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Publishable Executive Summary

This deliverable summarizes the significant Year 3 progress in defining, consolidating, and realizing AI-ready edge hardware and system concepts, and in assessing KPI achievements at WP1's use-case level. Y3 focused on moving from validated components and environments to finalized edge system concepts, covering hardware building blocks (sensing, communication, compute/acceleration, robotics, and manufacturing equipment) and their integration into coherent Edge/Fog/Cloud deployments. Key achievements include the refinement of target system architectures, the realization of integrated edge hardware set-ups suitable for operational environments, and the consolidation of deployment and integration practices building on the project's established software and interoperability foundations.

In parallel, the use cases performed KPI-oriented assessments to quantify progress against project objectives, leveraging the established testing and validation approach while emphasizing end-to-end operation in representative settings. The results provide evidence that AI-driven edge solutions can support improved monitoring, perception, automation, efficiency, and human–machine/robot collaboration under realistic constraints, while maintaining interoperability across heterogeneous devices and platforms. The deliverable captures the KPI evaluation approach and summarizes the outcomes at a publishable level, highlighting advancements in the maturity and operational readiness of the edge systems.

With the project concluding, the work culminates in a consolidated view of the final AI-ready edge hardware and system realizations and a cross-use-case summary of KPI achievements. The reported outcomes synthesize WP1's progress from component verification and integration testing to system realization and KPI-driven evaluation, supporting an overall assessment of the achieved technical readiness and the applicability of the developed edge system concepts in industrial contexts.

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1. Introduction

1.1 Objective and scope of the document

This document is a summary report on the AI-ready edge hardware and system concepts finalized and realized during Y3 of the AIMS5.0 project within WP1, and on the assessment of KPI achievements in the project's industrial use cases. The primary objective is to consolidate, at a publishable level, the resulting edge hardware/system realizations and their deployment context, and to report how the integrated solutions perform against the project's KPI framework in representative operational environments.

The document builds on the earlier component-level and integration-level testing and validation activities by shifting the focus to system concept consolidation and realization, and to KPI-driven evaluation at use-case level. It provides a unified view across heterogeneous edge computing configurations and cyber-physical deployments, while keeping the level of technical detail aligned with dissemination constraints. In addition, it summarizes the methodological approach used to assess KPI achievement (including the continued use of experimental and, where applicable, simulation-supported evaluation) as a consistent means of tracking maturity and performance across the use cases.

1.2 Structure of the deliverable report

Chapter 2 – presents the realized edge hardware/system set-ups and the KPI-related outcomes from the contributing partners. Each technical result is covered following a consistent structure aligned with the project's publishable reporting needs.

Section 2.* enumerates the technical result

Section 2.*.1 briefly introduces the technical result, its industry context, the need for it, and related usual challenges.

Section 2.*.2 provides a brief summary of the state of the art of the relevant technological field, capturing the starting point for the AIMS5.0 project, from that specific facet (e.g., components, integration status, and readiness).

Section 2.*.3 describes the effective technological advancements achieved during the project, focusing on the finalized system concepts and their realization as AI-ready edge deployments in representative operational settings.

Section 2.*.4 details, for each relevant technical result, the KPI assessment approach and the applied metrics (consistent with the Y2 review meeting), and summarizes KPI achievements at a high level, as well as any underachievement.

Chapter 3 – provides concluding remarks, summarizing the key Y3 outcomes in terms of AI-ready edge system realization and KPI achievement, and synthesizing the overall resulting maturity and readiness of the developed solutions.

With this structure we can go through past results from the early stages of the project, observe the development journey, and assess the final advancement status of each of them at the end of AIMS5.0.

2. Realized AI-ready edge hardware and KPI reporting

In this chapter, the realized AI-ready edge hardware and system concepts developed within the project are presented in an advancement–oriented manner, together with a publishable summary of the KPI-related outcomes achieved at project end. The results are reported and discussed highlighting the effective technical advancements compared to the state of the art at the start of the project start and reflecting the transition from component and integration progress to consolidated system realization and end-to-end evaluation in representative environments.

For each technical result, the chapter first recalls the SOTA, then describes the realizations of the edge hardware/system set-ups and finally summarizes the KPI assessment approach and the metrics used (aligned with the Y2 review meeting) along with the achieved results at a high level. This consistent structure supports a unified view of progress across heterogeneous industrial contexts while respecting dissemination constraints.

2.1 Multi-layered infrastructure for data processing and AI training/deployment

Partners: SAVVY, IDEKO, SORALUCE, GOIMEK

2.1.1 Introduction to the result

This section describes the technical result AI Techniques at Different Layers in Machine Tool Domain, developed within the AIMS5.0 project. The result focuses on the design, implementation, and validation of a multi-layer AI system for machine tool environments, combining edge, fog, and cloud resources with industrial hardware and firmware. The technical result has been developed and validated in collaboration between IDEKO, SAVVY, SORALUCE, and GOIMEK, and is demonstrated in Use Case UC05.

2.2.1 Industry Context, Need, and Challenges

Machining companies face a combination of challenges when moving towards data-driven operations, particularly due to the need to handle heterogeneous data streams across vastly different frequency ranges. At the data acquisition level, the main technical challenges arise from protocol fragmentation, lack of semantic interoperability, and the difficulty of integrating legacy equipment, combined with constraints in handling high-frequency data streams, ensuring time synchronization, and managing scalable, reliable edge-to-cloud data pipelines. From a data exploitation perspective, companies need to implement advanced signal processing techniques to extract meaningful features for AI models.

Finally, at the deployment level, organizations must balance the trade-offs between edge and cloud computing, ensuring real-time responsiveness where needed while maintaining scalability, cybersecurity, and efficient resource usage across the shop floor. These combined constraints make it challenging to implement robust, scalable, and production-ready industrial AI solutions.

2.1.2 State of the art at project start

Conventional shop-floor monitoring often relies on low-rate sampling (e.g., 1 Hz) that is suitable for general applications but insufficient for dynamic machining phenomena and transient events. To unlock advanced process characterization and quality assurance, manufacturing systems must access medium- to higher-frequency CNC internal signals (e.g., tens of milliseconds) to capture relevant drive/load behavior, vibration envelopes, and process instabilities. This requires carefully engineered acquisition mechanisms that: (i) access internal CNC variables without intrusive modifications to NC programs, (ii) avoid additional load on industrial PCs or real-time control loops, (iii) be capable of ingesting and managing data from multiple heterogeneous sources.

The baseline situation included SAVVY edge and cloud platform as a representative industrial solution and SORALUCE machine tools equipped with Heidenhain CNC controls, which provided data acquisition capabilities but lacked an integrated, automated AI deployment pipeline across system layers.

2.1.3 Achievements at project end

During the AIMS5.0 project, significant advancements were achieved with respect to the integration of AI techniques across different system layers in the machine tool domain.

At the edge layer, industrial Jetway IPCs equipped with custom firmware were deployed close to machine tools. These edge devices provide sufficient computational resources to execute AI inference tasks in real time and include embedded microservice orchestration capabilities. They are directly connected to machine sensors and controllers, enabling local processing of vibration, temperature, and other machine signals.



Figure 1: SAVVY Industrial PC installed for AI processing.

At the fog layer, rack-mounted servers' aggregate data from multiple edge devices, enabling site-level analytics and coordinated AI services. At the cloud layer, centralized platforms support large-scale AI model training, long-term data storage, fleet management, and global monitoring dashboards.

Hardware intended for deployment in industrial environments is required to be mechanically robust, thermally stable, and adequately protected against dust, vibrations, and harsh operating conditions. To support demanding AI workloads at the edge, fanless small form-factor GPU solutions were evaluated; however, limited compatibility with existing edge hardware was observed. Larger edge platforms were also considered but proved suboptimal due to integration and deployment constraints. Consequently, small form-factor NPU-enabled platforms, such as the AOPEN DEX5145 and TouchThink RK3568, were identified as a better fit, given their compatibility with the firmware and industrial requirements. In addition, Google Coral USB accelerators were shown to significantly improve inference performance for selected lightweight models. More powerful hardware options were also assessed to support future scalability of the edge infrastructure.

At the machine NC level, mechanisms for medium-frequency data acquisition from Heidenhain and Siemens NC controllers were developed and validated. For medium frequency acquisition, a data acquisition library has been developed for the Edge platform, capable of extracting and storing internal data from Siemens Sinumerik CNC and Heidenhain TNC7/TNC640 controllers, without requiring modifications to machine programs or introducing additional processing load on the industrial PC. The data acquisition system enables medium-frequency capture in parallel with the machine's operational cycles, providing an alternative to the native Siemens CNC TRACE functionality (high-frequency data acquisition). TRACE operates with real-time hardware within the control system and achieves higher sampling rates with deterministic behavior but requires the exclusive execution of dedicated cycles during its operation.

For continuous high frequency (HF) acquisition of vibration sensors, a solution composed of a Programmable Automation Controller (PAC) device and the Edge device has been developed, suitable for the requirements of AIMS5.0 Use Case 05. Raw accelerometer data is ingested, and frequency domain-based features are extracted at 1s frequency and transmitted through Modbus to the Edge.

Non-continuous on-demand HF NC capture has been implemented both for Heidenhain and Siemens Sinumerik TCP, allowing for trigger-based recording and transference via SFTP to the Edge device, adhering to the mechanisms and procedures each of these NC/PLC providers require.

SAVVY integrated the Eclipse Arrowhead Framework to enable a secure, interoperable, and scalable AI/ML pipeline across edge, fog, and cloud layers. The complete solution is integrated using a service-oriented approach, with secure communication and orchestration across layers. AI models are trained at

higher layers (using AI-Gym) and deployed seamlessly to the edge, where inference is executed close to the machine.

The system has been deployed and validated in a representative industrial environment at GOIMEK facilities, demonstrating feasibility under real shopfloor conditions and advancing the technology towards AI-ready edge deployments.

2.1.4 KPIs analysis

The KPI assessment for this technical result follows the methodology defined in the AIMS5.0 Validation Plan (D9.10). KPI evaluation was conducted through laboratory tests and shopfloor deployments.

- High-frequency data processing and feature extraction: Continuos 4kHz high frequency vibration data acquisition and processing and feature extraction at 1 s achieved, tested in lab condition and at shopfloor machine, with the use of an external PAC system (sensor->PAC->Edge device).
- Execution and processing of tool failure detection solution at 1s frequency: The application is succefully deployed at 1 s frequency. The inference time of the application has been measured through the application logs.
- A library for continuous MF data acquisition and enhanced edge services for data processing acceleration: Different combination of frequencies and variable number for Heidenhain and Siemens NC have been tested. Peak temporal resolution of 4 ± 0.9 ms for up to 30 NC variables with Siemens control.

AIMS project objective 1 success metrics (Annex 1 Part B of AIMS5.0 proposal):

- Quality & reliability of hardware components:%: By concentrating AI and ML capabilities in Arrowhead enabled IoT gateway devices and higher level monitoring systems, model performance and system resource usage metrics are seamlessly integrated to a centralised monitoring platform (fog or cloud), more easily tracked than model run in distributed individual devices. Improvement above15%, since in baseline situation no model performance metrics were available without physically accessing the devices.
- Improved Low-Latency Communication in IIoT applications:
    - The new AI&Ml pipeline optimizes model deployment and execution across the different layers (edge/fog/cloud) depending on the latency constraints of each model. This way, models requiring faster response run closer to the production equipment leveraging low latency communication infrastructure, while models that are not time critical run in the higher layers providing their results as required (on demand or asynchronously). Regarding efficiency, model training takes places on the higher levels (but within the same ecosystemI, taking advantage of the available greater system resources and freeing up resources in the edge level for time critical model execution.
    - More than 20x improvement in continuos acquisition speed (from continuos 1 s LF to less than 50 ms MF).
    - The MF solution collects data continuously during actual machining operations (unlike TRACE, which requires dedicated measurement cycles), increasing the efficiency in at least 20%.

2.2 3D Metal Printing for Luminaire

Partners: SIGNIFY

2.2.1 Introduction to the result

Signify has been developing a new generation of 3D metal printers, based on Direct Energy Deposition (DED) technology. In this technology metal powder is directed (blown) towards the target location (on a base plate) and is melted on the fly. This is contrast to powder bed AM metal printing, which is a layer-by-layer technology.

