cream Cheese, Mascarpone & Customized Products of top quality.

Motivation

The Galician region's industrial landscape in northwest Spain features an important weight of mid-sized manufacturing industries based on bio-inputs coming from its important bio- and primary sector (agrifood, fish, wood and others).

Waste generation, treatment and disposal is one of the main issues in the transformation & manufacturing sector working with bio-inputs. Apart from the obvious environmental impact, which shall be minimized or eliminated, companies incur in several costs that impact their daily business and profits. Moreover, it has an impact on society as well. Tackling and improving waste management and carbon footprint is one of the key problems to be solved by the manufacturing industry in the following years. Waste is originated by production processes (use of water, scraps, raw material waste, etc.) so one of the key points to be addressed is to include the optimization of these parameters in general production management, which is typically oriented to decrease costs and improve efficiency. Additionally, manufacturing processes are progressively shifting towards and being integrated in circularity schemes that help not only reduce waste but potentially turn one's waste into inputs for oneself or other within the circularity chain.

For Quescrem the main motivation behind the experiment is to improve the quality of the end product (cheese cream) and reduce waste to improve sustainability. More specifically, the industrial processes of the company are heavily oriented towards achieving the highest level of quality in its products as well as reducing variability in the organoleptic properties such as creaminess in its products. Also, one of the main objectives of the company to comply with sustainability goals is to reduce waste generation and optimize the use of raw materials, water and energy in manufacturing activities. In this regards, the idea of the project is to use process data stored in Quescrem's MES, as well as real-time data streams collected from production lines, in order to prescribe the optimal parameters that minimize waste (mainly permeate) and increase quality (e.g. homogenize cream cheese texture) as well as efficiency.

Objectives and benefits

The main objective for Quescrem in this project is that through the analysis of the data we store from our production process such as temperatures, pressures, fat, protein, etc., we can improve the quality of our products and reduce waste. A high percentage of the product that is released is out of specification, that is, parameters such as hardness, pH, composition or acidity are outside the standard values of the product and this is because the combination of parameters such as temperatures, pressures, flow rates, fermentation times, etc., significantly affect these values and therefore the importance of knowing for each family of products which are the optimal combinations of these parameters so that each product comes out within these standard values.

Waste reduction and carbon neutrality shall be one of the main targets to be achieved by EU manufacturing companies in order to achieve full sustainability. In order to have a good knowledge of industrial processes, aiming to optimize them and prescribe the setpoints that improve the efficiency and minimize waste, a good knowledge and modeling of processes shall be performed. Thus, digital twin technologies will be applied as a basis that enables a virtual representation of the plant, focusing not only on process variables obtained from PLCs or MES systems, but also considering waste related parameters (water and electricity consumption, raw materials waste kg, etc.). This digital twin will be created as a virtual representation in the edge where models of the different involved machines are continuously created and improved when drifting is detected. Moreover, approaches such as federated and incremental learning algorithms will be used to better create models and extract insights from the process.

The main objective is to apply analytic technologies at the edge digital twins in order to prescribe the best **process** parameters that minimize waste while keeping quality, efficiency and productivity at its best. xAI (explainable AI) methodologies will be applied in order to provide valid feedback to humans regarding the proposed decisions by the algorithms to increase trustworthiness. Security will be taken into account from the beginning of the use case, thus applying security-by-design.

Experiment team

Within the experiment, the participation of the following partners is planned:

- ***Quescrem***: as experiment leader and end user, the company will host and coordinate the experiment. This means that the company will develop new solutions to improve the quality of the end product (cheese cream) and reduce waste to improve sustainability.
- ***Gradiant***: is a Spanish ICT technology center, which aims to improve the competitiveness of companies by transferring knowledge and technologies in the fields of connectivity, intelligence and security. With more than 150 professionals and 14 applied patents, Gradiant has developed more than 340 different R&D&i projects, becoming one of the main engines of innovation in Galicia. In 2022, Gradiant's turnover reached 8,5 million euros, working with more than 370 clients in 30 countries over the past 13 years. In this experiment Gradiant aims to apply several edge computing and AI technologies in order to help Quescrem achieve its objectives as defined in previous sections.

3.6.1 AS-IS scenario

QUESCREM's **operations** - Figure 12 - are performed in **local systems**, relying only on **traditional fieldbus communications** and on a **local server infrastructure** to store information.

Figure 12 Quescrem factory

Current systems don't use specific standards, apart from REST APIs, database connection through SQL languages and in some cases OPC-UA to get data from the process line. No AI or edge technologies have been incorporated into the company. Thus, during the AI REDGIO project a specific infrastructure will be deployed in order to orchestrate AI services at the edge and manage their lifecycle through the application of MLOps methodologies.

3.6.2 Technical Implementation

The technical solutions that will be adopted for the **on-line monitoring** of different physical parameters *e.g.* of parameters such as temperatures, pressures, flow rates, fermentation times, etc., are reported in the following:

- **MES (TrakSYS)**: it is currently being implemented in Quescrem and provides real-time data collection, analysis and reporting capabilities that allow it to monitor the production process and make data-driven decisions to improve efficiency and quality. The MES keeps track of all the process variables and allows to formulate manufacturing orders depending on the product that needs to be produced. It allows sending recipes to the machines in the physical process so they can start working with the established ingredients and quantities to create the final product. The MES interacts with the machines and sensors deployed in the manufacturing shopfloor, with the ERP and APS.

- **APS (Siemens OPCENTER):** its objective is to optimize production planning and scheduling and create the final manufacturing orders that will be passed to the formulation system and the MES. Thus, this service interacts basically with the ERP to get the MOs and with the MES to pass them in the correct order.

- **ERP (SAP):** the ERP solution used by Quescrem in their operations is SAP. It manages providers, customer orders, reception of raw materials as well as financial costs. This service interacts with the MES, the WMS and the APS.

- **WMS (Fast Process):** the WMS is used to manage and optimize the flow of materials and finished goods, helping to reduce costs and improve overall efficiency by providing real-time visibility into inventory levels and optimizing storage and picking processes. The WMS interacts mainly with the ERP.

3.6.3 TO-BE scenario

This experiment will use ML models for real-time processing from sensor data-streams collected from production equipment and lines. These models will be able to solve multivariate regression and classification supervised problems. Moreover, they will be the basis of the prescription system to dynamically reduce waste and optimize fabrication setpoints to ensure quality.

The expected solution to be deployed in Quescrem's industrial site aims mainly to increase end product quality and the overall efficiency of the manufacturing process while also minimizing the generation of waste (milk permeate) in order to increase sustainability. As explained in previous sections, this will be achieved through the deployment of several AI technologies at the Edge and more specifically a module for the prescription of the process parameters that guarantee achieving the constraints previously mentioned. Thus, the TO-BE scenario will be similar to the one presented in the Figure 13.

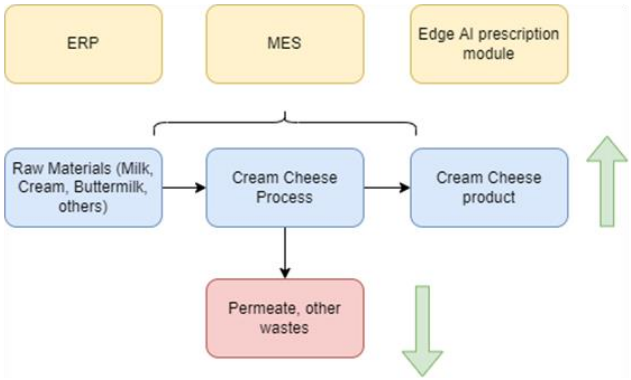


Figure 13 Quescrem TO-BE process flow diagram

Scenario 1 : Prediction of target variables (waste, efficiency, quality)

In this scenario AI Edge models will be implemented and deployed within the experiment's facility with the aim of monitoring the production process and estimating values of KPIs regarding quality and waste. These models will estimate both the quantity of waste and the value of the KPI related to quality (cheese-cream). Moreover, these models will be containerized in order to be easily orchestrated within the IT infrastructure. The outputs of these models will feed into the prescriber of production setpoints.

Scenario 2 : Optimization and prescription of production setpoints

In this scenario an AI based optimization module will be implemented and deployed within the experiment's facility with the aim of recommending the production parameters that minimize waste and optimize quality of products (i.e. cheese-cream) - Figure 14. This component will provide optimal setpoints using the outputs of prediction models deployed in scenario 1, among other inputs. In addition, this component will be containerized in order to be easily orchestrated within the IT infrastructure.

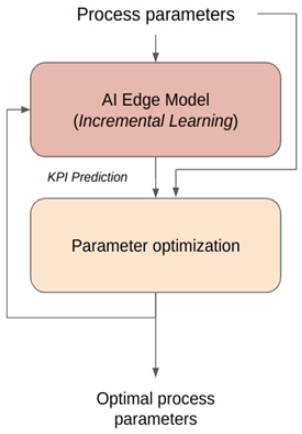


Figure 14 High-level architecture of Scenarios 1 and 2

Scenario 3 : Orchestration of AI services

In this scenario a system for orchestration of AI models within the IT infrastructure of the experiment will be developed. This system will use software containers and Kubernetes based technologies, such as KubeEdge, to efficiently manage AI components along the edge-cloud continuum.

3.7 SME Pilot VI CAP (Wales, UK): Intelligent Contextualised Visual System for Error Reduction

SME description

CAP Engineering Services Ltd is a SME machine builder and Systems Integrator, specialising in intelligent automation equipment. CAP provides a turnkey solution from design to manufacture, including Mechanical and Electrical Design, CNC Machining and fabrication, electrical panel building, machine assembly, PLC programming and Systems Integration and testing.

Motivation

CAP Will work with DMIW and C2K to integrate different production systems (inc. Industreweb™, PLCs and other control devices), embedded technologies (AI, CPS, IoT) and human operator knowledge, into a single unified digital visualisation platform.

Using the Industreweb™ Platform, Control 2K and CAP Engineering will develop an innovative AI- based Contextualised Visual System (CVS) that will collect, analyse, and present data to the operator to reduce any errors in the production process and minimise errors on the product lines of one of C2K's key customers.

Objectives and benefits

Using the AI REDGIO 5.0 architecture, we will access the relevant toolkits being developed under the project to create added value within the production process, enabling a variety of outcomes including access to specialised knowledge in the production system; access to production data for process improvement and efficiency; and transfer of human-to-machine and machine-to-human knowledge.

The focus will be on the creation of an AI-driven process checks to replace mandatory manual **inspections to validate the correct assembly** and quality of components used on a high-precision production line for the aerospace domain.

- We will collect intelligence on how the process effects the end result and offer parameter changes (self-healing production)
- The solution needs to be cost effective, designed for the SME Systems integrator and provide better data than traditional vision systems, more geared towards process improvements rather than simply pass/fail.

Experiment team

The stakeholders that will be involved in this project are:

- **CAP**: is the leader SME of the project and aims to integrate different production systems embedded technologies, and human operator knowledge into a single unified digital visualisation platform.
- **Control 2K** is the technology provider, supplying the platform which will allow the experiment components to interact using the market-leading Industreweb™ Data Integration Platform, which forms the basis of both the Didactic Factory Experiment: IWOKs Knowledgebase system and the AI-driven vision system outlined in this experiment.

CAP and C2K will work together to integrate the vision system and knowledgebase, initially into the existing didactic factory for testing, and then into the 'Intelligent Contextualised Visual System for Error Reduction' deployed by CAP Engineering (CAP) at the customer premises.

3.7.1 AS-IS scenario

The component to be assembled is an aerospace fastener used in the latest composite aircraft fuselage. It consists of 3 separate parts and is made of either Aluminium, Titanium, or stainless steel; the lathe needed to make the fuselage and its 3D drawing are shown in Figure 15.

Figure 15 CAP machine and CAD representation of the aircraft fuselage

Currently, the component is assembled manually by an operator, placed into a nest fixture in the chuck of a lathe. The assembly is then swaged to create fixing between the outer to components capturing the centre – Figure 16. The process takes approximately 30/40 secs per part and the quality of the process is largely dependent on the skill and experience of the operator.

The process is slow and manually completed, creating opportunities for errors and each component has to be manually inspected before the next component can be completed.

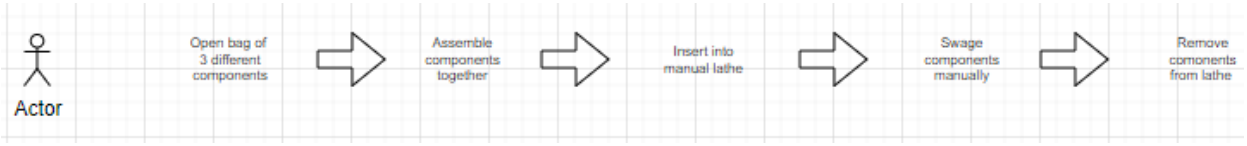


Figure 16 CAP Process

The project team is in the process of designing a new, AI-driven, automated quality process to speed up the quality management process and resolve defects as they are being produced.

3.7.2 Technical Implementation

The automated cell prototype has been built within the DMIW workshop to allow for extensive testing – Figure 17. The characteristics of the optimized process are reported in the following:

- The hardware used is a combination of a new automated Swaging machine, designed and constructed by CAP Automation; a reconfigurable Cobot made by Inovo™ and a vision system powered by Zebra Aurora.
- The Software used comprises of the Industreweb™ Data Integration Platform, made by Control 2K, the Zebra Aurora Vision system and an AI model based using Python script.
- The system is connected together via ethernet using the Industreweb platform as a central data layer between the various systems.
- Standard used: OPCUA, Ethernet, MQTT

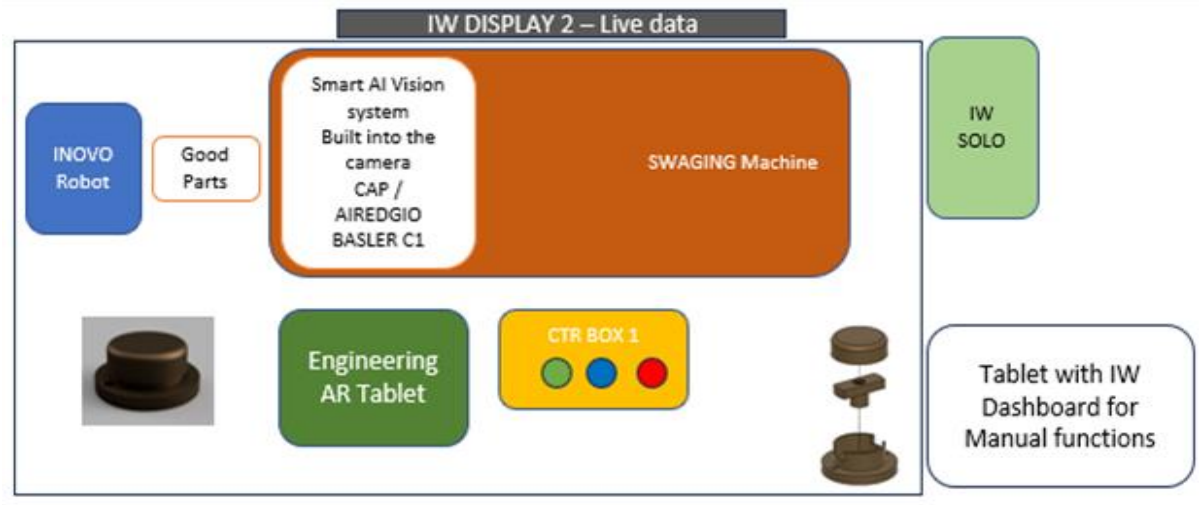


Figure 17 The automated cell prototype scheme

3.7.3 TO-BE scenario

The experiment will aim to improve the process by replacing the manual swaging task with an automated process, combined with an intelligent vision system to check the quality of the completed parts – **Error! Reference source not found.**. Data gathered from the vision system will be fed into a knowledgebase system to enable the operator to focus on quality assurance.

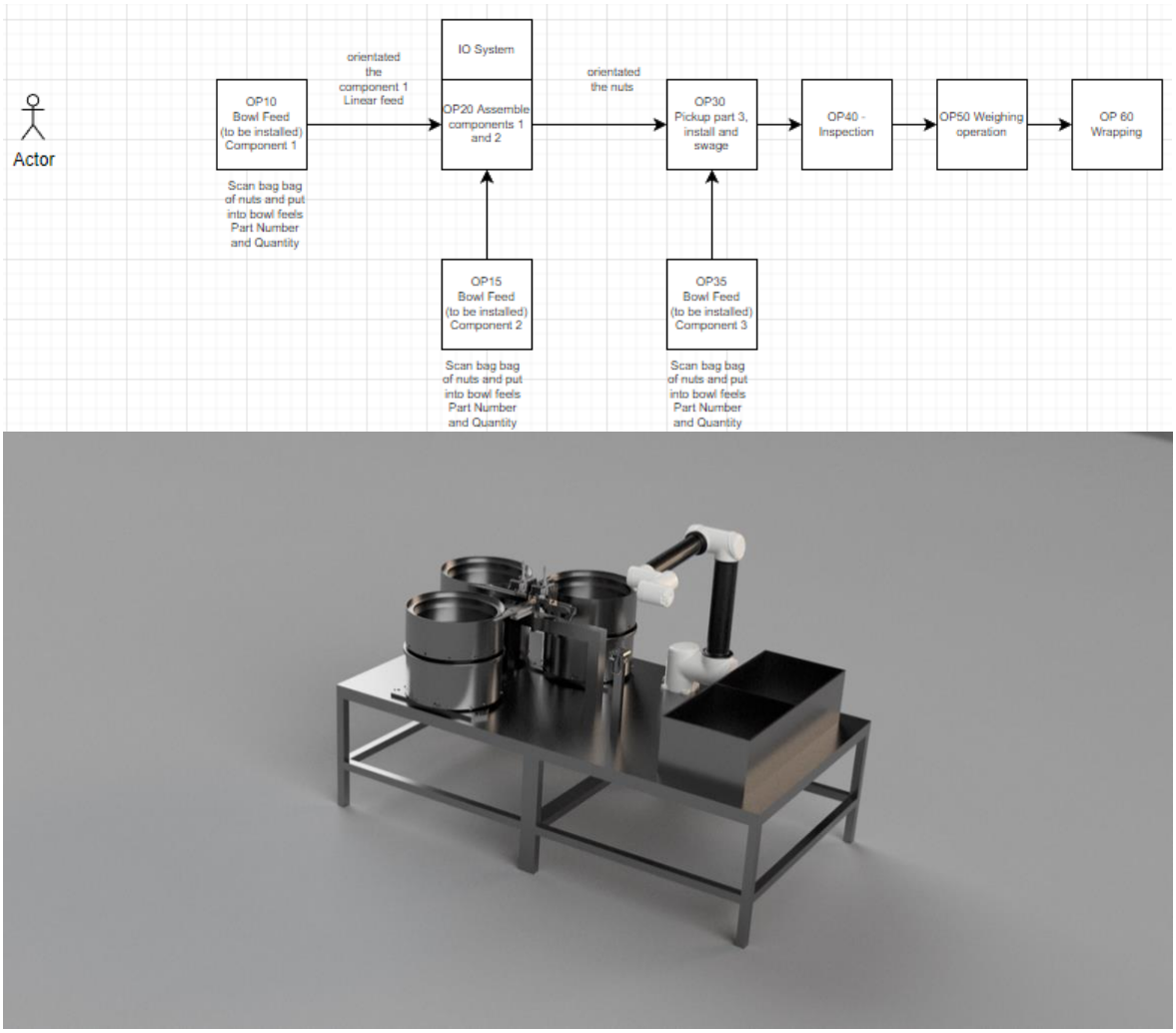


Figure 18 TO-BE process flow diagram

A detailed description of the TO-BE scenario is reported in the following:

- fasteners are to be fed from a pair of 400mm bowl feeder for auto loading and refilling without stopping production
- station 1 assembles components
- station 2 pneumatically swages the components together.
- full network connection allowing for connection to network and all production data available remotely
- with a cycle time of approximately 3-4 seconds per part, allowing for an output of 900-1200 parts per hour
- the unit should run unaided for approximately 1 hour
- all components are to be inspected prior to release.

An additional image of the 6 axis cobot is reported in Figure 19.

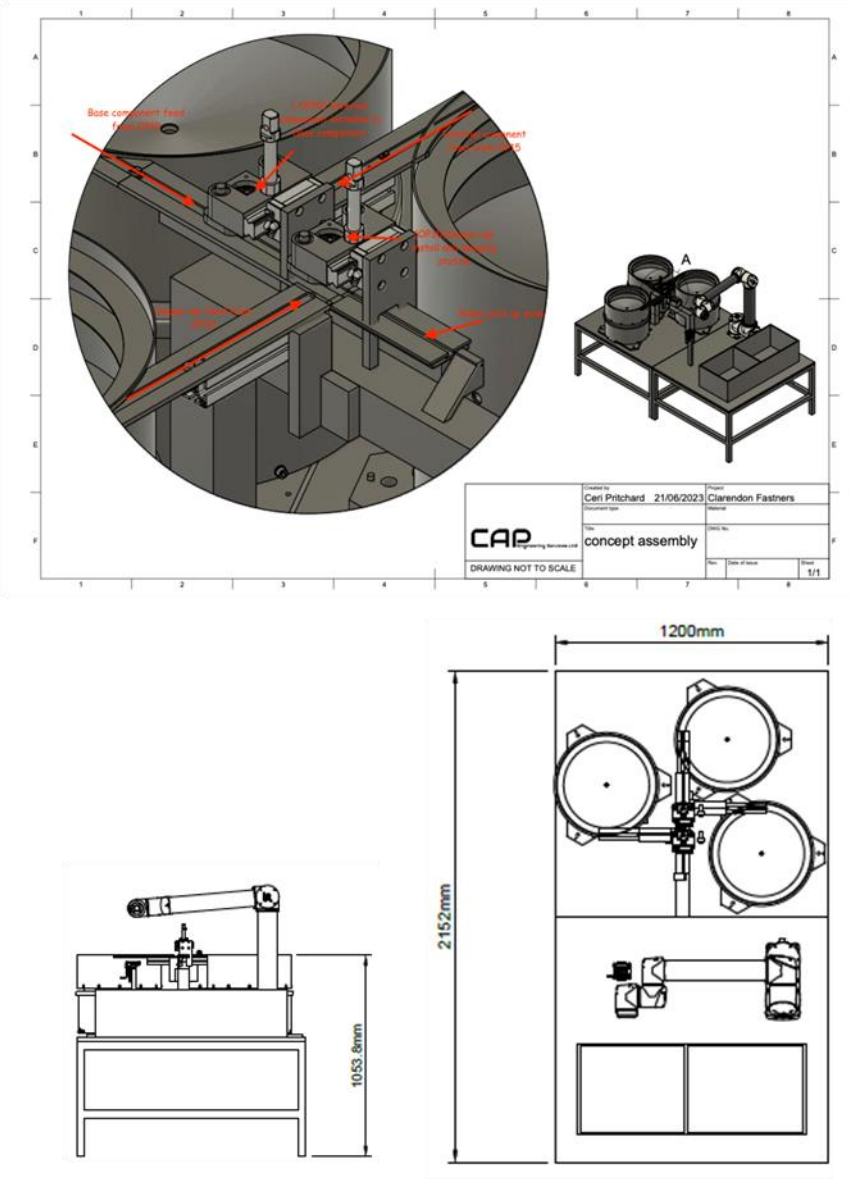


Figure 19 CAP's 6 axis cobot

The machine control will be completed using a Siemens S7 1200 PLC using a KTP700 HMI touch screen for operator control. Final inspection will be completed using pressure curve monitoring with initial verification completed using Keyence IV3 AI camera inspection systems. All these elements are reported in Figure 20.

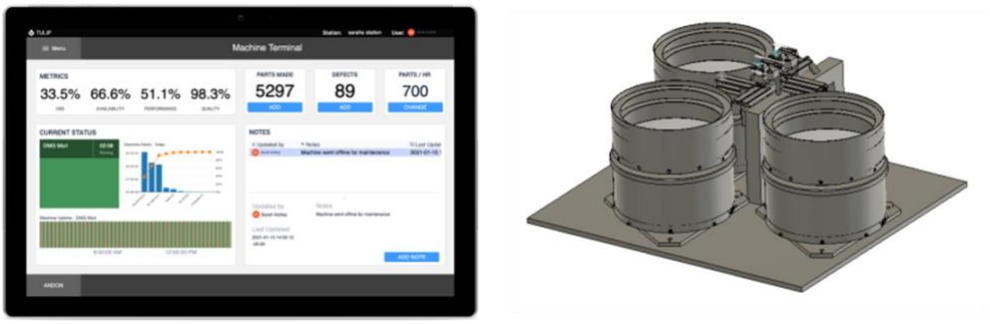


Figure 20 KTP700 HMI touch screen and Keyence IV3 AI camera inspection

The unit will also be fitted with an industrial PC allow for remote connection and Data acquisition. This allows remote access of:

- the machines current state
- any alarms or problem
- current part numbers, quantities etc...
- failure modes and pressure data.

3.8 SME Pilot VII KATTY FASHION (Romania): development of a product defect detection system for clothing items

SME description

KATTY FASHION is a bespoke womenswear services company offering product design, development and manufacturing. It is one of the most innovative SMEs in the nortw-est of Romania thanks to its Zero Pre-Consumer Resource Waste Strategy and unique digital transformation path that awarded us the Factory of the Future title as the winner of BoostUp Transform CLC East EITM competition.

Motivation

The KAF Quality Assurance (QA) department inspects the product quality last, and if a defect is found there, the customer will be dissatisfied. The QA work is currently done manually using a detailed checklist with subjective evaluation. In this case, AI can simplify the QA tasks and improve process efficiency and objectivity. In order to fully build the Fashion Factory of the Future, this adds to KAF's strategy for transformation to a digitally enabled smart & circular business model. Thus, the aim of the project is the development of a product defect detection system with the following functionalities: acquire product images; manipulate images by an embedded AI tool; extract information about the nature and severity of the product defect; send alerts to the QA personnel in charge of the product check. The developed system should be able to assist the QA team in validating the correctness of the operations done for the analyzed item based on close integration with the initial design characteristics.

Objectives and benefits

The main objective of the experiment is to offer a technical alternative, through automation, to the manual operation of evaluating the **quality** of the products made by KAF. In addition to this, in the following Table 1 are reported more specific objectives of QUAD-AI@E project:

Table 1 Specific objectives of QUAD-AI@E project

Objectives	Benefits
Automated QA process	Objective and complete QA report for clients
Minimise the chance of producing substandard products	High quality products delivered to clients
Reducing loss and wastage in the production	Less pollution, lower production costs
Make related jobs more attractive for humans	Larger hiring pool, higher wages due to better specialisation
Increasing the cadence of quality analysis	Reduce time waste: increase the pace of the quality analysis process from 15-20 minutes to a maximum of 5 minutes/product
Avoiding the transfer to the market of defective products	Ensuring a superior quality of the analysis through the system
Eliminating repetitive tasks and monotony	Lower employee burnout, the support granted to a human operator; visual analysis of defects by a human operator is tiring, requiring very good visual acuity and a good ability to concentrate
Making it possible for the same tasks to be performed, but with fewer hours of labor.	Productivity increase

Experiment team

Within the experiment, the participation of the following partners is planned:

- ***Katty Fashion SRL***: is the end-user application experiment SME.
- **Technical University "GH. Asachi**" Iasi: is the technology provider/DAF

During AI REDGIO 5.0 Katty Fashion will be the end user of the implementation of the QAD-AI@E solution, developed by TUI Iasi, in the real clothing manufacturing environment. More specifically, we will work together with TUI Iasi in developing an AI that can detect production defects.

