TALON

Autonomous and Self-organized Artificial Intelligent Orchestrator for a Greener Industry 4.0

Deliverable

D2.1-Use Case, KPIs, Requirements, Specification, Slices & Technology Enablers Definition Report

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Definitions and acronyms

AI	Artificial Intelligence
API	Application Programming Interface
AQI	Air Quality Index
AR	Augmented Reality
BDA	Big Data Analytics
CA	Consortium Agreement
CAMs	Clustering-based Anonymisation Mechanisms
CNC	Computerised Numerical Control
CNNs	Convolutional Neural Networks
DL	Deep Learning
DoA	Description of Action
DT	Digital Twins
DTC	Digital Twin Consortium
E2C	Edge-to-Cloud
EC	European Commission
EDM	Educational Data Mining
EE	Energy Efficiency
EHRs	Electronic Health Records
EU	European Union
FSL	Few-Shot Learning
GCS	Ground Control Station
GDPR	General Data Protection Regulation
GIS	Geographic Information System
GKE	Google Kubernetes Engine
GPU	Graphical Processing Unit
GRU	Gated Recurrent Unit
IoT	Internet of Things
GA	Grant Agreement
GANs	Generative Adversarial Networks
KPI	Key Performance Indicator
LA	Learning Analytics
LOS	Loss-Of-Signal
LSTM	Long Term Short Term
MDF	Multimodal Data Fusion
MCQ	Multiple Choice Questions
ML	Machine Learning
MoM	Minutes of the Meeting
MUST	Minimum Usable SubseT
NLP	Natural Language Processing
NFRs	Non-Functional Requirements
OCP	Open Compute Project Foundation
OT & IT	Operational and Information Technologies
PII	Personally Identifiable Information
POV	Point-Of-View
PPE	Personal Protective Equipment
QoS	Quality of Service
RBAC	Role-Based Access Control
RNNs	Recurrent Neural Networks
SotA	State-of-the-Art
SLA	Service Level Agreement
SRS	Software Requirements Specification
SSO	Single Sign-On
StRS	Stakeholder Requirements
SyRS	System Requirements Specification

TrLs	*Trust Levels*
UAVs	*Unmanned Aerial Vehicles*
UATVs/UxVs	*Unmanned Aerial and Terrestrial Vehicles*
UCs	*Use Cases*
VIP	*Value Innovation Platforms*
VR	*Virtual Reality*
XAI	*Explainable Artificial Intelligence*
YAML	*YAML Ain't Markup Language*

Disclaimer

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Executive Summary

The vision of TALON is to design and develop next-generation industrial systems in terms of performance, adaptation, explainability, trustworthiness and transparency. TALON aims at sculpturing the road towards the next industrial revolution by developing a fully automated AI architecture capable of bringing intelligence near the edge in a flexible, adaptable, explainable, energy and data efficient manner.

Deliverable D2.1 Use Case, KPIs, Requirements, Specification, Slices & Technology Enablers Definition Report, hereafter referred to simply as D2.1, details the four (4) Use Cases (UCs) which will be used in the TALON project to validate the AI Orchestrator and capabilities of the platform, while conversely indicates ways by which UCs will benefit through TALON in achieving their business goals. The process begins by presenting the TALON stakeholders and their goals, depicting UCs, requirements, and Key Performance Indicators (KPIs). Each use case is analysed based on its scope, objectives, and details, describing the “AS-IS” and “TO-BE” conditions and workflows, illustrating specific scenarios through steps, and particularizing on specific metrics. It should be noted that all four UCs in their respective chapters are aligned with the TALON key features as enumerated from the system’s functional and non-functional requirements, the technology enablers, and the state-of-the-art technologies. The present document formulates the input for all further technical design stages and serves as a reference point for all readers to understand the unique features derived from each Use Case.

1 Introduction

The main aim of the deliverable D2.1 Use Case, KPIs, Requirements, Specification, Slices & Technology Enablers Definition Report is to document TALON's demonstrator descriptions and technology enablers; identify the TALON supported Use Cases (UCs) and help analyse the needs risen from the demonstrators' challenges; and derive the requirements and stakeholders of the platform. Each use case follows the same approach by documenting the scope, objectives, and details; collecting information through a structured questionnaire on the execution context of each demonstrator; illustrating the "AS-IS" and "TO-BE" conditions and workflows; defining steps of execution to realise the scenarios; defining and enumerating the Stakeholder Requirements (StRS); providing tangible metrics of success through Key Performance Indicator definition. Besides, D2.1 serves as a reference point for the technical stages of the upcoming period and for deeper partner understanding of the UC scenarios.

The present D2.1 concludes the effort cycle of Task 2.1 Use Case, KPIs, Requirements, Specification, Slices & Technology Enablers Definition. This task was initiated at the beginning of the project, to be used as an input for D2.1 and the forthcoming deliverable of D3.1 Architecture & Platform Design Blueprint. The Use Cases are a cornerstone proof-of-concept for TALON. D2.1 will serve as input during the technical alignment phase of the TALON project where questions such as "which parts of the TALON architecture will be used" and "how does TALON assist in solving problems at hand or achieving KPIs for UCs." It should also be noted that D2.1 is a reference point throughout the project for all technical Work-Packages.

The structure of the present deliverable is as follows:

- **Section 2** presents the methodology we have followed to elicit the stakeholder requirements.
- **Section 3** identifies the TALON stakeholders and their goals.
- **Section 4** presents the: (i) UC1: Automatic UATVs Coordination; (ii) UC2: I5.0 Automation and Planning; (iii) UC3: AR/VR for Training and Maintenance; and (iv) UC4: Human-Robot Collaboration.
- **Section 5** presents the functional and non-functional requirements, as well as the traceability matrix.
- **Section 6** presents the technological axis and the state-of-the-art paradigms from the literature, existing projects and the industry for edge-to-cloud (E2C) computing, as well as the TALON Consortium's plans to extend these paradigms beyond the state-of-the art.
- Finally, **Section 7** draws the conclusions.

2 TALON Requirements Elicitation Methodology

The intention behind requirement elicitation is to identify quality Stakeholder Requirements (StRS) that can be implemented into software development modules. This chapter provides a comprehensive description of the activities and techniques followed in the reporting period within the TALON Consortium.

The requirements engineering method followed in TALON complies with the ISO/IEC/IEEE 29148:2018 [1] standard, which describes two main processes or practices.

Table 1. Requirements engineering processes.

Process	Purpose	Output
Stakeholder Requirements Definition Process	To define the requirements for a system that can provide the services needed by users and other stakeholders in a defined environment.	Stakeholder Requirements Specification (StRS)
Requirements Analysis Process	To transform the stakeholder, requirement-driven view of desired services into a technical view of a required product that could deliver those services.	Software Requirements Specification (SRS) System Requirements Specification (SyRS)

In this frame, we have specified the required workflows and processes to be implemented in the engineering activities that result in the Stakeholder Requirement Specification (cf. Sections 4.1.6, 4.2.6, 4.3.6, and 4.4.6). In the deliverable D3.1 Architecture & Platform Design Blueprint, we will extract and maintain a living Requirements Traceability Matrix. This matrix will establish traceability links between requirements and their sources, such as stakeholders, software, system, and business objectives. It will ensure that changes and updates to stakeholder requirements can be traced back to their origins, allowing for better management and decision-making throughout the TALON project lifecycle.

In a nutshell, during the first ten (10) months of the TALON project and in the context of Task 2.1 the activities performed are, as follows:

- Stakeholder identification: Initiated by identifying all the relevant stakeholders who have an interest in the system and the TALON project. This included end-users, subject matter experts, and other relevant parties.
- Stakeholder analysis: Understood the goals, perspectives, and expectations of each stakeholder.
- Elicitation techniques: Selected appropriate techniques to gather requirements from stakeholders. We conducted bilateral interviews, workshops and brainstorming per use case, collected five (5) questionnaires aligned with the different demonstration scenarios and documented in a structured and aligned manner the analysis results.

- Elicitation session preparation: Planned and prepared the elicitation sessions by creating an agenda, defining goals, and determining the scope of each session, including the topics to be covered, the key questions to be asked, and any specific artifacts needed.
- Elicitation sessions: Engaged the four (4) Use Case leaders (i.e., PROBO, FACTOR, KU and CERTH) of TALON through the chosen techniques, including interviews, workshops, and brainstorming. The outcome per use case was to provide detailed information about their needs, expectations, assumptions, prerequisites, and constraints.
- Requirements documentation: Captured and reported the elicited requirements in a structured manner. We used common templates and diagrams and unified enumerations to ensure that the requirements are clear, concise, and traceable back to their sources.
- Requirements prioritisation: Prioritisation has been applied to stakeholder requirements using the MoSCoW technique [2] to understand and manage priorities. The letters stand for:
    - **M**=Must Have.
    - **S**=Should Have.
    - **C**=Could Have.
    - **W**=Will not Have this time.
- Requirements verification: Verified that the documented requirements meet the intended purpose and are consistent with the stakeholders' expectations. In the following period, we will monitor and validate that the requirements are aligned with the overall goals and objectives of the project.

The steps followed during the requirements elicitation and analysis process are depicted in Figure 1 and detailed in the following sections.

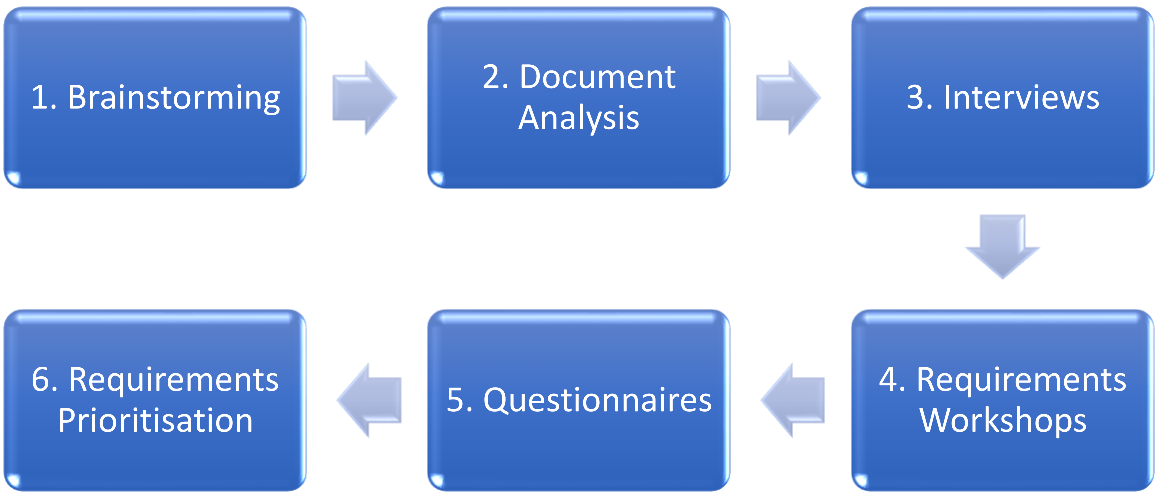

Figure 1. Stepwise Requirements Elicitation Process.

The TALON project employed six (6) different requirement elicitation techniques presented in the following.

2.1 Brainstorming

Brainstorming was used to identify the demonstration landscape per use case and produce a broad set of options. Its virtual sessions via organised tele-conference calls facilitated the clarification and answers to specific questions such as:

- What options are currently available to resolve the business needs?
- What technological factors are constraining the Use Case partner from moving ahead with an approach or option?
- What can the TALON Consortium and its technical partners do to solve business needs / problem?

Brainstorming fostered the collaboration among the TALON partners and facilitated the creation of an action plan, by defining specific tasks, assigning responsibilities, and setting deadlines, to implement the selected ideas.

2.2 Document Analysis

Document analysis facilitated the requirements elicitation by studying available documentation on existing approaches and solutions, identifying relevant information. In this frame, we analysed per use case the business plans, statements of work, existing processes, and system specifications, among others. Identifying and consulting all the potential sources of requirements had as an outcome a good requirements coverage.

2.3 Interviews

In TALON, we also conducted group interviews, while keeping a good balance to manage dynamics and keep the discussions concentrated. At least two (2) participants represented each use case partner. During the group interviews, we collaboratively collected notes as the Minutes of the Meeting (MoM) to capture the key points, insights, and any action items. At the end of each interview group, we summarised the main discussion points and planned the next steps or re-scheduled further interviews when it was necessary.

2.4 Requirements Workshops

Requirements workshops were held monthly. The workshops helped to generate ideas for new features, identify the current state (AS-IS) and the desired future state (TO-BE). Further details in the use cases elaborate on the scenarios in a stepwise manner for each case, and ensure alignment with TALON's technology enablers, technical offerings, and research objectives.

2.5 Questionnaire

A closed-ended questionnaire was circulated among the Use Case partners who were asked to answer a set of guided questions and provide clarifications regarding their demonstrator. All the collected questionnaires are provided in the Annex I – Questionnaires of D2.1. The questionnaire covered all relevant topics to facilitate the requirements elicitation and documentation. In the future, we will revisit these questionnaires during demonstrators' validation to identify any missing options or potential gaps.

2.6 Requirements Prioritisation

The use of MoSCoW technique [2] has been proven efficient for the TALON project. Each use case partner in collaboration with the responsible technical partner have indicated a prioritisation in the requirements implementation and support by the TALON System as **M**=Must, **S**=Should, **C**=Could, and **W**=Will not have. It overcame the problems associated with simpler prioritisation approaches which are based on relative priorities:

- The use of a simple high, medium, or low classification is weaker because definitions of these priorities are missing or need to be defined. Nor does this categorisation provide the business with a clear promise of what to expect. A categorisation with a single middle option, such as medium, also allows for indecision.
- The use of a simple sequential 1,2,3,4… priority is weaker because it deals less effectively with items of similar importance. There may be prolonged and heated discussions over whether an item should be one place higher or lower.
- The specific use of Must Have, Should Have, Could Have or Will not Have this time provides a clear indication of that item and the expectations for its completion.

The MoSCoW rules are defined as follows:

- **Must Have:** These provide the Minimum Usable SubseT (MUST) of requirements which the project guarantees to deliver. It answers to the question 'what happens if this requirement is not met?' If the answer is 'cancel the project – there is no point in implementing a solution that does not meet this requirement,' then it is a Must Have requirement. If there is some way around it, even if it is a manual and painful workaround, then it is a Should Have or a Could Have requirement. Categorising a requirement as a Should Have or Could Have does not mean it will not be delivered; simply that delivery is not guaranteed. These may be defined using some of the following:
    - No point in delivering on target date without this; if it were not delivered, there would be no point deploying the solution on the intended date.
    - Not legal without it.
    - Unsafe without it.
    - Cannot deliver a viable solution without it.
- **Should Have:** One way of differentiating a Should Have requirement from a Could Have is by reviewing the degree of pain caused by the requirement not being met, measured in terms of business value or numbers of people affected. Should Have requirements are defined as:
    - Important but not vital.
    - May be painful to leave out, but the solution is still viable.
    - May need some kind of workaround, e.g., management of expectations, some inefficiency, an existing solution, paperwork etc. The workaround may be just a temporary one.
- **Could Have:** These are the requirements that provide the main pool of contingency, since they would only be delivered in their entirety in a best-case scenario. When a problem occurs and the deadline is at risk, one or more of the Could haves provide the first choice of what is to be dropped from this timeframe. Could Have requirements are defined as:
    - Wanted or desirable but less important.
    - Less impact if left out (compared with a Should Have).
- **Will not Have this time:** These are requirements which the project team has agreed will not be delivered (as part of this period). They are recorded in the Prioritised Requirements List

where they help clarify the scope of the project. This avoids them being informally reintroduced later. This also helps to manage expectations that some requirements will simply not make it into the Deployed Solution, at least not this time around. Won’t Haves can be powerful in keeping the focus in the current stage of the project on the more important Could Haves, Should Haves and particularly the Must Haves.

3 TALON Stakeholders and Their Goals

This chapter provides a comprehensive description of the TALON platform stakeholder, application, and user roles analysis. Stakeholders are divided into three categories which are based on their role in the edge-to-cloud (E2C) ecosystem and their interests and relations are further investigated, to identify TALON's key stakeholders. Moreover, the applications that may benefit from TALON outcomes are classified into four categories and are further explored using stakeholder interviews.

3.1 The Stakeholders Categories

TALON platform is a complex system which potentially engages multiple stakeholder roles to fully exploit all its components and make it altogether available as a turn-key solution. Based on the technical analysis of the platform, the following paragraphs introduce the identified user roles for the TALON ecosystem. From the table below, we observe that the TALON ecosystem involves four technical roles with diverse responsibilities. Some of these responsibilities may overlap among users of the platform which, at first, may seem to lead to confusing interpretation of user role duties. However, usually for small software teams, the silver lining between roles in the development team are quite blur, with team members often taking responsibilities spread across different user roles (e.g., service developer and operator). In the following, the TALON Stakeholders and User Roles and descriptions are designed to clarify and summarize each actor's roles. Table 2 presents the Stakeholder Categories within the TALON project.

Table 2. Stakeholder Categories.

Categories	Description
First Responders (UC1)	First responders are individuals who are trained and equipped to be the first to arrive and aid in emergency situations. In the context of TALON, Firefighters can use the outcome of UC1 to monitor and promptly respond to fires, hazardous materials incidents, and other emergencies.
Police Officers (UC1)	Police Officers may respond to emergency calls, accidents, and incidents reported by the public. This can involve providing first aid or responding to emergency situations.
Manufacturing Employees (UC2; Scenario 1 and UC4)	Manufacturing employees are individuals who work in the manufacturing industry, which involves the production of goods on a large scale. They play a critical role in the creation, assembly, and packaging of various products across different sectors. Their key activities in TALON include quality control, production and assembly, safety, and compliance.
Optical Network Engineers (UC2; Scenario 2)	Optical Network Engineers are professionals who design, implement, and maintain optical computer networks for organisations. They are responsible for ensuring the smooth and efficient operation of network infrastructure, connectivity, and services.
In-Training Machine Operating Personnel (UC3; Scenario 1)	In-Training Machine Operating Personnel refers to individuals who are undergoing training to become proficient in operating specific machines or equipment within a manufacturing or industrial setting.

	These individuals are typically learning the skills and knowledge required to safely and effectively operate machinery used in production processes.
Remotely Connected Maintenance Expert or Personnel without maintenance expertise (UC3; Scenario 2)	A Remotely Connected Maintenance Expert, also known as a remote maintenance technician or remote support specialist, is an individual who provides technical assistance, troubleshooting, and maintenance services to clients or organisations from a remote location. Personnel without maintenance expertise will get guidance by the remote maintenance technician to resolve on-site issues.

3.2 The Applications Categories

Cloud Orchestration: Cloud orchestration refers to the process of automating and managing various cloud resources and services to optimize their deployment, provisioning, and configuration. It involves coordinating and controlling the interaction of different components and services within a cloud infrastructure to ensure efficient and reliable operations. Cloud orchestration typically involves the use of orchestration tools and frameworks to streamline the management of cloud resources. Here are some key aspects of cloud orchestration:

- Monitoring and Adaptation: Orchestration tools provide monitoring and scaling capabilities to ensure optimal performance and resource utilisation. They monitor resource usage, application performance, and system health, allowing automated scaling based on predefined policies and thresholds.
- Policy-based Governance: Cloud orchestration allows the enforcement of policies and governance rules across the cloud infrastructure. It ensures compliance with security, regulatory, and performance guidelines by automating policy enforcement and monitoring.
- Self-Service Provisioning: Cloud orchestration enables self-service provisioning, allowing users to request and provision cloud resources and services through a user-friendly interface. It empowers users to deploy and manage their applications and services within defined boundaries and policies.

Unmanned Aerial Vehicles Applications: Drones, also known as unmanned aerial vehicles (UAVs), have a wide range of applications across various industries. Their ability to fly autonomously or be controlled remotely makes them versatile tools for different tasks. Here are some common drone applications:

- Environmental Monitoring: Drones are used for environmental monitoring and conservation purposes. They can monitor wildlife populations, track changes in ecosystems, survey protected areas, and identify illegal activities like poaching or deforestation.
- Disaster Management: Drones play a crucial role in disaster management by providing real-time situational awareness. They can assess damage, monitor disaster-affected areas, and support emergency response efforts by delivering supplies, communication equipment, or medical aid to affected regions.
- Search and Rescue: Drones are deployed in search and rescue operations to locate missing persons in large or inaccessible areas. Equipped with thermal cameras, they can detect heat signatures and help rescuers identify individuals in need of assistance.

Manufacturing Applications: Manufacturing applications refer to the various ways in which technology and software are used in the manufacturing industry to improve efficiency, productivity, and overall operations. These applications can span a wide range of areas within manufacturing, including product design, production planning, inventory management, quality control, and supply chain management. Here are some common manufacturing applications:

- I5.0 Automation: Industrial robots and automation systems are extensively used in manufacturing for tasks such as assembly, material handling, welding, painting, and packaging. These technologies improve efficiency, precision, and speed in production processes.
- Internet of Things (IoT): IoT devices and sensors are deployed in manufacturing to collect real-time data from machines, equipment, and products. This data can be analysed to optimize processes, predict maintenance needs, and enable smart manufacturing.
- Data Analytics and Artificial Intelligence (AI): Advanced analytics and AI techniques are used to analyse manufacturing data, identify patterns, predict failures, optimize production, and enable predictive maintenance. These technologies help in improving decision-making and operational efficiency.

Edge, Mobile and AR/VR Applications: It refers to objects that are connected and able to interact with each other and extend the Internet to the physical world [87]. Augmented Reality (AR) and Virtual Reality (VR) have gained significant popularity in recent years due to their immersive and interactive experiences. E2C computing can manage the delay-sensitive tasks and some of the data volume to support such kind of applications. Here are some common AR and VR applications:

- Education and Training: AR is used in educational settings to create interactive and immersive learning experiences. It allows students to visualize complex concepts, explore virtual models, and engage in interactive simulations, enhancing understanding and retention of information.
- Industrial Maintenance and Repair: AR is used in industrial settings to provide real-time guidance and information during maintenance and repair tasks. Technicians can wear AR-enabled devices that overlay step-by-step instructions, visual cues, and relevant data onto the physical equipment, improving efficiency and reducing errors.
- Training and Simulation: VR is used for training in various industries, including aviation, military, healthcare, and heavy machinery operation. It offers realistic simulations that enable trainees to practice skills, experience scenarios, and develop muscle memory in a safe and controlled environment.

Figure 2 sketches the categories of applications that are expected to capitalize the benefits of the E2C technologies of TALON.

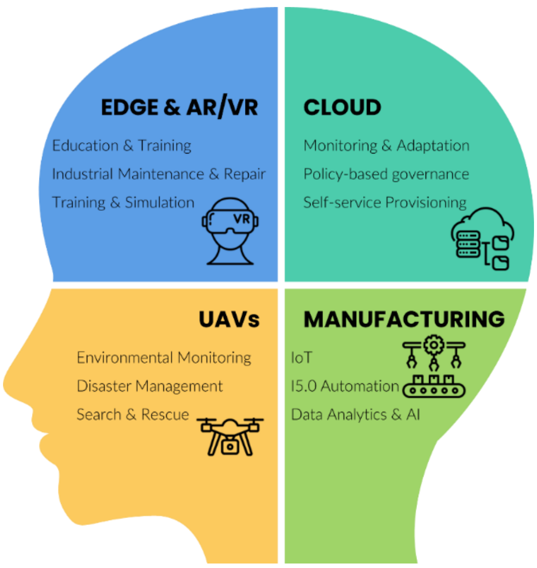

Figure 2. Categories of Applications.

3.3 The User Roles with the TALON System

The multiple benefits that E2C computing technology offers are broadening the range of potential user roles. These diverse user roles can derive advantages from this technology, whether they are individual users or organisations, from three different positions: (i) use services deployed at the edge and/or cloud, (ii) develop services deployed at the edge and/or cloud, and (iii) design and operate edge infrastructures. These positions form the three categories of user roles with the TALON System as presented in Table 3.

Table 3. User Roles with the TALON System.

Categories	Description
End user of a service / application	They could be individuals or groups of users who are interested in using edge/fog technology to enhance their approaches, to solve a problem in their market, to outperform competition etc.
Service developers / providers	They could be individuals or companies that possess the technical knowledge to develop and support E2C and AI applications. The main motivation for this layer of user roles, is to expand their expertise and operations to new markets using state of the art tools and technologies, having revenue as their final goal.
E2C infrastructure providers	This category of stakeholders includes large companies operating in the Information Technology market, who produce devices throughout the (IT) ecosystem (e.g., network devices, IoT devices, standalone micro-processors etc.) or who provide their infrastructure for communication establishment (e.g., Internet Service Providers, operators of cellular networks, etc.).

4 Use Cases, Requirements and KPIs

In this chapter, we delve into the four (4) primary use cases of the project, providing comprehensive descriptions, objectives, and identification of both current and desired states. However, the focus of our exploration is to identify the Stakeholder Requirements (enumerated as StRS) and Key Performance Indicators (KPIs) associated with each use case. The KPIs are defined and linked with each use case objectives to be easier for the reader to search for them if needed. By thoroughly understanding the needs and expectations of the stakeholders involved, we can establish clear benchmarks and metrics to measure the success and effectiveness of our future solutions.

4.1 UC1: Automatic UATVs Coordination

4.1.1 Use Case Description

Scope: Edge AI networks are expected to support several heterogeneous use cases with diverse set of requirements ranging from low-latency to energy-efficiency, security, flexibility, scalability, and trust. An indicative use case is Unmanned Aerial and Terrestrial Vehicles (UATVs or UxVs) coordination, which need to make fast and real-time decisions concerning stops and turns, based on image recognition, when confronted with critical situations, such as collision avoidance with unexpected aerial and/or pedestrian obstacles [1].

In the last decade, UATVs have been enlisted in an ever-increasing range of applications. The common characteristic of all UATVs is that they can be controlled remotely or programmed to travel autonomously over their coverage area. However, to achieve ultra-low latency and high autonomy for efficient operation, a high level of coordination is required that would constitute such mixed swarms of UATVs to perform optimised trajectory planning, real-time target tracking, and many others. At the same time, environmental awareness is becoming more present in our societies. A need has arisen to evaluate and control the pollution levels in our lower atmosphere and, especially, to determine sources over which it would be important to act to reduce these levels when certain limits are surpassed. To this end, TALON aims to substitute the handcrafted policies and the policies with low levels of automation used nowadays for UATV control in various applications with state-of-the-art intelligent techniques capable of highly automating and optimizing the orchestration of coordinated UATV swarms.

Objectives: The objective of this use case is to reduce the response latency AI algorithms need to be executed in the edge [4]. Connections with the cloud will still need to exist to feed and improve the "centralised" learning system, which in turn will feed back the aggregated data and learnings of smart devices at other UATVs and propagate them back to the central intelligence built and supported by the cloud [5]. This approach enables minimisation of the data load for analysis and transit; thus, increases the energy efficiency by means of decreasing the energy consumption, while significantly reducing the latency and the network usage [6]. The main objectives are highlighted below, while the respective KPIs definition is further detailed in Section 4.1.6:

Table 4. UC1 Objectives and KPIs.

Objective	KPI Identifier
Response latency reduction	KPI_01
UATV-to-Node communication latency	KPI_02

Energy Efficiency (EE)	KPI_03; KPI_04
Data Efficiency	KPI_03

Details: State-of-the-Art (SotA) centralised orchestrators are capable of trajectory planning with completeness guarantees, but require full state information, which is not available to UATVs, and are too computationally expensive for real-time operation. On the other hand, distributed solutions use local optimisation methods that can often cause UATVs to get trapped in local minima in cluttered environments. TALON aims to bridge this gap by using an Edge-to-Cloud (E2C) AI-Orchestrator that learns decentralised policies able to run efficiently in real-time. Therefore, it automatically synthesizes an efficient plan that does not allow UATVs to get trapped in many cases. Unlike other intelligent methods for trajectory planning, TALON's solution assumes a continuous space with time-varying neighbours and generates safe, dynamically coupled policies. Also, the TALON E2C AI-Orchestrator will consider both single and double integrator dynamics, as well as achieve significantly higher success rates compared to SotA UATV coordination approaches.

TALON's AI-orchestrator will reduce the response latency by broadening the execution field of AI algorithms in the E2C continuum and shifting the balance of intelligent systems operation towards the edge. This way, TALON will: i) enable minimisation of the data load for analysis and transit, ii) increase the energy efficiency by means of decreasing the energy consumption, and iii) reduce the latency and the network usage. However, connections to the cloud are still required to feed and improve the "centralised" learning system, which in turn will return the aggregated data and learnings to all UATV swarms and propagate them back to the central brain in the cloud.

4.1.2 Questionnaire Responses

A dedicated questionnaire has been answered by the UC1 team members and the PROBOTEK team, which can be found in Annex I, section 9.1.

4.1.3 AS-IS Conditions and Workflow

PROBOTEK has already developed two frameworks for coping with the difficult problem of orchestration of UATVs and the ability to cope with dynamic environments. The two frameworks are:

- AiRFLOW: Autonomous and Intelligent Robotic Flight for Orchestrated work (AiRFLOW) is an ecosystem of mini platforms, frameworks, utilities, applications and processes that manages and orchestrates entities in an abstraction layer with the scope to synchronize UxVs and various IoT devices, as depicted in Figure 3.

