D6.1 AI REGIO Experiments Plan v1

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Abbreviations Table

AI: Artificial Intelligence

SME: Small Medium Enterprise

DIH: Digital Innovation Hub

NLP: Natural Language Processing

IoT: Internet of Things

CHP: Combined Heat and Power

Executive Summary

One of the key objectives of AI REGIO is to fill the gap currently preventing DIHs and SMEs from implementing Innovative AI (Industry 5.0) for their manufacturing systems.

This goal is partly accomplished in the context of Work Package 6 “Beyond Experiments”, by designing and implementing AI-driven experiments in DIHs and SMEs.

This deliverable provides a description of the first iteration plan of the AI REGIO 17 experiments, including seven SME-Driven experiments (in Four Motors regions) and ten DIH-driven experiments (in the other 9 Vanguard regions). The experiments were categorized in four different clusters in order to group the experiments sharing the same AI challenges and consequently to foster the communication between them (inter and intra-regional communication).

1 Introduction

The aim of the AI-REGIO project is to fill 3 major gaps currently preventing AI-driven DIHs from implementing fully effective digital transformation pathways for their Manufacturing SMEs: at policy level the Regional vs. EU gap; at technological level the Digital Manufacturing vs. Innovation Collaboration Platform gap; at business level the Innovative AI (Industry 5.0) vs Industry 4.0 gap. The AI-REGIO project commenced in October 2021 (M01) and this report, Deliverable 6.1 "AI REGIO Experiments Plan V1" (D6.1), is the first from the project's Work Package 6 (WP6) "Beyond EXPERIMENTS: AI DIH regional facilities from demos to champions".

AI-REGIO project includes 17 experiments, including 7 in Four Motors regions and 10 in the other 9 Vanguard regions. All experiments focus on demonstrating innovative AI applications in several Manufacturing domains: metal sheets, machine tools, industrial encoders, automation systems, plastic products, modular production.

Table 1 presents the experiments, which are divided into 4 main clusters according to the main addressed technological domain. The clusters address experiments willing to adopt Artificial Intelligence in:

i) Product Engineering and Lifecycle Management domain, mainly leveraging on expert systems able to support operators in maintenance operations within the product lifecycle as well as during design and planning phases (Cluster 1);
ii) Factory Efficient and Sustainable Manufacturing domain, mainly focused on introducing intelligent tools and solutions to support the planning and scheduling phases, in order to optimize demand forecasting and manufacturing processes (Cluster 2);
iii) Quality Control and Predictive Maintenance domain, mainly to optimize quality control processes and strategies, as well as after-sales activities (Cluster 3); and
iv) Robotics and Human Interaction domain, mainly to support operators in daily activities with the use of expert systems, robotics arms and augmented reality devices (Cluster 4).

Table 1 Experiments by cluster

	Four Motors Regions	Vanguard Regions
Cluster 1: "Product Engineering and Lifecycle Management	Exp 02 - NLP for Maintenance Report Analysis in Machine Tools Exp 03 - Anti-Tampering Devices for Connected Objects Exp 04 - AI for better life cycle and project management for plastronic product	Exp 15 - Water Leakage Detection
Cluster 2: Factory Efficient and Sustainable Manufacturing	Exp 05 - AI-based Predictive Dynamic Production Planner	Exp 10 - AI-based Process Control c/o ARMAC Exp 12 - IoT and AI for Real-time Production Planning Adjustments (production) Exp 17 - AI-enabled Platform for Zero Defect

Cluster 3: Quality Control and Predictive Maintenance	Exp-07 - Predictive Analytics for Autonomous Mobile Robots	Exp 09 - AI-based Process Control c/o S/PARK DEVENTER-1 Exp 13 - AI-enhanced control strategy for production environment Exp 14 - A Smart Predictive Maintenance Toolbox for drawing lines of car body element Exp 16 - IDSS for predictive quality assurance
Cluster 4: Robotics and Human Interaction	Exp 01 - Machine Vision for Warehouse Optimization Exp 06 - AI-Supported Robot Trajectory Optimization	Exp 11 - Automatic Capability Matchmaking for Re-configurable Robotics Platform Exp 08 - AI-enabled Operators Assistance through AR

All the experiments are organized into two iterations:

Iteration 1: from M6 to M21

Iteration 2: from M25 to M36

The two iterations have been defined per DoA in this high-level timeline that is common for all experiments. However, the experiments are free to schedule their work in different manner for their convenience, depending on the availability of needed resources and iterations' internal steps results.

The following two alternatives for the distribution and planning of experiment progress and work in the two iterations are foreseen:

- an experiment expects to achieve its main results during the first iteration, and it will work during the second iteration to improve the achieved outcomes by, for example, adding new functionalities.
- an experiment will take both the two iterations period to achieve the final outcome.

After the first iteration there will be time to assess the results and the impact of the developed solutions and to start planning the second iteration activities (M22-M24).

Deliverable D6.1 presents the plan of the 1st iteration of AI REGIO experiments. The presentation of the plan is organized by clusters. The concept of each experiment is briefly presented, then the first iteration plan is introduced. Collection of the experiments concept and plan has been conducted using the Trial Handbooks (THB) content from WP2. Experiments concept description was extracted the THB chapter 1 and experiments plan from THB chapter 2.

2 Experiments Plan (M21)

2.1 Cluster 1 – Product Engineering and Lifecycle Management

Cluster 1 contains three experiments:

(i) Experiment 02: "Natural Language Processing for Troubleshooting" which provides a troubleshooting tool capable of helping both operators and enterprises in diagnosis and maintenance procedures.

(ii) Experiment 03: "Anti-Tampering devices for connected objects" which introduces an AI tool capable of designing 3D tracks representations for anti-tampering systems.

(iii) Experiment 04: "AI for better life cycle and project management for plastronic products" which collects industrial challenges information aiming to create a unique and consistent source of data across the entire product lifecycle.

2.1.1 Experiment 02: "Natural Language Processing for Troubleshooting" , Intellimech

Experiment 02 is an SME-driven experiment in Lombardy, led by Consorzio Intellimech and focused on product Engineering & Lifecycle Management.

2.1.1.1 Experiment 02 concept

Experiment 02 provides a troubleshooting tool capable of helping both operators and enterprises in diagnosis and maintenance procedures. This troubleshooting system will be divided into the user interface subsystem, the elaboration subsystem, and the knowledge subsystem. The user interface is responsible to handle the interactions with the operator, the elaboration subsystem processes the operator's inputs to find the most probable failure and the knowledge subsystem represents the available data that the system refers to for solving the incoming issue. The experiment is aimed at improving the current troubleshooting system, including its basic user interface that is currently based on closed-ended questions, and its limited source of knowledge.

NLP based tools will be exploited to achieve a troubleshooting system featuring advanced human-machine interaction based on free text to speech dialogue, capable of accommodating mistakes and with a self-learning mechanism, that will automatically enrich its knowledge over time by analysing the ongoing issues. Moreover, three possible scenarios have been identified in the experiment. The first scenario involves a smart contact centre, that processes and redirects the inquiries to the corresponding expert. The second one covers a troubleshooting system that is able to deduce the damaged component. Finally, the third scenario includes the failure mode, by conducting a dialogue with the operator.

2.1.1.2 Experiment 02 Plan

Activity	Period	Responsible
Experiment concept finalization	M1-M6	Intellimech
Technical and functional requirements definition	M7-M9	Intellimech
1st prototype release of self-learning module	M10-M21	Intellimech
Human-machine interface development	M10-M21	TXT

Table 2 – Experiment 2 1st Iteration plan

The detailed activities that in the context of the foreseen experiment are:

Phase 1 "Concept finalization": M1-M6 (Intellimech)
Task 1.1: Definition of the experiment main goals
Task 1.2: Definition of the experiment team and provider support
Phase 2 "Requirements specification": M7-M9 (Intellimech)
Task 2.1: Definition of the technical and functional requirements
Phase 3 "1st prototype release of self learning module": M10-M21 (Intellimech)
Task 3.1: Development of the 1st prototype
Task 3.2: Testing with the end-user
Task 3.3: Verification and lessons learnt
Phase 4: "Human-machine interface development": M10 – M21 (TXT)
Task 4.1: Text to speech functionality development
Task 4.2: Speech to text functionality development
Task 4.3: Integration with the system

2.1.2 Experiment 03: "Anti-Tampering Devices For Connected Objects", S2P

Experiment 03 is an SME-driven experiment in France, led by S2P and introduces an AI tool capable of designing 3D tracks representations for anti-tampering systems.

2.1.2.1 Experiment 03 concept

With the increase of electronic and connected objects everywhere, the confidential information contained in storage chips/boards (as for example banking data, military information, medical and personal data, etc.) need to be protected from theft. Someone can steal them using dedicated software, but another way is to tamper physically with the device and get direct access to chips to copy the secured data.

To avoid this, on top of the electronics chips/boards, S2P adds a plastic cover that integrates full 3D conductive tracks with a complex structure design by engineers to cover the complete surface. It acts as a sensor to detect any physical intrusion in the system: if the track is broken, the data is erased from the memory.

Currently these 3D meshes are fully designed by engineers, as adding the 3D tracks everywhere on the cover, ideally with different/random meshes for each produced part in order to make it even more difficult for pirates to enter the system is a very complex and long process.

Experiment 03 is aiming to develop a design tool that acts as an engineer in an autonomous way. Machine learning and/or Expert systems will be used to develop the design tool.

2.1.2.2 Experiment 03 plan

Activity	Period	Responsible
Experiment concept definition	M1-M6	S2P
Technical and functional requirement	M7-M9	S2P
AI EXPERT SYSTEM development	M9-M14	Techno. PROVIDER
First trials	M14-M21	S2P

Table 3 – Experiment 03 1st Iteration plan

The detailed activities in the context of the foreseen experiment phases are the following:

Phase 1 "Experiment concept definition": M1-M6 (S2P)
Task 1.1: Definition of the experiment main goals
Task 1.2: Definition of the experiment team and provider support

Phase 2 "Requirements specification": M7-M9 (S2P)
Task 2.1: Definition of the technical and functional requirements
Task 2.2: Definition of the business requirements

Phase 3 "AI EXPERT SYSTEM development": M9-M12 (S2P and Techno provider)
Task 3.1: To be defined
Task 3.2: To be defined

Phase 4 "First trials": M12-M21 (S2P)
Task 4.1: To be defined
Task 4.2: To be defined

2.1.3 Experiment 04: "AI for better life cycle and project management for plastronic products", SWARM

Experiment 04 is an SME-driven experiment in Auvergne-Rhône-Alpes, led by SWARM. It collects industrial challenges information aiming to create a unique and consistent source of data across the entire product lifecycle.