3.8.1 AS-IS scenario

The QA work is currently done manually using a detailed checklist with subjective evaluation of the following defects:

- non-linearity of the seams
- fringing the textile
- stains on fabric
- buttons wrong placement

3.8.2 Technical Implementation

Currently, on the technical side, the experiment is at the requirements gathering and design stage. The technical implementation is not enough defined yet. However, a monocular camera will be integrated to capture image frames of the clothes (the product under test) which will be numbered (e.g., 00, 01, 02, ..., 10, 11, 12, ..., nm) to be easily identified. Each product under test will have its own code (ex: KAF_M023), this code will help manage the data saved in the database.

3.8.3 TO-BE scenario

The QUAD-AI@E system will be included in the production process in the QA phase for the finished products to be stored and delivered to the final KAF client. The products offered by KAF are clothing items intended especially for ladies and are produced in small series (10-20 pcs.). Each series has as a reference a template that is validated following a thorough analysis by a human operator in close coordination with the product development team. This reference will constitute the comparative reference for the UAPs.

The QUAD-AI@E system consists of:

- an image acquisition subsystem
- image preprocessing subsystem
- AI image processing subsystem

Fuzzy logic algorithms will be used for defect detection in clothes as part of edge computing systems. Fuzzy logic is a mathematical framework that deals with reasoning and decision-making in situations that involve uncertainty and imprecision. It allows for the representation and processing of vague or ambiguous information.

All the subsystems will work together to automate the QA workflow – Figure 21 – as much as possible given the workflow and relevant QA activities.

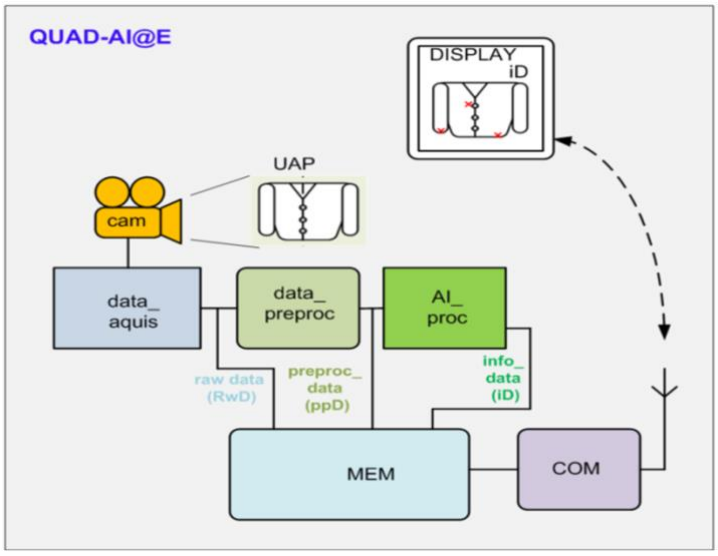


Figure 21 QUAD-AI@E - block scheme

There are two scenarios identified, the difference between them being that in the first a model of the product is used to check for production differences, in the second scenario only generic defect being sought.

Scenario 1: Automatic evaluation of finished products based on the provided UAP model

It is a comparative evaluation by referring to a reference product. The identification of possible defects in the UAP is done by adopting a reference product that is validated as being without defects. Using the reference data from the product development workflow, the UAP is evaluated for correctness of manufacturing steps:

- The operator will place the UAP in the necessary position for starting the assessment.
- The operator sets the reference against which the UAP comparison will be made and triggers the automatic evaluation process by the QUAD-AI@E system.
- The result is generated and stored as requested by the operator.
- The operator analyzes and does a first validation of the results.
- Appropriate measures are taken based on the applicable internal QA process and the report from the system.

Scenario 2: Automatic evaluation of finished products based on generic defect assessment

It is a comparative evaluation related to certain typologies of defects. The identification of possible defects in the UAP is done through the successive analysis of certain areas of the product and the automatic identification, through AI algorithms, of certain typologies of defects that are in a database. The assessment scenario is the following:

- The operator will place the UAP in the necessary position for starting the assessment.
- The operator configures the necessary defect checks and characteristics against which the UAP comparison will be made and triggers the automatic evaluation process by the QUAD-AI@E system.
- The result is generated and stored as requested by the operator.
- The operator analyzes and does a first validation of the results.
- Appropriate measures are taken based on the applicable internal QA process and the report from the system.

The concept underpinning QUAD-AI@E experiment is the development of a product defect detection system with the following functionalities: to acquire product images; to manipulate images by an embedded AI tool; to extract information about the nature and severity of the product defect; to send alert to the QA personnel in charge of the product check. The experiment builds on integrating AI at the edge technology into a product defect detection system prototype suitable for quality control automation in textiles industry.

3.9 Synthesis of SME Industrial Scenarios

As could be seen from the previous chapters, the SME experiments are quite different from each other and involve many different fields of application.

Nevertheless it is possible to derive some common aspects to describe the experiments and to map their needs – Figure 22. We have used the 3 Axis introduced in §2:

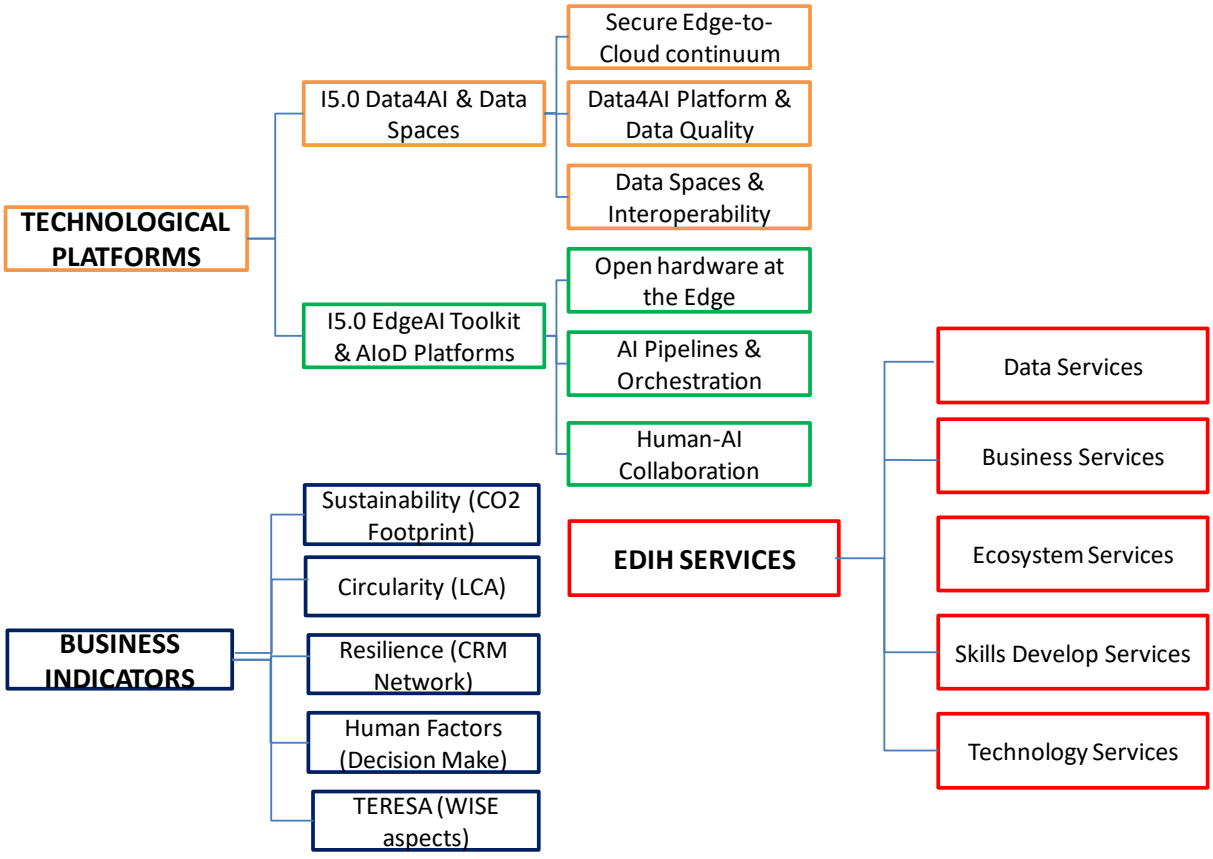


Figure 22 The AIREDGIO 3Axis Maps

The graphs below – Figure 23 and Figure 24 – show the most important features needed at technological level and the necessary services for the developing and deployment of the SMEs experiments.

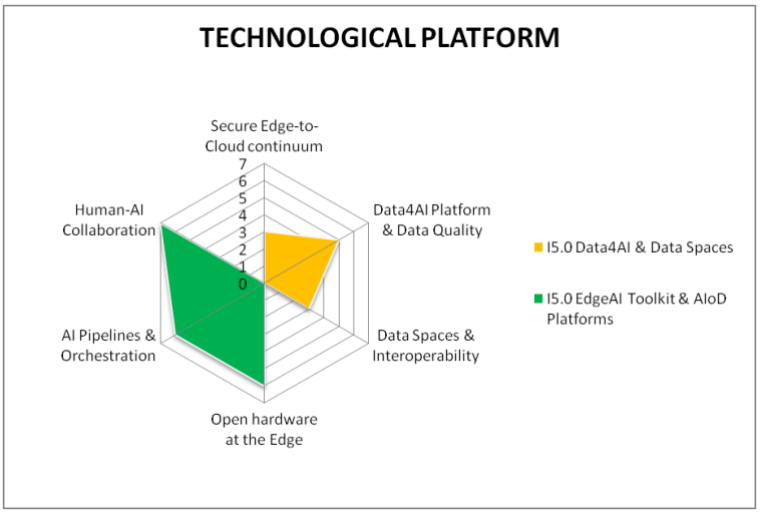


Figure 23 SME-driven experiments' technological needs

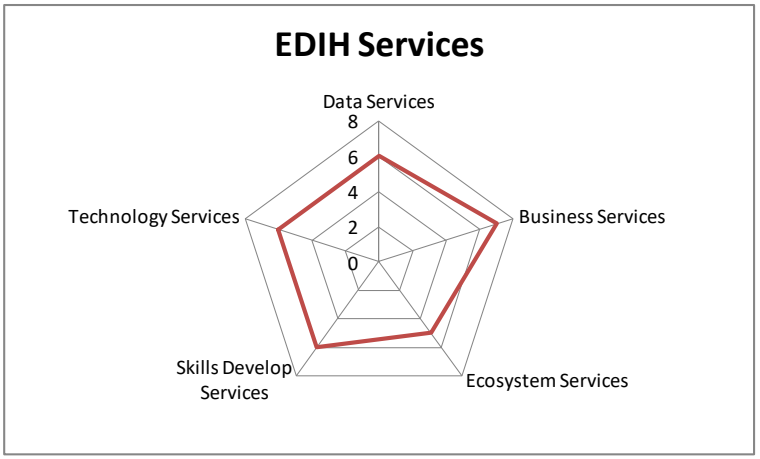


Figure 24 SME-driven experiments' EDIH services needs

While these two axes will be used to organize the support of the SMEs experiments, the third axis will be used to assess the impact and results of the experiment implementation.

The results of analysis conducted for each experiment is reported in the tables below – Table 2, Table 3, and Table 4.

Table 2 The SME-driven experiments' needs versus Technological Platforms

Pilot	Organization name	I5.0 Data4AI & Data Spaces (WP4)			I5.0 EdgeAI Toolkit & AIoD Platforms (WP5)		
		Secure Edge-to-Cloud continuum	Data4AI Platform & Data Quality	Data Spaces & Interoperability	Open hardware at the Edge	AI Pipelines & Orchestration	Human-AI Collaboration
I	SCAMM	Confidentiality of the IIOT data produced between edge and cloud	Missing values in input data can't be filled by synthetic data, but have to be addressed somehow	Sharing data with supplier means data interoperability (different formats standards)	Additional hw must be installed for collecting data from the production line: Process parameters from the PLC (they are not stored anywhere at the moment) Images of the defects have to be processed at the edge to extract synthetic indexes about product quality	The AI models should be orchestrated in a pipeline. Deep Learning model to detect and evaluate products defects NLP model to process operators input about detected issues and applied solutions (Company knoweledge management) Machine Learning model to correlate process parameters with quality indexes generated at the edge by DL model	Operators need to interface with the AI system whenever the AI system detects a defect, operators are informed through a user interface. Operators verify the issue and apply corrective actions to restart production. Description of the issue + applied solution has to be input in the knoweledge management system through the available user interface It is also possible to ask the operator to assess whether the AI system produced a false alarm through the available user interface
II	PERNOUD	No Current plans to send data out of Enterprise in Phase 1	Data preprocessing and cleaning activities are expected	N/A	Hardware must be added to collect information directly from the machine PLC	TBD	Human-AI collaboration is the key collaboration for the experiment success. Human will receive information and prescription form AI and decide to use it as it is or to modify it according to expert vision
III	GPALMEC	At this stage of the project we do not plan to send data outside the machine. We might be interested in case of a further develop of the project.			Edge hardware is needed process IoT and sensor data for localization	TBD	Human-AI collaboration already guaranteed: driver receives the information from the AI logic and decides the next movement. Driver can always override the AI decision.

Pilot	Organization name	I5.0 Data4AI & Data Spaces (WP4)			I5.0 EdgeAI Toolkit & AIoD Platforms (WP5)		
		Secure Edge-to-Cloud continuum	Data4AI Platform & Data Quality	Data Spaces & Interoperability	Open hardware at the Edge	AI Pipelines & Orchestration	Human-AI Collaboration
IV	POLYCOM	Edge to local cloud connectivity is needed that provides secure and reliable communication channel. The data security is not critical but data privacy should be provide especially if local cloud is not in the same network.	To improve the robustness of the data processing pipelines data validity needs to be verified before analytics in order to verify whether the ML algorithms are valid for the considered data set (detection of model extrapolation, detection of missing/defect data)	N/A	Edge hardware is needed to process the data locally, close to the data sources, the analytic's results are transfered to the central system (local cloud)	Central management of edge deployed algorithms that would provide a possibility to monitor the edge deployed algorihtms (status, performance) and possibility to deploy new pipelines from central system	Operators are monitoring the outputs of the AI solutions and annotate the special cases that were falsly detected as anomalies or not detected by the algorithms. This will represent an input for continous model imrpovement.
V	QUESCREM	No current plans to transfer data outside the enterprise's facilites, at the moment	Data preprocessing and cleaning activities are expected	N/A	AI models are expected to be run on a generic edge environment	The AI pipeline needed is very simple: it will involve the collection of real-time production data and the forecasting of new KPIs predictions (at the edge) and the prescription of the optimal production parameters (at the cloud).	Operators will label the results provided by the prediction module that will be developed. Also operators will monitor the predictions and prescriptions provided by the system.

Pilot	Organization name	I5.0 Data4AI & Data Spaces (WP4)			I5.0 EdgeAI Toolkit & AIoD Platforms (WP5)		
		Secure Edge-to-Cloud continuum	Data4AI Platform & Data Quality	Data Spaces & Interoperability	Open hardware at the Edge	AI Pipelines & Orchestration	Human-AI Collaboration
VI	CAP	No Current plans to send data out of Enterprise in Phase 1	Industreweb.cloud platform will host Data Management Tools	Open to discuss opportunities	Industreweb (TM)	Industreweb Data Platform	Dashboards that are context sensitive
VII	KATTY FASHION	Confidentiality of the 3D models and patterns used as input for the QA Analysis	QA analysis results needs to be complex enough to be validated by a junior QA team member	The 3D models and patterns used as input for the QA Analysis are confidential to each customer/supplier and cannot be shared between them. But each customer/supplier data is processed by product development team to obtain a standardized model of data needed for production, which is close to industry standards.	Edge hardware is needed to be able to shorten the QA check duration. AI models are expected to be run on a generic edge environment.	Each product will be analyzed by a pipeline of AI model based on provided model data. A result of this analysis is expected before moving to the next product.	Operators need to interface with the AI system to indicate the defect type and location. Would be usefull to mark the defect as valid, invalid, fixed, not fixable.

Table 3 The SME-driven experiments' needs versus EDIH services

Pilot	Organization name	Data Services	Business Services	Ecosystem Services	Skills Develop Services	Technology Services
I	SCAMM	Implementation of the architecture to collect, storicized and analyse data, as well as of the user interface to interact with the AI tool	Connection to funding sources; Identification of opportunities; Creating consortia	Technology scouting; Communication; Trend watching; Visioning and strategy development	• AI at the Edge training course for Operators • Human-AI interaction training	A test before invest service is needed before going to production (feasibility study, technology concept development, concept validation)
II	PERNOUD	N/A	Productivity improvement	• Provision of support in identifying and analyzing emerging and emerging technologies	• AI at the Edge training course for Operators • Human-AI interaction training	Search for technology provider
III	GPALMEC	Data acquisition, storage and analysis for: • remote supervision • predictive maintenace • remote assignment of the working area • safety improvement by knowing where the machine is, should an accindent involving driver happen	• Connection to found sources • Identification of opportunities willing to implement the technology	• Technology scouting • Communication • Trend watching • Services impact assessment	• Human skills maturity • Human up-skilling, re-skilling training • Educational programs	• New ideas, assessment and feasibility study to identify suitable technology for on filed localization and routing • Product dempnstration
IV	POLYCOM	• Data acquisition and Sensing - Support for data integration from exsisting infrastructure (MES, QA systems, Moulding machines) • Data acquisition and Sensing - Support for Industrial Architecture design (Edge, Local Cloud) that would enable more proactive analytics (data pipelines)	• Business Training and education - Identification of opportunities and best practices covering predictive maintenance in moulding processes	N/A	• Skills improvement - Acquisition of skills in data integration standards and good practices • Skills improvement - Industrial IT skills (Edge/Cloud/IT Security) • Skills improvement - Production data analytics skills	• Ideas manageent and materialization - good tehnological practices for predictive maintenance of moulding machines and tools

Pilot	Organization name	Data Services	Business Services	Ecosystem Services	Skills Develop Services	Technology Services
V	QUESCREM	• Possible provision of support in the creation of DATASpaces for future stages of the experiment	• Provision of Intellectual Property advice •Support in identifying and attracting financing instruments • Support in the identification of new market/business opportunities through strategic analysis of the ecosystem and trend watching • Provision of support in cooperation and collaboration among organisations for exploiting common opportunities	• Provision of support in identifying and analyzing emerging and disruptive technologies • Provision of support in developing trend reports • Provision of support in establishing strategic relationships for the business, and generating a reliable network to boost the development of the business.	• Provision of support in defining a roadmap based on the enterprise characteristics • Provision of support in defining an action plan for implementing the desired level of Industry 4.0 skills • Organization of trainings, courses or workshops focused on AI at corporate level, operational and technology specific level.	N/A
VI	CAP	• Data collection from IIoT devices and production equipment • Provision of Edge Analytics • Provision of Contextualised Vision System	• Lean and Six Sigma Manufacturing techniques • Quality and continuous improvement	N/a	N/a	New integration between vision systems and self-healing manufacturing processes incorporating AI
VII	KATTY FASHION	• Data acquisition and sensing: Provision of support in data acquisition through data in motion models and services. • Decision-making: Provision and development of decision support services • Physical-human action & interaction: Provision of support/consultancy services for human-Machine Interface	• Identification of opportunities: Support in the identification of new market/business opportunities through strategic analysis of the ecosystem and trend watching.	• Technology scouting: Identification of emerging technologies, • Trend watching: Provision of trend reports	• Process & organizational maturity: Maturity assessment, Maturity strategy development (Definition of a roadmap based on the maturity model assessment) • Human capabilities maturity: Human skills Repository, Skills strategy development, Definition of an action plan and support in implementing the desired level of Industry 4.0 skills) • Skills improvement: Human up-skilling, re-skilling training, Educational programs	• Contract research: Strategic and Specific R&D (Demonstration of the feasibility of an idea or project through its temporary or provisional realisation)

Table 4 The SME-driven experiments business indicators

Pilot	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
I	SCAMM	Process optimization will allow the minimize the production of defective products and, thus, to reduce waste and energy consumption improving process sustainability.		Improved process monitoring and transparency will have a positive impact on SCAMM's relationships with its customers.	The tool will support the operator by providing warnings and suggesting possible corrective actions based on previous experiences. The operator remains in charge of confirming the highlighted criticality and eventually stopping production, as well as of performing corrective actions integrating system suggestions with his/her personal knowledge and expertise.	Wellbeing inclusiveness safety and ergonomics
II	PERNOUD	Schedulling optimization will allow to reduce energy comsuption (relatrively to production volume) and the expert system will allow to include criteria about dedicted period for high energy consumption	N/A	Through a more efficient organisation, the company will be more resiliente during crisis. Moreover, reducing lead time will improve relation with customer.	As a decision making tool, the technology will not replace the operator, will help him and he will keep the final word.	The experiment will reduce the number of repetitive action done by methods and scheduller.

Pilot	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
III	GPALMEC	Safety improvement reduces the accident probability and contributes to lower the service action needed and, therefore, the waste produced	N/A	Safer vehicle gather the attention of more customers, leading to a sales increment	The augumented driving provides help to driver to avoid harmful situations, to correct wrong manouvres and to unload the fatigue of driving and looking after the taks to be performed. In some cases, the driving help just informs the driver, leaving the decision to him. In other cases, like line keeping and obstacle avoidance, the vehicle activelly participates in the driving but the driver always is able to override the action.	• **Well-being, comfort and acceptance:** comfort and the well-being improved by reducing the stress of being constantly concentrated on the driving, on the obstacles avoidance and on the task to be accomplished acceptance: self-confidence improvement by lowering the difficulties of driving a vehicle and letting the driver to perform difficult tasks by himself • **Inclusion and special categories of workers:** Not educated workers might not be tech-savvy and, therefore, not be willing to use driving help Less skills needed for driving might attract interest of more worker, leading to an inclusion imporvement by being part of a working team • **Safety of the workers:** Safety improvement guaranteed by the augumented driving that

Pilot	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
						helps to recognise dangerous driving conditions; to avoid obstacles; to correct wrong manoeuvres; to unload driving stress and fatigue • **Ergonomics and Improving working conditions:** Fatigue and stress reduction and less workers' skills required by letting the vehicle look-after some driving task
IV	POLYCOM	The tool will provide more insight on process equipment conditions, leading to more targeted maintenance actions with increased lifetime of machine/tool parts.	N/A	Steps toward the predictive maintenance will provide higher resilience of the company due to reduce unplanned downtimes and delays.	The tool will provide more insightfull working conditions. The final decision for maintenance action is still in hand of the operators and maintenance team.	N/A
V	QUESCREM	This experiment aims to prescribe optimal production parameters in order to improve sustainability by minimizing the generation of waste (perneate) and	N/A	One of the expected results from the experiment is to be able to imrpove the quality of the company's end product (cream cheese), which is expected to	The prescription module that will be developed aims to provide recommendations to the operators regarding the optimal production parameters in order to support their decision making.	N/A

Pilot	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
		maximizing the quality of the end product.		have a positive impact on the company		
VI	CAP	The proposed experiment will reduce CO2 emmissions by reducing waste and energy consumption in the manufacturing process.	Components made in the experiment are fully recycleable and will be reused	The swaging proces and quality checking will create a better product for industry.	Human and machine interaction will create a new method of working, operators will have the ulitmate decision making powers.	The experiment will increase safety and improve ergonomics
VII	KATTY FASHION	Process optimization will allow the minimize the delivery of defective products and reduce waste.	Depending on the defect type, products are fixed, recycled (if not possible not fix, but parts of them can be reused) or trown out to waste. The experiment aims at increasing the number of fixed product.	Improved process monitoring, automated and objective QA process will increase the clothes delivery quality and increase the trust of the customers	As a decision making tool, the technology will not replace the operator, will help him and he will keep the final word.	The experiments will increase the wellbeing of the QA team, reducing the repetitive actions.

4. Industrial Scenarios from the DF experiments

In the§4 the 14 Didactic Factory experiments are presented:

Table 5 Didactic factory experiments

DF name	Experiment name
DFI POLIMI I4.0Lab (Lombardy, Italy)	Industry4.0Lab
DFII UNIBO ACTEMA (Emilia-Romagna, Italy)	E2Mech
DFIII JSI E2-Lab (Slovenia)	Self-evolving monitoring system for assembly production lines
DFIV BIC (Brabant, Nederland)	Flexible Manufacturing – Vision Enhancement through Synthetic Data
DFV UniTwente AMC (Nederland)	IIoT SmartBox
DFVI FBK 4.0iLab (Trentino, Italy)	4.0 iLab FBK
DFVII MAKE PM50 Flanders, Belgium)	Predictive Maintenance 5.0
DFVIII DMIW (Wales, UK)	Digital Manufacturing Innovation Hub
DFIX MADE (Lombardy, Italy)	BEhAI – Adapting quality inspection system to human behavior and human states
DFX TUIASI I4.0 (Romania)	Implementation of QAD-AI@E solution in the real clothing manufacturing environment
DFXI CTU RICAIP (Czech Republic)	AI-driven Monitoring of Robotic Assembly Process
DFXII AAU Smart Lab (Denmark)	AAU Advanced IoT
DFXIII PBN amLab (Hungary)	SunSync: AI solution for optimizing recycling in industry at the level of am-LAB's DF
DFXIV Industrial Logistics Lab (Galicia, Spain)	Galicia DF

For each experiment AS IS and TO BE scenarios have been defined, and the current status of deployment has been described.

4.2 DFI: POLIMI - I4.0Lab (Lombardy, Italy): Industry4.0Lab

DF description, Motivation, Objectives and benefits

Industry4.0lab is a Didactic Factory (DF) part of Politecnico di Milano (POLIMI, located in Lombardy region), whose aim is to train MSc Engineering students through hands-on activities which traditional study curricula usually lack. The facility hosts indeed a manufacturing line devoted to the assembly of small electronic devices, accompanied by isolated robotic assets which accomplish material handling activities and/or are devoted to cooperate with humans in the tasks devoted to end-of-life of electronic devices.

Human-Robot Interaction (HRI) represents a rapidly emerging field and a current trend in manufacturing engineering. Within this domain, collaborative robot (cobot) technology has gained significant attention as a solution to enhance human-based operations, ensuring a delicate balance between the flexibility of human operators and the reliability and high productivity rates offered by automation. Despite their user-friendly interface compared to traditional robotic-based automation, cobots still require certain setup activities whenever there are changes in the semi finished product types or operations.

To enable seamless adaptability, operators are tasked with manually editing the cobot's workflow, making hardware decisions regarding both the cobot and end effector. Although this operation typically relies on the operators' expertise, in highly flexible environments like the de-manufacturing of electronic boards from diverse applications and eras, the operator's knowledge may not be sufficient to differentiate between various equipment options. To address this challenge, an experimental setup is proposed, integrating camera

vision and a diverse range of robots and end effectors. Machine Learning (ML)-based algorithms will be employed to cluster the boards to be processed based on their physical dimensions and the compatibility with available handling equipment. This data-driven approach aims to streamline the decision-making process for hardware setup, enhancing efficiency and accuracy. Moreover, cobots are generally characterized by lower accuracy and may be unable to handle the smallest circuit components. To overcome this limitation, the proposed solution will also entail identifying which circuit components can be dismounted by the cobot itself and which require human worker intervention. This intelligent allocation of tasks further optimizes the collaboration between humans and robots, capitalizing on their respective strengths.