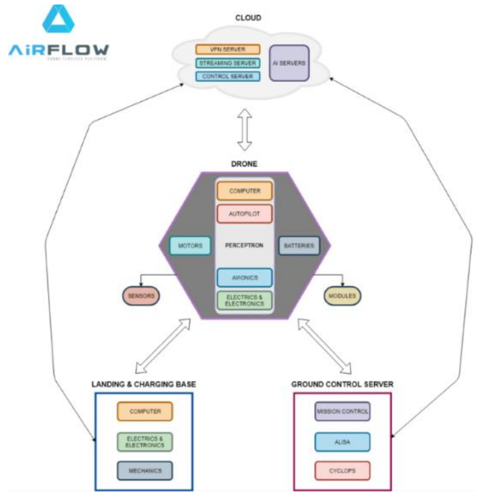

Figure 3. AiRFLOW Architecture Diagram.

- Dragonfly: It is a platform and interface for enabling real-time AI-based decision-making for dynamic environments. Dragonfly enables monitoring of the surroundings of a drone and integrates with sensors with the scope to automatically manage its path, routing, battery consumption etc., as depicted in Figure 4.

The Dragonfly module, currently, enables autonomous obstacle avoidance. The current process is automated for a single drone. It receives information from sensors and a Geographic Information System (GIS) to decide in real-time the next relative move. The Dragonfly module exists inside the drone or at the edge mobile suitcase (called TALOS) that interconnects the drone with the AiRFLOW ecosystem.

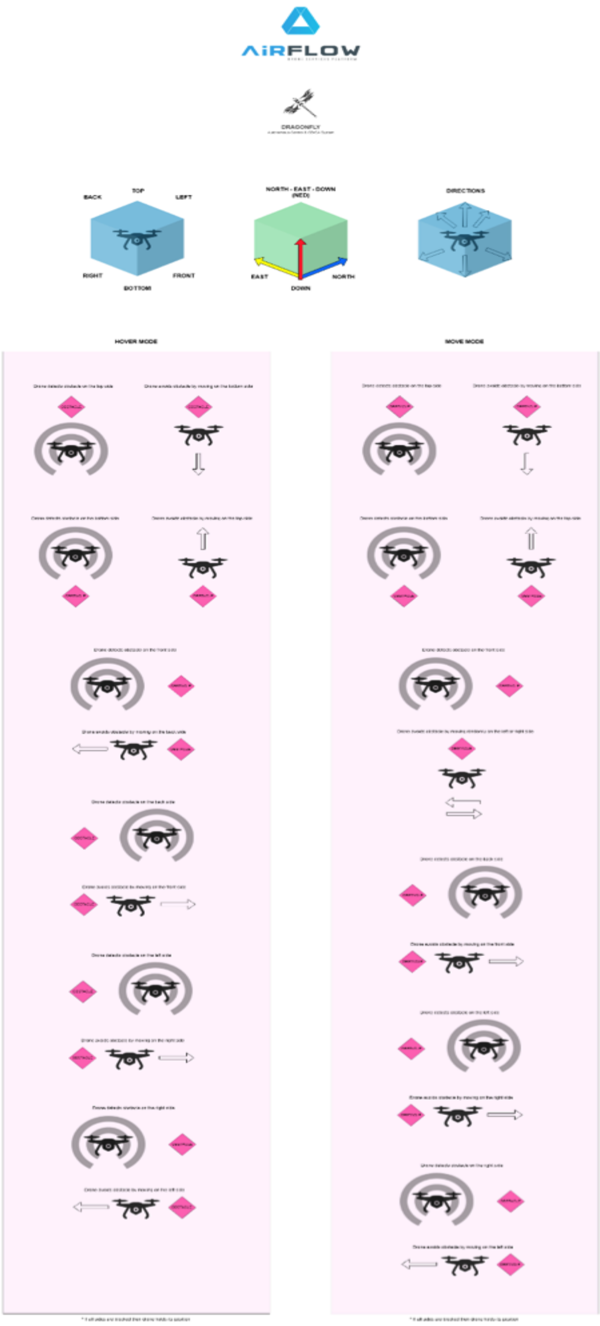

Figure 4. Dragonfly Process Diagram.

4.1.4 TO-BE Conditions and Workflow

The TO-BE conditions will enhance the current workflow by utilizing the cloud as the main orchestrator and at the same time will support control and autonomous obstacle navigation with more than one drone simultaneously. Finally, it will enable an aggregated and advanced system to gather data from all drones.

The use case assumptions and prerequisites to realise this use case are presented below.

Use case conditions
Assumptions
To realise this demonstration, we take the following assumptions: - Four (4) or more drones will be integrated in TALOS (PROBOTEK's mobile-GCS). - There will be enough space and pre-setup obstacles and a scenario to follow. - The test case will be to highlight the ability of a swarm to exchange information in real-time while coordinating autonomously.
Prerequisites
The prerequisites for UC1 are as follows: - Integration to be completed before the Pilot/Proof-of-Concept. - A clear predefined process needs to be defined. - An early cloud orchestrator mechanism and APIs ready to function with the local GCS.

4.1.5 Steps – Scenarios

This section presents UC1 demonstration scenario in steps.

Table 5. UC1 Usage Scenario.

Actor: First Responders (mainly fire fighters)
Alternative Actors: Police Officers
Actors interested in the outcome: Fire Department, Police, Civil Protection, Green/Environmental Organisations and Civilians
Scenario Overview: Four (4) drones fly in a cubical formation above a small area inspecting and tracking people, cars, and detecting fire & smoke. Based on ground sensors, the formation changes to track fire and provide a unified and complete picture to the operation team in a Command & Control Center.
Scenario: We need a small area with trees and ground. We will use two (2) types of sensors: • Fire (temperature); and • Gas (CO2). We will also use a couple of IP cameras. We will setup a few sensors on the ground and the trees to be able to gather historic data from the environment. We plan to place the cameras in the outskirts of the area. After that, we will use statistical information collected by the sensors to be triggered under certain thresholds. The statistical information collected will be used to train an AI model to suggest triggers for possible fire alerts when the cameras detect fire or smoke or both.

We will utilize four (4) drones for our scenario. The drones will be connected to a local base station and will be triggered to fly when detecting critical events or incidents by the sensors or cameras, or when receiving alerts for thresholds exceeded. The drones will begin to fly in a cubical formation. The formation assists in inspecting and tracking people, cars, and detecting fire and smoke (also from their own cameras). In the other end there is a Command & Control Center (C&CC) which monitors all the drone streams, ground camera streams and sensor events in real-time from a common interface. Based on various triggers from any sensor or camera or a drone camera, the formation changes dynamically to track fire and provide better coverage. The formation of the drones is not pre-set. Instead, it will be formed in an ad-hoc manner based on the above goals. This way, we will prove how a unified and aimed picture can be achieved by autonomously operated drones.
Benefits: Prevention, rapid detection of smoke and/or fire, early response to crisis, assistance to first responders, real-time view of the situation, tracking and counting of assets, and protection of human lives.
Challenges: Connectivity of the sensors, connectivity of the swarm of drones, ability to fly over a heated area with flames, telco coverage.

The steps that will be followed to meet this usage scenario are presented in Figure 5.

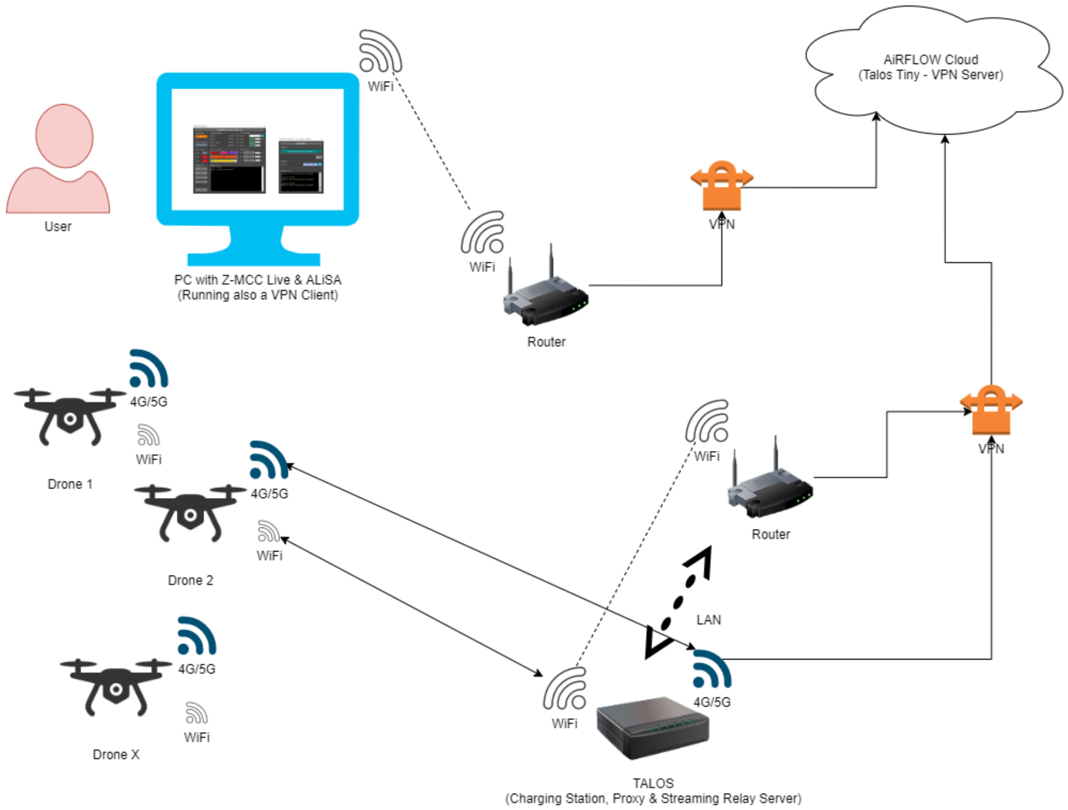

Figure 5. Use Case Diagram of UC1.

4.1.6 Requirements and KPIs

The Stakeholder Requirements (StRS) of Use Case 1 are presented in Table 6.

Table 6. UC1 Stakeholder Requirements.

Stakeholder Requirements			
Requirement ID	**Category name for requirements**	**Category description**	**Priority (M/S/C/W)**
StRS01	Secure access	Secure access should grant single sign-on (SSO), secure tunnelling, authentication, and certification only to designated end users, devices, and services / applications.	M
StRS02	Deterministic and bounded system and response time latency	The response time among processes and devices should be recorded to ensure that priorities and smart policies enable latency reduction.	S
StRS03	Inter-node or inter-process communication	The AI Orchestrator should interact with edge nodes and services to ensure decreased interaction to the possible minimum.	M
StRS04	Energy efficiency	The AI Orchestrator should enforce smart policies to preserve energy consumption on operated flights.	S
StRS05	Effective resource utilisation	Abundant monitoring probes both at the edge and cloud should collect, report and feed analytic pipelines to trigger runtime and offline adaptations.	C
StRS06	Dynamic resource provisioning	The analytic pipelines should predict via classification and regression and optimally dimension the provisioning of resources to support on demand adaptations.	M
StRS07	Autonomous obstacle navigation	The AI Orchestrator should communicate with more than one drones, drones should interact among them, and an optimal route navigation planning algorithm should compute optimal paths to avoid collision.	S
StRS20	Resource allocation and deployment	The system should optimally allocate computing resources to decrease inter-nodes communication and decrease transmission latency.	S
StRS22	Definition, Customisation and Monitoring of Metrics	The system should monitor and log data on how the processes and applications interact.	M

StRS23	Analytics execution	The system should monitor and log data on how the processes and applications interact and allocate CPU, RAM, energy, etc. to compute optimal execution analytics.	S
StRS25	Optimisations	The system should translate the optimal execution analytics onto SLAs and SLOs, enforce policies and support runtime adaptations by means of objective – target optimisation.	C
StRS26	Behaviour and Performance Monitoring	The system should monitor the processes and applications and extract behavioural execution patterns.	S

The Key Performance Indicators of Use Case 1 are presented in Table 7.

Table 7. UC1 Key Performance Indicators.

Key performance indicators			
ID	**Name**	**Description**	**Reference to mentioned use case objectives**
KPI_01	Latency reduction	Decrease response time to < 150ms	Latency reduction
KPI_02	UATV-to-Node communication latency	>90% decrease in UATV-to-Node feed forwarding latency	UATV-to-Node communication latency
KPI_03	EE and Data Efficiency	>80% reduction in transferred data/size	Energy Efficiency; and Data Efficiency
KPI_04	EE on operated flights	>30% energy conservation on operated flights	Energy Efficiency

4.2 UC2: I5.0 Automation and Planning

4.2.1 Use Case Description

Scope: Industrial automation and planning in manufacturing plants are equipped with an abundance of sensors, cameras, machines, and computer interfaces in a distributed network that need to cooperate in order to ensure high efficiency of the manufacturing procedure [7], quality of the products [8], high availability of the optical links and safety of the employees [9]. In this use case, the AI architecture should support high automation by means of self-optimisation as well as fast- and self-healing in case of attack, without sacrificing explainability, robustness, and/or accuracy [10].

In more detail, self-healing, and self-optimised systems, which use ML and distributed learning approaches, can be used to ingest a non-stop stream of data to make the machines more efficient [11]. In this scenario, an edge AI computing system notices that a feed tank, measured by means of accuracy levels, is low and informs the production machine to slow down to avoid running out of raw material contributing to high availability and efficiency. At the same time, it signals the upstream processes to speed up and notifies the plant operators via the digital twin interface about what is happening by means of explainable artificial intelligence (XAI) [12]. The core contribution of edge AI in this use case is to ensure the uninterrupted production by automating the various processes in the factory, increase the performance of the systems by utilizing novel ML and distributed learning techniques, enabling the machines to constantly self-heal or self-correct their processes, as well as provide explainable solutions for the management and augmentation of complete factory workflow.

Objectives: The objective of this use case is to enrich with explainable results the understanding of optical link faults, evolve manufacturing towards the zero-defect paradigm and the direction of the next industrial era, i.e., I5.0. Specifically, by studying and optimising the processes and workplans of industrial manufacturing, it is possible to not only considerably reduce the costs of the company's resources related to the avoidance or even treatment of defective products, but also the refinement of the overall production chain regarding efficiency, safety, adaptability, and flexibility. To achieve this, TALON will evolve the SotA manufacturing line into a qualification system based on a continuous process validation sustained on AI to certificate its manufacturing quality level and guarantee the inalterability of product and process data to its customers. The main objectives are highlighted below, while the respective KPIs definition is further detailed in Section 4.2.6:

Table 8. UC2 Objectives and KPIs.

Objective	KPI Identifier
Quality ratio increase	KPI_05
Reduction of scrap material	KPI_06
Lower environmental footprint	KPI_07
Increase in effectiveness and production line optimisation	KPI_08
Increase in availability	KPI_09
Better explain the reason of faulty optical links and decrease their instances, and therefore increase the reliability of optical fault analysis	KPI_10; KPI_12
Increase in overall equipment effectiveness	KPI_11

Details: This demonstrator will focus on approaching AI to the manufacturing processes by self-automating and self-healing the machine's behaviour, avoiding defects and optimizing the effectiveness of the factory, therefore, ensuring the highest quality level on the production. To this end, the demonstrator will advance the state-of-the-art by investigating the point of failure of optical interconnections, monitoring and classifying different loss of signal scenarios (i.e., scenario supported by TEI) by applying explainable AI techniques and thus boosting the transparency and trustworthiness of optical communications. In addition, the demonstrator will monitor the status of the tools inside the manufacturing machines by harvesting the data from sensors installed inside the machines and the shopfloor of FACTOR. It will also demonstrate the reusability of the developed explainability mechanisms by adopting their outcomes and quantifying the results. Specifically, the quality of the manufactured parts will be measured through intelligent vision cameras. Both data will be analysed by edge AI algorithms, finding patterns that can lead to equipment breakages, faulty parts, and machine problems and automating the corrective actions to avoid them. Also, by creating a balance between the flexibility of manual supervision, the efficiency and repeatability of machines, it is possible to achieve production flexibility, product mix and reconfiguration. Digital Twins (DT) of physical systems will be employed for testing and validating production strategies before realizing them.

This demonstrator will highlight and intelligently orchestrate the resources available throughout the E2C continuum of the I5.0 ecosystem to perform the necessary analysis, structuring and normalizing of sensing data, as well as derive an optimal coordination plan and manufacturing line optimisation. TALON's developed technologies will lead industrial manufacturing to qualify the health of the processes and ensure the quality of the products, avoiding defects and optimizing the processes. Data gathered by the sensors will be aggregated in an organised and useful way to be analysed by the algorithms which will learn the correlation between variables, identify the most critical path of the production line and how to interfere to avoid future failures and defects. A feedback loop between the algorithm and the machine variables will be implemented, enabling corrective actions determined by the algorithms to avoid future errors. Therefore, the optimisation of the process, the avoidance of wasted material and the improvement of energy efficiency will be key benefits of this demonstrator.

This demonstrator will also investigate the root cause for a fibre interconnection fault due to a loss-of-signal (LOS). The more rapid is the classification the faster the network operator can fix the issue or put in place further investigation actions. Current level of information to the operator is binary information (loss of signal alarm on/off). With the data driven approach the information can be more precise and provide a first estimation of the root cause together with the basic alarm information. In addition to the binary link presence (i.e., LOS alarm ON or OFF), it is possible for optical devices to read a time series of the received optical power before and during the link drop. This requires a specific data collection process by the optical module host unit, producing a time series of power readings associated to the LOS information. The XAI capabilities of TALON will provide a classification of the failure based on the time series and an explanation of the classification to support further fault investigation.

4.2.2 Questionnaire Responses

A dedicated questionnaire has been answered by the UC2 team members and the FACTOR, UPV and TEI teams, which can be found in Annex I, section 9.2.

4.2.3 AS-IS Conditions and Workflow

As far as the Scenario 1 is concerned focusing on the zero-defect cases and the minimisation of the scrap production, when the raw material arrives to FACTOR, it is stored in the machine until it is needed for the machining process. The engineering team establishes the configuration of the operation parameters in the process and in the machine, depending on the features of the part to be manufactured. During the machining process, the machine is monitored, and the data are collected from several sources, including:

- The CNC machine: temperatures in the engines (e.g., signals_data.csv) and alarms (e.g., alarms_data.csv).
- External Sensors: temperatures, humidity, and power consumption (e.g., sensor_data.csv).

During the manufacturing, quality check of the manufactured parts is conducted. The procedure is that only one part is checked per period (e.g., one part per hour is checked) so that, if it is faulty, all the parts in that period are checked or are discarded. The fact that the quality check is performed periodically generates large amount of scrap, since it is possible that the machine has been manufacturing faulty parts during the whole period.

The quality check is also registered (e.g., in the quality_data.csv file) and, as said previously, if the checked part has defects, it will generate scrap and the operation parameters shall be reconfigured by the engineering team. In case that the quality of the manufactured parts is within the range of the stablished tolerances, the manufacturing will continue without changes, except for minor modifications, performed by the operator, if minor deviations are detected.

The lathe that will be used as pilot in the project is the "Nakamura 2". This machine has two-opposed spindles, milling on both turrets and a Y-axis on the upper side, ensuring that flexible machining is performed simultaneously on either spindle with the upper and lower turrets.

Figure 6. Machine Nakamura 2.

There are various types of data that are already being collected:

- Data from the CNC machine: From the machine, using the software MTLINKi, we monitor the temperatures of the engines and alarms from the machine, which can indicate any malfunction. These data are stored in csv files. Sample data from alarms and temperatures monitored by the MTLINKi software are presented in Figure 7 and Figure 8.

DateAndTimeOf Occurrence	TimeSpanOfOccurrence(minute)	EquipmentName	MachineName	AlarmKind	AlarmNumber	AlarmMessage
17/10/2022 21:11	2.85	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA
17/10/2022 21:10	0.88	NAKA 2	Nakamura2	PS	91	PATH02 NO REALIZA RETORNO A REFERENCIA EN PARO AVANCE
17/10/2022 21:10	0.98	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA
17/10/2022 21:09	0.84	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA
17/10/2022 19:19	4.4	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA
17/10/2022 18:00	0.05	NAKA 2	Nakamura2	SV	409	PATH01 (Z1)DETECCIÓN PAR ANÓMALO
17/10/2022 17:59	0.05	NAKA 2	Nakamura2	SV	409	PATH01 (Z1)DETECCIÓN PAR ANÓMALO
17/10/2022 17:43	9.15	NAKA 2	Nakamura2	SV	409	PATH01 (Z1)DETECCIÓN PAR ANÓMALO
17/10/2022 17:40	1.14	NAKA 2	Nakamura2	SV	409	PATH01 (Z1)DETECCIÓN PAR ANÓMALO
17/10/2022 17:39	0.27	NAKA 2	Nakamura2	SV	409	PATH01 (Z1)DETECCIÓN PAR ANÓMALO
17/10/2022 17:31	6	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA
17/10/2022 15:58	8.78	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA
17/10/2022 14:15	3.75	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA
17/10/2022 12:49	1.12	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA
17/10/2022 11:20	1.64	NAKA 2	Nakamura2	MC	3123	PATH01 CAMBIO DE BARRA

Figure 7. Sample of alarms collected by Nakamura 2.

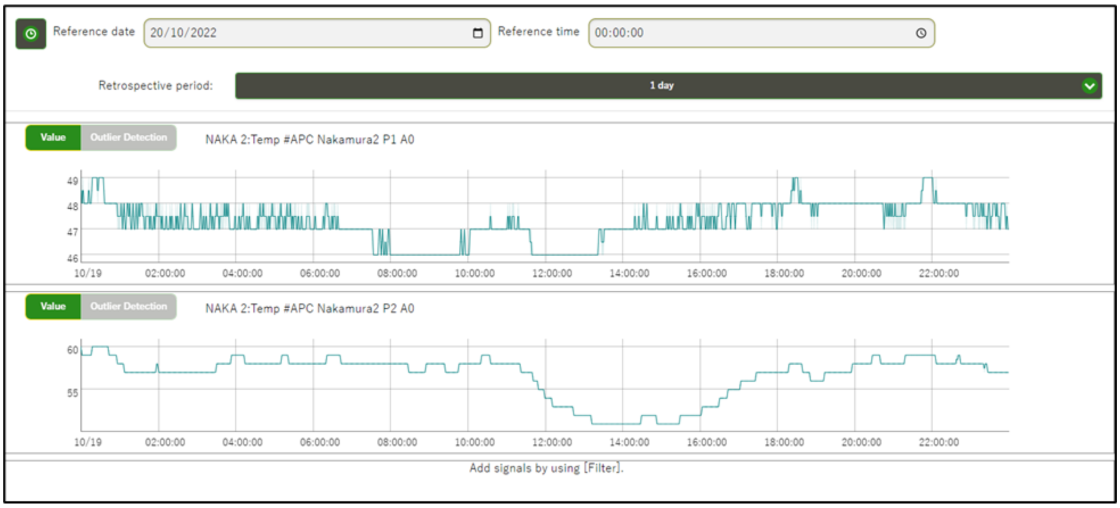

Figure 8. Temperatures monitored from Nakamura 2 presented by the MTLINKi Dashboard.

- Data from external sensors: There are also several sensors installed in the Nakamura 2, including: (i) power consumption in the turrets (3 sensors); (ii) total power consumption (1 sensor); temperature in engines (6 sensors); room temperature (1 sensor); room humidity (1 sensor); and lubricant temperature (1 sensor). These data are being collected in MySQL and can be export to csv.

#	consumo_tot	corriente_x_torreta_inferi	corriente_z_torreta_inferi	corriente_z_torreta_superi	humed
1	5.86661	-0.339988	0.072338	-0.177228	69.864
2	8.3261	-0.325521	0.072338	0.36169	69.8785
3	8.26823	-0.325521	0.0651042	1.7976	69.9002
4	15.7697	3.1901	0.0542535	-0.169994	69.9002
5	10.9664	-0.318287	0.191696	-0.169994	69.9002
6	7.8559	-0.318287	0.0759549	-0.169994	69.9508
7	8.15249	-0.325521	0.072338	-0.169994	69.9363
8	8.04398	-0.325521	0.0542535	-0.169994	69.9291
9	8.26099	-0.325521	0.0759549	-0.169994	69.9363
10	8.44184	-0.325521	0.072338	-0.173611	69.958

Figure 9. Sample of data collected by external sensors (MySQL).

consumo_total	corriente_x_torreta_inferior	corriente_z_torreta_inferior	corriente_z_torreta_superior	humedad_amb	temperatura_amb	temperatura_motor_2	temperatura_motor_3	temperatura_motor_5	temperatura_motor_7	temperatura_motor_8	temperatura_motor_9	temperatura_taladrina	fechahora
793.547	-0.318287	0.546152	0.672743	57.458	288.035	497.504	349.935	399.523	428.313	499.385	364.656	355.216	21/10/2022 12:15
173.394	-0.303819	0.072338	-0.188079	574.725	288.115	497.432	34.979	399.667	427.988	49.906	364.583	354.275	21/10/2022 12:14
78.559	-0.303819	0.0397859	-0.180845	574.725	288.115	497.432	349.863	399.306	428.349	498.843	36.48	354.275	21/10/2022 12:14
796.441	-0.318287	0.0217014	-0.141059	57.458	288.035	497.323	349.863	39.974	428.639	498.626	36.48	354.275	21/10/2022 12:14
911.458	-0.245949	0.036169	-0.180845	574.725	288.035	497.432	34.979	39.992	42.806	498.806	364.619	353.588	21/10/2022 12:14
806.568	-0.26765	0.0397859	-0.180845	57.487	288.115	497.541	349.826	399.523	428.168	498.806	364.764	35.319	21/10/2022 12:14
792.824	-0.303819	0.260417	-0.177228	575.087	288.035	497.613	349.609	39.974	428.313	498.951	364.619	353.045	21/10/2022 12:14
806.568	-0.318287	0.036169	0.546152	575.087	288.035	497.504	349.935	399.776	42.853	498.517	364.764	353.045	21/10/2022 12:14
10.272	119.358	0.0434028	-0.177228	574.942	288.035	497.251	349.609	399.523	428.602	498.806	364.837	353.045	21/10/2022 12:14
835.503	-0.318287	0.0542535	-0.195312	574.942	287.876	49.736	349.935	399.486	42.853	498.698	364.764	353.045	21/10/2022 12:14
844.907	-0.318287	0.036169	-0.195312	57.487	287.876	497.432	349.826	400.065	428.349	498.843	364.764	352.973	21/10/2022 12:14
826.099	-0.318287	0.0578704	-0.159144	574.725	287.876	497.179	349.826	399.414	428.168	498.517	364.692	351.924	21/10/2022 12:14
823.206	-0.318287	0.115741	-0.195312	57.458	288.035	49.736	349.682	399.378	428.349	498.336	364.873	351.816	21/10/2022 12:14
690.828	-0.318287	0.036169	-0.16276	574.725	287.876	497.034	349.501	399.414	428.349	498.481	364.764	351.816	21/10/2022 12:14
858.652	-0.318287	0.795718	-0.188079	57.458	288.035	497.179	349.754	399.378	428.313	498.409	364.837	351.816	21/10/2022 12:14

Figure 10. Sample of data collected by external sensors (csv).

- Data related to quality check: Regarding the quality of the manufactured parts, the check is performed manually and periodically. For example, the machine is manufacturing 30 parts per hour but only one of them is checked, if the check is done every hour, it is possible that the machine has been manufacturing faulty parts during a whole hour. This is the reason of the big amount of scrap in some cases and what needs to be improved. Every check is performed by the operator and the results are introduced manually in an excel file, indicating the measurement of every dimension and if it is inside the tolerances (green), out of the tolerances (red) or in the tolerances but deviated (yellow).

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Referencia:	0959150050				9.1	10	13	14
TOL SUPERIOR					12.70	14.60	5.00	15.000
NOMINAL					12.60	14.50	4.75	14.970
TOL INFERIOR					12.50	14.40	4.50	14.948
METODO					PIE DE REY	RELOJ COMP	RELOJ COMP	MICROMETRO
FRECUENCIA					1 HORA	1 HORA	1 HORA	1 HORA
Fecha	Hora Inicio	Hora Fin	Nº Operario	Comentarios	Variable	Variable	Variable	Variable
20/07/2022	3:51	3:51	139	Etiqueta Roja 000 Eti	12.600	14.730	4.850	14.990
20/07/2022	3:51	3:55	95	Etiqueta Roja 0	12.620	14.500	4.780	14.990
20/07/2022	5:11	5:13	95	Etiqueta Roja 0	12.610	14.500	4.770	14.980
20/07/2022	6:05	6:10	200	Etiqueta Roja 0	12.590	14.510	4.780	14.970
20/07/2022	7:09	7:14	200	Etiqueta Roja 0	12.580	14.500	4.780	14.980
20/07/2022	8:26	8:28	200	Etiqueta Roja 0	12.580	14.520	4.765	14.980
20/07/2022	9:11	9:25	200	Etiqueta Roja 0	12.570	14.510	4.810	14.960
20/07/2022	10:19	10:22	200	Etiqueta Roja 0	12.580	14.506	4.750	14.980
20/07/2022	11:10	11:13	200	Etiqueta Roja 0	12.590	14.510	4.780	14.980
20/07/2022	12:16	12:24	200	Etiqueta Roja 0	12.600	14.508	4.780	14.980
20/07/2022	13:20	13:23	200	Etiqueta Roja 0	12.590	14.520	4.800	14.980
20/07/2022	14:14	14:17	184	Etiqueta Roja 0	12.610	14.510	4.780	14.980
20/07/2022	14:55	15:00	184	Etiqueta Roja 0	12.610	14.510	4.780	14.980
20/07/2022	16:04	16:07	184	Etiqueta Roja 0	12.590	14.500	4.770	14.980
20/07/2022	16:53	16:56	184	Etiqueta Roja 0	12.610	14.500	4.770	14.980
20/07/2022	17:56	17:59	184	Etiqueta Roja 0	12.600	14.510	4.820	14.980
20/07/2022	19:05	19:07	184	Etiqueta Roja 0	12.610	14.500	4.790	14.980
20/07/2022	20:06	20:08	184	Etiqueta Roja 0	12.620	14.510	4.790	14.980
20/07/2022	20:50	20:53	184	Etiqueta Roja 0	12.600	14.500	4.790	14.980
20/07/2022	22:08	22:14	95	Etiqueta Roja 0	12.620	14.500	4.780	14.990
20/07/2022	22:52	22:55	95	Etiqueta Roja 0	12.610	14.500	4.770	14.980

Figure 11. Sample of quality check data.

