



AID4SME | Open Call #2

Annex 1.1 Challenges Description

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Domain 1: Combined AI and Data solutions for DATA COLLECTION

Challenge 1.1 Augmented sensing solution

Challenge and context: Forces, stresses, torques, and power are direct indicators of a system's well being. However, these quantities are typically expensive, difficult and intrusive to measure. Digital twins approach within AID4SME can help alleviate these hurdles for use cases inside and outside the consortium. Digital twins offer a paradigm shift where computational models of various complexities are merged in a coherent framework and linked to online measurement data available on a physical system. This paradigm allows for a hyper-realistic representation of process behaviour, enabling novel engineering applications and process improvements, such as virtual or augmented sensors. Augmented sensing uses cheap, readily available, non-intrusive, and robust physical sensors to collect data from the real asset component in a digital twin. The desired, yet unknown, quantities are estimated, resulting in a real-time/online virtual sensor fed with real measurement data enriched with physical insights.

Use case and expected solution: Within the consortium, Arçelik requires an augmented sensing solution for its refrigerator production facility, which undergoes approximately 120 mold changes per month. Each change necessitates manual, iterative adjustments, causing about 60 tons/year of polyurethane waste and about 60 minutes of facility downtime per model change. This results in approximately 160K euros in annual costs due to production capacity loss. The solution will enable accurate monitoring of forces, stresses, or other relevant physical quantities during plastic mold changes in the refrigerator production line. It will provide real-time feedback and predictive insights to reduce manual intervention and iterative adjustments during mold changes, minimize polyurethane waste, and reduce facility downtime. For this industrial high TRL application, Arçelik has foreseen the following Key Performance Indicators (KPIs): (i) First time-right adjustment of the mold; (ii) Reduce facility downtime by 15%; (iii) Decrease annual waste by 3 tons; (iv) reduction in energy consumption per mold change. These KPIs are initial indicative numbers and may evolve during the execution of the projects. Besides this high-TRL application, KU Leuven has technology blocks available at TRL 4 and low-TRL playgrounds to develop and test augmented sensing solutions, specifically for mecha(tro)nic system level dynamics, and model-based augmented sensing in electro-thermo-mechanical applications in the manufacturing industry. For application on the low-TRL research lab playgrounds, the focus will be on the technological development of the augmented sensing solution with TRL 9 together with the SME.

Specification for use case: SMEs are invited to propose a use case leveraging their own technology or solving their problems at hand, which will be further elaborated together with the consortium partners. Inspirational examples can be based on system identification, parameter estimation, force estimation, etc. The consortium offers low-TRL research lab playgrounds as well as one high-TRL industrial application (as detailed above). SMEs applying for this challenge should specify which TRL level they would like to target. For the industrial application, three consortium partners will support SMEs in developing an augmented sensing solution to optimize the mold adjustment phase, targeting difficult-to-measure quantities and ensuring a comprehensive understanding of the manufacturing process. The data will be fed to an AI-based digital twin decision support tool, enabling first-time-right adjustment of the mold by the operator.

Expected solution: Currently, two operators visually inspect specific control points at the end of the production line and perform the necessary operations. The operators decide whether the refrigerator cabinets meet the required quality standards. However, there are no predefined measurement gauges,

objective criteria, or tolerance limits in place. As a result, the process is highly dependent on operator experience and is therefore prone to human error and inconsistency. Cabinets that pass the quality inspection are transferred to the next station for completion of the remaining operations. Non-conforming cabinets are diverted to a separate conveyor line for further inspection, rework, and repair activities. The objective is to implement an automated inspection and control station equipped with advanced sensors and camera systems. When the cabinets arrive at the control point, the sensors and cameras will automatically inspect all predefined quality parameters. The system will analyze and display all inspection results in real time on a monitoring screen, while simultaneously storing all collected data in a centralized database for traceability and further analysis. All inspection criteria, tolerance limits, and quality parameters will be defined in collaboration with the Quality Department of Arçelik.

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource optimization:

- Operator count from 2 operators to 1 operator for mold adjustment
- First-time-right adjustment of the mold
- Reduce facility downtime by 15%
- Increasing production capacity by 3%
- Decrease annual waste by 3 tons
- Scrap rate decrease 20%
- Annual cost savings: Approx. €160k/year

Green Deal impact

Examples of KPIs adequate for measuring the Green Deal alignment of previous proposals for this challenge:

- First-time-right adjustment of the mold
- Reduce facility downtime by 15%
- Decrease annual waste by 3 tons.
- Product life extension - Increase in mean time between product replacements
- Energy saved - Energy otherwise wasted in start/stop cycles & idling
- Material footprint intensity - Reduction in combined material use
- CO2e avoided - Greenhouse-gas savings

Social impact

- Operator-dependent decision-making will be reduced through AI-supported and data-driven quality control systems.
- Reduction of repetitive manual inspection activities will improve ergonomics and working conditions for operators.
- The solution will contribute to workforce upskilling by increasing the use of digital manufacturing and AI-assisted decision-making tools.

- Reduction in polyurethane waste will support environmental sustainability and decrease the carbon footprint of the production process.
- Lower scrap and rework rates will improve resource efficiency and support sustainable manufacturing practices.
- Reduced downtime and improved production efficiency will strengthen the competitiveness of the European manufacturing industry.
- The project will accelerate the adoption of Industry 4.0 technologies within manufacturing environments.
- Improved traceability and standardized quality control processes will increase product reliability and customer satisfaction.

Domain 2: Combined AI and Data solutions for creation of INSIGHTS

Challenge 2.1 Product-production Digital Twins

Challenge and context: Traditional design cycle paradigms in manufacturing have been optimised to their limits, and further gains are expected from cross-stage optimisation through combined AI and Data solutions. Digital information is becoming available in large amounts during different stages of product design, manufacturing, useful life, and recycling. Digital twins enable the collection and comprehensive management of all digital information linked to a unique product asset, exploiting it for added value creation within the same stage at which the data was collected. Leveraging these technologies, the manufacturing industry is on the verge of fully reaching Industry 4.0's digitalization potential, where digital twins play a central role at both the product level and at the production level. Manufacturers are striving to reduce their ecological footprints by minimising energy consumption, material use, and waste. AID4SME is committed to overcoming these challenges for use case owners both inside and outside the consortium.

