Fluently – The essence of human-robot interaction

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Project Acronym FLUENTLY

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Brief description:

In this deliverable, we investigate the three use cases to be conducted in Fluently in terms of the as is situation as well as blueprints for the way they will be performed with Fluently technology. We also detail the twelve KPIs that will be used to evaluate the developed technology.

Creator	SDU
Contributors	ODE, UBATH, TUE, ROBOVERSE, DFKI, SUPSI, CIM, MEM, PA, MCH
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1 Executive Summary

In this deliverable, we investigate the three industrial use cases (the MEM, CIM and PA use case) which provide the framework for the development of the Fluently technology. In the MEM use case provided by Malta Electromobility Manufacturing Limited, we work on battery disassembly with the main aim of increasing the efficiency of the recycling process in terms of energy use, outcome and human safety. The CIM use case provided by Competence Industry Manufacturing deals with the introduction of cobots in the production of nacelles in aircraft industry to increase through-put as well as human working conditions. Finally, the PA use case provided by Prima Additive deals with repair of metal blades and similar items by means of additive manufacturing. For all three uses cases, we look at the current processes and how the introduction of Fluently technology can improve these processes in terms of twelve Key Performance Indicators (KPIs) covering aspects such as Programming effort, Self-awareness, Human awareness and Process recipes acceptance.

By that, this deliverable provides a basis for the further work of the project in terms of target-processes and their evaluation.

1.1 Acronyms and abbreviations

Acronym	Meaning
KPI	Key Perforance Indicator
Cobot	Collaborative Robot
EV	Electric vehicle
LIB	Li-ion battery
CRM	Critical raw materials
DED	Direct Energy Deposition
EOL	End of Life
AR	Augmented Reality
AMR	Autonomous Mobile Robot
OEE	Overall Equipment Effectiveness
OLE	Overall Labor Effectiveness
OEM	Original Equipment Manufacturer
AR	Augmented Reality
VR	Virtual Reality
XR	Extended Reality

2 Introduction

This deliverable contains the description of the manufacturing practices while addressing productivity efficiency and challenging aspects related to the three targeted industrial value chains of Fluently. It provides the appropriate context to synthesize a number of production scenarios which will be considered as benchmarks throughout the project to convert the current production lines into working environments enabling a true bonding between human and robot working as teammates towards shared manufacturing objectives.

In this respect, the deliverable collects the description of the products, manufacturing processes, tools and equipment data and information flow specific to each use case and identifies improvement opportunities while considering also the specific end-user requirements toward more efficient production scenarios. Moreover, a discussion with respect to the relevant KPIs targeting the quantification of the improvement in terms of process efficiency, human wellbeing and acceptance is also included. By that, D2.1 concretizes the concepts described in the Fluently-proposal and gives important directions for the work in the remaining project period. Since changes will occur while the Fluently technology is developed, we expect updates on the blueprints of the use cases to be made by adding greater details on the human-robot collaborative tasks and layouts, which will be captured within the deliverable D5.1.

This deliverable is structured as following: after a short description of the approach employed for the definition and collection of the requirements for the reference use cases, the sections 3-5 describe the current context of the production scenarios associated with each use case, identifies opportunities for improvement and project how the use case will be performed with the Fluently technology by means of a blueprint. The section 6 details the Key Performance indicators (KPIs) that will be applied in Fluently while emphasizing which are the most relevant for each individual use case. We finish with a conclusion in section 7.

2.1 Requirements definition of reference use cases

To prepare this deliverable, the project partners have collectively worked and collaborated to gather and formalize the information related to all use cases. The WP2 KoM meeting on 15th of September 2022 was the first possibility to communicate with all partners about the existing use cases and possible improvement of their blueprints in Fluently. Next, SUPSI, SDU, ODE, TUe, Roboverse, UBath and IRIS defined the data collection strategy centered around a questionnaire containing four main sections: (1) general use case description, (2) part specification, (3) process & equipment and (4) manufacturing data. The content and structure of the questionnaire was subsequently unified based on the input received from the tech providers and online sessions were organized with each end user (CIM - Competence Industry Manufacturing 4.0 on 24.11.2022, MEM - Malta Electromobility Manufacturing Limited on 28.11.2022 and PA - Prima Additive on 02.11.2022) aimed at providing a more detailed understanding of the company operation, their products and current manufacturing practices. An initial set of requirements and opportunities were identified, supporting the characterization of the current workflows, the definition of the improved manufacturing operations enabled by the Fluently solution and highlighting the impact of the project.

The information was consolidated during the visits at the end user premises (PA on the 30th of November, CIM and MEM on 1st of December). Additionally, on the 21st of December a site visit at the company Leonardo, in which the use case of CIM is conducted, was performed.

Following these sessions, SDU, ODE and SUPSI led the activities towards formalizing the information and creating the workflow, with the aid of Roboverse, TUe and UBath. The maps were then analyzed in depth, unclear areas identified, and the findings communicated with the end users in order to refine them in an iterative fashion.

In addition, these sessions offered valuable insight towards which parts would be suitable to be considered in the Fluently project as demonstrators. This information forms the basis upon which the design of the families of products and processes is done for each use case and will be used as benchmark throughout the project running period. It includes not only parts geometry and variants, but also materials, tools, current manufacturing, inspection and monitoring processes, the associated process chains and equipment as well as skills and capabilities required for the jobs.

3 Use Case 1 (MEM) - Fully manual dismantling and recycling process

3.1 Company information

MEM is an SME founded in October 2020 addressing the manufacturing of electric vehicles in Malta. It is allowed to use all IPR and patents granted to I-FEVS[1], a company based near Torino. In fact, MEM and I-FEVS are collaborating on all technical aspects related to electromobility with the idea to prepare the next step of electrification in the road, water, and air context. The current focus is on e-bikes. The recycling of their batteries is the object of the Fluently use case.

MEM is setting up a laboratory-training center for robotics and Industry-4.0 operations. The laboratory is expected to continue his operations through support of the local funding agency Malta Enterprise, EU grants and through programs dedicated to training. The laboratory-training center is considered a key to also train personnel that will be employed to manufacture e-bikes and e-cars. It is going to also train people for other industries as well and by that will have a high social impact**.** The MEM laboratory-training center will gradually become the R&D reference for the MEM manufacturing facility for e-bikes and other EVs. Strong collaboration is expected with local Universities and Industries as well as other EU R&D organizations.

3.2 Current state

The electrification of the European automotive industry and vehicle fleet is evolving rapidly and the number of electrical vehicles like cars, buses, trucks and e-bikes (the focus of this use case) is expected to significantly increase in the next 10 years. This calls for optimal recycling and reuse of used battery packs from battery electric vehicles. In the recycling process, the battery needs to be disassembled to extract the inner black mass from the battery cells containing cobalt, nickel, lithium, and other valuable materials, to refine the mass through advanced chemical processes to reuse it in new batteries. This is important to ensure a sustainable production of electrical vehicles where the EVs industry needs to reduce the earth raw materials needed for battery production.

There is a significant environmental risk if used EV-Type LIB are not properly disposed of, as the outer layer of an EV-Type LIB is covered by a plastic, aluminum, or an iron shell and the inner layer contains a cathode, anode, an aluminum or copper foil, an adhesive, a porous polyethylene or polypropylene separator material and an electrolyte. Although the main materials of an EV-Type LIB do not contain mercury, cadmium, lead or other toxic heavy metal elements, they do contain cobalt, nickel, copper, manganese, organic carbonates in certain materials and chemical substances such as the cathode material or electrolyte. After the battery is exposed to the wind and sun its casing is easily broken. Once the battery case is ruptured, potential pollution sources inside the battery are directly exposed to the environment. Organic solvents during decomposition or hydrolysis could cause irreversible damage to the environment, particularly the atmosphere, water bodies, soil and precious ecosystems. Long-term enrichment effects of heavy metals such as nickel, cobalt and copper, could result in harm to human health (carcinogenic, teratogenic, and mutagenic). The challenge is defining easy to apply procedures to dismantle the pack into battery cells from the gap filler and from electrical and electronic parts in relation to the gap filler used.

There are several stages a used battery must pass through on its journey toward reuse or recycling. All the

[1] I-FEVS: Interactive Fully Electrical Vehicles, www.ifevs.com/

batteries received in recycling plants are usually inspected and evaluated and marked for further traceability in the subsequent stages of handling. Traceability is important for quality and requirements are increasing.

Figure 1 shows a just opened, complete e-bike battery pack with individual battery modules visible inside the pack. The modules each contain battery cells, which contain valuable battery materials, which could be used in the production of new batteries.

Figure 1: Battery pack of the IFEVS-MEM e-bike. Left: pack with open case. Right: section of the pack. When the battery pack is filled in with a gap filler it becomes a mono-block that cannot be opened for maintenance. The gap filler homogenizes the temperature while electrically insulating the cells from each other and from the rest of the electrical electronic architecture. Certain types of gap fillers, once full cured, become as hard as a block of cement making the full battery pack very resistance to vibrations, water penetration and high temperature excursion but also difficult to be dismantled usually requiring cryogenic cooling. For other types of gap fillers the dismantling is easier in that the gap filler after curing remains relatively soft similarly to what happens with the pastes used in the electronic world.

The battery packs (Figure 2) have to be opened by expert staff to perform initial inspection like voltage measurements confirming that the battery can be dismantled safely. All of this process including discharging is done according to strict safety requirements. Remaining power in the pack can be fed into the power grid helping to power the recycling process. The potential of battery remanufacturing can be only fully harnessed if the battery packs are disassembled up to single cells, which are then sorted by its quality (Kampker et al., 2020). Currently, a major part of the manual operations goes into the extraction of the cells from the pack.