The AS-IS workflow of the Scenario 1 focusing on zero-defect cases and the minimisation of the scrap production is depicted in Figure 12.

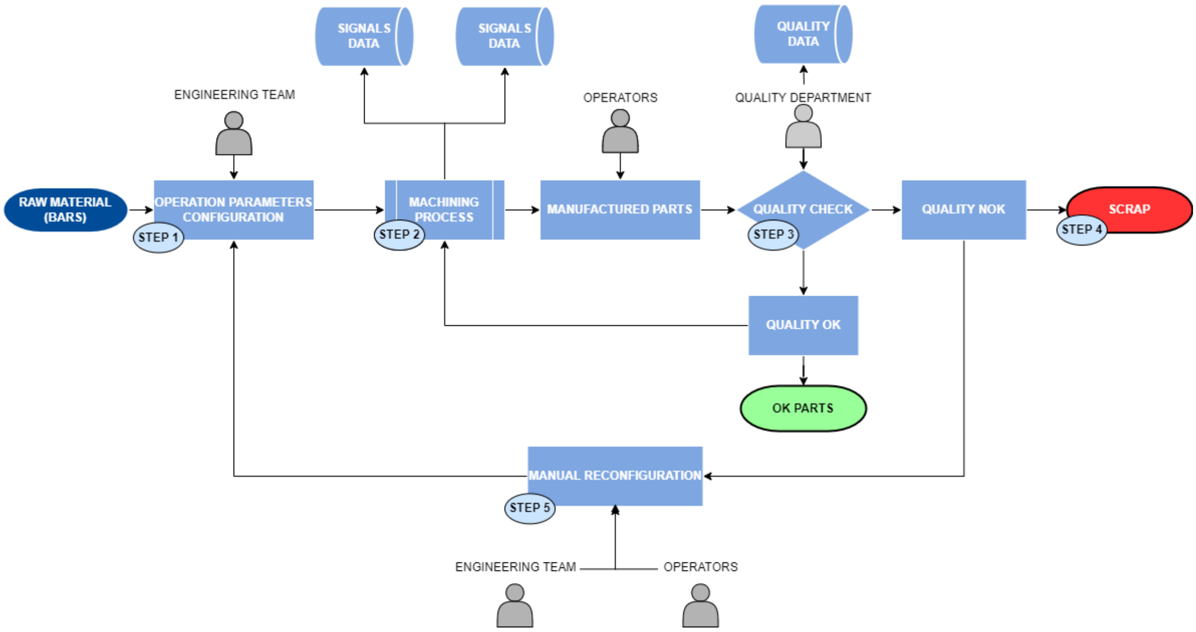


Figure 12. UC2 Scenario 1 AS-IS Workflow.

As far as the Scenario 2 is concerned focusing on the explanations of optical link faults, the simple alarm is currently mediated by a complex network management system. To realise this demonstration, it would be possible to embed the existing dataset of loss-of-signal events and make them available to the TALON components as if they were coming from a physical HW. In this scenario, we will investigate the classification of the root cause for the fibre interconnection faults. A primary option to troubleshoot the network outage and justify why this happens is to explain the behaviour of the loss-of-signal. The more rapid is the classification the faster the network operator can fix the issue or put in place further investigation actions. Current level of information to the operator is reporting a binary classification result (i.e., loss of signal alarm on/off). With the data driven approach the information can be more precise and provide a first estimation of the root cause together with the basic alarm information. Figure 13 and Figure 14 show the current action flow and how the information is being logged.

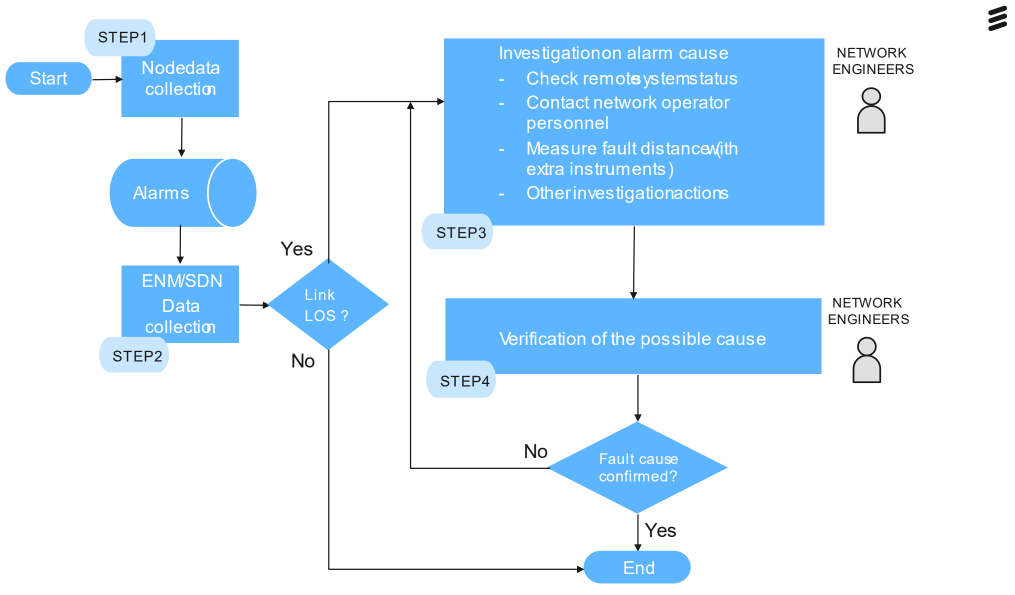


Figure 13. UC2 Scenario 2 AS-IS Workflow.

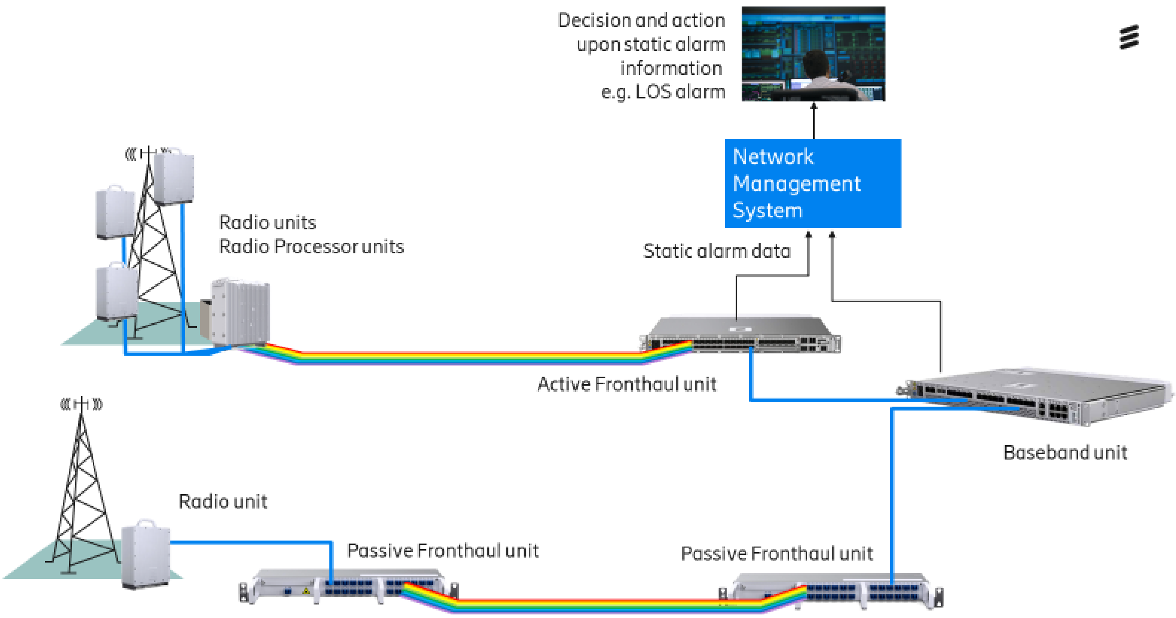


Figure 14. UC2 Scenario 2 AS-IS Use Case Diagram.

4.2.4 *TO-BE Conditions and Workflow*

The TO-BE conditions will enhance the current manufacturing workflow by achieving an on-line connection between the digital twin and the manufacturing line. The dynamic simulation will enable quantitative assessment of the proposed solution, while the DT will be continuously evolved from manual data syncing to automated and real-time data thus enabling greater usefulness at system level. Specifically, the TO-BE conditions of the manufacturing use case are twofold. On the one hand, it will apply AI on/near the manufacturing line by i) eliminating the efficiency failures caused by the state of the cutting lubricant, ii) minimizing the breakage of the cutting tools (e.g., due to the lack of cutting lubricant, or the blockage of cooling channels of the tools), iii) facilitating diagnosis and evaluation of breakage incidents, iv) ensuring that the tools work within their optimum range, v) predict equipment damage, and vi) implementing an efficient inspection of all manufactured parts, particularly complex parts. On the other hand, this uses case will take advantage of the explainable, optimised and scalable AI tools provided by the TALON ecosystem in order to improve the investigation of faulty optical links by i) recording the shape of RX power drop, ii) determining its correlation with the root cause, iii) getting inference from the TALON AI tools, iv) exploiting the combination of different AI models, v) comparing different hyperparameters and training datasets, vi) explaining correct and incorrect results, and vii) aggregating the results. TALON will integrate the latest industrial automation systems and robust optimal communications for fast and optimal manufacturing operations in combination with novel AI models, techniques, and capabilities, thus combining robot strength, velocity, predictability, repeatability and precision with orchestrated intelligence, flexibility, and reusability.

The use case assumptions and prerequisites to realise the scenarios of this demonstrator are presented below.

<table>
<tr><th>Use case conditions</th></tr>
<tr><td>Assumptions</td></tr>
<tr><td> Scenario 1: Assumptions for zero-defect cases and the minimisation of the scrap production
This use case will be demonstrated in the FACTOR facilities and using real data coming from the machine Nakamura 2. The data that will be collected and used for the development will be real data, generated during the normal daily work of the machine in the real environment of a manufacturing SME.
Scenario 2: Assumptions for the optical link fault classification scenario
Optical technology related assumptions:
The SFP optical modules used for the data collection of the RX power samples do support “fast” digital diagnostic polling, i.e., can record and expose the received power samples with a granularity down to 5ms.
The SFP module host units can perform the required data collection through the SFP optical modules serial interface.
The power drop events are properly triggered in the data collection process, i.e., the reported events are relevant solely to the transitions happening during the RX Loss of Signal events. This triggering can be performed by the host or in principle by the SFP module.
The above assumptions are fulfilled in the dataset included as TEI contribution in the TALON project, but they are not necessarily valid for all SFP modules in the market nor for all SFP modules hosts in a network. The proposal of the introduction of such assumptions as an optical product best practice is in scope to the TALON project in the standardisation work package. </td></tr>
<tr><td>Prerequisites</td></tr>
<tr><td> The prerequisites for UC2 are as follows:
Scenario 1: Prerequisite for the zero-defect cases and the minimisation of the scrap production </td></tr>
</table>

Usefulness and quality of the data to be confirmed before development; and A data repository that guarantees the correct storage of data for the development of the use case. **Scenario 2:** Prerequisite for the optical link fault classification scenario: Dataset related prerequisite: The RX power drop events, recorded as time series in the TEI dataset, can be used to train a supervised learning model.

The TO-BE workflow regarding the Scenario 1 of this use case is depicted in Figure 15.

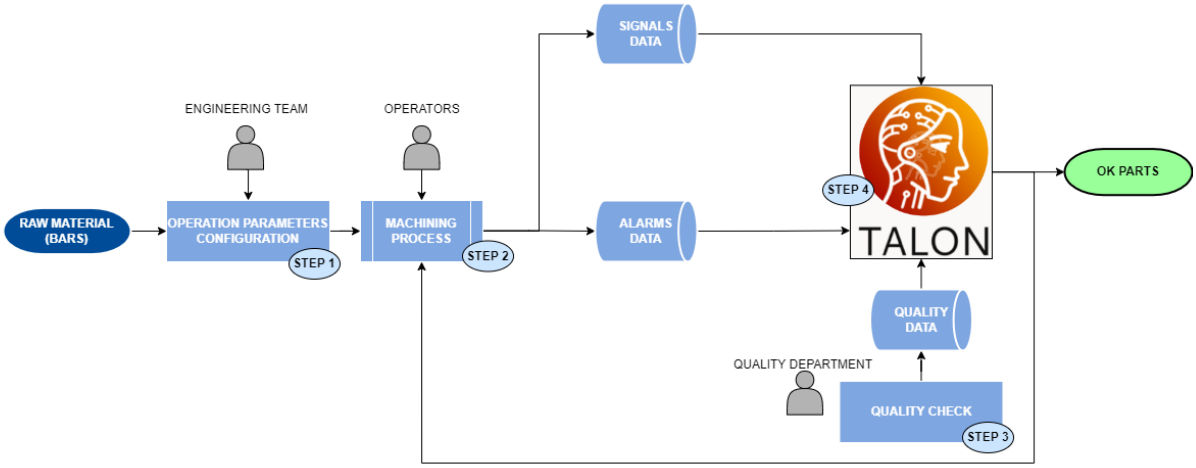


Figure 15. UC2 Scenario 1 TO-BE Workflow.

The TO-BE workflow regarding the Scenario 2 and the explainability of optical link faults is depicted in Figure 16 and Figure 18. A labelled dataset with power drop time series around the LOS events will be made available to the TALON Consortium to realise this scenario. As depicted in Figure 16, the RX Power time series collection is happening only around the power drop. Then the XAI data container is further used in STEP 4 to verify the possible cause of the LOS events.

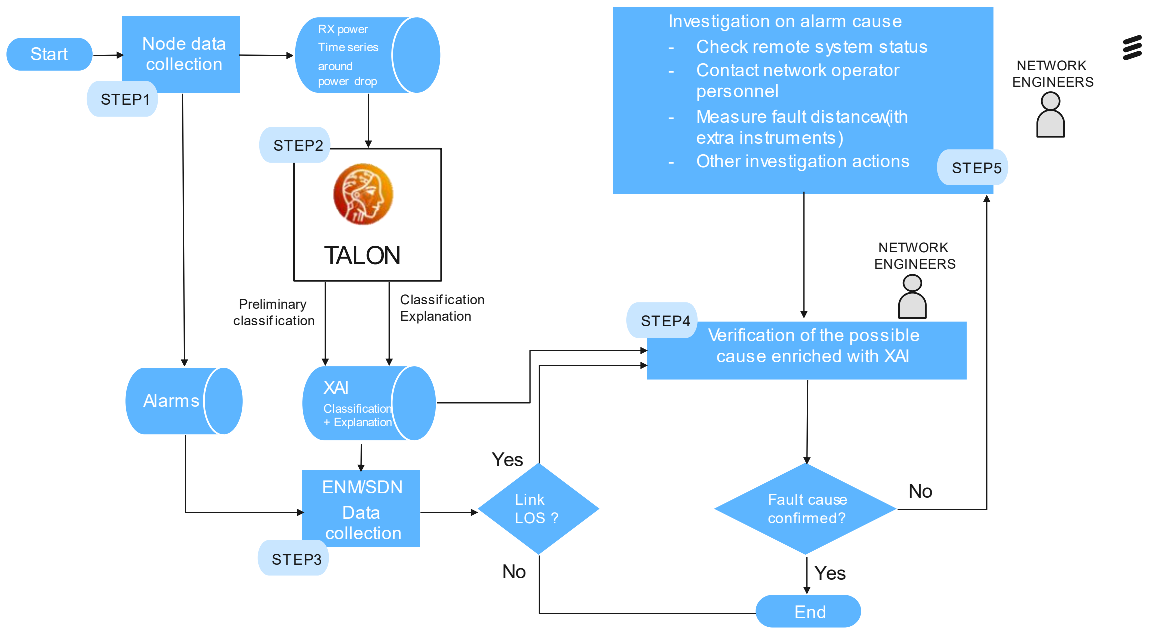


Figure 16. UC2 Scenario 2 TO-BE Workflow.

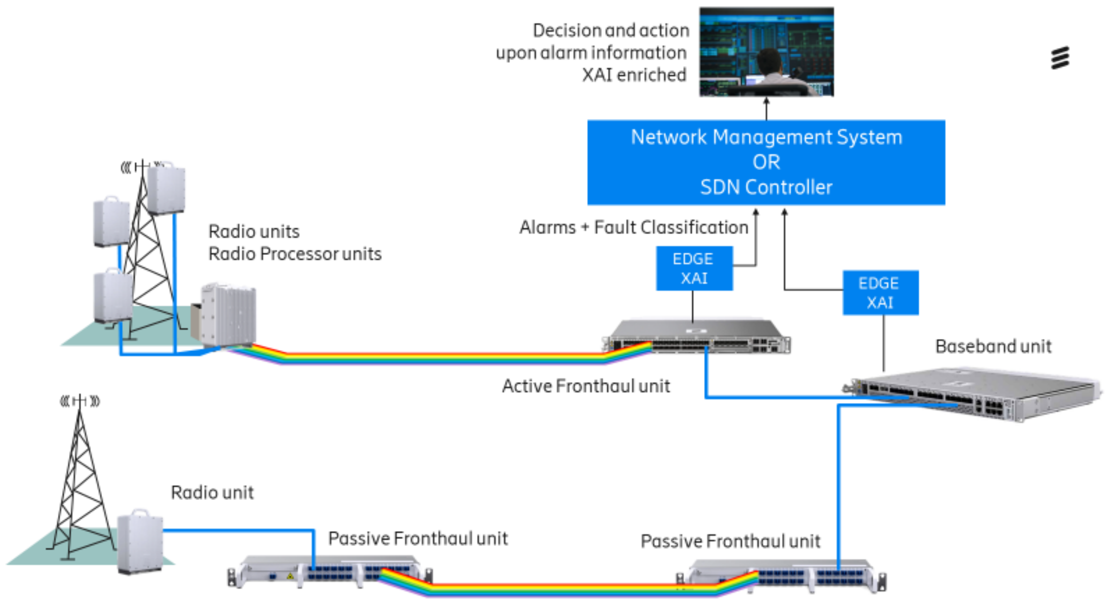


Figure 17. UC2 Scenario 2 TO-BE Use Case Diagram.

The assumptions and the expectations upon UC2, Scenario 2 are that the RX power shape in case of Loss-Of-Signal event is correlated with the cause of the fault itself. This assumption can be validated by training one or more classification models with a dataset of RX power drop time series collected while reproducing a known set of failures.

Extending the classification models with the introduction of explainability may improve the trustworthiness of the process and facilitate its introduction in a network management or network controller system.

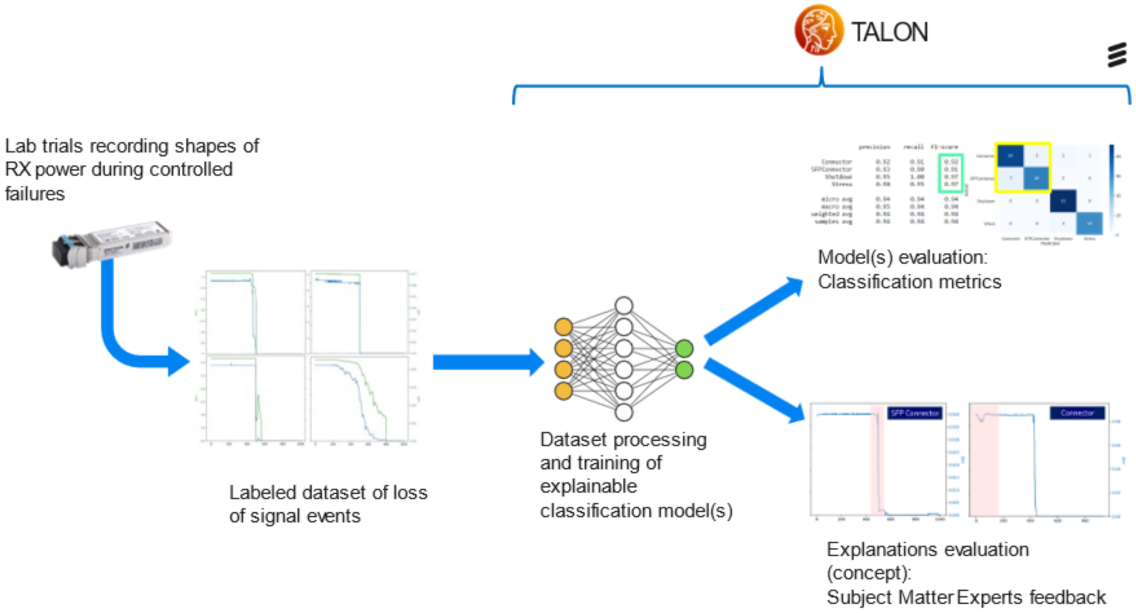


Figure 18. UC2 Scenario 2 details.

4.2.5 Steps – Scenarios

This section presents UC2 demonstration scenarios in steps.

Table 9. UC2 Usage Scenario.

Actor: Employees of the Manufacturing Department from FACTOR; Network engineers dealing with optical communications from TEI
Alternative Actors: Employees from the Engineering Department and the Quality Department
Actors interested in the outcome: All the departments in the company, especially the Quality Department; Customers that need better quality in the manufactured parts; and Metal Machining companies, which have similar problems and objectives.
Scenario Overview: During the manufacturing of metal parts in a machining process, all the data collected in real time from the machine and from the manufactured parts must be analysed instantly by trained AI / ML algorithms so that it could be possible to predict a malfunction in the machine that can lead to a decrease in the quality of the parts.
Scenarios Regarding the **Scenario 1**, the FACTOR team monitors the machines, collecting data such as temperatures, speed of the tools or power consumptions. All that data can be analysed and used to develop predictive algorithms, so that the system could be able to recommend to the operator what parameters should be modified and, how it should be done, to maintain the high quality of the parts being manufactured, avoiding then defects and scrap. In a future stage, it could be interesting even to make the machine auto reconfigure by itself. In the very first step of the scenario, it is important to establish what kind of data will be necessary to collect from the machines, guaranteeing the optimal algorithm development. Moreover, currently the quality check of the manufactured parts is a discontinuous process, since the operator usually

check the quality of only one part per hour and this information is not sent to the system, being a necessary input data for the expected system. In this context, it will be also necessary to establish a quality check protocol that allows to monitor the quality of every part and feed the system with the results. The success of the final system and the impact of the TALON Solution will be validated through a set of KPIs. Regarding the **Scenario 2**, the focus is on the maintenance and support of the optical network within the manufacturing plant and between different sites belonging to the same manufacturing organisation. The optical network infrastructure monitoring is typically based on the collection of performances and alarms from the optical nodes, also collecting information from the pluggable optical modules (SFP) belonging to the various links. The ability of quickly identifying the possible cause of a failure is a strategic factor to reduce the recovery time after a loss of signal event. In this scenario the target is to implement one or more supervised machine learning model(s) to classify the possible fault cause and to include an explanation of the classification to consolidate the operator confidence in the process.
Benefits: The successful development of this scenario will bring many benefits for the metal machining industry, since all the effort will be converted into parts of good quality, avoiding scrap and losses of time. The benefits will be not only for companies, but also for the environment since there will not be an insufficient use of energy or materials. If there are no defects in the manufacturing, all the resources consumed by the company are converted into final product, with no losses. Last, the benefits for the Scenario 2 are the improvement of the availability of the optical network in the production plant, with the reduction of time to repair of the failures, and then the overall maintenance cost reduction of the internal connectivity.
Challenges: Availability of data in real time, occurrences of damages and faults in optical communications, availability of labelled data for optical links fault explanation, necessity to improve the protocol to check the quality of the parts.

The steps that will be followed to meet the Scenario 1 of UC2 are presented in Figure 19, while the steps that will be followed to meet the Scenario 2 of UC2 are presented in Figure 18.

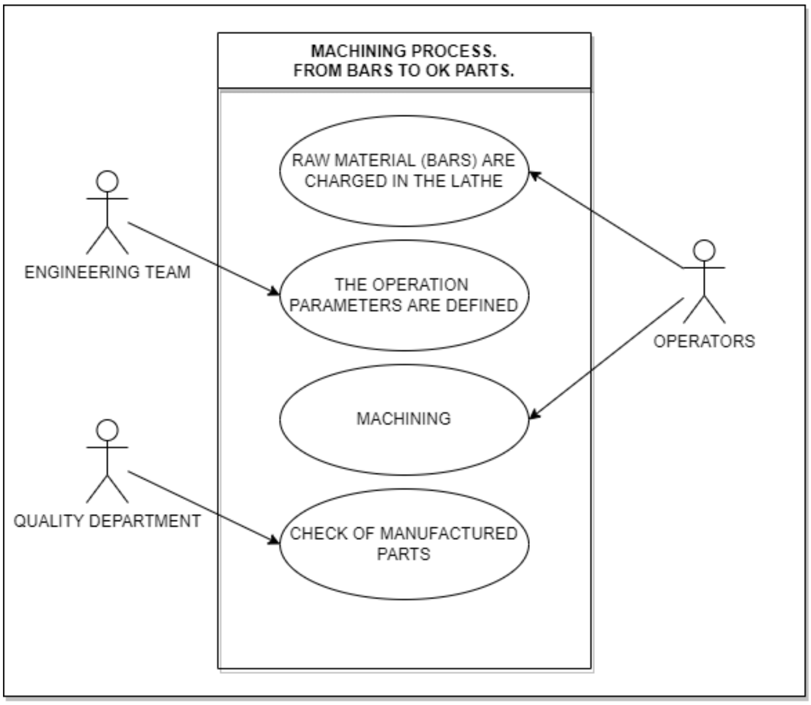


Figure 19. UC2 Scenario 1 Use Case Diagram.

4.2.6 Requirements and KPIs

The Stakeholder Requirements (StRS) of Use Case 2 are presented in Table 10.

Table 10. UC2 Stakeholder Requirements.

Stakeholder Requirements			
Requirement ID	**Category name for requirements**	**Category description**	**Priority (M/S/C/W)**
StRS01	Secure access	Secure access should grant single sign-on (SSO), secure tunnelling, authentication, and certification only to designated end users, devices, and services / applications.	M
StRS08	Anomaly detection	Network traffic should be collected and logged to analyse and report on abnormal events / incidents.	S
StRS09	Prompt detection and report of failures via efficient data operations	Data operations including data collection, curation, learning and analysis should promptly detect and report on defects. This should increase the efficiency of the production line.	M
StRS10	Hybrid and optimised learning	Optimised learning and correlations over events and time series data from sensors should detect and	S

		report on breakage and damages of the cutting tools (e.g., due to the lack of cutting lubricant, or the blockage of cooling channels of the tools).	
StRS11	Self-healing and Self-correcting	AI algorithms should learn over the collected and curated data to facilitate the prompt diagnosis and evaluation of breakage incidents.	S
StRS12	Data operations and queries	Exploratory data analysis on top of the collected data should provide reports to ensure that the tools are working within their optimum range.	M
StRS13	Labelled predictions on equipment damages through AI capabilities	Different AI models should be trained to benchmark, compare, and select the most suitable model per case. The comparison should be extended to support different hyperparameters and training datasets to avoid overfitting and false positives.	M
StRS14	Abundant reporting and visualisations	The system should support an efficient inspection and descriptive analysis of all the manufactured parts, particularly the complex parts.	S
StRS15	Explanations on optical link faults	XAI algorithms should be trained on top of the shape of power drops to provide explanations about the root cause of the fault and its correlation with the deployed environment. The XAI algorithms should be able to explain their inferences to increase the operators' confidence in the classification process.	S
StRS16	Digital Twins	The system should create a reliable virtual representation of the training subject (in our case, this is Nakamura 2).	C

The Key Performance Indicators of Use Case 2 are presented in Table 11.

Table 11. UC2 Key Performance Indicators.