However, one of the main challenges faced in this endeavor is the limited availability of diverse electronic boards for testing and training purposes. To address this issue and enhance the reliability and performance of the final solution, a preliminary step involves generating synthetic data. This synthetic data generation process will ensure that the ML algorithms have access to a diverse and extensive dataset, enabling the system to handle a wide range of real-world scenarios effectively.

The fusion of HRI, collaborative robot technology, and ML-based algorithms offers a promising approach to increase the productivity of the DF and to enrich the didactic offer to POLIMI students. By enabling seamless adaptability, intelligent task allocation, and leveraging synthetic data for robust training, this solution holds the potential to enhance the efficiency, flexibility, and productivity of manufacturing processes involving electronic boards, thus contributing to the advancement of Industry 5.0.

The experiment aims at improving the efficiency of a HRI task in executing highly flexible activities. In particular it targets a handling-oriented clustering of shapes derived by an image processing. After this clustering a data-driven (and properly trained) algorithm for the selection of the most effective combination of cobots and end effectors is supposed to be implemented. The expected results comprise:

- Improved efficiency for electronic boards handling (decrease of crack and of drops during manipulation).
- Diminished setup time.
- Diminished variance due to specific worker's expertise.
- Increase of multidisciplinary skills trained to thesis students.

Experiment team

The experiment team involved in this project is composed by:

- ***POLIMI*****:** is the business experimentation. It is a polytechnical university located in Milan and it is participating to the experiment by the department of Management, Economics and Industrial Engineering, exploiting the physical infrastructure of its DF "Industry4.0lab". This laboratory, in particular, hosts a semiautomated assembly line and several robots used for HRI, in particular for what concerns the tasks of operators' assistance. The involvement of the Manufacturing Group research team is deemed a crucial factor for the experimentation success, given the arising research area of Industry5.0, which includes a series of studies about the best and most sustainable practices that human-centric manufacturing can exploit in the near future. POLIMI will indeed provide its physical infrastructure, as well as the technical capabilities of its staff in the area of robotics and data management and exploitation.

- ***MADE s.c.a.r.l.***: is one of the eight Italian competence centers and is a recognised Digital Innovation Hub. In the context of the experimentation, MADE will provide its competences in terms of industrial needs, market opportunities, but will also leverage on its equipment pool, which includes several cobot solutions. The availability of cobots to be exploited during the experiments will also provide a

wider set of options to be tested and benchmarked via simulation and physical experimentation in the context of

4.2.1 AS-IS scenario

The AS-IS scenario sees the operator detecting the PCB to be dismantled and autonomously starting the cobot task the material is handled through. The PCB is hence positioned by the cobot in a backheated table and disassembled by the operator with a specific set of hand tools.

4.2.2 Technical Implementation

The technical implementation that will be made during the experiment is:

Hardware

- Franka Emika Panda – Research Edition: 7 degrees-of-freedom collaborative robot.
- Universal Robotics UR5e: 7 degrees-of-freedom collaborative robot.
- Intel d435i: stereoscopic camera.

Software

- Robot Operating System (ROS), Open Source development suite for robotics applications

Communication channels

- ROS topics, ROS services, handled at an operative system level or via REST protocol for external services.
- Standard used: ROS.

4.2.3 TO-BE scenario

The scenario of the solution sees the developed algorithms providing current time instructions about the gripper to be mounted on the selected cobot. The cobot and the gripper will be selected from a pool of equipment available in the POLIMI and MADE facilities, in a first moment in a virtual factory environment.

The successful deployment of the ML infrastructure will save the operators from time wasting activities, and to avoid time losses (and consequent stresses) due to the handling failures by the cobot current implementation.

4.3 DFII: UNIBO – ACTEMA (Emila-Romagna, Italy): E2Mech

DF description, Motivation, Objectives and Benefits

ACTEMA is the DF managed and operated by the ACTEMA research group of DEI (Department of Electrical, Electronic and Information Engineering “Guglielmo Marconi”) of the University of Bologna. The DF develops methods and technologies in the fields of:

- Advanced control of mechatronic systems, power electronic systems and industrial automation plants.
- Condition monitoring, diagnostics and prognostics of plants and machines.
- Design and development of innovative embedded control, actuation and monitoring platforms, oriented to edge computing.

The proposed experiment is placed in the context of automatic machines, in particular that of servomechanisms (mechatronic chains). This is motivated by the growing interest in the development of

techniques and methodologies aimed at making the aforementioned systems "smart", with particular attention to minimizing the economic effort for maintenance and energy consumption of the same. The primary target of the experiment is therefore oriented towards **Condition Monitoring and Prognostics** (CM&P). In this framework, we propose the development of a methodology that allows the analysis and implementation of CM&P techniques for a variety of servomechanisms. Secondly, the aim is to hybridize CM&P and control techniques for the smart management of mechatronic chains, with regard to the development of a "lower energy" sustainable mechatronics.

The experiment will be carried out at the Laboratory of Automation and Robotics (LAR) at DEI-UNIBO. The main challenge in setting up a generalized framework for the proposed Condition Monitoring and Prognostics is the complexity of the dynamics of the mechatronic chains under study. For this reason, the use of AI and machine learning techniques is crucial to learn these dynamics from the data collected from the system, despite having a prior knowledge of its physics. With regard to the data, the approach takes into account the fact that these can often be collected in a questionable way (noise, missing data, absent/wrong labels), and that an exhaustive dataset for the description of the system in question is rarely available (for example, tests are too expensive, or the servomechanism is produced in a series of instances and not all can be tested). For this reason, the proposed methodology adopts the paradigms of continuous learning and transfer learning, exploiting edge computing systems in an edge-cloud architecture.

The experiment is developed along three main lines:

1. Development of an edge-computing platform for reliable time-consistent data gathering, elaboration and interfacing with cloud-computing systems, possibly including power units to drive motors and smart actuators.
2. Development of algorithms mixing AI methods, physics modelling and automatic control techniques for CM&P of standard servomechanisms, and advanced control and CM&P of innovative servomechanisms, leading to more sustainable mechatronics.
3. Analysis of tools and procedures to help the overall development process.

As far as the benefits are concerned, the attention is first placed on the "test before invest" approach of the CM&P: E^2-Mech experiment will show to SME how to achieve CM&P for their servomechanisms. Furthermore, the described approach aims to reduce energy consumption of automatic machines (sustainability).

Experiment team

The experiment team involved in this project is composed by:

1. ACTEMA research group (DEI-UNIBO): developing, managing and operating the didactic factory. The main research direction are:
    - Advanced control of mechatronic systems, power electronic systems and industrial automation plants.
    - Condition monitoring, diagnostics and prognostics of plants and machines.
    - Design and development of innovative embedded control, actuation and monitoring platforms, oriented to edge computing.
2. ART-ER: helping in advertising the experiment to SMEs (mainly in the automatic machine field).

4.3.1 AS-IS scenario

The main objective of the CM&P consists in the estimation of the state of health of the analyzed system, in order to prevent the failure and to optimize its maintenance: the identification of phenomena that compromise its performances allows to maximize reliability and consequently, in an industrial scenario, profit. Usual activities for CM&P of standard servomechanisms mainly branch out into three sub-scenarios:

1. **No CM&P at all**: run to failure approach (corrective maintenance). This approach is indicated in cases where the cost/benefit ratio is in favor of repair or replacement rather than constant monitoring of the system. These are diagnostic systems that are not particularly structured, often based on timeouts with respect to certain operations foreseen by the system. For example, if a motion necessary to close a mechanical part does not occur within a given time interval, an anomaly is signaled to the machine operator: this triggers the problem finding process, which generally takes place by consulting troubleshooting tables.

2. **CM using simplistic manually-tuned thresholds on available process signals**: the main criticality of this approach lies in its intrinsic "custom" nature: similar but not identical instances of the same system often require manual fine-tuning of the model parameters and thresholds. Furthermore, in order to develop reasonable thresholds, knowledge of various failure scenarios (and in different intensities) is required. This results in an important counterpart to the major advantage of this type of approach, namely the versatility and simplicity of applicability. A common occurrence of this approach is related to the following error for electrical axes: a threshold is defined to detect instances in which the system struggles to follow the expected trajectory, so as to signal an anomaly, possibly prior to a total fault. The problem remains of the arbitrariness of the placement of the threshold, often defined manually and bearer of a partial and poor contribution from the point of view of the real information content of the signal.

3. **Attempts to apply more advanced approaches, usually based on data-driven AI/Machine learning**: these mainly consist of preliminary data collection (possibly with over-sensorization) and learning of models. The main problem lies in the difficulty of populating an exhaustive dataset of all operating conditions, intended as a variety of nominal and fault states. The difficulties associated with this task are many:

    - The a priori identification of all nominal operating states (especially if the considered mechanism is able to perform multiple tasks), and fault states is not easy; let alone their combinations with different operating regimes of the system.

    - The data collection campaign is expensive from the point of view of time and consequently from the economic point of view, especially if the mechatronic chain is inserted in an industrial context. In these cases, a machine downtime in the workshop implies a reduction in productivity, if not the total stop of the production process.

    - The main suppliers of data collection equipment offer solutions that are difficult to understand (for example, there is often no real temporal determinism in the transmission and labeling of data; this leads to inconsistency and degradation in the quality of the dataset) and without a real automated pipeline (which is why, if the mechanism is inserted in an industrial/workshop context, human intervention is required with the consequent use of time and resources, if not an actual downtime).

4.3.2 Technical Implementation

The technical implementation that are mentioned in the framework of AI REDGIO 5.0 are:

Methods

1. Simulations in Matlab/Simulink/Simscape of mechanisms imported from CAD files. Detailed friction modeling added along the mechanism. Generation of large amounts of synthetic data, also adopting parallel simulation tools.
2. Exploiting the proper lumped-parameter approach, Euler-Lagrange formulation is adopted for control/diagnostic-oriented modeling of conservative parts. Data driven approaches based on Neural Networks are exploited to model overall friction effects on actuated joints.
3. Data collection from real prototypes is ongoing.
4. Modeling of wear and tear's effect, based on a-priori knowledge, educated guesses and data, is ongoing.

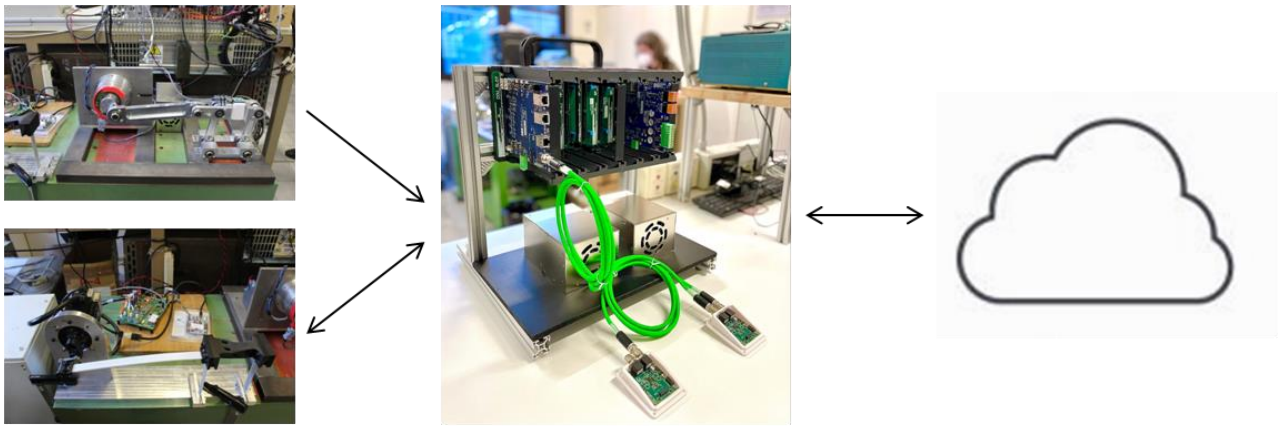
Platforms

1. Proper execution model has been defined to implement tasks, exploiting an ACTEMA's proprietary RTOS on the ACTEMA's Embedded/Edge platforms, based on Single core Cortex M4 and Tri-core 2xCortex A7 and 1xCortex M4, respectively
2. Beckhoff PLC platform has been tested and investigated for alternative solution.

4.3.3 TO-BE scenario

The UNIBO - ACTEMA experiment could be summarized in the following Figure 25. In this case the AI technologies will be used for:

- **Continuous learning**: use of techniques aimed at mitigating the need to have an exhaustive dataset of the operating conditions of the system available before implementing CM&P solutions.
- **Artificial Neural Networks**: use of algorithms aimed at solving:
  - the need to approximate functions for which an analytic expression is not known (RBF, CNN)
  - the development of generative models in conjunction with the Continuous Learning framework (AutoEncoder, Diffusion Models).
- **Transfer Learning**: consequence of the need not to instantiate the algorithmic structure ex novo for similar but not identical occurrences of a given system.



Standard and innovative resonant low-power mechanisms for high-end automatic machine with proper process and monitoring sensors (FIELD)

Elaboration, control and actuation platform with enhanced computing performance (EDGE) for:
• CM&P of both standard and innovative mechanisms exploiting AI, physics driven modelling and control tools to reduce the needed data.
• (High performance control of the innovative resonant low-power mechanism exploiting the above tools)

Cloud (or on-premises) data storing and computing to support computationally-intensive learning and adaptation (CLOUD).
Reliable and time-consistent data and elaboration management will be guaranteed exploiting hard-realtime features of the edge platform.

Figure 25 ACTEMA TO-BE scenario

4.4 DFIII: JSI (Slovenia)- E2-Lab: Self-evolving monitoring systems for assembly production lines

General description, Motivation, Objectives and Benefits

Assembly production processes and machines are either equipped with rather simplistic diagnostic systems, or in special cases, supported by highly specialized model-based diagnostic methods that are custom made and tuned to the specific machine. But often the custom-made diagnostic solutions are not financially viable due to high effort of development and, on the other hand, simple solutions do not provide the sensing capabilities to detect performance deviations quickly enough to prevent process stoppages. The proposed experiment is motivated by the above-identified problem and the ambition to test and demonstrate approaches that could be applied widely for the assembly production lines that perform repetitive production operations and that require only moderate implementation and operation effort.

The DF experiment is a generalization of SME PILOT IV POLYCOM (SLOVENIA): MAXIMIZATION OF AVAILABILITY, **PRODUCTION QUALITY** AND EFFICIENCY OF MOLDING MACHINES.

Experiment concept

The aim is to provide a platform that would support development and demonstration of solutions that build on semi-unsupervised data-based learning using hybrid approach that combines information of continuous data and sequential events. The benefit of such systems is to self-learn from the production operation and to characterize and notify the deviations in otherwise repetitive process operation, while providing concise insight about production operation state, process operation deviations, fault occurrences and localization of the fault sources.

The main concept of the experiment will be to prepare the experimental environment (sensorics and platform), prepare demonstration algorithms, and to perform didactic exploitation that would lead to new innovations and demonstration in the production environment.

Site

The experiment will be performed at the actual industrial setup at company Domel (Slovenia), where a part of the actual DC drive assembly production line will be used as a demonstration platform.

Challenge

The deficit of model based diagnostic methods is that a lot of effort (experimentation, analysis, development, fine tuning) is needed to build the mathematical model. Moreover, the resulting model is valid only for a particular type of process. All this makes the implementation of data-based diagnostic systems complex and expensive. On the other hand, AI solutions are under a challenge to properly distinguish between usual deviations between patterns due to stochastic phenomena in the process and deviations due to faults and degradations of the process. This challenge will be addressed in this experiment where the demonstrator will support development and testing of the AI empowered solutions that are able to learn characteristic patterns of the repetitive process and use this knowledge for monitoring purposes.

Main experiment objective is to establish a platform for demonstration and testing of diagnostic systems for production assets that are smart, self-learning and non-invasive to the existing production peripheral (add-on monitoring systems). Demonstration of such solutions on production line would increase the acceptance of data-based solutions and would increase the replicability for wide-spread production cases. Moreover, the established demonstrator would provide a platform to directly compare the performance of similar solutions that are self-learning and lead to decreased involvement of human needed for the set-up.

Another objective is the didactic exploitation of the platform for development of new innovative solutions. Data from actual production line will be prepared for students in order to gain more experience with the actual data-analytics problems and to educate them the whole development chain from concept to the final demonstration. This will provide more practical and realistic experience that would be valuable for their further career.

The demonstrator is not directly linked to the actual production performance, rather the benefits would be achieved on:

- improved accuracy and robustness of the diagnostic systems
- improved self-learning phase, with less initial inputs required by operators
- new innovations that could have commercialization potential
- training of new generation of engineers
- promotion of digitalization and adoption of AI solutions.

The benefits that such monitoring systems that are the scope of the demonstration would bring to the industrial environment are:

- support operators to quickly identify and localise faults and act proactively regarding to the upcoming faulty conditions
- reduce unplanned downtimes and increase OEE
- reduce the involvement of human needed for setup
- support production changes as the monitoring system self-adapts to the new production setup

Experiment team

JSI

Jozef Stefan Institute is the leading scientific research and development organization in Slovenia covering a broader spectrum of disciplines: physics, chemistry, electronics, automation and information technologies, nuclear reactor engineering and energetics. Department of Systems and Control directly involved in this demonstration works mostly on applied research, development of control systems, and transfer of knowledge into industrial applications. Within this framework the following research areas are assessed and products are being developed: advanced methods and algorithms for automatic control, procedures and software tools for design and implementation of control systems, process modelling for process control, optimization and diagnostics, smart factories, process diagnostic and condition monitoring, design and implementation of specialised measurement and control electronic modules for various applications. The mission of the department is a transfer of research results into industrial practice. In this way, we completed a number of control-oriented projects for industrial sector (chemical, steel, electric motor production, district heating, fuel cells, hydrogen technologies, etc.).

The JSI will technically coordinate this demonstrator. JSI will prepare the demonstrator hardware covering upgrade of the current sensors, acquisition of the actual state from PLCs and preparation of the distributed local distributed platform. Moreover, JSI will collaborate to prepare the initial algorithms to be tested on the platform.

UL

University of Ljubljana is an institution with a very rich tradition. It was established in 1919 on the foundations of a long-established pedagogical tradition. It is a very large university, with 50,000 undergraduate and postgraduate students, taking over 300 different undergraduate and postgraduate study programmes. The Laboratory of control systems and cybernetics at University of Ljubljana, which is one of the involved partners in this demonstrator, is one of the departments on Faculty of electrical engineering. The department has more than 50 years of experience in the field of modelling, simulation and automatic control. It currently consists of 5 professors, 3 assistants, 4 researchers and 2 junior researchers. The department has completed more than 90 projects, where 25 had international participation. The research performed in the laboratory is oriented to the theory and application of modern methods of computer control as well as to the modelling and simulation of dynamic processes. Beside traditional approaches, adaptive, predictive and multivariable systems are studied together with AI approaches based on fuzzy logic, neural networks and expert systems. Recent investigations deal also with discrete-event and hybrid systems.

UL will be responsible for performing didactic exploitation of the platform. They will organize and perform the seminars with their students that will lead to new solutions to be tested on the platform. Moreover, UL will also participate at the development of the initial solution to be tested on the demonstrator.

KCSTV

KCSTV is a Competence centre for advanced control technologies and a cluster connecting the research institutions, services providing engineering companies and industrial companies end-users of control technology. KCSTV was founded by the engineering companies providing services which are members of the Technology Network Process Control Technology consortium in order to promote collaboration among different partners in research and development projects.

The role of the KCSTV in this experiment will be to coordinate the experiment and to provide administrative support.

Domel

Demonstrator will be hosted by the KCSTV member Domel. which is not directly represented in the project. Domel is a global manufacturer of electric motors and strong supplier of expert solutions for further developments of cutting-edge technology in the field. Domel takes an active part in the business of cleaning technology, ventilation systems, industrial and laboratory applications, automotive industry, medicine and e-mobility. Domel is oriented towards special applications where advanced technologies are needed. It is strongly focused on electric drives driven by electronically commutated - brushless motors for automotive industry, clean room technology, HVAC systems and Fuel Cells as well. Domel is a member and cofounder of SIHFC (Slovenian Hydrogen and Fuel Cell Technology Platform) and RCVT (Research Centre for Hydrogen Technologies).

Within the project, Domel will provide one of their production and assembly lines for Avanty use case. They will upgrade the assembly line machines with additional sensors, implement collection of measured data during production / assembly steps and link the measured data to the product ID. They will also participate in experimentation to find the relation between End-of-line quality check measurements and measurements performed during production and assembly steps.

The role of the Domel will be to host the demonstrator, provide reasoning of the production specifics.

4.4.1 AS-IS scenario

System for automated monitoring of the assembly lines will be implemented on part of the actual production process at Domel. The considered process is performing the final quality inspection of the DC drives that are being assembled in the line. The production line produces 3 different motor types, each with many subtypes, the production has a short operation cycle (~10s) and produces up to 4000 pieces daily.

The three considered production cells contain actuators that manipulate the items, conveyor belt that moves the items among the cells and each cell has its own operating steps that perform inspection of the manufactured items. The production line produces several different types of the products, that each has its own requirements for final monitoring. Consequently, also the quality assessment steps performed by the considered production line can vary.

Current system does not have any specialised monitoring system installed that would monitor the performance of the production line. There is only a simplistic monitoring developed as part of the low-level control system.

4.4.2 Technical Implementation

- **Hardware**:
  - Raspberry Pi, Orange Pi, ESP32
- **Software**:
  - Arrowhead platform
  - NodeRed
  - Grafana
  - InfluxDB
- **Communication channel/s**:
  - TCP/IP, REST
- **Standard used**:
  - OpenAPI/Swagger

Arrowhead platform was implemented in small-scale setup (testing of Service Registrsy, Authenticator, Orchestrator and Event Handler services) on RPI, OrangePI and ESP32 hardware.

4.4.3 TO-BE scenario

The experiment will establish an industrial process environment from the class of assembly production processes where different self-learning diagnostic systems could be tested. To be general, replicable and minimum-invasive, such diagnostic systems should use only standard signals, that are easy to install on existing production processes without the need to change existing control software or hardware equipment of the process and that use typical process signals (electric currents, pressures, sound etc.). The main idea is to recognize patterns generated by technological equipment of the repetitive processes and use these patterns for monitoring.

The detection of patterns and repetitive actions from process signals will results into digital representation of the process (i.e. Digital twin) which will be defined as the discrete-event model of the system. Identified Digital twin of the process will enable simulation and virtualization of the actual process, which will support the operators to better monitor and explain actual production operations.

The digital platform will consist of edge device that will provide a platform for distributed deployment of the solution close to the data sources (e.g. production lines/machines). The production monitoring results will be further sent to the central system that will provide system visualization.

The use-case will consist of discrete production process for final quality control at the DC drive assembly line that consist several repetitive production steps. The platform will be prepared and integrated into the process in order to provide a broad spectrum of measured process variables, i.e. signals of sensors and actuators, and also signals from general peripheral variables (*e.g.*, pressure and flowrates of pneumatic systems or electric supply currents of electric actuators).

The selected process will enable generation of the operational data and simulation of different faulty conditions. This will provide a platform for demonstration and comparison of different self-evolving monitoring systems.

As part of the use-case the platform will be used to implement and demonstrate one such solution, which could be set as a benchmark for future similar approaches – Figure 26**.**

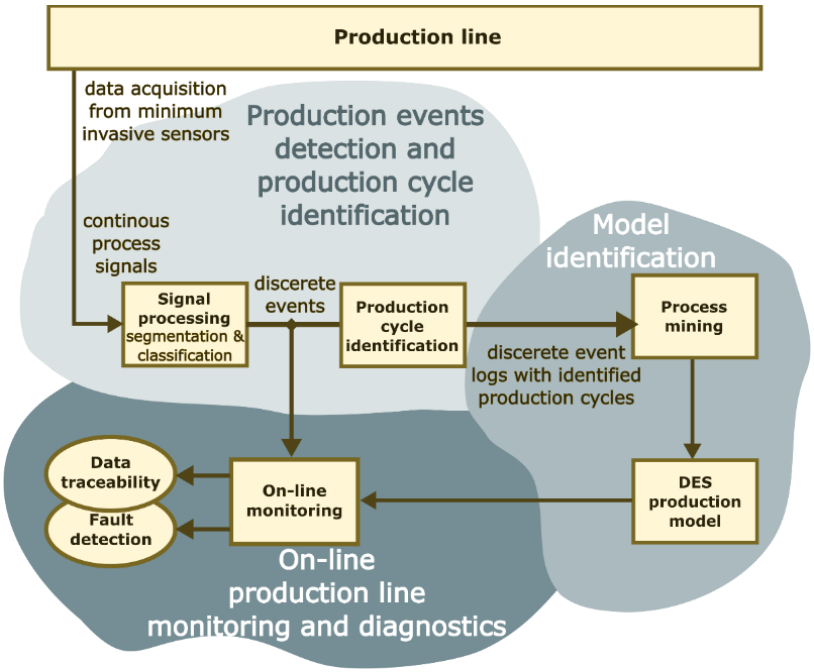


Figure 26 AI analytics for on-line monitoring of the assembly production lines

4.5 DFIV: Brainport Industries - Flexible Manufacturing

DF description, Motivation, Objectives and Benefits

Brainport Industries designs, develops and manufactures leading, advanced, precise and intelligent high tech equipment. They are present on the international market for high-mix, low-volume, high-complexity machines have been outsourcing the manufacturing of sub-assemblies and larger non-core submodules to strategic suppliers for quite some time and are now increasingly outsourcing the design and development of the equipment they manufacture as well. What they're doing in fact, is giving suppliers full responsibility for these modules, from design through to manufacturing. This shift is driving suppliers to push their own boundaries in terms of feasibility and responsibility, and to extend their reach across international borders in order to tap into new, foreign markets.

Brainport Industries is the world's leading open supply chain for High Tech companies; they provide a fertile ground and a solid structure for collaborative projects whether they are related to technology, market or people. It's an environment that provides for a continuing flow of knowledge workers and experts and enables suppliers to increase their output and steadily grow into market leaders.

In our pursuit of advancing automation in manufacturing processes, Brainport Industries is initiating an experiment titled "Vision Enhancement through Synthetic Data." The motivation behind this experiment stems from the challenges encountered in our current vision system and bin picking setup. The primary issues include difficulties in accurately identifying objects due to reflections and imperfections, leading to errors in sorting and handling by the robotic system. The experiment revolves around the application of synthetic data to improve the performance of our vision system. Synthetic data, carefully generated to mimic real-world scenarios, is expected to aid in training the system to better recognize and handle objects, even in challenging conditions. By integrating synthetic data into the training process, we aim to assess its impact on reducing error margins and enhancing overall system accuracy.

The implementation of the "Vision Enhancement through Synthetic Data" experiment holds the promise of transformative advancements in manufacturing processes. The following three bullets outlines the three paramount business benefits anticipated from the successful execution of this innovative experiment:

- **Enhanced Product Quality**: the primary objective of the experiment is to significantly improve the accuracy of object recognition and sorting. This improvement directly translates to enhanced product quality by reducing errors in the manufacturing process, ensuring that products meet or exceed specified standards.
- **Increased Productivity**: the implementation of synthetic data aims to streamline the workflow by minimizing errors in the vision system. This efficiency boost is expected to lead to increased productivity, as fewer resources will be spent on correcting errors, allowing for a more seamless and efficient production process.
- **Cost Reduction**: reduced errors and increased productivity are directly linked to cost reduction. The experiment anticipates a decrease in costs related to material waste, labor associated with error correction, and potential rework. This financial benefit contributes to the overall cost-effectiveness of the manufacturing process.