Use case and expected solution: Inside the consortium, Arçelik operates extruder processes to blend virgin plastic material with plastic scrap. Flaws in the mixing rate can lead to discolouration and cracking, generally caused by high ratios of recycled material. Arçelik seeks a product-production digital twin solution to optimise material mixing ratios based on real-time measurement of visual and mechanical properties of the different plastic source materials. This aims to increase the ratio of recycled plastic, enhancing sustainability while maintaining quality and reducing scrap. Additionally, Arçelik's consumer electronics refurbishing factory, which refurbishes over 50000 products annually, seeks to reduce the amount of refurbished products by combining augmented sensing (cf. challenge 1.1) and a product-production Digital Twin to optimise End-of-Life Product Refurbishment processes by assessing the health and predicting the remaining lifespan of components. For this industrial high-TRL application, Arçelik has foreseen the following activities/Key Performance Indicators (KPIs): (i) improvement of existing sensors and integration of new ones in the extruder machine; (ii) integration of visual, dimensional (width, length, thickness) and mechanical quality control systems into the existing extruder machine; (iii) creation of a digital twin of the developed system; (iv) determination and control of optimal process parameters (screw, speed, mold and barrel temperatures, gear pump pressure, cooling water temperatures, material mixing ratios, etc.) using AI and data analysis; (v) reduction in maintenance costs, waste rates, and energy consumption; (vi) 5% increase (1200 tons) in recycled plastic content in Arçelik refrigerator products; (vii) resolving 95% of quality control issues; (viii) reduction in virgin material usage. This list is not exhaustive but rather indicative. Additional KPIs will be studied and can be integrated to ensure quality outcomes. Besides this high-TRL application, KU Leuven has technology blocks available at TRL 4 and low-TRL playgrounds, namely a fully equipped injection moulding laboratory facility, to develop and test related solutions. This allows to link the manufacturing process to product quality in mecha(tro)nic applications. For application on the low-TRL research lab playgrounds, the focus will be on the technological development of a dedicated product-production simulation framework for injection moulding manufacturing processes.

Specification for use case: SMEs are invited to propose a use case leveraging their own technology or solving their problems at hand, which will be further elaborated together with the consortium partners. Inspirational examples can be based on system identification, quality control, process parameter optimisation, etc. The consortium offers low-TRL research lab playgrounds as well as one high-TRL industrial application (as detailed above). SMEs applying for this challenge should specify which TRL level they would like to target. For the industrial application, the consortium partners will guide and mentor SMEs

to deploy a straight-through digitalization (STD) approach in the challenges. More specifically for this challenge, a product-production digital twin for their extruder processes for blending virgin and regrind plastic and masterbatch materials will be developed and demonstrated at TRL 9 at the high-TRL playground of Arçelik.

Expected solution: Inside the consortium, Arcelik produces plastic sheets using extruder machines. Process parameters, material type, and material ratios are critical factors affecting production quality. Errors in these parameters cause quality defects such as discoloration, cracks, black spots, and similar defects on the plastic sheet. Arcelik is seeking an AI-supported digital twin solution to optimize the production process and material usage using real-time visual and dimensional measurement systems. This solution aims to increase the usage ratio of regrind materials, reduce scrap quantity, decrease energy consumption, and improve sustainability.

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource Optimisation

Key Performance Indicators (KPIs) for AI-supported digital twin integrated into extruder production line are as follows:

- Increasing the usage ratio of regrind plastic material by 5%
- Reducing the baseline scrap rate by 15%
- Reducing annual energy consumption by 8%
- Reducing operator training time by 30%

Green Deal impact

- Increasing the usage ratio of regrind plastic material by 5%
- Reducing the baseline scrap rate by 15%
- Reducing annual energy consumption by 8%

Social impact EMPTY

- Reducing operator training time by 30%
- Improving operator competencies and technical skills

Challenge 2.2 Automated monitoring hygiene inspection for refurbishment

Challenge and context: Currently, within the consortium, Arçelik handles approximately 70,000 returned or rejected products per year. These products are processed through an automated sorting system in which each unit is scanned via a QR code, providing access to its complete historical documentation and traceability information, including an initial assessment of its refurbishment potential. For products identified as suitable for refurbishment, cleanliness and surface condition are assessed individually using swab tests and ATP detectors, requiring approximately 30 minutes per product. Although effective, this approach is time-consuming, provides limited spatial information, and does not support predictive or scalable, data-driven decision-making. The main challenge, therefore, lies in improving how cleanliness, sanitation, and surface condition are assessed in manufacturing and refurbishment processes, while reducing inspection time and supporting objective refurbishment decisions

Use case and expected solution: This use case focuses on the development of an AI-based decision-making model to objectively determine the cleanliness status and surface condition of manufacturing equipment and parts. The proposed solution combines AI with optical sensing technologies to enable contactless, scalable, and industrially applicable cleanliness monitoring.