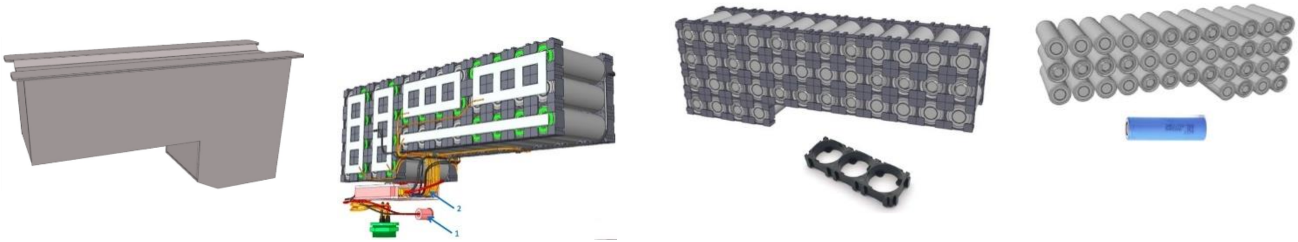


Figure 2: Components of the IFEV-MEM battery pack (from left to right): aluminum box , battery pack harnesses, connectors and BMS, battery cells storage box and pack of battery cells.

According to (Beaudet et al., 2020) the main targets that a LIB recycling process should achieve are three:

- high-quality products: ideally recyclers should aim at recovering battery CRMs with battery-grade quality, so to achieve a “closed-loop recycling”, and thus avoiding “downcycling”;
- competitive collection and recycling costs: the market price of recycled products should cover the costs of collection, transport, storage, and processing of spent LIBs, as well as a reasonable return on

investment for recyclers, so that the price of recycled products is competitive with the cost of raw materials;
- low environmental footprint: LIB recycling is driven also by reducing the negative environmental impacts of landfilling and of mining and refining of virgin raw materials. However, also LIB recycling generates water contaminants and requires energy, although being less intensive than primary production; thus, environmental impact analysis should be carried out to evaluate the sustainability of each LIB recycling process.

The best way to address these targets is to proceed with a "surgical" disassembly of the cells (after their extraction from the pack), that allows the removal of each component material in its pristine state, without breaking in pieces (no dusts), therefore without contaminating the other materials. As a general procedure after the cell opening, all materials are sorted and recycled. Up to now, this kind of disassembly work has been performed manually without much automated aid, and with high health risks for the factory workers. This is the main reason why most high-volume industrial solutions for cell recycling do not involve this kind of disassembly, and opt for the safer, although energy and cost intensive shredding followed by a number of post-processing operations that help separating the material such as pyrometallurgy or hydrometallurgy (Diekmann et al., 2017). A more controlled dismantling and disassembly of LIBs has many advantages over shredding of the components.

The cost savings for disassembled cells are always comparable or larger than cells which have been shredded. This is due mainly to the purity and yield of the products but also to the simpler flowsheets (Thompson et al., 2021).

In the case of cylindrical batteries, anode cathode and separator sheets are stacked one upon the other, then wound to form a tight roll. In a disassembly process, the roll needs to be opened avoiding any mixing of the components: the higher the purity of the material we can extract from the cells, the fewer purification steps need to be taken before reusing such material, therefore decreasing the environmental impact of the overall recycling process(Baazouzi et al., 2021; Thompson et al., 2021). In fact, product purity is essential for LIB recycling, as very low levels of contamination could render a material unusable for EV batteries (Kwade, 2018; Li et al., 2017). There is a growing school of thought that disassembly can lead to higher purity and higher value products (Harper et al., 2019).

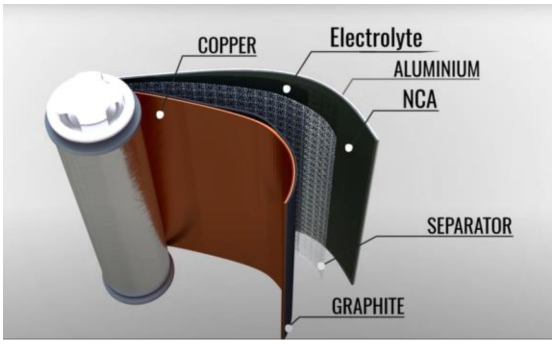


Figure 3: Main components of a battery cell with NCA (Lithium nickel cobalt aluminum oxides) chemistry

Considering the variety of batteries, one can argue that the approach to cut the cell open cannot be completely general and must be adapted for the particular system being used. Nevertheless, despite certain minor differences existing in the disassembly process as a result of varying design elements, each battery pack typically contains the same components, with the process of removal remaining somewhat similar (Harper et al., 2019; Wegener et al., 2015). While aiming to implement a generalized disassembly procedure, valuable insight can be gained by dismantling a battery of one type.

Figure 4: Sequence of operations for the dismantling of a battery cell (from left to right): circular cuts at both extremities of the battery, longitudinal cut and removal of the outer shell, rolled internal components of the cell, unrolled coils of electrode layers.

The manual dismantling of several battery cells as performed by SUPSI (see Figure 4) confirmed the criticalities related to the health and safety aspects.

Following upon the online session, the visit at the facility in Turin and the subsequent discussion it was highlighted that, amongst the various types of batteries, the NMC chemistries cylindrical cells are far the most used in EVs and consumer products. Two references, namely 18650 and 21700, are the most adopted format both in the e-bike and on several other types of EVs. Additionally, the 4680 are currently adopted by several auto OEMs.

Currently, at MEM a battery dismantling process is not available yet and a disassembly line does not exist (no information available for the process & equipment and manufacturing data sections of the questionnaire to describe the as-is situation). However, in this field, a range of technologies are already used now, to make battery recycling possible. Automation of the dismantling process is deemed crucial for the sustainable handling of the rapidly increasing numbers of used battery packs. Major bottlenecks in the automation were identified with respect to two workflows: battery pack disassembly (phase 1) and cell disassembly allowing for clean material recovery (phase 2).

Phase 1. Why battery pack disassembly?

For an effective circular economy, it would be beneficial to consider battery pack disassembly strategies promoting greater purity waste streams and the reuse/recycling of at least a specific number of components. However, due to the very high variety of LIBs in terms of size, shape and model the automatic disassembly of battery packs is in limited use in the recycling industry. In addition, certain uncertainties related to the EOL scenarios increase the complexity of planning and operation of disassembly procedures. In this respect, the non-contact detection, classification, and specific quality control measurement enabling an advanced strategy planning for disassembly automation would be the tendency of future battery recycling process.

Traditionally, the remanufacturing industry is characterized by disassembly of a product up to an optimal depth of disassembly. By the replacement of some parts, the specification and reliability of the original product can be repristinated. In this light, we might envisage a simple replacement of spent modules within a specific battery pack. However, due to the product architecture and the reliability characteristics such an approach cannot recover the full residual value of battery cells for specific applications (e.g., EV battery packs). It is likely that the most accurate EOL decisions could be made on used single battery cells, especially if use history data were available, so it is of outmost importance to develop methods to disassemble battery packs up to cell level (and to not stop at module level). It is also necessary to offer a guarantee on remanufactured batteries, which is translated into the necessity of predicting the residual life of cells and set acceptance criteria for the reuse in remanufactured batteries.

Phase 2. Why cell disassembly?

Following upon the testing activities and the validation of the recycling route, the battery cells move to the cell disassembly and clean material recover stage.

The manual disassembly is impractical due to the exposure to hazardous and flammable materials such as chemicals potentially formed during the cutting process or with exposure to air. Moreover, it requires adapted safety equipment and is costly, rather labor-intensive and sensitive to noises. Therefore, an automatic dismantling of the battery cell without human intervention in the cutting process is preferred to safely and efficiently recover critical materials from the battery cells. This recovery approach will enable the direct reuse/recycling of materials in the supply chain for remanufacturing without breaking down their chemical structure.

Prior to opening the cells, the human operator needs to ensure that the open circuit voltage is low enough to commence a safe teardown. All relevant risk assessment and documents should be completed to ensure a safe scheme of work is followed due to the potentially toxic nature of these materials and the risk of sparking and/or fire.

Subsequently, an automation of the cutting procedure with the support of a laser-based process would allow this process to be scaled up rather easily. The contactless separation technology by laser cutting is classified among the thermal material removing, which enables a high automation due to the potential of high-speed operating, of accuracy, its wear-free characteristics and high system availability (Jansen et al., 2018).

The collaborative evaluation of the state-of the-art workflows and potential opportunities for improvement lead to the development of a workflow (see Figure 5) providing useful information with respect to the demonstrator.