Key performance indicators			
ID	**Name**	**Description**	**Reference to mentioned use case objectives**
KPI_05	Quality ratio increase	Quality ratio is the measurement of the poorly manufactured parts within the manufacturing process. Is the result of the division of the well-produced parts over the total manufactured parts.	Quality ratio increase
KPI_06	Reduction of scrap material	The scrap is the raw material that is not transformed into a final part. The optimisation of the process will reduce this scrap by reducing the parts that are manufactured with wrong dimensions.	Reduction of scrap material
KPI_07	Lower environmental footprint	The optimisation of the process and the reduction of the scrap will reduce the environmental footprint, since the machine will be working for manufacturing only good parts. If the process is not optimised, it will produce some wrong parts, that leads in a high environmental footprint.	Lower environmental footprint
KPI_08	Increase in effectiveness and production line optimisation	Effectiveness' measurement can be evaluated as the velocity of the manufacturing process. It measures the ratio between the Planned Run Time per Produced Quantity and the Actual Production time. The Planned Run Time is the theoretical time that is expected to take to manufacture a part, and the Actual Production Time is the time elapsed between the manufacturing of two consecutive parts.	Increase in effectiveness and production line optimisation
KPI_09	Increase in availability	Availability is the relation of the time that the machine is manufacturing good parts and the time that the machine should have been manufacturing good parts. Every time that the machine is stopped for any reason, it is not manufacturing good parts, which implies a loss in productivity.	Increase in availability
KPI_10	Decrease investigation efforts	Decrease the need of manual investigation in the events of loss of signal in the optical links, limiting the manual investigation to the wrongly classified events	Decrease maintenance cost
KPI_11	Increase in overall equipment effectiveness	OEE is the product of Quality Ratio, Availability and Effectiveness, and it measures the main efficiency of the factory	Increase in overall equipment effectiveness

		plant, being the main target of manufacturers to enhance.	
KPI_12	Increase optical fault analysis reliability	Increase the reliability in the overall fault analysis process with the support of explanations from the machine learning model	Improve investigation quality

4.3 UC3: AR/VR for Training and Maintenance

4.3.1 Use Case Description

Scope: Augmented Reality (AR) / Virtual Reality (VR) for training and maintenance demonstrates how edge AI could be used to create AR/VR in the plant to train employees on how to use equipment and new processes, such as ensuring the health and safety of the workers by guiding them through a hazardous environment towards assisting maintenance. It also helps repair workers with remote expertise to detect product faults during quality inspections [13]. One of the challenges with using VR headsets is that they are heavy and/or unable to process significant amounts of data, which makes them impractical for the above scenarios, while taking processing off the device and into the cloud results in too much latency and can sometimes make the wearer feel nauseous [14]. However, this problem can be eliminated by processing and rendering the data on an edge AI node – either on-site or on a network edge, thus ensuring low-latency, trustworthy and accurate AR/VR solutions [15]. The utilisation of trustworthy and XAI algorithms that can be run with high performance in a secure and private edge network node will enable the next-generation, high-precision education and training concept in manufacturing that focuses on building blue collar worker competencies in human-AI collaboration.

Modern industrial infrastructures, whether they be critical or not, utilize a big plethora of interconnecting systems, often consisting of hundreds if not thousands of sub-components or dependencies, in need of constant monitoring and maintenance. This leads to a high demand of highly trained and specialised personnel with the required knowledge to survey, diagnose and subsequently maintain or service the equipment used in the respective infrastructures. Especially in multilocational infrastructures, where mobile service departments undertake the maintenance tasks, including targeted personnel exponentially increases the operational costs, while the aspect of mistakes or on-site accidents becomes ever more prominent.

Thus, the need to robustly train maintainers and service crew in either currently utilised equipment or forthcoming state-of-the-art one and guide them through the process is imminent. TALON will take advantage of the AR/VR technology, offering a real-time interactive environment in conjunction with novel gamification methodologies, using this technology to enhance both the training and the on-site operations. Leveraging SotA AI-enabled smart systems, operating on the edge, will offload the computational backend of the AR/VR function, enabling easy transportation and deployment on maintenance sites, reducing latency while unlocking a wide range of remotely supported specialised operations.

Objectives: The objective of this use case is to illustrate the utilisation of AI-enabled function deployed on the edge supporting real time onsite AR/VR guided maintenance and support crew training and in extent human-AI collaboration. This demonstrator will deploy, assess, and demonstrate the applicability of AR/VR support on hazardous environments. The goal is to help maintenance and repair workers with remote expertise to diagnose and repair specialised equipment. This scenario will build on the premise of the additive aspects of the AI-enhanced AR/VR technology for industrial applications, highlighting its innate utilisation in the TALON platform to protrude reusability to human implicated maintenance and possibly hazardous tasks, while reducing the latency and computational load that is present in such systems. The main objectives are highlighted below, while the respective KPIs definition is further detailed in Section 4.3.6:

Table 12. UC3 Objectives and KPIs.

Objective	KPI Identifier
Latency time reduction	KPI_01
AI-human collaboration effectiveness	KPI_13
Decrease in AR-to-node AR point-of-view (POV) transmission latency	KPI_14
Increased reusability and training attendance rate	KPI_15
Increased gesture / environment recognition	KPI_16
Preserve workers' sensitive and personal identifiable information	KPI_17

The configuration of the UC3 with the TALON offerings is depicted in Figure 20.

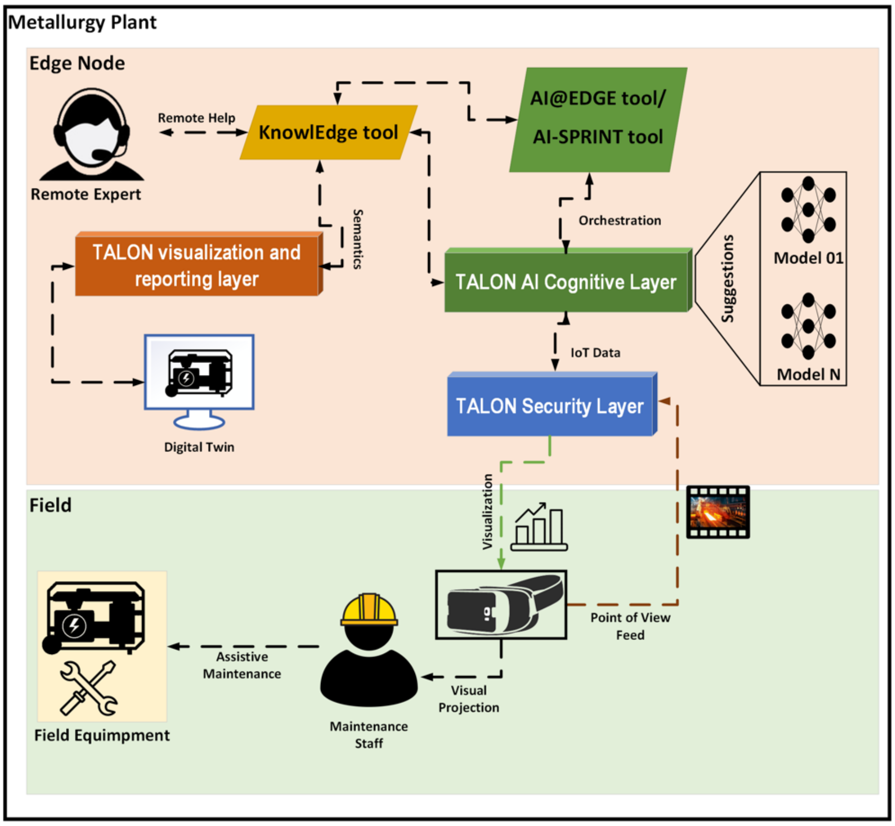


Figure 20. Configuration of the TALON UC3.

Details: This demonstrator is split into two scenarios. The first scenario includes the VR training, while the second scenario (or scenario 2) includes the AR maintenance. In this first scenario, users perform training activities in VR environments in a controlled and restricted location. VR is applied to improve the learning experience and the overall engagement offering interactive activities based on digital twins simulating real working environments. The VR training tool will offer automatic feedback and will generate a report containing the results to the participants and supporting personnel.

Multiple activities will be provided to support a variety of training methods. Two different quiz type tasks will be presented to the participants, as follows:

a) The first task presents Multiple Choice Questions (MCQ) where the user needs to answer to a written question, optionally accompanied by an image as a visual aid. To proceed with the task the user needs to select her answer from a provided list using virtual items in the VR environment.
b) The second task is an extension of the first, where the participant needs to answer a question with added interactivity elements. The question is accompanied by one or multiple virtual objects and the user needs to examine, manipulate, or combine the objects to find the solution to the question. Multiple answers will be provided, like the first task, and could be submitted by either via a virtual object or a digital button, depending on the nature of the question.
c) The third task involves a digital recreation of the Nakamura-Tome WT-150 II CNC Turning Centre Machine. The Digital Twin will be used to simulate certain scenarios involving the machine. During these scenarios, the participant will be tasked to recognize certain parts of the machine or perform a set of interactions related to the machine.

The tasks are encapsulated within a session. At the end of each session the participant will be presented with a result screen which will offer an overview of how the participant has performed.

Additionally, the training process also requires other modules, including data extraction and analytics to monitor the effectiveness of the trainee. On the edge using a local server (i) an analytics component will be deployed, so the personnel can monitor an individual's training progress. The edge server will also host the (ii) data generated by the VR training application. This data includes questions and tasks performed during the training process and the digital representation of the virtual objects appearing during the VR training. Making these files accessible on the edge provides the training personnel the ability to expand or correct the training material. Provided by the TALON architecture the edge server (iii) will also host a security layer where anonymisation of certain data will take place. This data will be transferred to the cloud for long term storage and monitoring purposes. Based on the data provided by the edge the analytic solution on the cloud will be able to monitor the overall effectiveness and progress of the VR training solution, encompassing multiple use-cases separated on different edge nodes. The VR training scenario involves on the field, edge and cloud computing capabilities as depicted in Figure 21.

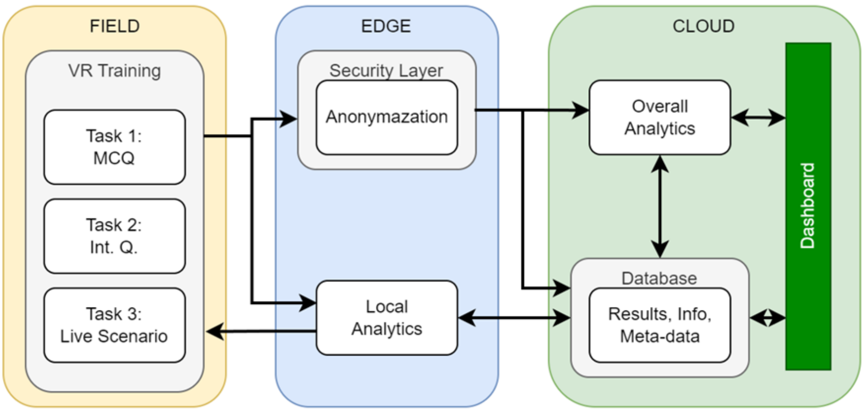


Figure 21. VR Training Scenario of UC3.

The VR training solution requires multiple devices available at the field and on the edge, as follows:

a) A VR headset (e.g., Oculus Quest 2), provided by Kingston University for the duration of the project will host the VR training application. The headset includes VR controllers that allows the participant of the VR training to interact with the virtual environment.
b) To host the data required by the VR application, the security layer solution, and the local analytics solution are required at the edge. The server unit is required to fulfil the desired functionalities, be able to connect to the internet and communicate with the cloud and a local wireless network.

In the second scenario, we aim to improve the AR maintenance. We propose AR maintenance support system to improve production quality and reduce delays caused by maintenance procedures. In this scenario, the maintenance personnel operating in the field are equipped with an optical see-through head-mounted display that allows augmented information to be displayed during the maintenance process. Additionally, to the AR capabilities, the device is also capable of streaming a multimedia feed supporting embedded audio and visual sensors. The AR capabilities also support virtual interactive elements projected on the extended environment by the AR device, voice commands and hand gestures that allow the maintenance personnel to convey additional information. The multimedia information is broadcasted to an expert, situated on an edge device. Based on the feed, the expert can assess the situation in real-time and using audio or text messages or virtual indicators, information panels, or by superimposing highlights on certain parts of the machine via the AR device, will be able to support the maintenance personnel operating on the field. Due to the technologies involved, the expert is not required to be at the premises of the operating facility. Parallel to the expert personnel the information and multimedia feed are also processed by an AI-powered support module which performs scene analysis recognizing and highlighting certain elements of the machine, assisting the maintenance personnel.

There are several technical requirements to realise the architecture of this scenario. First, the AR device used by the maintenance personnel in the field, (e.g., Microsoft HoloLens 2), is provided by Kingston University for the duration of the project. On the edge, the expert personnel will require a personal computer to run the application that receives the information stream broadcasted by the AR device and to send messages back to the AR device. The edge module requires a server computer, with high performance capabilities, which will host the AI models. All these processes require a reliable network connection to convey high broadband dependent data streams and to communicate with the cloud components. From the edge and field, as depicted in Figure 22, the system will transfer information to the cloud via a security layer to assure the anonymisation of the data. These data include operational logs from the machine, sensitive facial information, maintenance logs, and other relevant information. Services on the cloud will receive this data where more resource intensive operations will be performed. A predictive system analyses the provided data and provides information regarding the maintenance processes and potential faults. These pre-emptive measurements will allow the users to reduce production delays caused by faulty machinery and will contribute toward a more reliable work environment. The AR Maintenance scenario is depicted in Figure 22.

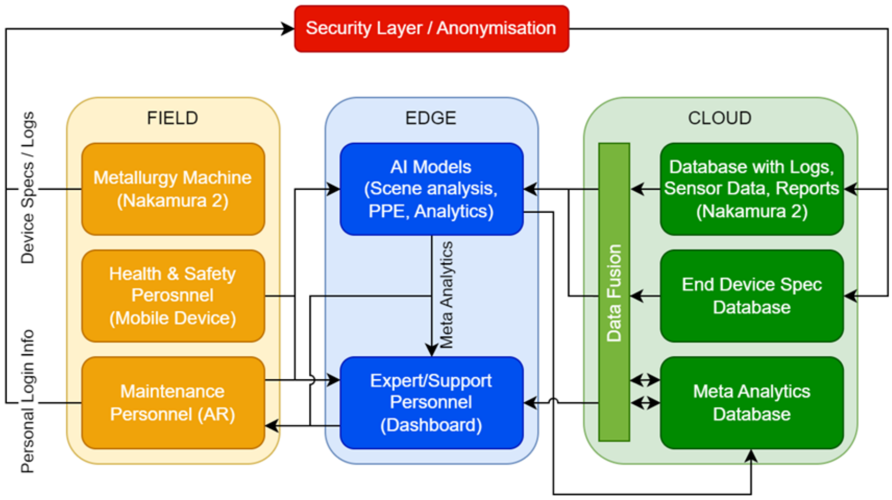


Figure 22. AR Maintenance Scenario of UC3.

To realise UC3, we will additionally use the following components:

- Nakamura-Tome WT-150 II (FACTOR): A CNC (Computerised Numerical Control) Turning Center Machine, with upper and lower 24 station turrets, used in machining parts in medical, electronics, and aerospace industries. Operating the machines and retrieving operational information is happening via a control panel using buttons and a touch screen, which runs a NT SmartX software. An extensive list of manuals, regarding the operations, structure and architecture of the machine are provided by FACTOR as depicted in Figure 23.
- TEI Tools: (i) Health & Safety monitoring mobile app: The application is based on a multimedia stream utilizing scene-analysis techniques to identify personnel on the field and validate if the personnel are wearing all the regulatory personal protective equipment (PPE), ensuring higher safety at the work area. It receives as input images and generates as output bounding boxes. (ii) Anonymisation: Via the anonymisation tool the data are anonymised removing personal or sensitive information and then is transferred to the cloud or edge. It receives as input records or images with personal details and generates as output the anonymised records.
- AI@Edge (8BELLS): The tool provides a platform to define and evaluate KPIs which can be used to analyse the overall performance of the related processes. It receives as input system and monitoring metrics and generates as output KPIs and performance analytics.
- AI-SPRINT (UPV): The tool receives operation and sensor logs, provided by the machine, and maintenance reports, provided by maintenance personnel. Using this data, the solution identifies anomalies and patterns of operating behaviours which informs the human actors of possible issues regarding the operating machines. It receives as input tabular data, logs, and reports, and generates as output predictive analytics and anomaly detection.
- Multimodal Data Fusion (MDF) (CERTH): Data preparation operations and AI Systems will be provided by CERTH as core activity of Task 5.5 (i.e., UC3 / Pilot 3). The type of this artefact will be a research item and/or software, including python libraries (Pandas, Numpy, Scikit-learn, LGBM, Keras, Tensorflow, PyTorch), Docker, and MongoDB. This artifact will contribute to this use case as follows. It will optimize the data preparation for CNC through a combination of advanced techniques and machine learning algorithms for improved analytic results. MDF consists of three (3) main components:
  a. Analytics component: Based on operation and sensor logs provided by the machine, and maintenance reports provided by the maintenance personnel, the tool will provide

predictive analytics on possible faults and issues that may occur during the operation of the machine. It receives as input tabular data, logs, and reports, and generates as output predictive analytics and fault detection.

b. Data fusion: The solution uses data fusion techniques to identify connection between data from separate sources, providing a wider perspective on the condition of the operating devices. It receives as input various data structures (e.g., timeseries with different parameters), and it generates as output fused data (e.g., fused single timeseries).

c. Dashboard: The tool uses a dashboard to communicate results with human actors via visual analytics. It receives as input various data analytics and raw data (e.g., timeseries), and generates as output visual analytics data.

Figure 23. Machine Nakamura 2 Panel.

4.3.2 Questionnaire Responses

A dedicated questionnaire has been answered by the UC3 team members and the KU, UPV and FACTOR teams, which can be found in Annex I, section 9.3.

4.3.3 AS-IS Conditions and Workflow

Currently, the training workflow is not digital, and includes printed manuals and an expert's assistance on shopfloor. Also, the training of the employees is being held without immersive technologies, no feedback and with no means to validate the results or adapt the training material and conditions to the training / personal needs of the trainee. The AS-IS workflow is depicted in Figure 24.

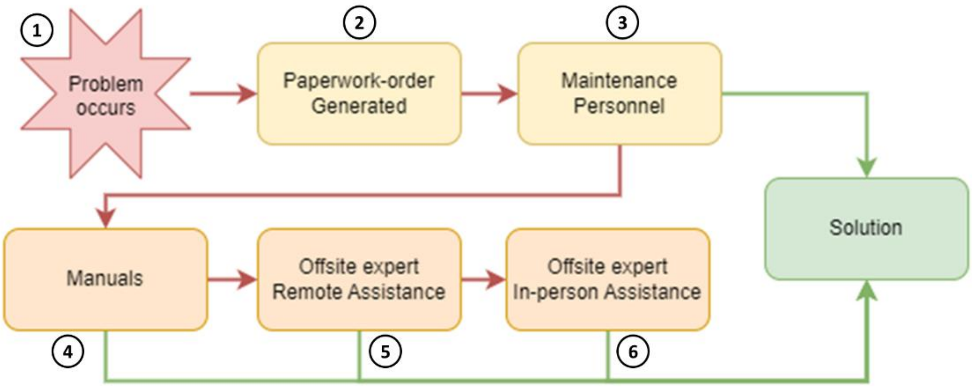


Figure 24. UC3 AS-IS Workflow. The steps a maintenance employee takes to fix a problem.

The AS-IS maintenance workflow currently takes the steps, as follows:

1. The problem appears.
2. The paperwork order is being generated.
3. The maintenance personnel try to fix the issue based on personal experience and existing knowledge.
4. The maintenance personnel check the maintenance manual for instructions.
5. The maintenance personnel contacts the offsite expert for assistance, who provides recommendations based on the problem description.
6. The offsite expert needs to arrange a visit to the premises of the end user to fix the problem.

Almost all these steps are time consuming process which require a lot of waiting time resulting in longer off-time of the production line and delays in the manufacturing process. The paperwork order also creates difficulties for long lasting data conservation and adds additional work processes when the information needs to be transferred digitally.

4.3.4 TO-BE Conditions and Workflow

The TO-BE conditions will focus on two scenarios, one for i) AR/VR training of specialised crew and one for ii) onsite assistive maintenance. In the first scenario, a selected team of maintainers will undergo training for maintenance regarding the equipment located in the FACTOR metallurgy plant. The environment will be simulated through VR headsets to support scenarios for fully immersive training. Information from a digital twin simulating the infrastructure will be fed to the TALON visualisation and reporting functionalities in conjunction with the modules developed in the frame of TALON's AI capabilities where targeted models will be produced to manage the emulation. These models will accumulate data related to the training scenario and reproduce the training environment. Each person will follow the scenario achieving a goal set, while real time reports will be transmitted to remote specialists for interactive guidance. In the second scenario, the demonstration will also take place on the premises of FACTOR's metallurgy plant, where specialised crew will be used for maintenance tasks. The personnel will carry AR headsets connected to the edge nodes of the infrastructure. The staff will proceed to diagnose and service the equipment. In parallel, real-time AR point-of-view (POV) feeds will be securely transmitted to the edge, where a remote specialist reviews the data and consults the onsite staff. The data operations and AI capabilities of TALON will facilitate the input analysis, enrich it with semantic information which will be then sent and displayed on the AR headsets, informing the onsite staff about hazardous materials or dangers in the environment and projecting useful information about the service process, such as, access points, equipment, etc. Throughout the scenarios, automatic reports will be generated. The TO-BE workflow will be divided in two scenarios, i.e., the training workflow and the maintenance workflow, as follows:

<u>Future Training Workflow</u>

1. The personnel are immersed to the facilities and devices using VR glasses.
2. Interactive tasks are available, and the personnel can select them.
3. The available VR tutorials are:
    a. Quiz - Multiple Choice Questions (MCQ) for knowledge improvement.
    b. Quiz - Interactive questions for learning and enhancing skills.
    c. Live scenarios for training to improve situational awareness and critical thinking.
4. The personnel receive the score and feedback.
5. The personnel receive personalised recommendations for further training.
6. The training is constantly updated with new materials.

The TO-BE workflow of the future training activities is depicted in Figure 25.

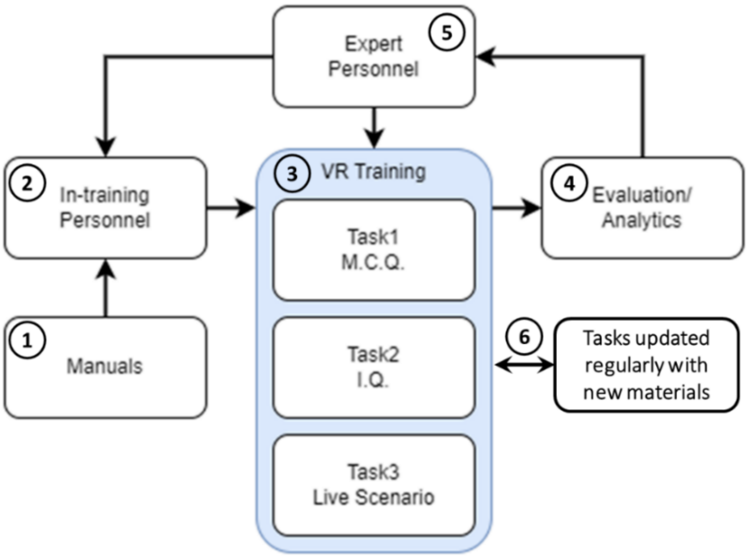


Figure 25. UC3 TO-BE Workflow.

Future Maintenance Workflow

1. A problem occurs.
2. Personnel without expertise equipped with the AR glasses.
3. The personnel move to the device and the problem indicator.
4. Multimedia and info are captured and transferred to an offsite expert.
5. AI models provide guidance and instructions.
6. An offsite expert provides guidance with the support of the AI in the augmented environment to solve the problem without visiting the premises of the on-field personnel.

Figure 26 depicts the TO-BE workflow of the future maintenance activities using the TALON's offerings.

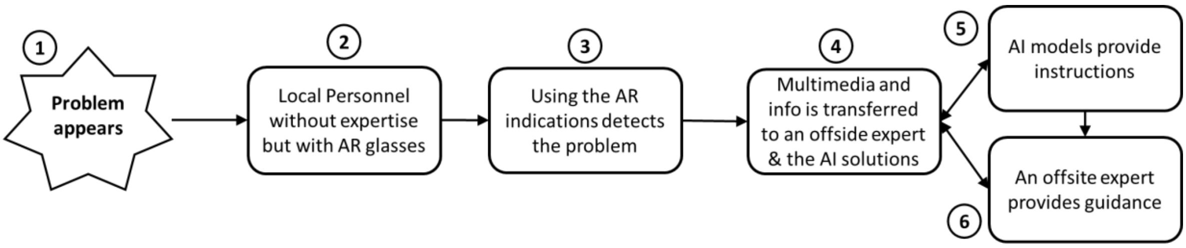


Figure 26. UC3 TO-BE Workflow (AR Maintenance Scenario).

The use case assumptions and prerequisites to realise the scenarios of this demonstrator are presented below.

Use case conditions
Assumptions
The scenarios of the UC3 will be demonstrated and executed in the premises of FACTOR's metallurgy plant at the area where the Nakamura 2 machine is located.
Prerequisites

The prerequisites for UC3 are as follows: • An empty 4m x 4m floor space. • VR and AR glasses. • Server for the AI-edge support.

4.3.5 Steps – Scenarios

This section presents UC3 demonstration scenarios in steps.

Table 13. UC3 Usage Scenario 1.

Actor: In-Training Machine Operating Personnel
Alternative Actors: Researchers
Actors interested in the outcome: Factories, Teaching/Training Departments
Scenario Overview: Instead of a one-on-one training session in an industrial environment involving real machinery, a VR environment provides a flexible alternative.
Scenario: A minimum of 4m x 4m empty floor space is required. In-training personnel equips a VR device and starts the VR Training application. The application guides the participant through a set of questions and tasks: 1. Set of multiple-choice questions, where the participant needs to select the correct one from a set of provided possible answers. The question is in written form and might be accompanied by an image reference. 2. Set of interactive questions and tasks, where the participant needs to perform a variety of interactions with the virtual objects to find the correct solution. 3. An interactive live scenario, where the participant needs to resolve a certain malfunction. At the end of the training scenario, still in the application, the participant is provided with the marks and evaluation of their performance. The participant is also provided with a reference code, which could be used to identify the personnel for later manual review. After the training ends, the Training Department will be able to access the training results.
Benefits: The virtual environment allows the simulation of a variety of scenarios, some of which might end up with personal or property damage if it would be done in real-life scenario, resulting in a safer and more cost-effective training process.
Challenges: To create a reliable virtual representation of the training subject; and to provide a variety of interaction methods to support wide variety of training scenarios/concepts.

Table 14. UC3 Usage Scenario 2.

Actor: a) Personnel without maintenance expertise, and b) remotely connected maintenance expert
Alternative Actors: Researchers

Actors interested in the outcome: Factories, Device Provider, Maintenance Departments
Scenario Overview: A local worker without maintenance expertise but with AR glasses and remote immersive support detects and fixes the problem with the Nakamura 2 machine.
Scenario: It is required for the local worker to be close to the Nakamura 2 machine and the AR device to be connected to the remote support centre. The local personnel equip the AR glasses and start the AR maintenance application. The application guides through the participant to perform the required steps: 1. The local worker with the AR application verifies if the area is safe (personnel with safety equipment and no hazards, such as fire or smoke, are detected). 2. The local worker with the support of the AI and the augmented indications detects the problem. 3. The AI recognises the issue and offers automatic suggestion with visual aid. 4. Simultaneously the remote maintenance expert provides further recommendations with visuals to indicate the expected steps and actions. At the end of the maintenance scenario, related analytics are provided regarding the system accuracy and performance.
Benefits: The AR solutions offer faster maintenance improving the production quality and reducing delays. Moreover, reduces the costs for training since less maintenance experts are required and travelling costs to visit the premises of the operating facility.
Challenges: To create a reliable AI solution based on computer vision that will offer reliable, robust, and fast scene analysis.

4.3.6 Requirements and KPIs

The Stakeholder Requirements (StRS) of Use Case 3 are presented in Table 15.

Table 15. UC3 Stakeholder Requirements.

Stakeholder Requirements			
Requirement ID	**Category name for requirements**	**Category description**	**Priority (M/S/C/W)**
StRS01	Secure access	Secure access should grant single sign-on (SSO), secure tunnelling, authentication, and certification only to designated end users, devices, and services / applications.	M
StRS02	Deterministic and bounded system and response time latency	The response time among processes and devices should be recorded to ensure that priorities and smart policies enable latency reduction.	S
StRS03	Inter-node or inter-process communication	The AI Orchestrator should interact with edge nodes and services to ensure decreased interaction to the	S

		possible minimum and improved AR-to-node communication to the possible maximum.	
StRS14	Abundant reporting and visualisations	The system should support an efficient inspection and descriptive analysis of all the manufactured parts, particularly the complex parts.	C
StRS16	Digital Twins	The system should create a reliable virtual representation of the training subject (in our case, this is Nakamura 2).	C
StRS17	Data anonymisation and protection	Employees' sensitive data and personal identifiable information (e.g., faces, and/or textual / numerical data) should be anonymised to ensure increased personal data protection.	S
StRS18	Programmable networks and distributed intelligence	The system should provide data offloading capabilities, traffic prioritisation and distributed intelligence via programmable switches and networks in cloud execution contexts.	S
StRS19	AI capabilities	The system should analyse collected data to reproduce the environment and manage emulations linked with the training scenario.	C
StRS20	Resource allocation and deployment	The system should optimally allocate computing resources to decrease inter-nodes communication and decrease transmission latency.	S
StRS21	Few-Shot learning / Transfer learning	The AI models for scene analysis and safety level detection (PPE, fire) should be trained using few-shot learning or if the application needs to generalise better, with transfer learning.	C
StRS22	Definition, Customisation and Monitoring of Metrics	The system should monitor and log data on how the processes and applications interact.	S
StRS23	Analytics execution	The system should monitor and log data on how the processes and applications interact and allocate CPU, RAM, energy, etc. to	S

		compute optimal execution analytics.	
StRS24	Efficient data storage and services placement	The system should monitor and log data on how the processes and applications interact to take decisions about efficient data storage and services placement.	S
StRS25	Optimisations	The system should translate the optimal execution analytics onto SLAs and SLOs, enforce policies and support runtime adaptations by means of objective – target optimisation.	C
StRS26	Behaviour and Performance Monitoring	The system should monitor the processes and applications and extract behavioural execution patterns.	C

The Key Performance Indicators of Use Case 3 are presented in Table 16.