Multispectral and hyperspectral vision, together with infrared thermography, can be used for the early assessment of cleanliness and hygiene conditions in manufacturing and refurbishment environments. Hyperspectral imaging (HSI) enables the capture of objective, spatially resolved information on surface contamination, including organic residues (e.g. proteins, fats, and sugars), moisture, and cleaning-agent residues, over large areas and without physical contact. Infrared thermography (IRT) complements this capability by identifying temperature anomalies associated with residual moisture, improper cleaning, or incomplete drying processes. Compared to conventional RGB imaging, multispectral and hyperspectral data provide significantly richer spectral information, enabling more reliable discrimination of surface conditions and contamination types. Currently, LEITAT has the HSI and IRT systems available under laboratory conditions to develop a proof of concept of an AI-based predictive model for cleanliness assessment at TRL 4. Arçelik will provide the industrial playground, contributing real manufacturing equipment and parts to train the models and supporting their validation under real industrial operating conditions

Specification for use case: SMEs are invited to propose a use case that contributes to the development of an AI-based predictive model and demonstrates the capability to integrate and validate HSI- and/or IRT-based decision-making models in industrial environments, bridging laboratory developments and production-line implementation. In particular, the consortium is interested in engaging SMEs capable of providing and deploying multi/hyper-spectral imaging (HSI) cameras or proposed optical sensing technologies for testing and validation under real industrial operating conditions. The consortium offers a low-playground, provided by LEITAT, where optical sensing technologies and AI-based decision-making models can be developed and validated under laboratory conditions, and a high-playground, provided by Arçelik, where the developed solutions can be tested, integrated, and validated under real industrial operating conditions

Expected solution: AI-based, contactless inspection system that assesses the cleanliness and surface condition of manufacturing equipment and refurbished products by combining hyperspectral imaging (HSI) and, where applicable, infrared thermography (IRT). The system will generate objective, spatially resolved cleanliness indicators by detecting organic residues, contamination, moisture, and cleaning-agent residues over large surface areas, supporting automated and data-driven refurbishment decisions. Developed initially as a proof of concept under laboratory conditions at LEITAT (TRL 4), the solution will be integrated

and validated in real industrial environments with TRL 9 at Arçelik, enabling scalable deployment in manufacturing and refurbishment processes while reducing inspection time, costs, and waste.

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource optimization

- Inspection time per day: Reduced from ~2hours (ATP/swabs) to minutes using AI-based optical inspection
- Labour efficiency: ~126,000 labour hours saved per year (based on 70,000 units)
- Spare part recovery efficiency: Increase to 90% for refurbishment-eligible products
- Annual cost savings: Approx. €13.6 million/year (avg. product value €130)

Green Deal impact

- Impact: Returned products reused ~70,000 units/year refurbished instead of discarded
- Material savings: Approx. 7,000 tonnes of material saved/year (≈100 kg per unit)
- Reduction in consumables: Decrease in swabs, reagents, water, and cleaning chemicals
- Carbon footprint reduction: Lower emissions due to reduced new manufacturing and logistics

Social impact

- Worker safety & ergonomics: Reduced repetitive manual inspections via contactless sensing
- Workforce upskilling: Introduction of AI-based inspection and decision-support tools
- Job quality: Shift from manual inspection tasks to higher-value supervisory roles

Challenge 2.3 Energy system Digital Twin decision support tool

Challenge and context: Grid operators increasingly face grid balancing challenges due to rising energy demand and the growing share of decentralized renewable energy production. To balance power generation and demand, a portfolio of energy storage technologies can be deployed, including electrochemical storage (e.g., batteries, hydrogen technologies) and thermal energy storage. Thermal storage can play a significant role by shifting heating or cooling loads, improving sector coupling, and reducing peak electricity demand. Moreover, with the advances in thermophotovoltaic (TPV) technology that provides conversion from heat to electricity, thermal storage enables output of both electricity and heat. However, energy conversion and storage equipment, including both electrical and thermal systems, incur capital and operational expenditures that ultimately affect the final price of delivered energy. Optimal sizing and integration of local renewable generation, electrical storage, and thermal energy storage are therefore essential to achieving an economically efficient and flexible energy system. Due to numerous variables, such as time-dependent profiles of energy consumption (electric and thermal), renewable generation, storage state dynamics, and dynamic pricing signals, and their nonlinear interdependencies, optimal system configurations cannot be derived analytically. This challenge calls for AI and data-driven solutions to optimally size, coordinate, and control distributed energy resources, including microgrids with integrated thermal and electrical storage.

Use case and expected solution: The expected solution should enable the microgrid operator to determine the optimal sizing of local energy assets to reliably meet both electrical and thermal heating energy demands. In addition, it should incorporate advanced energy management capabilities that control grid assets operation in a way to stabilize the grid, reduce the overall costs, and enable the microgrid to offer ancillary services. The proposed sizing and real-time operational strategy should minimize total energy costs, reduce capital expenditures for both electrical and thermal energy storage systems, and limit curtailment or wastage of renewable energy, while maximizing the value of distributed resources through intelligent grid control.

Specification for use case: A Digital Twin (simulation model) of local energy systems and real-life measurements of energy consumption will represent a core of the playground. The provided Digital Twin enables simulation of thermal and electrical energy balance over a desired time and observing economic results as a function of equipment sizes and prices. The digital twin will be used to experiment and test microgrid control algorithms for different pricing scenarios. The main focus of the scenarios will be on inclusion of novel thermal energy storage solutions and provision of ancillary grid services. The selected third party is expected to have experience with provision of ancillary (grid) services and is expected to contribute with the following:

- Develop an optimization algorithm for optimal sizing of a microgrid components using a microgrid Digital Twin
- Develop a microgrid grid energy control algorithms using predictions of heat and electricity needs
- Implement and test the developed solutions in a digital environment with real world data and for different scenarios
- Demonstrate operational scenario of ancillary grid services together with the use of thermal storage solution

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific,

Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource optimisation

- Decrease of investment for energy storage system for the reference scenario (% reduction in CAPEX for energy storage),
- Decrease costs of electricity and heat for the reference scenario utilizing predictive energy storage and smart energy management.