2.1.3.1 Experiment 04 concept

The aim of SWARM labs is to collect industrial challenges from members and try to give the best answers or recommendations. The Production Lab focuses on additive manufacturing and IoT Design. Among others, the application areas include production conception, digital simulation, topology optimization, design for additive manufacturing, systems performances, predictive maintenance, environment and energy, etc. The ambition of SWARM is to create datasets with all the inputs and outputs of the engineering & production workflow of a system including iterations, explored tracks, abandoned tracks, successful practices and failures.

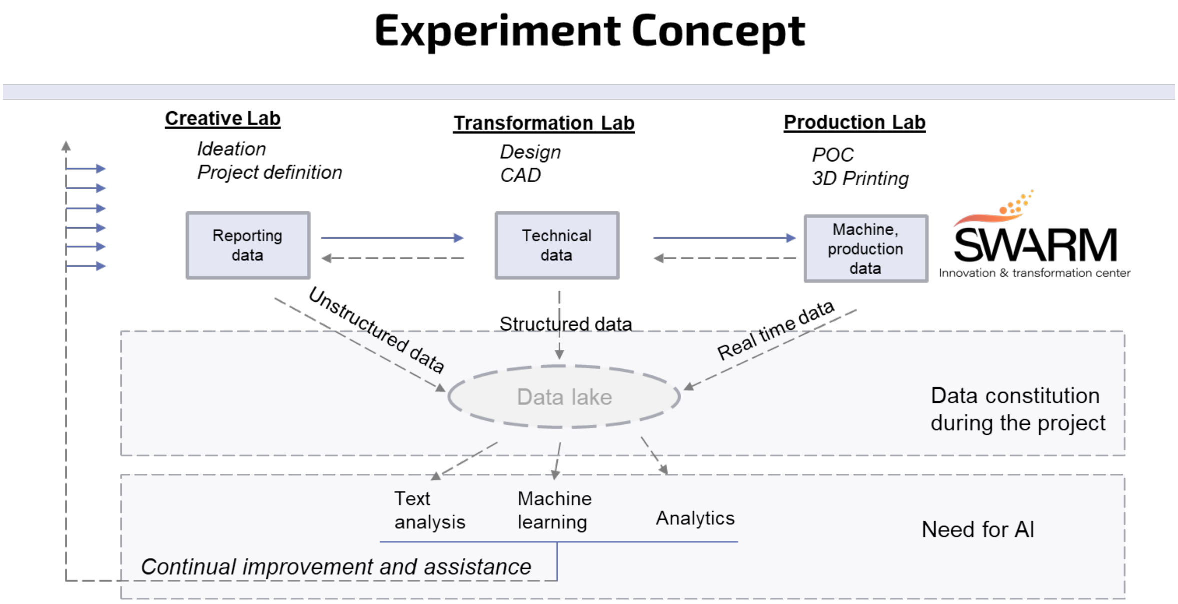

Figure 1 Experiment 04 concept

SWARM is driven by the motivation to shorten the engineering cycle and investigate a large panel of product options to bring services to SMEs for new products and processes design.

SWARM plans to use AI for continuous improvement of some issues on the basis of historical project execution and rule basis system, especially for plastic products. The challenge lies on the consolidation of all the available information: engineering information, project management information, different deliverables, technical data, machine and production data.

2.1.3.2 Experiment 04 plan

Activity	Period	Responsible
Experiment concept definition	M1-M6	SWARM
Technical and functional requirement	M7-M9	SWARM
Data architecture definition	M9-M14	SWARM
Module connectivity and Data Lake management	M14-M21	SWARM

Table 4 – Experiment 04 1st Iteration plan

The detailed activities in the context of the foreseen experiment phases are the following:

Phase 1 "Experiment concept definition": M1-M6 (SWARM)
- Task 1.1: Definition of the experiment main goals
- Task 1.2: Definition of the experiment team and provider support

Phase 2 "Requirements specification": M7-M9 (SWARM)
- Task 2.1: Definition of the technical and functional requirements
- Task 2.2: Definition of the business requirements
- Task 2.3. Identification of the existing components and their development needs

Phase 3 "Data Architect definition": M9-M12 (SWARM)
- Task 3.1: Definition/ Description of data sources and data sets (unstructured data, structured data, real time data)
- Task 3.2: Identification of the existing data cleaning and classification tools

Phase 4 "Module connectivity and Data Lake management" M12-M21 (SWARM)
- Task 4.1: Extraction and cleaning information
- Task 4.2: Modelling Data lake

2.2 Cluster 2: Factory Efficient and Sustainable Manufacturing

Cluster 2 contains four experiments:

(i) Exp 05 "AI-based Predictive Dynamic Production Planner" which introduces a planning and scheduling module for production processes.

(ii) Exp 10 "AI-based Process Control - Armac", which applies AI to forecast the heat demand based on the weather conditions and information for the city of Purmerend, in order to increase energy efficiency.

(iii) Exp 12 "Intelligent Computer Vision for Digital Twin and Reinforcement Learning for Assembly Line Balancing", which dynamically allocates production resources to manufacturing tasks to better face uncertainties.

(iv) Exp 17 "Industrial processes AI-based Optimization", which develops a predicting model trained on historical data of machining control parameters and supervised by the quality control at the end of the lines.

2.2.1 Experiment 05: "AI-based Predictive Dynamic Production Planner", Hohner Automaticos

Experiment 05 is an SME-driven experiment in Catalonia, led by Hohner Automáticos S.L. and focused on introducing a planning and scheduling module for production processes.

2.2.1.1 Experiment 05 concept

This experiment introduces a planning and scheduling module for the production process. The module includes two smart tools, one for production orders sequencing based on available assets, labour and plant capacity, and another for demand forecasting. The planning and scheduling module is linked with the legacy systems in order to support the production manager and inventory manager in the day-to-day activities on the shop floor. The experiment is aimed at the improvement of the production efficiency and reliability of supplies due to an optimization in the use of manufacturing orders, stock knowledge, human capabilities and assets availability, among others. Moreover, the dynamic planning and scheduling helps to: (i) know the status and priority of each work order on the shop floor; (ii) know all operations in the manufacturing process; (iii) know which assets or resources are required for each work order; (iv) know when the assets or resources are required and when they will be available; and (v) know the timings and delays between operations for more realistic production lead times.

The module, based on AI techniques such as Machine Learning, Constraint Programming and Heuristics, will exploit structured and non-structured data from shop floor and legacy systems to have an impact on aspects such as productivity, quality, costs, service, maintenance, among others.

2.2.1.2 Experiment 05 plan

Activity	Period	Responsible
Concept definition	M1-M6	Hohner Automáticos S.L. and Eurecat
Requirements specification	M7-M9	Hohner Automáticos S.L., and Eurecat
Task Sequencer / Optimizer prototype & test	M10-M21	Hohner Automáticos S.L. and Eurecat
Demand Forecasting prototype & test	M10-M21	Hohner Automáticos S.L. and Eurecat

Table 5 – Experiment 05 1st Iteration plan

The detailed activities in the context of the foreseen experiment phases are the following:

Phase 1: "Concept definition"; M1-M6

Task 1.1: Definition of the experiment main goals

Task 1.2: Definition of the experiment team and provider support

Phase 2: "Requirements specification"; M7-M9

Task 2.1: Definition of the technical and functional requirements

Phase 3: Task Sequencer/Optimizer prototype & test; M10-M21

Task 3.1: Problem definition (cost function, problem restrictions, and penalties)

Task 3.2: Problem modelling (involved attributes, relations among them, inputs, and outputs)

Task 3.3: Prototyping phase applying SoA research over the defined problem.

Task 3.4: Validation and test of the first prototype

Task 3.5: Tuning, adjustments, and report of the first prototype

Phase 4: Demand Forecasting prototype & test; M10-M21

Task 4.1: Determine business objectives & data mining goals

Task 4.2: Data understanding (collection, description, exploration, and validation)

Task 4.3: Data preparation (selection, cleaning, integrate and format)

Task 4.4: Modelling of the demand forecasting solution

Task 4.5: Validation, evaluation and tuning of the model

2.2.2 Experiment 10: "AI-based Process Control - Armac", SKU (Radboud University) & ARMAC B.V.

Experiment 10 is a DIH-driven experiment in the East of the Netherlands, led by Radboud University and focused on incorporating monitoring AI solutions (based on the assets of SKU) for their products and/or processes, that incorporates measurement and monitoring technologies (sensors and sensor networks).

2.2.2.1 Experiment 10 concept

The objective in this experiment is to test AI solutions for a customer of ARMAC B.V. with the aim to implement this solution in the operational control environment delivered and maintained by ARMAC B.V. In this way ARMAC gains experience in applying AI solutions for their customers. The customer is SVP, which is a district heating (DH) system of the city of Purmerend. The test involves the optimization of the DH system through the application of AI using weather forecast information from the city of Purmerend; currently the weather is used by operators to estimate the heat demand. In this DH, the heat production comes from three production plants. One biomass-fired production unit that provides 80% of the heat production and two gas fired CHP plants mainly used as spare/reserve capacity. Purmerend is however, an efficient DH in the Netherlands, utilizing local CO_2 neutral resources in the production with a broad network and many costumers connected. Despite this plant has been considered efficient, as the source fuel is kept being ecologically sustainable, there is a need for further efficiency increase from the operational side. The system is not driven by the supply, but the demand of customers for heat. The heat demand is estimated from the operators' expertise, that use previous experience, the weather conditions, the day of week and the season, as basis for decision making. However, this kind of control is non-optimal, and might be inaccurate, mainly because the weather conditions can vary greatly in a short period of time, affecting the heating demand, and leading to heat loss. The adoption of AI comes to overcome this problem. The AI will be applied to forecast the heat demand based on the weather conditions and forecast information at the city of Purmerend. It is expected that the energy efficiency will increase after the adoption of AI. This will help the operators along the decision making on heating demand, saving energy and keeping the system more efficient.

The experiment will be composed by the Radboud University as the experiment leader, Armac as the technology provider and the DH at Purmerend as the experimental site. The historical data available are from about 10 years of operation. They include the temperature, pressures, heating demand and weather conditions from 35000 dwellings. To better forecast the heater demand, this project will apply AI technologies using weather conditions and weather forecast information at the city of Purmerend. The following technologies will be employed: deep learning, supervised learning, and expert systems.

2.2.2.2 Experiment 10 Plan

Activity	Period	Responsible
Concept definition	M1-M6	SKU & ARMAC
Requirements specification	M7-M9	SKU & ARMAC
1st Prototype & test	M10-M21	SKU & ARMAC
Validation, fine tuning and reporting	M10-M21	SKU & ARMAC

Table 6 – Experiment 10 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

Phase 1 "Concept definition": M1-M6 (SKU, ARMAC)

Task 1.1: Definition of the experiment main goals

Task 1.2: Definition of the experiment team and provider support

Phase 2 "Requirements specification": M7-M9 (SKU, ARMAC)

Task 2.1: Definition of the technical and functional requirements

Phase 3 "1st prototype & implementation": M10-M21 (SKU, ARMAC)

Task 3.1: Development 1st prototype

Task 3.2: Test at control infrastructure of SVP by ARMAC (in at least 1 substation)

Phase 4: "Validation, fine tuning and reporting": M10 – M21 (SKU, ARMAC)

Task 4.1: Validation stage of the first prototype

Task 4.2: Fine tuning, adjustments of models & infrastructure

2.2.3 Experiment 12: "Intelligent Computer Vision for Digital Twin and Reinforcement Learning for Assembly Line Balancing", INESC TEC

Experiment 12 is a DIH-driven experiment in Porto (Norte region of Portugal), led by INESC TEC and focused on dynamically allocating production resources to manufacturing tasks to better face uncertainties like machine failures and unavailability of operators.