Besides these, we also expect benefits on process effectiveness, optimized production, improved company image, strategic competitiveness in the long run, employee empowerment and data-driven decision making.

In summary, the implementation of the experiment is expected to yield tangible benefits across various business facets, ranging from improved product quality and increased productivity to cost reduction and an enhanced company image in the industry. These outcomes align with Brainport Industries' commitment to innovation and excellence in manufacturing processes.

Experiment team

The experiment team involved in this project is composed by:

- ***Brainport Industries***: is the primary initiator and overseer of the experiment. Brainport Industries provides the overarching vision, resources (Didactic Factory), and strategic direction for the implementation of synthetic data in the vision system and bin picking setup. It also coordinates the experiment towards the AI REDGIO 5.0 project and is responsible for all administration and reporting activities.

- ***DEMCON***: plays a crucial role as the SME actively involved in the experiment. As a specialist in high-tech systems and products, DEMCON contributes domain expertise, particularly in the areas of automation, robotics, and vision systems. Their role involves implementing and adapting the technologies tested in the experiment to real-world manufacturing applications.

- ***EDIH South Netherlands***: As an EDIH, the hub provides a collaborative platform, expertise, and support for digital innovation. EDIH South Netherlands facilitates the experiment by offering access to digital technologies, knowledge sharing, and networking opportunities. Their role is pivotal in connecting various stakeholders, fostering collaboration, and ensuring the experiment aligns with broader digital innovation goals.

4.5.1 AS-IS scenario

The experiment will be conducted at our Didactic Factory, Factory of the Future, utilizing the existing vision system and bin picking setup. This DF closely collaborates with the EDIH South Netherlands and a lot of connected SMEs. This real-world environment ensures that the challenges faced during daily operations are accurately reflected in the experiment, providing valuable insights into the effectiveness of the proposed solution.

The core challenge lies in mitigating errors caused by reflections and imperfections in the objects within a mixed bin. Traditional vision systems may struggle with accurate identification and sorting in such scenarios. In our DF we have already invested in a high-end vision system. However, the need for Artificial Intelligence (AI) arises as we seek a more intelligent and adaptive system capable of learning from both real and synthetic data. AI will enable the vision system to improve its object recognition capabilities, ultimately optimizing the efficiency of the robotic handling process. Through this experiment, Brainport Industries aims to push the boundaries of automation, leveraging AI and synthetic data to overcome existing limitations and enhance the precision of manufacturing processes

4.5.2 Technical Implementation

The experiment is not started yet. Adjustments on the technical part still need to be made.

4.5.3 TO-BE scenario

By successfully implementing this experiment, Brainport Industries expects the following enhancements in the TO-BE scenario:

- Synthetic data integration significantly advances the vision system's object recognition capabilities. The AI model, trained on a comprehensive dataset that includes synthetic variations, excels at identifying objects even in challenging scenarios, such as those with reflections and imperfections.

- The enhanced accuracy of the vision system translates into precise robotic handling. The robotic system, guided by the improved AI model, can efficiently pick and sort objects, reducing errors and enhancing the overall efficiency of the bin picking process.

- The experiment introduces real-time monitoring of the manufacturing process. The AI model continuously analyzes data from the vision system, allowing for adaptive adjustments to operating conditions. This self-adaptive capability optimizes efficiency and product quality in real-time.

With the success of the experiment, Brainport Industries foresees a notable reduction in operating costs. The improvements in productivity, coupled with fewer errors, contribute to a more cost-effective manufacturing process. This, in turn, enhances resource efficiency. The success of the experiment positions Brainport Industries as a technological leader in the (regional) manufacturing domain. The organization gains a competitive edge by showcasing an innovative approach that leverages AI and synthetic data for improved efficiency and quality control. In this TO-BE scenario, the integration of synthetic data into the vision system and bin picking setup propels Brainport Industries towards a future of enhanced manufacturing capabilities, marked by increased productivity, cost efficiency, and a competitive technological edge in the industry.

4.6 DFV: UniTwente - AMC(Nederland): IIoT Smart Box

DF description, Motivation, Objectives and Benefits

AMC is an industrial shop floor whose aim is to offer innovative services to strengthen the (manufacturing) industry in the region and beyond. More specifically, AMC offers the industry the opportunity to:

- experience state-of-the-art manufacturing technologies
- experiment with new ways of configuring their manufacturing systems
- engage in projects in the AMC
- conduct feasibility studies and work on proof-of-concepts
- access other field labs for challenges outside of our expertise.

The Industrial Internet of Things (IIoT) connects sensors, software and machinery to the Internet to collect, analyze and process large amounts of data. IIoT is the adaptation of Internet of Things (IoT) technology in manufacturing. With the development of advanced IT technology, the IIoT provides predictive maintenance, optimizes production processes, improves product quality, and provides all-round real time monitoring. It aims to create a smart and more efficient industrial production environment. A similar term to IIoT is Cyber Physical Production System (CPPS). IIoT applications can be considered as specific implementations of CPPS. Cyber Physical Production System is a key concept for digitalization of manufacturing. However, realizing the digitization of manufacturing and implementing IIoT applications in enterprises and industries have encountered many challenges, especially in small and medium-sized enterprises (SMEs). For example, cost is very sensitive for SMEs. There are various machines of different periods and types in SMEs, and connecting and collecting data from all these heterogeneous machines is also an obstacle. On the other hand, the flexibility of system configuration is required due to variant machines. Meanwhile, the security of data transmission and storage need to be well considered. During integrating data from different devices and levels, the load balancing and hierarchical distribution of edge computing capabilities and further data processing and data analysis are also critical. Large-scale devices and applications pose challenges for architecture and performance in manufacturing . The application of advanced algorithms such as machine learning and deep learning promises the values, nevertheless there is shortage of corresponding expertise. In particular, the challenges in applying artificial intelligence algorithms to the manufacturing environment are such as data quality, which includes whether there are enough types and quantities of data to obtain the corresponding features, as well as data noise. The efficiency of the

algorithm is limited to industrial environments and requirements. Matching of real-time data requirements and algorithm performance.

The above mentioned are common obstacles and challenges that SMEs will encounter in implementing manufacturing digitization. In this experiment, several smart tools (i.e. smart boxes) will be presented and the corresponding overall architecture will be proposed and implemented. The experiment will be performed at the corresponding SMEs and DF AMC etc.

The main objectives of this experiment is to help SMEs to implement **IIoT architecture** and relevant AI applications with the low-cost, easy expansion, flexible customization and low-effort deployment. The architecture and tools components presented in this experiment are designed to address the obstacles and challenges mentioned above for implementing digitization in SMEs.

The benefit of this project consists in the improvement of the product quality and productivity for the application of the real-time monitor and predictable smart maintenance will also help to reduce the escape rate and waste of production. Those applications and smart production plan applications can also improve OEE and reduce energy consumption.

Experiment team

The experiment team involved in this project is composed by:

- ***AMC***: is the technology provider
- Manufacturing **SMEs** and **DFs** could be the end users of this experiment.

4.6.1 AS-IS scenario

Different SMEs develop into different levels in the digitization of manufacturing. In the usual scenario, the different machines and equipment have different degrees of digitalization, information and data are isolated, and data communicate and store on different independent platforms that cannot communicate and share with each other. Lack of data integration. The potential value of data cannot be fully mined due to the lack of AI-related algorithms and applications.

4.6.2 Technical Implementation

The technical implementation that are mentioned in the framework of AI REDGIO 5.0 are:

Hardware

- Single-Board computers (eg. Raspberry PI) , Sensors, Cloud Server

Software

- Open source IoT platforms like Ubuntu, Python, etc…

Communication channel/s

- Ethernet, Bluetooth, etc…

Standard used

- OPC UA, MQTT, HTTPS, etc…

4.6.3 TO-BE scenario

The scenario of this experiment will be a cumulative form that architecture and functionality will be added gradually, finally reaching the comprehensive industrial IoT application. First, the machines and equipment in the plant are collected through smart boxes. Use a standard and unified open protocol platform to transmit and store data. This makes it easy to integrate with other production software systems. Combined with AI algorithms to provide comprehensive smart monitoring of factories in different levels, such as OEE,

predictable smart maintenance. Furthermore, Improve production efficiency, reduce material waste, optimize production plans, reduce energy consumption, and provide sustainable manufacturing.

4.7 DFVI: FBK - 4.0iLab (Trentino, Italy): 4.0iLab

DF description, Motivation, Objectives and Benefits

FBK-4.0iLab DF supports tech-transfer activities (co-design, prototyping and technological integration of 3rd-party solutions) of IoT sensing applications, cognitive techniques and advanced ICT solutions for the control of connected machines, plants and monitoring of industrial environments and processes.

4.0iLab FBK is a DF-driven experiment in Trentino, Italy, led by FBK and focused on advanced ICT solution, IoT and AI based industrial solution supporting companies willing to adopt port and test those technologies in their premises and in their processes.

Current industrial applications fostering data and AI are typically designed to be executed in the cloud, an environment that offers advantages in terms of computation capacity but that, at the same time, opens challenges from a technical and business perspectives. Shifting computation to the edge offers businesses significant advantages, including improved user experience, cost efficiency, real-time insights, enhanced security, and offline functionality. It enables better scalability, regulatory compliance, and addresses edge-specific use cases, ensuring redundancy and resilience. Embracing edge computing aligns with business objectives, making it an increasingly attractive option for various industries and applications.

I4.0Lab Didactic Factory at FBK is a facility created to support tech transfer activities (co-design, prototyping, and technological integration of 3rd-party solutions) of IoT sensing applications, cognitive techniques, and advanced ICT solutions for the control of connected machines and plants and monitoring of industrial environments. The FBK 4.0iLab is functional for realizing prototypes in the context of IoT and AI-based industrial applications.

The experiment aims to transition AI-based methodologies and techniques from the cloud to the network's edge, facilitating improved efficiency and effectiveness in industrial applications such as **predictive maintenance, product traceability, and quality control**.

Experiment team

The experiment team involved in this project is composed by:

- ***FBK***: will be responsible for developing the technological components required to perform the experiments in the didactic factory.
- ***HIT (Hub Innovation Trentino)***: as partner with Confindustria Trento of the regional DIH, will provide DIH services for an orientation toward the innovation ecosystem. HIT will facilitate the connection between local companies and FBK, supporting collaboration throughout the experiment.

4.7.1 AS-IS scenario

I4.0Lab is a joint laboratory involving different research units of FBK – Figure 27. Its purpose is to support and facilitate the technological transfer activities towards companies within the scope of the so-called Industry 4.0. I4.0Lab allows FBK to pool diverse technological competencies from various fields of applied research relevant to the industrial domain. These competencies include prototyping capabilities, hardware and software integration skills, and technological assets (both "open source" and solutions derived from the research and innovation activities of the involved research teams). The main goal is to enable researchers to collaborate with companies in co-designing, prototyping, and integrating advanced solutions for the future digital factory.

The laboratory aims to offer these competencies and capabilities in the form of service offerings to businesses. These services include guidance on specific Industry 4.0 topics, specialized technological and consulting assistance, support for research, innovation, and development projects, as well as specialized training services in the field of Industry 4.0. I4.0Lab focuses on thematic areas aligned with the objectives outlined in FBK's industrial plan for Industry 4.0. Particularly, it concentrates on addressing the issues and finding solutions related to:

- design and validation of critical systems
- advanced monitoring of production systems
- **Diagnostic functionality** and **predictive maintenance** for machines and production systems

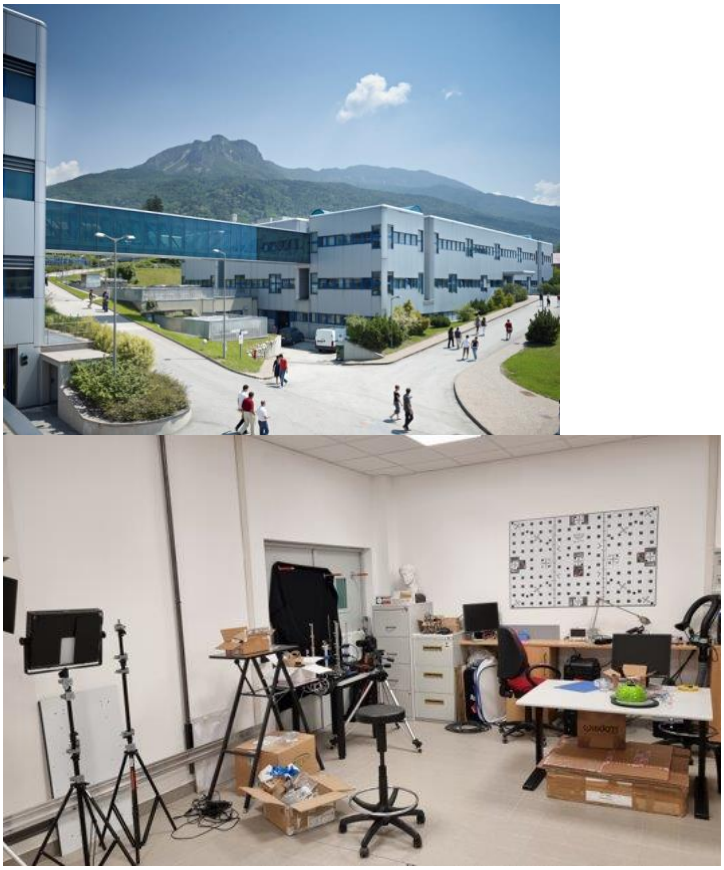


Figure 27 BFK Didactic Factory

4.7.2 Technical Implementation

The technical implementation that are mentioned in the framework of AI REDGIO 5.0 are:

Hardware

- Cloud resources, on-premises computing edge servers, GPUs (Nvidia), AI accelerators (Google Coral TPU, Intel NCS2, Jetson Nano), microcontroller-based boards (ESP32, ESP32-S3, STM32, Arduino).

Software

- Software orchestration (Kubernetes), performance monitoring (Prometeus, Grafana, ..), MLFlow, IoT platform (ThingsBoard), data consolidation and management (proprietary framework); on embedded hardware: micropyhton, FreeRTOS.

Communication channel/s

- Wired and wireless channels.

Standard used

- OPC-UA, Modbus, MQTT, Wi-Fi, BLE

4.7.3 TO-BE scenario

Setup a testing environment for the generation of multiple and diverse deployment scenarios for edge-distributed applications, automatic testing execution and collection of performance metrics, along with a data analysis console. After proper storage and indexing of the data, we will apply different optimization algorithms and strategies to evaluate the possible improvement of the application undervaluation such as bottlenecks, resource misuse, etc…. The testing environment will be configured to fulfill the desired requirements imposed by the application KPIs; an example is reported in Figure 28.

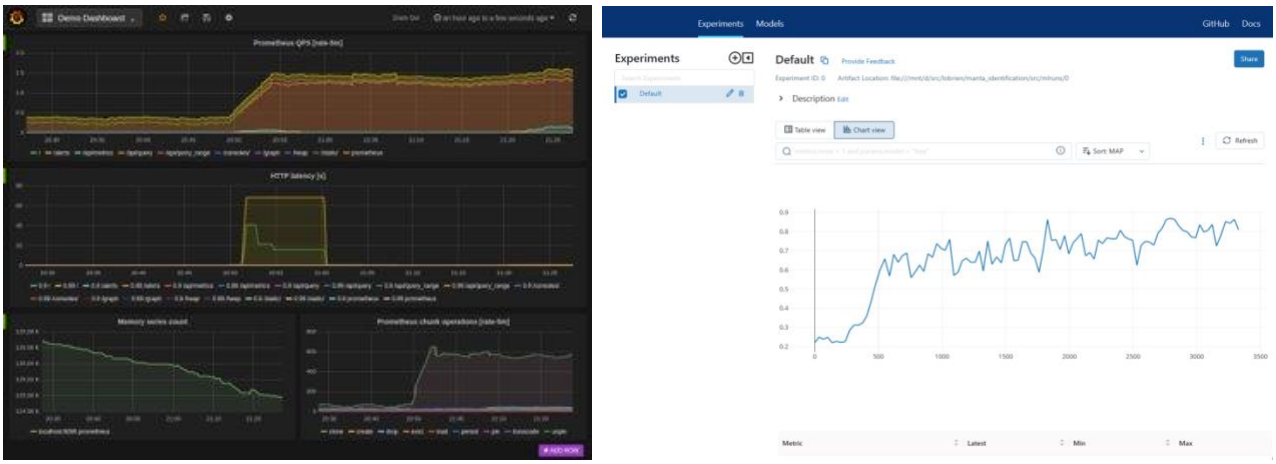


Figure 28 Testing environment

4.8 DFVII MAKE - PM50 (Flanders, Belgium): Predictive Maintenance 5.0

DF description, Motivation, Objectives and Benefits

Predictive Maintenance 5.0 Didactic Factory (PM50) is part of Flanders Make, a “fully operational” Digital Innovation Hub in the DIH Catalogue. The PM50 DF consists of a fleet of seven drivetrain setups with safety casing and with vibration, temperature, load, and speed sensors for accelerated lifetime tests of bearings and for dissemination and training activities, with on-the-fly AI-based processing of raw data by a central computer (depicted in the photo) or in the cloud to detect and diagnose bearing faults.

Predictive maintenance, where machine assets are continuously and algorithmically monitored using sensors, is essential to:

- avoid unplanned downtime of production lines
- avoid low-quality products/scrap by the production line

- avoid escalation of damage to the equipment.

Therefore, predictive maintenance is crucial to improve the sustainability of the manufacturing industry. A major cause of machine downtime, scrap products and escalation of damage are bearing faults. Since predictive maintenance of bearings typically requires sensors with a high sampling rate and a high sampling resolution and since many sensors are needed to cover one or several production lines, an excessive amount of total data bandwidth is needed if AI-based data processing is done centrally (e.g., in the cloud). Moreover, security, latency, network availability, and confidentiality issues arise when processing such data centrally. To avoid these issues, and therefore make predictive maintenance more secure, more robust, and lower cost for companies (and in particular SMEs), there is a transition from Industry 4.0 to Industry 5.0: transitioning from AI methods in the cloud to AI-based processing on the (extreme) edge. For Flanders, this transition is an opportunity to improve the sustainability and the competitiveness of the approximately 40 Flemish technology providers in this sector and of approximately 1000 Flemish manufacturing companies and organizations, most of them SMEs.

The experiment is located in Leuven, Belgium, and consists of:

1. Upgrading the existing Didactic Factory (DF) concerning Predictive Maintenance called “Smart Maintenance Living Lab” from Industry 4.0 (I4.0) to Industry 5.0 (I5.0) with AI on the edge.

2. Providing dissemination events so that engineers of SMEs can experience I5.0 and its key technologies hands-on using this upgraded DF.

3. Providing dissemination events so that decision makers of SMEs are objectively informed, including business case analyses and sustainability aspects, about the ongoing global transition from I4.0 to I5.0.

A part of our existing Predictive Maintenance DF is depicted in Figure 29. The DF consists of a fleet of seven drivetrain setups (four are depicted in Figure 17) with safety casing and with vibration, temperature, load, and speed sensors for accelerated lifetime tests of bearings and for dissemination and training activities, with on-the-fly AI-based processing of raw data by a central computer (depicted in the photo) or in the cloud to detect and diagnose bearing faults. In this way, the DF illustrates the domain of AI for Manufacturing.

Figure 29 PM50 facilities

The training activities help engineers get acquainted with new technologies in the domain of condition monitoring of industrial machines. The experiment will move the AI-based processing of raw measurement data from the central computer (or cloud) to the individual drivetrain setups (i.e., to the edge), to obtain AI-on-the-edge; Figure 30 illustrates this transition.

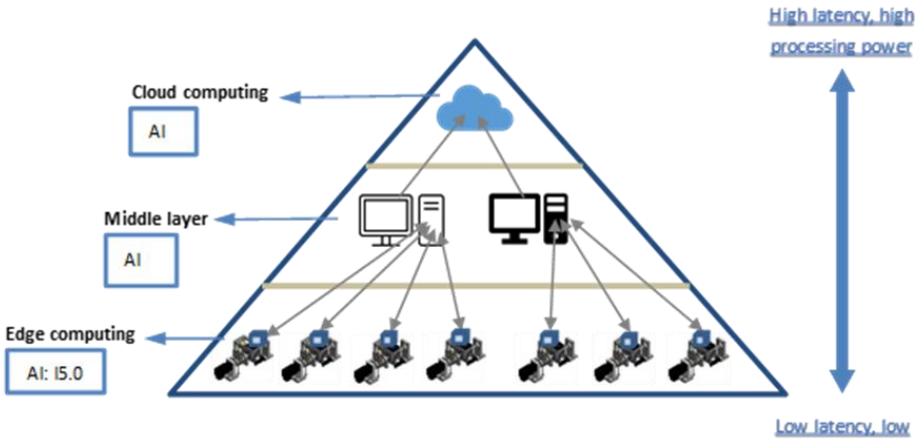


Figure 30 Transition from cloud to AI-on-the-Edge

AI-based data processing can be present in all levels of the pyramid: on the cloud, in a middle layer, and on the edge. The experiment will incorporate the essential AI-based data processing from the middle and cloud layers into the edge layer. In this way, the differences between I4.0 and I5.0 can be well illustrated in a single DF. Moreover, AI solutions that cover multiple layers will be implemented, validated, and compared, for example where AI is used in the edge computing layer to extract essential features, in this way drastically reducing the amount of bandwidth needed, combined with AI used in the middle or cloud computing layers for fleet-wide learning.

The upgraded DF uses open technologies, including open standards like FIWARE and OPC UA, open software like tinyML, and open hardware.

The upgraded DF will be used to:

1. Guide engineers in product lines to get familiar with I5.0 as part of an up- or re-skilling pathway towards successfully adopting I5.0.
2. Guide decision makers of SMEs in their business case analysis.

The knowledge transfer to engineers will be through hands-on, on-site workshops, with themes covering various aspects of a I5.0 predictive maintenance system, through newsletters, and through webinars. The themes that are covered are schematically depicted in Figure 31 include all essential aspects of an I5.0 Predictive Maintenance solution:

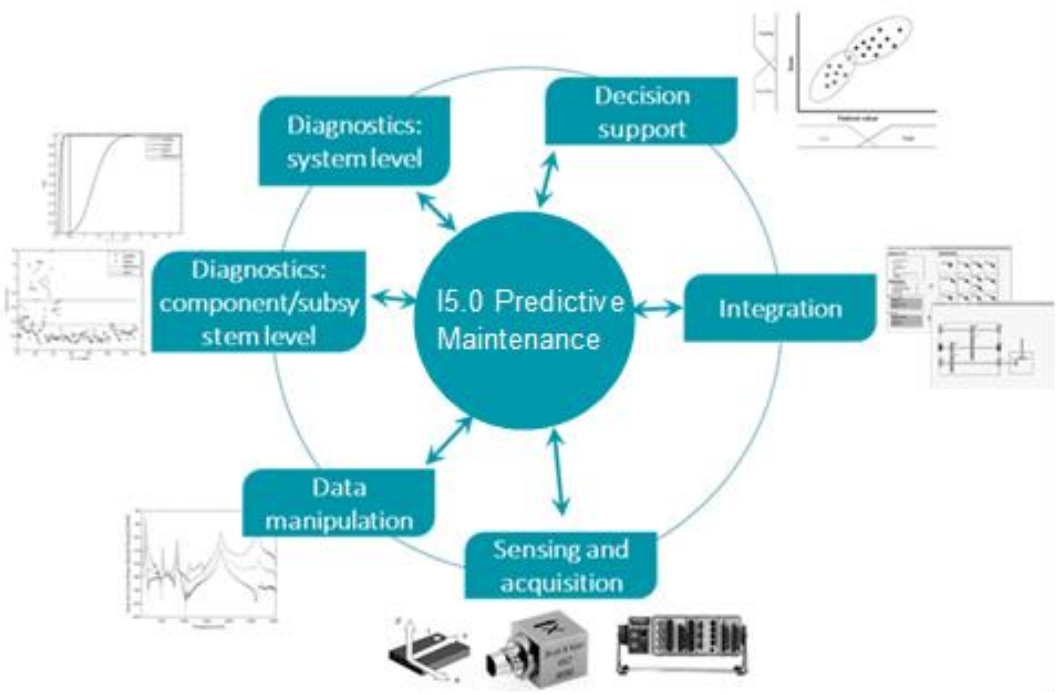


Figure 31 I5.0 Predictive Maintenance solution

While the DF illustrates predictive maintenance by focussing on bearings, all dissemination events are given in the wider context and includes other machines and machine parts, like gears, valves, electrical motors, etc…

The guidance of decision makers of SMEs consists of a business-case analysis and a knowledge database with benchmarks for various hardware components, like sensors and edge computing components. While the protocol for the business-case analysis is generic, the outcome of the business-case analysis depends on various business-specific inputs like current maintenance strategy, historical defects, machine and operating conditions, and environmental conditions.

Experiment team

As previously mentioned, end users will include engineers of industrial machinery and decision makers pondering investments in machine monitoring setups.

Flanders Make is a “fully operational” Digital Innovation Hub in the DIH Catalogue. Moreover, we are partner in various H2020 DIH projects of which DIH-WORLD (H2020-DT-ICT-03-2020) aligns most with the topics of AI REDGIO. Through DIH WORLD, Flanders Make provides:

- SME technological support
  - full technological support of Flanders Make to SMEs taking part in the experiments
- Test before invest
  - to open up the Didactic Factory infrastructure for companies for SMEs to experience Industry5.0 in real lab environment
- Skills and training
  - to re-skill the engineers from SMEs for the adoption of I5.0 related technologies in predictive maintenance

Independently, Flanders Make also provides:

- Prototyping
- Testing and validation
    - To test and validate the prototypes built with the aim to deploy AI-based predictive maintenance to SMEs

4.8.1 AS-IS scenario

Apart from trainings, the DF is used for research in prognostics for aging of bearings and to perform accelerated lifetime tests; an example is reported in Figure 32. The DF — consisting of the 7 drivelines — generates measurement data of failing bearings under the well-known operating conditions, which are stored as meta-data.

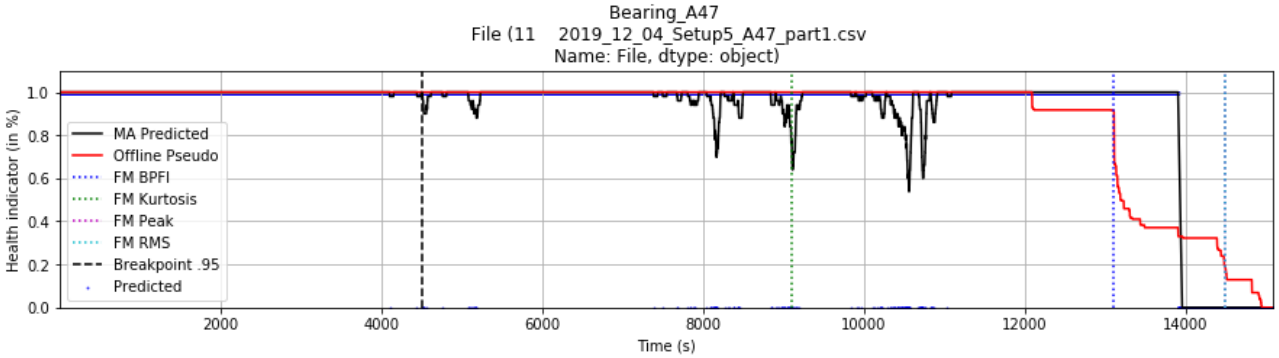


Figure 32 Prognostics simulation for ageing of bearings

The periodical snapshots of accelerometer data are uploaded to an Obelisk[1] cloud platform. Several AI-based algorithms for prognostics have been implemented and benchmarked. Also conventional frequency analysis algorithms are available for benchmarking, as well as various (Kalman) filters. A real-time Grafana dashboard is available.