Green Deal impact

- Improve local consumption of renewable energy (% increase in renewable energy self-consumption),
- Ancillary service fulfillment rate (%), share of requested ancillary service energy/power that is successfully delivered. $(\text{Delivered service} / \text{Requested service}) \times 100$
- Ancillary service activation success rate (%), percentage of service requests that are activated correctly and on time

Domain 3: Combined AI and Data solutions for DECISION SUPPORT

Challenge 3.2 Automated machine selection for parts production

Challenge and context: Many complex production processes are still partially controlled by operators with highly specialized, tacit knowledge that is difficult to formalize and document, posing risks to product quality, process reliability, and long-term industrial competitiveness if lost. At the same time, shopfloor operations often rely on simple but repetitive manual tasks, such as pick-and-place activities involving movement between workstations, which require coordinated perception, manipulation, and locomotion but are rarely described in a way that enables direct automation. The challenge is therefore twofold: to capture and structure human instructions and operator know-how, and to translate them into executable actions for robotic systems operating in dynamic production environments. In this context, adaptive DWI are essential, as they enable instructions to be both human- and machine-readable and adaptable to operational conditions. The AID4SME framework provides a foundation for addressing these challenges through AI-driven decision support, knowledge representation, and cyber-physical systems. As a representative use case, the project focuses on enabling a humanoid robot to learn and execute a simple pick-and-place task with locomotion between workstations based on human-provided instructions. This use case represents the execution layer of decision support, where high-level decisions—such as machine selection for parts production—are translated into actionable instructions and physically carried out on the shopfloor by the robot. In this way, the project demonstrates a practical pathway for bridging human expertise, AI-based decision-making, and autonomous robotic execution in real production environments.

Use case and expected solution: The challenge addresses the need to formalize and digitalize operator knowledge and translate it into actionable instructions for robotic systems. Capturing and representing this knowledge requires combining structured knowledge capture methodologies with AI-based approaches capable of linking human actions with process context. The use case focuses on a practical and demonstrable scenario, where a humanoid robot learns and executes a simple pick-and-place task involving locomotion between workstations based on human-provided instructions. The proposed solution leverages imitation learning and reinforcement learning to enable the robot to learn from demonstrations and structured DWI, transforming human-readable instructions into robot-executable workflows. The approach is supported by theoretical and methodological developments, including knowledge representation, instruction modelling, and AI-based learning strategies. The resulting system will demonstrate that a humanoid robot can reliably execute a defined task in an industrial setting, enabling improved process consistency, reduced dependency on manual execution, and a scalable pathway for integrating human-centric AI and humanoid robotics into smart manufacturing systems.

Specification for use case: The use case focuses on enabling a humanoid robot to autonomously perform a simple pick-and-place task involving locomotion between two or more workstations in a production environment at LTH Castings. The humanoid robot is to be provided by the solution provider and is not part of the playground infrastructure. The task includes object detection, grasping, transportation, and precise placement, while navigating safely between predefined locations on the shopfloor.

The system shall support the following functional specifications:

- Task definition and execution: Pick an object from a defined source location (e.g., bin or fixture), Walk to a target workstation using predefined or dynamically generated paths, Place the object at a designated position with sufficient accuracy and repeatability
- Instruction handling: Input provided as human-readable instructions (text and/or video-based demonstrations), Transformation of instructions into structured DWI, Conversion of DWI into robot-executable action sequences
- Learning and adaptation: Use of imitation learning for initial task acquisition, Use of reinforcement learning for optimisation and robustness, Ability to adapt execution based on environment conditions (e.g., object position variability)
- Perception and navigation: Multi-modal perception using stereo vision (≥ 3 cameras) and LiDAR, Object detection and localisation, Environment mapping and safe navigation between workstations
- Development approach: Initial validation in simulation environment (digital twin of workspace), Gradual transition to real-world deployment (Sim2Real), Use of virtual sensors and synthetic data where applicable.

Expected solution: The resulting system will demonstrate that a humanoid robot can reliably execute a defined task in an industrial setting, enabling improved process consistency, reduced dependency on manual execution, and a scalable pathway for integrating human-centric AI and humanoid robotics into smart manufacturing systems.

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource optimisation

- Successful execution of the full pick–transport–place cycle
- Task execution speed reaching at least 50% of human baseline performance
- Instruction-to-execution setup time ≤ 4 hours
- Reliable operation across multiple repetitions with consistent results

Green Deal impact

- Part damage or scrap rate during automated pick–transport–place operations (%)
- Energy consumption per successfully completed handling cycle (Wh/cycle or kWh/100 cycles)

Challenge 3.3 Battery production digitalwork instructions & skill capturing

Challenge and context: Battery manufacturing processes combine automated inspection systems with human decision-making in critical steps such as electrode coating and quality control. In such contexts, inspection systems (e.g. camera-based solutions) can be used to detect defects during production, but detecting a defect is only the first step: Operators must determine which actions should be taken to correct the issue or prevent its recurrence, such as checking machine parameters or investigating upstream causes. In current production practice, the corresponding corrective actions remain dependent on operator expertise. These decisions rely heavily on operator expertise, which is often tacit, experience-based, and not systematically captured. At the same time, industrial initiatives such as electronic workstations (eWS) aim to centralize documentation and ensure compliance, but do not capture how experienced operators respond to specific production situations, such as defect occurrences. As a result, knowledge related to defect handling and process adjustments remains largely tacit, leading to variability in decision-making across operators and shifts. This impacts product quality, process stability, and scalability, particularly in fast-growing environments such as gigafactories. The challenge is therefore to capture, structure, and formalize operator knowledge related to defect handling and decision-making, and to integrate it into adaptive DWI that complement existing eWS systems by providing context-aware, actionable guidance to operators during production.

Use case and expected solution: The use case focuses on defect detection and operator intervention recommendation in battery production, particularly in electrode coating process where identified anomalies require human decision-making. When a defect is detected, operators must decide which machine parameters to verify, which corrective actions to perform, or whether upstream processes are the root cause.

The expected solution aims to capture (vision-based or sensor-based approaches) and formalize expert knowledge associated with defect handling and translate it into adaptive digital work instructions integrated with workstation-level systems. This includes:

- Linking detected defects to recommended corrective actions or parameter checks.
- Providing context-aware guidance based on process conditions and operational context.
- Supporting operators with relevant documentation, alerts, and task-specific instructions.
- Ensuring traceability between defect detection, decisions taken, and outcomes.