2.2.2 State of the art at project start

At the start of AIMS5.0 DED printers were available solely for high end applications, with the initial R&D and developments done by Fraunhofer. Some specific companies are offering OTS DED printers.

These printers are, however, high investment machines (multiple 100k Euros), dedicated to high tech/high product fabrication, such as e.g., avionics parts, rocket motors.

Metal luminaires for Outdoor applications are typically fabricated using energy-consuming die casting, which is a technology in which molten metal is used and that strongly relies on expensive mold (limiting flexibility and prohibits realistic high diversity low volume product manufacturing. Hence, the wish for a cost-effective technology that allows high diversity, low volumes, full additive/digital, that meets the business requirements of consumer products.

2.2.3 Achievements at project end

Within AIMS5.0 Signify has designed and realized a FUMO (functional module, first-of-a-kind) DED-based AM metal printer machine that meets the requirements in terms of cost. Business cases have been worked out for multiple luminaire product families (and meet expectations/however confidential information).

The FUMO is based on industrial-available OTS components and parts, but some customization was applied to the parts. Some photographs of the realized machine in its dedicated environment (shielded area for laser and powder safety) are shown next as example. More details are provided in D9.10 (final review document).



Figure 2: FUMO machine in its dedicated environment.

Purpose was/is to provide our internal business partners, and machine suppliers, guidance to allow manufacturing more industrial-compliant 3D printer machines. This has been shown to be successful, but next steps need to be made now.

The FUMO has been developed including multiple sensors and data processing functionality, to allow for process monitoring and securing safe operations. Sensing functionality that is implemented in this Gen. 1 FUMO are a.o. visible light sensors for overall monitoring of actuators and product generation, thermal image sensors combined with real-time data processing to analyze details of powder flow and melting process, thermal sensors to anticipate on laser beam deviations, etc. A feedback loop method is also enabled (for real-time process adaptation) but has not been implemented (yet).

2.2.4 KPIs analysis

KPIs for this (sub) use case within UC7 of Signify are focused on first-of-a-kind realization of a consumer business-compliant DED 3D printer machine and making it available for our business. We can state that this has been achieved by designing and manufacturing a FUMO machine, which has been running in the meantime for over 1000 hours, processing over 100 kg of Al metal printer, and realizing multiple industrially-requested product samples for quality evaluation and customer feedback. Examples and details of this will be provided in D9.10.

2.3 AI Supported Task and traffic management station for AMRs

Partners: TUBITAK

2.3.1 Introduction to the result

This result focuses on the development of an Explainable AI (XAI) supported Task & Traffic Management System (TTMS) specifically designed for in-factory logistics. The system is integrated into Use Case 8 (UC08) and utilizes a React-based graphical user interface (GUI) to provide operators with the authority to monitor and control autonomous operations. The architecture includes a task distribution module and a traffic management module to coordinate robot movements efficiently.

2.3.2 State of the art at project start

At project inception, standard industrial traffic management solutions, such as the native algorithms provided by OMRON, exhibited significant operational inefficiencies. These systems relied on fixed waiting positions for area control; AMRs were required to pause at these checkpoints before every movement to verify the safety of the path, which resulted in prolonged operational cycle times.
In addition, human-robot interaction was limited to basic "wait-and-stop" or "stop-and-go" behaviors. AMRs lacked the capability to predict human trajectories or adjust their paths dynamically in a socially aware manner, leading to frequent interruptions and bottlenecks in high-traffic factory environments.

2.3.3 Achievements at project end

Socially Aware Navigation: TUBITAK developed a module that allows AMRs to navigate by forecasting and avoiding human trajectories using LSTM networks and Graph Attention networks.

Human-Aware Navigation via Gesture Recognition and Voice Feedback: AMRs dynamically update their paths in response to workers' gestures and provide real-time vocal feedback to communicate their actions to nearby humans.

Optimized Traffic Management: With the proposed algorithm, AMRs operate without predefined waiting or control points. Instead, real-time data including positions, velocities, and planned paths are continuously analyzed to predict potential collision points, and appropriate motion commands are generated accordingly. Additionally, user-defined controlled zones are configured via the GUI, enabling context-aware traffic management behaviors within designated areas.

Real-Time Monitoring: Real-Time Monitoring and Control: A complete GUI was implemented, enabling real-time visualization of AMR locations and status updates, along with operational control capabilities, system analysis reports, and logging functionalities.

2.3.4 KPIs analysis

Navigation Efficiency: Based on the initial simulation and field tests, the system achieves a 20% reduction in normalized mission completion times across diverse layout topologies, demonstrating a substantial increase in cycle efficiency regardless of transport distances. Furthermore, the newly implemented dynamic re-routing algorithms successfully decrease the total fleet idle time caused by static waiting positions at intersections and narrow corridors from 15% to less than 5% of the total operational duration.

XAI Performance: User experience simulations and human-in-the-loop tests indicate a 35% improvement in operators' comprehension of the robot's intent during unexpected traffic maneuvers, reducing cognitive load and operational hesitation. Furthermore, the localized transparency provided by XAI outputs delivers a 40% faster resolution in human-robot spatial conflicts at shared intersections.

2.4 Physiological Signal Collection and Physio Classifier with Electroencephalography Headset

Partners: TUBITAK

2.4.1 Introduction to the result

This research focuses on estimating user motion intention by analyzing physiological signals (EEG and EMG) to control industrial skeletons. By using AI techniques, the system aims to create a smart manufacturing interface where the exoskeleton responds intuitively to the user's cognitive and physical states.

2.4.2 State of the art at project start

Historically, EEG (Electroencephalography) was primarily utilized in medical fields for diagnosing brain disorders or in highly controlled research environments. In the context of industrial exoskeletons, most systems relied on physical sensors (like force or pressure sensors) rather than cognitive intent. The use of non-invasive EEG for real-time motion intention in a noisy factory environment remained a significant challenge, with limited integration between neural activity and mechanical assistance.

2.4.3 Achievements at project end

Multi-Modal Hardware Integration: Successfully integrated a 16-channel EEG device and a single-channel EMG sensor for simultaneous brain-muscle signal acquisition.

Real-Time Command Processing: Developed a signal processing pipeline that analyzes data through subject-based AI models to output real-time motion commands for the exoskeleton.

Comprehensive Experimental Validation: Conducted trials with five participants (S1-S5, including both males and females) under diverse scenarios.

Scenario-Specific Testing: Validated the system's performance in opening/closing the exoskeleton and lifting weights at two different load levels.

2.4.4 KPIs analysis

System Accuracy: Achieved a high average classification accuracy of **81.32% ± 7.09** across all subjects.

Peak Performance: Demonstrated peak performance in specific participants, such as **90.0% accuracy** for Subject S4.

Adaptability: The system proved capable of distinguishing between load levels and system states, making it suitable for future long-term industrial use.

2.5 Human Detection and Gesture Recognition System for AMRs

Partners: SU

2.5.1 Introduction to the result

The Human Detection and Gesture Recognition System for AMRs enables safe and intuitive human–robot interaction in shared factory environments. The system combines AI-based human presence detection, gesture recognition, and 3D localization to allow Autonomous Mobile Robots (AMRs) to perceive, understand, and react to human workers.

By integrating vision-based perception with temporal AI models, the system supports both safety-critical functions (e.g., human detection and obstacle awareness) and interaction capabilities (e.g., gesture-based commands). This result forms a key building block for human-aware navigation and contributes directly to efficient and trustworthy intra-logistics operations.

2.5.2 State of the art at project start

At the beginning of the project, existing solutions for human detection and gesture recognition in industrial environments were typically limited in robustness and integration. Most systems focused either on basic object detection or on gesture recognition in controlled settings, often lacking real-time performance and reliability in dynamic factory conditions.

Furthermore, limited integration of 3D perception and temporal understanding reduced the ability of AMRs to interpret human intent and react appropriately. Human–robot interaction was often restricted to predefined interfaces, with minimal support for natural, vision-based communication.

2.5.3 Achievements at project end

By the end of the project, a fully integrated AI-based perception system has been developed and validated in realistic test environments. The system combines real-time object detection, temporal gesture recognition, and 3D bounding box estimation into a unified pipeline suitable for embedded deployment on AMRs.

The developed solution enables reliable detection of human presence, accurate recognition of multiple gesture classes, and spatial understanding of the environment. These capabilities allow AMRs to operate safely around humans while also supporting intuitive interaction through gestures, significantly improving usability and acceptance in industrial settings.

2.5.4 KPIs analysis

The system has achieved all targeted KPIs, demonstrating powerful performance across perception and interaction tasks. Human presence detection reached an accuracy above 95% within a 5-meter range, ensuring reliable awareness of nearby workers for safety-critical operation.

Gesture recognition achieved 85% accuracy across five predefined gesture classes, confirming the system’s capability to interpret human commands in real-time scenarios. Additionally, the 3D perception module delivered 75% Intersection over Union (IoU) for bounding box estimation, indicating solid spatial localization performance for navigation and interaction purposes (Figure X).

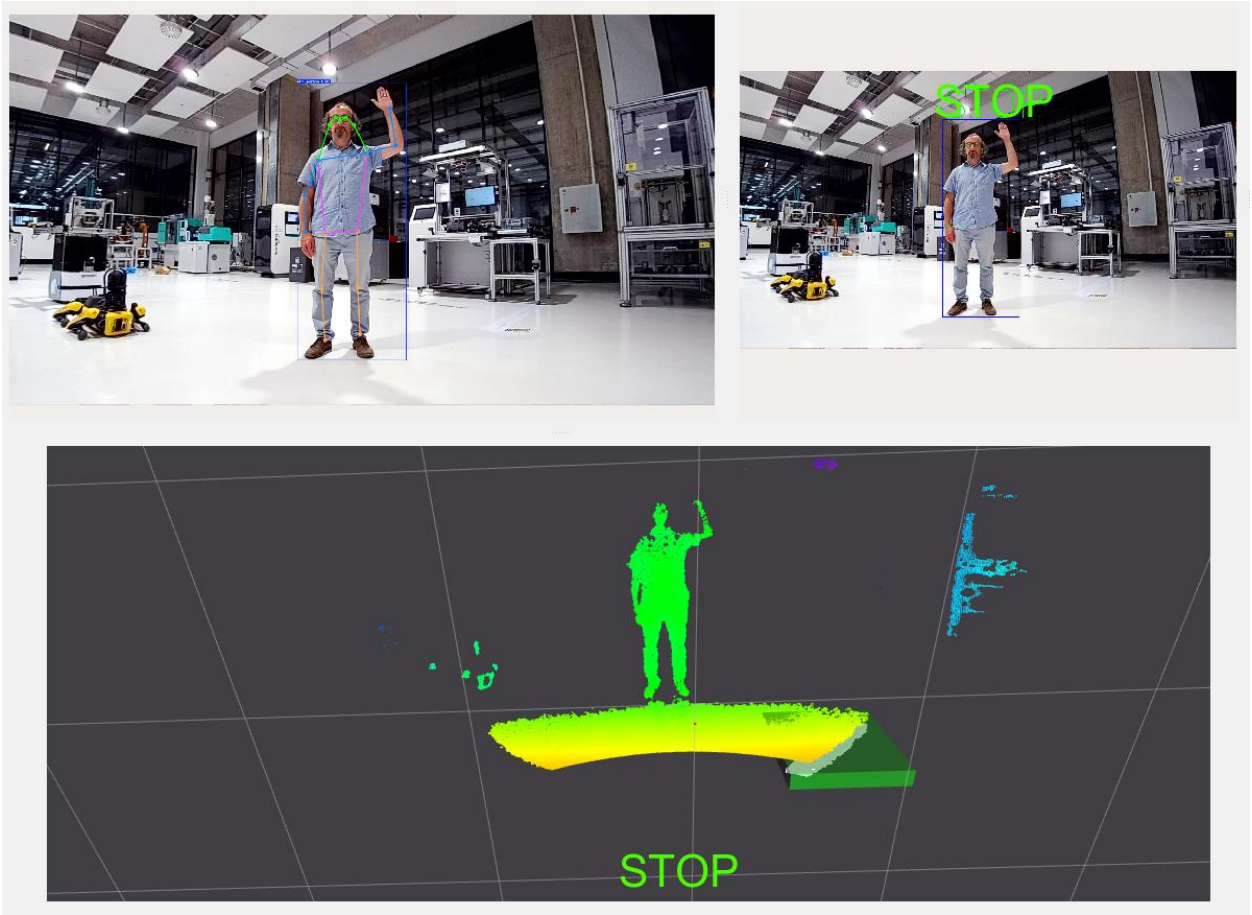

Figure 3: Gesture recognition tests. Top Left: Features extracted from images to be used for gesture classification, Top Right: Human detection marked with bounding box and gesture recognition result added as text on top, Bottom: Result from depth sensor.