A central Beckhoff industrial computer adjacent to each case of the DF connects to all PLCs and sensors, as well as to the cloud platform. In Figure 33, a graphical human-machine interface is reported.

[1] https://obelisk.ilabt.imec.be

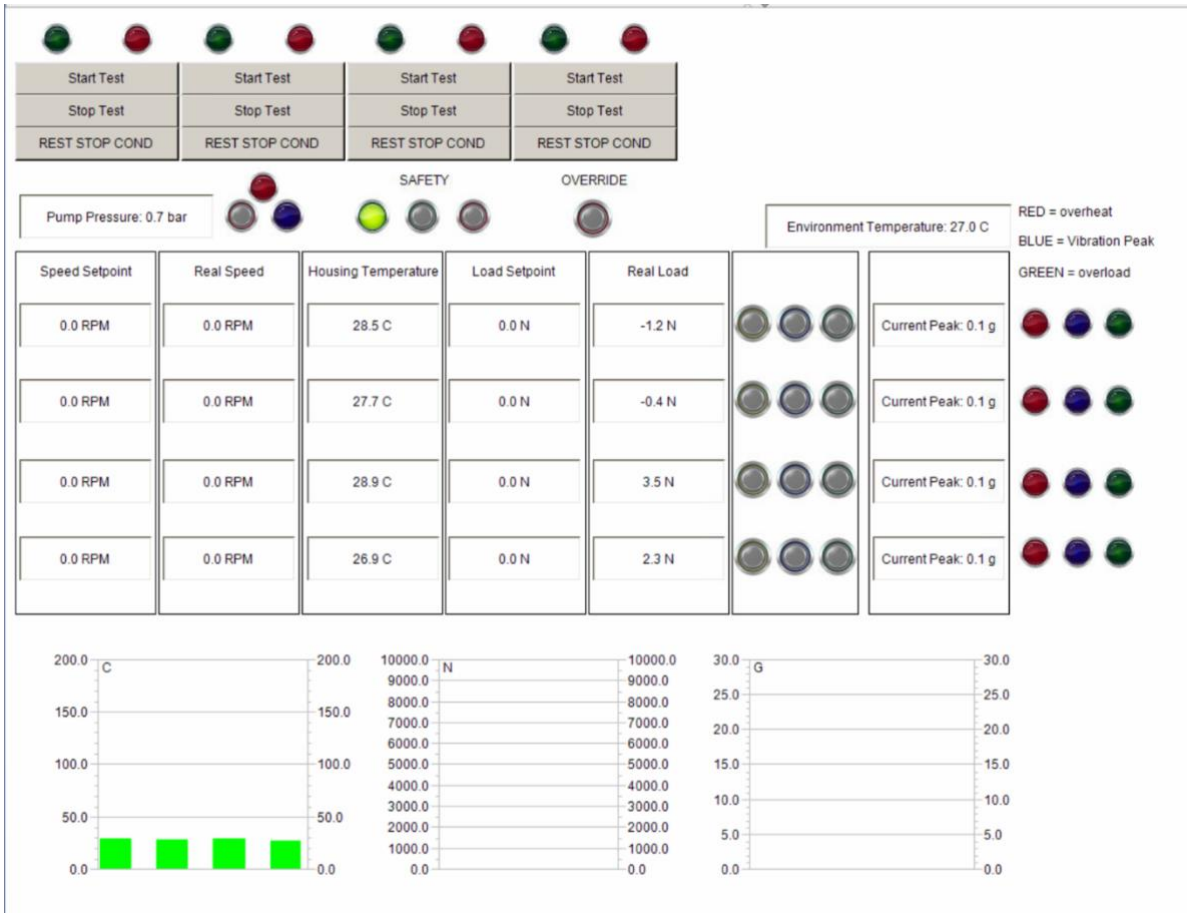


Figure 33 Graphical human-machine interface

4.8.2 Technical Implementation

The experiment consists of the upgrading the existing **Didactic Factory** (DF) concerning Predictive Maintenance called "Smart Maintenance Living Lab" from Industry 4.0 (I4.0) to **Industry 5.0** (I5.0) with **AI on the edge**

The upgraded DF uses open technologies, including open standard like **FIWARE** and **OPC UA**, open software like **tinyML**, and open hardware.

4.8.3 TO-BE scenario

Model distillation, reduced precision, and/or tinyML models (in order of decreasing hardware capabilities) will play an important role to support low-resource edge inference. When there is a need to support diverse edge compute hardware capabilities but the monitored machines are identical, Once-For-All training[2] can provide a low-cost solution that retains accuracy. If the network is unreliable, federated learning techniques can be used to still obtain a good model. The envisioned scenario is primarily extreme edge tinyML classification models for early fault detection, though somewhat larger regression models for RUL prediction can also be tested.

[2] Cai, Han, et al. "Once for All: Train One Network and Specialize it for Efficient Deployment." *International Conference on Learning Representations*. 2020.

4.9 DFVIII DMWI (Wales, UK): IndustreWeb Operator Knowledgebase (IWOK)

Description, Motivation, Objectives and Benefits

Industreweb Operational Knowledge System (IWOKs) is an DF-driven experiment in the UK led by the Digital Manufacturing Innovation Hub Wales (DMIW) and focused on the use of **AI for decision making** in the manufacturing process, as part of the Industrial Pilot VI (CAP ENG Wales UK): Intelligent Contextualised Visual System for Error Reduction.

The purpose of this experiment is to take a typical production scenario, demonstrated using the Mini 'Didactic' Factory at the DMIW facility, and use the data to create a stream of information which the IWOK system can use to suggest a solution for a problem to the Operator. The Operator can use their 'human' sensors to verify the solution and confirm/decline the solution to 'teach' the machine how to fix the problem itself the next time the problem occurs. This experiment is motivated by the need to provide a higher degree of accuracy in automated problem solving and speed up a resolution using an AI-driven solution matrix.

Eventually, this will create a living Knowledge base between the Operator and the Machine that can be used to predict and avoid problems before they occur or simply to self-heal the production process as its happening. The outcomes of this experiment have the potential to guarantee global improvements in real-time data handling, architecture security, stability and the scalability of automation/industrial systems; as well as explore the link between human and machine knowledge in a production system.

If successful, this experiment will enable the transfer of human experience into a set of data-driven parameters which can be used for on-the-job training, production improvements and self-healing processes.

The successful solution presents a commercial opportunity for the Technology Provider as a real-life product for production improvement.

Industry 4.0 has made it possible to collect data from otherwise 'off-line' processes and use this information to calculate productivity, energy usage, and maintenance requirements, as well as 'visualise' the process itself through operational data such as cycles, counts and actions. As a result:

- we are better able understand the current situation and analyse faults as they occur
- the next step is to predict and avoid failures and automate improvements in performance.

Currently, interpretation of errors is based on the Operator's knowledge and understanding of the problem and the known issues with the machine or process. Improvement of the process can only be achieved by either mitigating the risk or avoiding the problem completely - to achieve this, the raw data needs to be transformed into knowledge with can then be shared between the Operator and the machine.

Our objective in this experiment is to develop an enhanced, Lean+ Knowledge Base within the Industreweb Logic Engine, using the production data and the Operators knowledge and sensory inputs (e.g., smell, sight, feel) to create a semantic data model (SDM)* repository of resolutions, fixes, or improvements, which the Operator will verify to complete the learning cycle, thus teaching the Engine to propose an improvement before a fault occurs. The end result will create a living, semantic knowledgebase facilitating an Industry 5.0 solution using Industry 4.0 technology. This will provide:

- faster and more accurate fault resolution
- mitigation or avoidance of production errors
- an AI-Driven, automated healing process based upon extensive human knowledge.

Experiment team

- The **Digital Manufacturing Innovation Hub Wales DMIW** is an independent DIH focused on the industrial commercialisation of innovative technologies. DMIW facilitates a demonstration of the latest Industry 4.0 technologies including PLC and control systems connectivity, cloud-based data capture, AI Vision Systems, haptic feedback, CPS and embedded technologies, Gamification and multi-vendor integration across a range of digital and analogue sensors. This will be used, combined with the Industreweb™ platform provided by Control 2K (C2K) to form the basis of the IWOKs experiment.
- **Control 2K** is the technology provider developing the IWOKs Knowledgebase system, based upon the market leading Industreweb™ Data Integration Platform.

Control 2K and DMIW will work together to integrate the knowledgebase into the existing didactic factory, which will then be implemented into the 'Intelligent Contextualised Visual System for Error Reduction' deployed by CAP Engineering (CAP).

4.9.1 AS-IS scenario

The Smart Factory demonstration is a Festo Didactic Factory currently configured to provide a simple production process, used to showcase typical Lean manufacturing methodology tools such as KANBAN, PokeYoke and KAIZEN. This unit has been extended incorporate Industry 4.0 methodologies and to demonstrate the digitisation of production and collection of data.

The unit is made up of 4 stations – Figure 34, each with a different vendor control system, all communicating and connecting via the **Industreweb™ Data Integration Platform** supplied by Control 2K. Industreweb™ is essentially a software PLC which uses tagged data coming from the sensors and control systems, translated and transmitted via MQTT, to provide real-time monitoring over each element of the production process.

Figure 34 DMIW test unit

The Smart Factory is currently used to support training courses (supplied by Control 2K) and help with consultancy and prototyping, providing a tool for diagnosing and demonstrating typical manufacturing issues, such as Production Monitoring and KPIs, Reporting and Alerting, Worker Safety and Traceability.

The Smart Factory configuration presents the researcher with an accurate representation of the complete production cycle, from the initial order (via an eCommerce website) and resource planning (ERP);

to fulfilment, including processing, quality checking and shipping. To demonstrate the Lean Manufacturing methodologies, the Industreweb™ platform has been configured to collect data from specific datapoints in the process to present counts, alerts and other data in live web-based dashboards than can be viewed and configured online.

The current configuration of the Smart Factory is a manual (operator driven) process with sequential steps to complete an order as per the online order. Similar to a real-life production process, it is subject to errors and breakdowns in the process due to either machine faults or operator error and these need to be successfully diagnosed and fixed before production can be restarted.

4.9.2 Technical Implementation

The Smart Factory Rig comprises of four FESTO Didactic Units, simulating a four-stage manufacturing process. Each station is controlled by an independent Programmable Logic Controller (PLC): Siemens S7 (S7 Protocol), Omron Schneider (Modbus), Siemens 1500 ASi (OPC UA).

The stations include:

- Goods In – Part Feeder, pneumatic plunger/part pusher/pickup/transfer carriage
- Processing – Pneumatic turntable, pillar drill, pressure reader
- Pick and Place – Pneumatic swing-arm and plunger
- Good Out – Conveyor system, pneumatic auto-selection sorting rack.

The four stations are linked together in sequence using the Industreweb™ Data Integration Platform, a software PLC which captures data using a library of bespoke protocol connectors; transmitted via MQTT in real time, coming to and from the production process, e.g., the PLCs and sensors (such as proximity sensors, pressure sensors, etc).

Asset data from the production process is captured by the Industreweb platform and stored in an SQL database. An AI based vision system will be used to determine faults in the production process (Zebra Aurora).

- **Hardware**: Festo Didactic Factory, PLCs (Siemens, Omron, Schneider), Industreweb™ Edge hardware
- **Software**: Industreweb™ Data Integration Platform
- **Communication channel/s**: Ethernet
- **Standard used**: OPCAU, MQTT, MODBUS, Profinet

4.9.3 TO-BE scenario

The IWOK system will use data gathered from the operator and the machines during normal production to set a benchmark for optimum operation – Figure 35. This information gathered will be used to create a ‘Golden Image’ of the best possible parameters for the best quality product. This will then be compared against data during each production cycle.

The system will be able to compare data from sensors with that which is stored within the knowledge base and suggest improvements (e.g. increase or decrease of pressure, temperature, position) to support the production of a specific part. As the operator makes changes and records the result, the IWOK will build up a set of ‘instructions’ for the operator based on the best optimised performance.

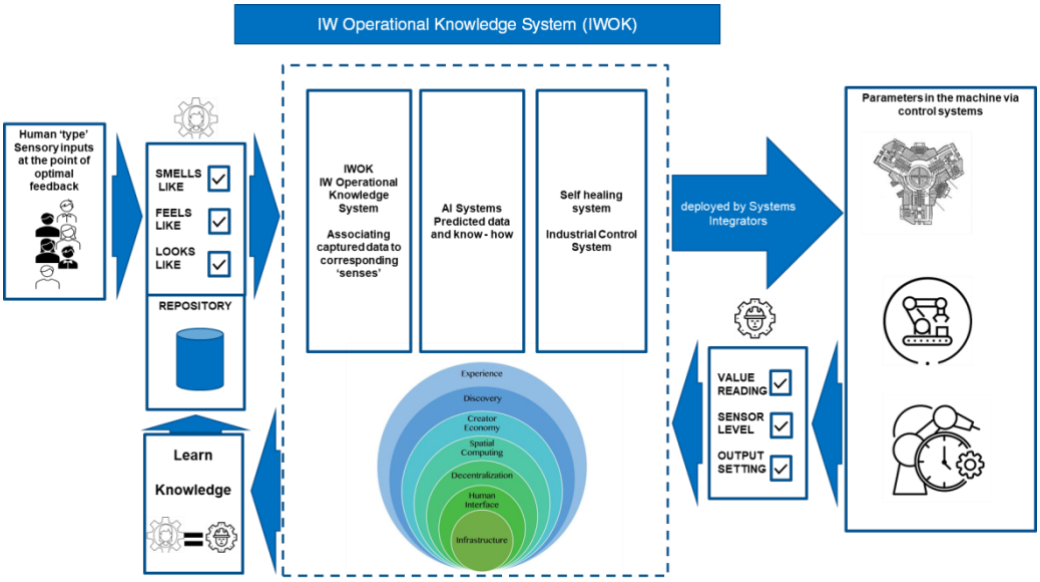


Figure 35 DMIW TO-BE process flow diagram

- Sensors and vision system monitor the component specification
- Data is streamed via the broker to the IWOK Analytics
- A quality issue caused by xxx means the dimensions start becoming too low
- The ML Stream detection identifies the issue and calls the Fault Service
- The new Asset Fault is logged, and picker up by the line engineer
- Using the web app they are guided through the RCA tree – as they progress the results are tracked which weights the final solution for the next time this fault occurs.

Data from each machine Station will be translated from the ICS native protocol by the Industreweb Collect edge device. This data is then transmitted by MQTT to the production broker, which is subscribed to by the master Industreweb Collect edge server. Based on rules configured via the Industreweb Global Administration tools error events will be detected in near real-time. These rules could be as simple as an integer error code number being raised by the PLC or could be complex compound rules based on a number of criteria

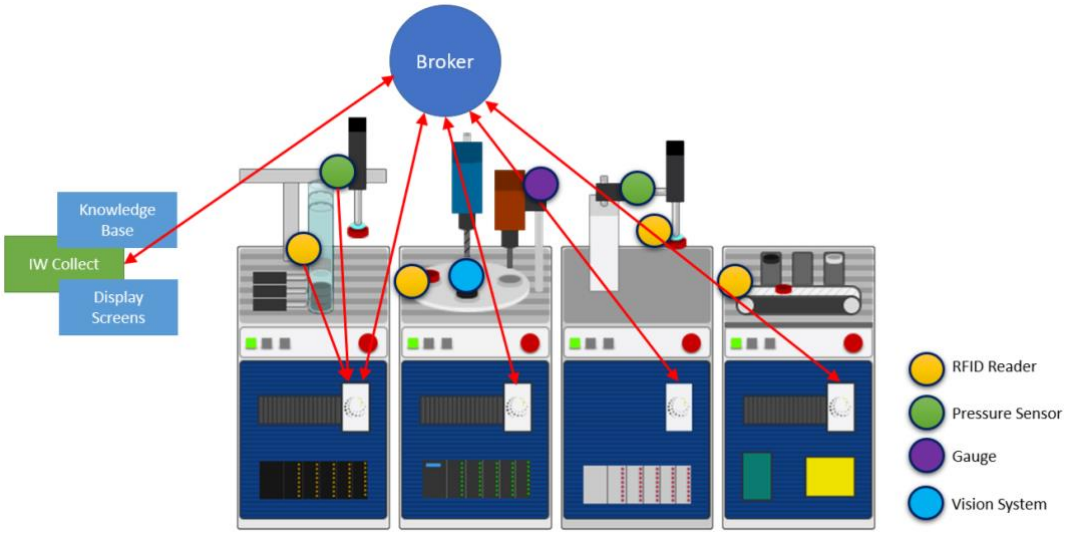


Figure 36 Knowledge Base Triggered by machine fault

The detection of a machine Error will instigate an instance of the corresponding solution tree workflow in the Knowledge Base component – Figure 37. This will notify the maintenance engineer who will be guided via the solution tree UI to resolve the issue. The ML component will build on this traditional detection by modelling and continuously monitoring the process and raising a fault to instigate a solution tree instance before a serious issue happens.

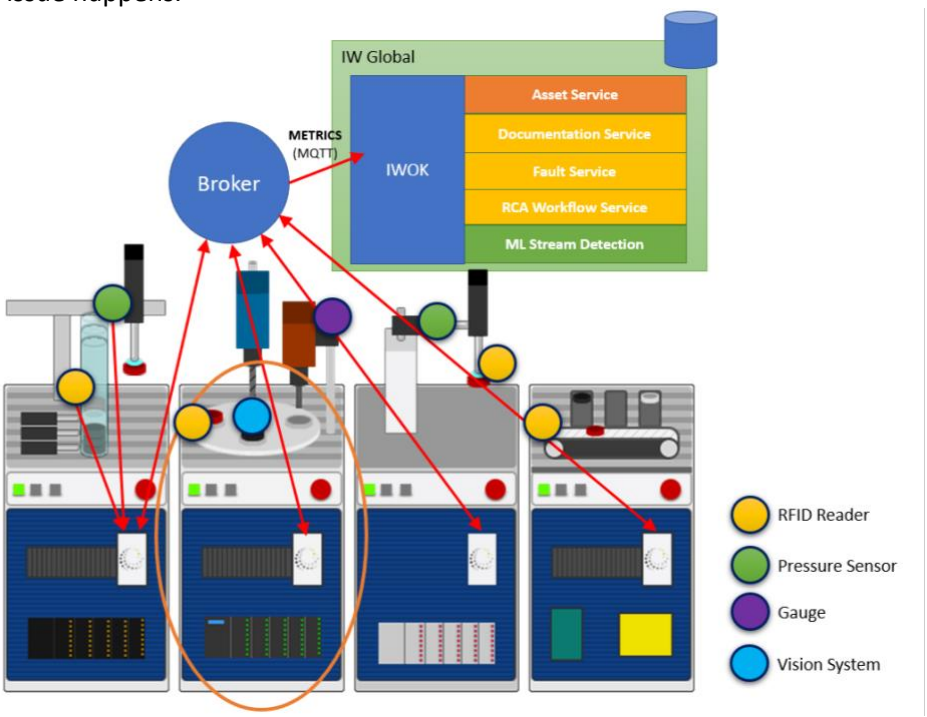


Figure 37 AI Fault Detection

Integration with Platforms

The Experiment will use the Industreweb™ Data integration platform as a secure data layer between the different systems, to collect and translate the machine data via an MQTT broker. Data will be processed at the Edge, monitored and controlled via a server-based Administration suite.

Additional connectors for the Arrowhead platform and additional data models will be included in the connector library.

AI Aspects of the Experiment

Expectations from AI in the AIREDGIO 5.0 Experiment: Machine and Operator inputs will be collected from the production sequence to ascertain the optimum values to produce the desired defect rate. Each time a fault is introduced, the resolution (data/value/action) will be recorded in a database to create a decision tree based on RCA. This will become the data model for the AI system.

Related AI Perspective, the experiment may enable self-healing production processes to become mainstream in industry.

Regarding applicable AI Technologies, the experiment will use a Vision system, knowledge-base, and dynamic work instructions.

Collaborative Intelligence in the AIREDGIO 5.0 Experiment: The experiment will combine the data from the production process and the operator's feedback to correctly determine if a resultion to a fault is successful or unsuccessful and adjust the suggested fix of the production process to correct any defects. The combined knowledge will create the potential for a self-healing process based on 'learned' results.

Suitable Edge AI Paradigm: All data and systems within the experiment will use Edge processing via the Industreweb platform.

ML-Ops Lifecycle and AIREDGIO 5.0 experiment: *steps of the ML-Ops Lifecycle in AI REDGIO 5.0. Indicate current status (pending, ongoing, completed, blocked) for experiment.*

- Requirements Engineering: **Completed**
- ML Use cases prioritization: **Completed**
- Data Availability Check: To ensure that the necessary data is available and accessible for use in a machine learning project: **Ongoing**
- Data Engineering: **Ongoing**
- ML Model Engineering: To design and develop machine learning models that can perform complex tasks with high accuracy and reliability: **Pending**
- Model Validation: To evaluate the performance and accuracy of a machine learning model and to ensure that it can generalize well to new data: **Pending**
- ML Model Deployment: To integrate a trained machine learning model into a production environment so that it can be used to make predictions or decisions based on new data: **Pending**
- CI/CD pipelines: The purpose of continuous integration and continuous deployment (CI/CD) pipelines is to automate the machine learning model development and deployment process: **Pending**
- Monitoring and Triggering: To continuously monitor the performance of machine learning models deployed in production environments and trigger actions when necessary: **Pending**

4.10 DFIX: MADE (Lombardy, Italy): BEhAI – Adapting quality inspection system to human behavior and human states

DF description, Motivation, Objectives and Benefits

In a manufacturing context, following an operator in charge of doing quality control of some products already analyzed by a traditional vision system, we will try to acquire information from the operator for the purpose of **adapting the behavior of the robot** in charge of enslaving both the machine and the operator to the **psychophysical state of the operator**.

The experiment will take place in MADE. The goal is to find a **direct relationship between environmental/biomechanical/biometrical data and the psychophysical state of the operator** so as to adapt the automated cycle to the condition of the human being, maximizing individual well-being and business productivity.

One of the most known issues in the manufacturing domain is the fuzzy predictability of operators: the efficiency of a human operator follows indeed some deviations expressing various phenomena including fatigue, cognitive stress, skills gap and lack of experience. In this sense, it is emerging the needs for automation machine to become aware, understand and adapt the causes of such uncertainty linked to human factors such as: different human states and behavioural context.

PROBLEM 1_HUMAN STATES UNDERSTANDING. Machines have to deal with different human physical and psychological state.

Automation system need to cope with uncertainty during interaction, especially when dealing with cognitive and psychological factors that are not fully observable and hard to infer such as the states representing the dynamic environment and human behavior (e.g., intents, goals, preferences).

PROBLEM 2_CONTEXT ADAPTIBILITY. Machine have to deal wit different environmental factors affecting human states

Automation machines need to communicate their behaviours to agents (i.e. humans and other robots in the environment) in a clear and understandable manner. Therefore, robots need to be context-aware: being able to perceive and understand their surroundings and adapt their functionalities accordingly.

PROBLEM 3_HUMAN SKILLS UNDERSTANDING. Machines have to deal with human with different skills

Automation system need to cope with uncertainty during interaction, especially regarding different level of human skills.

All the BEhAI challenges are schematically reported in Figure 38

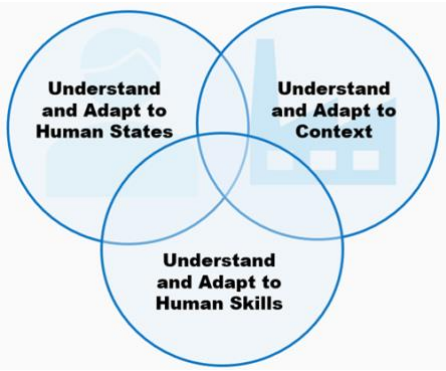


Figure 38 BEhAI challenges

EXPERIMENT CONCEPT

BehAI concept will deploy *AI data pipelines* and *intelligent vision system* on quality process, addressing the following domain:

a. IMPROVE WORKING CONDITIONS, LOWERING PSYCHO PHYSICAL STRESS OF OPERATORS

In a manufacturing industrial setting, *the technology used in manufacturing need to adapt to the needs and diversity of workers in the industry*, rather than having them continually adapt to ever-changing technology and environment. An intelligent agent based on data generated by sensors can be applied to monitor psycho-physical stress and cognitive safety of the operator: *Work environment, Biomechanical data, Biometric data.*

Therefore, starting from an initial sample of the various data relating to the single operator and analyzing the data collected, it is possible to form contexts and minimize the stochastic factors present in collaborative industrial environments. An **intelligent vision-base**, will acquire additional high-level information about its surroundings and, in the context of information about the human co-workers including motion information (poses, joint velocities, etc.) human psychological and cognitive states, which can be represented through facial expressions or body language

b. MACHINERY ADAPTION TO OPERATORS SKILLS, INCLUDING LOW SKILLED, NEW AND OLDER OPERATORS

Today, data related to operator skills, including experience, is observed and annotated manually, making **the creation and implementation of data pipelines completely manual and potentially biased.** Additionally, AI ML training allows the system to adapt to the experience and skills of the operators. In particular, considering a work cycle in which the operator is called to carry out a second check of the quality of some components, passed to the operator by a collaborative robot which serves the quality control line, the

intelligent agent could command the robot : seat and/or workbench height change, raise/lower the robotic arm to adapt to the operator, robot cycle speed adaptation, recommend a break, recommend a job change for the current shift, change some environmental conditions (intensity of light, change the ambient temperature as much as possible or turn on a fan/warmer), communicate with the operator to solicit/attract his attention. In addition, AI ML training allow the system to adapt to experience and skills background of the operators making. This will facilitate task scheduling in high evolving environment, with high job rotation slowing upskilling of operators towards digital and automated process.

SITE.

The experiment is implemented in MADE Competence Center, Via Durando 10 (Milano). MADE is one of the 8 Italian Competence Centers and European Digital Innovation Hub by European Union. Thanks to the large demo-center of over 2500 m^2 - Figure 39, it provides an I4.0 – based pilot production facility for pioneering test, demonstration and development project realization. The experiment takes place in the **Quality, Traceability 4.0 use cases area** accommodates a miniature assembly line equipped with vision tools and machine learning for in-line identification of defects. This use case wants to show an integrated product traceability line based on serialization with new 4.0 codes. This area houses an automated line that supports the use cases of traceability and quality control through machine vision.

Figure 39 MADE facilities

Objectives and benefits are described in Table 6.

Table 6 BEhAI objectives and benefits

TYPOLOGY	OBJECTIVES	BENEFITS
Technical Objectives	Acquire data related to operators' stress, such as work environmental data (e.g. temperature, pressure, humidity); biomechanical data (e.g. postural effort); and biometric data.	Increased efficiency, *efficacy and* resilience of overall manufacturing system.
	Analyze and acknowledge operators state	
	Identify specific human state by associating AI feedback to the single operators	
	Adapt manufacturing task to the identified state	
Business Objectives	Decreased of costs linked to unskilled labour	Decreased efficiency costs, increased of labour productivity
	Decreased production costs	
	Increased product quality and value (i.e. decrease of defective components)	
Social Objectives	Upskilling of operators	Increase of operators' wellbeing, decision-making (i.e. empowerment) and ability to bring innovation.
	Increased of operator wellbeing and satisfaction	
	Increase of operators' employability	
	Higher employment rate of low skilled labour	
	Inclusion of frail workers category	

Experiment team

Team is composed by: Maria Rossetti (Project Manager), Ottavia Villain (Jr Project Manager); Gianmaria Peruzzi (Technical Manager)

4.10.1 AS-IS scenario

Currently, the cycle involves a robot integrated in an automated inspection line for quality (visual) inspection of certain components.