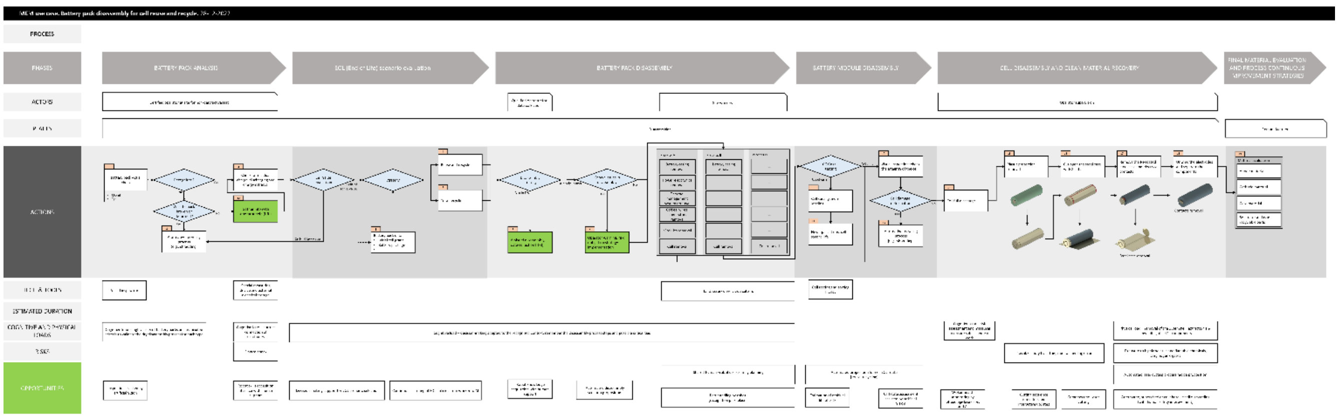


Figure 5: Blueprint of the dismantling of battery packs and the included battery cells. This figure is also provided in higher resolution in the appendix.

In order for the disassembly processes to become part of the commercial recycling procedure for LIBs, there must be a potential for them to be automated. To enable such a value chain, within the Fluently project, we will consider disassembly activities involving high cognitive and physical workloads as well as particular risks for the human health at the main candidates for automation. Initially, we will establish a testbed to develop, integrate and demonstrate novel technologies for automating the disassembling process of e-bikes battery packs using NMC 21700 cylindrical cells. Currently, these battery cells are the most produced type of cells and have a wide range of applications from laptop batteries to EV and e-bikes. Further down the road of the implementation of the Fluently solution, additional considerations will be made with respect to the automation tasks in order to accommodate other types of battery packs (cells with different chemistry, shape and size) while reducing the change-over time.

The automation challenge requires the testbed to be collaborative with true human robot interaction (power & force limiting – ISO/TS15066) because many processes like discharging and voltage measurement must be done by humans. On one hand, the testbed aims at involving collaborative robots with attached custom end-effectors (e.g., grippers, screwdriver) and vision system to recognize the battery pack, to support decision making activities related to the selection of strategies adapted to a specific context (e.g. untypical wear-offs of individual cells, handling of possible failures during dismantling) and to automate their execution. On the other hand, following upon the extraction of the battery cells from the pack, an automated solution will be proposed for their teardown with the support of a laser-based process.

3.3 Future state with the Fluently system

The Fluently global vision for the testbed promotes the central concept behind the circular economy where the aim is to extend the life of sub-assemblies (e.g., battery modules if applicable) and single components (battery cells) by reuse/ remanufacturing of parts and components of products (battery packs) which have reached their EOL stage. The development pipeline (see Figure 5) consists of a systematic framework towards human-robot collaborative disassembly based on perception, cognition, decision-making, execution and evolution across the following modules:

AI-powered detecting of different types and conditions of battery packs:

An integrated vision system with ML/Ops technologies utilized to enable fast re-training and re-evaluation of the model quality using e.g., metrics like precision/re-call. The vision system will evolve to detect the state of the battery casing as well as the type of battery packaging applied based on brands and sizes, with or without gap filler or what type of gap filler it has been adopted. A crucial aspect is to support the decision making on how to extract the cell from the pack. With direct reference to the IFEVS-MEM battery packs the main differentiation is on the type of gap filler used and it is worthwhile distinguishing between gap fillers and foams which usually have very little thermal conductivity. Filling the voids in between the cells with a gap filler allows a much better heat distribution and dissipation (the typical thermal conductivity of the gap filler is 4W/mK against the thermal conductivity of air which is 0.02W/mK).

Improve the battery pack disassembly process through a fluent and natural human-robot interaction to streamline the battery cell extraction:

The aim of this Fluently testbed is preparing the future needs to dismantling battery packs such as those introduced by TESLA in large EVs and by I-FEVS in his urban EVs and E-bikes. We here propose a model for battery pack dismantling, enabling the maximum security for the operator and the highest recovery of the cell materials with focus on the improvement of the disassembly rate. The model takes into account the differences between the various brands and designs for battery packs: the (robotic) interface for the operator has the ability to draw data, from a shared database, regarding the design of the battery pack, disassembly information, tips and warnings, cell age and chemistry. All such information is then used to define the ideal disassembly process for each particular battery pack (and possible process recipes for the disassembly of the embedded cells) while considering a shared human-robot task planning where humans and robots work closely together and support each other to complete a disassembly process. Within such planning, the identification of the presence and the type of gap filler might be critical for the planning of the downstream operations. Apart from the difference in cost, weight and physical properties, some gap fillers might require cryogenic cooling without which the extraction of the cells would be very difficult (Munro, 2022) while on other case with softer polymer-based gap fillers the cells can be easily extracted.

Another important aspect is the specific material value of each cell chemistry which can be used as a decision factor to support the selection of a more adapted EOL route for the battery cell.

The entire testbed will be based on the recognition of verbal commands and gestures which communicate requests for processing and execution of a disassembly task. Furthermore, it will give full consideration to the development and implementation of a skill acquisition interface – to enable a more intuitive definition and teaching of tasks to the robots and allow humans to transfer their domain knowledge and cognitive abilities to them. This will enable in the future a faster adaptation of processing capabilities of the robots with respect to new battery types while improving the disassembly rate (operation time is the main factor influencing the rate of output). Eventually, the robot endowed with the Fluently technology will gradually build knowledge about the main disassembly criticalities which can be used to formulate design-for-disassembly guidelines to be considered during the design of the next generation battery packs.

Laser-based techniques to automate the battery cell disassembly:

In comparison with state-of-the-art methods, Fluently proposes a dry disassembly process. By removing each constituent component in its pristine state, we reduce to the minimum any other refining process: less water contamination, fewer pre-and-post-treatments of materials and enable a more direct battery remanufacturing cycle. Furthermore, by employing an automated cutting process, the need for human interaction with the battery cell itself during disassembly is minimized. This would reduce the chances of human error or potentially harmful accidents from occurring. Thus, this can significantly increase the safety aspects of the disassembly process.

4 Use Case 2 (CIM) – Inspection and maintenance process

4.1 Company information

COMPETENCE INDUSTRY MANUFACTURING 4.0 S.C.AR.L. (CIM4.0) is a non-profit organization, born in the context of a national tender for the creation of the national competence centers network, and supported by a public / private partnership ecosystem. Its aim is to provide strategic and operative support instruments for enterprises towards the digital transformation of industrial processes, as well as to strongly accelerate, at local and national level, the transformation process of a wide portion of Italian SMEs.

CIM4.0 is composed of stakeholders from multiple sectors. Among its founding members are three Public Bodies (two academic entities and Turin's Chamber of Commerce), two enterprise associations, and 22 Europewide/Worldwide Enterprises, representing multiply supply chains such as automotive, aerospace, system and machinery experts, Software (SW) / Hardware (HW) technology providers, system integrators, and service/energy/telco providers (see Figure 6).

Figure 6: Stakeholders of CIM4.0

The CIM4.0 team is composed by 20 specialized personnel directly with CIM4.0 and additional 138 professional employees with the Consortium members involved in the activities through several Working Groups (WG) (divided as 82 senior technical fellows, 34 junior resources, a number of associate professors and 15 full professors).

CIM4.0 leverages on the exploitation of its so called "pilot lines", developed to test technological matureness of innovative solution with high TRL, providing companies with an actual place capable of lighten the approach to new technologies, new markets and new business models, to test new processes and products before bringing innovations to the market (targeting high TRL solutions, starting from TRL5 and developing values up to TRL 9). Within the Pilot Lines, it is possible to find cutting-edge technologies and machinery in the fields of Digital Factory, Artificial intelligence, and Additive Manufacturing.

The Digital Factory testing facility is an Industry 4.0 (I4.0) based environment aiming at demonstrating ICT technologies for manufacturing. Those technologies allow companies to evolve and transform processes through their digitalization, as well as, to create new solutions, becoming more competitive, dynamic, and efficient. The available technologies, applied to the industry sector, are IoT, CS, 5G, advanced robotics, AI applied to predictive maintenance and vision systems, big data, ergonomics, extended reality (XR), digital retrofitting, and digital twin.

The **Additive Manufacturing (AM) test facility** is a state-of-the-art center dedicated to the industrialization of metal additive manufacturing where it is possible to develop new products, optimize process parameters, qualify products or processes, produce new prototypes or pre-series products, and to perform technological and business analysis for comparison with conventional production. Currently, more and more industrial sectors find, based on these approaches, new ways to meet the challenges of the market, further shortening the time to market, revolutionizing the design, and creating new products.

CIM4.0 is a certified training organization, aiming at complementing the educational offers of universities and ITS. It offers custom training on technologies for digitalization based on specific needs with 50% discount to SMEs. Thanks to EXPAND initiative, the capacity of CIM4.0 aims to be multiplied by a factor of three. CIM4.0 has been engaged by the Italian Ministry for the Economic Development to manage a set of public funding, to be delivered through tenders for innovation projects. CIM4.0 has been able to manage two tenders distributing funds of 3.4 M€ in total. CIM4.0 has also a substantial (in relation to its foundation date) track record at EU funding level, with five projects (EDIH EXPAND, HE Fluently, HE GreenSME, H2020 ECOFACT, and H2020 OpenQKD). CIM4.0 is also partner of the CTE-NEXT, which promotes the acceleration of start-ups and technology transfer.