Table 16. UC3 Key Performance Indicators.

Key performance indicators			
ID	**Name**	**Description**	**Reference to mentioned use case objectives**
KPI_01	Latency reduction	Decrease response time to < 20ms. This is related to the AR maintenance scenario focusing on the AR to edge communication	Latency time reduction
KPI_13	AI-human collaboration effectiveness	>50% AI-human collaboration effectiveness. Increase of the human satisfaction during the AR-maintenance scenario that is powered by AI models. And improved user experience and interaction during training activities	AI-human collaboration effectiveness
KPI_14	AR-to-node AR POV latency reduction	>90% decrease in AR-to-node POV transmission latency	Decrease in AR-to-node AR point-of-view (POV) transmission latency
KPI_15	Increased reusability	Training attendance rate > 95%	Increased reusability and training attendance rate
KPI_16	Increased environment recognition	>90% accuracy through increased environment recognition	Increased gesture / environment recognition

KPI_17	PII preservation	100% PII preservation via facial, numerical, and textual data anonymisation	Preserve workers' sensitive and personal identifiable information

4.4 UC4: Human-Robot Collaboration

4.4.1 Use Case Description

Scope: Human-Robot Collaboration (HRC) aims to expand the level of automation in the increasingly complex manufacturing landscape [16]. By creating a balance between the flexibility of manual processes and the efficiency and repeatability of machines, it is possible to achieve production flexibility as well as product mix and reconfiguration [17]. To fulfil this goal, TALON will utilize computer based virtual models of physical systems (digital twins - DT) to test and validate production strategies before taking them into practice [16]. Specifically, the proposed HRC assembly station will consist of a robot manipulator and a human operator that jointly complete the manufacturing process in a collaborative fashion. In the system design phase, the DT will be used to design and select the resources of the assembly system corresponding to the production requirements and its relationship with the rest of the system. The dynamic simulation will enable quantitative assessment of the proposed solution, while DT will be continuously evolved from manual data syncing to automated and real-time data thus enabling greater usefulness at system level. Also, in the operational phase the DT will contribute towards the (a) dynamic task distribution by task complexity rating and event-driven simulation [18]; (b) Intuitive robot programming to avoid manual programming efforts; (c) human-safety assessments [19]; (d) generating data logs for critical actions by integrating sensorial data; (e) embedding AI to get the system self-learned and make decisions according to its past experiences [20]. Achieving a live connection between DT and the physical system can make DT to operate in the real-world.

Human skills are the main driver that enables producing high value products in Europe's fifth industrial revolution. Thus, the manufacturing processes are based on utilizing these skills. TALON aspires the integration of the latest industrial automation systems for assembly operations in combination with human capabilities, combining robot strength, velocity, predictability, repeatability and precision with human intelligence and skills. These challenges require the intelligence of the ecosystem to be performed directly on or near the sensing entities to guarantee faster and deterministic reaction. TALON envisions to deploy and orchestrate the indoor localisation service for efficient, explainable, and safety-critical new industry. Therefore, a hybrid solution involving the safe cooperation of operators with autonomous and adapting robotic systems through a user-friendly interaction is proposed.

Objectives: The main objectives are highlighted below, while the respective KPIs definition is further detailed in Section 4.4.6:

Table 17. UC4 Objectives and KPIs.

Objective	KPI Identifier
Increased object recognition	KPI_16

Preserve workers' sensitive and personal identifiable information	KPI_17
>70% reduction in AI-to-AI communication latency	KPI_18
>30% robot production efficiency	KPI_19
Robust computer vision models by achieving >80% accuracy in environment recognition and augmentation	KPI_20
15% increase in assembly efficiency	KPI_21
>70% increase in personnel safety	KPI_22

Details: UC4 aims to expand the level of automation in the increasingly complex manufacturing landscape through HRC. It will take place in CERTH and will be divided into four phases; the real-environment scenario, the annotation of the real-scenario data, the simulation of the factory environment (DT), and the evaluation of the simulated model compared to the real scenario.

For the realisation of UC4, two scenarios could be followed. The first scenario is to assess the drone in the outdoor environment of CERTH building, by flying the drone in a specific area, while some volunteers from the staff of the department will participate by acting as the workers of the factory, wearing helmets or objects that need to be detected.

Alternatively, the drone could be used in one of the rest pilots of TALON project, e.g., in the environment of FACTOR, where the drone could fly in the factory premises, if possible, videos will be created, and the results of this analysis will later become annotated by CERTH. That way, a dataset will be created on one of the project's pilots, which will be a simulation of an industry and will help us to validate the precision indicators of the algorithm that is initially created. Finally, two datasets will be developed: one annotated dataset from a real environment, one from the factory, and one simulated dataset for the evaluation of our model. The results of this analysis will show the precision of our model.

Orchestration and explainability are key concepts for achieving HRC and ensuring highly efficient production execution in terms of cost and time. The advantages of TALON's approaches lie in the utilisation of efficient heuristics and multi-criteria-based task assignments. To this end, UC4 will be facilitated by the TALON's developments by using the methods and software tools for determining the optimal orchestration of assembly/disassembly operations, such as i) the extraction of assembly tasks, ii) the generation of all the feasible alternative plans through intelligent search algorithms, and iii) the evaluation of these plans using multi-criteria decision-making tool as well as DTs. In addition, UC4 will investigate scenarios for trustworthy and safe operations by i) highlighting worker safety zones, ii) visualizing the robot's trajectory, iii) provisioning the production and assembly process information, and iv) notifying for warnings and alarms.

The origin of the data regarding the human-safety assessments will be collected by one drone owned by CERTH. The drone will be equipped with a camera attached to its surface, which will collect images and/or videos from the surroundings of the factory. The drone will fly in the factory premises to detect dangerous working situations / conditions, e.g., detect workers that work without helmets, protection glasses, etc. The data required to realize the scenario of DT linked with the resources of the manufacturing assembly system will be specified in the progress of the project.

4.4.2 Questionnaire Responses

A dedicated questionnaire has been answered by the UC4 team members and can be found in Annex I, section 9.4.

4.4.3 AS-IS Conditions and Workflow

Currently, safety conditions in a workspace are not monitored through HRC. This means that a manager (possibly a field engineer) walks around the working place and monitors the conditions, e.g., by checking if all workers wear the necessary safety equipment. If he/she founds persons that are not following the safety rules of the factory, he/she asks them to follow them, e.g., to wear their helmets or glasses, based on the specific circumstances. So, human eye and human perception are the only monitoring mechanism in these factories. As a result, the possibility of an error or misinterpretation of the rules can lead to possible mistakes that might be dangerous for the safety of the workers and the factory in general.

The AS-IS workflow regarding the safety of field engineers currently takes the steps, as follows:

Start: Field Engineer

1. Maintenance: this is the first step, where the field engineer monitors the working conditions and checks for dangerous behaviours.

   If there is no violation of safety regulations, then the working environment is safe and no indications for compliance are required.

2. Safety Risk: If the maintenance and thus the safety regulations are violated, then there is a safety risk, which leads to a notification from the field manager to the worker that there is a dangerous situation and a possibility of an accident if he/she will not follow immediately the safety regulations, e.g., if he/she will not immediately wear his/her helmet.

3. Danger/Accident: This is the 3rd step of process. If safety rules are not followed, then there is a high possibility of an accident in the working environment.

End: Safe Work Environment

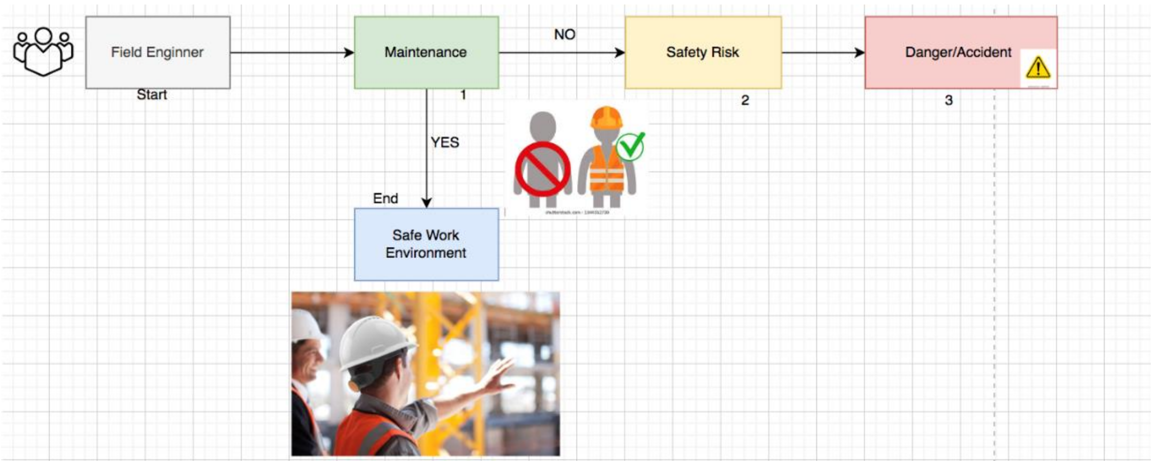


Figure 27. UC4 AS-IS Workflow.

In the AS-IS scenario, all the above-described steps are monitored by humans and their validation cannot be secured. By the implementation of HRC in this process, we plan to improve all these steps, starting from the monitoring / inspection of the working environment to the identification of the dangerous situations using alerts and messages to inform workers for the possible risk of an accident, and finally to the validation that safety rules are followed, to secure the safe working environment.

4.4.4 TO-BE Conditions and Workflow

The TO-BE conditions will focus on the HRC for the monitoring of the safety conditions inside a factory and the early notification of the workers if a dangerous situation or a possibility of accident is noticed.

Start: Field Engineer / Drone (Human-Robot Collaboration)

1. Maintenance: this is the first step, where the drone (robot) monitors the working conditions and checks for dangerous behaviours. The operator of the drone is the field engineer (human).
2. CERTH Preprocessing AI pipeline → Multi Object Detection: This is the second step, where the images/videos that are collected by the drone, are analysed on a computer.
3. Assess Work Safety: This is the third step, if the objects that wanted to be identified are captured in the collected data, e.g., helmets, glasses that are worn by the workers, then there is no violation of safety regulations, thus the working environment is safe and no indications for compliance are required, then the next step is 4a.
4. 4a) Objects are successfully identified and the working environment is safe→End-final step: TALON visualisation: Safe conditions in the factory.

   4b) If the objects, e.g., helmets, glasses are not detected, then the working environment is not safe and next step is 5.
5. ALERT- Danger/Accident: If the safety regulations are violated, then there is a safety risk, which leads to an ALERT that there is a dangerous situation and a possibility of an accident if the worker will not follow immediately the safety regulations, e.g., wear a helmet.
6. Follow safety rules: If there is an ALERT for unsafe conditions, then the worker must follow the rules to make conditions safe and continue his/her work.

End: Safe Work Environment - TALON Visualisation Dashboard

<u>Future Field Engineer Safety Assessment</u>

1. A drone collects videos/images, in a factory and selected objects regarding the assurance of safety conditions in the working environment are detected by the drone, e.g., workers wear helmets/glasses.
2. Multimedia (videos/images) after being captured, they are transferred to a server for analysis.
3. A preprocessing AI pipeline → Multi Object Detection, is used to identify the objects.
4. Problem occurs: objects are not detected.
5. An alert notifies the field engineer regarding this dangerous situation and the possibility of an accident.
6. The field engineer can inform the specific worker and ask him/her to follow the rules to prevent a possible risk situation.
7. Working environment is kept safe.

The TO-BE workflow of the future filed engineer safety assessment is depicted in Figure 28.

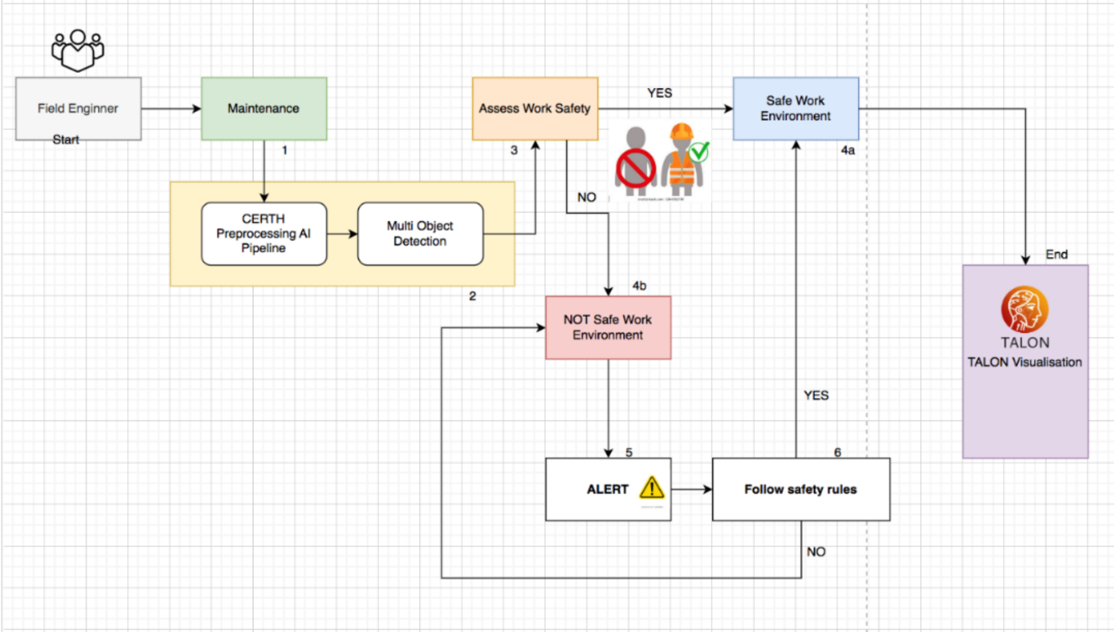


Figure 28. UC4 TO-BE Workflow.

Use case conditions
Assumptions
UC4 will be demonstrated and executed on the premises of the outdoor area of the CERTH building in Thessaloniki, Greece, and/or in the factory indoor environment of one the rest pilots of the project, e.g., FACTOR's indoor working space.
Prerequisites
The prerequisites for UC4 are as follows: • A large and high-ceiling indoor working space, where the drone could be safely fly or a large outdoor floor space. • Real workers or people acting as workers for the test, wearing helmets and/or glasses. • A drone (that will be offered by CERTH for both scenarios). • A memory card to collect the images/videos from the drone. • Server for the images/videos storage and analysis.

4.4.5 *Steps – Scenarios*

This section presents UC4 demonstration scenario in steps.

Table 18. UC4 Usage Scenario.

Actor: Drone Operator
Alternative Actors: Computer operator, workers, managers

Actors interested in the outcome: Workers, managers of the factory, Others may include: (i) software development companies that develop computer vision algorithms; and (ii) UAV manufacturers that assembly robot vehicles with a camera and a GPU.
Scenario Overview:
Scenario: 1. The drone will be equipped with a camera attached to its surface, which will collect images and/or videos from the surroundings of the factory. 2. The drone will fly inside the factory to detect dangerous situations/conditions working, e.g., detect workers that work without helmets, glasses, etc. The drone will conduct multi object detection, using YOLOX or TensorFlow for classification. Both software tools have dependencies with OpenCV. For the specific scenario of object detection, a segmentation procedure is not required. Computer vision will be used and the YOLOX will be trained through aerial images (e.g., people wearing helmets). The procedure is as follows: first it is important to specify the objects that need to be detected by the drone, then these objects are reflected in classes and last the YOLOX is trained to detect the objects. The drone is equipped with a Jetson Xavier module which can manage a volume of 10.000 scores. 3. The drone can keep a record of the fights made and can present default details, such as date of the flight, time, location etc. Regarding the size of the data collected during the flight, there is a limitation in storage. The steps to be followed are as follows: I. The drone collects and keeps captures on a memory stick/card attached to it and then the analysis of these data is taking place on a computer. II. Streams are collected, e.g., online frames (through a link) while the drone is operating and are analysed onsite. The scenario to be followed depends on the function that the user needs for the specific pilot. **Preprocessing for image segmentation:** Local pre-processing is not required in the specific scenario. However, if necessary for another case/scenario, it can be done. Two approaches could be used for segmentation: a) semantic segmentation, where parts of an image, which belong to the same class, are clustered together (pixel-level prediction) or b) bounding boxes.
Benefits: Risks can be limited and working conditions can be kept safe.
Challenges: The level of automation in the increasingly complex manufacturing landscape will be expanded through HRC and enhanced situational awareness inside the pilot site. Unsafe working conditions can be identified easily and faster and thus the risk of an accident in the working environment can be avoided. HRC will provide higher percentages of security in the factory, as well as will eliminate possible human errors in the detection of risk situations in the working environment.

4.4.6 Requirements and KPIs

The Stakeholder Requirements (StRS) of Use Case 4 are presented in Table 19.

Table 19. UC4 Stakeholder Requirements.

Stakeholder Requirements			
Requirement ID	**Category name for requirements**	**Category description**	**Priority (M/S/C/W)**
StRS01	Secure access	Secure access should grant single sign-on (SSO), secure tunnelling, authentication, and certification only to designated end users, devices, and services / applications.	M
StRS03	Inter-node or inter-process communication or AI-to-AI communication	The AI Orchestrator should interact with edge nodes and services to ensure decreased interaction to the possible minimum. Inference will be performed to speed up the AI-to-AI communication.	S
StRS14	Abundant reporting and visualisations	The system should support an efficient inspection and descriptive analysis of all the manufactured parts, particularly the complex parts.	S
StRS16	Digital Twins	The system should create a reliable virtual representation of the training subject (in our case, this is the indoor factory environment).	C
StRS17	Data anonymisation and protection	Employees' sensitive data and personal identifiable information (e.g., faces, and/or textual / numerical data) should be anonymised to ensure increased personal data protection.	C
StRS19	AI capabilities	The system should analyse collected data to reproduce the environment and manage emulations linked with the training scenario.	C
StRS20	Resource allocation and deployment	The system should optimally allocate computing resources to decrease inter-nodes communication and decrease transmission latency.	C
StRS26	Behaviour and Performance Monitoring	The system should monitor the processes and applications and extract behavioural execution patterns.	C

The Key Performance Indicators of Use Case 4 are presented in Table 20.

Table 20. UC4 Key Performance Indicators.

Key performance indicators			
ID	**Name**	**Description**	**Reference to mentioned use case objectives**
KPI_16	Increased object / environment recognition	>90% accuracy through increased object recognition	Increased object recognition
KPI_17	Preservation of anonymisation	100% preservation of anonymisation via facial, numerical, and textual data anonymisation	Preserve workers' sensitive and personal identifiable information
KPI_18	AI-to-AI communication	>70% reduction in AI-to-AI communication latency	Reduction in AI-to-AI communication latency
KPI_19	Production efficiency	>30% robot production efficiency	Robot production efficiency
KPI_20	Robust AI models	>80% in environment recognition and augmentation accuracy	Robust computer vision models
KPI_21	Assembly efficiency	15% increase in assembly efficiency	Robust computer vision models
KPI_22	Personnel safety	>70% increase in the personnel safety	DT models, multimodal object detection

5 System's Functional & Non-Functional Requirements

The main functional and non-functional requirements of the project are identified and addressed in this chapter. Understanding the functional requirements is essential as they directly align with the needs and expectations of the stakeholders involved. By listing and detailing these requirements, the chapter provides a clear roadmap for the development team to follow. Additionally, it highlights the importance of non-functional requirements, which may not be visible in the architectural design but are crucial for optimal project solutions.

5.1 Functional Requirements

5.1.1 Access and Security

Table 21. Authentication and Authorisation Requirement.

ID	FR01
Title	Authentication and Authorisation
User Roles	End user of a service / application; Service developers / providers; E2C infrastructure providers
Description	The authentication and authorisation functionality should control the access to the E2C TALON resources and ensure the confidentiality, integrity, and availability of sensitive information.
Reference UC	UC1; UC2; UC3; UC4
Link to StRS	StRS01

Table 22. Data Anonymisation Requirement.

ID	FR02
Title	Data Anonymisation
User Roles	Service developers / providers
Description	Data anonymisation functionality should remove and alter personally identifiable information (PII) from data sets in such a way that the data can no longer be linked to specific individuals. The goal of data anonymisation should be to protect privacy while still allowing for analysis, research, or other legitimate uses of the data. In TALON, facial, textual, and numerical anonymisation should be supported.
Reference UC	UC3; UC4
Link to StRS	StRS17

Table 23. DLTs for Security and Privacy Requirement.

ID	FR03
Title	DLTs for Securing AI/ML models weights

User Roles	End user of a service / application; Service developers / providers; E2C infrastructure providers
Description	A distributed ledger, such as blockchain, should be employed to secure AI/ML model weights for (i) data integrity (i.e., the weights of AI/ML models can be stored on a distributed ledger, ensuring their integrity and preventing unauthorised modifications); (ii) version control and provenance (i.e., the ledger can maintain a transparent and immutable history of model weight updates, allowing for version control and easy tracking of changes); and consensus (i.e., agreement upon the correctness of model weight updates in federated machine learning settings).
Reference UC	UC3; UC4
Link to StRS	StRS19

Table 24. Anomaly Detection Requirement.

ID	FR04
Title	Anomaly Detection
User Roles	End user of a service / application; E2C infrastructure providers
Description	Anomaly detection should identify patterns, suspicious activities, errors, or changes in the system that deviate significantly from the expected behaviour within a network. It should automatically detect any anomalies that may require further investigation or immediate action.
Reference UC	UC2
Link to StRS	StRS08

5.1.2 AI-fuelled Orchestration

5.1.2.1 Service Modelling and Enactment

Table 25. Service Modelling (aka “Configurations”) and Enactment Requirement.

ID	FR05
Title	Service Modelling and Enactment
User Roles	End user of a service / application; Service developers / providers
Description	Service Modelling and Enactment should graphically describe application topology, denote intercommunication and dependencies among the applications' services and sub-components. Structured YAML Ain't Markup Language (YAML) or JSON files should be used for the configurations.
Reference UC	UC1; UC3; UC4
Link to StRS	StRS03

Table 26. NG-SDN and Distributed Intelligence Requirement.

ID	FR06
Title	NG-SDN and Distributed Intelligence
User Roles	Service developers / providers
Description	The Distributed Intelligence should abstract the control plane and move it to a centralised controller, which communicates with the network devices. This separation should allow for programmability, flexibility, and easier management of the network.
Reference UC	UC3
Link to StRS	StRS18

5.1.2.2 Orchestration

Table 27. AI Swarm Orchestration Requirement.

ID	FR07
Title	AI Swarm Orchestration
User Roles	End user of a service / application; Service developers / providers; E2C infrastructure providers
Description	Swarm orchestration should manage and coordinate a swarm of autonomous entities or agents to achieve a common goal. In swarm orchestration, multiple individual agents should work together in a decentralised manner, leveraging local interactions and simple rules to exhibit emergent behaviours and accomplish complex tasks, such as obstacle avoidance, trajectory, and energy planning.
Reference UC	UC1
Link to StRS	StRS04; StRS05; StRS06; StRS07

Table 28. Resource Allocation and Deployment Requirement.

ID	FR08
Title	Resource Allocation and Deployment
User Roles	Service developers / providers; E2C infrastructure providers
Description	The optimal resource allocation and deployment should efficiently distribute resources to achieve the best possible outcome or maximize a certain objective. It involves making decisions on how to allocate resources such as time, idle slots and computing nodes in a manner that optimises data and services placement, response time, and energy efficiency.
Reference UC	UC1; UC3; UC4
Link to StRS	StRS02; StRS20; StRS24

Table 29. Definition, Customisation and Monitoring of Metrics Requirement.

ID	FR09
Title	Definition and Monitoring of metrics
User Roles	Service developers / providers; E2C infrastructure providers
Description	By migrating knowledge from the AI@EDGE project, TALON should adopt the methodology crafted for the end-to-end process of defining, customizing, and measuring Key Performance Indicators (KPIs) within the platform. This process should initially provide a schema which will hold every metric necessary to describe specific KPIs and then develop a method to keep track of these metrics, possibly in real time, for the system to self-improve and self-evaluate the performance of the platform.
Reference UC	UC1, UC3
Link to StRS	StRS22

Table 30. Data Monitoring, Collection and Aggregation Mechanisms Requirement.

ID	FR10
Title	Data Monitoring, Collection and Aggregation
User Roles	Service developers / providers; E2C infrastructure providers
Description	The TALON System should be able to periodically pull monitoring data from all its assigned agents. The orchestration system shall periodically pull aggregated monitoring data from the storage system of the TALON Orchestrator and the Edge devices for all deployed applications. FR10 should give input to FR11 to train and enforce smart orchestration strategies.
Reference UC	UC1; UC3; UC4
Link to StRS	StRS26

Table 31. AI Model Training and SLOs Requirement.

ID	FR11
Title	AI Model Training and SLOs Optimisation
User Roles	End user of a service / application; Service developers / providers
Description	The TALON System should provide the capability to train AI models and support smart and adaptive strategies for the metrics collected by FR09 to meet the respective business objectives and KPIs.
Reference UC	UC1; UC3
Link to StRS	StRS23; StRS25

5.1.3 AI Cognition

Table 32. Self-healing and Self-correcting Requirement.

ID	FR12
Title	Self-healing and Self-correcting
User Roles	End user of a service / application; Service developers / providers
Description	It should develop and train AI models to autonomously detect, diagnose, and repair damage or faults without external intervention. The AI algorithms should learn over the collected and curated data to facilitate the prompt diagnosis and evaluation of breakage incidents in the manufacturing contexts. Also, different AI models should be trained to benchmark, compare, and select the most suitable model per case.
Reference UC	UC2
Link to StRS	StRS11; StRS13

Table 33. Hybrid and Optimised Learning Requirement.

ID	FR13
Title	Hybrid and Optimised Learning
User Roles	Service developers / providers
Description	Optimised Learning should detect and report on breakage and damages of the cutting tools; support meta-learning to learn how to quickly adapt to new tasks or categories using a limited amount of labelled data; data augmentation to increase the diversity of the supporting dataset; and generalisation on top of a few labelled examples to overcome the data unavailability.
Reference UC	UC2; UC3
Link to StRS	StRS10; StRS21

Table 34. AI Capabilities and Transfer Learning Requirement.

ID	FR14
Title	AI Capabilities and Transfer Learning
User Roles	Service developers / providers
Description	The AI capabilities for scene analysis and safety level detection (PPE, fire) should be trained using transfer to leverage knowledge learnt from one task or domain to improve performance on a different but related task or domain.
Reference UC	UC2; UC3
Link to StRS	StRS21

Table 35. Data Operations Requirement.

ID	FR15
Title	Data Operations
User Roles	Service developers / providers
Description	Data operations including collection, cleaning, enrichment, and alignment, as well as querying for exploratory data analysis should be performed on the collected data to produce reports and ensure that the tools are working within their optimum range.
Reference UC	UC2
Link to StRS	StRS09; StRS12

Table 36. Digital Twins Requirement.

ID	FR16
Title	Digital Twins
User Roles	End user of a service / application; Service developers / providers
Description	Digital Twins should simulate and optimize manufacturing processes, monitor equipment performance, monitor working condition safety measures via augmented images and predict maintenance needs
Reference UC	UC2; UC3; UC4
Link to StRS	StRS16

Table 37. XAI and Monitoring Requirement.

ID	FR17
Title	XAI, Monitoring and Reporting
User Roles	End user of a service / application; Service developers / providers
Description	The TALON System should provide understandable explanations regarding optical link faults, imbalanced data and data that need curation and cleaning. Through a stepwise approach, it should support transparency, trustworthiness and interpretability of the data and the results of black-box AI models.
Reference UC	UC2
Link to StRS	StRS15

Table 38. Data Lifecycle Management Requirement.

ID	FR18
Title	Data Lifecycle Management

User Roles	End user of a service / application; Service developers / providers; E2C infrastructure providers
Description	The Data Lifecycle Management should support the underlying database and distributed storage systems of the TALON project and the back-end processes to manage data, from its creation or acquisition to its eventual storage and querying.
Reference UC	UC1, UC2, UC3, UC4
Link to StRS	StRS12

Table 39. Visualisations Requirement.