2.2.3.1 Experiment 12 concept

A typical manufacturing line is composed by a set of workstations, physically aligned in sequence, where a set of fixed resources, humans and equipment, accomplish a set of operations on parts that are being manufactured and assembled in order to produce a family of products. The parts that are transformed or assembled on each workstation flow along the manufacturing line, passing through all the workstations that comprise the line at a fixed speed, so as to accomplish a pre-defined rate of production at the end of the line. The production rate to reach is directly related with the takt time imposed by the demand of the clients of the considered manufacturing line. Usually, this is specified as the relation between the available working time per shift and the rate of customer demand for the same shift. For instance, the takt time imposed on an assembly line producing automotive engines may dictate that the line must produce one motor per minute, in order to satisfy the imposed demand of the market.

The initial conception and deployment of this class of manufacturing line considers the estimated demand of the market for a future time horizon and the number of workstations and productions resources to involve. Initial studies define the skills required for the operators and equipment and the times for them to accomplish manufacturing tasks. Operators and equipment are assigned to manufacturing tasks so as to remove bottlenecks or excess capacity in the line. The aim is to achieve a balanced manufacturing line, where operator and equipment times match the production rate needed to achieve the target task time. Most of currently available manufacturing lines have been conceived this way, by considering a given family of products, a set of existing automation technology and equipment, and very specialized operators. This has assumed configurations that perform very well (with the range of initial assumptions) but are not flexible and easily transformed to cope with new requirements coming from the market, in terms of product variants, new products, or new quantities. As time passes and the line is subject to adaptations, it starts to show unbalanced behaviour related to the assignment of tasks to operators and equipment. Cycle times on some workstations start to deviate from the initial defined range of values and the production schedule defined by the Manufacturing Execution System soon gets unsynchronized with the reality.

In this industrial setting, a digital twin is used to mirror and represent the factory floor in a digital manner. This digital twin is created and managed by a software entity named Advanced Plant Model (APM) that allows to:

- Manually represent and populate the digital model according to what is represented in the real world (e.g. racks, palettes, kits of parts, workstations and robotic manipulators).
- Request robotic agents to execute robotic tasks on a given place (e.g. workstation) and provide them with all the space information that they required to accomplish the task.
- Communicate with robotic agents during the execution of robotic tasks to obtain information about the progress of the skill execution, the agents' movements and about any transition of processed pieces. All of this information is also represented in the digital model and guarantees a close relation between reality and its digital representation.

Despite the usefulness of this digital twin, it comes with some limitations:

- The act of populating the digital model with information based in the real world is somewhat static, meaning that this initial effort is done by a human being, by placing certain models (racks, conveyors, robots, etc…) in their correct positions, based on the floor map.
- During the execution, if an existing object moves on the factory floor or if a new object is inserted, the digital twin has no way to automatically represent it, without creating a new model with that object manually added. This creates some problems in highly dynamic environments.
- The update of the information contained in the digital model highly depends on the information passed by the deployed robots. This information is sometimes not sufficient or incomplete, as they do not use any type of cameras or sensors for this mapping, but this information update is performed according to status updates on the progress of their tasks.
- Testing a new floor layout may be complicated in a real scenario, due to the difficulty in altering the location of real-life objects. This issue is further aggravated when this testing position does not translate to a final deployment.

Experiment 12 considers a manufacturing line aimed at producing different types of products by performing a set of assembly operations (Figure 2). The manufacturing line comprises:

- A fixed number of workstations physically aligned in sequence;
- Inbound and output buffers on each workstation, dictating the quantity of products that may be stored at the entrance and exit of each workstation;
- An automated transport of the products along the line, moving the WIP ("work-in-progress") from workstation to workstation;
- A set of production resources with different skills. Human operators and mobile and fixed collaborative robotic manipulators comprise the class of production resources.

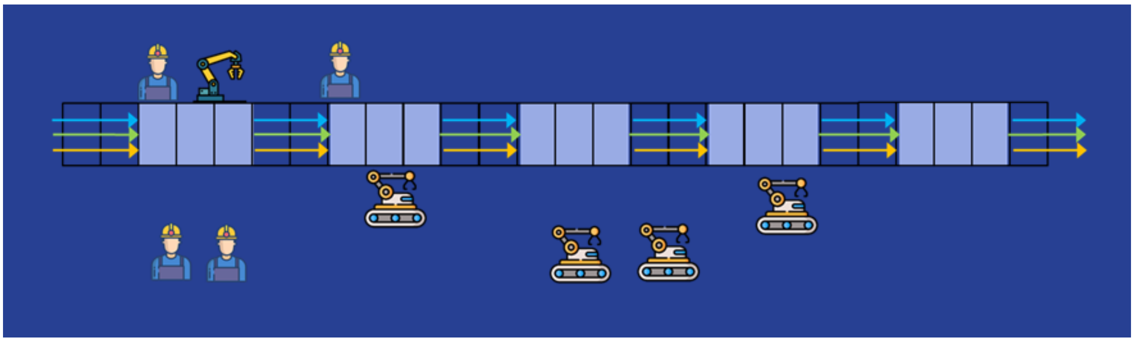

Figure 2 – Experiment 12 Assembly line

It's assumed that human operators and mobile robotic manipulators are dynamically assigned to workstations and that the time required to move in the manufacturing line is much smaller than the time related to the realization of manufacturing operations.

Typically, management of an assembly line goes through two phases. Balancing, where rules are defined for task-workstation, and task-resource allocation, performed by some mathematical optimization method. Usually, this is done during the setup of the line. Scheduling of operations is performed by a manufacturing Execution System (MES), defining the sequence of tasks, start-up and finish times, and allocation of production resources to workstations and tasks.

During the execution of the operations in the assembly line, there are two main causes of uncertainty: machine failures and unavailability of operators. Additionally, processing times are stochastic. Among other things, these factors contribute to deviations in the expected processing times defined by the MES system.

A first part of this experiment aims to dynamically allocate production resources to manufacturing tasks to better face these uncertainties. A task-resource allocation function will be defined through Reinforcement Learning so as to assign production resources to tasks during the operation of the line possibly overriding the default assignment defined in the production schedule. A neural network will be trained to better decide which resource to allocate to a task. The general goal of the experiment is to re-balance the manufacturing line (assign tasks to workstations and resources) so as to minimize the number of production resources and workstations to use while keeping a constant cycle time aiming to achieve the imposed throughput on the line (takt time).

The second part of the experiment aims to advance the limitations of the digital twin by combining the existing digital representation with the usage of computer vision integrated with artificial intelligence methods deployed either on the robot, the cloud, or at the edge. This will allow to achieve a system with more dynamism and reliability. In detail:

- It allows the act of populating the world model to be dynamic, meaning that the robots using these technologies can populate it almost autonomously, when they encounter an unidentified obstacle.
- During execution, when a new object would be detected by some robot, it would trigger their identification process, to reason what type of object it encountered and its current position, allowing for a dynamic update of models in the digital representation.
- Having the robots equipped with cameras for discovering new objects, the information passed to the digital model would be considerably larger, more reliable, and complete.
- This new approach is not limited to application in real scenarios. Rather, the training of an AI model to identify new objects, as well as different floor layouts, can be easily done using simulation techniques, without relying in real scenarios, thus greatly accelerating the development process.

The second part of the proposed experiment consists in making use of computer vision techniques in a set of factory floor robots to identify new objects/obstacles in the environment and send this information to the Digital Twin representation, updating it accordingly in a dynamic manner. The object identification will be done using artificial intelligence techniques, where models can be trained based on specific industrial objects/machinery, either in real scenarios or in simulation. It is important to note that such computer vision processes (image recognition/identification) can be very heavy in terms of computation power, meaning that local execution might not be ideal. With this being said, it would be interesting to consider offloading these heavy tasks to an edge layer or to rely on cloud computational services.

Each task execution request sent by the APM to a robotic agent will contain information about the real world. During execution, the robotic agents will sense their surrounding environment to extract information regarding which objects are present, their position and orientation. Robotic agents meeting an object for the first time will have to identify it, recognize it and extract useful information from it. All collected information will then be compared to the information that came from the APM. If an inconsistency is detected it will be reported by the robotic agent that found it. A graphical representation of the real world should always be visible on the APM, which must be updated at runtime as soon as an event happens in the real world.

2.2.3.2 Experiment 12 Plan

Activity	Period	Responsible
Experiment concept finalization	M1-M6	INESC TEC
Technical and functional requirements definition	M7-M9	INESC TEC
Prototype of the Intelligent Computer Vision for Digital Twin using a simulated environment, version 1.0	M10-M21	INESC TEC
Prototype of the Reinforcement Learning for Assembly Line Balancing Enhancement using a simulated environment, version 1.0	M10-M21	INESC TEC

Table 7 - Experiment 12 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

A1 "Experiment concept finalization": M1-M6
Task 1.1: Definition of the experiment main goals
A2 "Technical and functional requirements definition": M7-M9
Task 2.1: Definition of the technical and functional requirements
A3 "Prototype of the Intelligent Computer Vision for Digital Twin using a simulated environment, version 1.0": M10-18
Task 3.1: Prepare simulated environment
Task 3.2: Acquisition and processing of point clouds
Task 3.3: AI-based object recognition
Task 3.4: Global and local object localization
Task 3.5: Specification of the communication interface with the Advanced Plant Model
Task 3.6: Development of the digital twin inconsistency detection module, integrated with the Advanced Plant Model
A4 "Prototype of the Reinforcement Learning for Assembly Line Balancing Enhancement using a simulated environment, version 1.0": M10-18
Task 4.1: Prepare simulated environment
Task 4.2: Develop first version of the Assembly Line Balancing component
Task 4.3: Specify the communication interfaces between the components (Assembly Line Balancing, MES, Reinforcement Learning (training and execution), Advanced Plant Model and Production Manager)
Task 4.4: Develop first version of the Reinforcement Learning training component
Task 4.5: Develop first version of the Reinforcement Learning execution component
Task 4.6: Integrate all components

2.2.4 Experiment 17: "Industrial Processes AI-based Optimization", Tecnalia & Mecanifran

Experiment 17 is a DIH-driven experiment in Basque Country, led by Tecnalia and focused on developing a predictive model trained on historical data of machining control parameters and supervised by the quality control at the end of the lines. Experiment 17 will be implemented with a Spanish SME: Mecanifran.