Overall, these results validate the effectiveness of the proposed approach and confirm its suitability for deployment in human-centric manufacturing environments.

2.6 Wireless communication enhancement testbed and tool

Partners: GUT

2.6.1 Introduction to the result

The wireless communication enhancement testbed developed the challenge of evaluating reliability and robustness of wireless links in complex and interference-prone environments. This is particularly relevant for industrial and cyber-physical systems, where dense deployments and coexistence of multiple technologies in shared frequency bands (e.g., 2.4 GHz) may significantly degrade communication performance.

The result provides a low-cost, scalable, and experimentally controllable platform for testing connectivity, interference resilience, and adaptive antenna techniques. The testbed supports both packet-level and signal-level evaluation, enabling assessment of key metrics such as RSSI, SNR, SINR and packet error rate (PER).

The main objective is to enable realistic and repeatable validation of wireless communication enhancement methods, including beamforming and interference mitigation, under controlled yet representative conditions. The result targets improvements in communication reliability, robustness to interference, and reproducibility of experimental evaluation, which are critical for AI-driven edge systems relying on wireless connectivity.

The result is related to the UC11, which part of it is focused on the AI-based mechanisms for reliable wireless communication security, where methods for the wireless communication connectivity enhancement methods are presented, that are developed, tested, validated in the testbed which is, in this case, used as a representation of the indoor farming environment.

2.6.2 State of the art at project start

At the start of the project, wireless communication evaluation relied mainly on two approaches: high-end laboratory measurements and simplified experimental testbeds. Laboratory setups (e.g., anechoic chambers, signal generators) provided high accuracy but were costly, complex and not suitable for rapid or large-scale experimentation.

On the other hand, existing low-cost testbeds based on commercial radios enabled packet-level evaluation of connectivity and interference but offered limited control over signal characteristics and interference properties. In particular, they lacked the capability to generate controlled, repeatable, and configurable interference at the waveform level.

Software-defined radio (SDR) platforms were increasingly used for interference generation and signal-level experimentation, but typically in ad-hoc setups without integration into structured, automated testbeds. This limited reproducibility, scalability, and usability of experiments.

Initial project activities focused on antenna validation and basic connectivity testing using BLE-based setups and controlled measurement environments. However, limitations remained in terms of interference realism, measurement flexibility, and experiment automation.

The main gap identified was therefore the lack of an integrated, low-cost, and automated testbed combining packet-level communication, SDR-based interference generation and reproducible experiment orchestration.

2.6.3 Achievements at project end

By the end of the project, GUT developed and validated an enhanced wireless communication testbed integrating BLE-based connectivity testing with SDR-based interference generation and centralized experiment control.

The finalized system consists of a central transceiver and 36 distributed agents arranged in a circular topology, enabling direction-dependent evaluation of wireless links. The testbed operates in the 2.4 GHz band and combines multiple hardware building blocks, including BLE nodes and embedded controllers.



Figure 4: Testbed layout.

The implemented architecture enables remote orchestration of experiments through a centralized server and Python-based control framework. The platform supports configurable packet transmission, simple jamming generation, RSSI measurements and packet error rate analysis. Additionally, all measurement data are automatically collected and stored in a time-series database for further analysis.

The developed testbed was validated using an ESPAR antenna capable of switching between 4096 radiation patterns. Experimental results confirmed the ability of the system to evaluate connectivity enhancement algorithms and interference mitigation methods under repeatable conditions. The platform provides a scalable and flexible environment for future AI-assisted wireless optimization research.

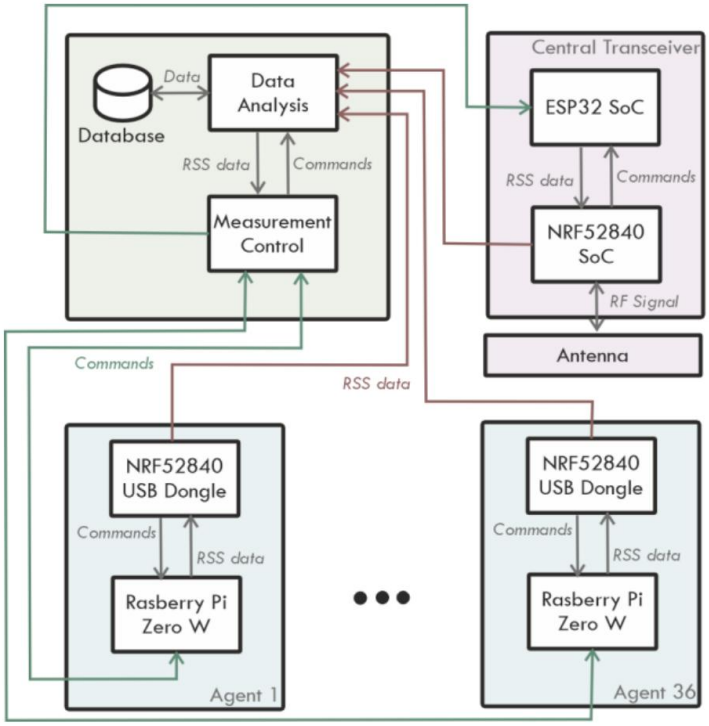

Figure 5: System architecture.

The testbed supports advanced measurement capabilities, including estimation of noise floor, RSSI, SNR and SINR, enabling both packet-level and signal-level evaluation. Validation experiments performed with an ESPAR antenna demonstrate the ability to capture direction-dependent interference effects and to assess the impact of antenna pattern selection on communication performance.

2.6.4 KPIs analysis

The KPI assessment was aligned with the WP2-wide objectives related to communication reliability, IIoT communication efficiency, and productivity improvement. Evaluation was performed experimentally using the developed wireless testbed under controlled communication and jamming scenarios.

The results demonstrated improved robustness and reliability of wireless communication through adaptive antenna pattern selection and controlled interference testing, supporting the WP1 target of approximately 15% improvement in communication quality and reliability.

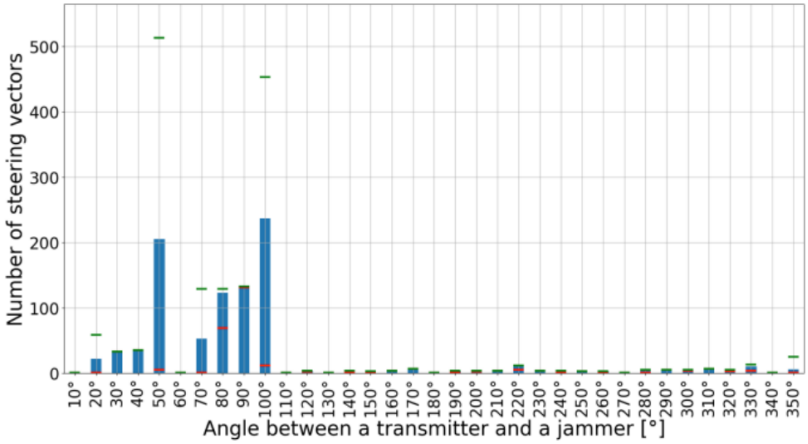

Figure 6: Number of scanned radiation patterns before a set threshold of connectivity indicator improvement was achieved.

The developed platform also supports improved low-latency IIoT communication by enabling rapid and repeatable testing of connectivity enhancement methods and communication optimization strategies. The results achieved contribute toward the targeted improvements of approximately 10% in communication responsiveness and 20% in communication efficiency.

Additionally, the automated and scalable architecture of the testbed reduces the effort required for wireless communication validation compared to traditional laboratory-based approaches, supporting the targeted productivity improvement of approximately 10%. The platform also provides a basis for future predictive maintenance and lifecycle management approaches through continuous monitoring and analysis of wireless communication quality indicators.

2.7 Mobile Sensor Platform for semiconductor manufacturing cleanrooms

Partners: UzL, IFD

2.7.1 Introduction to the result

Infineon Dresden already worked on sensor data fusion for stationary systems, such as simple robotic arms used to operate fixed installations. For this purpose, data from a radar sensor were fused with data from Time-of-Flight (ToF) cameras, and based on this fusion, algorithms were researched to enable such systems to function effectively. Infineon Dresden possesses extensive expertise in factory automation through various automation solutions, including rail- and ceiling-mounted loading and unloading systems, as well as automated guided vehicles (AGVs).

Automation solutions in worldwide semiconductor factories for automated loading-and unloading of wafers based on AGVs exhibit significantly lower performance compared to other systems, particularly in terms of uptime and Overall Equipment Effectiveness (OEE). Moreover, their operation in production environments is more challenging due to interactions with human workers. One major cause of these issues is the currently insufficient sensor technology required for rapid system control.

IFD worked in strong cooperation with UzL with the aim to build upon the results achieved with sensor fusion in stationary systems by investigating a sensor data fusion solution specifically for mobile systems. This solution can be integrated into automated guided vehicles (AGVs) or even humanoid robots, enabling real-time responsiveness. IFD discussed their results with UzL, and the mobile sensor fusion was established in the lab of UzL based on requirements, and results by IFD. Both partners analyzed the results of this work.

2.7.2 State of the art at project start

Prior to this project, the state of the art in multisensory fusion for industrial environments at IFD was limited to combining radar and time-of-flight (ToF) camera data on stationary platforms e.g., fixed robotic stations. The deployment of fused sensor data on mobile robotic systems has not yet been demonstrated. Accordingly, the project sought research sensor-fusion methods and system architectures suitable for mobile applications, thereby enabling future autonomously navigating robotic platforms.

2.7.3 Achievements at project end

At the end of the project within Y3, the partner IFD and UzL elaborated a comprehensive pilot hardware platform to establish a robust Sensor Fusion use case for mobile robotic systems. This project integrated heterogeneous sensing modalities with high-performance edge computing and custom robotic actuation to enable advanced environmental perception and navigation. The current demonstrator is shown in Figure 7.

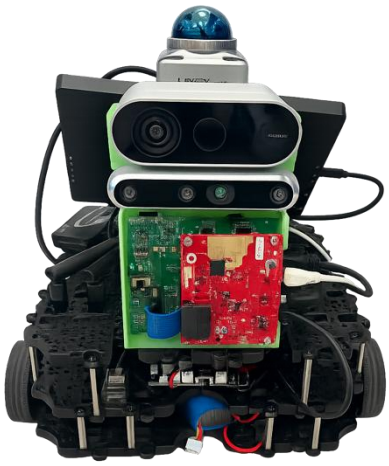

Figure 7: Smart Sensor Platform.

The following Key Hardware Integration was used:

- **Advanced Vision & Depth Sensing:** Designed a multi-camera setup to capture high-fidelity visual data and depth information. This included a Time-of-Flight (ToF) camera (Orbbec femto Bolt). Previously, specialized Flexx2 and Flexx2 VGA modules were integrated to support imaging requirements.

- **Radar Integration:** Enhanced the perception stack by incorporating the TI AWR 1843Boost FMCW radar sensor, enabling robust object detection and velocity estimation in challenging lighting conditions where optical sensors may struggle.
- **Edge Computing & Processing:** Leveraged the NVIDIA Jetson Orin NX as the central processing unit which can provide AI performance up to 157 TOPS. This powerful edge AI module facilitated real-time data processing, algorithm execution, and the fusion of multi-modal sensor data streams.

Figure 7: Smart Sensor Platform

- **Ego-motion Estimation:** To estimate the mobile platform‘s velocity, a 3D Lidar sensor with built-in IMU (Livox Mid 360) is used. A very lightweight and efficient lidar inertial odometry estimation algorithm has been used to calculate the mobile platform‘s motion which is needed to be subtracted from Radar‘s doppler velocity, to get correct velocity of the detected object**s.**
- **Mobile Base:** Utilized the Robotis TurtleBot3 as a basis for the demonstrator and to evaluate the sensing and detection capabilities.