ID	FR19
Title	Visualisation Dashboard
User Roles	End user of a service / application; Service developers / providers
Description	The visualisation dashboard should support a graphical user interface that displays visual representations of data, metrics, and key performance indicators (KPIs) of the TALON project in a consolidated and easily understandable format.
Reference UC	UC2; UC3; UC4
Link to StRS	StRS14

5.2 Non-functional Requirements

Non-Functional Requirements (NFRs) define the qualities, or overall characteristics, of a system and may impose constraints on the design or implementation. These qualities, many of which are documented in ISO/IEC Standard 25010:2011 [21], may include functionality, performance, security, and maintainability to name a few. Deliverable D2.1 puts special emphasis on collecting functional requirements. These requirements are the primary source for the formulation of the high-level architecture. However, it is highly crucial to elaborate on the non-functional requirements. Non-functional requirements, sometimes called quality requirements, provide constraints on the functional requirements, specifying which kinds of qualitative characteristics are important for certain functions. Since there are not specific standards on how to provide such qualitative characterisation, ISO/IEC 25010:2011 standard has been selected as a cornerstone model for TALON. It could be argued that such a model is appropriate because of its wide adoption and its generalisation. It defines a taxonomy of characteristics and sub-characteristics, as depicted in Figure 29 that addresses quality issues.

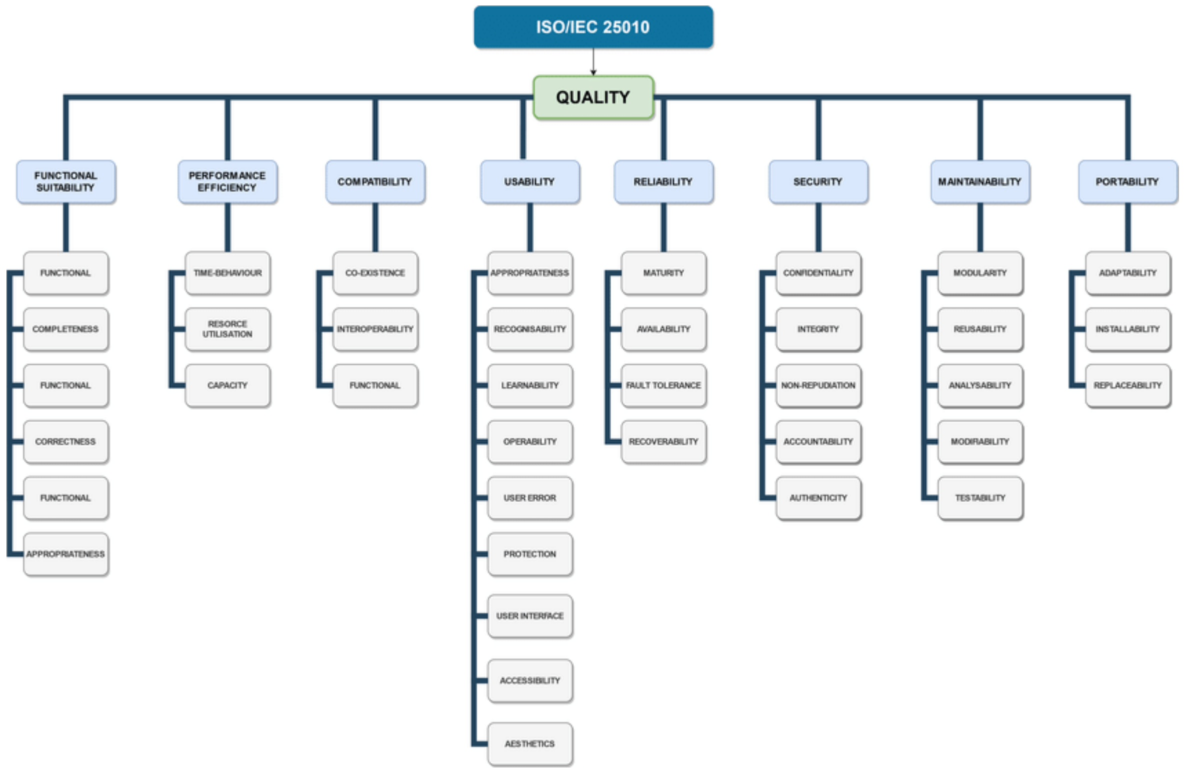


Figure 29. ISO 25010 software product quality requirements classes.

The quality model classifies software quality in a structured set of characteristics and sub-characteristics as follows:

- **Functional suitability**: It refers to a set of attributes that bear on the existence of a set of functions and their specified properties. The functions are those that satisfy stated or implied needs. Indicative sub-characteristics include Functional completeness and correctness.
- **Reliability**: It refers to a set of attributes that bear on the capability of software to maintain its level of performance under stated conditions for a stated period. Indicative sub-characteristics include Maturity, Fault Tolerance, Recoverability, Reliability Compliance.
- **Usability**: It refers to a set of attributes that bear on the effort needed for use, and on the individual assessment of such use, by a stated or implied set of users. Indicative sub-characteristics include Understandability, Learnability, Operability, Attractiveness, Usability Compliance.
- **Efficiency**: It refers to a set of attributes that bear on the relationship between the level of performance of the software and the amount of resources used, under stated conditions. Indicative sub-characteristics include Time Behaviour, Resource Utilisation, Efficiency Compliance.
- **Maintainability**: It refers to a set of attributes that bear on the effort needed to make specified modifications. Indicative sub-characteristics include Analysability, Changeability, Stability, Testability, Maintainability Compliance.
- **Portability**: It refers to a set of attributes that bear on the ability of software to be transferred from one environment to another. Indicative sub-characteristics include Adaptability, Install-ability, Co-Existence, Replaceability, Portability Compliance.

- **Security**: It refers to a set of attributes that define the degree to which a product or system protects information and data so that persons or other products or systems have the degree of data access appropriate to their types and levels of authorisation.
- **Compatibility**: It refers to a set of attributes that define the degree to which a product, system or component can exchange information with other products, systems, or components, and/or perform its required functions, while sharing the same hardware or software environment.

Each quality sub-characteristic (e.g., adaptability) is further divided into attributes. An attribute is an entity which can be verified or measured in the software product. Attributes are not defined in the standard, as they vary between different software products. The table below summarizes the number of non-functional requirements that are relevant to TALON and their ‘interpretation’ in the TALON context.

Table 40. Relation of ISO 25010 Requirements with TALON.

ISO 25010 Non-Functional Requirement	Relationship to TALON
Compatibility.Coexistence	The ability of the TALON System to run along other pieces of software without interfering with them in a negative way, or being impacted negatively itself
Compatibility.Interoperability	The ability of the TALON System to communicate and interact with other software components
Functional suitability.Functional completeness	The degree to which the TALON System functionality has been specified in full, to cover all functional requirements
Functional suitability.Functional correctness	The degree to which the TALON System functionality performs with correct behaviour and results (proper testing)
Maintainability.Modifiability	The degree to which the TALON System functionality can be parametrised, configured, or modified while still performing correctly
Maintainability.Modularity	The degree to which the TALON System components can be changed without significantly impacting the design of the overall behaviour
Maintainability.Reusability	The degree to which the TALON System components can be deployed in different scenarios
Modifiability.Testability	The degree to which a TALON System component can be evaluated to behave correctly
Performance.Capacity	The degree to which the TALON components are scaling
Performance.Resource utilisation	The degree to which a TALON System component uses system resources efficiently

Performance.Time behavior	The latency and throughput of TALON System components
Portability.Adaptability	The extent of a TALON System component's ability to run on different underlying platforms and systems
Reliability.Availability	The degree to which the TALON System and its components are available at the required times
Reliability.Fault tolerance	The degree to which the TALON System can manage errors and faults while still performing correctly
Reliability.Recoverability	The ability of the TALON System to recover its state and data after a fault
Security.Accountability	The ability to trace the actions of actors using the TALON System
Security.Authenticity	The ability to correctly identify the entity issuing a request to the TALON System
Security.Confidentiality	The degree to which the TALON System ensures data protection
Security.Integrity	The degree to which the TALON System prevents unauthorised access to data
Usability.Accessibility	The degree to which the TALON System can be used by various types of end-users easily
Usability.Appropriateness recognizability	The degree to which various types of end-users can recognize that the TALON System meets their business needs

6 Technology Enablers

This chapter explores different paradigms for each component and outlines the developing objective of the project in the context of the latest technology trends. The chapter includes a comprehensive state-of-the-art of cutting-edge technologies, examining their strengths and potential applications.

6.1 Underlying Technologies

6.1.1 Access and Security

6.1.1.1 Authentication and Authorisation

Existing paradigms: Today major cloud and edge service providers utilize some customised forms of Role-Based Access Control (RBAC) model along with specific authorisation policies enabled by policy-based access control models. To enable fine-grained access control and overcome limitations of existing access control models, there is an imminent need to develop a flexible and dynamic access control model for securing edge devices, data, and resources in E2C architectures. Ammer et al. *[22]* introduced $HABAC_{\alpha}$, an Attribute Based Access Control model for smart-home edge devices that governs user-to-device authorisation. It captures users, environments, operations, and device characteristics / attributes. An attribute is a function that takes an element such as a user and returns a certain value from its range. User / Session attribute functions set is the set of attributes associated with both users and sessions. Each session inherits a subset of the attributes of its unique user creator. This is controlled by the unique user creators. The device attribute functions set consists of attributes related to devices. The operation attribute functions set is a collection of attributes corresponding to different operations. For example, if someone wishes to characterize "X" operations, she may create an operation attribute entitled “X" and associate it with those operations. Environment-state attribute functions set describes the environment condition of the current instance of time. Bhat et al. *[23]* developed a formal Attribute-Based Access Control model for edge devices to enable flexible and fine-grained access control for billions of smart devices, users, resources, and applications in a real-world IoT platform. They defined eight core entities of the model - Devices, Certificates, Things, Shadows, Topics, Rules, Groups, and Operations. They extended the AWS-IoTAC model *[24]* and supported the specification of fine-grained security policies using attributes of various entities, such as IoT devices, virtual objects, and topics. In addition to the new access control components, the proposed ABAC model uses components of AWS-IoTAC and the typical cloud Identity and Access Management policies.

What we plan to do in TALON: In TALON, we plan to follow a similar approach and provide the mechanisms to support authentication and authorisation on top of heterogeneous clouds, and edge nodes to facilitate end users utilize resources and functions from various underlying infrastructures that are managed and governed by different organisations. In this way, we plan to decentralise the administration of access among users, devices (i.e., edge, and cloud based) and applications / data. Therefore, the authentication and authorisation mechanisms are responsible to support services for secure interaction in the TALON framework, user credentials at role and organisation level, policies specification and enforcement. The authentication and authorisation mechanisms will provide a horizontal infrastructure which will manage enhanced and distributed access control over the heterogeneous cloud, and edge nodes taking into consideration specificities regarding subject attributes (i.e., who accesses and how), environmental attributes (i.e., where is the origin of the request, edge, cloud and how e.g., browser, pod/agent, producer/consumer process, etc.), resource and action attributes (who is the owner, what time created, etc.).

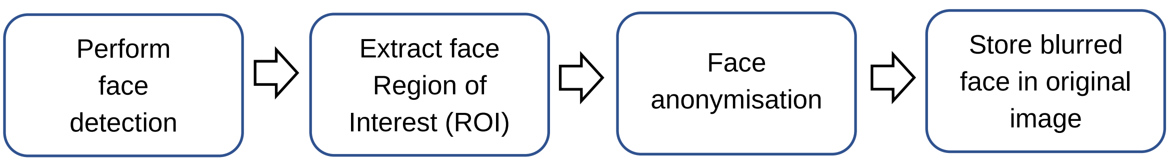
6.1.1.2 Data Anonymisation in Textual and Numerical Data

Existing paradigms: Abdul Majeed et al. [25] categorise clustering-based anonymisation mechanisms (CAMs) based on data types and provide an extensive review of existing CAMs and evaluation metrics. CAMs are highlighted for their superiority over traditional anonymisation methods, and their relevance in computing paradigms like social networks, IoT, cloud computing, AI, and location-based systems. The article also discusses compromising CAMs and identifies research gaps. Technical challenges and future research opportunities are discussed, making this the first systematic work covering CAMs across various data types and computing paradigms. Suntherasvaran Murthy et al. [26] examine the privacy risks associated with storing personally identifiable information (PII) in databases. The authors compare five anonymisation techniques using a common dataset and evaluate their strengths and weaknesses. The results indicate that suppression is the most efficient technique while swapping is the least efficient. Furthermore, swapping is found to be resource-intensive, whereas suppressing is less resource-consuming. This research contributes to understanding and implementing effective privacy preservation techniques in the digital era of data collection and storage by organisations. Additionally, Chunchun Ni et al. [27] established a paradigm for evaluating data anonymisation to evaluate anonymisation algorithms in terms of performance, privacy preservation, and data utility. The trial outcomes showed how well the framework performed in assessing de-identification features and preventing improper use of anonymised data.

What we plan to do in TALON: The TALON project's decision to deploy anonymisation is motivated by the increasing need for privacy protection brought on by the global adoption of IoT and the promising applications of Industry 4.0/5.0. The importance of gathering and processing private information while respecting privacy has been highlighted by introducing rules like General Data Protection Regulation (GDPR). TALON will create a data anonymisation system that includes standardised procedures for removing Personally Identifiable Information (PII) from both structured and unstructured data formats to address such issues. The system can recognize and anonymize typical things like names, emails, and phone numbers by using Natural Language Processing (NLP) and machine learning. It will focus on anonymizing free-form text documents, which often contain unstructured data, and employ techniques to identify text structures representing entities. By incorporating anonymisation, TALON will ensure secure information sharing, compliance with privacy regulations, and effective countermeasures against cyber threats.

6.1.1.3 Data Anonymisation in Imagery and Facial Data

Existing paradigms: GDPR requires that personal data be processed in a way that ensures appropriate security, including protection against unauthorised or unlawful processing and against accidental loss, destruction, or damage. Anonymisation (Recital 26 GDPR) and pseudonymisation (art. 4 GDPR) meets these requirements, as it allows data to be used without revealing personal information about the individuals involved. In contrast to anonymisation, data pseudonymisation is the reversible process of transformation of personal data. This is the reason why GDPR considers pseudonymised data as personal data. Therefore, purpose limitation, storage limitation, integrity and confidentiality must be granted after the data has been pseudonymised. Existing paradigms for image and video anonymisation or pseudonymisation are made up of 4 distinct phases, as follows:



There are dozens of face detection solutions, both proprietary and open source, offering various features, detecting multiple faces to more complex objects included in the images/video, such as license plates.

The best proprietary face detection software solutions (not for free) are:

- Amazon Rekognition, based on deep learning and fully integrated in AWS. Able not only to detect but also to recognize faces (out of the TALON's scope). It can detect basic emotions.
- Microsoft Azure Cognitive Services Face API includes age estimation, gender, and emotion recognition, as well as landmark detection.
- Face++, face analysis cloud service, provides services like gender and emotion recognition, age estimation, and landmark detection They primarily operate in China and its parent company, Megvii has been sanctioned by the US government in late 2019.
- Kairos, the API endpoints include identifying gender, age, facial recognition, and emotional depth in photos and videos.
- Face Recognition and Face Detection API (Lambda Labs) provides face recognition, facial detection, eye position, nose position, mouth position, and gender classification.
- Trueface is a face recognition company for enterprises, providing features like gender recognition, age estimation, and landmark detection as a self-hosted solution.

In the open-source side, we can find excellent solution too:

- Ageitgey/face_recognition is a GitHub repository with 40k stars, one of the most extensive face recognition libraries. However, the latest version released as late as 2018 and has 99.38% model recognition accuracy, which could be much better in 2023. It also does not have a REST API.
- Deepface is a framework for Python with 1,5k stars on GitHub, providing facial attribute analysis like age, gender, race, and emotion. It also provides REST API.
- FaceNet developed by Google uses the Python library for implementation. The repository boasts of 11,8k starts. Meanwhile, the last significant updates were in 2018. The accuracy of recognition is 99,65%, and it does not have REST API.
- InsightFace is another Python library with 9,2k stars in GitHub, and the repository is actively updating. The recognition accuracy is 99,86%. They claim to provide a variety of algorithms for face detection, recognition, and alignment.
- InsightFace-REST is an actively updating repository that aims to provide convenient, easily deployable and scalable REST API for InsightFace face detection and recognition pipeline using FastAPI for serving and NVIDIA TensorRT for optimised inference.
- OpenCV is not an API, but it is a valuable tool with over 3,000 optimised computer vision algorithms. It offers many options for developers, including Eigenfacerecognizer, LBPHFacerecognizer, or lpbhfacerecognition face recognition modules.
- OpenFace is a Python and Torch implementation of face recognition with deep neural networks. It rests on the CVPR 2015 paper FaceNet: A Unified Embedding for Face Recognition and Clustering.

Face anonymisation aims to protect individuals' privacy by altering or obscuring their facial features in images or videos. Here are some commonly used approaches:

- Blurring or pixelation: This technique involves applying a blur or pixelation filter to the facial region, rendering it unrecognizable. The level of blurring can vary, ranging from mild to strong, depending on the desired degree of anonymity.
- Geometric distortion: By distorting facial geometry, it becomes challenging to identify the person. Techniques like face warping, where facial landmarks are adjusted or moved, can be employed to alter the appearance of the face without completely removing it.
- Image and video inpainting: Inpainting methods aim to fill in the gaps left after removing a face from an image or video. These algorithms analyse the surrounding context and generate plausible content to replace the anonymised region. State-of-the-art inpainting techniques utilize deep learning models, such as generative adversarial networks (GANs), to produce realistic replacements.
- Face swapping: This technique involves replacing the original face with another face from a different source while preserving the facial expressions and head movements. Deep learning approaches, such as conditional GANs or facial landmark-based methods, can be used for accurate face swapping.
- Low-dimensional representation: Some methods aim to represent the face using a low-dimensional feature vector, such as a face template or a face descriptor. This representation retains essential characteristics while discarding identity-specific information, enabling the anonymisation of facial data.
- Anonymisation through anonymised identities: Instead of directly manipulating the facial features, this approach assigns anonymised identities to individuals. The identities can be random or consistent across different frames, preventing the recognition of specific individuals.
- Privacy-preserving face detection: This technique focuses on detecting faces in images or videos without revealing identifying information. It involves detecting the presence of a face while intentionally suppressing or omitting details that can be used for identification.

It is important to note that the effectiveness of these techniques can vary depending on factors such as the quality of the input data, the robustness of the anonymisation algorithm, and the threat model being considered. Ongoing research is continuously advancing these techniques to improve their accuracy and privacy preservation capabilities.

What we plan to do in TALON: We plan to develop a configurable image / video anonymisation module granting:

- The best face detection option (Haar cascades / HOG + Linear SVM / Deep learning-based face detectors/…) offered by the open source OpenCV that meets TALON's needs;
- A face anonymisation based on blurring or pixeling that meets TALON's needs with a tuneable anonymisation deep level;
- The possibility to choose if image / video should be anonymised or pseudonymised;
- Storage limitation, in case of pseudonymisation choice, enabling the *Right to erasure* (also known as '*right to be forgotten*') according to Art. 17 GDPR; and
- An auditor function, in case of pseudonymisation choice, that remove possible original image/video older than a configured retention period (Recital 39 GDPR: personal data cannot be kept indefinitely).

6.1.1.4 DLTs for Security and Privacy

Existing paradigms: A technical analysis that demonstrates the importance of blockchain technology across various sectors is needed, to investigate and analyse the state of the art in this subject given the fast pace of Blockchain research. In a decentralised Blockchain network, data resides in a distributed ledger. Participants can write, read, and verify transactions but cannot delete or modify them. Recorded transactions in the ledger are protected for integrity, authenticated for authenticity, and prevent repudiation. A consensus protocol ensures a unified record among all participants [28]. Blockchain finds implementation across various domains, including healthcare where it addresses interoperability concerns in electronic health records (EHR) frameworks and prevents unauthorised alteration and malicious misuse of patient's data [29]. In another study [30], the instructions between the swarm drones are communicated on blockchain technology, boosting the safety of consensus among drones, and thus enhancing communication and decreasing energy consumption. All in all, privacy of personal data and procedure optimisation are fundamental pillars to build blockchain on.

What we plan to do in TALON: Blockchain technology offers a range of benefits for enhancing security and privacy and TALON incorporates essential features such as transparency, encryption, immutability, and consensus. The envisioned blockchain mechanism ensures a secure network for information exchange. Therefore, a permission-based ledger will be employed to validate, authenticate, and grant access to new users. This approach guarantees that only verified nodes, trusted by the network, are permitted access. Each transaction's data is encrypted, enhancing the authenticity and integrity of the information. Moreover, the immutability of TALON's blockchain ensures that transactions recorded in the blockchain remain unaltered. Blocks are added to the network, when the nodes reach a consensus and once the block is added, it is chained with the previous block. This ensures that any unauthorised modification to the blockchain, disrupts the chain and changes can be easily traced back. Finally, TALON's blockchain technology finds utility in storing sensitive information, including drone details (such as battery status, location, and moving directions) and images (or image paths), safeguarding their confidentiality.

6.1.1.5 Anomaly Detection

Existing paradigms: In conventional techniques for heterogeneous information-based anomaly detection for network activity, it is necessary to constantly update the prior knowledge with human experts. An efficient method proposed to get around this issue by Shi and Shen [31] is unsupervised anomaly identification, employing automated clustering approaches to create centroids from the network packets and eventually dissecting the centroids into "normal" and "anomalous" groups. Another innovative approach which can also recognise formerly unknown patterns, utilizes recurrent neural networks (RNNs) to grasp the subtleties and complicated interconnections of compressed and tokenised network flows as introduced by Radford et al. [32]. Finally, two different frameworks leveraging long-short term memory networks and personalised federated anomaly detection to identify network anomalies were introduced by Pei et al. [33].

What we plan to do in TALON: For TALON purposes, an anomaly detection module will be deployed in the security layer of the platform, to provide an even higher level of security and privacy to the system. This tool comprises two utilities, the network activity monitoring, and visual analytics subcomponents. This AI – enabled security module will have the capacity to sniff potential malicious network activity on a network to monitor and analyse some specific communication protocols. To that end, an ML-based sensor will be trained utilising various methods such as optimised distributed gradient boosting trees and feedforward or multi layered perceptron neural networks, meeting the network requirements of the project. The corresponding results of the potential malicious network flows will be communicated to the security administrators through a JSON format and visualised through a user-friendly uncongested visualisation using advanced visualisation graphs.

6.1.2 AI-fuelled Orchestration

6.1.2.1 Microservices Architectural Paradigm

Existing paradigms: The evolvement of new software development paradigms is following the need for development of applications that adhere to the notions of modularity, distribution, scalability, elasticity, and fault-tolerance [37]. A micro-service architectural approach is considered as the resulting set that arises from the decomposition of a single application into smaller pieces (services) that tend to run as independent processes and have the ability to inter-communicate usually using lightweight and stateless communication mechanisms (e.g., RESTful APIs over HTTP) [38]. These (micro-) services are built around business capabilities and are independently deployable by fully automated deployment machinery. For (micro-) services, there is a bare minimum of centralised management, and such services may be written in different programming languages and even use different data storage technologies [39].

What we plan to do in TALON: In TALON, we will advance the -Ops programming paradigm. The impact of new architectures - like microservices - on the network and the resources (edge-to-cloud infrastructure) that deliver those services is not always evident to developers. We plan to employ DevOps and AIOps as a cultural force and as a good paradigm for more efficient implementations. Collaboration in the design and architectural phase will go a long way towards improving not only the efficacy of the deployment pipeline but the performance and efficiency of applications across the entire operational spectrum of TALON.

6.1.2.2 NG-SDN and Distributed Intelligence Functionalities

Existing paradigms: Since SDN became the heart of the networking industry, there has been a lot of head nodding and ancillary mention of L4-7 services eventually becoming part of the overall fabric. However, there are still inherent challenges in bringing those services to a centralised controller responsible for directing the flow of packets throughout the network [34]. SDN is the next generation network that decouples the control plane from the data plane of forwarding devices by utilizing the OpenFlow protocol as a communication link between the data plane and the control plane [35]. The SDN defines two important features: first, separate the data plane and control panel, and second, the controller platforms can control multiple forwarding elements using a well-defined API (Application Programming Interface), such as OpenFlow, one of the successful protocols. Not only do they simplify network management, but they also open development gateways to each control plane and data plane, allowing for many network innovations and distributed intelligence [36].

What we plan to do in TALON: IN TALON, we will design an SDN traffic measurement and decision-making framework employing machine learning and deep learning methods on top of the collected data. Data will be collected from different agents and layers for abundant and distributed knowledge gaining. ML and DL methods will be useful for proper network resource distribution, advanced routing, bandwidth provisioning and enforcing policies for correcting communication drops. We will realise this by providing an interface for connecting the control plane and the programmable data plane via the P4 compiler.

6.1.2.3 E2C Computing and Applications Orchestration

Existing paradigms: TALON's E2C computing, and applications orchestration is a cloud-native technology that consists of a set of modules aimed at planning, deploying, and managing workloads in the edge-to-cloud continuum. The environment baseline is represented by Kubernetes at its state of the art, so to have container orchestration capabilities and some fundamental automation mechanisms working off the shelf, like deployment and scaling actions, network overlays, load balancing features, and self-healing capabilities.

What we plan to do in TALON: In TALON, we plan to extend the above-described baseline at different levels of abstraction to build an entire TALON orchestration ecosystem across cloud and edge domains: for example, at the core level, the scheduling module will make use of the Kubernetes Scheduling Framework [40] along with a series of custom components at the application level, that boosts the orchestration processes through some “smart” AI-powered capabilities built on top of 5 pillars:

1. Topology Awareness: A resource manager sub-component will be delivered to keep track of the resource consumption and availability in the whole infrastructure as well as to assist the administrators in the federation of cloud and edge environments.

2. Security: Any orchestration activity will be performed considering constraints and authorisation policies to keep the environment safe and consistent.

3. Application Lifecycle Management: A Zero-Touch approach will be adopted by default to deploy and scale applications in the most transparent way, reducing any manual and tedious tasks performed by the operators. Nevertheless, the application lifecycle manager provides a set of APIs that will open a direct interaction, whenever it is required, with the managed processes in the Edge to Cloud continuum.

4. AI Operations support by design: The above-mentioned Lifecycle Management feature will be extended to support the canonical processes behind the development of AI-based applications and the production of deep learning models. To achieve that, E2C Computing and Applications Orchestration will deliver full Machine Learning and Federated Machine Learning workload management coverage so that TALON users will be able to run training tasks and federated training tasks with ease, exploiting TALON’s green and smart allocation mechanism.

5. Green and Smart Operations: The E2C computing, and applications orchestration middleware will continuously consume power-consumption-related metrics from both the cloud and edge aggregator modules. Thanks to the connection with the underlying hardware sensors (i.e., Intel’s Running Average Power Limit Sensors [41]), it will perform a power consumption screening and promote the distribution of workload requests on the lesser exploited nodes belonging to the same elected node category. Time by time, telemetry will serve predictive models to enrich the knowledge of the component and schedule more efficiently upcoming requests via the communication with TALON’s scheduler.

Overall, E2C Computing and Applications Orchestration, matches the target TALON execution environments with every possible workload request, relying on the combination of deterministic and AI-based approaches.

6.1.2.4 Optimal Resource Allocation and Coordination

Existing paradigms: Traditionally, data generated in battery-constrained devices, such as sensors, need to be transferred to remote cloud servers for related task processing, due to the limited computational capabilities of the data generating nodes. However, this transfer can induce high latencies and network congestion concerning the immense amount of data that needs to be moved to cloud servers for processing. This is the reason why leveraging edge computing is a notably more logical approach to task offloading, especially for delay intolerant applications. This creates a 3-layer continuum that involves the data generating end devices, the edge devices, and the cloud servers where tasks can be offloaded, based on the quality-of-service (QoS) requirement that originate from the respective service-level agreements (SLAs). The traditional approaches for the edge-to-cloud

(E2C) task offloading are rather opportunistic since they involve conventional optimisation tools that are more suitable for short-term task offloading, where the dynamics of the edge and cloud layers remain unaltered [42], [43], [44], [45], [46]. However, their adaptation is poor to the realistic dynamic environments concerning edge and cloud resource availability together with the possible reliability fluctuations related to the end device-edge-cloud communication links. Hence, automatic approaches are needed for better coping with realistic dynamic conditions.

What we plan to do in TALON: By leveraging the large amounts of network data that will be collected in TALON and originate from resource monitoring tools and logging mechanisms, we will develop ML-based methods that will decide whether a particular task needs to be offloaded and, if so, at which layer. In addition, again through ML-based means, the scheduling of the task in the designated layer will be performed by considering the execution time, the energy consumption, CPU utilisation, and reliability. Emphasis will be given on: (i) Supervised-learning related approaches, where the offloading decision problem will be formulated as a multiclass classification problem and the computational resource allocation problem as a regression problem; and (ii) Deep-learning approaches. Such methods have been implemented in various varying network condition scenarios for the computation and task offloading minimisation overhead.