2.2.4.1 Experiment 17 concept

Mecanifran is a Spanish SME in the automotive sector focused on the machining process of nuts and screws. The industrial process is not very flexible and requires orders of high quantities to have revenues; so few new references are produced per year (four or five). These pieces are part of wheel bearings used in the automotive sector.

The machining process has the following characteristics:

- Short machining times, around four seconds per piece.
- The machining process must be stable and robust, with a constant tooling wear.This is so important that the usual working protocol establishes a conservative tooling maintenance, with frequent tooling change to avoid unexpected/unprogrammed line stops.

The Mecanifran industrial process consists of 13 lines of numeric control, each of them with up to three lathes. At the end of the line, there is an automatic supervision machine in charge of evaluating the quality of the nuts/screws. The quality of these pieces is quite strict, and very much related to the status of the tooling used for the machining. Currently, the approach to maximize the quality of the produced pieces is quite simple and conservative, based on replacing the tooling as soon as possible before their performance starts degrading.

These tooling change has an important impact on the annual costs, so a maximization on the tooling usage, while maintaining the machining quality, would impact considerably on the company accounts.

Focusing on one line, the savings would come from a decrease of the cost of tooling (less tooling will be required), while at the same time the programmed stops will decrease, thus maximizing the machine availability.

The standard procedure in the plant uses one operator to manage several lines (usually two). The stipulated number of pieces produced to change a tooling in a machine is around 500, being four seconds the average time of a piece to be produced. So, every 33 minutes a tooling change happens. These lines are asynchronous among them, which means that the tooling change is not synchronized at all. The tooling change time takes around four minutes.

The operator, with no other help, must manage in parallel the tooling changes of the machines of these two lines, which is a cause of stress for the operator when the limit of 500 pieces is reached by several machines at the same time or quite close (the tooling changes of several machines overlap).

The operator could benefit from a holistic planning that considers all machines they manage. This planning could minimize these overlapping, and even increase the number of machines to be managed by that same operator. Three advantages would come from this global tooling change strategy: maximization of the number of machines managed by every operator, reduction of their stress when they must change tooling in several machines that reach the number of pieces threshold in the same time interval, and maximization of the availability of every machine (currently the stop time of one machine is impacted by its tooling change time, but also by the tooling change in other machines, since the same operator that manages all of them). This general planning will not be part of the experiment at the moment and remains an open objective for iteration 2.

The main objectives of the experiment are:

- **Objective 1:** Maximization of the tooling usage time of every machine, while maintaining the machining quality. The expected solution will be a predictive model trained on historical data of machining control parameters and supervised by the quality control at the end of the lines.
- **Objective 2:** Optimization of machine control parameters configuration to maximize the tooling life while the quality of the production is maintained. The expected solution will consist of an optimization tool on top of the previous predicting model. This optimization tool will provide a set of solutions to maximize the tooling lifetime of the modelled machine. This solution will prescribe the controlling parameters of the machine.
- **Objective 3:** Coordination of the tooling change in all the machines. This objective would face the tooling change considering the impact of machines among themselves, instead of just one by one.

The experiment will focus on objectives 1 and 2. The third objective will remain open for the second iteration.

2.2.4.2 Experiment 17 Plan

Activity	Period	Responsible
Experiment concept finalization	M1-M4	TECNALIA
Technical and functional requirements specification	M1-M4	TECNALIA

Data collection	M4-M10	TECNALIA
Development of optimization prototype engine (1st version)	M10-M16	TECNALIA
Development of first human-machine interface (1st version)	M13-M16	TECNALIA
Component integration	M16-M21	TECNALIA

Table 8 – Experiment 17 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

A1 "Experiment concept finalization": M1-M4
Task 1.1: Definition of the experiment main goals
A2 "Technical and functional requirements specification": M1-M4
Task 2.1: Definition of the technical and functional requirements
A3 "Data collection": M4-M10
Task 3.1: Prepare the infrastructure to collect new data from the case company
Task 3.2: Collecting data from the case company and analysing the data
A4 "Development of optimization prototype engine (1st version)": M10-M16
Task 4.1: Development of optimization prototype engine
A5 "Development of first human-machine interface (1st version)": M13-M16
Task 5.1: Creating a specification document for the GUI
Task 5.2: Implementing the GUI according to the specification
A6 "Component integration": M16-M21
Task 6.1: Integration of components

2.3 Cluster 3 : Quality Control and Predictive Maintenance

Cluster 3 contains six experiments:

(i) Exp 07 - "Predictive Analytics based on few-shot learning" which focuses on making the usage of robots more robust and efficient while making a significant impact in maintenance and service intervals as well as in early detection of sensor faults.

(ii) Exp 09 - 'AI-based quality control of measurement system' which focuses on AI quality control system for groundwater level sensors

(iii) Exp 13 - "AI-enhanced control strategy for production environment" which provides a service aimed at SMEs for assessing their needs and identifying the kind of AI-enhanced innovation that better fits their production lines.

(iv) Exp 14 - "Smart Predictive Maintenance Toolbox for drawing lines of car body element" which introduces automated analysis and diagnosis techniques using AI for the predictive maintenance of the machines in the stamping sector.

(v) Exp 15: "Water Leakage detection" which focuses on developing an AI based reasoning tool for water leakage detection using satellite remote sensing data as well as ground data.

(vi) Exp 16 - "IDSS predictive quality assurance" which presents an experimental solution which will be capable of increasing the awareness among SMEs about the benefits of AI. This investigation will focus on Quality Control in multiple levels (automation & integration, objectiveness & precision and productive increments in QC supervision).

2.3.1 Experiment 07: "Predictive Analytics Based on Few-Shot Learning", Arculus

Experiment 07 is an SME-driven experiment in Ingolstadt/Munich- Germany, led by Arculus and supported by FZI, focused on making the usage of robots more robust and efficient while making a significant impact in maintenance and service intervals as well as in early detection of sensor faults.

2.3.1.1 Experiment Concept

Autonomous Mobile Robots (AMR) have experienced an increasing commercial push in recent years. Due to the technical progress in the field of autonomous driving and the associated supply chain, other industries such as intralogistics are also benefiting. Suppliers such as Nvidia, due to the high demand in autonomous driving, are developing Systems on Chips components that enable high computing power with low energy consumption. One example is the Nvidia Jetson 2. In addition, the market for safety-related components such as LIDAR systems is becoming more affordable. This enables a new generation of logistics robots in the intralogistics sector.

This leads to a transformation from Automated Guided Vehicles (AGVs) to AMRs and thus to a whole new kind of flexibility of human-to-machine or machine-to-machine interactions.

AMRs offer the following advantages over AGVs:

- dynamic assignment of sources to sinks via a master control
- no manually pre-calculated routes for the robot to follow
- simpler scaling of robot fleets due to less preparatory work during installation (route definition)
- Over-the-air update functionalities similar to a Tesla cars are possible and thus an increase in value of the devices over runtime

The significantly extended solution space leads to an increased pull effect of the end users. At the same time, however, the expanded application capability also increases the demands on the reliability of the system. More complex application scenarios with higher environmental dynamics increase the pressure on the service and maintenance team of an AMR provider. Added to this is the challenge of using a comparatively young technology, in contrast to established hardware that has been widely tried and tested in use.

Arculus aims to make the use of robots more robust and efficient using targeted AI technologies from the application area of "predictive maintenance". The primary aim is not to optimize the control and localization algorithms, but to optimize and improve those processes that have the greatest impact on the organization in the course of scaling. These include, among others:

- Optimization of maintenance intervals
- Reduction of regular service intervals such as (scanner cleaning, ...) by replacing a service call according to schedule with a service call according to actual need
- Early detection of sensor faults (Lidar, IMU, Camera, ...) to ensure proactive fault clearance of the system

The following requirements must be met for success:

- Prediction of specific situations is accurate and stably repeatable
- The data pipeline from customer projects is continuous and automatable

2.3.1.2 Experiment 07 Plan

Activity	Period	Responsible
Definition of the system concept	M1-M3	ARC
Solution requirements	M4-M6	ARC /FZI
Development of the Data extraction pipeline	M7-M13	ARC
Development of data integration pipeline	M13-M21	FZI

Table 9 – Experiment 07 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

Phase 1: Definition of the system concept: M1-M3 (ARC)

Task 1.1: Definition of the experiment goals

Task 1.2: Definition of the required profiles of the development team

Phase 2: Requirements of the solution: M4-M6 (ARC / FZI)

Task 2.1: Definition of the technical and functional requirements

Phase 3: Development of the data extraction pipeline: M7-M13 (ARC)

Task 2.1: Develop and extract all relevant and flaged dataset for Streampipe application

Phase 4: Development of data integration pipeline: M12-M21 (FZI)

Task 4.1: Classification of fault types

2.3.2 Experiment 09: 'AI-based quality control of measurement system', SKU & Royal Eijkelkamp B.V

Experiment 09 is a DIH-driven experiment in the East of the Netherlands, led by Radboud University and focused on AI quality control system for the groundwater level sensors of Royal Eijkelkamp B.V.

2.3.2.1.1 Experiment 09 Concept

Royal Eijkelkamp B.V. develops, produces and sells all kinds of solutions for environmental monitoring. Their current problem concerns their groundwater level sensors, which they installed and maintain in a considerable part of east Netherlands to monitor drought. In fact, they are faced to univariate statistical control of measurement data (groundwater height) and they have no knowledge on root causes for out-of-calibration data. The aim of the experiment is to develop an AI-powered quality control system to quantify the quality of measurement and find root causes of faults.

This AI based quality control system will:

- Provide a score for the measurement;
- Detect fault and find the root causes;
- Assist maintenance staff, and products quality improvement.