At its core of the Smart Sensor Platform sits the processing unit: an NVIDIA Jetson Orin NX. The first input is provided by the RGB camera, and the resulting images are segmented using a fine-tuned yolo model with a custom created dataset. The system outputs pixel-wise segmentation masks and class labels. The current demonstrator uses a model fine-tuned for the detection of humans and tools, but the setup is flexible and allows any kind of classes depending on the used model.

The next input is provided by a Time-of-Flight camera. A ToF depth image consists of a rectangular array of pixels where each pixel represents a distance. Using the segmentation masks, the system isolates the pixels within the mask, eliminates outliers, and averages the values to integrate distance data into the output.

The third input consists of detections from a FMCW radar. Unlike the RGB and TOF cameras, the radar does not provide a pixel frame, but rather individual detections with distance and velocity values. The smart sensor platform clusters these radar detections, assigns them to objects, and fuses the distance values with those from the TOF camera using a Kalman filter.

To utilize the detection methods on a moving robot, the Smart Sensor Platform uses the combination of LiDAR and IMU data to continually estimate its own movement and position and corrects the radar detection by its own speed.

This new hardware and software solution runs at approximately 15 fps, which is a significant upgrade over the static baseline system supplied by IFD (3.5 fps).

The complete sensor fusion and data processing pipeline is shown in Figure 8.

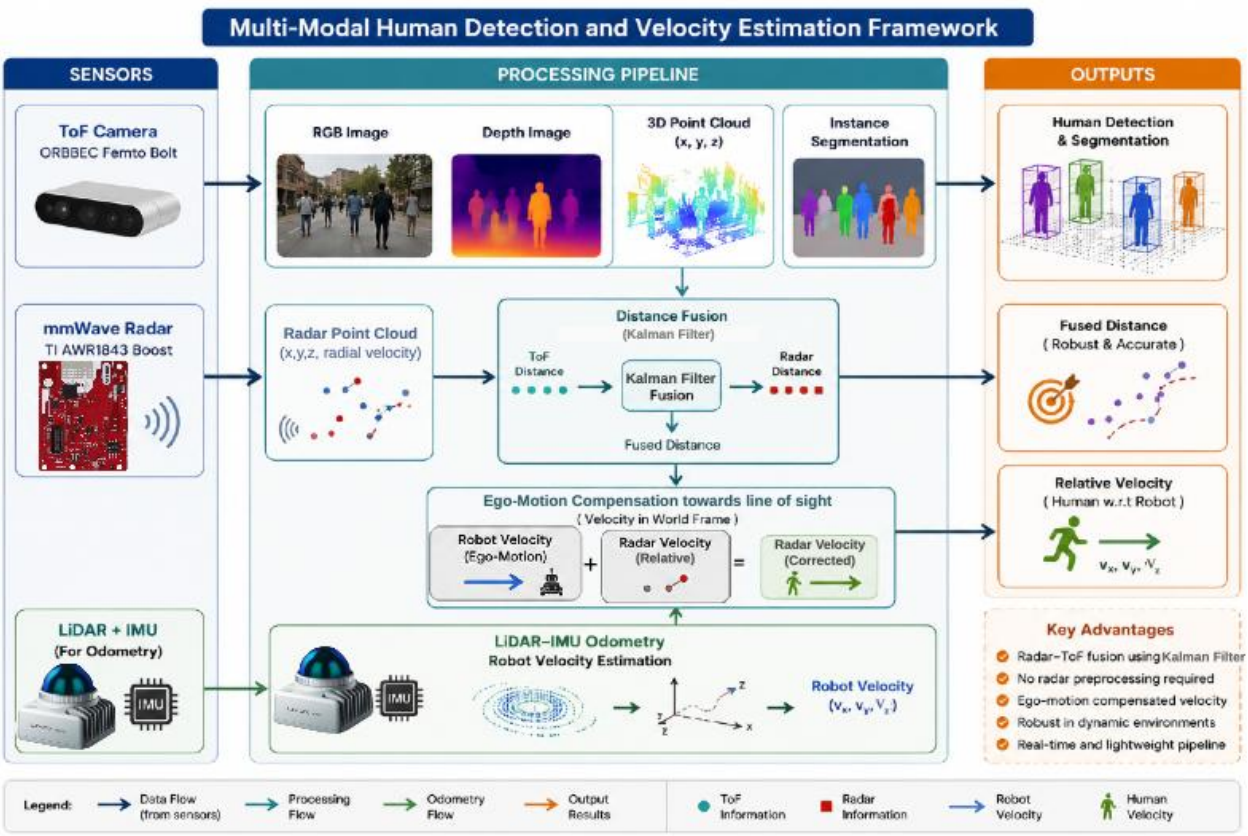

Figure 8: Sensor Fusion and Data Processing Pipeline

Validation experiments were conducted in the 300 mm fabrication-line cleanroom at IFD to evaluate the system's capability to detect and semantically label not only personnel but also equipment and miscellaneous objects present in this special production environment.

This hardware configuration successfully demonstrated the feasibility of fusing optical, depth, and radar data on a mobile platform, laying the foundation for autonomous navigation and real-time obstacle avoidance in dynamic environments.

2.7.4 KPIs analysis

In cooperation between the two partners IFD and UzL, the use of a mobile sensor fusion could be shown as a demonstrator. Compared to the base system supplied by IFD at the start of the project, the demonstrator system runs at **~15fps compared to ~3.5fps, an improvement by more than 300%**, thus contributing to the following WP1 KPI:

Metrics on improved quality & reliability of hardware components; **improvement by 15% demonstrated.**

2.8 FOUP-Sensor-Platform

Partners: IFD, HOST

2.8.1 Introduction to the result

The aim of this use case is to research predictive maintenance solutions for high-volume transportation systems such as conveyor and rail-bound transportation systems. Within this use case, 5 partners worked together to achieve the project goals. The use case consisted of 5 following sub use cases:

Sub-use case 1: Research of a sensor platform for detecting defective parts in OHT shuttles for the 300 mm lines at IFD and IFAT.

Sub-use case 2: Research of a test environment for recording critical vibrations on conveyor-based transport systems in 200 mm production, such as at IFAG (Site Regensburg) and IFD.

Sub-use case 3: Research of a test environment with an AI model to detect wear on components such as bearings in the transport system at the partner HoST.

Sub-use case 4: Research of software for a mobile smart phone application by TUD for use in FOUPs in the 300 mm line to detect faults in the transport system.

Sub-use case 5: Labeling of any components in the clean room that could lead to malfunctions of AGVs in cooperation between UzL and IFD.

In the figure below, the 5 sub cases are shown again individually in graphic form.

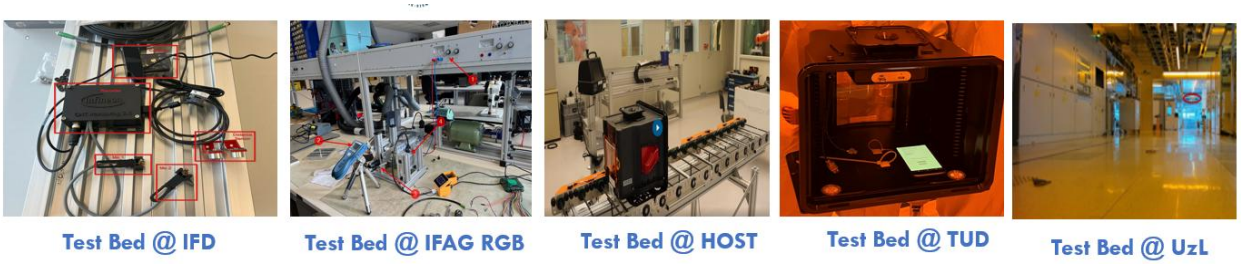

Figure 9: Individual pictures of each FOUP sub-use case.

2.8.2 State of the art at project start

State of the Art for a modern 300 mm OHT-based Automated Material Handling System (AMHS) is still largely defined by a preventive-maintenance-centric operating model across all subsystems. Predictive maintenance is typically not feasible because distributed condition-monitoring sensors and the associated analytics layer are not in place; consequently, the health of hoists, tracks, vehicles, and transfer modules is ensured through scheduled, manual inspection and control by highly skilled maintenance personnel. This dependence on planned upkeep and human expertise leaves fabs vulnerable to unplanned hardware failures, which can cascade through the tightly coupled transport network and result in disproportionately high manufacturing losses. Worker safety and human–machine interaction are predominantly supported by stationary people-detection solutions (e.g., fixed area scanners, light curtains, or interlocks), providing robust but static protection that does not adapt to dynamic traffic patterns or temporary work zones. Taken together, these characteristics describe a mature yet conservative AMHS: reliable under planned conditions, but with limited capability to anticipate failures or mitigate their impact proactively.

2.8.3 Achievements at project end

New hardware at two distinct locations the 300 mm cleanroom at IFD was installed as a demonstrator to enable fast, reliable detection of defective parts in OHT vehicles and to identify faults in the AMHS as a predictive maintenance application. This pilot was supported by the creation and curation of a comprehensive dataset comprising more than 1,000 sensor recordings, which should be used for rigorously separated into good and bad classes to ensure high-quality training and validation. Based on this dataset machine-learning models on the OHT system were installed and demonstrated a potential for anomaly detection on OHT vehicles using the new hardware platform. Potentials for future faster fault detection solutions in high-volume transport systems and increased uptimes of wafer transportation and storage systems were shown by identifying issues earlier and more consistently. By avoiding unnecessary scrapping of high-value components—such as 300 mm OHT vehicles, it could be successfully demonstrated that significant material costs and time could be saved, while also reducing the environmental footprint associated with wafer transport, handling, and storage.

To investigate solutions for further reduction of cost and broadening monitoring coverage, IFD collaborated with TUD to deploy simple smartphone applications as low-cost sensor nodes for monitoring critical shocks and vibrations on lot conveyors and OHT systems. In parallel, IFD cooperated with HoST and IFAG (Site Regensburg) on a flexible measurement setup approach capable of examining bearing noise at different speeds, enhancing the ability to diagnose wear and predict failures. Collectively, these achievements demonstrated the potential to strengthen predictive maintenance capabilities across the AMHS, and to improve system availability, and delivered measurable potentials for cost and sustainability benefits

2.8.4 KPIs analysis

The main KPIs of this project are presented within WP6 for UC13.

Maintenance efforts for the control of the OHT shuttles demonstrated reduction potentials of up to 50 % and also demonstrated maintenance costs reduction potentials of up to 50 %. Detailed reports and figures are presented within UC13.

2.9 Customary Sensor System Solutions

Partners: IFAG FE

2.9.1 Introduction to the result

Subproject advanced RFID System:
The project undertaken by IFAG FE aimed to develop a reliable and stable RFID (Radio Frequency Identification) system. This system was designed to operate effectively within the challenging environment of semiconductor production. The primary goal was to overcome the demanding boundaries that existed in this setting, which the previous RFID systems were unable to handle adequately.

Subproject sonic based sensor development:
The development of the sonic-based sensor is primarily focused on a highly automated ceiling transport and storage system, which incorporates a customized bearing system specifically designed for use in a clean room environment. Despite initial successful operation, it was unexpectedly discovered that the rolling bearings in the linear axis guide were experiencing unusually elevated levels of wear after a certain period. Replacing these bearings is a complicated and time-consuming process that requires specialized knowledge and skills. However, the development of this sensor technology has significant potential to transform the maintenance and operation of systems that rely on rolling bearings. By enabling the early detection of bearing damage, this technology allows for a proactive maintenance strategy, which can help reduce downtime, lower maintenance costs, and optimize overall system performance.

2.9.2 2.9.2 State of the art at project start

Subproject advanced RFID System:
The previous RFID systems (Fig.1) which were used in the semiconductor production environment had significant limitations. One of the major issues was their inability to provide a reliable identification. In a high automation production environment, secure material identification is not just beneficial but mandatory. It ensures that all materials and products are correctly identified and tracked throughout the production process, which is crucial for maintaining quality, efficiency, and compliance with regulatory standards. Up to three different hard- and software solutions were implemented to cover a wide range of performance levels. The average reading success rate of these solutions was 98% over a four-month analysis period, indicating a high level of reliability. However, despite this high success rate, an annual effort of 36 PM/Year was required to recover from the effects of erroneous readings.