The proposed approach combines knowledge representation methods with AI-based techniques capable of modelling relationships between defect patterns, process conditions, and operator decisions/solutions for resolving the production problems. The solution should extend existing documentation systems (e.g., eWS) by enabling dynamic, situation-aware guidance rather than static instructions. The resulting system will demonstrate improved process consistency, reduced variability in defect handling, and enhanced operational efficiency, contributing to more robust and scalable battery manufacturing processes.

Specification for use case: The use case focuses on supporting operator decision-making in response to defects detected by inspection systems, while integrating with existing workstation-level documentation systems. The system shall support the following functional specifications:

Defect-driven guidance:

- Identification of defect types from inspection systems and mapping to recommended corrective actions or parameter checks
- Instruction handling and integration:
- Transformation of expert knowledge into structured Digital Work Instructions
- Integration with existing documentation systems (e.g., work instructions, checklists, safety procedures)
- Delivery of alerts and updates when instructions or process conditions change

Skill and context awareness:

- Consideration of operator qualifications (e.g., training, certification) when delivering guidance
- Adaptation of instruction detail based on operator experience level

Knowledge capturing and modelling:

- Extraction and formalisation of expert decision-making practices
- Linking operator actions with process conditions and outcomes

Traceability and monitoring:

- Recording of actions taken and checks performed (e.g., process controls before/during manufacturing)
- Monitoring of compliance with required procedures

Development approach:

- Initial validation in a controlled lab environment (low TRL)
- Progressive integration and demonstration in an industrial pilot environment (TRL7)

Expected solution: The resulting solution will demonstrate improved process consistency, reduced variability in defect handling, and enhanced operational efficiency, contributing to more robust and scalable battery manufacturing processes.

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource optimization

- Reduction in scrap rate associated with defect handling
- Improved consistency of operator decisions across shifts and teams
- Reduction in defect recurrence due to improved corrective actions
- Reduction in response time to detected defects
- Improved compliance with procedures and execution of required process controls

Green Deal impact

Please ensure that KPIs are measurable throughout the project duration and avoid vague, indirect, purely technical/performance oriented or non-quantifiable indicators. These KPIs should highlight how your proposal advances one area (or several) within the Green Deal scope and objectives.

Examples of KPIs adequate for measuring the Green Deal alignment of a proposal for this challenge:

- Reduction in scrap rate associated with defect handling (%)
- Reduction in material waste per battery cell or electrode (kg/unit)
- Reduction in energy consumption linked to rework and repeated inspections (%)

Challenge 3.4 Automated warehouse and internal logistics management

Challenge and context: Manufacturing companies increasingly operate highly automated and complex production environments, in which internal logistics such as buffer warehouses management, pallet flows, automated forklifts operations, and the deployment of AMRs have a direct impact on production continuity, energy consumption, and overall operational efficiency. This is particularly relevant in metal-part production settings, where production rhythms can be variable, intermediate buffers are often constrained, and disturbances can rapidly propagate across the shop floor. Despite the increasing levels of automation in production equipment, the execution and coordination of internal logistics are still frequently governed by fixed rules, manually triggered actions, or dispatcher-based decision-making. As a result, logistics resources are often used sub-optimally, leading to inefficient fleet utilization, unnecessary transport movements, delayed machine supply, increased operator effort, and avoidable production interruptions. In such environments, the lack of real-time coordination between production needs and logistics execution becomes a major barrier to both efficiency and resilience. Typical inefficiencies include:

- delayed response to machine-originated transport requests;
- poor prioritization of urgent logistics tasks;
- unnecessary empty movements and excessive transport distances;
- low fleet utilization due to unbalanced task allocation;
- weak coordination between conventional forklifts and AMRs;
- reduced resilience under disturbances such as machine stoppages, variable cycle times, and temporary congestion.

Digital Twin based control and decision-support frameworks address these limitations by enabling a more integrated, event-driven, and adaptive approach to internal logistics management. By combining real-time machine signals, logistics state information, and operational context, such frameworks can support dynamic task generation, prioritization, fleet allocation, and routing decisions. This is especially relevant in industrial contexts characterized by heterogeneous equipment, variable demand patterns, and frequent disturbances. However, effective deployment remains challenging due to the complexity of the underlying decision architectures, the need to integrate smoothly with existing machines, forklifts, AMRs, and IT systems, and the requirement to ensure practical usability in real production environments. AID4SME is flexible to overcome these challenges for use case owners inside and outside the consortium. Inside the AID4SME consortium, LTH would like to develop a smart planning tool for their automated buffer warehouse and internal logistics system. This digital twin-based tool should enable them to optimise internal workflows for the automated transporting around 200 pallets on the shop floor.

Use case and expected solution: The expected outcome is a smart, dynamic, AI-optimized fleet management engine that uses machine-triggered inputs (KLICI s stroja) as operational events, dynamically assigns transport tasks, optimizes resource use within the agreed scope, and provides an operator-facing communication layer for forklift operators and AMRs. The solution requirements are as follows:

Data availability and event inputs

For challenge preparation and low-TRL research activities, partners will work with pre-provided historical data samples and clearly documented data schemas by LTH. These are expected to include data such as, where available:

- machine-triggered inputs;

- machine and line status signals;
- warehouse and buffer status;
- pallet and material flow data;
- forklift task logs and localisation data;
- AMR mission and execution data;
- operator interaction logs; and
- production planning and order context.

Live data ingestion, system integration, and validation against the industrial environment are led by the selected SME together with LTH in the higher-TRL playground. LTH will clarify which data are directly available, which are only available as historical samples, and which indicators would need to be derived by the SME. Data and developed solutions should be made available for non-commercial (research) purposes to consortium members beyond the project duration, and a dual-licensing approach allows consortium members, especially LTH, to use the solution after project completion.