Leonardo-Finmeccanica, is among the world's top ten companies in Aerospace, Defense and Security and Italy's leading industrial company. As one of CIM's stakeholders for the aerospace sector, Leonardo is providing one of the use cases for the Fluently project.

Operational since January 2016 as a one company organized into business divisions (Helicopters; Aircraft; Aerostructures; Avionic and Space Systems; Land and Naval Defense Electronics; Defense Systems; and Security and Information Systems), Leonardo-Finmeccanica competes in the most important international markets by leveraging its areas of technology and product leadership.

Listed on the Milan Stock Exchange (LDO), as of December 31, 2015, Finmeccanica reported consolidated revenues of 13 billion euros and has a significant industrial presence in Italy, the United Kingdom and the U.S.

Leonardo is a leader in the nacelle manufacturing sector and also operates in partnerships and through collaborations such as that with the company MHD, a joint venture with Safran Nacelles.

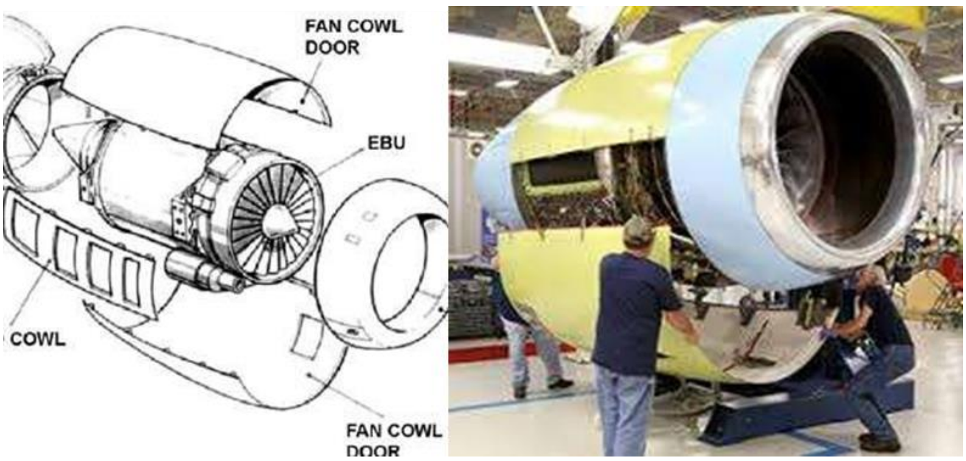


Figure 7: Nacelle at Leonardo

Leonardo is actively involved in research in this area, particularly in aspects of reducing the noise impact of commercial aircraft engines. The production of nacelles for aircraft engines takes place at the Venegono Superiore (VA) plant of Leonardo's Aircraft Division which has seen significant growth in production accruals over the years, reaching an average of more than 500 annual deliveries. With more than 15,000 units built, Leonardo produces nacelles (see Figure 7) for Airbus' large airliners, Embraer regional aircraft, Sukhoi Superjet 100, Comac ARJ21 and Dassault's executive jets.

Leonardo's engineering and manufacturing capabilities enable it to design and build nacelles that meet complex acoustic, aerodynamic, and structural requirements, managing the various stages of product life including logistical support.

CIM 4.0 is designing a new engine nacelle production line. Starting from Leonardo's current production facility (Venegono plant), the plant is being totally rethought, decreasing manual activities and introducing new production techniques.

Relevant for the Fluently project is the development of a virtual production line which involves the following:

Virtual reality (VR) of the entire production line (Tecnomatix Process Simulate SW), contents:

- Representation of the machines (AMR, bridge crane, cobot, etc.), parts and people with more definition and details in the areas where training is possible;
- Visualization of ergonomics;
- Green-field: representation of the production environment (i.e., walls, industry structure);
- Components in production represented with an intermediate level of detail;
- Dashboards (tools include Kibana, Grafana, etc.) showing information about machines, energy consumption, production data or overall status in real time.

TRAINING VR: panels guiding the operator in step-by-step operations, possible voice feedback from a virtual assistant, machines giving answers based on the given input.

- Performance Visualization: dashboard of production data (machine operating hours, maintenance information, display of number of assembled parts, information on number of workers required, etc.), sw: Plant simulation.
- Realization of the demonstration physical station to perform all operations: positioning, fixing, drilling, nailing, assembling parts.

Creation of **Augmented Reality (AR) software**, to obtain:

- Visualization with 3D viewers of the physical demonstrator (COBOT, AMR,...)
- Possible graphical visualization of real time data (e.g., the temperature generated around a hole, the missing time to the end of the drilling process, etc... (this requires interaction with external software – feasibility to be explored);
- Dashboard for each component for which one has info (serial number of the component being processed, material, etc.)
- Digital Twin of real machines: production control and optimization (e.g., a digital model of COBOT), performing virtual commissioning.
- Implementation of AI on the demonstrator (quality control, activity monitoring).
- Predisposition for machine learning (predictive maintenance, reduction of production errors over time)
- Immersive training (real bench and machines, CAD digital workpieces that the operator can get his hands on) guided procedure, alerts, warnings, help messages appear to the operator.

While it is not considered being feasible to introduce substantial changes to current production routines due to certification processes that are particular to the aviation industry, we will in the following take offset in an existing use case from an active production line and explore how Fluently could be utilized in such processes. The results are expected to be integrated in the virtual production directly and to be utilized in future production lines.

4.2 Current state

This use case focuses on production operations (assembly, fixing and control) on large objects in space. The material of the final items components is metallic (special alloys of titanium, aluminum, steel, etc.) and composite with the particularity of being flexible/deformable before assembly. Wide dimensional variability requires a particular focus on the correct positioning and locking of individual work pieces relative to each other.

The production is located in an indoor facility, with no temperature or humidity conditioning, in the presence of workers. Need for conditioning will need to be analyzed to reduce general or localized expansions of tools & materials causing deformations in objects. Solution might need aspirators in areas where liquid shims are positioned and polymerized. Other constraints (e.g. IP needs, ATEX) are unknown.

The objects are components of nacelles of aircraft engines: inlet cowl and fan cowl. The current total assembly flow has a duration of approx. 1 week. Configuration and dimensions can be variable per batch. Activities are currently carried out completely manually and with widespread use of hard jigs and hand tools.

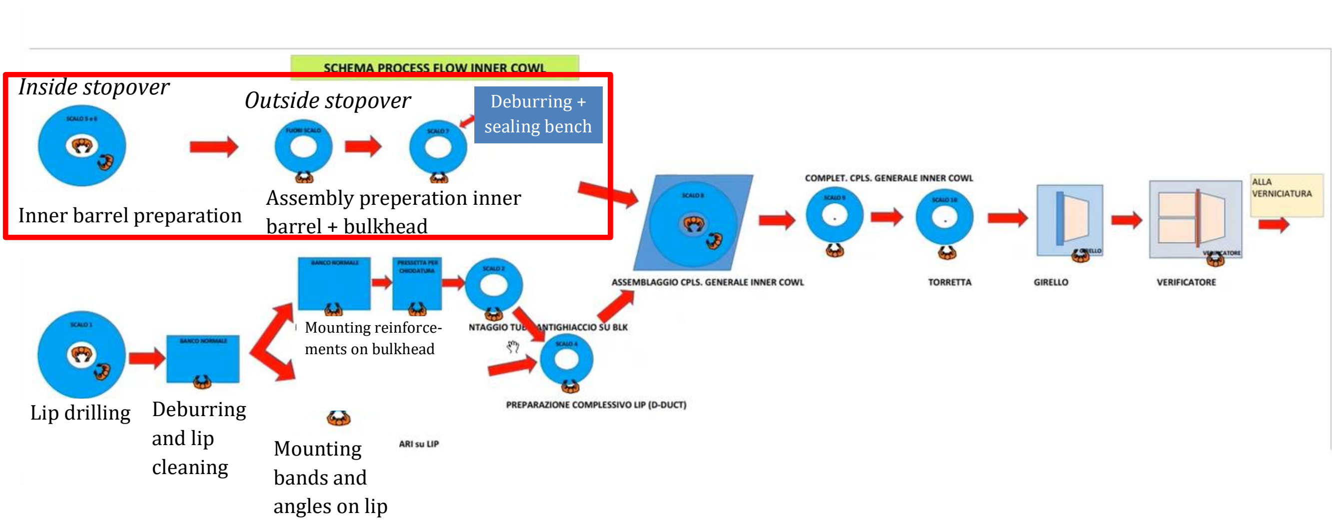


Figure 8: Schematic overview of the assembly processes. Top part. the preparation and assembly of the inner barrel (highlighted with the red box); bottom part: lip assembly.

The overall process of assembling a jet engine enclosure is shown in Figure 8 which schematically illustrates the assembly process, which core parts are involved in the individual steps, and how many workers are involved. Two of the main processes have been identified as being relevant for Fluently: the preparation and assembly of the inner barrel, covered in more detail below, and the assembly of the lip (details can be found in the appendix 9.4).

The assembly of the inner barrel consists of two major phases: A) the preparation of the inner barrel and B) the assembly of the inner barrel and bulkhead.

A) INNER BARREL PREPARATION:

The description of the inner barrel preparation consists of two main parts: 1) the initialization involving fixtures and the proper alignment of the workpieces and 2) the actual assembly operations.