6.1.2.5 Smart Policy Manager

Existing paradigms: One of the most well-established paradigms of a smart policy manager for pricing is the technique of dynamic pricing. This method refers to the practice of adjusting prices in real-time based on various factors such as demand, competition, customer behavior and market conditions. A smart policy manager for pricing following the paradigm of dynamic pricing, utilizes advanced AI algorithms and data analysis techniques to adjust prices in real-time. It collects and analyses data from various stakeholders, formulating strategies based on insights gained by those data and continuously monitors factors like demand, competition, and market conditions. Through automated adjustments, it optimizes prices at different levels, considers inventory levels, sales target, and customer segmentation. This kind of system incorporates testing and optimisation methodologies to validate strategies and provides performance evaluation and reporting features.

What we plan to do in TALON: Integrating a smart policy manager for pricing into the TALON system offers significant advantages. TALON is a comprehensive system designed to enhance the efficiency and effectiveness of intelligent systems. By embedding the smart policy manager within TALON, businesses can leverage its real-time data analysis by exploiting a dynamic pricing algorithm equipped with automated adjustment capabilities. This integration enables us to optimize pricing strategies at the edge, allowing for quick decision-making and responsiveness to changing market conditions. All these features stem from the ability of TALON's AI Orchestrator to provide the data needed to perform this kind of analysis in rea-time and in an optimal manner. The seamless integration of the smart policy manager within TALON empowers stakeholders to maximize revenue, minimize response latency, and improve overall system performance.

6.1.2.6 AI Swarm Orchestration

Existing paradigms: A drone swarm is a group of drones that work together to achieve a common goal. All the individual drones work in unison to complete tasks using distributed coordination, with each communication sent out by one drone providing the others with up-to-date information about their environment and roles in the mission. As their commands are based on real-time data, these swarms react quickly and precisely to changes in their surroundings.

What we plan to do in TALON: In TALON, the AI swarm orchestration will be led by the PROBOTEK team. PROBOTEK's approach and architecture is vastly different from previous approaches that follow the exclusive edge-to-edge or point-to-point communication model and edge processing.

PROBOTEK utilizes a new technology and technique. By connecting an intermediate Ground Control Station (GCS) that inter-connects and controls all drones simultaneously and by sending heavy (data-wise) messages to a cloud server to do the computationally expensive processing, we introduced a more efficient architecture that supports off-the-shelf products and custom-made drones that function seamlessly.

More specifically, the SotA proposed by PROBOTEK manages the swarming process as follows:

- Each drone is not required to have a high-end CPU/GPU or TPU on-board.
- Each drone gets connected to a common GCS with the typical drone telemetry.
- The GCS coordinates locally the drones by sending literally bits and bytes through the telemetry which is already optimised so that it does not deplete the battery.
- To accommodate the swarming capabilities, the GCS requests a local buffer of information that is being updated by the AI Orchestrator running on the cloud on a remote location.
- The AI Orchestrator is utilizing the power of the cloud resources to do the computationally intensive work online and download data to the GCS.
- The GCS utilizes the AI Orchestrator progressively by actively mapping their location among other data and either strategizes by micro-processing on the ground or calls the AI Orchestrator again.

6.1.3 AI Cognition

6.1.3.1 Self-healing and Self-correcting Mechanisms

Existing paradigms: The most promising techniques for time series classification are deep neural networks using Recurrent Neural Networks (RNN) patterns like LSTM (Long Term Short Term), Bidirectional LSTM or GRU (Gated Recurrent Unit) patterns [47], [48], [49], [50]. One of the approaches for few shot learning is fine tuning a pre-trained model with data specific for new use cases [51], [52], [53]. This approach is a little complex to implement. A very promising technique is to use available pre-trained transformers [54]. The time series nature of the data adds additional complexity and makes it difficult to use other approaches. Survival analysis, the core AI learning task consists of learning the probability of a failure occurring on a time window in the future, rather than predicting when the failure will occur [55]. The name survival analysis roots back to the first applications of these types of models in the health sector. The first survival models learnt the probability of a patient surviving several years from now based on some demographic and clinical information. The models produce what is called a hazard curve or survival curve, where the x axis represents time (years in the case of patients, or production shifts or days in the case of predictive maintenance) and the y axis represents the probability of failure [56]. The area of this curve provides an estimation of the risk (if the area of the hazard curve is high, then so is the risk) that can be used to support decision making. For predictive maintenance, there is no need to predict when a failure will occur with precision, but rather, what is the risk of waiting several production shifts without a maintenance operation.

To create supervised learning machine learning models, means that there is the need for a labelled dataset with knowledge of failures that have occurred [57]. Also, if one has time series data, she needs to do some pre-processing to prepare the info for survival analysis, and basically, for the processing, she needs to group the data in the time domain (the parallelism is between a shift without failure and a patient without cancer), meaning that the effectiveness of this type of models can severely benefit from few-shot learning approaches. In the literature, the main technique used is data augmentation to increase the number of examples for training [58]. Another approach is to train a time series classification model and then use transfer learning or few shot learning techniques to implement the survival analysis model [59], [60].

Time series classification: The core task is to predict the occurrence of an event happening in a future instance of time. The training dataset consists of time data series containing independent variables (e.g., sensor data in predictive maintenance) and a categorical variable describing the state one would like to predict (for instance, an alarm code in predictive maintenance. Similar to time series regression, the models are trained to predict the future states from the current state and several previous current states.

What we plan to do in TALON: In TALON we aim to develop a few-shot learning model to extract the skills of the operators from data from their reports. This will help on targeted upskilling of the operators. To achieve this a pre-trained set of transformers will be used and fitted to the data from the operators reports, which will create an efficient few shot learning model and could lead to high efficiency of the model.

The second development in TALON will be to predict the occurrence of an event happening in a future instance of time. More specifically, the events that will be studied are alarms from a specific manufacturing machine and link the alarms with the required maintenance actions. The training dataset consists of time data series containing independent variables (e.g., sensor data in predictive maintenance) and a categorical variable describing the state one would like to predict (for instance, an alarm code in predictive maintenance. Similar to time series regression, the models are trained to predict the future states from the current state and several previous current states.

6.1.3.2 Federated Learning

Existing Paradigms: As stated in the work from Abreha et al. [61], which presented a comprehensive survey on Federated Learning, Edge Computing that extends Cloud Computing can be combined with Deep Learning, which produces promising results in a large number of domains. To enhance this concept, the authors proposed Federated Learning aiming to increase models' performance, without the need of exchanging data across different devices, or clients. Based on the work from Rjoub et al. in [62], they used federated learning in combination with the YOLO model aiming to improve autonomous vehicles' safety in snowy weather conditions. The results indicated that the proposed method produced the best trade-off between speed and performance compared to the centralised methods. Finally, Chhikara et al. [63] presented a work in which they applied federated learning in a UAV swarm for the prediction of air pollution in timeseries data using Air Quality Index (AQI). More precisely, they used a global server that was orchestrating the learning process, and several UAVs which performed local training. The results showed that the proposed method had better results than the method that it was compared with.

What we plan to do in TALON: With the main goal being to preserve the privacy of data during the training of AI models, TALON will support Federated Learning, in which multiple participating devices/clients/nodes collaboratively train an AI model, without the need of exchanging data. In doing so, TALON will use the Flower framework, a continuously evolving framework that has made the implementation of federated learning settings simple. Flower has already integrated and provides a number of state-of-the-art aggregation techniques, such as FedAvg, FedProx, and a variety of optimisation aggregation methods such as FedAdagrad, and FedAdam. Moreover, Flower currently supports Keras, TensorFlow, PyTorch, and scikit-learn frameworks, making it an extremely flexible and scalable solution for implementing federated learning. More specifically, federated learning is planned to be implemented in most of the use cases of TALON, such as fire and smoke detection, and fault detection. Finally, it is worth mentioning that Flower constantly evolves by adding new features and supported frameworks, with one of the latest and most important integrations being the support of the FedProx aggregation strategy and XGBoost Classifier.

6.1.3.3 Few-Shot Learning

Existing paradigms: Few-Shot Learning (FSL) is a machine learning method characterised by a small dataset containing supervised information particular to the target domain. Because of the pursuit of AI skills equivalent to human performance and the necessity for cost-effective learning, FSL has received a lot of attention [64], [65]. In this domain, many machine learning techniques, such as meta-learning, embedding learning, and generative modelling, have been presented. FSL is linked to other methods such as weakly supervised learning, transfer learning, and meta-learning. FSL development is centred on three important components: data, model, and algorithm. FSL approaches use past knowledge to improve training data and supplement available supervised information. Translation, flipping, scaling, and rotation are standard data augmentation techniques used in FSL as a pre-processing step to incorporate different types of invariances, allowing the model to capture changes in the data [66]. Prior knowledge can be also used to the models themselves. When numerous related tasks are provided, multitask learning is used to enable simultaneous learning by exploiting both task-generic and task-specific information [67]. In FSL, parameter tying is an approach for encouraging similarity among the parameters of distinct tasks. Parameter tying enhances knowledge transfer across tasks by matching the layers of two convolutional neural networks (CNNs) using certain regularisation terms. Another technique is embedding learning, in which samples are transferred to a lower-dimensional space. This approach seeks to group similar samples together while clearly distinguishing between divergent samples [68]. Task-invariant embedding algorithms learn a generic embedding function from a large-scale dataset with a variety of outputs, allowing them to be used directly to fresh few-shot training datasets without the requirement for retraining.

What we plan to do in TALON: In TALON and the related use cases, machine learning and computer vison algorithms are required for object detection and scene analysis. These are essential for applications related to safety (e.g., fire and protective equipment detection) and to support augmented reality that relies on scene understanding methods. To address these needs advanced deep learning and computer vison models such as YOLO will be introduced and retrained using few-shot learning offering exceptional speed and accuracy. These solutions and models incorporate the latest developments in the field and are highly versatile, capable of being deployed on different hardware platforms ranging from edge devices to cloud APIs. The approach taken in the development of these models differs from the mainstream real-time object detectors currently available. In addition to optimizing the model architecture, the focus will be also on optimizing the training process. The goal is to enhance the accuracy of object detection without increasing the inference cost. This involves the incorporation of specific modules and optimisation techniques, such as Meta-Learning and Data-Level approaches based on augmentation and generative networks. Moreover, the developed and trained models in TALON are expected to be evaluated and demonstrated as part of the related pilots and scenarios focusing on fire, personal protective equipment (PEE) and scene analysis for the FACTOR facilities to support AR applications for maintenance.

6.1.3.4 AI Capabilities, Data Operations, Digital Twins and Transfer Learning

Existing paradigms: Matteo Perno et al. [69] highlight the difficulties businesses experience while implementing digital twins (DTs) in the process industry, which has gotten less research attention than other industries. Fei Tao et al. [70] analyse enabling technologies and tools for digital twin modeling and provide a thorough analysis of digital twin models, including their application field, hierarchy, discipline, dimension, universality, and functionality. They also provide insights and suggestions for future research directions. Additionally, Dalia Abdulkareem Shafiq et al. [71] highlight the use of Educational Data Mining (EDM) and Learning Analytics (LA), focusing on the application of supervised Machine Learning (ML) and Deep Learning (DL) techniques while identifying gaps in the use of ensemble and unsupervised learning clustering techniques as well as the underutilisation of non-traditional factors in predicting student performance. The use of deep neural networks, support vector machines, artificial neural networks, decision trees, and ensemble learning techniques in Big Data Analytics (BDA) is highlighted by Isaac Kofi Nti et al. [72]. They also explore the application domains, difficulties, and potential directions for future study in this area.

What we plan to do in TALON: For user and system requirements, TALON will consider various use cases and the system overall. New Key Performance Indicators (KPIs) are introduced to provide meaningful measurements that quantify the benefits generated by AI to ensure the effective achievement of TALON's objectives. The use of application-specific slices is heavily emphasised, allowing the predictive analytics capabilities of LSTM to be tailored to the unique requirements of many domains. Accurate predictions will be feasible across a variety of disciplines thanks to TALON's use of deep learning and transfer learning, which will harness the knowledge gained from one domain and apply it to another. Adversarial Generative Adversarial Networks (GANs) offer an advanced modelling technique for simulating digital twins of Nakamura-Tome machines. These digital twins serve as virtual replicas, enabling organisations to accurately replicate and analyse the behaviour, performance, and operational characteristics of these machines. By employing GANs, TALON will facilitate a digital twin simulation process, highly realistic and representative of real-world machines. The generator network within the GAN will generate synthetic data that closely mimics the time series provided by Nakamura machines, whereas the generated data will be evaluated by a discriminator classifier. This solution will allow TALON to optimize machine performance, predict needs and make decisions for operational efficiency.

6.1.3.5 XAI, Monitoring and Visualisations

Existing paradigms: According to the work presented by Islam et al. [73], the number of publications on XAI has rapidly grown in recent years, covering, and finding applications in almost all the domains. More precisely, their analysis based on 137 papers resulted in plenty of findings, such as that visual explanations should be used as they are more understandable to end-users. Furthermore, they found that most of the explainability methods that are currently being developed, like variations of SHAP, LIME, and GradCAM, are focused on deep learning and ensemble models, instead of other types of AI/ML models. The work from Salih et al. [74] presented that SHAP, and LIME can effectively provide explanations for the predictions when working with tabular data, even in sensitive domains, like finance, and health, where these explanations can be significantly expensive, or critical.

What we plan to do in TALON: In the context of TALON, eXplainable Artificial Intelligence (XAI) will be implemented by utilising four (4) Trust Levels (TrLs). Trust Level 1 (TrL1) focuses on how reliable the data source is, by applying a number of different methods on raw data, such as null detection for timeseries to find any disruptions in the incoming data, or identify corrupted images, or other inconsistencies that are critical to be reported. Next, Trust Level 2 (TrL2) deals with data analysis by implementing techniques like Imbalance Identification, and Outlier Detection, among others. Furthermore, Trust Level 3 (TrL3) and Trust Level 4 (TrL4) mainly focus on the explainability and interpretation of the decisions and predictions that the AI models made, the level of bias that may be observed, and the generalisation ability of those models. For instance, algorithms like SHAP, LIME, and variations of GradCAM will be implemented. Finally, it is important to note that each trust level's results will be visualised in the XAI mini page of TALON.

6.2 State of the Art Technologies

6.2.1 From International Foundations

As organisations generate data from Internet of Things (IoT) devices, smart sensors, and other devices on the edge of their networks, this data must be collected, stored, and processed. To extract business insight from this data, it must flow seamlessly between edges, clouds, data centres, and users in a wide variety of work locations and environments. One driver for today's E2C approach is the growing need for real-time data-driven decision-making, especially at the edge. For example, I5.0 automation, UAVs orchestration, and more depend on artificial intelligence (AI) and machine learning (ML) systems that can determine, in a fraction of a second, if an object is another drone, a person, or a damaged manufacturing element. The E2C approach offers a unified experience with the same agility, simplicity, and pay-per-use flexibility across an organisation's entire hybrid IT estate. This means that organisations no longer must make compromises to run their mission-critical apps, and crucial enterprise data services can leverage both on-premises resources and the public cloud.

With computing models' evolution having shifted from cloud to fog and edge-based architectures, the demand for the foundation of a sustainable network ecosystem is higher than ever. Thus, the Open Compute Project Foundation (OCP) expands to the Open Edge ecosystem via the edge gateway base specification. This gateway specification will be the catalyst for the development of a new and resilient open enterprise edge computing applications, with wide participation from OEM network equipment vendors.

Besides, the OCP Foundation pursues interoperability in industrial automation by creating and maintaining open specifications that standardize communication of acquired process data, alarm and event records, historical data, and batch data to multi-vendor enterprise systems and between production devices. The goal for OCP is for it to be the foundation for interoperability for moving information vertically from the factory floor through the enterprise of multi-vendor systems as well as providing interoperability between devices on different industrial networks from different vendors.

Last, the Digital Twin Consortium (DTC) and OCP Foundation announced a liaison agreement to accelerate the development and adoption of digital twin-enabling technologies. Collaboration on standardisation requirements has been agreed. Their common activities also include realizing interoperability by harmonizing technology components and other elements; aligning work in horizontal domains for adoption in vertical domains and use cases, proof of concepts, and Value Innovation Platforms (VIP) programs; and developing and understanding open-source reference implementations.

This amalgamation of foundations that are willing to collaborate, the participation of interdisciplinary experts from cloud-to-edge computing, industrial automation, data science and digital twins in synergies highly indicate the openness to advance technology in horizontal and vertical industries.

6.2.2 From Projects

We are at the beginning of a new technological revolution as disruptive technologies such as machine-to-machine communication, Big Data, AI, and human-machine collaboration aim to transform crucial industries such as manufacturing, industrial automation, disaster management, etc. However, the domains will reach their true potentials only through the convergence of Operational and Information Technologies (OT & IT). The European Parliament claims that "[…] this convergence will be achieved through the new concept of Edge-to-Cloud (E2C) Computing, which is a logical extension from Cloud Computing towards the edge of the network (where machines are located), enabling applications that demand guarantees in safety, security, transparency, explainability and real-time behaviour.". That is the reason European Commission has allocated significant number of resources towards this direction. The projects dealing with similar scientific and technological aspects like TALON are listed below:

1. **ACCORDION:** It aims to establish an opportunistic approach in bringing together edge resource/infrastructures (public clouds, on-premises infrastructures, telco resources, even end-devices) in pools defined in terms of latency, which can support NextGen application

requirements. To mitigate the expectation that these pools will be “sparse,” providing low availability guarantees, ACCORDION will intelligently orchestrate the compute & network continuum formed between edge and public clouds, using the latter as a capacitor. Deployment decisions will be taken also based on privacy, security, cost, time, and resource type criteria. The slow adoption rate of novel technological concepts from the EU SMEs will be tackled though an application framework, which will leverage DevOps and SecOps to facilitate the transition to the ACCORDION system. With a strong emphasis on European edge computing efforts (MEC, OSM) and 3 highly anticipated NextGen applications on collaborative VR, multiplayer mobile- and cloud-gaming brought by the involved end users, ACCORDION is expecting to radically impact the application development and deployment landscape, also directing part of the related revenue from non-EU vendors to EU-local infrastructure and application providers.

2. **AI Swarm Orchestration:** Currently certain work has been done and a previous EU project has tried to tackle down the problem but from the perspective of utilizing UxV in a way to utilize sensors to assist in parallel with the difficult task of data acquisition under critical conditions. This is the Unmanned Heterogeneous Swarm of Sensor Platforms (EuroSWARM) project funded by EDA. Several other projects around the world (from US to Japan) try various approaches on the same architecture. However, the continuous use of edge computing power and therefore the demand for larger batteries works against the endurance and flying capabilities of a drone.
3. **PLEDGER:** It aims to provide a new architectural model as well as a set of software tools that will prepare the future development of the next generation of edge computing. The project will allow edge computing providers to secure the stability and effective performance of the edge infrastructures. It will also allow edge computing users to understand the nature of their applications, research understandable quality of service metrics and optimise the competitiveness of their infrastructures. The project intends to introduce the set of tools in the application fields of manufacturing, mixed reality, and smart cities.
4. **MLSysOps**: It will achieve substantial research contributions in the realm of AI-based system adaptation across the cloud-edge continuum by introducing advanced methods and tools to enable optimal system management and application deployment. MLSysOps will design, implement, and evaluate a complete framework for autonomic end-to-end system management across the full cloud-edge continuum. MLSysOps will employ a hierarchical agent-based AI architecture to interface with the underlying resource management and application deployment/orchestration mechanisms of the continuum. Adaptivity will be achieved through continual ML model learning in conjunction with intelligent retraining concurrently to application execution, while openness and extensibility will be supported through explainable ML methods and an API for pluggable ML models. Flexible/efficient application execution on heterogeneous infrastructures and nodes will be enabled through innovative portable container-based technology. Energy efficiency, performance, low latency, efficient, resilient, and trusted tier-less storage, cross-layer orchestration including resource-constrained devices, resilience to imperfections of physical networks, trust, and security, are key elements of MLSysOps addressed using ML models.
5. **CODECO:** It is a cognitive, cross-layer and highly adaptive Edge-Cloud management framework with a unique orchestration approach that provides support for data management and governance decentralised data workflow; dynamic offloading of computation and computation status; and adaptive networking services (TRL5). In the core of the CODECO framework are privacy preserving decentralised learning mechanisms to i) reduce latency and power consumption from the far Edge to Cloud; ii) adjust the computation in real-time to available Edge-Cloud constraints; iii) adjust running services into the needs of the application, the data sources, the surrounding context; iv) benefit from a flexible networking infrastructure that adapts to the needs of active services; and v) democratize the technology to a faster

market adoption of the toolkit, as well as products and services derived from it. CODECO proposes the following assets: i) A1: Open, cognitive toolkits and smart Apps, integrating the elastic and advanced concepts to manage, in a smart and flexible way, containerised applications across Edge and Cloud (dynamic cluster and multi-cluster environment; ii) A2: A developer-oriented open-source software repository, to be available in an early stage of the project, thus allowing for early exploitation of initial, advanced results and a better adaptation throughout the project lifetime; iii) A3: Training tools, to support the development of services based on the CODECO framework; iv) A4: Use-cases across 4 domains (Smart Cities, Energy, Manufacturing, Smart Buildings), as the basis for experimentation and demonstrations; v) A5: Open Calls and multiple community events, based on the different use-cases and including the different CODECO stakeholders; vi) A6: CODECO integration into the large-scale EdgeNet , experimental infrastructure, to assist in the building of experimentation and novel concepts by the research community.

6. **EDGELESS:** It is set to efficiently operate serverless computing in extremely diverse computing environments from resource-constrained edge devices to highly virtualised cloud platforms. By taking advantage of AI/ML solutions, it will enable automatic deployment and reconfiguration to fully exploit compute resources available on clusters of nearby edge nodes. EDGELESS will define novel orchestration systems that provide a flexible horizontally scalable compute solution able to fully use heterogeneous edge resources, while preserving vertical integration with the cloud and the benefits of serverless, including its application programming model.

6.2.3 From Industry

Industrial stakeholders have also allocated a significant number of resources towards the E2C direction. Some popular solutions are listed below:

1. AWS for the Edge: AWS edge services deliver data processing, analysis, and storage close to the endpoints, allowing to deploy APIs and tools to locations outside AWS data centres. End users can build high-performance applications that can process and store data close to where it is generated, enabling ultra-low latency, intelligence, and real-time responsiveness.

2. Distributed Cloud Edge: Distributed Cloud Edge enables to run Google Kubernetes Engine (GKE) clusters on dedicated hardware provided and maintained by Google that is separate from the traditional Google Cloud data center. Google delivers and installs the Distributed Cloud Edge hardware on premises. Deploying workloads on a Distributed Cloud Edge installation functions in a similar way to deploying workloads on cloud based GKE clusters. After the hardware has been deployed, the cluster administrator provisions Distributed Cloud Edge clusters by using the Google Cloud console or the Google Cloud CLI. In addition, the network administrator configures the Distributed Cloud Edge networking components so that the workloads can communicate with the local network and each other. The application owners can then deploy workloads to those clusters. Distributed Cloud Edge supports running workloads in Kubernetes containers and on virtual machines, including GPU-based workloads, which run on NVIDIA Tesla T4 GPUs.

3. Azure Stack Edge: Azure Stack Edge is an AI-enabled edge computing device with data storage and transfer capabilities into Microsoft Azure. Also, for professionals, the Azure Stack Edge Pro with GPU offers a Hardware-as-a-Service solution. Microsoft ships a cloud-managed device that acts as a network storage gateway. A built-in Graphical Processing Unit (GPU) enables accelerated AI-inferencing.

4. IBM Edge Computing: Edge computing with 5G creates tremendous opportunities in every industry. It brings computation and data storage closer to where data is generated, enabling

better data control, reduced costs, faster insights and actions, and continuous operations. In fact, by 2025 [76], 75% of enterprise data will be processed at the edge, compared to only 10% today. IBM provides an autonomous management offering that addresses the scale, variability, and rate of change in edge environments. IBM also offers solutions to help communications companies modernize their networks and deliver new services at the edge.

5. Oracle Roving Edge Infrastructure: Oracle Roving Edge Infrastructure is a cloud-integrated service that puts fundamental Oracle Cloud Infrastructure services where data is generated and consumed. Roving Edge Infrastructure devices provide high-performance computing, such as analytics, machine learning, and location-based services, and storage capabilities that operate with intermittent or no internet connectivity. Roving Edge Infrastructure is the extension of the Oracle Cloud Infrastructure tenancy. The request to have virtual machines and objects from the tenancy loaded onto Oracle Cloud Infrastructure devices and device clusters by creating and configuring Oracle Cloud Infrastructure device node or cluster resources in Oracle Cloud Infrastructure. These nodes and clusters function as requests for the corresponding devices and indicate what Oracle Cloud Infrastructure-based content is to be pre-loaded, or provisioned, on them.

7 Conclusion

This deliverable includes the results of the stakeholder analysis which was conducted during the first ten (10) months of the TALON project as part of the Task 2.1 “Use Case, KPIs, Requirements, Specification, Slices & Technology Enablers Definition”. Therefore, the underlying computing landscape, the TALON stakeholders, and actors as well as the categories of applications, technologies (e.g., digital twins, federated machine learning, AI-fuelled orchestration, blockchain, etc.) and use cases were explicitly defined, to meet the scope of this deliverable which was the extraction of the functional and non-functional requirements and the definition of the stakeholders and technology enablers.

This deliverable aimed to specify in an explicit and coherent manner the functional and non-functional requirements, considering the stakeholder’s needs and following the ISO/IEC/IEEE 29148:2011 and MoSCoW technique, to facilitate the way towards the definition of TALON platform architecture (D3.1; to be submitted at M12).

D2.1 reported in Section 2 the requirements elicitation methodology; in Section 3 the TALON stakeholders and their goals; in Section 4 the four (4) use cases along with their objectives, scope and details; in Section 5 the functional and non-functional requirements along with a traceability matrix; in Section 6 the technological axis and the state-of-the-art paradigms from the international foundations, existing projects and the industry for edge-to-cloud (E2C) computing; while Section 7 summarised the main outcomes and concluded the deliverable.