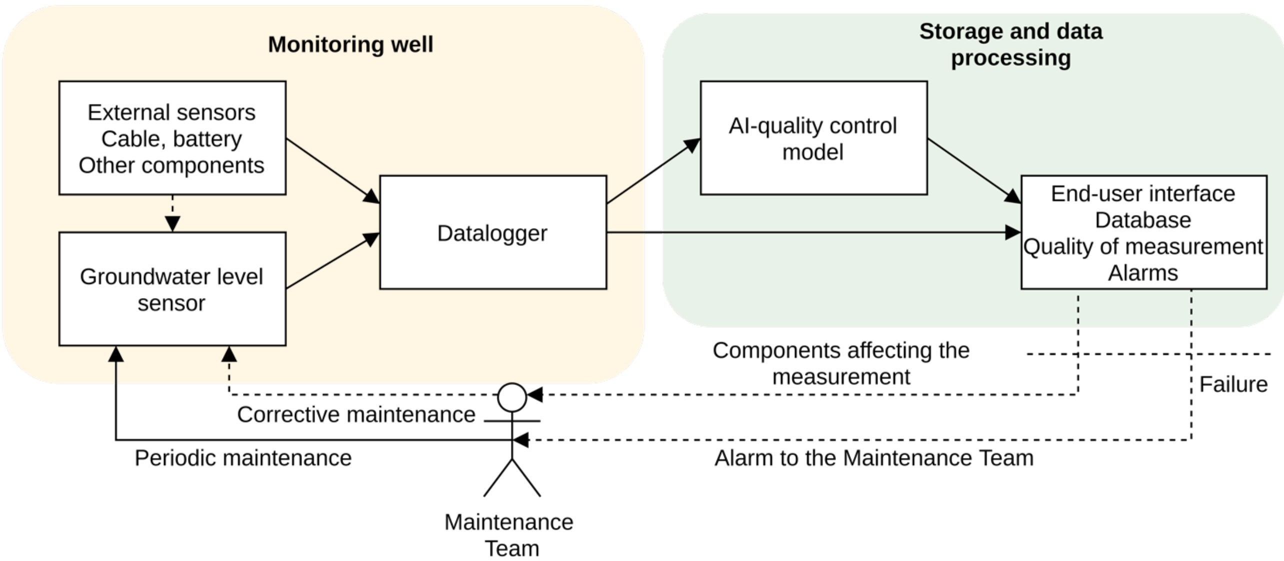

Figure 3 Experiment 09 concept

2.3.2.1.2 Experiment 09 plan

Activity	Period	Responsible
Concept definition	M1-M6	SKU, Eijkelkamp
Requirements specification	M7-M9	SKU, Eijkelkamp
1st prototype & Implementation	M10-M21	SKU, Eijkelkamp
Validation, fine tuning and reporting	M10-M21	SKU, Eijkelkamp

Table 10 – Experiment 09 1st Iteration plan

Phase 1 "Concept definition": M1-M6 (SKU, Eijkelkamp)
▪ *Task 1.1: Definition of the experiment main goals*
▪ *Task 1.2: Definition of the experiment team and provider support*
Phase 2 "Requirements specification": M7-M9 (SKU, Eijkelkamp)
▪ *Task 2.1: Definition of the technical and functional requirements*
Phase 3 "1st prototype & implementation": M10-M21 (SKU, Eijkelkamp)
▪ *Task 3.1: Development 1st prototype*
▪ *Task 3.2: Test using new data of Eijkelkamp*
Phase 4: "Validation, fine tuning and reporting": M10 – M21 (SKU, Eijkelkamp)
▪ *Task 4.1: Validation stage of the first prototype*
▪ *Task 4.2: Fine tuning, adjustments of models, infrastructure & report of the main findings*

The detailed activities in the context of the foreseen experiment Phases are the following:

2.3.3 Experiment 13: "AI-enhanced Control Strategy for Production Environment", ART-ER

Experiment 13 is a DIH-driven experiment in Emilia-Romagna Region, led by ART-ER and focused on providing services aimed at SMEs for assessing their needs and identifying the kind of AI-enhanced innovation that better fits their production lines.

2.3.3.1 Experiment 13 Concept

The experiment will provide end-users (SMEs) an instrument to implement AI and AI-related technologies into their production environment. Benefits for end-users can be achieved in terms of time and costs reduction, final product quality and better production plant management in general, with the possibility to allow interaction between the production line management and other services (e.g. predictive maintenance, digital twins...). A better production line management will also allow for productivity enhancement and reduction of dead costs, such as warehouse management and waste management. Thanks to AI enhanced predictions, activities inside the production environment will be fine-tuned, allowing for a better efficiency and cost reduction. Moreover, the AI-enhanced management tool will provide support in terms of energy efficiency and machine allocation. Training algorithms on different datasets from different experiences will allow the acquisition of methodologies from other production sectors, fostering cross-contamination.

Two scenarios are considered:

Scenario 1

A SME asks for better optimization of the production line controlling strategy in order to obtain higher overall production line efficiency. The need is also linked to the arising amount of discarded products at the end of the line, and the need to obtain higher quality standards. The Laboratory on charge of the Experiment performs an assessment on the state of the art of the production lines and proposes some solutions. All the solutions have 3 phases of implementation. First, the setup of relevant sensors for the collection of data to be used training the training of the AI algorithms and for real-time solution. Data already collected from machines during the production can be used as well, while some real time input from the worker is collected too. These data and information are used to identify the most appropriate controlling strategy to optimize with the production manager. The optimization of the strategy is sketched in graphs and figures in order to identify the best logical workflow to optimize using an algorithm. Secondly, the AI experts inside the Laboratory identify and tune the most fitting AI algorithm to be used. This is a critical task, that requires some experimentation and tests on real time environment, as well as the availability of clean, tagged and interpreted data from the first phase. The third phase is the embedding and implementing phase. AI enhanced algorithms need to be integrated in production line management systems, and production managers and workers need to be trained regarding the best use, sharing of good practices and performing demo assessment. For bigger production lines, adoption should be done in steps.

Scenario 2

An SME asks for better control of safety for workers and machines in the production line. The need is also linked to the raising mean age of employees, and the need to avoid the emergence of occupational diseases from long-term inaccuracies, wrong movements and working in a standing position on a prolonged and regular basis inside the production environment. The Laboratory on charge of the Experiment performs an assessment on the state of the art of the production lines and proposes some solutions. All the solutions have 3 phases of implementation. First, the setup of relevant sensors and cameras to collect data from the machines and operators, that will be used to train AI algorithms for real-time solution hints and suggestions. Data collected in the past, both from the machines and the operators will also be used, while some real time input from the worker is collected too. In this particular scenario, the need for an external expert on Health and Safety may be required. These data and information are used to identify the best controlling strategy to optimize with the production manager, the Human Resources (HR) manager and the workers (all or representatives). During the second phase, the AI experts inside the Laboratory identify and tune the best AI algorithm to be used. This is a critical task, requiring some experimentation and tests in a real time environment, as well as the availability of clean, tagged and interpreted data from the first phase. The third phase is the embedding and implementing phase. AI enhanced algorithms need to be integrated in production line management systems and in machine interfaces: they will be in charge of alerting both the worker and the production manager on any potentially dangerous situation (wrong repeated movement, injuries, misuse of Individual Protection Devices). Workers, Production line and HR Manager need to be trained. Similar to the previous phase, , support from a specific Health expert would be suggested in this phase too.

2.3.3.2 Experiment 13 Plan

Experiment 13 will be developed in the bigger frame of the AI DEMO LAB GRID project and focuses on the setup of a service for manufacturing SMEs needing to improve and enhance their production environment control strategy.

The development of the experiment will proceed in steps from M1-M21, starting from the design of the first version and concept of the service next to end-users, up to fine tuning it through a first proto-experience cycle.

This process will continue until the first use case validation, planned for M25-M30. The final outcome will come at the end of the second iteration.

Activity	Period	Responsible
Experiment concept finalization	M1 – M12	ART-ER
Technical and functional requirements definition	M8 – M15	ART-ER
First proto-experiences and tests	M15 – M21	ART-ER

Table 11 – Experiment 13 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

Experiment concept finalization M6-M12

Definition of the experiment goals and identification of most relevant user's needs.

Technical and functional requirements definition M8 – M15

Identification and definition of the technical and functional requirements

First proto-experiences and tests M15- M21

Development of final services and test in real or simulated environment

2.3.4 Experiment 14: "Smart Predictive Maintenance Toolbox for Drawing Lines of Car Body Element", AIN

Experiment 14 is a DIH-driven experiment in Navarra, led by Asociación de la Industria Navarra AIN and focused on introducing Artificial Intelligence techniques in the Predictive Maintenance of stamping presses.

2.3.4.1 Experiment Concept

Condition Monitoring of machinery and industrial installations by vibration measuring and analysis is widely used in the industry on machines in which the consequences, in case of failure, can lead to large production losses and repair costs. Historically it has been applied to rotating machines. However, its use in non-rotating machinery such as stamping presses, and in particular those used in the automobile industry, is very limited. On the one hand, the acquisition of data for its analysis is complex due to the impact that occurs in each stamping cycle. This causes the need to treat the vibration signals so that only the valid information related to the condition of the drive components (shafts, gears, bearings, etc.) remains. On the other hand, fault analysis and diagnosis, although technically feasible, is extremely laborious, making it practically unfeasible from an economic point of view due to the need for expert personnel in signal analysis and high-end dynamic signal analyzers. This fact acts as a barrier to the access of stamping companies to the advantages of Predictive Maintenance.

For these reasons, the possibility of introducing automated analysis and diagnosis techniques, using Artificial Intelligence, is of the utmost interest since:

- It could improve the reliability and availability of stamping facilities by reducing downtime due to unforeseen breakdowns.
- It would reduce the analysis times of specialized personnel.
- It would reduce the costs of the Predictive Maintenance service for stamping companies, facilitating the access of SMEs to the advantages of failure prevention technologies.
- It would improve the ability for failure anticipation by enabling faster analysis, quasi in real time.
- It would improve the competitiveness of the stamping sector by reducing production costs due to unforeseen failures, as well as the Predictive Maintenance service provider.

This experiment consists of demonstrating the feasibility of introducing Artificial Intelligence techniques in the Predictive Maintenance of stamping presses through the collaboration of:

- A Technology Centre that develops and implements AI algorithms.
- A Predictive Maintenance service provider that will implement AI in its monitoring and diagnostic tools.

- An automobile manufacturing company (end user) that makes its stamping facilities available for the experiment.

2.3.4.2 Experiment 14 Plan

The experiment is based on an existing vibration monitoring system of a stamping press for automobile body elements, based on the AIN_CMS (Condition Monitoring System) developed by AIN. The development of the experiment has been planned in two iterations: i) development of the first version of the smart fault diagnosis module (M1-M21) and ii) development of the maintenance platform and improvement of the IA module (M19-M36).

The plan for the 1st iteration is as follows:

Activity	Period	Responsible
Definition of the system concept	M1-M3	AIN
Solution requirements	M4-M6	AIN
Development of the smart fault diagnosis module	M7-M21	AIN

Table 12 – Experiment 14 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

Phase 1: Definition of the system concept: M1-M3 (AIN)
Task 1.1: Definition of the experiment goals
Task 1.2: Definition of the required profiles of the development team
Phase 2: Solution requirements: M4-M6 (AIN)
Task 2.1: Definition of the technical and functional requirements
Phase 3: Development of the smart fault diagnosis module: M7-M21 (AIN)
Task 3.1: Classification of fault types
Task 3.2: Data cleaning, external data entry and classification
Task 3.3: Training and testing different AI algorithms
Task 3.4: Programming and verification of the first version of smart module

2.3.5 Experiment 15: "Water Leakage Detection", Mariborski Vodovod d.o.o. & University of Maribor

Experiment 15 is an SME-driven experiment in Slovenia, led jointly by Mariborski Vodovod d.o.o. and University of Maribor and focused on developing an AI-based reasoning tool for water leakage detection using satellite remote sensing data as well as ground data.