The robot's task is to pass the components judged "scrap" by the automated system to the operator, who will perform a second check.

The limitations of this way of working are more than one:

- In case of many scraps detected by the automated system, the operator will be overloaded, thus reducing the quality of the inspection and increasing the overall time of the process.
- At the end of the control of a batch, the measured quality also depends on the operator, which is a variable that can be measured only to a certain extent. Therefore, the only way to perform further effective control requires checking the entire batch.

In the case portrayed it's possible to see that by not considering the operator's workload and pisco-physical conditions, there is no possibility of operator time/performance optimization.

4.10.2 Technical Implementation

The operator monitors the rejects selected by vision system, equipped with artificial intelligence for quality analysis. Components recognized as “rejects/scraps” are passed to the operator for the check or placed inside a storage unit by a collaborative robot "Fanuc CRX-10iA."; additionally, sample components that are deemed good will also be selected randomly.

The objective of the experiment is to enhance and make the robot intelligent to improve the operator's work experience in three different aspects:

- Improve the operator's ergonomics during the verification process;
- Adjust the operator's workload based on their psychophysical conditions;
- Ensure a comfortable working environment with low stress levels.

To implement these improvements, the following is required:

- An employee database with their physical characteristics and preferences;
- Onboard sensors to read the operator's real-time status and adjust the workload based on their psychophysical conditions;
- Hardware to process data acquired from the sensors;
- Storage to store sensor outputs and operator efficiency data;
- Creation of an algorithm to adjust the robot's behavior based on the operator's psychophysical state.

The hardware to be implemented to provide these improvements can be categorized as such:

- Robot: Fanuc CRX-10iA
- Camera for component verification: Siemens MV540-H
- Sensors to monitor the working environment and operator's status: TBD
- Environmental Sensor; Infrared Camera; High-resolution and high-frequency camera for facial recognition of the operator; PPG sensors; Ambient noise microphone; Humidity sensor.
- Hardware for processing sensor outputs: TBC - computer equipped with GPU or Siemens Tensorbox
- Software for operator status analysis: TBC
- Data Storage: TBC – Cloud or Edge SSD

Communication Module: TBC – ETH; MQTT; OPC-UA; MTConnect; MODBUS; Profinet

4.10.3 TO BE scenario

In the final scenario – Figure 40, which may have varying degrees of maturity and depth, the intelligent agent will best adapt the workstation to the operator, calibrating itself accordingly to both physical and, in a more limited way, psychological/behavioral characteristics by:

- adapt the workload by buffering at times of greatest operator pressure.
- recommend breaks, shift changes, role changes.
- modify one's accelerations to less impact the operator's perception.

- modify environmental conditions (lights, conditioning) to bring the worker back to his or her comfortable zone.
- do further testing on components found to be "good" at times when the worker is less overworked and in better condition.
- create a control "reliability index" derived from psychophysical analysis and associate it with the batch produced to make any subsequent controls more effective.
- Increasing or decreasing production cycle trying to keep it appropriate to the operator's optimal conditions without having to rely only on standard performance curves and ensuring high quality and at least sufficient productivity.

At these stages the system, with reinforcement learning, will have a way to make itself more and more efficient by verifying the outcome of its actions.

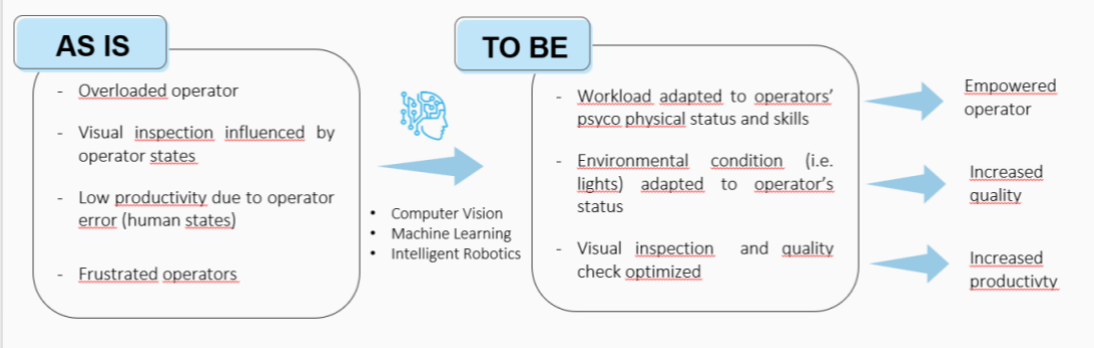


Figure 40 BEhAI: AS IS - TO BE scenario

Expectations from AI in the AIREDGIO 5.0 Experiment: A vision-based modality, intelligent agent can acquire additional high-level information about its surroundings and, in the context of information about the human co-workers including motion information (poses, joint velocities, etc.) human psychological and cognitive states, which can be represented through facial expressions or body language. This can form contexts and minimize the stochastic factors present in collaborative industrial environments. Today operators' skill related data, including experience, are observed and note manually, making creation and deployment of data pipelines fully manual. In addition AI ML training allow the system to adapt to experience and skills background of the operators making. This will facilitate task scheduling in high evolving environment, with high job rotation slowing upskilling of operators towards digital and automated process. Data pipelines will be shared

Related AI Perspective: Computer Vision, Machine Learning, Robotics & Automation;

Collaborative Intelligence in the AIREDGIO 5.0 Experiment: AI understand human states, working environment and subsequently adapt manufacturing task to the state, skill and behaviour of the operators

Suitable Edge AI Paradigm: TBC

ML-Ops Lifecycle and AIREDGIO 5.0 experiment: pending

4.11 DFX: TUIASI I4.0 (Romania): Implementation of QAD-AI@E solution in the real clothing manufacturing environment

DF description, Motivation, Objectives and Benefits

The **TUIASI** DF models aim to provide hands-on and interactive research and training in applications of advanced technologies. Its main components are:

- autonomous omnidirectional robots
- artificial vision systems
- collaborative manipulator
- 3D printed electronics manufacturing system.

The experiments is based on the KATTY Fashion quality Assurance process. The KAF Quality Assurance department inspects the product quality last, and if a defect is found there, the customer will be dissatisfied. QA work is currently done manually using a detailed checklist with subjective evaluation. AI can simplify QA tasks and **improve process efficiency and objectivity**. In order to fully build the Fashion Factory of the Future, this adds to KAF's strategy for transformation to a digitally enabled smart & circular business model.

The concept underpinning the experiment is the development of a product defect detection system with the following functionalities: **acquire product images; manipulate images by an embedded AI tool; extract information about the nature and severity of the product defect; send alerts to the QA personnel in charge of the product check**. The developed system should be able to assist the QA team in validating the correctness of the operations done for the analyzed item based on close integration with the initial design characteristics.

The experiment will be implemented in the QA room of the KAF factory and will be integrated in the existing production workflow.

The experiment has 4 main Steps:

- **Requirements engineering**: KAF and TUI are working together to identify, analyze, document, and manage the needs and expectations of the QA team that will use the the developed system
- **Validation and verification**: KAF and TUI will work together to validate that the system specifications captures all the QA team requirements verify that the system will meet the agreed specifications
- **Test Deployment**: KAF QA team will use the system in a non-critical production environment while double checking that the result are as expected. It is expected to have small updates on the system and its specifications.
- **Production Deployment**: KAF QA team will use the system in a real production environment. TUI will help integrate the system in the KAF Digital Twin platform.

AI challenge:

QA is a tedious work that is very subjective and needs a lot of training data. Complexity of clothes produced by KAF is high. Currently all the QA at KAF is done manually, a phone being used to document relevant issues of later training of the production team or improvement of production workflows.

The AI part of the QUAD-AI@E system will deploy Computer Vision related algorithms for preprocessing and AI processing of the captured image Multiple algorithms for pre-processing are analysed in conjunction

with a supervised learning AI. In deep analysis of defects for segmentation of provided good/bad annotated images is ongoing. The results of the hands-on analysis will decide the direction of the AI design

The Artificial Intelligence technology used will be of the Fuzzy systems type, in this sense it is useful to create and train a database with possible defects in clothes

The main objective of the experiment is to offer a technical alternative, through automation, to the manual operation of evaluating the quality of the products made by KAF

Experiment team

The experiment team is formed by:

- **Katty Fashion** (SME) is a bespoke womenswear services company offering product design, development and manufacturing. Founded in 2003 in NE Romania, Katty Fashion is, to date, one of the most innovative SMEs in the NE of Romania thanks to its Zero Pre-Consumer Resource Waste Strategy and unique digital transformation path that awarded us the Factory of the Future title as the winner of BoostUp Transform CLC East EITM competition.
- The **TUIASI didactic factory** models Industry 4.0 innovative aspects of a production plant aiming to provide hands-on and interactive research and training in applications of advanced technologies. Its main components are: (i) autonomous omnidirectional robots; (ii) artificial vision systems; (iii) collaborative manipulator; (iv) 3D printed electronics manufacturing system. During AI REGGIO 5.0 Katty Fashion will be the end user of the implementation of the QAD-AI@E solution, developed by TUI Iasi, in the real clothing manufacturing environment. More specifically, we will working together with TUI Iasi in developing an AI that can detect production defects

TUI and KAF will work together to analyze the QA process and refine the requirements that will be used by TUI to create the QUAD-AI@E system to be used in the QA department by the KAF team.

4.11.1 AS-IS scenario

The state of the art could be summarized as **i**) defining the concept of QUAD-AI@E, **ii**) designing a block diagram of the automatic defect detection system, **iii**) designing a processing flow using AI fuzzy algorithms, iv) classification of a first category of defects- acquisition of images with a Raspberry PI development system. All these action are summarized in Figure 41

The concept underpinning QUAD-AI@E experiment is the development of a product defect detection system with the following functionalities: to acquire product images; to manipulate images by an embedded AI tool; to extract information about the nature and severity of the product defect; to send alert to the QA personnel in charge of the product check. The experiment builds on integrating AI at the edge technology into a product defect detection system prototype suitable for quality control automation in textiles industry

The system consists of a frame in Cartesian coordinates on which a monocular camera is mounted that moves in Cartesian coordinates so that it can capture image frames of the clothes (the product under test), these frames being numbered (eg: 00, 01, 02, ..., 10, 11, 12, ..., nm) so that they can be easily identified. Each product under test will have its own code (ex: KAF_M023), this code will help manage the data saved in the database.

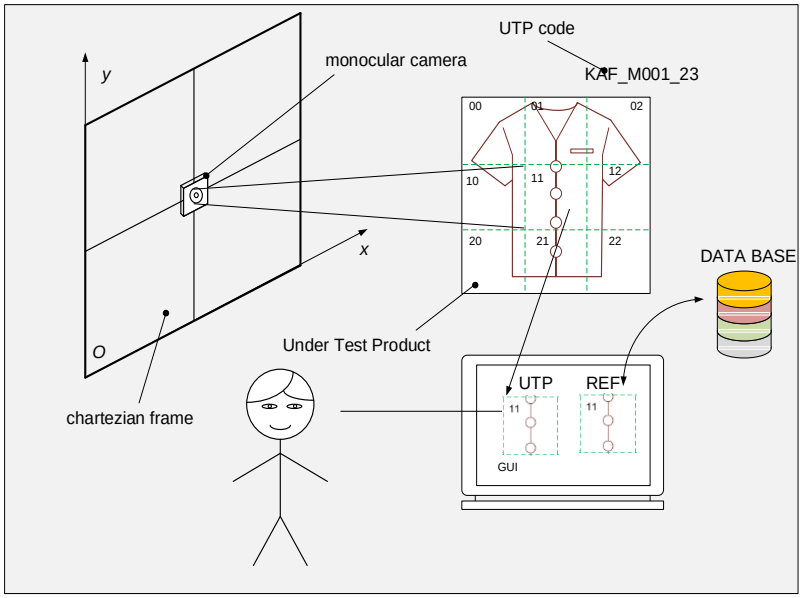


Figure 41 TUIASI AS-IS scenario

Actually, the defects classification are the following:

a) the non-linearity of the seams

b) fringing the textile

c) stains on fabric

d) buttons wrong placement

4.11.2 Technical Implementation

Currently, on the technical side, the experiment is at the requirements gathering and design stage. The technical implementation is not enough defined yet.

Technical issues

Product quality testing (QA), at the end of the manufacturing process, is necessary and the success of the product on the market and implicitly the success of the business largely depends on it. In the fashion industry, the analysis of the quality of finished products is done manually, by a human operator, which implies the existence of some disadvantages: long analysis times, the excessive responsibility of some people, the possibility of escaping certain defects that compromise the quality of the product in front of the customers.

Technical solution

The technical solution is to use a device that performs quality analysis automatically and indicates possible defects that have resulted from the production process. The **QUAD-AI@E** device is included in the production process in the QA (Quality Assessment) phase for the finished products to be stored and delivered to the final beneficiary. The products offered by KAF are clothing items intended especially for ladies and are produced in small series (10-20 pcs.). Each series has as a reference a template that is validated following a thorough analysis by a human operator. This reference will constitute the comparative reference for the products under test.

4.11.3 TO-BE scenario

The QUAD-AI@E system will be included in the production process in the QA (Quality Assessment) phase for the finished products to be stored and delivered to the final KAF client. The products offered by KAF are clothing items intended especially for ladies and are produced in small series (10-20 pcs.). Each series has as

a reference a template that is validated following a thorough analysis by a human operator in close coordination with the product development team. This reference will constitute the comparative reference for the UAPs. The QUAD-AI@E system consists of:

- an image acquisition subsystem
- image preprocessing subsystem
- AI image processing subsystem

Fuzzy logic algorithms will be used for defect detection in clothes as part of edge computing systems. Fuzzy logic is a mathematical framework that deals with reasoning and decision-making in situations that involve uncertainty and imprecision. It allows for the representation and processing of vague or ambiguous information.

All the subsystems will work together to automate the QA workflow as much as possible given the workflow and relevant QA activities.

4.12 DFXI CTU RICAIP (Czech Republic): AI-driven Monitoring of Robotic Assembly Process

DF description, Motivation, Objectives and Benefits

The experiment "AI-driven Monitoring of **Robotic Assembly Process**" is didactic factory experiment in Czech republic led by Czech Technical University in Prague. The primary objective of this experiment is to showcase the prowess of AI-driven real-time monitoring in a robotic assembly line scenario. Specifically, the experiment focuses on a delta robot that assembles a compact 4-wheel vehicle. The central challenge in this monitoring process lies in identifying nonOK states. This is achieved through the analysis of force and torque time series data collected from sensors positioned on the robot's end effector. The ultimate goal of this monitoring system is to promptly detect any anomalies as soon as they manifest. This early identification enables the implementation of corrective actions at the earliest juncture, thereby substantially enhancing the efficiency of the assembly process.

The problem at hand is meticulously framed as a real-time anomaly detection task within the realm of multidimensional time-series data. This formulation allows for the application of machine learning techniques with a high degree of efficiency.

The key benefits of the AI-driven monitoring are:

- Enhanced Efficiency: The integration of AI-driven monitoring leads to a noticeable boost in the overall efficiency of the assembly line. This is primarily due to the timely detection of anomalies and the subsequent implementation of corrective measures.
- Reduced Downtime: Swift identification of nonOK states translates to a reduction in downtime, as corrective actions are initiated promptly. This minimizes disruptions in the assembly process.
- Improved Quality Assurance: By ensuring that only "OK" states are processed, the system significantly enhances the quality assurance process, leading to a higher standard of final products.
- Data-Driven Insights: The system generates valuable data insights that can be leveraged for process optimization, resource allocation, and future planning.
- Potential Applications: Beyond the realm of robotic assembly lines, this AI-driven monitoring approach holds the potential for wider applications in various industries, ranging from manufacturing to quality control in complex assembly processes.

- Continual Improvement through Iterative Learning: The system's capacity for learning and adaptation ensures continual improvement over time. As more data is gathered and analyzed, the monitoring system becomes increasingly adept at identifying and responding to anomalies.
- Scalability and Integration: The architecture of this monitoring system is designed with scalability in mind, allowing for seamless integration with diverse robotic systems and assembly line configurations.
- Cost-Efficiency and Resource Optimization: Through targeted anomaly detection, resources can be allocated more efficiently, contributing to cost savings and a more sustainable operational model.

Experiment team

The experiment is conducted at the Czech Institute of Informatics, Robotics, and Cybernetics (CIIRC) of the Czech Technical University in Prague (CTU), Czech Republic. CTU stands as one of Europe's oldest technical universities and is a paramount institution in the Czech Republic, renowned for its high-caliber education and a venerable tradition of pioneering science and engineering. With approximately 1.7K dedicated members of academic staff, 18.5K students, 8 faculties, and 6 institutes, CTU epitomizes excellence in technical education and research.

Among these institutes, the Czech Institute of Informatics, Robotics, and Cybernetics (CIIRC CTU), inaugurated in 2017 in a state-of-the-art facility, takes a forefront position. This institute's core focus spans industry, energy, smart cities, and health, encompassing both fundamental and applied research. A pivotal commitment for CIIRC CTU lies in bridging the gap between academic innovation and real-world application, thereby driving technological advancement. The institute endeavors to centralize exceptional research in the domains of robotics, intelligent systems, distributed and complex systems, automatic control, computer-aided manufacturing, bioinformatics, and biomedicine.

CIIRC CTU actively promotes horizontal collaboration across all facets of CTU, fostering synergistic partnerships with other universities, research establishments, and corporations. Moreover, the institute spearheads the national initiative on Artificial Intelligence (AICZECHIA) and is a pivotal participant in European AI networks such as CLAIRE (https://claire-ai.org/) and ELLIS (https://ellis.eu/).

The research team is composed of two integral parts: the first encompasses researchers from the Intelligent Systems for Industry Research Group, including Martin Macaš, Petr Kadera, and Václav Jirkovský. This segment is tasked with the development and integration of cutting-edge machine learning algorithms. The second segment is comprised of researchers from the Testbed for Industry 4.0, led by Pavel Burget, which is responsible for the operationalization of the robotic assembly line.

Crucially, this experiment is intricately linked with the Czech EDIH CTU, the nation's digital innovation hub for Artificial Intelligence, dedicated to transferring reliable solutions and services to the energy, industry, health, and transportation sectors. This strategic alignment is poised to facilitate the provision of the didactic factory and its associated experiments and demonstrations to SMEs and a broad industrial audience. SMEs play a vital role as potential end-users of the methods developed within the experiment. They stand to benefit from the efficient monitoring and quality control solutions, contributing to enhanced productivity and product quality in their operations. The National Center of Industry 4.0, an exceptional national ecosystem comprising over 50 industrial partners, which is an integral part of CIIRC CTU (https://www.ncp40.cz/), further fortifies the dissemination efforts.

The methods developed within this experiment hold immense potential for industrial companies seeking to streamline the monitoring and control of their process quality. Throughout the AI REDGIO 5.0 project, the experiment will be consistently presented to industrial partners across various opportunities, ensuring a robust exchange of knowledge and expertise.

By elucidating the roles of the stakeholders, we provide a comprehensive overview of their contributions and significance in the context of the experiment. This also highlights the collaborative nature of the initiative, where various entities come together to drive innovation and advance the field of AI-driven real-time monitoring in the realm of robotic assembly lines.

4.12.1 AS-IS scenario

The production process is the robotic assembly process performed by the Flexlink Delta robot with conveyor whose pallets can be precisely tracked and the robot's movements can be synchronized with those of the pallets. The robot assembles small car wheels by first mounting the wheel on the wheel axle and then adding the tires. A more detailed description and a video can be found in the following link: https://testbed.ciirc.cvut.cz/labs/testbed/flexlink-delta/.

Currently, only some of the final assembled products are inspected by humans. The inspection is time-consuming and not complete. Even in case of complete sampling, the problem can be detected only after the end of the assembling process that is currently in-progress. Currently, a camera based inspection is implanted and deployed as a reference for the force and torque sensor based detection on the edge.

4.12.2 Technical Implementation

At this moment, a normal PC as an edge server for AI on the edge implementation in the above experiment is entirely feasible. The PC has a capable CPU with multiple cores and threads to handle the computational demands of real-time AI processing. Sufficient RAM is crucial to store and process data efficiently. No graphics processing unit is needed since the AI model, which is being proposed, can be implemented efficiently and does not need it. Sufficient storage is an obvious feature.

The model is prototyped in Matlab and implemented in Python and a specialized edge AI software that allows for the efficient deployment of AI models on edge devices which optimizes the models for the specific hardware available will be considered. 5G connectivity is available and OPC UA communication protocol is used for communication between robot and edge device.

4.12.3 TO-BE scenario

Following the implementation of the experiment, there will be an ongoing monitoring of in-process variables to promptly identify any not-OK states – Figure 42. The hypothesis posits that adequate detection can be achieved solely from the analysis of force and torque signals, offering a cost-effective and computationally efficient solution. This assertion will be substantiated through a comparative assessment with a computer vision-based detection method and a combined approach.

The proposed scenario is illustrated in Figure 42, where the in-process variables encompass data obtained from the force sensor and/or camera. The three experimental scenarios are outlined as follows:

- **Scenario 1** – not-OK State Detection using Camera: Continuous acquisition and analysis of images from the camera will serve as the primary in-process variables.
- **Scenario 2** – not-OK State Detection using Force and Torque Sensors: Continuous collection and analysis of force and torque data will be employed as the primary in-process variables. This scenario is the AIREDGIO5.0 use case.
- **Scenario 3** – not-OK State Detection using both Image and Force/Torque Sensors: Both force/torque data and images from the camera will be continuously gathered and utilized as in-process variables for detection. This scenario is optional within AI and will be considered only if a preliminary feasibility study will confirm its potential efficiency.

These scenarios constitute the experimental framework for evaluating the effectiveness of nonOK state detection methods in the context of the experiment.

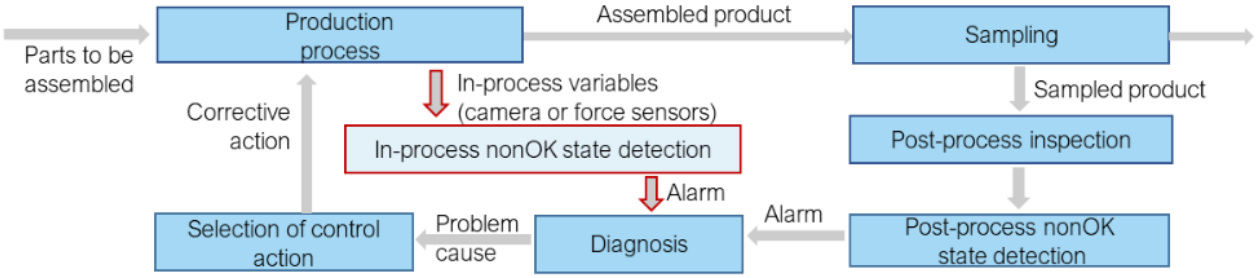


Figure 42 RICAIP TO-BE flow diagram

Integration with Platforms

At this moment, the system is in a development stage and we still do not know if and how the experiment will be integrated within AI-On-demand Platform and Data4AI Platform.

Expectations from AI in the AIREDGIO 5.0 Experiment

Force and torque values in three axis are acquired every couple of seconds and a dynamic time warping distance is computed from all prototypes. If the distance from the nearest prototype exceeds a threshold, alarm is triggered. After the assembly of each part, the whole signal is used to update prototypes using online k-means clustering method with dynamic time warping metric. This defines the one step of continual learning:

- Related AI Perspective: Continuous learning, clustering, anomaly detection.
- Applicable AI Technologies: Dynamic time warping and online k-means clustering.
- Collaborative Intelligence in the AIREDGIO 5.0 Experiment: The operator will provide labels for the machine learning.
- Suitable Edge AI Paradigm: the edge AI paradigm that should be supported for the purposes of the experiment.
- ML-Ops Lifecycle and AIREDGIO 5.0 experiment:
    - Requirements Engineering: ongoing
    - ML Use cases prioritization: completed
    - Data Availability Check: ongoing
    - Data Engineering: ongoings
    - ML Model Engineering: ongoing
    - Model Validation: pending
    - ML Model Deployment: pending
    - CI/CD pipelines: pending
    - Monitoring and Triggering: pending

4.13 DFXII AAU Smart Lab (Denmark): AAU Advanced IoT

DF description, Motivation, Objectives and benefits

The **AAU Smart Lab** at Aalborg University is a "small Industry 4.0 factory" integrating and demonstrating Industry 4.0 technologies, built around FESTOs CP factory, which is a small modular, and expandable factory integrating many relevant Industry 4.0 technologies (e.g. IoT, AI, Robotics, simulation, digital twins, clouds/edge, 5G ...). In the framework od AI REDGIO 5.0, the experiment will update the AAU IoT suitcase with data analytics/machine learning capabilities.

Motivation

- Help SMEs to take advantage of the benefits of IoT technology.
- Provide a solution to SMEs to extract meaningful insights data by leveraging the capabilities of the AAU IoT suitcase.

Concept

- Collect data from through sensors such as vibration sensor, temperature sensor.
- Use data analytics/machine learning algorithms to extract valuable insights.
- IoT suitcase is an ideal platform for this project as it provides a wide range of sensors and data acquisition capabilities, making it easier to collect data from different sources.

Challenge

- Data quality: IoT data can be noisy and inconsistent, which can make it difficult to extract meaningful insights.
- Integration: Integrating the AAU IoT suitcase with existing systems can be challenging, especially if the systems are not compatible.
- Expertise: Developing and implementing data analytics/machine learning algorithms requires specialized expertise, which may not be available in SMEs.
- Others, *e.g.*, data security, data privacy, etc…

The objective of the AAU IoT solution is to:

- Improve operational efficiency: by collecting and analyzing data from sensors, SMEs can identify inefficiencies in their production/operations and take steps to optimize them.
- Enhance product quality: IoT data can help SMEs to monitor the quality of their products in real-time, identify defects, and take corrective action.
- Reduce costs: IoT data can help SMEs to identify areas where costs can be reduced, such as maintenance, and waste reduction.
- Enhance company image: By demonstrating a commitment to innovation and technology, SMEs can enhance their reputation and attract new customers

Experiment team

The end-user could be manufacturing SMEs. The technology providers and experiment team is AAU Smart Lab (DF).

4.13.1 AS-IS scenario

Preliminary experiments are conducted in AAU Smart Lab together with VELUX. Main focus is to design and validation the ML methods for detect irregularities and mistakes in the screwdriving process, to ensure better **quality control** of the products and improve efficiency of the manufacturing process. The experiment setup is shown in the following Figure 43.