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9 Annex I – Questionnaires

9.1 UC1: Automatic UATVs Coordination

Item	*Further description of item*	*Answer*
1 General info		
Use case #	*From what use case is this information?*	*1*
Name(s)	*Name(s) of person who fill-in this questionnaire*	*George Delaportas*
Date	*Date this questionnaire filled*	*02/11/2022*
Contact method	*In case we have some additional questions, in what way can we contact you*	*Email: delaportas@probotek.eu*
2 Problem in general		
Typical problem	*What typical problem from this use case can be solved or improved by using data-driven approaches ('TALON way')?*	*All the referred in the scope*
Future situation: how	*Shortly describe how the solution for this problem could be done in TALON way*	*TBD*
How common	*Is this a common problem within this sector, or is it rather specific?*	*No. This is new.*
Frequency	*How often does this problem occur for the end user?*	*The end-users will not understand the "problem" or affected directly.*
What is the main benefit	*What is the main benefit of solving this problem?*	*Anti-congestion and obstacles avoidance of drones, low power consumption, resiliency, efficiency of execution*
Main stakeholder	*Who is the main stakeholder that benefits from solving this problem?*	*Companies, public sector, end-users*
End user	*Is the main stakeholder also the end user, or are there other end users?*	*Indirectly through the result, yes*
Other stakeholders?	*Are there any other stakeholders who benefit from solving this problem?*	*TBD*
3 Current situation		
If applicable: How much used	*What estimated fraction of the end users make use of the current solution?*	*TBD*
If applicable: Why not?	*If not all end users use the available solution, why is that?*	*Not seeing the value if the scenario is not a complex one*
Is there any available data to be used from DAY 0 in the frame of TALON	*If yes, please give some details on data descriptions and features (what kind of data, in a DB, message queues or other - specify), data schemas, data size, data format and how they can be immediately used?*	*Mostly bits, bytes, and JSON streams*
Is there any available cloud / edge infrastructure to	*If yes, please give some system and technical details by means of OS / existing software, resources dimensioning, etc.*	*Yes. Proprietary of PROBOTEK.*

be used in the frame of TALON		
Workflow diagram of the ***CURRENT (AS-IS)*** *situation is thoroughly presented and explained in Section 4.1.3.*		
4 Future situation		
Change of use?	*Do you expect that more/less end users will make use of the future solution than in the current situation?*	*Yes*
Impediments	*Do you see any impediments why end users would not want to use the future solution?*	*No*
Workflow diagram of the ***FUTURE (TO-BE)*** *situation ("After TALON") is thoroughly presented and explained in Section 4.1.4.*		
5 More about data (future)		
Data required	*Looking at the roles you just described for the future situation, summarize the required data required*	*TBD*
Data generated in TALON	*What data should be generated in the frame of TALON?*	*TBD*
Missing data	*What data are missing or need to be collected?*	*TBD*
Restrictions / impediments	*Are there any restrictions / impediments to obtain this data?*	*TBD*
6 More about infrastructure (future)		
Computing resources required	*Looking at the roles you just described for the future situation, summarize the required computing cloud / edge resources required*	*TBD*
Restrictions / impediments	*Are there any restrictions / impediments / implications to be considered regarding the computing cloud / edge resources?*	*TBD*
7 More about the stakeholder(s) of this problem		
Stakeholder size	*How many stakeholders for this problem are there in your area of interest? E.g., how many of these farmers / breeders / companies / .... are there in your region?*	*TBD*
How typical	*If you take a typical stakeholder in mind, how typical is this stakeholder? Are they all similar, or are they all hugely different?*	*TBD*
Distinguishing features of stakeholders	*Give a list of features that distinguishes the stakeholders, most distinguishing feature on top.* *Also give an indication of the range of these features*	*TBD*
With whom to communicate	*With whom do the stakeholders most likely discuss the problem here?*	*George Delaportas, delaportas@probotek.eu* *Ioannis Androulakis, androulakis@probotek.eu* *Chris Mavronas, mavronas@probotek.eu*

Peer Network	*Do stakeholders typically have a peer network around them, through which they can exchange information with each other regarding the problem presented here?*	*Yes*
Typical journals or other outlets	*Do stakeholders typically inform themselves through other sources such as internet websites, mobile phone apps, newsletters, specialised magazines?*	*Yes*
8 Any additional comments?		
Comments	*Please feel free to give additional information or anything else*	*N/A*

9.2 UC2: I5.0 Automation and Planning

Scenario 1:

Item	***Further description of item***	***Answer***
1 General info		
Use case #	*From what use case is this information?*	*Application of AI to the manufacturing processes by self-automating and self-healing the machine's behaviour, avoiding defects and optimizing the effectiveness of the factory and, consequently, ensuring the highest quality level on the production.*
Name(s)	*Name(s) of person who fill-in this questionnaire*	*Alfredo GIMENEZ | Pablo ROCAMORA (FACTOR)*
Date	*Date this questionnaire filled*	*26/10/2022*
Contact method	*In case we have some additional questions, in what way can we contact you*	***alfredo@factorsl.es (697949270)*** ***p.rocamora@factorsl.es (667310616)***
2 Problem in general		
Typical problem	*What typical problem from this use case can be solved or improved by using data-driven approaches ('TALON way')?*	*Discontinuity between quality checks and production validation generate a level of scrap that must be reduced. We work with very restrictive CpK, complex parts, and effort to get zero defects is too high, in scrap and intellectual effort.*
Future situation: how	*Shortly describe how the solution for this problem could be done in TALON way*	*A continuous process that analyses produced parts quality 100% and can generate correction recommendation on real time with reduce considerable the scrap and the intellectual effort required to adjust parameters*
How common	*Is this a common problem within this sector, or is it rather specific?*	*It is a general problem in the sector that limits the capacity of the factories to produce parts in time, cost, and quality.*
Frequency	*How often does this problem occur for the end user?*	*Several times per week*
What is the main benefit	*What is the main benefit of solving this problem?*	*Reduce scrap, increase productivity, gain in productive talent (intelligent people working in intelligent solutions most of the time).*
Main stakeholder	*Who is the main stakeholder that benefits from solving this problem?*	*Stakeholders are identified at 3 levels:* *Customer (higher quality at less cost)* *Suppliers (the system can be extended to improve the quality of the supplied products, improving their profitability).*

		Internal stakeholders: - *Operations: Manufacturing conditions are automatically improved 24/5 generating capacity to improve other processes and not to be everyday correcting errors.* - *Quality: eliminate handmade measurements, gaining in reliability and time.* - *Logistics: Expeditions can be prepared faster, as the number of product reworks or selection is reduced.*
End user	*Is the main stakeholder also the end user, or are there other end users?*	*End users are the Operations and Quality stakeholders.*
Other stakeholders?	*Are there any other stakeholders who benefit from solving this problem?*	*This work methodology opens several opportunities to involve new business models and new stakeholders, consequently.*
3 Current situation		
If applicable: How much used	*What estimated fraction of the end users make use of the current solution?*	*All. The whole production is impacted by the current way of working*
If applicable: Why not?	*If not all end users use the available solution, why is that?*	
Is there any available data to be used from DAY 0 in the frame of TALON	*If yes, please give some details on data descriptions and features (what kind of data, in a db, message queues or other - specify), data schemas, data size, data format and how they can be immediately used?*	*Factor has a Data storage that will be shortly convert into a Data Repository where all information available will be combined (Operations, Quality, Logistics, ERP, Sales)*
Is there any available cloud / edge infrastructure to be used in the frame of TALON	*If yes, please give some system and technical details by means of OS / existing software, resources dimensioning, etc.*	*Data Repository is a cloud-based solution that will be done available through the i4Q project. The i4Q Data Repository (i4QDR) is a distributed storage system that will oversee receiving, storing, and serving the data in an appropriate way to other solutions. This solution is suitable to support and enhance a high degree of digitalisation in companies with most manufacturing devices acting as sensors or actuators and generating vast amounts of data.*
*Workflow diagram of the **CURRENT (AS-IS)** situation is thoroughly presented and explained in Section 4.2.3.*		
4 Future situation		
Change of use?	*Do you expect that more/less end users will make use of the future solution than in the current situation?*	*The future solution will improve the process so end users will want to use it to improve their manufacturing lines.*
Impediments	*Do you see any impediments why end users would not want to use the future solution?*	*No impediment is expected. We expect that the usual impediments will be manage during implementation.*
*Workflow diagram of the **FUTURE (TO-BE)** situation ("After TALON") is thoroughly presented and explained in Section 4.2.4.*		
5 More about data (future)		
Data required	*Looking at the roles you just described for the future situation, summarize the required data required*	*Main data is automatic quality checks information (dimensions) and associated production data (part by part).*
Data generated in TALON	*What data should be generated in the frame of TALON?*	*Associative data between dimensions and tolerances and production parameters.*
Missing data	*What data are missing or need to be collected?*	*Automated quality checks are the main challenge on data collection*
Restrictions / impediments	*Are there any restrictions / impediments to obtain this data?*	*Replace Go/No-go manual check by automated processes. AI recommendations to improve the process can clash with the machine availability to*

		receive external reprogramming. We assume in any case an initial phase where recommendations are addressed to operators. However, overcoming this impediment, would open opportunities for a highly autonomous manufacturing system.
6 More about infrastructure (future)		
Computing resources required	*Looking at the roles you just described for the future situation, summarize the required computing cloud / edge resources required*	*Edge computing resources are very depending on the volume that local traffic would require (For instance, photos vs 3D points clouds). We do not know if the current WIFI infrastructure would be sufficient or 5G will be required.*
Restrictions / impediments	*Are there any restrictions / impediments / implications to be considered regarding the computing cloud / edge resources?*	*Not known at this point. Same as in point 5.*
7 More about the stakeholder(s) of this problem		
Stakeholder size	*How many stakeholders for this problem are there in your area of interest? E.g., how many of these farmers / breeders / companies / .... are there in your region?*	*Stakeholders are identified at 3 levels:* *Customer (higher quality at less cost). Size is similar or bigger than FACT.* *Suppliers (The system can be extended to improve the quality of the supplied products, improving their profitability). Size is similar or smaller than FACT.*
How typical	*If you take a typical stakeholder in mind, how typical is this stakeholder? Are they all similar, or are they all hugely different?*	*Identified stakeholders are similar among them. Potential stakeholders are from other sectors which are very demanding in documentations and certifications, not our focus at this moment, unless a revision on requirements would happen.*
Distinguishing features of stakeholders	*Give a list of features that distinguishes the stakeholders, most distinguishing feature on top.* *Also give an indication of the range of these features*	*1) High tolerance requirements that require from CpK not reachable. (Range 4 out of 5)* *2) Quality in finishing and treatments (2/5)* *3) Delivery time (1/5)*
With whom to communicate	*With whom do the stakeholders most likely discuss the problem here?*	*Sales Department*
Peer Network	*Do stakeholders typically have a peer network around them, through which they can exchange information with each other regarding the problem presented here?*	*Unknown. Customers have sectorial associations; however, we do not know which exchange level they have between them on those networks.*
Typical journals or other outlets	*Do stakeholders typically inform themselves through other sources such as internet websites, mobile phone apps, newsletters, specialised magazines?*	*Unknown. Customers publish their achievements; however, we guess that the information is partial and not fully reliable.*
8 Any additional comments?		
Comments	*Please feel free to give additional information or anything else*	

Scenario 2:

Item	***Further description of item***	***Answer***
1 General info		
Use case #	*From what use case is this information?*	*2 and scenario about optical link fibre fault classification (I am not sure if there is a number to this use case)*

Name(s)	*Name(s) of person who fill-in this questionnaire*	*Marcello Morchio, Annamaria Fulignoli TEI*
Date	*Date this questionnaire filled*	
Contact method	*In case we have some additional questions, in what way can we contact you*	*marcello.morchio@ericsson.com, annamaria.fulignoli@ericsson.com*
2 Problem in general		
Typical problem	*What typical problem from this use case can be solved or improved by using data-driven approaches ('TALON way')?*	*The classification of the root cause for a fibre interconnection fault is the first step in the troubleshooting of a network outage due to a loss-of-signal. The more rapid is the classification the faster the network operator can fix the issue or put in place further investigation actions. Current level of information to the operator is a binary information (loss of signal alarm on/off). With the data driven approach the information can be more precise and provide a first estimation of the root cause together with the basic alarm information.*
Future situation: how	*Shortly describe how the solution for this problem could be done in TALON way*	*In addition to the binary link presence (loss-of-signal, i.e., LOS alarm ON or OFF) it is possible for optical devices to read a time series of the received optical power before and during the link drop. This requires a specific data collection by the optical module host unit, producing a time series of power readings associated to the LOS information.* *The TALON Cognitive Layer is expected to be able to provide a classification of the failure based on the time series and an explanation of the classification to support the further fault investigation.* *Ericsson did experiments in this area, and we can share a dataset of labelled time series of received optical power to be used to train a classifier with XAI.*
How common	*Is this a common problem within this sector, or is it rather specific?*	*The fibre fault is typical of any optical network infrastructure: mobile network fronthaul or backhaul, data network inside or across data centres, or cabled industrial plants. The troubleshooting process to fix LOS issues is similar in all cases.*
Frequency	*How often does this problem occur for the end user?*	*For geographical network it is common, and it is mitigated with some fibre redundancy. Inside the industrial plants there is not much experience because industry 4.0 is a young area. It may depend on the specific type of industry with moving parts around the factory.*

What is the main benefit	*What is the main benefit of solving this problem?*	*Faster time to resolution in case of network outage*
Main stakeholder	*Who is the main stakeholder that benefits from solving this problem?*	*The network operator*
End user	*Is the main stakeholder also the end user, or are there other end users?*	*The end users are the users of the network. Usually, a LOS problem is hidden to the end user by network redundancy.*
Other stakeholders?	*Are there any other stakeholders who benefit from solving this problem?*	*Telecom vendors may benefit from the accumulated knowledge build thanks to extensive data collection.*
3 Current situation		
If applicable: How much used	*What estimated fraction of the end users make use of the current solution?*	*The current solution, i.e., the simple LOS alarm, is used by 100% of the users*
If applicable: Why not?	*If not all end users use the available solution, why is that?*	
Is there any available data to be used from DAY 0 in the frame of TALON	*If yes, please give some details on data descriptions and features (what kind of data, in a db, message queues or other - specify), data schemas, data size, data format and how they can be immediately used?*	*The current simple alarm solution is usually mediated by a complex network management system which cannot be used in the context of TALON. As a baseline option we might think of a simplified service providing simple optical interface status and/or current received optical power reading.*
Is there any available cloud / edge infrastructure to be used in the frame of TALON	*If yes, please give some system and technical details by means of OS / existing software, resources dimensioning, etc.*	*For the TALON demo it would be possible to embed the existing dataset of loss-of-signal events and make them available to the TALON components as if they were coming from a physical HW.* *The messages can be arranged as required, either including the pure LOS ON/OFF alarm or the extended received power profile.*
*Workflow diagram of the **CURRENT (AS IS)** situation, including roles involved:* *See Section 4.2.3.*		
4 Future situation		
Change of use?	*Do you expect that more/less end users will make use of the future solution than in the current situation?*	*The adoption of the future solution depends on many factors:* 1. *The actual ability to predict the right fault cause and the relevant explainability. This is inside TALON scope;* 2. *The availability of the HW and Firmware prerequisites in the optical nodes. This is touched marginally by TALON in terms of POC, and it is not core into TALON architecture; and*

		3. *The integration of the solution in a full-fledged network management system or at least local operator system. This is outside TALON scope.*
Impediments	*Do you see any impediments why end users would not want to use the future solution?*	*See above*
Workflow diagram of the ***FUTURE*** *situation ("After TALON"), including roles involved:* *Ericsson can provide a labelled dataset with power drop time series around the LOS events. On the classification, TEI has some experiments done in terms of a rudimental POC and we have no experience on XAI at all.* *See section 4.2.4.*		
5 More about data (future)		
Data required	*Looking at the roles you just described for the future situation, summarize the required data required*	*The existing dataset is sufficient.*
Data generated in TALON	*What data should be generated in the frame of TALON?*	*See above and section 4*
Missing data	*What data are missing or need to be collected?*	*The current dataset should be fine*
Restrictions / impediments	*Are there any restrictions / impediments to obtain this data?*	*It is not possible to generate new data within the TALON pilot network.*
6 More about infrastructure (future)		
Computing resources required	*Looking at the roles you just described for the future situation, summarize the required computing cloud / edge resources required*	*Data ingestion from optical nodes requires a cloud/edge data pipeline.* *The dimensioning of the computing resources (CPU/GPU) is not yet clear. As the occurrence of a fault is not very frequent, a single computing engine with optional GPU may serve a significant number of optical nodes (say in the range of hundreds) assuming that the data pipeline is able to properly queue the input data in case of multiple failures in a short time range.*
Restrictions / impediments	*Are there any restrictions / impediments / implications to be considered regarding the computing cloud / edge resources?*	*The latency requirements between the fault and the prediction of the root cause are not specified as the application is new. It is advisable that a latency between one and few minutes is acceptable considering that currently there is no such a prediction at all.*
7 More about the stakeholder(s) of this problem		
Stakeholder size	*How many stakeholders for this problem are there in your area of interest? E.g., how many of these farmers / breeders / companies / .... are there in your region?*	*Network operators are usually big companies in the telecom business; thus, their number is limited. In the enterprise, industrial business this may increase including medium enterprises. However, Ericsson is a global company, and the*

		optical networks are spread well beyond the regional level.
How typical	*If you take a typical stakeholder in mind, how typical is this stakeholder? Are they all similar, or are they all hugely different?*	*There may be different perspectives to the serviceability issues among customers. On one hand fast trouble classification is a booster for the service, on the other hand this is more information to be managed, thus the prioritisation of the alarms and of their consequent actions may vary from customer to customer.*
Distinguishing features of stakeholders	*Give a list of features that distinguishes the stakeholders, most distinguishing feature on top.* *Also give an indication of the range of these features*	- *Telecom vs Enterprise network operators;* - *Size of the network managed / number of network maintenance centres / operators; and* - *Frequency of network issues associated with optical fibre faults.*
With whom to communicate	*With whom do the stakeholders most likely discuss the problem here?*	*Usually, operators escalate the problems to the telecom equipment vendors.*
Peer Network	*Do stakeholders typically have a peer network around them, through which they can exchange information with each other regarding the problem presented here?*	*There are trade conferences on telecom topics and namely on optical topics (e.g., ECOC). Moreover, there is an industrial alliance relevant to the optical modules technology evolution (MOPA) where Ericsson is an active partner.*
Typical journals or other outlets	*Do stakeholders typically inform themselves through other sources such as internet websites, mobile phone apps, newsletters, specialised magazines?*	*Yes*
8 Any additional comments?		
Comments	*Please feel free to give additional information or anything else*	*-*

9.3 UC3: AR/VR for Training and Maintenance

Item	***Further description of item***	***Answer***
1 General info		
Use case #	*From what use case is this information?*	***AR/VR for training and maintenance***
Name(s)	*Name(s) of person who fill-in this questionnaire*	*Alfredo GIMENEZ | Pablo ROCAMORA (FACTOR)* *Akos NAGY | Vlad LI (KU)*
Date	*Date this questionnaire filled*	*04/11/2022*
Contact method	*In case we have some additional questions, in what way can we contact you*	***Email*** ***FACTOR:*** *Alfredo GIMENEZ* *alfredo@factorsl.es* *Pablo ROCAMORA* *p.rocamora@factorsl.es* ***KU:*** *Akos NAGY* *A.Nagy@kingston.ac.uk*

		Vlad LI *V.Li@kingston.ac.uk*
2 Problem in general		
Typical problem	*What typical problem from this use case can be solved or improved by using data-driven approaches ('TALON way')?*	*Machine preparation and maintenance are recurrent operations. Most of the activities are repetitive and easy to remember, however, frequently, complexity appears, that required from expert assessment. Furthermore, during maintenance it is essential to ensure that staff meet the health and safety requirements (e.g., PPE).*
Future situation: how	*Shortly describe how the solution for this problem could be done in TALON way*	*The possibility to jump quickly and easily into the assessment from an expert that is available but far from the machine would be a plus. Therefore, to overcome these issues three approaches are proposed. First to offer offline VR training support so personnel can familiarize themselves with the equipment and the environment prior to using it or performing maintenance tasks. Second TALON offers real time maintenance support using AR devices (e.g., HoloLens) by transmitting multimedia information to an off-site expert and receiving feedback powered also by AI models for scene analysis. Finally, to support the health and safety requirements an automated system for Personal Protective Equipment (PPE) detection and verification is considered.*
How common	*Is this a common problem within this sector, or is it rather specific?*	*It happens 3-4 times per day, and we are confident that this is a usual problem in the industrial sector. Additionally, it is essential for new personnel aiming to improve their induction training,*
Frequency	*How often does this problem occur for the end user?*	*3-4 times per day and more often during the induction of new personnel.*
What is the main benefit	*What is the main benefit of solving this problem?*	*Faster and more precise solution to problems.* *Improve the understanding of preparation and maintenance operations as baseline for future training.* *Automating and/or shortening processes that require frequent repetition or multi-person contact will improve productivity.* *Maintenance cost reduction due to real time support and advanced learning processes.* *Increase productivity by reducing the required time for maintenance or the time a device is not available.*
Main stakeholder	*Who is the main stakeholder that benefits from solving this problem?*	*The operator and operations department and the maintenance department.* *The device manufacturer since it helps to improve their quality and overall cost.*
End user	*Is the main stakeholder also the end user, or are there other end users?*	*End users are part of the operations and part of the maintenance department.*
Other stakeholders?	*Are there any other stakeholders who benefit from solving this problem?*	*As a result, production time and product quality improve. The whole company benefits and the final customer. So, all the clients/customers of the end user have a benefit due to lower maintenance costs and increased production speed and quality. The personnel due to increase health and safety solutions.*
3 Current situation		
If applicable: How much used	*What estimated fraction of the end users make use of the current solution?*	*Currently, when the preparation team or the maintenance team have issues, they must call their superiors for assessment. But the proposed*

		TALON solution based on AR/VR is not available and it is not used by the end users.
If applicable: Why not?	*If not all end users use the available solution, why is that?*	*Due to lack of time, they do not call their superiors every time, so the risk of making an error increase.* *Plus, the proposed AR/VR solutions are not available yet since most of these technologies are not commercial products at this stage.*
Is there any available data to be used from DAY 0 in the frame of TALON	*If yes, please give some details on data descriptions and features (what kind of data, in a db, message queues or other - specify), data schemas, data size, data format and how they can be immediately used?*	*Only verbal records from operations and maintenance department. Today they are comfortable asking their superiors for advice.* *There are available operation logs from the Nakamura machine, maintenance logs and the related manuals.* *Videos and images of the device are also available.*
Is there any available cloud / edge infrastructure to be used in the frame of TALON	*If yes, please give some system and technical details by means of OS / existing software, resources dimensioning, etc.*	*We have a local server that has the capacity to make local calculations. No cloud solution for the moment but planned.*
*Workflow diagram of the **CURRENT (AS-IS)** situation is thoroughly presented and explained in Section 4.3.3.*		
4 Future situation		
Change of use?	*Do you expect that more/less end users will make use of the future solution than in the current situation?*	*It is expected to have more end users that will integrate this solution and processes for their personnel training and device maintenance.* *Also, the device manufacturers will start offering support of these solutions*
Impediments	*Do you see any impediments why end users would not want to use the future solution?*	*Current cost for the AR glasses and the required edge server with GPU support, but it is expected for their cost to drop significantly soon.* *Personnel and end users are not familiar with these modern technologies and improved HCI interfaces including trustworthy AI solutions may help to overcome these limitations.*
*Workflow diagram of the **FUTURE (TO-BE)** situation ("After TALON") is thoroughly presented and explained in Section 4.3.4.*		
5 More about data (future)		
Data required	*Looking at the roles you just described for the future situation, summarize the required data required*	*Device manual* *Historic device log files* *Images and videos of the device*
Data generated in TALON	*What data should be generated in the frame of TALON?*	*Digital Twin of the device* *Meta analytics for maintenance*
Missing data	*What data are missing or need to be collected?*	*It is expected to visit the end user to scan the device and generate a 3D model.*
Restrictions / impediments	*Are there any restrictions / impediments to obtain this data?*	*Not at this stage of the TALON project*
6 More about infrastructure (future)		
Computing resources required	*Looking at the roles you just described for the future situation, summarize the required computing cloud / edge resources required*	*It is required an edge computer/server with GPU support* *High speed internet connection* *Cloud support to store and retrieve historic data and log files)*
Restrictions / impediments	*Are there any restrictions / impediments / implications to be considered regarding the computing cloud / edge resources?*	*For this project and demo KU can provide a laptop with powerful enough GPU to operate as an edge node.*

7 More about the stakeholder(s) of this problem		
Stakeholder size	*How many stakeholders for this problem are there in your area of interest? E.g., how many of these farmers / breeders / companies / etc. are there in your region?*	*Potential stakeholders:* - *Lemar* - *SMI Metal transformation companies*
How typical	*If you take a typical stakeholder in mind, how typical is this stakeholder? Are they all similar, or are they all hugely different?*	*Potential stakeholders vary in scale and maintenance process. Although there are similarities in execution, there are no standards for training and maintenance workflows. Every stakeholder has their own solutions.*
Distinguishing features of stakeholders	*Give a list of features that distinguishes the stakeholders, most distinguishing feature on top.* *Also give an indication of the range of these features*	*They use heavy machinery that often requires maintenance* *Maintenance needs to be as fast as possible* *Personnel needs to be trained to use the devices but without performing the training on the actual devices* *Need to follow specific health and safety protocols*
With whom to communicate	*With whom do the stakeholders most likely discuss the problem here?*	*Personnel: When a problem arises during a manufacturing process the stakeholder notifies maintenance personnel to minimize potential damage and delays.* *Clients/Customers: In case a problem affects the client (i.e.: delays) the stakeholder notifies the client to discuss the most convenient solution for both parties.* *Device manufacturers: In case the problem is not solvable by maintenance personnel at the premises the stakeholder may contact the manufacturers for assistance or replacement of part and equipment.*
Peer Network	*Do stakeholders typically have a peer network around them, through which they can exchange information with each other regarding the problem presented here?*	*SMI Metal transformation companies (North/Centre Spain)*
Typical journals or other outlets	*Do stakeholders typically inform themselves through other sources such as internet websites, mobile phone apps, newsletters, specialised magazines?*	*Websites, Newsletters*
8 Any additional comments?		
Comments	*Please feel free to give additional information or anything else*	*N/A*

9.4 UC4: Human-Robot Collaboration

Item	***Further description of item***	***Answer***
1 General info		
Use case #	*From what use case is this information?*	*Human-Robot Collaboration*
Name(s)	*Name(s) of person who fill-in this questionnaire*	*Georgia Apostolou*
Date	*Date this questionnaire filled*	*07.11.2022*
Contact method	*In case we have some additional questions, in what way can we contact you*	*Georgia Apostolou, gapostolou@iti.gr* *Ilias Gialampoukidis, heliasgj@iti.gr*
2 Problem in general		
Typical problem	*What typical problem from this use case can be solved or improved by using data-driven approaches ('TALON way')?*	*Imbalances between the manual processes and efficiency and repeatability of machines can be improved by using data-driven approaches of TALON, aiming to achieve production flexibility. The problem is related to the analysis of visual content from a UAV, edge processing on-board of the UAV and visual analytics.*

Future situation: how	*Shortly describe how the solution for this problem could be done in TALON way*	*TALON will utilize computer based virtual models of physical systems (digital twins - DT) to assess and validate production strategies before putting them into practice. Achieving a live connection between the DT and the physical system can make the DT act in the real-world. The operator of a UAV at the premises of CERTH will be able to assess and validate computer vision algorithms that are executed on cloud or edge environment from UAV videos.*
How common	*Is this a common problem within this sector, or is it rather specific?*	*It is a common problem that if faced, then it can guarantee faster and deterministic reactions during the manufacturing processes.*
Frequency	*How often does this problem occur for the end user?*	*This becomes more popular nowadays, especially when an enterprise has moved forward into its digital transformation.*
What is the main benefit	*What is the main benefit of solving this problem?*	*The level of automation in the increasingly complex manufacturing landscape will be expanded through HRC and enhanced situational awareness inside the pilot site.*
Main stakeholder	*Who is the main stakeholder that benefits from solving this problem?*	*Manufacturing companies*
End user	*Is the main stakeholder also the end user, or are there other end users?*	*The main stakeholder is also the end user*
Other stakeholders?	*Are there any other stakeholders who benefit from solving this problem?*	*Software development companies that develop computer vision algorithms, UAV manufacturers that assembly robot vehicles with a camera and a GPU.*
3 Current situation		
If applicable: How much used	*What estimated fraction of the end users make use of the current solution?*	*Currently monitoring the safety of indoor working environment is made manually in 90% of industries.*
If applicable: Why not?	*If not all end users use the available solution, why is that?*	*Indoor space in production line, permission to fly a drone might be restricted, extreme weather conditions*
Is there any available data to be used from DAY 0 in the frame of TALON	*If yes, please give some details on data descriptions and features (what kind of data, in a db, message queues or other - specify), data schemas, data size, data format and how they can be immediately used?*	*Visual data from UAVs, real-time data, resource-demanding cloud infrastructure with model updates propagated to the edge nodes.*
Is there any available cloud / edge infrastructure to be used in the frame of TALON	*If yes, please give some system and technical details by means of OS / existing software, resources dimensioning, etc.*	*The drone that will be used in the specific use case is equipped with a Jetson Xavier module which can manage a volume of 10.000 scores. It can keep a record of the fights made and can present default details, such as date of the flight, time, location etc. Data will be* collected on a memory stick/card attached to the drone and then the analysis of these data will be conducted on a computer.
*Workflow diagram of the **CURRENT (AS-IS)** situation is thoroughly presented and explained in Section 4.4.3.*		
4 Future situation		
Change of use?	*Do you expect that more/less end users will make use of the future solution than in the current situation?*	*Yes*
Impediments	*Do you see any impediments why end users would not want to use the future solution?*	*Yes (trained operator, extreme weather conditions)*
*Workflow diagram of the **FUTURE (TO-BE)** situation ("After TALON") is thoroughly presented and explained in Section 4.4.4.*		

5 More about data (future)		
Data required	*Looking at the roles you just described for the future situation, summarize the required data required*	*The AI models require annotated data so any computer vision algorithm should come along with a test dataset for validation purposes.*
Data generated in TALON	*What data should be generated in the frame of TALON?*	*Reuse data and test AI algorithms and solutions.*
Missing data	*What data are missing or need to be collected?*	*Imagery data collected by drones*
Restrictions / impediments	*Are there any restrictions / impediments to obtain this data?*	*If the collected images/videos include personal details (e.g., face characteristics of workers), then consent forms need to be signed to have end users consent and then perform facial anonymisation.*
6 More about infrastructure (future)		
Computing resources required	*Looking at the roles you just described for the future situation, summarize the required computing cloud / edge resources required*	*The edge resources are related to the GPU capacity and characteristics (Jetson GPU) that will be further defined according also to the needs of the other use cases of TALON.*
Restrictions / impediments	*Are there any restrictions / impediments / implications to be considered regarding the computing cloud / edge resources?*	*No, this pilot has lower TRL level than the other use cases. Any restriction or technical barrier can be examined during a lab test at CERTH.*
7 More about the stakeholder(s) of this problem		
Stakeholder size	*How many stakeholders for this problem are there in your area of interest? E.g., how many of these farmers / breeders / companies / .... are there in your region?*	*Within CERTH: 100-200 people* *Within FACTOR:300-500 employees*
How typical	*If you take a typical stakeholder in mind, how typical is this stakeholder? Are they all similar, or are they all hugely different?*	*A typical stakeholder is an industry with a large area, where many workers are work in parallel. The position and the working conditions of the workers can easily change since workers are walking in the working area. The monitoring of their personal safety (e.g., if they wear the appropriate safety equipment) and/or the monitoring of the general safety conditions in the working area are conducted by HRC. So, most stakeholders are quite similar.*
Distinguishing features of stakeholders	*Give a list of features that distinguishes the stakeholders, most distinguishing feature on top.* *Also give an indication of the range of these features*	*N/A*
With whom to communicate	*With whom do the stakeholders most likely discuss the problem here?*	*N/A*
Peer Network	*Do stakeholders typically have a peer network around them, through which they can exchange information with each other regarding the problem presented here?*	*No*
Typical journals or other outlets	*Do stakeholders typically inform themselves through other sources such as internet websites, mobile phone apps, newsletters, specialised magazines?*	*No*
8 Any additional comments?		
Comments	*Please feel free to give additional information or anything else*	-

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