2.3.5.1 Experiment 15 concept

Mariborski Vodovod is an SME located in Eastern Slovenia and is the main water supplier in this region.

The SME has developed its own modern sensor network system for monitoring water consumption. The pipe network has been renovated over the last 30 years, but due to financial limitations, some parts of pipe network are 50 years old. The monitoring consumption system provides real time data, therefore the goal of the experiment is to provide alarms that signal water leakage from the pipe network system.

The experiment will be focused on information extraction from a large-scale data. The data acquired by a flow sensor are recorded into the database without adequate reasoning being applied Therefore, the goal is to monitor water consumption and detect possible water leakage from the pipe network. AI will be used to for this purpose. The remote sensing data can be used to detect wet zones. Therefore, ALSO-2 from JAXA can be used to estimate wet cones over the water pipe network. Various methods can be used for soil moisture detection. The goal will be to automatically estimate wet zones over the waterpipe network, compare the results with the water consumption of the network and build up AI based reasoning for water leakage detection using satellite remote sensing data and ground data.

The water leakage concept monitoring can be divided into two separate experiments. The first one uses advantages of water flow meters that are installed over the entire water pipe network and the concept of soil moisture estimation using the remote sensing data. The problems of both approaches are listed below:

- Water consumption is measured using flow meters
- Water leakage can be identified using ratio between income and outcome
- Due to the length of the water pipe network, micro location cannot be precisely identified
- Some parts of the water pipe network are 50 years old

Gains of the proposed experiment include the impact on the preservation of natural resources and the increased water production and optimized management

- Using water flow meters 15-20% of water is lost within the pipe network. The goal is to use remote sensing technique to estimate soil moisture
- Constant monitoring using radar imagining satellite ALOS-2
- Precise definition of micro-location using soil moisture estimation techniques

The experiments concept for the two scenarios are depicted in the following figures:

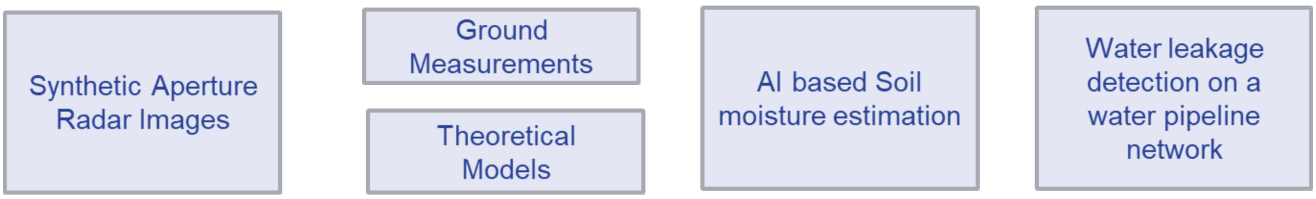

Figure 4 Concept of experiment with remote sensing data.

Figure 1 shows the concept using the remote sensing data that are acquired using a radar satellite ALOS-2, that operates in the polarimetric mode. Ground measurements are needed at the time of acquisitions in order to train a neural network. This task will be performed manually by selecting at least 200 ground points. The data using previous acquisitions, current acquisitions and the theoretical models will be used for train deep neural network.

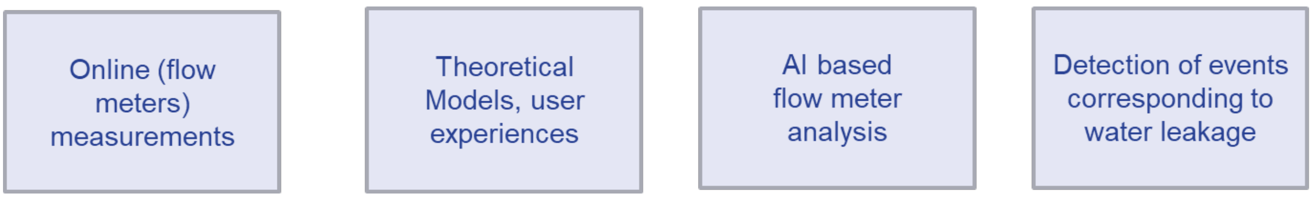

Figure 5 Concept with flow meters.

Figure 2 shows the outline of the experiment that uses online flow meters. Here the theoretical models and past experience of human operators will be used to predict a water leakage. A simple deep neural network will be designed to predict water leakages.

2.3.5.2 Experiment 15 Plan

Activity	Period	Responsible
Concept definition	M1-M6	University of Maribor & Mariborski Vodovod
Requirements specification	M7-M9	University of Maribor & Mariborski Vodovod
1st prototype & Test	M10-M21	University of Maribor & Mariborski Vodovod
Validation, fine tuning and reporting	M10-M21	University of Maribor & Mariborski Vodovod

Table 13 – Experiment 15 1st Iteration Plan

The detailed activities in the context of the foreseen experiment Phases are the following:

Phase 1 "Concept definition": M1-M6 (UM, MV)

Task 1.1: Definition of the experiment main goals

Task 1.2: Definition of the experiment team and provider support

Phase 2 "Requirements specification": M7-M9 (UM, MV)

Task 2.1: Definition of the technical and functional requirements

Task 2.2: Planning out the overall intelligent systems

Task 2.3: Planning the individual intelligent system machine learning (ML) components based on the data

Phase 3 "1st prototype & Test": M10-M21 (UM, MV)

Task 3.1: Data exporting and data overview

Task 3.2: Data exploration and feature engineering

Task 3.3: Development of the first prototype

Task 3.4: Testing the prototype using historic data

Phase 4: "Validation, fine tuning and reporting": M10 – M21 (UM, MV)

Task 4.1: Validation stage of the first prototype

Task 4.2: Fine tuning, adjustments of models, infrastructure

Task 4.3: Deployment of the prototype to the real-life infrastructure

Task 4.4: Reporting of the main findings

2.3.6 Experiment 16: "IDSS Predictive Quality Assurance", COMET

Experiment 16 is a DIH-driven experiment in Friuli – Venezia Giulia, led by COMET – Cluster Metalmeccanica FVG in close coordination with its relevant DIH IP4FVG (Node of Udine – Data Analytics and Artificial Intelligence) and the University of Udine. Exp 16 presents an experimental solution that will be capable of increasing awareness among SMEs about the benefits of AI. This investigation will focus on Quality Control (QC) in multiple levels (automation & integration, objectiveness & precision and productive increments in QC supervision).

2.3.6.1 Experiment 16 Concept

COMET – Cluster Metalmeccanica FVG (COMET) is the Regional Cluster for the Advanced Manufacturing in Friuli Venezia Giulia, Italy's North-Est most region, bringing together around 3,800 local manufacturing companies operating mainly in the mechanics, mechatronics and metalworking fields. Almost 48% of manufacturing companies operating in Friuli Venezia Giulia Region directly operate for the mechanics and metal processing sectors, thus representing a strategic asset for the whole regional ecosystem. Of these, the big majority is of small dimensions: the local business environment is mainly grounded on manufacturing SMEs.

Under coordination of the Regional DIH-IP4FVG[1], COMET will carry out an experiment that will be used to increase the awareness among its SMEs about the opportunities offered by AI in this particular domain.

At proposal stage, COMET purposely decided to address it towards a **broad investigation scope** represented by **quality control.** The underpinning idea is to provide local manufacturing companies with a use case, a pilot experiment, easily replicable and scalable, that might demonstrate the early identification of defects and failures in larger series production. Estimating early the potential faultiness could help local manufacturing companies on planning, controlling and executing productive activities in an optimized and predictive manner. The scope of investigation is of particular relevance in large-series production e.g. for local Tier 2 companies in the automotive sector, steel producing companies and metal industry suppliers, manufacturing enterprises producing anchors and wall plugs, etc. In this context, our idea is to focus on an **intelligent** system that, leveraging on machine learning, could be of **help to the decision maker** (i.e. the quality assurance manager) to **identify and detect** the defects, anomalies and outliers (i.e. **faulty pieces**) in an environment similar to the real one.

One local manufacturing SME producing components in big lots will be involved in the experiment, providing the faulty pieces that will be the object of the investigation. Large amounts of data will be the raw material on which the system will rely on, as AI technology makes it possible to identify regular patterns in available data and to use these patterns for a wide variety of analysis, decision-making, and prediction purposes.

COMET's belief is that an intelligent learning approach such as **Machine Learning** should be investigated and compared for manufacturing quality prediction. The use case will leverage on an intelligent approach, part of a broader family of learning methods based on artificial neural networks with representation learning.

2.3.6.2 Experiment 16 Plan

Activity	Period	Responsible
Experiment concept finalization	M1 – M8	COMET
Technical and functional requirements definition	M8 – M12	COMET
Data collection and modelling for the experiment	M12 – M21	COMET NISSATECH
Develop IA prototype engine	M12 – M21	COMET NISSATECH

[1] IP4FVG stands for Industry Platform for Friuli Venezia Giulia and it is the regional digital innovation hub, which COMET refers to.

Human-machine interface development	M12 – M21	COMET NISSATECH
Testing the software and the GUI with the experiment	M15 – M21	COMET

Table 14 – Experiment 16 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

Phase 1 "Concept finalization": M1-M8 (COMET)
Task 1.1: Definition of the experiment main goals
Task 1.2: Definition of the experiment team and provider support

Phase 2 "Requirements specification": M8-M12 (COMET)
Task 2.1: Definition of the technical and functional requirements
Task 2.2: Definition of the business requirements
Task 2.3. Identification of the existing components and their development needs

Phase 3 "Data collection": M12-M21 (COMET / NISSATECH)
Task 3.1: Prepare the infrastructure to collect new data form the case company
Task 3.2: Collecting product related data form the case company and analysing the data

Phase 4 "Develop IA prototype engine": M12-M21 (COMET / NISSATECH)
Task 4.1: Prepare data for the test
Task 4.2: Develop IA engine prototype
Task 4.3: Train the IA engine prototype

Phase 5: "Human-machine interface development": M12 – M21 (COMET / NISSATECH)
Task 5.1: Creating a specification document for the GUI
Task 5.2: Implementing the GUI according to the specification
Task 5.3: Integration with the system

Phase 6: "Testing the software and the GUI with the experiment": M15 – M21 (COMET)
Task 6.1: Testing the software and the GUI with the experiment

2.4 Cluster 4: Robotics and Human Interaction

Cluster 4 contains four experiments:

(i) Exp 01 - "Machine Vision for Warehouse Optimization" which focuses on the implementation of a system able to support operators in the warehouse to identify exactly the unique sheet they need at that time for further delivery to production line;
(ii) Exp 06 - "AI-Supported Robot Trajectory Optimization" which develops an optimization strategy based on Artificial Intelligence capable of maintaining the expected robot trajectory by performing automatic corrections over online machining inaccuracies that might appear during a task;
(iii) Exp 08 - "AI based AR in Assembly" which presents a new approach to Augmented Reality (AR) system instructions redirecting those scenarios into adaptative self-learning systems. Allowing to adapt a rigid learning AR "onboarding" procedure to the specific needs of each customer; and

(iv) Exp 11 - “Automatic Capability Matchmaking for Reconfigurable Robotics Platform” which aims to demonstrate an automatic capability matchmaking system capable of facilitating rapid design and reconfiguration of robotics platforms.