Subproject sonic based sensor development:
There were currently 12 automated ceiling transport and storage systems in productive use, and none of these systems have been equipped with a detection mechanism for defective bearings. As a result, these systems are prone to unforeseen downtime caused by bearing failures, which can lead to significant losses in productivity and efficiency. It is estimated that approximately 5% of the total uptime is lost per year due to unforeseen downtime causes, which translates to a substantial amount of time and resources being wasted. Furthermore, the manual operation efforts required to recover from these downtime events amount to around 24PM a year, which is a significant burden on the maintenance team.

2.9.3 Achievements at project end

Subproject advanced RFID System:
Within the Frontend Production, RFID systems are utilized at over 600 locations to identify material IDs, enabling informed command decisions and precise control over positions between manufacturing process steps. The evaluation and definition of an enhanced RFID system were accomplished through a series of development steps, including root cause analysis, hard- and software design, and systematic testing. This structured approach allowed for the thorough assessment and implementation of requirements for the new RFID system (Fig.2), ensuring reliable and efficient material identification and control throughout the Frontend Production process. After the development of the new RFID system successfully completed,

a comprehensive rollout plan was in place to ensure its seamless implementation. One of the key advantages of this new system is its versatility, as it can be used on any reading destination, providing a high degree of flexibility and convenience. Furthermore, the system has achieved a remarkable reading success rate of over 99.5%, demonstrating its exceptional reliability, accuracy in material identification and tracking.

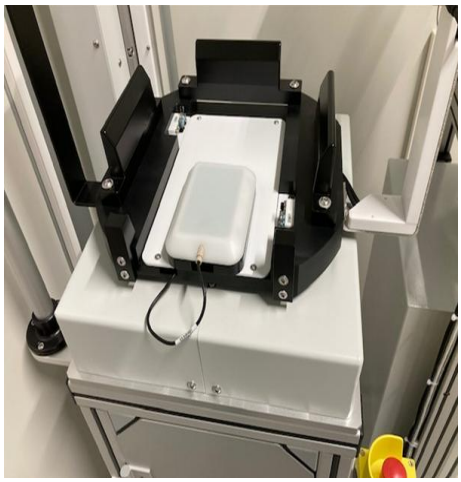

Figure 10: Previous RFID design.

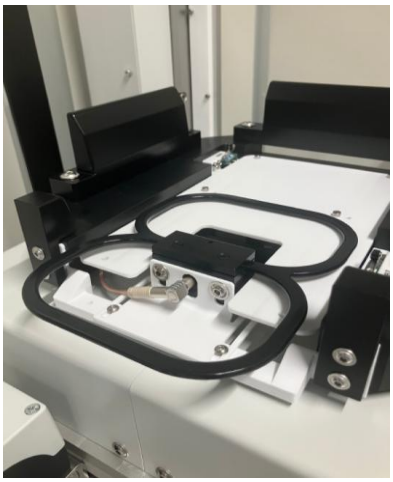

Figure 11: New RFID design.

Subproject sonic based sensor development:
The implementation (Fig.3 and Fig.4) of sonic-based fault detection has been successfully established and is now a functional part of the preventive maintenance strategy in this use case. To further improve the effectiveness of the sonic-based fault detection system, a deeper data analysis has been conducted to detect reliable failure patterns. This analysis will enable the identification of specific patterns and trends that are indicative of impending bearing failures, allows a accurate and reliable predictions during production. By analyzing data from this and for future use cases, the system can be reconfigured to detect a wider range of potential faults and failures, making it an even more valuable tool for preventive maintenance. The IoT solution used in this implementation has also demonstrated its versatility and usability for other sensor applications. The ability to integrate with a wide range of sensors and devices makes it an attractive option for a variety of use cases, from predictive maintenance to quality control and beyond. The scalability and flexibility of the IoT solution will enable it to be adapted and applied to a wide range of industries and applications, making it a valuable asset for any organization looking to leverage the power of IoT and data analytics.

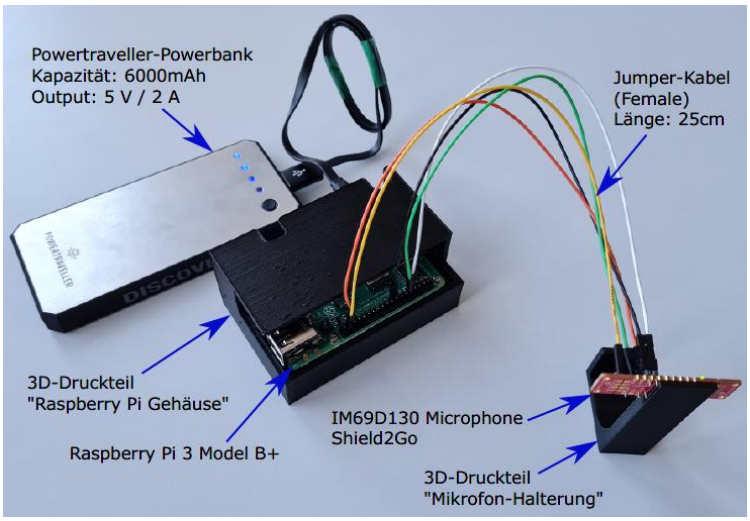

Figure 12: Sonic-based sensor kit.

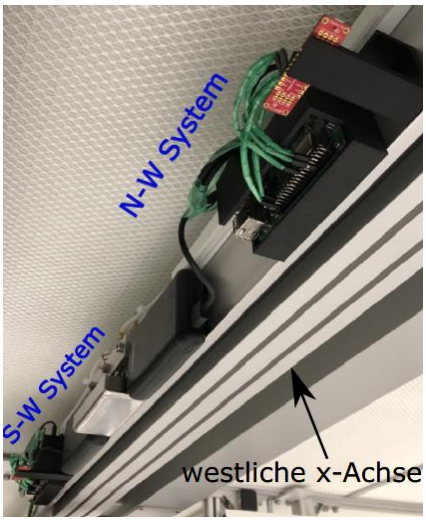

Figure 10: Sensor mounting area.

2.9.4 KPIs analysis

Subproject advanced RFID System:
Whitin the implementation of the new RFID system it is expected to significantly improve fab performance by reducing error readings, which previously occurred at a rate of 2250 per day, accounting for approximately 1.5% of total readings. By minimizing these errors, the new system aims to decrease the manual effort required to recover from error effects, resulting in a reduction of 24 PM per year. With the rollout of the new RFID system now complete, every reading station is equipped with the latest technology, ensuring that all material identification and tracking processes can be carried out with enhanced accuracy and efficiency. This comprehensive deployment of the new RFID system is a major milestone, marking a significant step forward in optimizing fab operations and improving overall productivity.

Subproject sonic based sensor development:
As a result, the effort required for manual operation and maintenance has been reduced by 24 PM a year, which is a significant achievement. This reduction in effort can be attributed to the ability of the sonic-based fault detection system to detect potential bearing failures before they occur, allowing for proactive maintenance to be performed and minimizing the need for manual intervention. The main KPIs of this project are presented within WP6 for UC13.

2.10 Surface Acoustic Waves (SAW) based sensors

Partners: FORTH

2.10.1 Introduction to the result

As part of the WP1 activities of the UC 16 (lead by THALES) the FORTH team is developing own – in house - Surface Acoustic Waves (SAW) based temperature sensors. The technology is developed in an approach that enables i) integration with the High-power High Electron Mobility Transistors (HEMTs) and ii) integration atop of Microwave Monolithic Integrated Circuit (MMIC) i.e., High-Power Amplifier. Successful implementation will allow chips and more specifically in the vicinity of the hot-spots, monitoring the temperature as result of the heat dissipation stemming from the high-power components (e.g., HEMTs). This will enable proper utilization of the RF-chips but will also provide valuable feedback for the design of the next generation of MMICs.

2.10.2 State of the art at project start

SAW based sensors are commonly utilized for various sensing applications. The FORTH team has background on developing SAW based sensors technologies. However, the envisioned implementation constitutes a totally new attempt/approach in terms of the device details and mainly with regards to the integration potential with the HEMTs and the MMICs. Therefore, several challenges must be addressed within the framework of the project.

2.10.3 Achievements at project end

Within the period of AIMS5.0, the design, the fabrication tasks for a dedicated "SAW-wafer" as well as RF-characterization have been successfully finalized, including i) stand-alone devices, ii) HEMTs-sensors pairs and iii) MMIC with integrated sensors on it. Parameters such as the distance and the orientation of the position of the SAW sensing element with respect to the HEMTs channels (i.e. the hot-spot) have been taken into consideration as presented in the following figure.

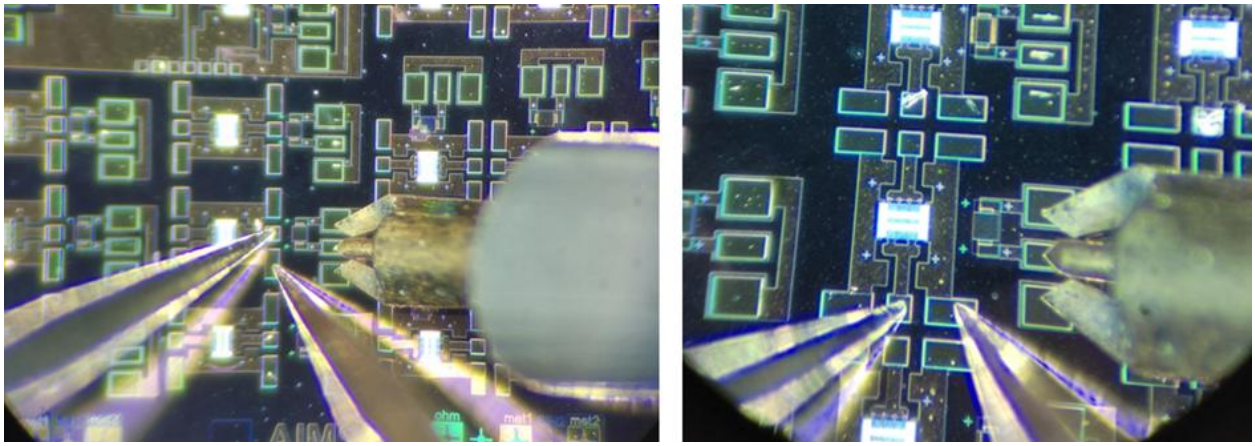

Figure 11: SAW devices in the vicinity of a HEMT in parallel (left) and vertical (right) orientation with respect to the channel during the RF characterization.

Typical results presenting response of the sensing element to the changes in the channel current density (i.e., heating) are presented in the following figure.

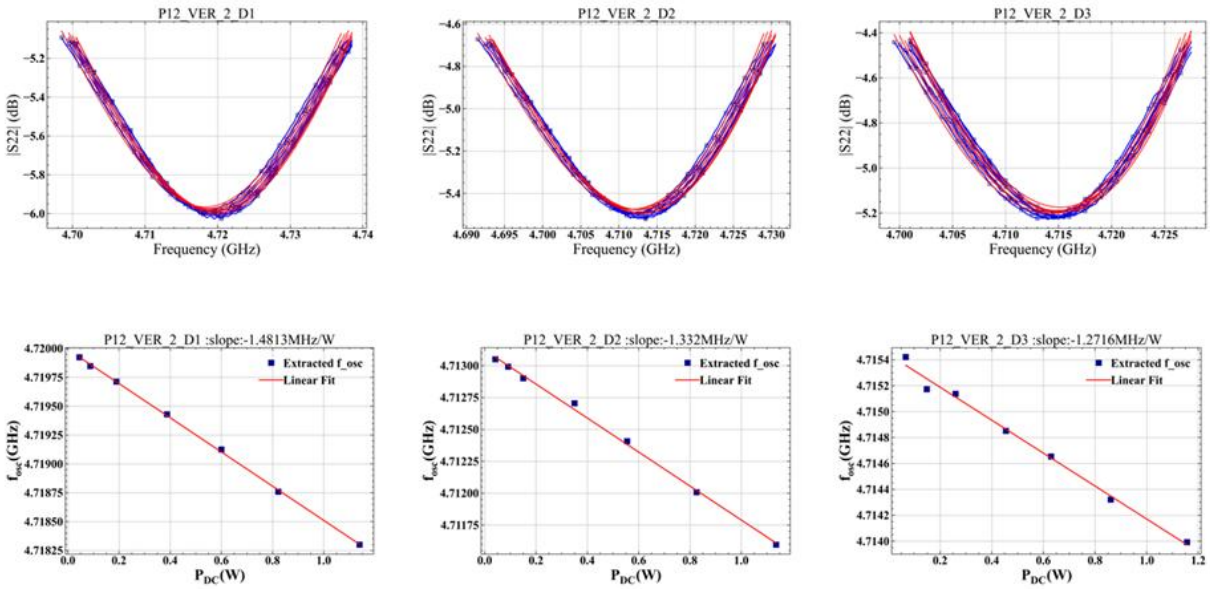

Figure 12: Typically obtained characterization results showing linear resonance shift with the handled power level, responsible for the temperature increase. The presented devices are in vertical orientation with respect to the HEMT's channel.