1) Fixtures (jigs), equipment and initialization:

- Perimeter platform for external processing
- Internal liftable platform for internal machining
- External fixed jigs (casting + NC machining) with guide bushings
- Internal fixed jigs (casting + NC machining) with guide bushings
- Hand-pushed pneumatic drill (by trained operators)
- Tube-suction
- Engine ring referenced by means of two pins, panels referenced by means of slot and angle brackets
- Loading and unloading pieces. by hand (2 workers)

2) Assembly operations

1. Placement of 2 acoustic panels (cf. Figure 9, part 1) Motor on slipway (upside down)-slot placement;
2. Motor ring positioning;
3. Button-hole tacking ring 4.05;
4. Positioning 2 bands Panel junction;
5. Ring disassembly for addition SHIM LIQUID on panel and release agent on ring;
6. Reassemble ring and perform fastening --> (curing 8 hours + *Drilling 4.05*);
7. *Drilling from inside with jigs between ring and panels 2.5 all holes + 4.05 top only*;
8. *Drilling strips with masks 2.5*
9. *Drilling* from outside with pilot holes between joint bands and panels. 2.5 all holes + 4.05 on top;
10. Place External banding (with shim) on panels;
11. *Drilling from outside with jigs between Joint Bands and panels*;
12. Perform fixings between motor ring and panels (pins per position);
13. Perform fixings between panels and bands only in the upper half with blind area rivets;
14. Perform fixings between panels and outer perimeter bands;

This procedure is followed by a quality check in terms of a visual inspection.

B) B ASSEMBLY OF INNER BARREL AND BULKHEAD

The description of the assembly of the inner barrel and the bulkhead consists of two main parts: 1) removal of temporary fasteners 2) the actual assembly operations.

1) Initialization outside fixture (jig) for completing inner barrel

1. Remove thorns and retail ring holes 4.85 from inside + make a calibrated countersink;
2. Removing the first part with basters and riveting 2 types;
3. Apply MLGPL collar pins to entire ring with screwdriver;
4. Stoningflange heads with probe;
5. Bulkhead left frame preparation;
6. Place left frame on bench; Nail 4 MS oilers.

2) Assembly processes

1. Flip and Place Inner barrel on fixture, inserting plug for P2/T2 Probe and plug + locking with destaco

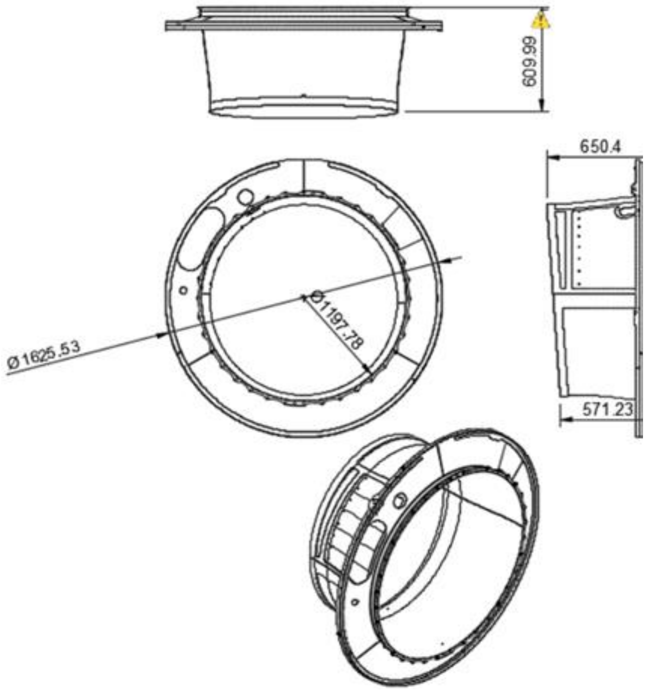
2. Place 3 BLK sectors on Inner Barrel, and stop angles for Fan cowl on perimeter stop
3. References with sliding saddles for angular position and locking with screw dowel + Teflon
4. Position Stiffeners, Pocket Support and Splice, via pilot holes and tooling
5. *Drill cpl. holes to diam. 4.05*
6. Disassemble parts, clean, Deburr and apply SEALANT MC238A2 on bench to side
7. Perform BASTING and Riveting/ Nailing East and Int. perimeter with 3 types of Rivets
8. In the 3 joint areas Re-tap at 4.05 per rivet type
9. After Check, pull out from stock and complete with 2 Joints and Clip support;

This procedure is followed by a quality check in terms of a visual inspection.

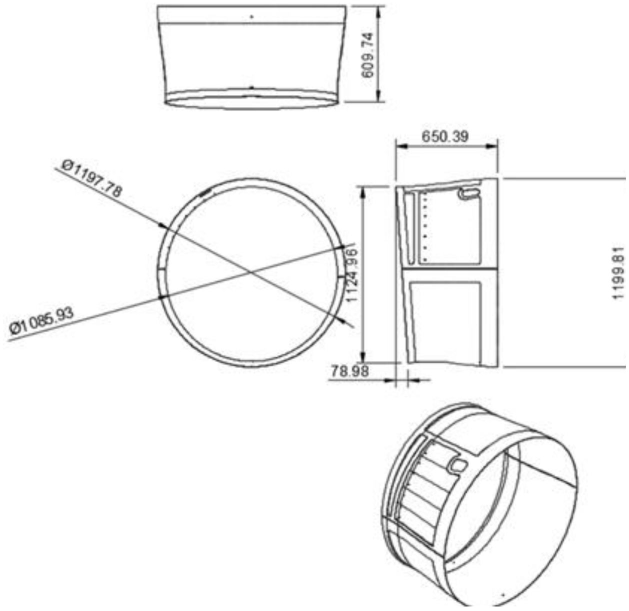
The total footprint of the assembled product varies approximately between 0.5 m and 3m inner diameter, a length/height of 0.7m and 1.0m and a weight between about 35Kg and 300Kg. Therefore, many transfer processes of items are done manually as long as their weight and size is limited, otherwise a portal crane is being used.

Related to the produced part that will be dealt with in the demonstrator station, the weight is about 20kg – the main components involved are illustrated on Figure 9 below. Example tools and fixtures are shown on Figure 10.

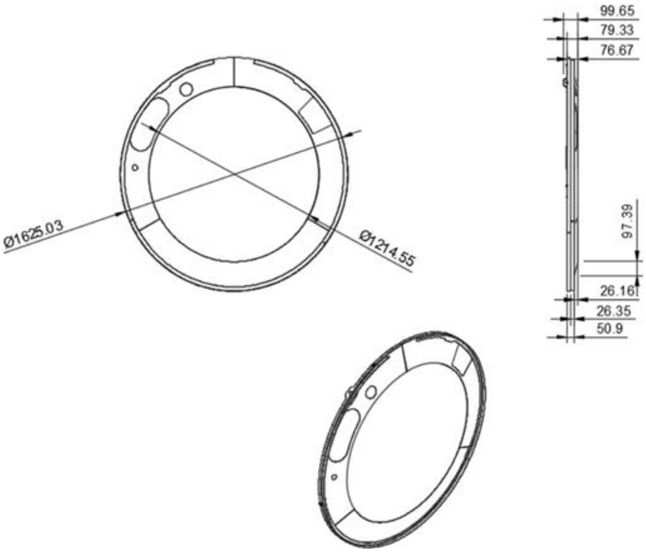
Overall Assembly:



Part 1 - Acoustic panals (two parts):



Part 2 - Bulkhead:



Part 3 - Engine ring:

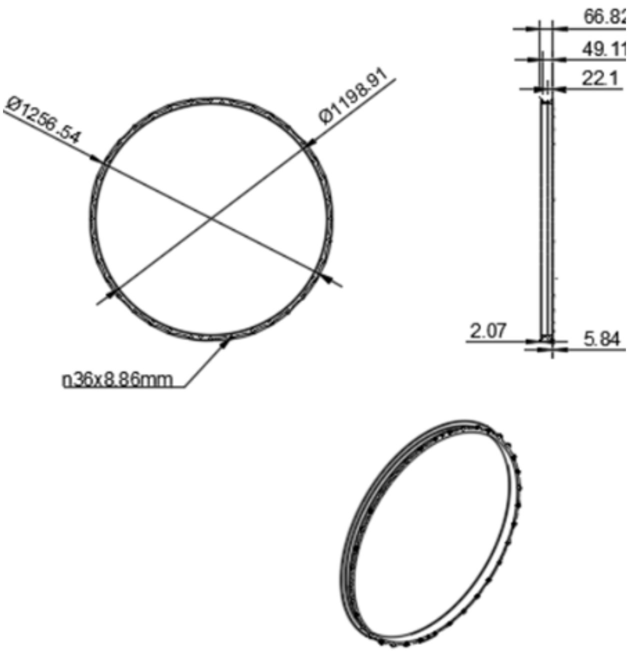


Figure 9: Drawings of the main components used in the above assembl processes. Upper left: Completely assembled module, 1-3: individual components involved.

Each component has different and variable dimensions and weights (from a few cm to over 1 m, from a few tens of grams to a several kgs). The tolerances on the product are strictly depending on the Design & Aircraft Program but are in the order of tenths of mm by position and shape, based on the size of the object. Special procedures have been developed to ensure that these requirements are met. This involves using temporary fasteners and smaller holes cut using CNC to ensure a correct alignment and subsequent drilling of holes to the correct diameter and applying additional temporary fasteners.

The overall procedure outlined above is summarized in a visual representation of the workflow, see Figure 11.

Figure 10: Top Left: Pneumaic drilling tool (weight: approx. 5-6 Kg). Bottom left: temporary fasteners and clamps. Right: Fixture (jig) for assembling the Front Bulkhead. The fixture includes numerous holes for guiding the drilling operations. The design of the jig allows for worker to approch the parts from all sides, also form inside the jig. Many of the fixtures designed for handling the assembled parts would be similar in size and shape.