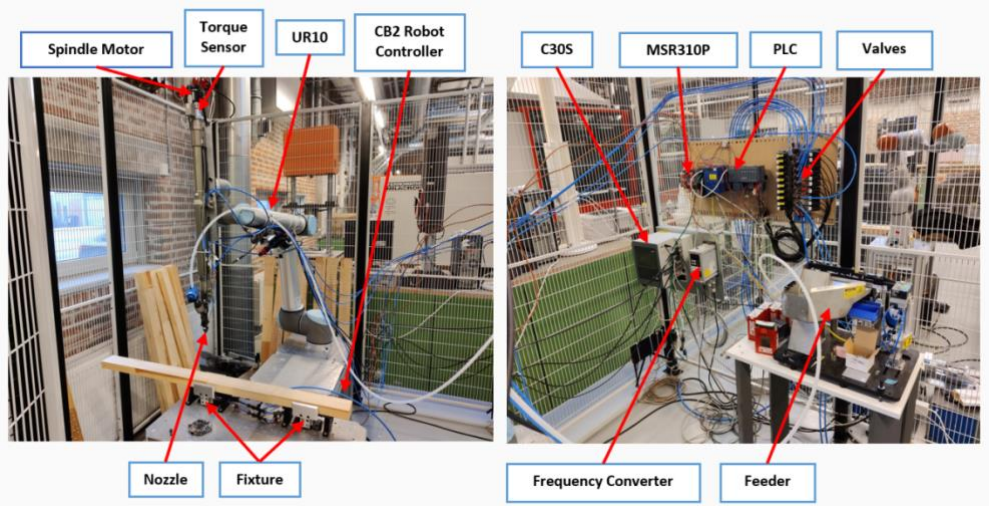


Figure 43 AAUM Smart Lab AS-IS scenario

4.13.2 Technical Implementation

- **Hardware**: UR10, AAU IoT box, Sensors (e.g., torque, microphone), data storage, computing server and power supply
- **Software**: Python, VSCode
- ML algorithms: KNN, SVM, RF
- **Communication channel/s**: MQTT, HTTP

4.13.3 TO-BE scenario

The to-be scenario focuses on building IoT solutions with data analytics and machine learning capabilities. To be specific, an integrated solution (*i.e.*, data collection and analysis will be applied on multi-sensors data input) will be provided. Data analytics and machine learning algorithms will be designed for 1) Data acquisition and monitoring: Provision of support in data collection through IoT box and monitor the production data in real-time. 2) Data analytics: Provision of support in data analytics/machine learning by analyzing collected sensor data.

Scenario 1 :

Improve production monitoring and production quality: monitoring the production in real-time, enabling them to respond quickly to changing conditions and improve decision-making. By analyzing sensor data, SMEs can predict when device is likely to fail and take preventative measures to avoid downtime and reduce maintenance costs.

4.14 DFXIII PBN amLAB (Hungary): SunSync: AI solution for optimizing recycling in industry at the level of am-LAB's DF

DF description, Motivation, Objectives and Benefits

Jozef Stefan Institute is the leading scientific research and development organization in Slovenia covering a broader spectrum of disciplines: physics, chemistry, electronics, automation and information technologies, nuclear reactor engineering and energetic.

This experiment aims to solve two main challenges:

- Energy Efficiency: we would like to make the best use of energy in systems that use solar panels and energy storage accumulators.
- Recycling Optimization: we aim to schedule recycling processes smartly to use clean energy efficiently and reduce reliance on non-renewable sources.

Experiment Concept:

We are implementing an AI-driven system that integrates data from various sources, like light levels, weather forecasts, and accumulator data. Here's how it works:

- Data Integration: We gather data from sources like light detectors, weather forecasts, and accumulator monitoring systems.
- Data Processing: We use AI to clean, format, and combine this data for analysis.
- AI Decision Logic: AI algorithms make real-time decisions about when to use energy from the accumulator and when to start recycling operations. This helps optimize energy use and align recycling with available energy.

Site: The experiment will be conducted by the technical staff of PBN's DIH, am-LAB which is located in Hungary, Vas County, Szombathely.

Challenge - Need for Artificial Intelligence:

We need AI for these reasons:

- Real-time Decision-Making: The experiment relies on quick decisions based on ever-changing variables. AI is great at handling this dynamic data.
- Optimization: AI can analyze large datasets and patterns to make the best choices for energy efficiency and recycling.
- Sustainability: AI helps balance factors to ensure recycling uses clean energy sources, aligning with sustainability goals and reducing carbon emissions.

In summary, this experiment uses AI to improve **energy efficiency and recycling** by making smart real-time decisions based on data from various sources, promoting sustainability and reducing environmental impact.

The experiments objectives are:

- **Energy Optimization:** The primary objective of this AI solution is to optimize energy consumption in a system that includes solar panels and an accumulator. This involves efficiently managing the use of power from the accumulator, considering real-time light levels, weather forecasts, and the need for recycling operations.

- **Recycling Control:** The system should initiate recycling processes when it's most advantageous in terms of available energy. This means identifying optimal timeframes based on the status of the accumulator and energy production from solar panels.
- **Resource Sustainability:** Ensure that the recycling module operates in a manner that aligns with sustainability goals, prioritizing the use of clean energy sources (e.g., solar power) and minimizing the use of non-renewable energy sources.

Experiment Team

The experiment is being developed and carried out by the Digital Innovation Hub of PBN (am-LAB). However, as soon as the experiment is complete it can be also showcased to different types of companies.

Advanced manufacturing (am-LAB unit):

am-LAB is a digital innovation hub and advanced manufacturing laboratory focuses on digital technologies, robotics, data science, extended reality and 3D technologies. A broad portfolio of connected technological devices is available in the laboratory, with in-house engineering staff. The technology transfer department cooperates with multinational technology suppliers from one side (SMC, UR, Formlabs, Keyence, etc) from the technology supplier side, and with a wide range of manufacturing companies from the customer side (Aptiv, IKEA, Ivy, TDK, MAM, Linde, etc.). The most recent technological development is a teaching and learning factory solution, an advanced demonstration and research-oriented production line with 6 stations, provided by SMC Corporation. It enables such in-house development like real-time data visualisation, augmented reality applications, predictive statistics, neural network-based image recognition. am-LAB was awarded the best digital innovation hub title of 2020, awarded at the first European Digital Innovation Hub conference.

4.14.1 AS-IS scenario

Current Progress:

We are in the early stages of this project. We have set up all the necessary systems, including APIs for controlling the recycling module and collecting data. We have also created a basic TensorFlow model generator. However, a critical piece is missing: we have not acquired the essential third-party weather forecasting data yet. This data is crucial for the project's success.

Key Points:

- We are in the initial data collection phase.
- All systems are set up and ready.
- We have control APIs and data collection in place.
- We have developed a basic TensorFlow model generator.
- Acquiring reliable third-party weather forecasting data is a priority, as it's vital for our project's next steps.

In summary, while we have made some foundational progress, we are currently focusing on obtaining the necessary weather data, which is a crucial component for moving the project forward.

4.14.2 Technical Implementation

- **Hardware**:
  - Windows server with docker environment
  - ESP-32
  - BLUETTI Solar Generator
  - Recycling module
- **Software**:
  - Python (FastAPI): Used for data collection and controlling the Recycling module.
  - C++: Used for programming the ESP-32.
  - TensorFlow: Utilized for AI prediction and decision-making.
- **Communication channel/s**: RestAPI, OPC-UA
- **Standard us**ed: Open Platform Communications United Architecture (OPC UA)

4.14.3 TO-BE scenario

Energy Optimization: the primary objective of this AI solution is to optimize energy consumption in a system that includes solar panels and an accumulator. This involves efficiently managing the use of power from the accumulator, considering real-time light levels, weather forecasts, and the need for recycling operations.

Recycling Control: the system should initiate recycling processes when it's most advantageous in terms of available energy. This means identifying optimal timeframes based on the status of the accumulator and energy production from solar panels. An example of the TO-BE scenario is reported in Figure 44.

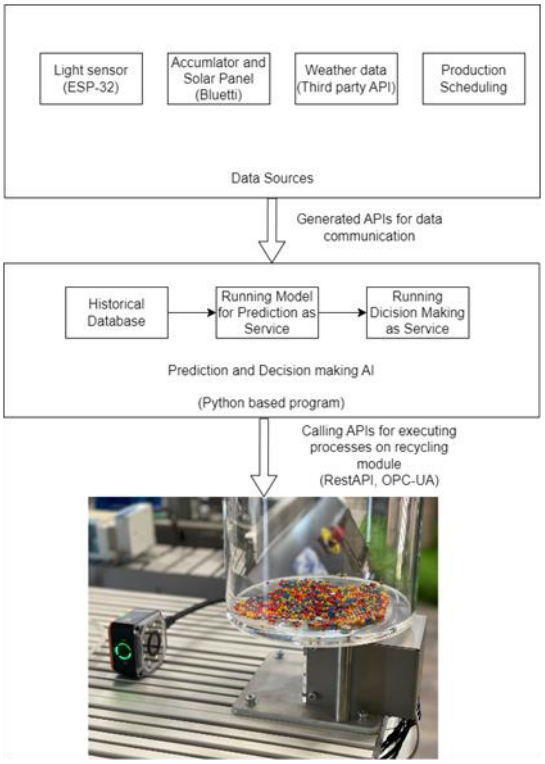


Figure 44 amLAB TO-BE scenario

4.15 DFXIV: Galicia Industrial Logistics lab (Spain): Galicia DF

DF description, Motivation, Objectives and Benefits

Galicia DF is a DF-driven experiment in Galicia (Spain), led by Gradiant and focused on the application of AI and Edge technologies in an industrial robot environment.

One of the main reasons for having a didactic factory in Galicia is to support the local manufacturing industry, which has a strong presence in the region (mainly automotive, naval and food industry). By providing training and development opportunities, a didactic factory could help to improve the skills and knowledge of local workers, increase productivity, and make local companies more competitive. Also, it would help to transfer knowledge to students regarding the application of novel technologies in real environments.

Another motivation for having a didactic factory in Galicia is to address the skills gap in certain industries or trades. By providing certification and training programs, a didactic factory could help to prepare workers for in-demand jobs and ensure that the region has the skilled workforce it needs to grow and prosper.

Finally, a didactic factory could promote innovation in the region by serving as a hub for research and development in areas such as automation, robotics, and digital manufacturing. This could help to drive innovation in local industries.

The proposed experiment in this Didactic Factory is to deploy at least an edge node that allows the creation of a **Digital Twin** of the facility and its systems (mainly **industrial robots**). This node will retrieve industrial process variables from industrial bus communications, such as Ethernet IP, Profinet or OPC-UA where available and store all the retrieved signals in a time series database.

The main objective is to provide a system where AI/ML models can be deployed in order to study approaches to optimize a virtualized production process both from the operational and energy efficiency points of view. Thus, the DF aims to be a testing environment where novel algorithms and approaches can be tested with the available process data in order to research improvements that could be further optimized later in a real environment.

This DF aims to achieve a TRL 4 as a testing environment.

Real-time analysis of manufacturing process data through AI algorithms at edge level will enable discovery of complex patterns and accurate predictions to support decision making. Traditional batch learning algorithms are designed to learn a model from the entire training data set at once.

These AI models are not appropriate for real-time analysis of data streams as they reveal poor performance while handling concept drift issues. Concept drift describes common and unforeseeable deviations in the underlying distribution of data streams overtime. Machine learning applications for real-time analysis will result in poor performance if efficient adaptation of models to different types of concept drift is not correctly addressed.

The objectives of this Didactic Factory experiment are to create a Digital Twin of the facility and its industrial robots, retrieve industrial process variables from various communication protocols, and store the data in a time series database. Additionally, the experiment aims to deploy and orchestrate AI/ML models at the edge to optimize the virtualized production process from both an operational and energy efficiency standpoint. By doing so, the Didactic Factory can provide a testing environment for novel algorithms and approaches that can be further optimized in a real-world production environment.

The benefits of this experiment are numerous. First, it can offer significant improvements in efficiency and energy consumption in the manufacturing industry, leading to reduced costs and increased productivity. Second, the Didactic Factory can serve as a valuable learning opportunity for students and trainees, allowing them to gain hands-on experience with cutting-edge technology and techniques that are in high demand in the modern workforce. Finally, the experiment can position the Didactic Factory as a hub for research and

innovation in the manufacturing industry in Galicia, attracting investment and promoting economic growth in the region.

Experiment team

ICT Provider: Gradiant

Gradiant, Spanish ICT technology centre, aims to improve the competitiveness of companies by transferring knowledge and technologies in the fields of connectivity, intelligence and security. With more than 150 professionals and 14 applied patents, Gradiant has developed more than 340 different R&D&i projects, becoming one of the main engines of innovation in Galicia. In 2022, Gradiant's turnover reached 8,5 million euros, working with more than 370 clients in 30 countries over the past 13 years.

Gradiant is backed by a board that includes representatives of the three Galician universities (Vigo, Santiago and A Coruña) and companies: Abanca, Altia, Arteixo Telecom, Egatel, Indra, Plexus, R, Telefónica, Televés; and INEO business association, which represents most of ICT Galician companies.

The commitment with quality is a constant from the beginning. Nine months after starting the activity, Gradiant achieved the Quality Management UNE-EN ISO 9001:2008; and one year later, UNE 166002 R&D&I Management Systems was obtained. In 2011, Gradiant was included in the demanding state registration of Technological Innovation Centres (known in Spanish as CIT). Since 2018, Gradiant has held the Certification in Information Security Management Systems UNE-EN ISO/IEC 27001.

After thirteen years of activity, Gradiant is positioned as a technology partner for the industry, oriented to their needs in the field of ICT, contributing their national and international experience in technologies for security and privacy; processing of multimedia signals; Internet of Things; biometrics and data analytics; and advanced communications systems.

In this experiment Gradiant aims to apply several edge computing and AI technologies, as well as cloud-native technologies, in order to provide the DF located in AIMEN's facilities with all the capabilities required in order to achieve the objectives described in previous sections.

Regional Innovation Office: GAIN

GAIN Axencia Galega de Innovacion is an agency for innovation and technology transfer located in Galicia, Spain. It was established in 2005 by the Galician government to promote the economic development of the region by supporting innovation and technology transfer in Galician companies and institutions.

GAIN offers a range of services and resources to help companies and institutions innovate, including financial support for research and development projects, technology transfer and licensing assistance, networking opportunities, and training and mentoring programs. The agency also works to promote entrepreneurship and to foster collaboration between industry, academia, and government.

4.15.1 AS-IS scenario

Prediction of target variables: *Incremental Learning based AI-Edge models*

This experiment will use ML models for real-time processing from sensor data-streams collected from production equipment and lines. These models will be able to solve multivariate regression and classification supervised problems. Moreover, they will be the basis of the prescription system to dynamically reduce energy consumption and optimize fabrication setpoints to increase productivity.

Incremental learning (IL) algorithms[3] and technologies are being studied, in addition to "traditional" AI/ML models, as they provide a noteworthy benefit within the scope of real-time analysis for edge AI applications. The model will incrementally learn as new data becomes available, efficiently adapting to unseen patterns and concept-drift issues without significant performance losses. The following feasible AI technologies and IL algorithms have been explored:

- **Prototype-based models[4]**

  Prototype-based models in ML make use of explicit representations of input data samples in terms of memorized examples or typical representatives for each class or category. These representatives are called prototypes. Prototypes are the patterns learned during the incremental model training procedure, and are therefore continually changing. As new data arrives, prototypes could be introduced, updated or eliminated from the model, providing a robust mechanism for concept-drift adaptation.

  During prediction, an unseen sample is labeled as the weighted average of the k-nearest prototypes' labels learned by the model until this moment. Local explanations of the model's predictions are also easily obtained. A feature importance score for every single input sample can be computed. This score will depend on the distance among the single sample and its k-nearest prototypes, providing insights related to the influence of explanatory variables over predictions.

  These types of models can be used for supervised classification and regression problems.

- **Deep Neural Decision Forests**

  Deep Neural Decision Forests[5] (DNDF) is a novel approach that unifies classification trees with the representation learning functionality known from deep networks. To combine these two worlds, a stochastic and differentiable decision tree model is presented, which steers the representation learning usually conducted in the initial layers of a (deep) network. The model differs from conventional deep networks because a decision forest provides the final predictions and it differs from conventional decision forests since DNDF proposes a principled, joint and global optimization of split and leaf node parameters.

  As the structure of the model is learned as a differentiable function, this allows for the updating of gradients through backpropagation mechanisms with small batches of data, which makes this type of algorithm extremely interesting for processing real-time data streams. Moreover, as DNDFs are also based on decision trees, their results and predictions are easily explainable to humans.

In order to avoid catastrophic forgetting of past knowledge while updating the model from new samples lifelong learning[6] (LFL) methods have been also considered. Some examples are reported in Figure 45:

- **Architectural strategies:** Dynamic modifications of the model's architecture are performed to make it learn new concepts or skills without interfering with old ones.

[3] Parisi, G. I., Kemker, R., Part, J. L., Kanan, C., & Wermter, S. (2019). Continual lifelong learning with neural networks: A review. *Neural networks*, *113*, 54-71.

[4] González Soto, M., Fernández Castro, B., Díaz Redondo, R. P., & Fernández Veiga, M. (2022, October). XuILVQ: A River Implementation of the Incremental Learning Vector Quantization for IoT. In *Proceedings of the 19th ACM International Symposium on Performance Evaluation of Wireless Ad Hoc, Sensor, & Ubiquitous Networks* (pp. 1-8).

[5] *Zhou, Z. H., & Feng, J. (2019). Deep forest. National science review, 6(1), 74-86.*.

[6] Maltoni, D., & Lomonaco, V. (2019). Continuous learning in single-incremental-task scenarios. *Neural Networks*, *116*, 56-73.

- **Regularization strategies:** the loss function is extended with loss terms promoting selective consolidation of the weights which are important to retain past memories. Include basic regularization techniques such as weight sparsification, dropout or early stopping.
- **Rehearsal strategies:** past information is periodically replayed to the model to strengthen connections for memories it has already learned. A simple approach is storing part of the previous training data and interleaving them with new patterns for future training. A more challenging approach is pseudo-rehearsal with generative or prototype models.

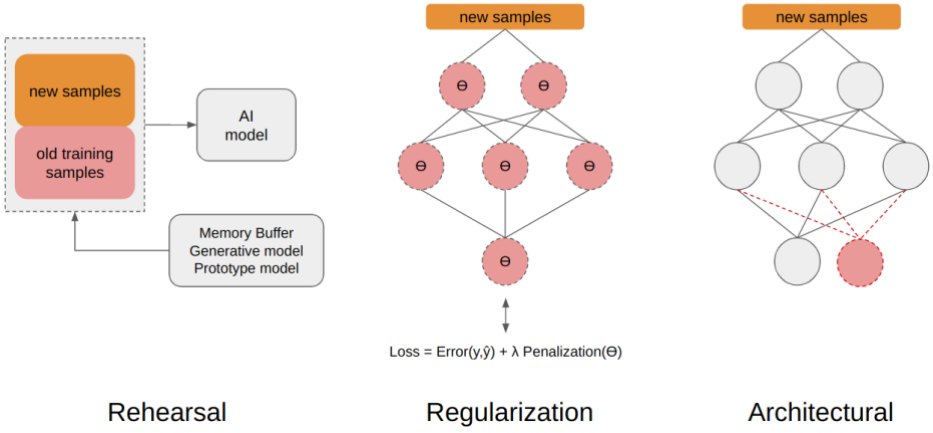


Figure 45 Lifelong Learning strategies

4.15.2 Technical Implementation

Regarding the technical implementation, the diagram in Figure 46 shows the proposed solution regarding the prediction model within this experiment:

- A prediction model based on DNDF, with incremental gradient descent updates to capture new knowledge from small batches of new labeled data. This model was implemented with *keras*[7].
- An online prototype based model acting as a generative or memory buffer (LFL rehearsal strategy) to avoid the forgetting of old knowledge interleaving past samples within the new labeled data in each gradient descent update. This component was implemented in python as shown in[8].

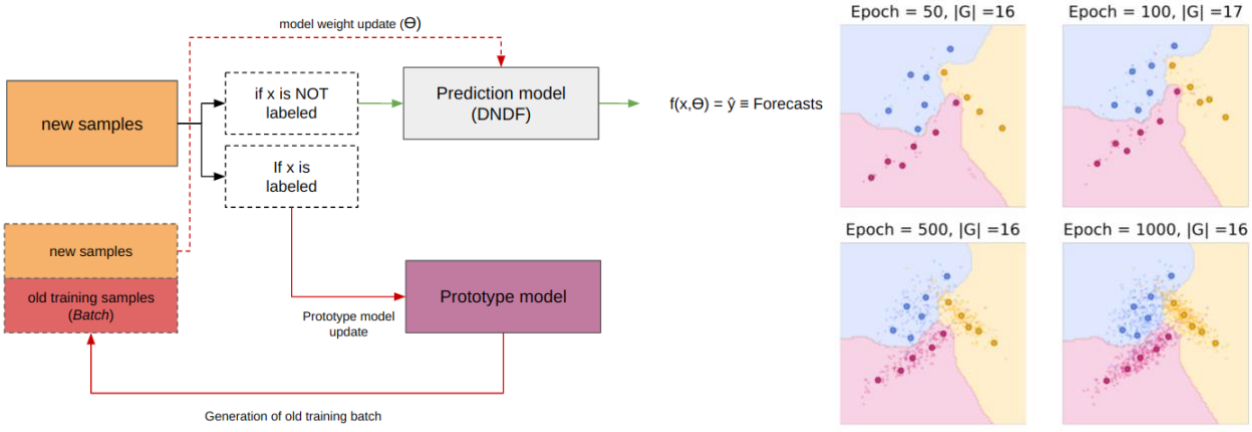


Figure 46 Technical implementation diagram of Incremental Learning implementation

[7] https://keras.io/examples/structured_data/deep_neural_decision_forests/

[8] González Soto, M., Fernández Castro, B., Díaz Redondo, R. P., & Fernández Veiga, M. (2022, October). XuILVQ: A River Implementation of the Incremental Learning Vector Quantization for IoT. In *Proceedings of the 19th ACM International Symposium on Performance Evaluation of Wireless Ad Hoc, Sensor, & Ubiquitous Networks* (pp. 1-8).

It is important to highlight at this point the main barriers and difficulties that we are facing while dealing with these technologies:

- **Catastrophic forgetting:** one challenge that must be addressed with these techniques is the fact that old knowledge might be removed from the model while processing new data.
- **Concept drift adaptation:** another main challenge that results from the application of these techniques is related with how to process and learn from non-stationary data.

Optimization and prescription algorithms

In order to optimize and prescribe the production process parameters automatically, optimization and prescription algorithms are being studied. This is required in order to minimize energy consumption and optimize productivity by using the outputs of the prediction module and other inputs.

Prescriptive analytics aims at suggesting (prescribing) the best decision options, incorporating the predictive analytics output and using artificial intelligence, optimization algorithms and expert systems in a probabilistic context in order to provide adaptive, automated, constrained, time-dependent and optimal decisions[9]. There are many state-of-the-art approaches combining heterogeneous types of predictive models (probabilistic, ML and statistical based ones) with several prescriptive analytics (mathematical modeling, Simulation, Evolutionary optimization, etc.). A schematic representation of this concept is reported in Figure 47.

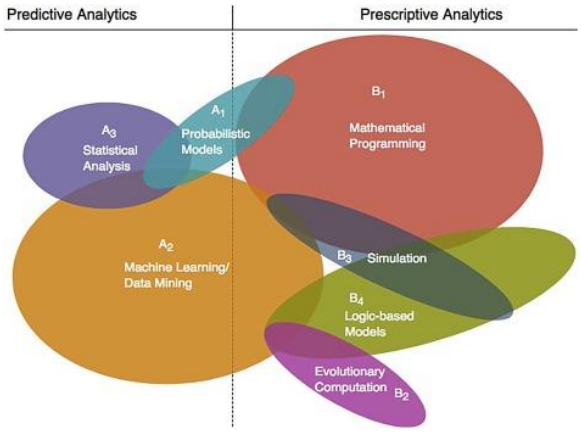


Figure 47 Lepenioti, Katerina, *et al.* "Prescriptive analytics: Literature review and research challenges." International Journal of Information Management 50 (2020): 57-70.

Regarding the technical implementation, the diagram in Figure 48 shows the design of the proposed solution for this experiment:

- A candidate set of production parameters is generated at the beginning.
- Historical production data is employed to train an anomaly detection model to detect abnormal combinations on this candidate set of production parameters.
- The prediction IL model developed in the previous scenario is employed to estimate the values of production KPIs from production parameters.

[9] Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, *50*, 57-70.

- From the initial candidate set of production parameters, production KPIs are estimated. Evolving optimization algorithms are then employed to iteratively explore and find the combination of production parameters that minimizes the values of forecasted KPIs.

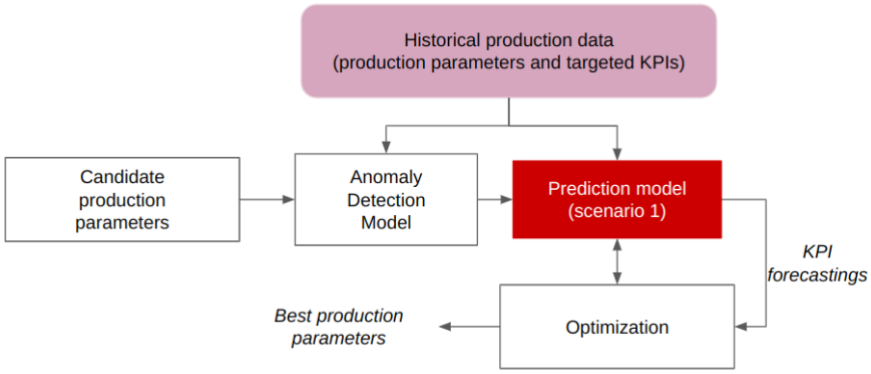


Figure 48 Technical implementation diagram of the optimization and prescription module

It is important to highlight at this point the main barriers and difficulties that we are facing while dealing with these technologies:

- **Near real-time optimization:** for the correct completion of this experiment it is required that the prescription of the optimal production parameters is fast.
- **Automatic prescription:** another main challenge that results from the application of these data-driven techniques is related to the fact that the real production process should not be explicitly modeled by complex mathematical equations. The behavior of the process (i.e. the relation between production parameters and KPIs) should be automatically inferred from historical data by an AI model to facilitate the productization and scalability of the proposed solution.

The technical implementation in the experiment regarding these technologies is scheduled to start at M10.

Orchestration of AI services

In order to ultimately orchestrate the AI models and modules developed throughout this experiment, cloud-native technologies must be used. To this end, a study of Kubernetes based technologies has already been started. These technologies will allow for the efficient management of AI components along the Edge-Cloud continuum. Particularly, the following technologies are the ones that we have already started to look into:

- **Docker:** it is the most popular tool available to develop, manage and deploy containers. It will be used to encapsulate applications and services as light and portable executable packages (containers).
- **Kubernetes:** it is the most popular platform for orchestrating containers in a cluster within Cloud environments. That is, Kubernetes will allow the automation of the deployment, management and scaling of containers over a set of servers that work as a single source of compute, storage and network resources (cluster).
- **KubeEdge:** AI services are expected to operate at the Edge. To this end, the management of the Edge-Cloud continuum orchestration and the application of MLOps methodologies is critical. KubeEdge has been identified as a novel platform that enables Edge computing and aims to extend the orchestration of containers to hosts at the Edge.

The technical implementation in the experiment regarding these technologies has not started yet according to the work plan. Therefore, details about this part of the technical implementation are yet to be defined.