2.10.4 KPIs analysis

This hardware technology is supporting the activities of UC 16 and will contribute towards the realization of more reliable RF-circuits, having less damage during their operation in demanding high-power conditions. The UC16 KPIs do not directly related to these hardware sensors (they are analyzed in detail in WP6 deliverables), nevertheless this successful development constitutes a great asset for our RF technology and fully support the following KPI:

Metrics on improved quality & reliability of hardware components; improvement by 15%

Exploitation of the SAW based temperature sensors will allow minimize the damage of the AIMS5.0 developed RF components and will provide valuable impact for the design and development of future implementation in the domain of MMICs.

2.11 RF MEMS based sensors and fabrication

Partners: THALES

2.11.1 Introduction to the result

This task is part of UC16 and more specifically of WP1 related activities. As part of this activity the THALES team is developing own – in house – RF leakage sensors based on mini-MEMS technology. On a high-power RF chip not all the components need to be able to deal with the high-power burden. RF leakage sensors are essential to protect components not designed to handle such high-power signals from potential damage. The THALES RF leakage sensors that are developed within this project are based on MEMS technology and more particularly these referred to as mini-MEMS within AIMS5.0. The main idea is based on the exploitation of the self-actuation phenomenon that stems from high power signals in MEMS devices.

2.11.2 State of the art at project start

THALES MEMS technology team is world leader in Radio Frequency Micro-Electro-Mechanical Systems. Even before the onset of the project activities on this technology refers to RF MEMS based sensors were part of THALES MEMS team portfolio. Particularly for the concept that is exploited within AIMS5.0, to the best of our knowledge, the THALES approach in this domain is unique. Preliminary, internal developments were already active but massive improvement has been recently achieved.

2.11.3 Achievements at project end

Within the period of the project, the design and the fabrication tasks for the mini-MEMS sensors have been successfully finalized, including various device configurations and optimization activities. Critical challenges such as the proper configuration with respect to the operation frequencies as well as suitable choice of materials and processes to achieve effective release for the moveable parts in submicron airgaps were successfully addressed. Following from these, the fabricated devices underwent details structural, nanoscale and RF-performance related characterization. The results confirm that the fabricated devices are meeting the desired specs with respect to the RF response (i.e., isolation and insertion loss) in the band of operation (please see D1.3 for more details).

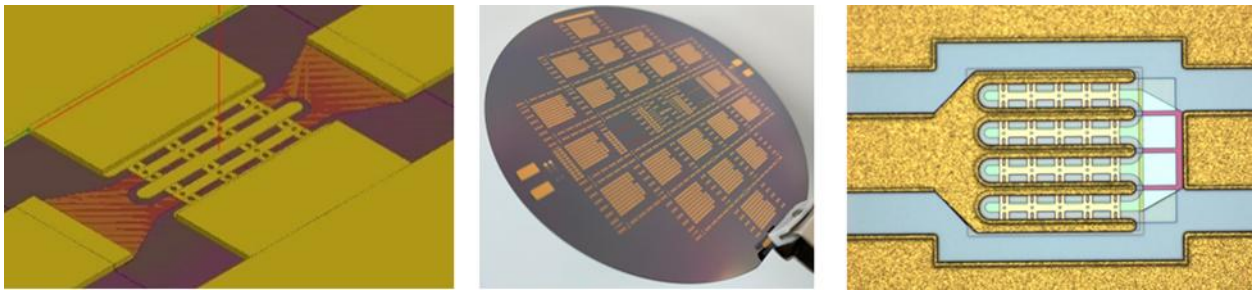

Figure 13: Typical image from the mini-MEMS design activities (left), a photo of a full wafer during fabrication (middle) and a photo of a mini-MEMS array configuration under the microscope (right).

2.11.4 KPIs analysis

This hardware technology is supporting the activities of UC 16 and will contribute towards the realization of more reliable RF-circuits, having less damage during their operation in demanding conditions. The UC16 KPIs are not directly related to these hardware sensors and are presented in detail in WP6 related deliverables, nevertheless this successful development constitutes a great asset for our RF technology and fully support the following KPI:

Metrics on improved quality & reliability of hardware components; improvement by 15%

Exploitation of the RF leakage sensors will minimize the damage of the AIMS5.0 developed RF components not made to withstand high RF power levels during the chip operation.

2.12 Smart Voting Wristband Arrowhead application

Partners: IFAG

2.12.1 Introduction to the result

At the outset of the project, there was no initial plan to develop the Smart Voting Wristband. Instead, the concept evolved organically from the activities and requirements of other work packages. It specifically emerged as a demonstrator under Work Package 4 (Digital Reference & Open Access Platform) in collaboration with Work Package 1 (Components and Systems). The development leveraged common engineering knowledge and available hardware components to build a practical, tangible use case. The primary technical objective of this result was to achieve a seamless integration of edge IoT sensors specifically capturing voting inputs into the Arrowhead Framework to successfully demonstrate a distributed provider-core-consumer architecture.

2.12.2 State of the art at project start

At the project's inception, the state of the art was represented by two early iterations of the voting wristband.

Version 1.0 served as a baseline feasibility prototype built around an ESP8266 microcontroller and a pressure-sensor input mechanism. This version offered minimal on-device user feedback and achieved an initial accuracy of approximately 70%, as pressure-based inputs proved sensitive to user-specific placement and contact conditions.

To improve upon this baseline, Version 2.0 transitioned the sensing modality to a Bosch BMI270 inertial measurement unit (IMU) for motion-based inputs. This architecture connected via Wi-Fi to register with a Raspberry Pi hosting the Arrowhead Framework core services (Service Registry, Authorization, and Orchestrator), allowing a FastAPI-based backend to process votes in real time. This setup formed the primary case study for Manuel Krummschmidt's master's thesis, which established an ISO/IEC 25040-based framework to evaluate baseline capacity, latency, and resource utilization.

Despite these improvements, the system still faced device feedback gaps, limited electrical noise isolation, and lacked the advanced multi-cloud orchestration needed for production-grade scaling.

2.12.3 Achievements at project end

By the end of the project, significant technical milestones were achieved to transition the Smart Voting Wristband into a highly accurate and stable system component. The primary firmware and software optimizations successfully raised the motion-based vote detection accuracy from an initial 70% baseline to approximately 90% under representative demonstration conditions. This substantial reliability increase was accomplished by restructuring the signal processing chain and replacing the original complementary filter with the advanced Madgwick sensor-fusion algorithm, which significantly minimized orientation drift during active, dynamic user movements.

In addition to gesture-recognition improvements, the end-to-end data flow and network synchronization were thoroughly stabilized. The backend polling loop was optimized to maintain a deterministic 50 Hz visualization update rate. To prevent a single disconnected or weak provider device from stalling the system, each request was guarded by a strict 100ms timeout and handled via a resilient exponential backoff schedule. Finally, cross-platform time alignment was established by implementing periodic NTP synchronization across the wristband units and the FastAPI consumer backend, enabling precise, quantifiable end-to-end latency measurements across live demonstration sessions.

2.12.4 KPIs analysis

The performance and quality metrics of the Smart Voting Wristband application were evaluated against key indicators spanning system latency, communication frequency, and operational stability.

- **Sensing and Recognition Accuracy**: The system achieved a core accuracy KPI of approximately 90% in motion-based gesture tracking under representative demonstration conditions, representing a major improvement over the 70% baseline alternative.
- **Data Flow and Pacing Stability**: The backend control loop successfully met its deterministic target pacing KPI of 50 Hz for visualization updates, delivering smooth and predictable real-time data streaming to the browser UI via Server-Sent Events (SSE).
- **Network Latency Bounding**: Network and provider interactions were strictly bounded, with an explicit request timeout KPI of 100ms implemented alongside an exponential backoff routine to ensure that failing or offline hardware nodes did not stall the polling loop.
- **UI Segment Latency Distribution**: Based on the captured latency data logs, the end-to-end timing statistics across the UI-relevant processing segment (server processing to browser render) were quantified using empirical percentiles:
    - **Server-to-Client Distribution**: Achieved a median (P50) latency of 80,960 µs, a P90 of 176,027 µs, and a P99 tail latency bounded at 213,473 µs.
    - **Client-Side Rendering**: In-browser data processing and chart visualization layout steps were highly efficient, yielding a median (P50) processing time of 5,000 µs, a P90 of 11,000 µs, and a P99 max peak of 17,000 µs.
- **Quality Evaluation Framework**: Long-term structural KPIs regarding system capacity, time behavior, resource utilization, and overall system usability were validated using an objective evaluation framework based on the ISO/IEC 25040 standard.

2.13 MLOps framework

Partners: DAC

2.13.1 Introduction to the result

The MLOps framework provides a software and methodology layer supporting AI-ready edge deployments by structuring the preparation, validation and lifecycle management of machine learning models and data. In AIMS5.0, the work focused on practical tooling for data annotation, model development support, AI validation, training data traceability, and machine unlearning concepts. The result is positioned as a supporting framework for Edge/Fog/Cloud AI workflows rather than as a standalone hardware component. Its deployment context is the preparation and controlled operation of AI models intended for industrial edge scenarios, where data quality, traceability and repeatable validation are required.

Industrial AI applications increasingly rely on models that are trained, updated, and deployed across heterogeneous environments, including Edge, Fog, and Cloud infrastructures. In such settings, the performance of the AI model alone is not sufficient. The complete lifecycle of data preparation, annotation, training, validation, deployment, and later updates must be controlled and repeatable.

The MLOps framework addresses this need by providing a structured approach and supporting tooling for AI model lifecycle management in industrial settings. The focus is on reducing manual effort in dataset preparation, improving traceability of training data, supporting validation of AI components, and enabling more efficient model development workflows.

Within AIMS5.0, the result is relevant for AI-ready edge deployments because Edge AI systems require reliable input data, validated models, and controlled update procedures before being used in representative operational environments. The scope of this result is therefore supporting the software and methodology layer around AI models, not the development of a dedicated edge hardware platform.

2.13.2 State of the art at project start

At the beginning of the project, many industrial AI workflows still relied on fragmented and partly manual processes for dataset preparation, model training, and validation. Data annotation often required substantial human effort, while model retraining and deployment were frequently handled in a project-specific way. This limited the scalability and repeatability of AI development for edge-oriented industrial applications.

Existing MLOps practices provided useful concepts such as model versioning, automated training pipelines, and deployment monitoring, but their adoption in industrial edge scenarios remained challenging. Typical limitations included heterogeneous data sources, limited availability of annotated production data, privacy and traceability requirements, and the need to validate AI models before deployment in operational environments.

The gap addressed in AIMS5.0 was therefore to adapt MLOps-oriented practices to the needs of industrial AI and AI-ready edge systems, with emphasis on dataset preparation, semi-supervised annotation, AI validation, training data traceability, and concepts for machine unlearning.

2.13.3 Achievements at project end

By the end of the project, the MLOps framework had been developed as a supporting software framework for industrial AI workflows. The work included methodology development and implementation of tooling for automated and semi-supervised data annotation, support for model development workflows, and concepts related to AI validation, data traceability, and machine learning.