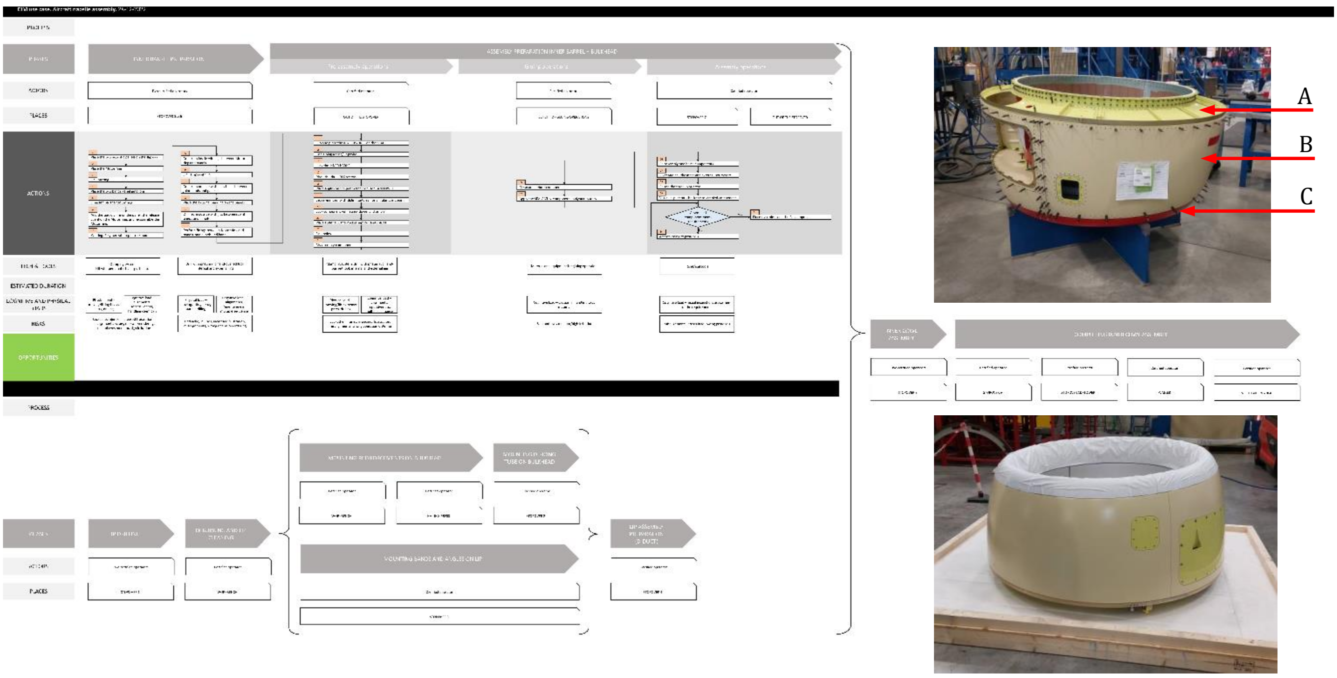


Figure 11: Overall process workflow for the preparation of the Inner Barrel and Bulkhead and their assembly. The top right image shows the assembled Bulkhead (A), Inner Barrel (B), and Lip (C). This figure is also provided in higher resolution in the appendix.

4.3 Future state with the Fluently system

The future assembly system has to be flexible & able, starting from separate individual components (from internal fabrication and/or supply chain), to produce end-items of different Aircraft Program with very short set-up and none or very few configuration's mistakes.

Use of industry 4.0 technologies (collaborative robots, AI, AR, VR, IoT, MES, Additive Manufacturing etc.), if cost effective, could be useful and appreciated. Proposed solutions must be user friendly and easy to achieve the promised targets (short implementation and quick learning curve).

The long-term target is to automatize parts or ultimately the entirety of the assembly & fixing steps to reduce overall nonrecurring specific cost, assembly flow and cost, floor space and to have a proper level of digitalization and Vertical / Horizontal integration. The solutions have to be flexible to permit assembly of several models of end-item in the same period, robust, affordable and reliable (OEE / OLE of the full production system greater than 90%), eliminate or drastically reduce non-value added activities, and improve quality level, safety and ergonomics.

The solutions must allow for reconfiguration for a range of products and be designed to be easily expanded in case of production rate increase and/or introduction of a new model. No a priori preference regarding gripping solutions are defined until now, but the components must not be damaged during the handling and positioning and the safety has to be warranted. Solutions will have to take into account the need for object identification and traceability and will have to perform quality check on the product (in-process and final check). Furthermore, the solution must be integrated into the production flow and coexist with manual activities. Aerospace grade quality is required: minimum ISO 9001 quality certification (ISO 9100 might also be required).

Fluently is considered to enable robots to be introduced into this context where relevant processes are those that involve two persons – where one is to be replaced by a cobot – or lengthy, repetitive tasks where a human worker can be supported by a cobot. The main idea is to free human resources which then can used for another process – currently, the limited number of available trained staff prohibits upscaling the production. In particular relevant for Fluently is the combination of high-level symbolic information (via speech) and low-level sensory information (vision, force or biophysical signals). By means of the Fluently device, it is possible to train the cobot to interact efficiently with the particular human worker. It will understand his or her utterances due to the personalized speech recognition and will communicate back in a coherent, understandable and appropriate (since personalized) form. By analyzing speech utterances and biophysiological signals (and potentially also vision-based mood recognition) the robot will be able to judge the psychological and cognitive state of the human and to adapt to his/her demands. A particular challenge will be the synchronization between speech, vision and force interaction.

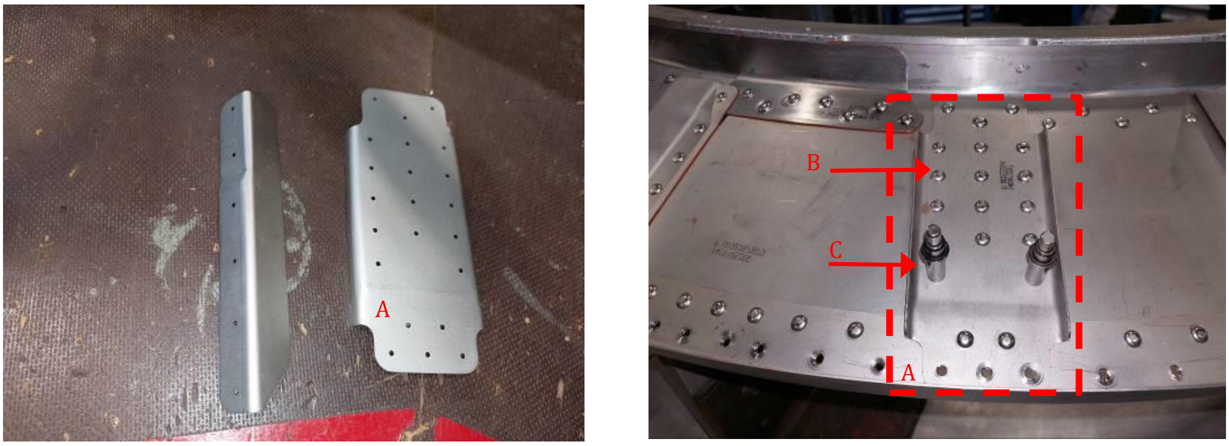


Figure 12: Left: two doubler parts with small holes using CNC machine. Right: Doubler part (A) mounted on Bulkhead with both permament rivets (B) and temporary fasteners (C).

In the following we will focus on the drilling operation since it is both reoccurring in many parts of the overall assembly process (highlighted italic above), time consuming and physically demanding for the worker.

Considering the individual drilling processes, we foresee the following steps

1. The human worker picks up components, such as the doubler, and places it on the jig together with rest of lip.
2. The human worker verifies the correct placement.
3. The human worker locks the position of the doubler on the lip with temporary fasteners.
4. The robot drills a set of holes
5. The human worker installs temporary fasteners, one for every second hole
6. Repeat step 4 and 5 until completed; temporary fasteners are removed again during the process.

CNC alone has insufficient precision, such the above process with drilled holes is performed. Introducing a cobot for the drilling has the advantage of a) relieving the human worker from the physically demanding task of operating the rather heavy pneumatic drill (with a weight of ca. 6 kg) and b) saves time since the worker doesn’t have to switch between the two tasks, drilling and inserting fasteners. For the interaction with the cobot to succeed, the cobot needs to adapt smoothly to the joint workflow with the human without relying on explicit command which can be expected to be inefficient at scale (some operations involving drilling and mounting fasteners take op to 9 hours to complete for one component), but also to respond to, e.g., verbal command, e.g. when the work flow has to be interrupted.

Once this use case is successfully addressed by the Fluently technology, it can be generalized to many other cobot situations in which similar assembly operations are utilized, but also tasks where robots and humans cooperate, e.g., joint manipulation of heavy objects that are currently performed by two or more human workers.

We see the individual drilling processes as the ones with the highest benefit for the end-user (in terms of cost reduction and work environment improvement) as well as for the project as such due to the multifaceted interactions required (the mixture of speech, gesture, biophysical signals allowing for an as smooth as possible workflow).

5 Use Case 3 (Prima Additive) - damaged metal part inspection and repairing

5.1 Company information

Prima Industrie is a world leading group in the development, production and marketing of laser systems for industrial applications and sheet metal working machines. The Group has 40 years of experience and over 13,000 machines installed in more than 80 countries and among the world's leading manufacturers in its reference market and has been listed on the Italian Stock Exchange since 1999. Prima Industrie today has four business units:

- *Prima Power* for the production of industrial laser and sheet metal machinery;
- *Prima Electro* with activities dedicated to industrial electronics;
- *Convergent Photonics* for the development of new laser sources and diodes;
- *Prima Additive* for the development, production and sale of Additive Manufacturing machinery.