4.15.3 TO-BE scenario

The expected solution to be deployed in this DF experiment aims mainly to deploy at least an edge node that allows the creation of a Digital Twin of the facility in order to reduce costs, improve efficiency and increase productivity. At the same time, the Didactic Factory is expected to become a testing environment for novel AI/ML algorithms and approaches with the available process data, including sensors, manufacturing equipment, and operators. As explained in previous sections, this will be achieved through the deployment of several AI/ML technologies at the Edge that leverage data from the industrial robots. Thus, the TO-BE scenario will be similar to the one presented in the following Figure 49:

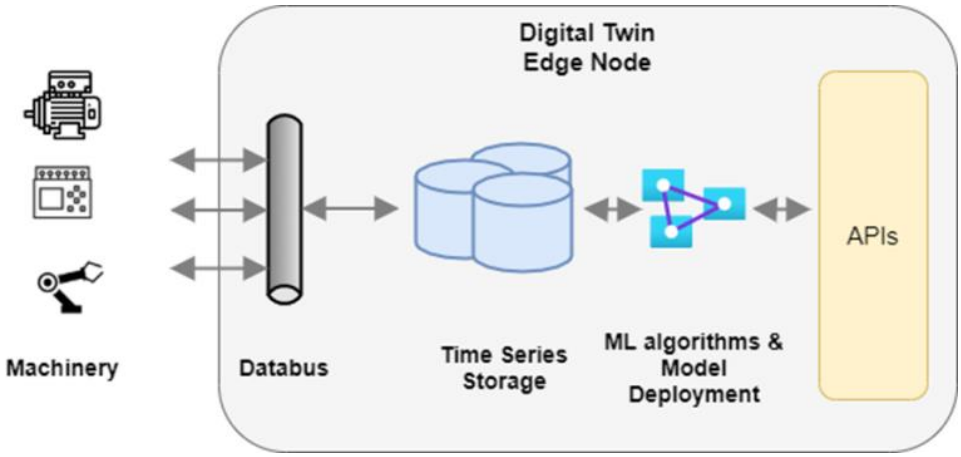


Figure 49 Galicia DF TO-BE diagram

Scenario 1 : Prediction of target variables

In this scenario AI/ML Edge models will be implemented and deployed within the DF's facility with the aim of monitoring the industrial process parameters and estimating values of KPIs regarding the industrial lines of AIMEN's facilities. These models will estimate the value of the KPIs regarding the industrial lines. Moreover, these models will be containerized in order to be easily orchestrated within the IT infrastructure. In addition, the outputs of these models will feed into the prescriptor of production setpoints.

Scenario 2 : Optimization and prescription of production setpoints

In this scenario an AI based optimization module will be implemented and deployed within the DF's facility with the aim of recommending the parameters that optimize the virtualized production process from both the operational and energy efficiency points of view. This component will provide optimal setpoints using the outputs of prediction models deployed in scenario 1, among other inputs. In addition, this component will be containerized in order to be easily orchestrated within the IT infrastructure.

Following Figure 50 shows an overview of the high-level architecture of scenario 1 and 2.

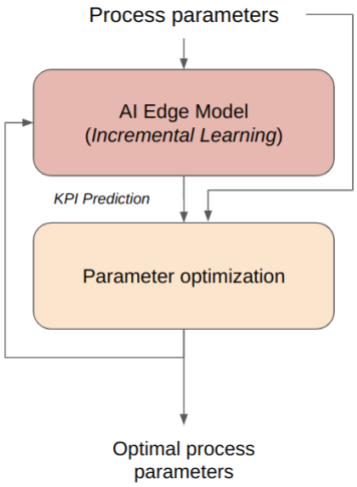


Figure 50 **High-level architecture of Scenarios 1 and 2.**

Scenario 3 : Orchestration of AI services

In this scenario a system for orchestration of AI models within the IT infrastructure of the experiment will be developed. This system will use software containers and Kubernetes based technologies, such as KubeEdge, to efficiently manage AI components along the edge-cloud continuum.

4.16 Synthesis of DF Industrial Scenarios

Similarly to what was done for the SME-driven experiments, the Didactic Factory experiments were also analyzed using the 3-axis map. The needs that emerged by applying the first two axes are represented in the graphs below – Figure 51 and Figure 52.

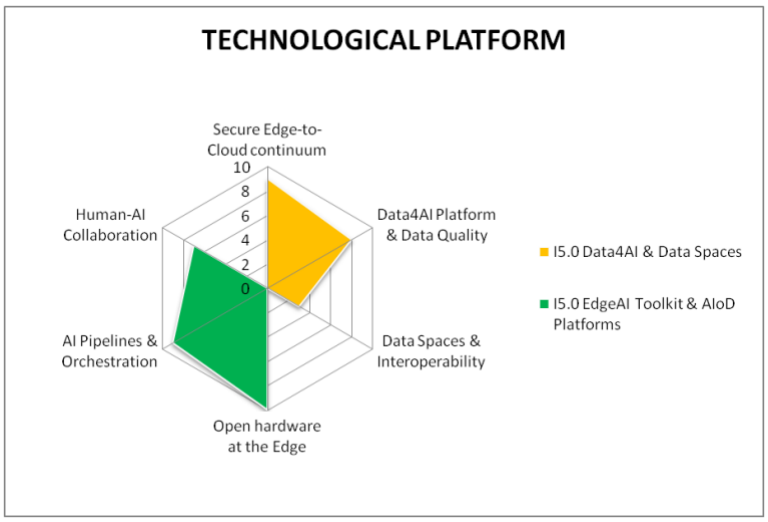


Figure 51 DFs' experiments technological needs

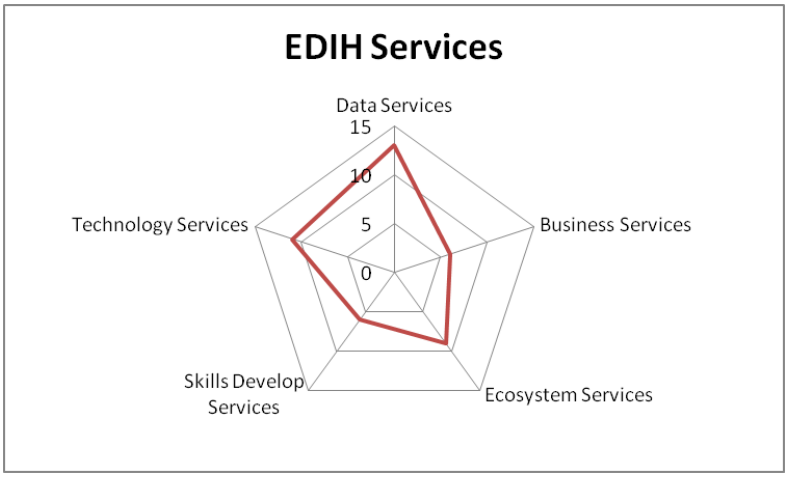


Figure 52 DF experiments' EDIH services needs

The following tables (Table 7, Table 8 and Table 9) present a summary of the analysis carried out.

Table 7 The DF experiments' needs versus Technological Platforms

DF	Organization name	I5.0 Data4AI & Data Spaces (WP4)			I5.0 EdgeAI Toolkit & AIoD Platforms (WP5)		
		Secure Edge-to-Cloud continuum	Data4AI Platform & Data Quality	Data Spaces & Interoperability	Open hardware at the Edge	AI Pipelines & Orchestration	Human-AI Collaboration
I	POLIMI - I4.0Lab	…	…	…	…	…	…
II	UNIBO - E2MECH	Privacy preservation (data should not be public)	N/A	N/A	…	…	…
III	JSI - IJS Systems&Control Lab	As the edge and local cloud may not be on the same local network, secure communication channel should be used	Basic detection of data validity (basic detection of missing or faulty data)	N/A	Time series will be processed close the data source (one process cell) and only aggregated results will be passed forward for monitoring and logging in local cloud	Deployment of new algorithms from central point could be useful to enable scalability of the system	Operators to support reasoning of detected segments and anomalies. Validation of the deployed algorithms and annotation of special cases.
IV	Brainpoint Industries-Flexible Manufacturing	…	…	…	…	…	..
V	UniTwente - AMC	Data processed within AMC or SME	N/A	N/A	Raspberry Pi is applied for proof of concept	N/A	N/A
VI	FBK - 4.0iLab	Different edge processing for evaluating the IIoT application	Data collected need to be process (verify, correct, clean) at the Edge	N/A	Different Hardware platform to test different Edge Scenarios	Basic ML Pipelines according to each IIoT application	N/A
VII	MAKE -PM50	N/A - open to discussion	N/A - open to discussion	N/A - open to discussion	N/A - open to discussion	N/A - open to discussion	N/A

DF	Organization name	I5.0 Data4AI & Data Spaces (WP4)			I5.0 EdgeAI Toolkit & AIoD Platforms (WP5)		
		Secure Edge-to-Cloud continuum	Data4AI Platform & Data Quality	Data Spaces & Interoperability	Open hardware at the Edge	AI Pipelines & Orchestration	Human-AI Collaboration
VIII	DMIW -Digital Manufacturing Innovation Hub	All data will be processed at the edge using the Industreweb platform provided by C2K	The AI interface will be built within the Industreweb platform using open source models	N/A	All data will be processed at the edge using the Industreweb platform provided by C2K	The AI interface will be built within the Industreweb platform using open source models	Operators will confirm actions suggested by the AI to improve the manufacturing process, the AI will also be used to train human operators.
IX	MADE - BEhAI	MAYBE (Biometrics data needs to be protected)	Redundant data/potentially not useful data	N/A	N/A - Open to discussion	Central management of edge-deployed algorithms / three pipelines dedicated to the analysis of the three main streams of data - Open to discussion	Adaptation of AI to the Human - monodirection - Open to discussion
X	TUIASI - I4.0	Most of the processes will be done locally on a SBC (acquire image, acces the database, detect if there is a defect or not, send an alert)	In the end will be a percentage if there is a defect or not, according to a model (reference)	it will be use a AI at edge platform with more or less conections to a specific data platform	SBC computer in order to run a few tasks (acquire image, process image, run AI fuzzy program, sens un alarm)	we are using fuzzy AI	QA personnel from KF will use a simple and compact HMI in order to send amd receive data
XI	CTU - RICAIP	Fast and simple anomaly detection at the edge and more time consuming validation or retraining	Potential concept drift must be checked, recognized and learned to prevent false positive detections.	N/A at this moment, in case of future deployment in multiple sites and multiple processes, different methods can work	...	...	Human confirms the AI decision and thus provides ground truth

DF	Organization name	I5.0 Data4AI & Data Spaces (WP4)			I5.0 EdgeAI Toolkit & AIoD Platforms (WP5)		
		Secure Edge-to-Cloud continuum	**Data4AI Platform & Data Quality**	**Data Spaces & Interoperability**	**Open hardware at the Edge**	**AI Pipelines & Orchestration**	**Human-AI Collaboration**
		of the detectors in the cloud		differently on different problem instances and evaluation could need to share and transfer data or their properties			
XII	**AAU - Smart Lab**	The solutions work locally only.	The data will be collected, cleaned and visulized for later processing.	The collected data will be saved withing the SME factory on the local server/platform.	The solution currently works locally. Edge devices could be possible to be used for deploying the data analysis/ML model.	The AI pipeline used in our case include: collecting real-time data, visulizing the data, reformat the data, modeling building/testing, and deployment on shopfloor.	Human operators will be able to monitoring the production data through the user interface. This can be used for assisting the operator to make adjustments and future planning.
XIII	**PBN - amLab**	NA	The data will be collected, cleaned for later processing.	The data will be stored on local server	to implement the AI device later on	Our AI pipeline and orchestration encompass data collection, processing, model development, real-time decision-making, deployment, and ongoing maintenance. These steps are designed to optimize energy usage, enhance recycling operations, and	N/A

DF	Organization name	I5.0 Data4AI & Data Spaces (WP4)			I5.0 EdgeAI Toolkit & AIoD Platforms (WP5)		
		Secure Edge-to-Cloud continuum	Data4AI Platform & Data Quality	Data Spaces & Interoperability	Open hardware at the Edge	AI Pipelines & Orchestration	Human-AI Collaboration
						promote sustainability in the context of our experiment.	
XIV	GRADIANT - Galicia Industrial Logistics Lab	No current plans to transfer data outside the DF's facilites, at the moment	Data preprocessing and cleaning activities are expected	N/A	Edge devices might be needed to complement the DF industrial lines in order to run the AI models at the Edge	The AI pipeline needed is very simple: it will involve the collection of real-time production data and the forecasting of new KPIs predictions (at the edge) and the prescription of the optimal production parameters (at the cloud).	Operators will label the results provided by the prediction module that will be developed. Also operators will monitor the predictions and prescriptions provided by the system.

Table 8 The DF experiments' needs versus EDIH services

DF	Organization name	Data Services	Business Services	Ecosystem Services	Skills Develop Services	Technology Services
I	**POLIMI - I4.0Lab**	Data collection from IoT devices and production equipment. AAS modeling of IoT devices and production equipment.	N/a	Federated network of DF for data and models sharing	…	…
II	**UNIBO - E2MECH**	ML tools to analyze the data	N/A	N/A	N/A	Cloud storage
III	**JSI - IJS Systems&Control Lab**	WE HAVE: • Data acquisition and sensing-data collection from analog sensors • Data processing and analysis - analytics of time-series data (preprocessing, segmentation, ML)	N/A	N/A	WE HAVE: • Skills improvement - training on the topics of signal processing, data analytics and ML	WE HAVE: • Provision of infrastructure & Verification and validation - Test before invest service specialised in testing and demonstrating the non-invasive equipment monitoring analytical approaches for assembly line

DF	Organization name	Data Services	Business Services	Ecosystem Services	Skills Develop Services	Technology Services
						production processes NEEDS: • Provision of infrastructure - Data and models sharing platforms to be reused in education or further research
IV	**Brainpoint Industries- Flexible Manufacturing**	Data collection, Data analytics, Data sharing on open standards (supply chain - SCSN - and predictive maintenance)	N/A	Facilitation and organising DF network	N/A	N/A
V	**UniTwente - AMC**	Data collection and Data analytics	Production systems service (e.g. optimized monitor and maintenance, AI etc.)	take the role of service user and service provider at the same time	N/A	Conduct feasibility studies and work on proof-of-concepts on topics of Smart Industry, Additive Manufacturing and AI system.
VI	**FBK - 4.0iLab**	• Data collection from IIoT Apps • Provision in Edge Analyticis	N/A	N/A	N/A	• Feasibility studies on Edge Ai techiques for IIoT Apps • Provision on monitor. techol. Infrastructure

DF	Organization name	Data Services	Business Services	Ecosystem Services	Skills Develop Services	Technology Services
VII	**MAKE -PM50**	WE HAVE: • Data acquisition from sensors on production equipment • Data analytics using ML models to detect upcoming component failures • Decision support using ML models to predict the remaining useful lifetime of monitored components	WE HAVE: • Connection to funding sources at regional level • Creating Consortia (companies and academia) for funded RDI projects at regional level NEEDS: • Consortium building at a trans-national level	WE HAVE: • SME and People Engagement through member companies and established networks • Ability and experience in raising awareness about AI for manufacturing NEEDS: • extend these capabilities to European level	WE HAVE: • Human up-skilling, re-skilling training trajectories through various regional and European projects NEEDS: • As this is not our core business, we can use support in developing training programmes	WE HAVE : • Technology Readiness assessments • Access to infrastructure and technological platforms • Concept validation • Prototyping • Strategic and specific R&D
VIII	**DMIW -Digital Manufacturing Innovation Hub**	• Data collection from IIoT devices • Provision of Edge Analytics • Provision of Knoweldgebase	• Look for funding opportunities to support SMEs	N/a	N/a	• Automating quality checking with AI • Development of knoweldge base and human/machine interface.
IX	**MADEcc - BEhAI**	NEEDS: Data processing & analysis - Data analytics Decision-making - Decision support and development (Definition of action thresholds) WE HAVE: N/A	WE HAVE: Project development - Strategic analysis and alignment of EU vs regional RDI investments, Identification of opportunities, Creating consortia, Development of proposals (link the experiments with other projects)	WE HAVE: Community building - SME and People Engagement, Communication DIH Innovation Development - Visioning and strategy development Ecosystem Governance - Services Impact assessment, Ecosystem strategy management	NEED: Skills Improvement Training - courses and a didactic factory will be done on the experiment's output (Tips or best practice on these types of didactic factories) WE HAVE: Process & Organizational Maturity - Maturity Assessment	WE HAVE: Contract research - Strategic and Specific R&D, Technology concept development/ Proof of Concept (PoC) Provision of Infrastructure - Access to infrastructure and technological platforms (MADE's partners present) Technical support on scale up - Concept validation Verification and Validation - Product demonstration

DF	Organization name	Data Services	Business Services	Ecosystem Services	Skills Develop Services	Technology Services
X	**TUIASI - I4.0**	* Data/image collection from camera * Defects clasification	N/A	N/A	N/A	The QUAD-AI@E device is included in the production process in the QA (Quality Assessment) phase for the finished products to be stored and delivered to the final beneficiary.
XI	**CTU - RICAIP**	Data collection, data analytics	Innovation spaces	Communication: Raising awareness about innovative AI technologies	Human upskilling, reskilling training	Strategic and specific R&D, Prototyping. (Quality monitoring and control via online anomaly detection)
XII	**AAU - Smart Lab**	We have • Monitor the production data in real-time • ML methods for analyzing collected data	We have • facilitate the decision making • Support future strategy making • Building connection with other ogranizations and SMEs to exploit potential opportunities	We have • connections with local and national and we aim at increasing EU project collaboration	We have • Students from Aalborg Universities and other students from local University College of North are trained on setup IoT service and data analysis. We need • attract new PhD and Postdoc students to our AAU Smart Lab.	We have • Conducted the experiments with VELUX in our AAU Smart Lab to test our data analysis and ML algorithms on Robot Screwing case. We aim • offering the IoT solution to SMES for solving their own production challenges.

DF	Organization name	Data Services	Business Services	Ecosystem Services	Skills Develop Services	Technology Services
XIII	PBN - amLab	Data Services involve collecting, organizing, and using data for our project. We gather information from various sources, process it, and make it ready for analysis. This helps us make informed decisions in real-time.	N/A	Facilitation of DIH Network; Our network can benefit from this experiment, and the companies of the network might be inspired of the solution.	N/A	Technology Services provide the tools we need for the project. This includes hardware like sensors and software for data analysis and communication. We also follow certain standards to ensure everything works together smoothly.
XIV	GRADIANT - Galicia DF	N/A	•Support in identifying and attracting financing instruments • Provision of support in cooperation and collaboration among organisations for exploiting common opportunities	• Provision of support in identifying and analyzing emerging and disruptive technologies	• Support in the organization and dissemination of trainings, courses or workshops focused on the technologies that will be showcased at the DF.	N/A

Table 9 The DF experiments business indicators

DF	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
I	POLIMI - I4.0Lab	…	…	…	…	…
II	UNIBO - E2MECH	N/A	N/A	N/A	Following the paradigm of continuous learning, human-AI interaction consists in the labeling of unknown conditions	N/A

DF	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
III	**JSI - IJS Systems&Control Lab**	Optimized and targeted maintenance actions will reduce maintenance actions and extend the lifetime of production lines.	N/A	N/A	Learning the process phases from the operators to improve the localisation of faults.	Acceptance and trustworthiness of ML solutions
IV	**Brainpoint Industries-Flexible Manufacturing**	…	…	…	…	…
V	**UniTwente - AMC**	Optimizing production processes and smart monitor and maintaining will reduces energy consumption and scrap rate	more precisely to predict the life cycle of machine tools or components for repair, recondition or remanufacturing	N/A	Model training, classification require human interaction	N/A
VI	**FBK - 4.0iLab**	N/A	N/A	N/A	N/A	• Acceptance of Edge AI IIoT App • Include non ML experts with App
VII	**MAKE -PM50**	The proposed experiment will reduce CO2 emissions by drastically limiting the upstreamed data volumes, saving power consumption by global and local network equipment and cloud servers.	N/A	N/A	The work of human operators will be facilitated by the experiments's resulting interpretation capabilities and decision support.	• Acceptance of Edge AI • Inclusion of non-ML experts • Increasing safety by reducing maintenance
VIII	**DMIW -Digital Manufacturing Innovation Hub**	The proposed experiment will reduce CO2 emmissions by reducing waste and energy consumption in the manufacturing process.	The experiment will promote learning and training within the process which will result in continuous improvement and more intelligent systems.	The IWOK system will provide a knowledgebase that can be transferred to other similar manufacturing processes.	Human and machine interaction will create a new method of working, operators will have the ulitmate decision making powers.	The experiment will increase safety and improve ergonomics

DF	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
IX	**MADE - BEhAI**	Enviroment: Reduction of defects Social: Improve happiness of the operators Econimic: Reduction of costs from scraps	N/A	N/A	The experiment is centered around the creation of a system to help the operator and his well-being and so help the operator in making better decisions (passively) - The experiment will not actively help in decison making.	Touch a bit of all the WISE aspects, but the experiment will focus more on the Inclusion aspects and Ergonomics - The technology will help the operator, providing the best work environment.
X	**TUIASI - I4.0**	N/A	N/A	N/A	N/A	N/A
XI	**CTU - RICAIP**	The optimised process will reduce the scrap rate of the assembly operation and thus reduce waste. Energy waisted for scrap production can be reduced by early stopping and correcting the process.	N/A	N/A	Human and machine interaction will create a new method of working where operators will keep the power of ultimate decision making. Human operator will be needed especially after process changes.	N/A
XII	**AAU - Smart Lab**	N/A	The provided data analysis methods potentially can be used for solving the similar production problem identifed on the shopfloor related to circularity.	AAU IoT solution helps SMEs to be able to identify the production issues and quickly response to it. Thereby, it supports resilience.	The solution will facilitate the human operator to monitor the production data and decision making.	Increase the acceptance of smart IIoT solution among all levels in the factory. Increase the efficiency, improve the production performace and easier decision making process, a worker-friendly solution.

DF	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
XIII	**PBN - amLab**	Sustainability (CO2 Footprint) means we are working to reduce our contribution to greenhouse gas emissions, especially carbon dioxide (CO2). We do this by using clean energy, being efficient with our energy use, recycling smartly, and keeping an eye on our emissions to make sure we're doing better over time. It's about being responsible and eco-friendly.	The model will be refined with multiple implementation and upgrade on demand in the monitoring process.	N/A	N/A	N/A

DF	Organization name	Sustainability (CO2 Footprint)	Circularity (LCA)	Resilience (CRM Network)	Human Factors (Decision Make)	TERESA (WISE aspects)
XIV	**GRADIANT - Galicia Industrial Logistics Lab**	The AI services will aim to optimize virtualized production processes from both the operational and energy efficiency points of view.	N/A	N/A	The AI services that are expected to be tested in the DF for this experiment aim to showcase how the provided predictions/prescriptions can support the decision making of industrial use cases operators.	• Since AI services regarding prediction and prescription capabilities are involved in this experiment, issues related to well-being and comfort may be needed to be taken into account, such as dependence and overconfidence on the machine, concerns/willingness in collaborating with a machine... • The main motivation is to create a site to showcase edge&AI novel technologies so companies and students can learn their use for their purposes. Therefore, it has inclusion implications, since effects on older or novice workers might be considered. • Health and safety of workers are considered since industrial lines with robotics equipment are present in the DF's facilities.

5. Conclusions and future outlook

The deliverable has presented the 3 axis used to monitor and support the 7 SME-driven Experiments and the 14 Didactic Factories Experiments:

- Technological Platform, based on WP4 activity.
- DIH Services, based on D-BEST methodology, developed in WP3.
- Business Indicators, based on KPIs developed in WP2, as part of the Trial Handbook presented in D2.1.

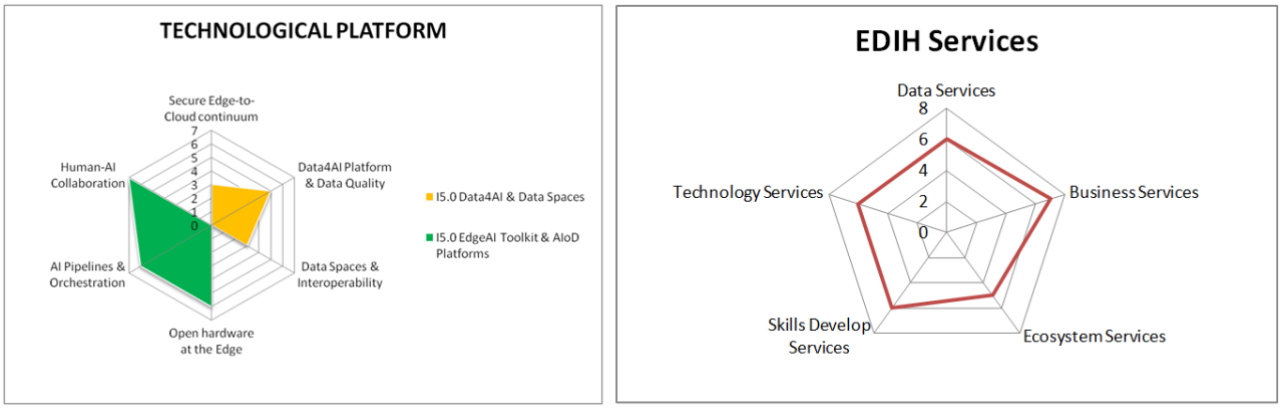


Figure 53 (Left) SME-driven experiments technological needs and (Right) SME-driven experiments' EDIH services needs

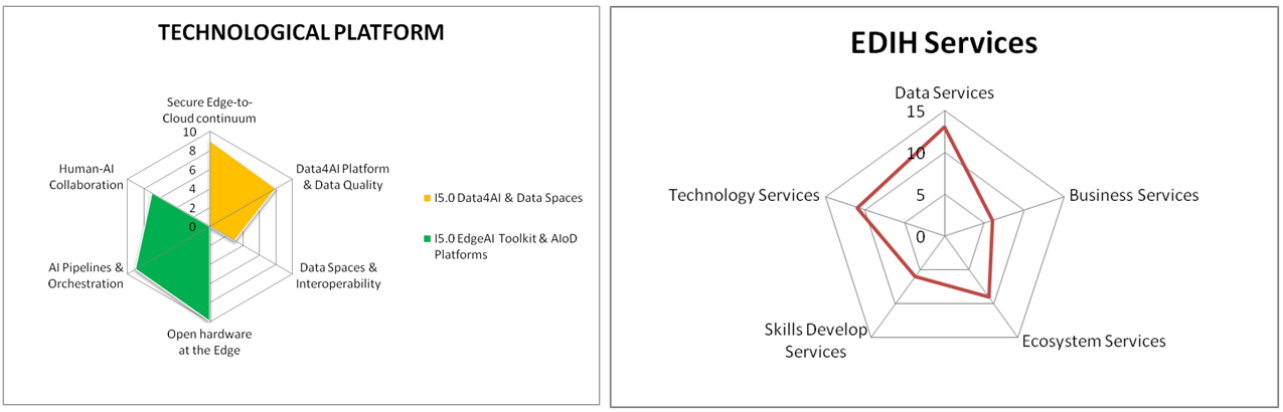


Figure 54 (Left) DFs' experiments technological needs and (Right) DFs' experiments EDIH services needs

Then a description of the AS-IS scenario, status of deployment, TO-BE scenario for each experiment has been showed.

The next step of the activities will concern the continuous monitoring and evaluation of the experiments; and in particular:

- T6.2 will monitor the 3 SME-driven Experiments belonging to AI REGIO project regions
- T6.3 will monitor the 4 SME-driven Experiments belonging to AI PILOT regions (Vanguard Initiative)
- T6.4 will monitor the 14 Didactic Factories Experiments

T2.2 activities will resume in month 21.