Figure below illustrates the implemented MLOps framework developed by DAC, showing the end-to-end workflow from industrial data ingestion and semi-supervised annotation to dataset traceability, AI validation, and deployment in AI-ready edge environments.

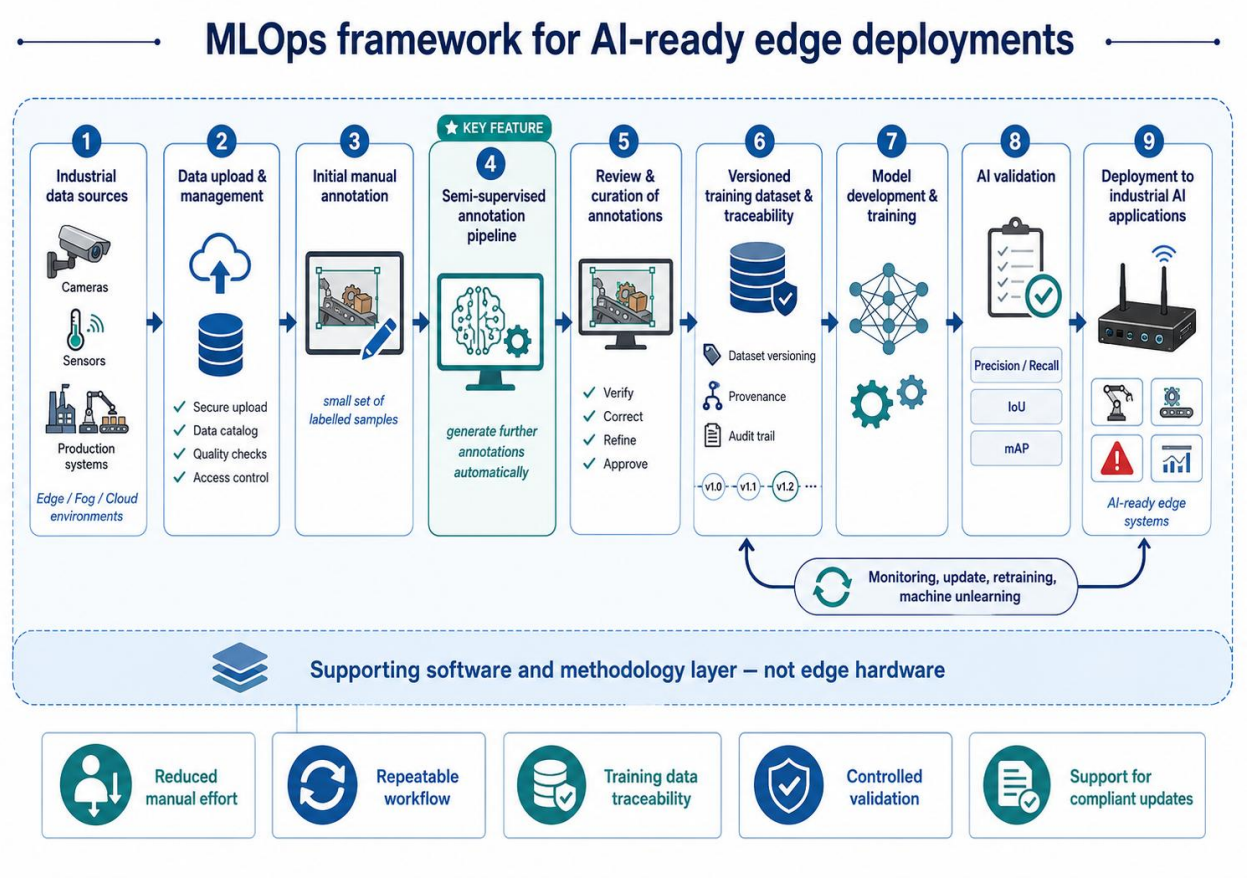

Figure 14: DAC MLOps framework for AI-ready edge deployments.

A key implemented element was an automated data annotation pipeline. The pipeline supports the preparation of training data by allowing a small number of samples to be manually annotated and then using this input in a semi-supervised process to generate further annotations. This reduces the need for fully manual dataset preparation and supports faster iteration of computer-vision-oriented AI models.

The work also addressed broader MLOps aspects, including automation of training-related workflows and mechanisms for handling data removal requirements from trained models. These elements are relevant for industrial AI deployments where data provenance, model updateability and compliance-related requirements must be considered.

The achieved result should be understood as an enabling framework for AI-ready edge systems. It does not replace the edge hardware components, but supports their use by improving the preparation, validation and lifecycle management of AI models intended to run in edge or edge-connected industrial environments.

2.13.4 KPIs analysis

The KPI assessment for the MLOps framework focuses on process-level and support-level indicators rather than on direct hardware performance metrics. Its contribution to WP1 is therefore indirect, by improving the preparation, validation, repeatability, traceability, and lifecycle management of AI models intended for AI-ready edge deployments.

The result contributes to the WP1 KPI framework by supporting:

- quality and reliability, through more repeatable dataset preparation, validation workflows, and training data traceability,

- efficiency and productivity, through a semi-supervised annotation workflow that reduces dependence on fully manual labelling,
- speed of AI development iterations, by connecting dataset preparation, annotation review, model development, and validation-related activities in a more structured workflow.

The main qualitative achievement is the implementation of a semi-supervised annotation workflow that uses a limited set of manually annotated samples as input for further annotation generation and review. This supports faster preparation of training datasets for computer-vision-oriented AI models and improves the repeatability of downstream model development.

The validation approach is based on functional verification of the workflow steps, including data upload, initial manual annotation, semi-supervised annotation generation, selection or review of generated annotations, and use of the prepared data in downstream AI model development. Where reference annotations are available, annotation quality can be assessed by comparing generated annotations against manually prepared samples using standard computer vision metrics such as precision, recall, IoU, or mAP, depending on the task.

No separate edge hardware KPI is claimed for this result, since the DAC contribution is a software and methodology layer supporting AI-ready edge deployment rather than a standalone hardware component. Its relevance to WP1 lies in enabling more reliable, repeatable, and auditable preparation, validation, and lifecycle management of AI models that can be deployed in edge or edge-connected industrial environments.

2.14 5G Campus Network measurement framework for QoS and KPIs

Partners: AITIA

2.14.1 Introduction to the result

This section presents an operational blueprint for ensuring Quality of Service (QoS) and Key Performance Indicator (KPI) observability within 5G Standalone (SA) private campus deployments. By validating an open architecture built upon the Open5GS core and the UERANSIM radio emulator, a programmatic framework has been successfully engineered to perform Deep Packet Inspection (DPI) and multi-interface session tracking. The primary value of this result lies in its production-ready methodologies for capturing distributed control-plane sequences and transforming them into quantifiable, actionable performance metrics. These metrics protect real-time loops essential for industrial edge computing and smart factory automation.

2.14.2 State of the art at project start

At the project's inception, private campus validation relied on coarse end-to-end user equipment benchmarks (such as localized ping tests and basic application-level throughput tracking). Traditional telecommunication performance visibility treated core components as closed black boxes, often lacking granular insight into distributed Service-Based Interfaces (SBI) or point-to-point reference points. Critical identifiers and transaction matching attributes (such as the correlation between Next-Generation Application Protocol boundaries and HTTP2 JSON endpoints) remained segregated. Consequently, intermittent connection drops during cell handovers or network slicing transitions could not be programmatically traced back to specific structural core failures, preventing precise optimization in ultra-reliable, low-latency communication (URLLC) environments.

2.14.3 Achievements at project end

By the close of the project, a virtualized verification platform was successfully built to dissect multi-layered control traffic across the AMF, SMF, AUSF, UDM, and PCF. The platform maps dynamic logical identifiers—correlating the RAN-UE-NGAP-ID and AMF-UE-NGAP-ID on the N2 interface directly to HTTP2 Stream IDs and URI context paths on the N11 interface.

Furthermore, the team comprehensively mapped the propagation of Single Network Slice Selection Assistance Information (S-NSSAI) across the Non-Access Stratum (NAS) and NgAP layers. This mapping ensures seamless session continuity during Xn-based cell transitions and slice modifications. Crucially, the passive probing framework successfully extracts raw, multi-interface transactions and transforms them into highly targeted, deterministic KPIs spanning the N11, N12, and N4 reference points.

2.14.4 KPIs analysis

AITIA has conducted an in-depth study of 5G Standalone (SA) network infrastructure, with a particular focus on the analysis and optimization of control plane communication in private 5G environments. The primary aim was to investigate protocol behavior and message sequencing to support robust data collection and transaction reconstruction across 5G core interfaces — a crucial capability for future edge-computing components operating on campus-level networks. The presented measurement setup will be further enhanced, and the results will be analyzed. The final goal of the work is to establish KPI measurement methodologies in the next period based on the current results.

Using the Open5GS open-source 5G SA core (as depicted in architecture and the UERANSIM simulator in a virtualized lab environment, we examined control traffic from multiple network functions including AMF, SMF, AUSF, UDM, and PCF. AITIA’s contributions centered on monitoring, tracing, and correlating signaling transactions across interfaces like N2, N10, N11, and N12 using a layered protocol stack including NgAP, NAS, and HTTP2/JSON.

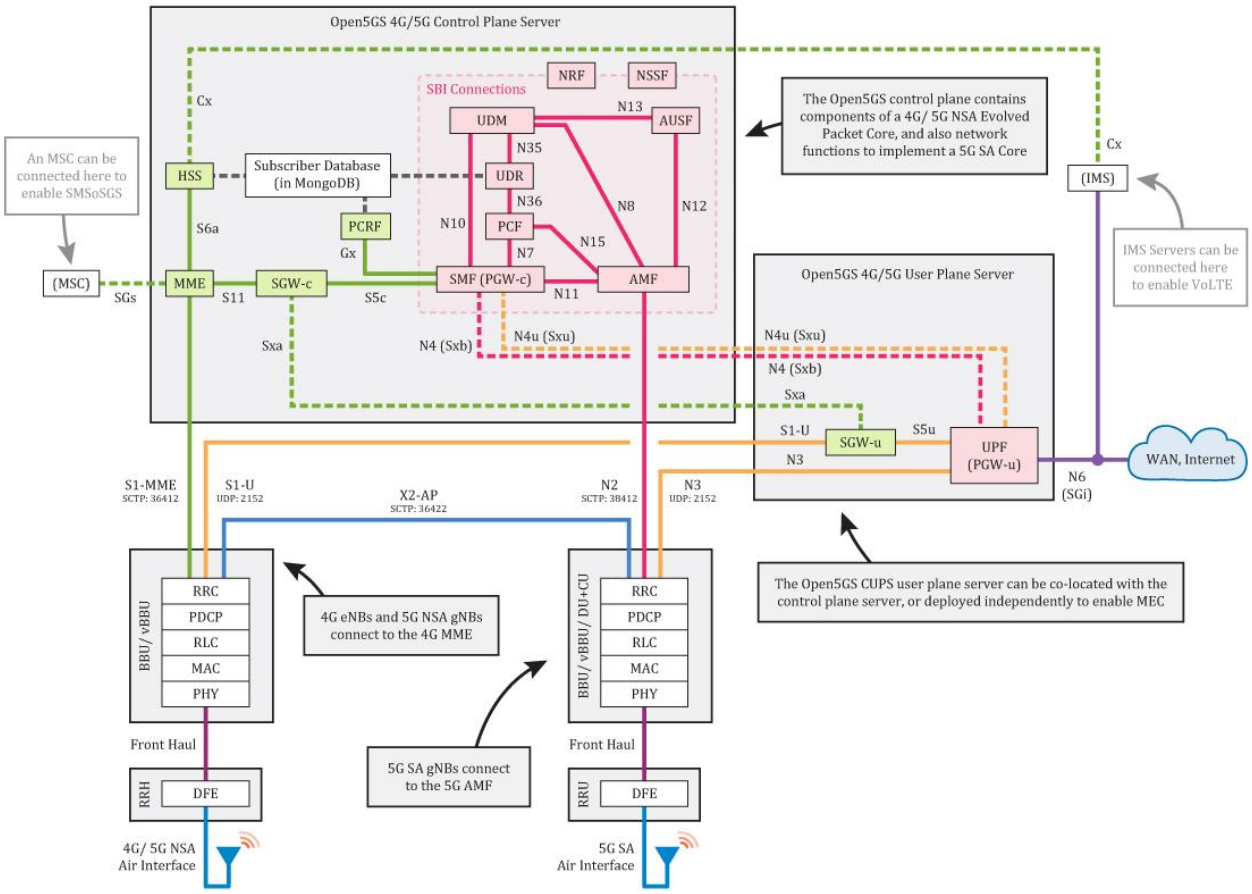

Figure 15: OPEN5GS architecture.