Prima Additive:

Prima Additive was established in 2018 based on a merger of 3DnT innovative start-up founded in 2015 and Prima Additive, one of the divisions of the Prima Industry Group with the objectives of design, development, engineering, production, marketing, installation and technical assistance of machinery, equipment, systems and mechanical, electrical, electronic and optoelectronic systems. Founded with the aim of attacking a rapidly expanding market of additive manufacturing of metal parts, the company has developed a very accurate development plan, first identifying the needs of industrial customers in the high-end aerospace and automotive sectors and subsequently technical solutions that are able to satisfy those needs. Today Prima Additive is part of a company group Prima Industrie S.p.A. with more than 1800 employees in total.

Prima Additive Technologies

Prima Additive Technologies **uses two technologies:**

*The **Powder Bed Fusion (PBF)*** process uses thermal energy to melt specific points on a layer of metallic powder. The thermal energy – produced from a laser source – melts the powder material, which then solidifies as it cools down and this way, each area of the part is manufactured. The part is built up into layers and so this process is repeated for each layer to create the part. After the melting of one layer, the platform lowers, and the powder recoater deposits a new layer.

The ***Direct Energy Deposition (DED)*** process uses focused thermal energy generated from a laser source to fuse powder metal sprayed at the focal point of the laser beam. This laser beam melts the deposited powder to the component. The laser is coaxial to the deposition head which moves in 3 to 5 simultaneous axes. A rotary tilt table can also be installed in order to keep the melt pool created in a horizontal plane. This capability makes the process suitable for adding features to existing parts as well as for repairs and coatings.

IANUS Cell

The IANUS cell (see Figure 13) is part of the second family of technologies developed by Prima Additive (DED solution), a compact DED platform based on a robotic cell suitable for 3D fabrication, reworking and R&D applications.

Figure 13 Prima Additive IANUS production cell

The IANUS cell:

- is an open platform with a robotic arm equipped with different technology solutions
- allows for precise, flexible, multi processes manufacturing (i.e., multiple manufacturing processes that can be carried out in the cell (additive manufacturing and welding for example).),
- can perform four different integrated processes: DED Powder, DED wire, Laser Heat Treatment, Laser Welding
- is also available with REAL_DED head

5.2 Current state

The online questionnaire session was the first opportunity for the project partners to get acquainted with the operating activities of Prima Additive (PA). With a solid presence on the hybrid additive manufacturing market, PA proposes solutions and services related to repairing applications for various sectors such as Oil&Gas, Automotive, Mold & Dies, considering a variety of alloys such as steel, nickel, titanium, chrome-cobalt and copper.

Within Fluently, the PA use case targets the improvement of additive manufacturing repairing process workflow associated with two classes of operations: feature addition and coating respectively. In the figure below, two main applications are highlighted, to be considered as use case demonstrators across the project: repairing of an impeller and the coating of a shaft.

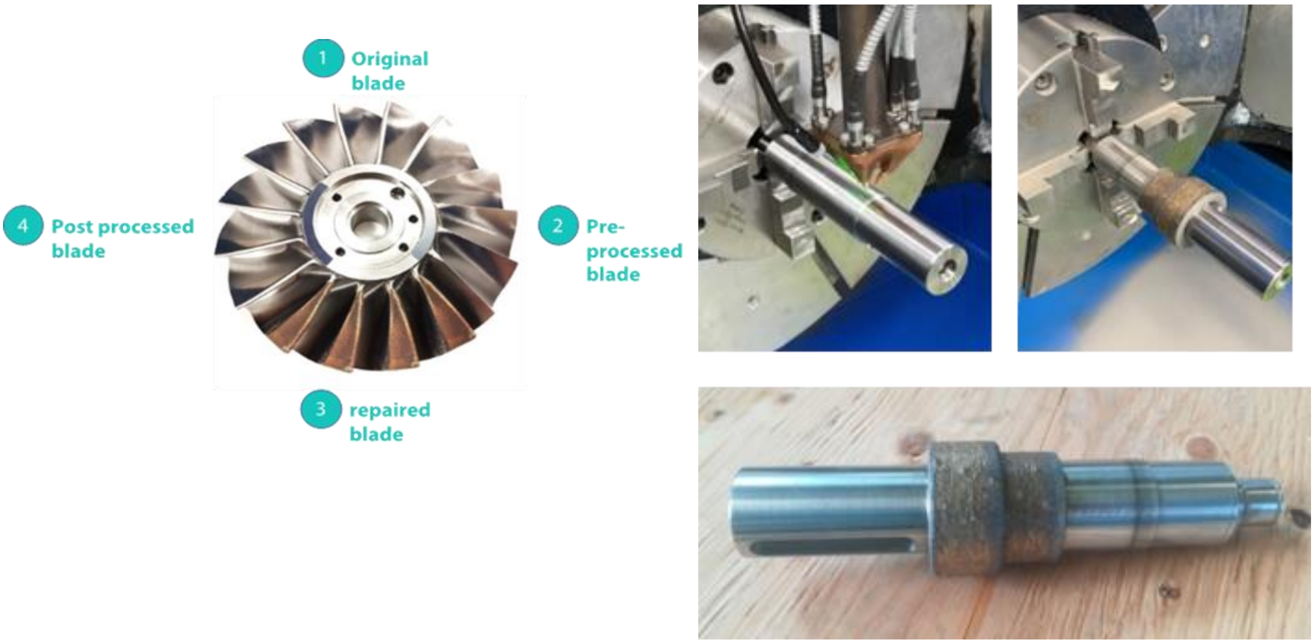


Figure 14: Prima additive part demonstrators: (left) impeller with main repair stages, (right) shaft before and after coating

While the Ianus cell offers high levels of process automation and flexibility (with the possibility to extend the number of axes from 6 to 8 with the support of a roto-tilt table during the execution of the deposition process), most of the workload of the application engineer is of a cognitive nature and is associated with manufacturing data preparation. Fundamentally, this preparation consists of the following sequence of phases: part inspection and defect analysis, reverse engineering, pre-processing (optional), repair process planning and preparation. Starting from the visual inspection of a damaged part and identification of the defect type, the application engineer must comply with a rather long decision path involving the step-by-step organization of a number of choices and their mapping to possible outcomes in relation to the best manufacturing strategy design and selection for a particular scenario. The blueprint in Figure 15 details aspects of high relevance for the PA use case.

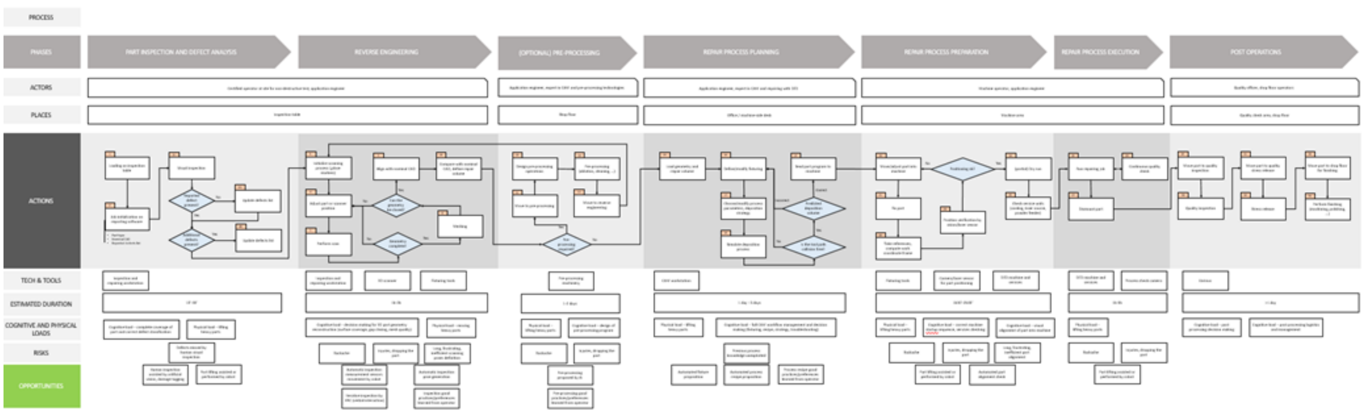


Figure 15: PA blueprint (a version which allows for zooming in can be found in the appendix)

For a better understanding, an example of the current state of the impeller blade repairing application context is provided below by introducing some of the most relevant steps and decision-making processes. Basically, the repairing process, as displayed in Figure 16, of the impeller blades (see Figure 17) consists of the following 12 steps:

1. Analyse the defect on the impeller. *This process is currently mainly by visual inspection and measurement (*Figure 17-*1)*
2. Decide on the repairing process, which is currently done manually based on the operators' experience:
   a. Prepare CAD/CAM file using the traditional engineering process software.
   b. Decide on parameters for IANUS (flow rate, laser energy, speed, hatching distance, layer thickness), based on operators' experience.
   c. Select the building strategy. *Often decided based on the knowledge of the worker and computer software. For every new job the ontology for repairing the impeller are re-defined, including, tool trajectories, placements of the objects, inner mechanical structures, etc.*
3. Check for singularities and possible collisions in the machine. *This is a general visual check to see if there is not anything obvious in the machine that could get in the way of the tools.*

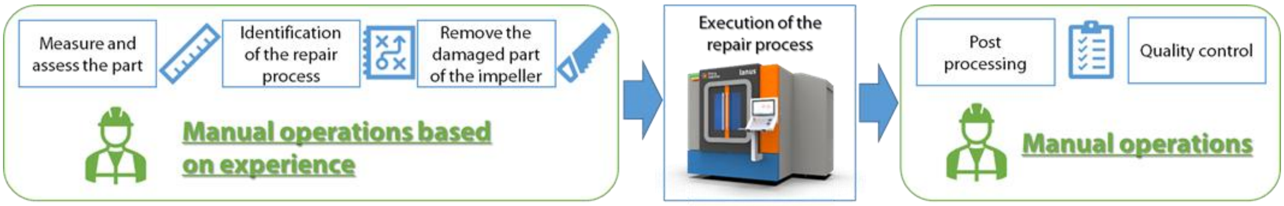


Figure 16: Current process

Remove defective part according to a known geometry (Figure 17-2).
The standard process used at Prima Additive is to remove material to the depth of the largest defect and remove the same amount of material on each damaged blade.