Route and fleet management

The core decision-support logic should assign tasks to available resources on the basis of constraints such as fleet availability; capability constraints; expected travel time and execution time; route constraints. The primary objective is to develop and validate an internal route and fleet management solution that interprets machine-triggered logistics inputs and supports prioritization and task allocation across conventional forklifts and one AMR demonstrator (AMR to be provided by solution provider). The selected SME may combine optimisation methods, scheduling algorithms with AI-based approaches.

Operator and system communication

The solution should include an operator-facing dispatch and feedback interface through which tasks are communicated to operators. This may take the form of an operator terminal, mobile interface, dashboard, or another practical dispatching mechanism proposed by the SME together with LTH in the higher-TRL playground. The interface should support actions such as:

- task notification;
- task acknowledgement or acceptance;
- completion feedback;
- exception handling; and
- reassignment of urgent machine-linked requests.

Specification for use case: The goal of this challenge is to move beyond static or reactive dispatching practices towards a data-driven solution of internal transport resources capable of improving responsiveness, reducing inefficiencies, and supporting more robust and sustainable production operations. The solution will be validated at TRL 6 in the LTH industrial environment through a pilot demonstration on the selected production line. The solution includes one AMR demonstrator provided by solution provider. Validation will assess technical feasibility, operational robustness, and measurable logistics improvement under realistic factory conditions. For external SME use cases, transferable results and deployment concepts will be evaluated up to TRL 7.

Expected solution: The primary objective is to develop and validate a solution enabling LTH to optimize efficiency, reduce logistics energy consumption, and production stops.

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource optimisation

- Improvement in fleet utilization, measured as the proportion of productive transport time relative to total fleet availability for forklifts and AMRs.
- Reduction in empty travel distance, measured as non-productive distance per vehicle per shift.
- Decrease in production stops caused by logistics delays, measured as the number and duration of machine stoppages caused by missing material, delayed pickup, or unavailable transport.
- Reduction in response time to machine calls, measured from event generation to task assignment and task completion.
- Improvement in warehouse and buffer space utilisation efficiency, measured through occupancy patterns, dwell time, and turnover efficiency.
- Task completion reliability, measured as the percentage of logistics tasks completed within the required service window.

Green Deal impact

Examples of KPIs adequate for measuring the Green Deal alignment of a proposal for this challenge:

- Reduction in internal logistics energy consumption, measured per shift and normalised per manufactured product unit.
- Reduction in empty travel distance, measured as non-productive distance per vehicle per shift.

Social impact

- Reduction in manual operator interventions, measured as the decrease in manually dispatched or manually corrected transport tasks per shift.
- Reduction in operator time spent on logistics coordination, measured in minutes per shift or per production batch.

Domain 4: Combined AI and Data solutions for AUTOMATION

Challenge 4.1 Smart energy management of unplanned machine downtime

Challenge and context: In high-volume and energy-intensive industrial parts production, a significant share of energy losses occurs during unplanned machine downtime, such as micro-stoppages, quality control stops, disruptions caused by tool malfunctions, or other unexpected interruptions. Unlike planned non-production periods, these events are often unmanaged from an energy perspective, leading to machines and auxiliary systems remaining in fully powered states while no value-adding operations take place. This challenge focuses on industrial production cells for parts manufacturing, where machines operate in cyclical modes and rely heavily on auxiliary and spatially distributed energy consumers, such as tool tempering units and compressed air systems. These subsystems remain in standby and continue to consume energy even when production cycles have stopped unexpectedly, resulting in unnecessary energy use, increased operational costs, and higher environmental impact. LTH currently operates several production cells where machine cycle information is available at PLC or sensor level; however, automated energy-aware control of auxiliary energy consumers during unplanned downtime is not yet implemented. Operators intervene manually or not at all, and auxiliary systems often remain in full operation during downtime. The challenge addresses the need to automatically detect machine cycles, identify unplanned downtime events in real time, determine appropriate energy mitigation strategies and dynamically transition machines and auxiliary equipment into appropriate standby or off modes. On the other hand, the estimated preparation time to continue production should be predicted and orchestrated control of auxiliary systems should be performed at process startup, without compromising production readiness or product quality once production resumes.

Use case and expected solution: The expected solution should provide an automated energy management system that continuously monitors machine cycle signals, production states, and energy consumption within an industrial production cell and provides an orchestrated control of most significant consumers linked to the observed operation. The solution shall include a smart tool tempering unit for aluminium diecasting process capable of individual monitoring and control of each tempering circuit within the diecasting tool and integration capability for real-time measurement, visualization and regulation with aim to integrate it within the demonstrated system. Based on this information, the system shall:

- Automatically detect machine cycle starts, normal cycle operation, cycle interruptions, and unplanned downtime events using real-time data.
- Distinguish between short micro stoppages and longer unplanned downtime to select appropriate energy saving strategies.
- Dynamically control machine operation states (e.g. run, standby, off mode) during unplanned downtime.
- Specifically optimize the operation of energy intensive auxiliary systems, with a focus on Tool tempering unit (TTU) and Air Management System (AMS).

Specification for use case: The solution will use data driven methods, combining rule-based logic with AI or machine learning techniques, to learn normal cycle behavior, automatically detect deviations, and continuously improve downtime classification and energy saving decisions. Moreover, it should provide a reliable indicator of the estimated time needed for re-activation of the auxiliary systems. The developed solution should be demonstrated in the industrial environment, where communication with the auxiliary systems should be resolved using standard communication protocols (OPC-UA, MODBUS, etc.). Finally,

the control of auxiliary services (TTUs and AMS) shall operate autonomously, without reliance on manual operator input, while remaining fully compatible with production control systems, safety constraints, and quality requirements.