Key factors include:

- Protocol analysis and record construction: We identified essential identifiers and parameters (e.g., RAN-UE-NGAP-ID, AMF-UE-NGAP-ID, IMSI, SUCI, GTP TEID) that are vital for assembling end-to-end signaling transactions, especially across interface boundaries. The message exchange during subscriber registration, session establishment, slicing, and mobility was comprehensively mapped and documented.

- Focus on slicing support and session continuity: The interaction between UE and core components during slice selection and switching was analyzed. We observed how slice-related identifiers (S-NSSAI) propagate through both NAS and NgAP messages and how these influence session contexts within the SMF and PCF.

- Stream correlation on service-based interfaces (SBI): We demonstrated how HTTP2 Stream IDs and URI paths (e.g., /nsmf-pdusession/v1/sm-contexts) can be used for transaction tracking and service correlation, key for observability in distributed 5G architectures.

- QoS and mobility support: Through path switch scenarios (XN handover), we analyzed the behavior of NgAP and NAS flows during radio mobility events, especially how new tunnel parameters and session context updates are propagated between the gNB, AMF, and SMF.

Based on the architectural findings and experimental data derived from the validation lab using the Open5GS 5G Standalone (SA) core and the UERANSIM emulator environment, AITIA establishes the technical framework for implementing Quality of Service (QoS) monitoring and Key Performance Indicator (KPI) extraction. These methodologies serve as the definitive "best practices" for verifying and optimizing communication loops within private 5G campus networks.

Control Plane Multi-Interface Data Collection & Session Stitching

To achieve deterministic performance for industrial processing elements, AITIA's platform processes distributed signaling sequences into unified Extended Data Records (XDRs) using a real-time Deep Packet Inspection (DPI) Probing Layer across point-to-point and Service-Based Interfaces (SBI).

Identifier Tracking on the N2 Reference Point: The platform tracks active sessions on the N2 interface (gNB <-> AMF) by extracting the dual identifiers assigned to each UE context: the RAN-UE-NGAP-ID from the gNB and the AMF-UE-NGAP-ID from the core.

- Initial Registration: Triggered via an NgAP Initial UE Message carrying a NAS Registration Request. If needed, an Identity Request/Response extracts the subscriber's Subscription Concealed Identifier (SUCI).

- Context Establishment: The AMF transmits an NgAP Initial Context Setup Request to configure runtime radio parameters (e.g., bit rates, security capabilities) and deliver the NAS Registration Accept.

- Session Teardown: Inactivity triggers a UE Context Release sequence (Request/Command/Complete), which the correlation engine logs alongside the specific termination cause.

State Correlation over Service-Based Interfaces (SBI): Distributed core interactions rely on HTTP2 REST operations where transactions are traced using the HTTP2 Stream ID.

- Resource Initialization: The AMF creates a session with the Session Management Function (SMF) via a POST request to /nsmf-pdusession/v1/sm-contexts.

- URI Reference Mapping: A successful creation returns a 201 Created status code and a unique context reference URI within the location header (e.g., /sm-contexts/{ID}). All subsequent session updates (/modify or /release) map directly back to this URI to ensure end-to-end tracking.

Network Slicing Optimization & Session Continuity

Private industrial networks depend on Network Slicing to isolate operational loops. This is driven by the Single Network Slice Selection Assistance Information (S-NSSAI) parameter. During initialization, the client provides a Requested NSSAI string, which the core validates against subscriber profiles before returning an Allowed NSSAI configuration inside the NgAP Context Setup and NAS Registration Accept responses.

During an Xn-based handover or radio mobility event, the target gNB issues an NgAP Path Switch Request containing a new User Plane GTP Tunnel Endpoint Identifier (TEID) and the target node IP address, while preserving the active S-NSSAI. To minimize packet drops and guarantee session continuity, the correlation engine must immediately confirm slice compatibility on the target cell. A mismatch triggers a Path Switch Failure or an Error Indication, dropping the context and generating excessive signaling overhead on the N11 modification paths.

To support continuous validation, the system transforms captured raw transactions into specific network metrics. These KPIs track deployment accessibility, mobility, and security. The most important ones are described below using compressed algorithmic definitions derived from the comprehensive multi-interface platform tables.

KPI	Interface	Algorithm
PDU Session Setup Failure rate	N11	HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „n2SmInfoType”=”PDU_RES_SETUP_FAIL” *divider*: HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „n2SmInfoType”=”PDU_RES_SETUP_REQ”
PDU Session Modification Failure rate	N11	HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „n2SmInfoType”=”PDU_RES_MOD_FAIL” *divider*: HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „n2SmInfoType”=” PDU_RES_MOD_REQ”
Path Switch Setup Failure rate	N11	HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „n2SmInfoType”=”PATH_SWITCH_REQ_FAIL” *divider*: HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „n2SmInfoType”=”PATH_SWITCH_REQ”
Successfull Handover rate	N11	HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „hoState”=”COMPLETED”
Unsuccessfull handover rate	N11	HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „n2SmInfoType”=”HANDOVER_PREP_FAIL” OR HTTP2 path = /nsmf-pdusession/v1/sm-contexts/{ID}/modify Request „n2SmInfoType”=”HANDOVER_RES_ALLOC_FAIL”

Table: N11 interface (AMF – SMF signaling).

Table: AMF – AUSF signaling in 5G AKA.

Successful 5G AKA rate	5G AKA transactions where

	„authResult” = „AUTHENTICATION_SUCCESS”
Unsuccessful 5G AKA rate	5G AKA transactions where „authResult”= „AUTHENTICATION_FAILURE” OR „authResult”= „AUTHENTICATION_REJECTED”

Table: N12 interface (AMF – AUSF signaling).

KPI	Algorithm
Session Establishment success ratio	Successful PFCP Session Establishment transaction rate
Mean time of Session Establishment execution	PFCP Session Establishment Request – Response mean time
Session Modification success ratio	Successful PFCP Session Modification transaction rate
Session Report success ratio	Successful PFCP Session Report transaction rate
Session Deletion success ratio	Successful PFCP Session Deletion transaction rate

Table: N4 interface (SMF – UPF signaling).

2.15 Interactive Edge Analytics

Partners: SA

2.15.1 Introduction to the result

The scope for partner SA at the outset of the project was to contribute to UC3 by processing data streams on autonomous lawn mowers. Applications in UC3 included predictive maintenance and estimation of residual value of equipment.

To make the lawnmower data queryable, the edge runtime of partner SA was extended with a ROS2 embedding. We also extended our platform with capabilities of on-line audio analysis on resource constrained edge devices. Using our platform, numerous models were developed pertinent to UC3.

The CPU used on the lawnmower was an ARM Cortex A72. Tangential to UC3, we also targeted alternative hardware platforms, including Risc-V.

2.15.2 State of the art at project start

Partner SA offers streaming analytics and AI platform designed for edge devices. As an end-to-end platform, SA enables efficient development, training, deployment, and orchestration of analytics, computational, and AI models. A technical description of our platform is provided on our web site, https://www.streamanalyze.com/under-the-hood. The edge runtime SA Engine provides numerous interfaces that make data queryable.

The AIMS5.0 project was an opportunity for SA to extend their platform with additional data sources and processing capabilities.

2.15.3 Achievements at project end

During the project, partner SA has extended their platform in two ways pertinent to WP1:

- SA Engine was extended with ROS2 interfaces, enabling analysis of signals in ROS2. This has been extensively used in UC3: Servitization and service delivery enabled by Zero administration, enabling edge analytics and model lifecycle management for the analysis of high frequency data in robotic mowers. The ROS2 integration is generic, so it can be used in other contexts as well.
- SA Engine was extended with capabilities for audio processing on resource constrained devices.
- SA Engine was ported to run on Risc-V. Running edge analytics software on open-source hardware such as Risc-V was an ambition expressed in the project plan (e.g. WP1, T1.2). Thus, the Stream Analyze platform enables interactive analytics and AI models on open-source edge hardware.
- SA Engine was used to deliver models pertinent to UC3, including battery health, ground quality, and cutting blade sharpness. In particular, the blade sharpness models provide continuous assessment of the sharpness of the blades in the lawnmower. This enables an important improvement in predictive maintenance: Instead of replacing blades on a fixed schedule, the blades can be replaced on-demand when they are becoming too blunt. This will save cost and resources, while maintaining consistently cutting quality.
- The model lifecycle management (including AI models) of the SA platform was improved. The SA platform not only allows its users to interactively query their fleet for edge devices. The SA platform also enables MLOps.

2.15.4 KPIs analysis

A detailed KPI analysis of UC3 is provided in D9.10 (Validation Plan). A key result is the effort reduction for model lifecycle management. In D9.10, we show how the end-to-end activity to develop an AI model

needed for service delivery was reduced from an estimated 40 days to 3.25 days. This is a reduction of ~92%, which achieves the target over the estimated state-of-the-art time to develop AI models, needed for service delivery (cf. DoA Part B 1.2.4.2.3).

In addition to the UC3 specific KPI, we have also targeted a central aspect of the AIMS5.0 project, which is the co-design of the edge and cloud parts of use-case demonstrators (Obj. 1).

- Partner SA implemented the parts of the network edge required to realize UC3.
- Partner SA explored and implemented the communication approaches for data transfer between edge devices and cloud. Furthermore, the models implemented in UC3 using the SA platform optimized the data transfer between edge devices and cloud.

Finally, the cutting blade sharpness assessment implemented by partner SA for UC3 is directly targeting the predictive maintenance improvement success metric (KPI) of WP1.

3. Conclusions

This deliverable summarized the final WP1 outcomes, focusing on the realization of AI-ready edge systems and their KPI-based evaluation in industrial use cases.

The work confirms a clear transition from component-level validation to fully integrated edge system deployments in representative environments.

Overall, the project demonstrates the viability and impact of AI at the edge across heterogeneous industrial scenarios, combining sensing, communication, and computing in distributed architectures.

Key conclusions:

- **System maturity**: end-to-end systems (e.g., multi-layer AI infrastructure for machine tools, integrated MLOps pipeline enabling full lifecycle deployment)
- **Edge AI impact**: real-time, automation (e.g., AMR perception & navigation systems, edge inference on industrial IPC/NPU platforms)
- **Integration**: edge–fog–cloud (e.g., SAVVY multi-layer architecture with Arrowhead-based orchestration)
- **Interoperability**: heterogeneous systems (e.g., service-oriented architecture, Arrowhead framework, 5G observability framework)
- **Industrial validation**: real environments (e.g., GOIMEK shopfloor deployment, cleanroom sensor platforms, AMHS predictive maintenance setups)

The KPI evaluation shows tangible improvements in performance and efficiency across use cases, mainly driven by specific technical advancements:

- **Accuracy**: perception, classification (e.g., gesture recognition, EEG-based classifiers, smart wristband sensor fusion improvements)
- **Latency**: reduced response times (e.g., edge inference deployment, optimized backend loops and real-time communication in wristband & AMR systems)
- **Reliability**: communication, hardware (e.g., wireless testbed with adaptive antennas, RF MEMS / SAW sensors for robust operation)
- **Maintenance**: predictive, cost reduction (e.g., FOUP sensor platform, sonic-based sensing, OHT monitoring with AI models)
- **Efficiency**: workflows, data handling (e.g., MLOps framework, semi-supervised annotation, edge analytics lifecycle reduction)

In several cases, targets were met or exceeded, confirming the technical readiness and applicability of the developed solutions in industrial contexts. Remaining challenges include further scaling, hardware optimization for edge AI, and extended long-term validation.

In conclusion, WP1 delivers mature, validated AI-ready edge systems, supported by concrete technological advancements, and provides a solid basis for industrial deployment and future developments.