2.4.1 Experiment 01: “Machine Vision for Warehouse Optimization”, Gualini Lamiere

Experiment 01 is an SME-driven experiment in Lombardy, led by Gualini Lamiere International and focused on the implementation of a system able to support operators in the warehouse to identify exactly the unique sheet they need at that time for further delivery to production line. Dimensions, thickness and material need to be carefully selected following the production line's indication; for doing so the sheets need to be handled in the most efficient way and in the shortest time.

2.4.1.1 Experiment 01 Concept

Set up in 1956, the company has acquired extensive experience in the construction of metal structural work. The warehouse of Gualini is the problem and the core of the pilot itself.

Gualini's warehouse is made of piles of heavy steel sheets. The sheets have different dimensions, thickness, structure and weight. The problems in Gualini's warehouse are extendable to many manufacturing companies and are related to:

- labelling
- recognition
- handling

of the steel sheet.

The piles are heavy with huge dimensions and for this reason, they need to be placed on the ground. The labelling is often inefficient due to the cover of the label made by the pile structure, while the frequent handling of the sheets exposes the label to a physics degradation. For example, the bar codes attached on each sheet in the pile can wear out, tear or get lost during the frequent handling. The responsibles of the warehouse, who receive punctual inputs from the production line, need to know exactly where to find the sheet they need, including its location within the piles and its exact position.

Each handling has an impact on men efforts, time and cost.

The experiment aims:

1) To “recognize” the characteristic of each steel sheet in terms of:

- Dimensions
- Thickness
- Material
- Position

With a more efficient cataloguing.

2) To know exactly the position of the needed steel sheets within the piles and inside the pile to reduce the handling.

Solving these issues would mean to take advantage of:

- autonomous and reliable data
- optimization in the operation, to save time and costs

2.4.1.2 Experiment 01 Plan

Activity	Period	Responsible
T1.1: Analysis of the physical environment and mapping of technical and environmental constraints	M6-M9	TXT

T1.2: Analysis of the State of the Art (SoA) of tracing hardware	M10-M12	TXT
T1.3: Analysis of the SoA of AI algorithms and selection	M10-M12	TXT
T1.4 Analysis of the SoA of metal identification	M10-M12	GUALINI
T1.5: First test on tracing data samples (iterative)	M12-M21	GUALINI
T1.6: Personalization of the AI algorithm (iterative)	M12-M21	TXT

Table 15 – Experiment 01 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

T1.1 the shopfloor of Gualini Lamiere has complex environmental conditions which impact the technical solutions that can be applied in the shopfloor. The first activity of the experiment phase (T1.1) is devoted to the analysis of the environment. The analysis of the environment and finding the right technologies is a highly demanding task as the environment is full of metals, with poor or without internet connection, etc

T1.2 the SoA of tracing systems will be addressed in order to define the best alternatives for the shopfloor.

T1.3 the SoA of literature AI algorithms will be addressed to select best alternatives

T1.4 the SoA of metal sheet identification will be addressed to surely identify metal sheets

T1.5 the selected tracing systems, AI algorithms and metal sheet identification selected technologies will be experimented together iteratively to validate the selection. Evaluation and comparison of different alternatives will be executed as well in this phase in order to find the best setup

T1.6 the literature algorithm selected from SoA will be personalised to the specific environment to increment results

2.4.2 Experiment 06: "AI-Supported Robot Trajectory Optimization", Kautenburger GmbH

Experiment 06 is an SME-driven experiment in Germany, led by Kautenburger Gmbh and focused on developing an optimization strategy based on Artificial Intelligence capable of maintaining the expected robot trajectory by performing automatic corrections over online machining inaccuracies that might appear during a task.

2.4.2.1 Experiment 06 Concept

The use of robot arms for industrial production has continuously increased, and the Robot processing cells are constantly gaining relevance in machining tasks as well. Kautenburger GmbH received clear signals from its own customers, particularly from the castings manufacturing sector, in the run-up to the application for the project that there was an enormous demand for robotic solutions for CNC machining. In particular, the goal of being independent from specific robot manufacturers will be met by a wide range of users in various industries (e.g., metal casting, plastic casting and white plaster finishing).

Kautenburger GmbH wants robots for the post/processing of cast metal and for white plaster products with certain absolute accuracy. Robot arm has its own advantages in comparison with CNC machines:

- Flexibility: Robot arm is suitable for more tasks including milling, drilling, roughing, cutting, grinding, brushing, polishing etc.

- high extension: Robot arm has better programmability, as many open-source and industry software providers are available in the fields of robot simulation, AI-technology integration, robot communication, robot trajectory planning, robot manipulation etc.
- lower cost: Robot arm has its advantages to process complex 3D geometry, which previously needs to be done by large-scale or more-axes CNC machines.

The main problem here are machining inaccuracies due to the limited stiffness of the robots. In order to correct these errors at runtime, complex and accurate stiffness models and processing force models should be built as a general solution. However, the stiffness model parameters can only be acquired experimentally and since this solution cannot be transferred to other robots, this is not a sensible procedure.

What this experiment expects to achieve is to develop a possible optimization strategy with the help of AI methods, which then makes it possible to maintain the desired robot trajectory during machining tasks even without absolute measurement of the tool centre point (TCP) at runtime. Several requirements should be fulfilled:

- the robot stiffness model can be generalized through an AI approach
- the TCP trajectory optimization has real-time ability
- the predictions of the AI-based model are stable and accurate.

The experiment will be separated into steps below:

1. Determine the experiment devices and build the experiment platform
2. Calibration and sensor synchronization
3. Identify the actual geometry of the workpiece
4. Generate the Computer Aided Design (CAD) model of workpiece and plan the machining trajectory
5. Collect data from all sensors which indicate the robot's working state in real-time
6. Train and test an AI-based model to replace the external trajectory measurement device e.g., Laser Tracker without any compensation strategy, the model is called "error detector"
7. Design an AI-based trajectory compensation strategy
8. Combine the "error detector" and the compensation strategy
9. Evaluation of the AI method effectiveness with both simple and complex trajectory
10. AI method training and deployment on different robot types

2.4.2.2 Experiment 06 Plan

For this experiment, two iterations' periods are necessary to achieve the final outcome. Phases and sub-tasks of each phase are listed below:

Activity	Period	Responsible
P1: Requirements and market analysis	M1-M4	FZI/ Kautenburger
P2: Literature search and concept of the experiment	M2-M8	FZI/ Kautenburger
P3: From scan to NC code (offline compensation preparation)	M6-M36	Kautenburger

P4: AI based compensation of the trajectory deviation	M2-M36	FZI/ Kautenburger

Table 164 – Experiment 06 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

Phase 1 "Requirements and market analysis": M1-M4 (FZI/Kautenburger)

Task 1.1 Kick-Off SME experiments M1

Task 1.2 background and requirement analysis M2-M4

Task 1.3 case and user story search in the field of trajectory tracking in robot machining M2-M4

Phase 2 "Concept and literatures of the experiments": M2-M8 (FZI/Kautenburger)

Task 2.1 Literature search: AI prediction and compensation methods M2-M6

Task 2.2 Literature search: detailed method of experiment establishment M2-M6

Task 2.3 Concept: Implementation and further development of 3D Scan and SprutCAM M3-M6

Task 2.4 Concept: Asset implementation: Process Integrated feedback management M3-M6

Task 2.5 Concept: which AI optimization strategy should be used and how to verify it M3-M6

Task 2.6 Concept: how to train and deploy the AI models on real robot platform M5-M6

Task 2.7 Concept: how to gather 3D Scan, SprutCAM and AI path optimization as a complete pipeline M5-M8

Phase 3 "From scan to NC code (offline compensation preparation)": M6-M36 (Kautenburger)

Task 3.1 Hardware selection and test setup M6-M10

Task 3.2 Development of 3D scan tool with cubic components M9-M20

Task 3.3 Development of SprutCAM tool with cubic parts M9-M20

Task 3.4 Further development of Toolchain 3D-Scan and SprutCAM with freeform geometric parts M22-M36

Task 3.5 Evaluation of the transfer quality from point cloud to NC code M9-M36

Phase 4 "AI based compensation of the trajectory deviation": M2-M36 (FZI/Kautenburger)

Task 4.1 Virtual modelling of the simulation environment M2-M17

Task 4.2 Design of the AI error prediction strategy and compensation strategy M3-M17

Task 4.3 Prototypical realization of the AI compensation concept in simulation environment M4-M17

Task 4.4 Evaluation of the simulation results M5-M17

Task 4.5 Hardware selection and test platform setup M9-M13

Task 4.6 Transfer simulative AI path error prediction method on real robot with offline methods M10-M36

Task 4.7 Transfer simulative AI compensation strategy to real robot with offline/online method for machining of both cubic and free-form geometrical workpiece M9-M36

Task 4.8 Evaluation of AI model performances during robot machining M20-M21/M34-M36

2.4.3 Experiment 08: "AI based AR in Assembly", Brainport Industries

Experiment 08 is a DIH-driven experiment in the Brainport region, led by Brainport Industries and Brainport Development (represented by the High-Tech Software Cluster) and focused on a new approach to Augmented Reality (AR) system instructions redirecting those scenarios into adaptative self-learning systems, thus allowing to adapt a rigid learning AR "onboarding" procedure to the specific needs of each customer.

2.4.3.1 Experiment Concept

The current training and guidance systems are static: all operators receive similar instructions. However, there is a great need to make such systems adaptive and self-learning using AI: Dynamic customization of operator guidance based on skill level, performance, errors, instantaneous operator capacity and operator knowledge and feedback to improve effectivity of instructions;

Experiment 08 aims to create the first steps towards adaptive AR/VR support for training and guidance in assembly making use of an AI-based adaptive algorithm, based on both productivity and quality as well as operator capacity and needs. Experiment 08 evaluation will focus on the human-machine interaction and acceptance of this kind of support systems.

An adaptive AI based Augmented Reality operator support system for manufacturing companies will increase competitiveness (productivity, quality, flexibility) and will be a solution to their problem of labour shortage. It will stimulate reshoring of production activities, improves added value of operators and development of their skills.