Expected solution: The expected solution should be demonstrated and validated under real production conditions with varying unplanned downtime scenarios. The solution should provide the following functionalities:

- Machine cycle detection from PLC signals, sensors, or energy signatures.
- Realtime identification of unplanned downtime events.
- Integration of monitoring and automated control of compressed air pressure and airflow, including supply of IoT-enabled AMS.
- Integration of automated control of TTU and supply of suitable TTU for the pilot.
- Energy aware control interfaces for production cells supporting standby and off modes.
- Orchestrated and on-time management of startup phases.

Key Performance Indicators: Key Performance Indicators (KPIs) should be defined as clear, objective criteria that demonstrate the relevance and impact of the proposed solution, covering at least two of the following dimensions—resource optimisation, Green Deal objectives, and social impact—and must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

The demonstrated solution will enable LTH to significantly reduce nonproductive energy consumption in parts production cells while maintaining production flexibility and responsiveness. The impact of the developed solution will evaluate changes compared to the baseline conditions (operation without the energy management system).

Resource optimisation

- Percentual increase in production recovery time, measuring the delay between cycle restart and stable production.

Green Deal impact

- Percentual reduction of energy consumption during unplanned downtime for managed machines and linked auxiliary systems.
- Percentual reduction in compressed air flow during unplanned downtime.

Challenge 4.3 Semi-automated EV battery disassembly for recycling

Challenge and context:Complex assemblies, such as EV batteries and motors, across manufacturers and vehicle models vary significantly. E.g., virtually each battery type has its own type of cables, bus bars, battery modules, and different types of cells. This variability makes the automation of EV drivetrain components dismantling for recycling challenging. Additionally, current EV batteries subjected to recycling are mainly Li-ion based, posing a multitude of hazards for recycling processes. Automating each process for each battery type is time-consuming and costly, if at all possible. Given the end-of-life state of such assemblies, there is often little to no reliable information on their internal composition, condition, or hazards. Therefore, battery recycling companies are (sub)consciously building a mental, written, or digital catalog of product-specific datapoints, based on the operator's experience. Capturing both operator actions and hazardous components (whether mechanical, electrical, chemical, or thermal) and subsequently registering them uniformly for each product type/variant would allow, on one hand, a more efficient manual disassembly for recurring models by integrating digital work instructions, and on the other hand, the opportunity to, where possible, automate specific hazardous, unergonomic, or repetitive tasks.

Use case and expected solution: A consortium partner has a laboratory for EV motor and battery dismantling available, with an industrial robot at TRL 4, specifically focusing on developing flexible human-machine collaborative demanufacturing processes. This partner has several technology blocks at TRL 4, leveraging computer vision and AI technologies from other areas, enabling the development of dismantling operations for different products without requiring specific robot programming for each. Another partner has significant knowledge and experience regarding, specifically, battery-related hazards and the required safety precautions. A missing key element is an operator interface that enables structured recording of manual operations, hazards, and status feedback, based on which the system can later present product-specific work instructions to the operator. All relevant product and process data should be logged in the Digital Product Passport (DPP), which can then be utilized to base future robotic/manual work instructions on. The consortium partners will support the selected SME by providing the following contributions:

- A suitable lab environment for the final demonstration, including a workbench setup with product clamping, a top frame for a projector and cameras, tool mounting, and demo case study products, including a dummy EV battery assembly and EV motors.
- A draft DPP data structure. The partner will demonstrate the use of the registered data in the DPP by the robotic disassembly system.
- In-depth knowledge and guidance in battery-related safety hazards.

Specification for use case: The consortium partners will guide and mentor SMEs to develop the operator's interface for a robot cell for semi-automatic dismantling of various EV component types, extending to overall mechatronic system demanufacturing approaches. In this solution, a human operator manually records operations on newly encountered products, of which some will later be performed by industrial robots and some, which a robot cannot perform, will still be performed by the operator, although supported by digital work instructions.

Expected solution

- Detection and logging of manual operations and hazards
- Detect and evaluate the manually performed operations, using common/smart hand tools (e.g., screwdrivers, pliers, cutters) and hand tracking (e.g., component pickup and component drop off), also incorporating hazard logging.

- Storage of manual operations and product data in a Digital Product Passport (DPP)

All relevant parameters (such as fastener locations and types, and relevant hazards) should be saved in a standardized digital format so that they can later be used to perform human-robot cooperative disassembly tasks on the same model type. All disassembly operations should be registered in such a way that a reusable (chrono)logical disassembly sequence is compiled.

Digital work instruction visualization

Intuitively display digital work instructions by projecting them on the workbench (2m width and 1,2 m depth) and on the product itself to reduce mental overload and to align instructions directly with the product and setup. To allow for the projection of markers and instructions on the complex geometries of the case study products, 3D mapping and multi-angle projection are required.

Hazard warning and monitoring visualization

Clearly display relevant operator safety instructions during manual disassembly. For example, highlight electrical contacts of battery modules that may still hold a charge, sharp objects, unknown chemical substances, warm surfaces, and other potential hazards. Use clear and unambiguous pictograms to reduce language dependence and support a safer working environment. In addition, proposals that include complementary monitoring systems are encouraged. This may include the integration of thermal vision systems, not only to detect potential thermal runaway events and trigger both local (work cell) and plant-wide safety alarms, but also to support monitoring, testing, and validation activities during disassembly operations.

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource optimisation

- Position accuracy of the recorded locations: The position accuracy of the recorded locations and operations should be at least $\pm 10\text{mm}$ and $\pm 10^\circ$.
- Reduction in teaching time for new product types: Increase the speed at which a new product type can be taught for robotic disassembly by a minimum of 50%, comparing manual data logging versus the implemented technologies.
- Reduction in time for supporting and intermediate actions: Achieve a minimal time reduction of 50% for supporting and intermediate disassembly actions, such as tool switching, picking and placing components in designated bins, cutting cables, or repositioning the product. These improvements should be measured separately from primary disassembly actions (e.g., unscrewing or prying), which are not expected to be significantly impacted by digital work instructions.
- Completeness of hazard logging and visualization: Log and clearly display all relevant hazard warnings on component/location level.

Green Deal impact

- Improved recovery of components and materials: Increase the share of disassembly steps for which components, fasteners, hazards, and removal sequences are correctly logged in the DPP, supporting more consistent separation and recovery of valuable or hazardous (battery) materials.
- Reduction in mixed or incorrectly handled fractions: Reduce the number of components or subassemblies sent to mixed, unknown, or manual rework streams due to missing product-specific disassembly information.
- Reduction in repeated teaching and rework effort for recurring product types: Reduce the need to repeatedly define disassembly instructions for the same product type by reusing previously recorded DPP data and digital work instructions.
- Improved safe separation of hazardous battery components: Increase the share of relevant electrical, thermal, chemical, and mechanical hazards that are logged and visualised at component or location level before removal.

Social impact

- Improvement of operator workload and usability: Demonstrate a measurable reduction in mental and physical workload associated with manual disassembly by implementing projected digital work instructions. This should be evaluated by comparing a limited guided approach (e.g. with printed paper instructions) with the proposed system, in a manner similar to [1], using a structured assessment method such as the NASA Task Load Index [2]. Evaluation should consider mental demand, physical demand, temporal demand, effort, frustration and perceived performance, while maintaining at least the same task success rate.

[1] W. Mahy, D. Gors, B. Van Doninck, H. Qin and J. R. Peeters, "Projection-Based Augmented Reality to Support Human Intervention in Robotic Disassembly: A Case Study for Bike Batteries," 2026.

[2] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research," 1988.

Challenge 4.4 Co-bot refrigerator door assembly solutions

Challenge and context: The development of new automation technologies for the manufacturing industry directly contributes to efficiency, safety, and human factors. Modular, reconfigurable, energy-efficient, and collaborative robots can enable industries to optimize their operations, reduce waste, lower their environmental impact, and improve human operator job attractiveness. The white goods factory of a partner is one area where collaborative robots can make a significant difference. This partner will provide a use case for their refrigerator production line, where refrigerator gaskets of different shapes and sizes are installed on refrigerator doors. Manual installation of the refrigerator gaskets poses ergonomic challenges, resulting in inefficiencies and potential product rejections. Partial (co-bot) automation of gasket installation, particularly flexible elastomer gaskets, presents unique challenges that require the integration of collaborative robotics and AI to optimize the installation process. This ensures precision, safety, and adaptability to the deformable nature of elastomers, as the co-bot must apply the right force on the flexible material without causing deformation. The partner seeks a co-bot solution to overcome these challenges while aligning with the Green Deal's focus on promoting worker well-being and safety.

Use case and expected solution: The solution enables to improve efficiency, operator ergonomics, and inclusiveness, and reduce waste. This will result in more efficient production processes, better utilization of machinery, and enhanced overall operational efficiency. The expected solution can utilize a catalogue of developed technologies validated in the lab (TRL 4), building on results from previously funded EU projects related to collaborative assembly, and can apply them in a working solution for the gasket installation use-case at TRL7. This will enable to improve efficiency, operator ergonomics, and inclusiveness, and reduce waste. This will result in more efficient production processes, better utilization of machinery, and enhanced overall operational efficiency. It will be demonstrated at TRL 9 at the high-TRL partner facility and will offer the means to be advanced to even higher TRL, including with all safety requirements for factory deployment. The AID4SME solutions will foster a sustainable and inclusive digital transition that benefits both manufacturing companies and society at large.

Specification for use case: The solution will enable improved efficiency, operator ergonomics, and inclusiveness, decrease waste, and increase the longevity of refrigerator doors through enhanced stability of gasket installation quality.

Instruction handling and integration:

- Transformation of expert knowledge into structured Digital Work Instructions
- Integration with existing documentation systems (e.g., work instructions, checklists, safety procedures)
- Delivery of alerts and updates when instructions or process conditions change

Skill and context awareness:

- Consideration of operator qualifications (e.g., training, certification) when delivering guidance
- Adaptation of instruction detail based on operator experience level

Knowledge capturing and modelling:

- Extraction and formalisation of expert decision-making practices
- Linking operator actions with process conditions and outcomes

Traceability and monitoring:

- Recording of actions taken and checks performed (e.g., process controls before/during manufacturing)
- Monitoring of compliance with required procedures

Development approach:

- Initial validation in a controlled lab environment (low TRL)
- Progressive integration and demonstration in an industrial pilot environment (TRL7)

Expected solution: The selected third party is expected to contribute with the following:

- Develop a co-bot-assisted gasket installation solution
- Integrate AI-based perception and control systems to allow the co-bot to adapt to different gasket shapes and models.
- Ensure compliance with safety and ergonomic standards, by reducing physical strain on human workers and improving workplace safety with co-bot working
- Demonstrate human-robot collaboration capabilities, where the co-bot supports rather than replaces the human operator, ensuring intuitive interaction and task sharing.

Key Performance Indicators: Key Performance Indicators (KPIs) should clearly demonstrate the relevance and impact of the proposed solution. They must address at least two of the following dimensions: resource optimisation, Green Deal objectives, and social impact. All KPIs must be SMART (Specific, Measurable, Achievable, Relevant and Time-bound), ensuring they remain quantifiable throughout the project

Resource optimisation

- Demonstrate effective and flexible autonomous processes (% 10 increase in assembly precision).
- Increase quality: robotized processes can more easily detect errors in production during the process itself (%10 reduction in installation errors).
- 5 % reduction in waste due to assembly defects

Green Deal impact

- 5 % reduction in waste due to assembly defects

Social impact

- Ensure the safety of workers in the vicinity.
- Improved efficiency: reduce the number of workers required at the production line (%50 reducing labour for gasket assy).
- Operator ergonomics: reduce operator/worker effort, as they will be able to focus on other tasks.
- Percentage of operators trained in safe procedures