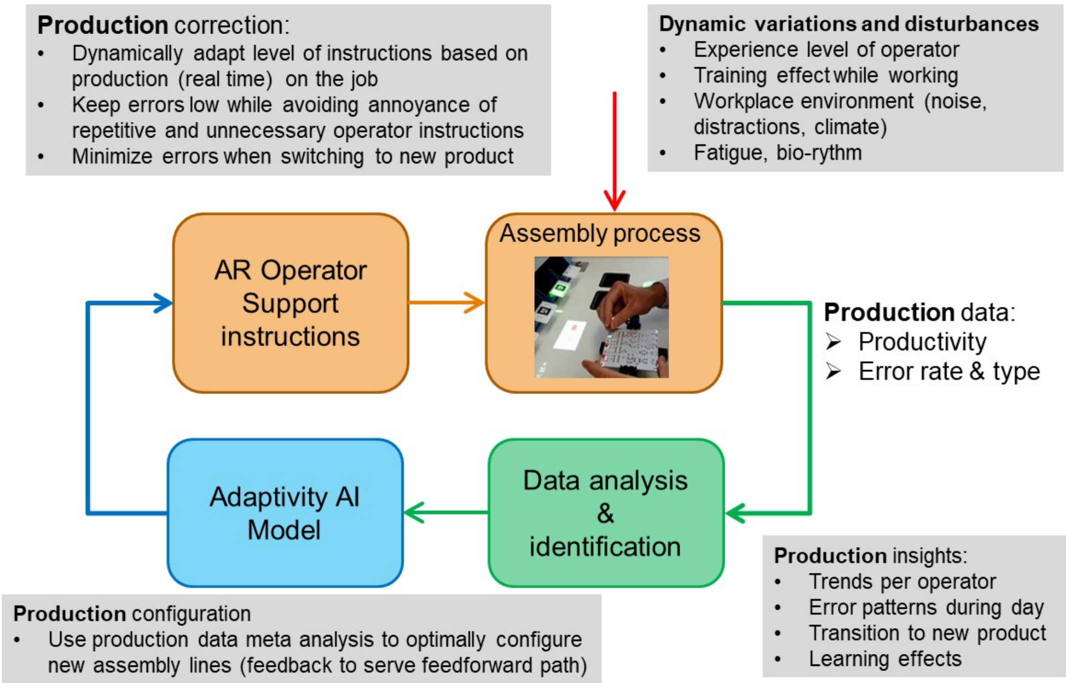

Figure 6 Experiment 08 concept

2.4.3.2 Experiment Plan

Activity	Period	Responsible
Phase 1 "Concept finalization"	M1-M6	BPI – BPD - TNO
Phase 2 "Requirements specification"	M7-M14	TNO
Phase 3 "1st prototype release"	M14-M21	TNO

Table 17 – Experiment 08 1st Iteration plan

The detailed activities in the context of the foreseen experiment Phases are the following:

Phase 1 "Concept finalization": M1-M6 (Brainport Industries, Brainport Development and TNO)
Task 1.1: Definition of the experiment main goals
Task 1.2: Definition of the experiment team and provider support
Phase 2 "Requirements specification": M7-M14 (TNO)
Task 2.1: Definition of the technical and functional requirements
Phase 3 "1st prototype release": M14-M21 (TNO)
Task 3.1: Development of the 1st prototype release
Task 3.2: Testing with the end-user
Task 3.3: Verification and lessons learnt

2.4.4 Experiment 11: "Automatic Capability Matchmaking for Reconfigurable Robotics Platform", Tampere University

Experiment 11 is a DIH-driven experiment in Tampere, led by Tampere University (TAU) and focused on demonstrating an automatic capability matchmaking system capable of facilitating rapid design and reconfiguration of robotics platforms.

2.4.4.1 Experiment Concept

Responsiveness is an important strategic goal for manufacturing companies operating in a highly dynamic environment characterized by constant change. Companies need to be able to rapidly design and reconfigure their production systems to meet the requirements of highly variating products. Traditionally, the production system design and reconfiguration planning are manual activities, and heavily dependent on the designers' experience and tacit knowledge to find feasible system solutions by comparing the characteristics of the product to the technical properties of the available resources. Browsing through resource catalogues (online or even paper catalogues) to find feasible resources for different product requirements and to compare them is highly time consuming. There is no standard way to describe the resources in the catalogues, which makes the comparison between different alternatives from different providers difficult. Depending on the complexity of the system, the number of needed components may be thousands. Furthermore, the combined capabilities and compatibility of the resource interfaces needs to be analysed during the resource selection. The cumbersome and slow search and filtering activity sets limitations to the number of resource alternatives that may be considered. This means that better solutions may be unintentionally neglected as the designer easily favours his/her former solutions, which might be sub-optimal – if even that – for the given problem. Thus, there is a need for intelligent decision support system that can reduce the time and effort needed for resource search and selection during system design and reconfiguration planning activities.

Experiment 11 aims to demonstrate an automatic capability matchmaking system to facilitate rapid design and reconfiguration of reconfigurable robotics platform. The concept is based on existing systems and technologies developed during H2020 project ReCaM[2]. These include:

- Formal ontology models, namely Manufacturing Resource Capability Ontology (MaRCO) and Product Model Ontology, for describing the capabilities of manufacturing resources and requirements of products, respectively.
- Resource Description format, which is an XML-based model to describe resources and their different characteristic, including capabilities, technical and business properties, and resource interfaces.

[2] https://cordis.europa.eu/project/id/680759/de

- Automatic capability matchmaking system implemented as a Web Service, which can be utilized by different design and planning tools to aid the designer to find feasible resources and resource combinations to specific product requirement.

Figure 7 presents the overview of the capability matchmaking. System Designer gives the matchmaking service an input which consists of the product requirement description (PRD) and the resource pool(s), including references to the resource catalogue(s) he/she wants to be considered during the matchmaking. In case of reconfiguration scenario, the input will (also) include the description of the existing system layout. The matchmaking system will then search through the resource pool(s) and try to find matching resources and/or resource combinations to each of the processes required by the product. As an output the Matchmaking system provides the output file, which includes found matches for each process step of the PRD.

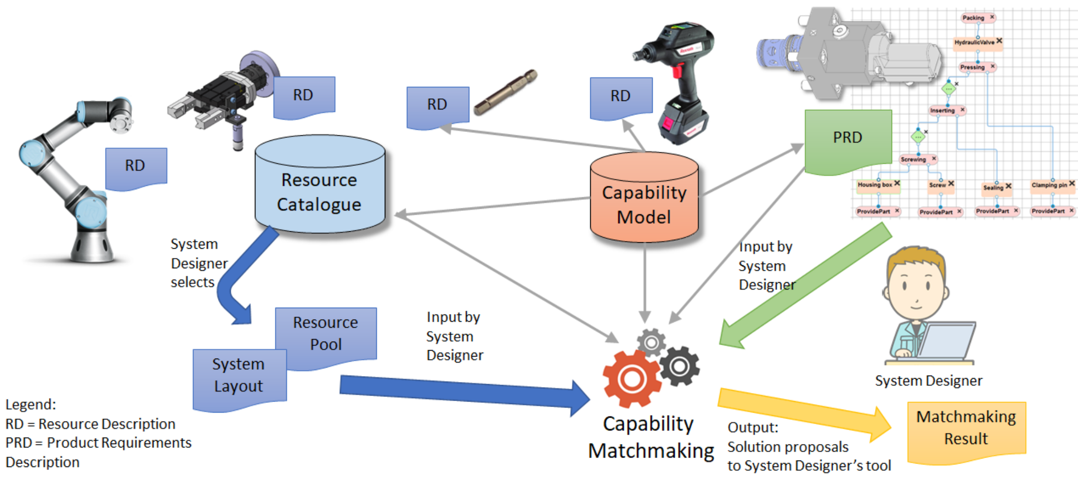

Figure 7. Experiment 11: Overview of the capability matchmaking

This AI REGIO experiment will apply the Capability Matchmaking system in a context of Reconfigurable robotics laboratory. The purpose is to extend the existing resource catalogue with a large set of new resource descriptions in order to be able to test and validate the system with larger search spaces. Furthermore, several new case products will be utilized to test the system with different requirements. Due to the new kind of resources and processes, the Capability Model needs to be extended with new capabilities. Also, the rule base needs to be extended to enable the combined capability calculation and capability matchmaking with these new capabilities. The efforts during the experiment will be focused on creating a large resource catalogue, which can be used, as such, as a search space for the experimentation service offered through the DIH network. The case products that are used for the experiment implementation, are real products from real companies.

2.4.4.2 Experiment Plan

Activity	Period	Responsible
Experiment concept definition	M3-M6	TAU
Technical and functional requirements definition	M7-M9	TAU
MM GUI development	M8-M15	TAU
Data collection and modelling for the demo case	M12-M16	TAU
Testing the MM software and the GUI with the demo case	M16-M21	TAU

Table 18. Activities during the 1st iteration.

The detailed activities in the context of the foreseen experiment Phases are the following:

Phase 1: Experiment concept definition, M3-M6, TAU

Task 1.1. Definition of the experiment concept and goals for the implementation

Task 1.2. Identification of potential case products

Task 1.3. Identification of resources needed

Phase 2: Technical and functional requirements definition, M7-M9, TAU

Task 2.1. Definition of the business requirements

Task 2.2. Definition of the functional requirements for the matchmaking system and GUI and associated use cases

Task 2.3. Identification of the existing components and their development needs

Phase 3: MM GUI development, M8-M15, TAU

Task 3.1 Hiring programmer for the GUI development

Task 3.2. Creating a specification document for the GUI

Task 3.3. Definition of detailed task list for the backend and frontend development

Task 4.3. Implementing the GUI according to the specification

Phase 4: Data collection and modelling for demo case, M12-M16, TAU

Task 4.1. Collecting product related data form the case company and analysing the data

Task 4.2. Collecting resource data related to TAU Robo Lab and HRC Pilot Line (i.e. Tampere Robotics Didactic Factory

Task 4.3. Creating a product requirement description (PRD) of the case product

Task 4.4. Creating resource descriptions of the selected resources

Phase 5: Testing the MM software and GUI with the demo case, M16-M21, TAU

Task 5.1. Running matchmaking scenarios through the GUI with the case data from Phase 4.

Task 5.2. Identification of the development needs for the next iteration.

3 Conclusion and Future Work

This deliverable, D6.1, presents the 1st iteration plan of the 17 SME- and DIH-driven experiments, comprising seven experiments in Four Motors regions and ten experiments in the nine Vanguard regions.

The outcomes presented in this deliverable have been based on information collected on TRIAL Handbook Chapter 1 and Chapter 3. The experiments concept and plan have been summarized and and grouped according to the identified clusters, which are:

i) Cluster 1 - Product Engineering and Lifecycle Management;
ii) Cluster 2 - Factory Efficient and Sustainable Manufacturing;
iii) Cluster 3 - Quality Control and Predictive Maintenance; and
iv) Cluster 4 - Robotics and Human Interaction.

For each experiment, the concept and the first iteration plan have been presented.

Finally, a new version of this deliverable will be presented on M24, which corresponds to the D6.1. This document will refine and update the information collected until now, and will include the plan of the experiments 2nd iteration (M25-M36). It will also include Open Calls winners' experimentations reports in AI REGIO facilities.