5. Insert impeller part into the robotic cell.
6. Calibration and alignment of the part. *This is mostly visually verified by the operator.*
7. Dry run the trajectories for the building of the part. *This is a sanity check – last check for any collisions and that the tool path is okay before proceeding with the actual rebuilding process.*
8. Start the process. Continuously check quality during the process.
9. Finish process (Figure 17-3).
10. Quality inspection of part.
11. Stress relieving of part.
12. Post process the part in the machine shop. *This includes polishing and checking the impeller meets tolerances (*Figure 17-*4).*

As previously mentioned, the very first step in the repairing workflow is to visually inspect the damaged part and ascertain the presence and type of defects. Common defects for an impeller, which can be identified based on a visual inspection, are sign of corrosion and wear, as depicted in Figure 17:

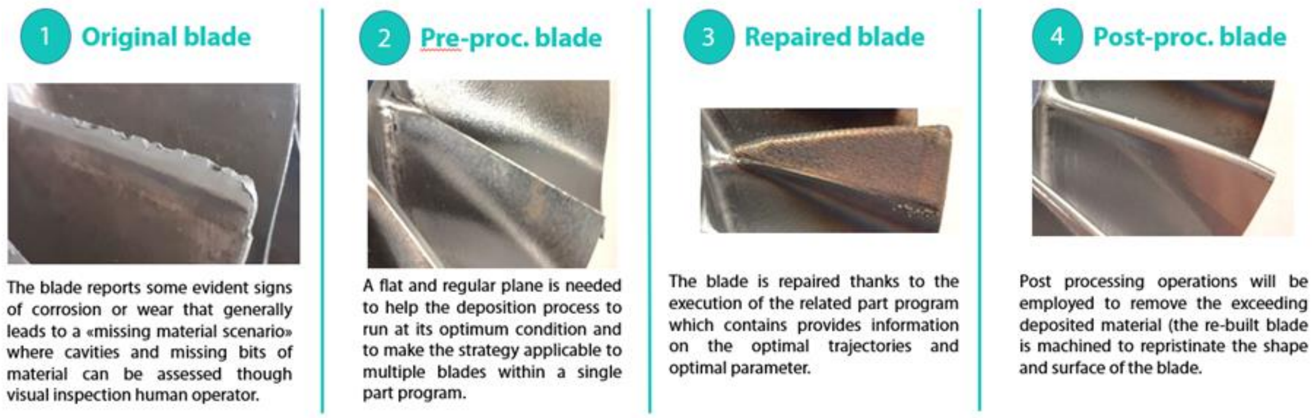


Figure 17: Selected steps in the repairing workflow of an impeller

Next to the visual inspection a more detailed inspection is required to measure the actual integrity, shape and dimensions of the part to be processed. These evaluations are in general performed by an operator/application engineer, but this process is time-consuming and quite expensive. Moreover, these inspections can be unreliable, for example, due to lack of training, fatigue, or unclear specifications.

Vision systems are recommended for critical inspections (enabling a repairing process) but a current problem with most vision systems that limit the use fixed cameras, making the system inflexible in its way of working. A fixed camera system, or other non-contact inspection instruments such as interferometers or pattern projection scanner, has problems reaching inaccessible areas of the product, such as the underside, inside, and around the product to be inspected.

The possibility of using 6 or higher DoF robots introduces flexibility into the inspection process: the integration of the quality control system to the robot control system significantly improves the performance of the entire manufacturing phase. Different solutions capable of reconstructing objects with specific levels of accuracy are already available. However, there is a high interest in the industrial and scientific communities to push even further these developments by integrating dedicated AI models and software modules to automate the generation of effective inspection and measuring strategies in function the part topology while mimicking with accuracy the motions executed by highly skilled technicians.

5.3 Future state with Fluently system

Based on the aforementioned considerations, an emergent need for a decision support system and the setup of a collaborative robotic inspection station capable of providing support to the application engineer during the inspection activities and subsequent decision-making activities pertaining to the preparation of the manufacturing data was identified.

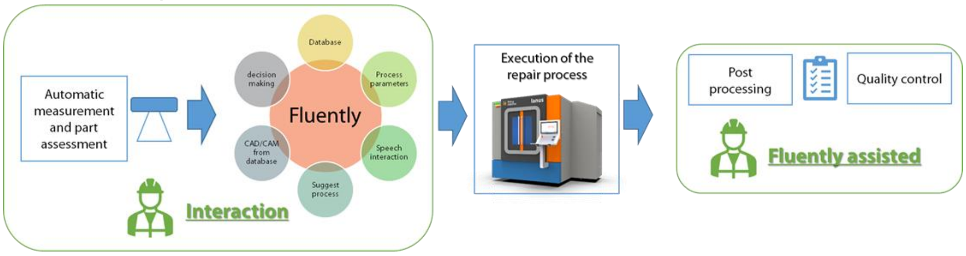


Figure 18: Future state of the process with applying the Fluently technology

The opportunities for improvement, enabled by Fluently technology, are introduced by proposing a future state workflow with focus on the decision-making aspects (Figure 18) similar to the one discussed in the previous section with respect to the repairing of the impeller's blades:

1. Analyse defect on impeller. *Rather than manual measurements, Fluently will use a vision system to recognise the part and the type of defects on the blades. With the addition of an robotic inspection station, Fluently may recognise how many parts are in the station and which ones need to be repaired.*
2. Decide on the repairing process. *Each of these steps involve Fluently making decisions the worker would usually do themselves based on their prior knowledge. Instead, Fluently suggests strategies, communicates these via a human machine interface with the worker and then the strategies can be accepted or rejected.* The strategies are represented as a digital model representing ontologies of the entire DED process carried out in the previous machine jobs. Based on this model ontologies for new jobs will be suggested to the operator.
   a. Prepare CAD/CAM file. *There will be a database of potential files and models for the part from which the 3D information can be extracted and used in the later process.*
   b. IANUS cell parameters setup (flow rate, laser energy, speed, hatching distance, layer thickness). *Fluently will recommend parameters based on the knowledge about the process and what has already previously been used and can be found in the database. A form of "auto-complete" for this process.*
   c. Select the material for building the re-building the impeller blades. *Fluently will propose the proper material and the amount used for the repair job, based on the pervious settings from the database.*
   d. Select the building strategy. *Based on the information from previous steps, Fluently recognises possible strategies and decides/advises on tool path selection. If the tool path cannot be reused, the Fluently system will guide the operator via speech, threw a manual trajectory definition process.*
3. Check for singularities and possible collisions in the machine. *The area inside the robotic cell will be scanned by Fluently and voice notification will be given to the operator if there are obstructions in the machine.*
4. Remove defective part according to a known geometry. *The actual process stays the same (this aspect is not considered in the use case). However, Fluently may advise the amount material to remove off each part/blade based on a 3D scan.* In this way production time and material usage can be optimized.
5. Insert impeller part into the robotic cell. *The collaborative robot of the inspection cell could load the part in the Ianus cell with Fluently supporting the part placement and clamping through voice commands.*
6. Calibration and alignment of the part. *Fluently can confirm when the part is placed correctly and where the DED process should start.*
7. Dry run of the trajectories for the building of the part. *Fluently will provide voice feedback to the operator if the dry run was successful.*
8. Start the process. Continuously check quality during the process. *Fluently aids in the check and measures the part during the process.*
9. Finish process.
10. Quality inspection of part. *Potentially to be carried out by the collaborative inspection robotic cells*
11. Stress relieving of part
12. Post process the part in the machine shop. *This includes polishing and checking the impeller meets tolerances.*

6 KPIs

In Fluently, we will measure the outcome by means of 12 Key Performance Indicators (KPIs) as defined below.

KPI 1: Programming effort

A production plan needs to be flexible to production changes and demands. A hidden cost of production can be identified in the time needed to replan and reorganize a workflow for the production of a new component. For example in the context of the MEM use case, the plant should be flexible to variation in the battery cell model and accommodate easily the arrival of unexpected types and model. The planning time needed to adapt for the dismantling of a new model can be computed as the time needed in order to replan and reorganize the production for a new cell and it a measure of flexibility.

KPI 2: Fast response to repurposing changes in production requirements

For Leonardo's nacelle production (CIM-use case), the process will be reconfigured using new production tools and machines. The workers' activities will also have to change to adapt to this new process, designed to increase versatility and production rate.

For the Fluently project, the following will be implemented:

1. A physical demonstration workstation, which is a significant unit of the production line;
2. virtual reality programmes of the entire future production line (allowing to monitor key production parameters, the possibility of training, immersive tours visualising the line, ergonomics and interfaces).

The KPI for identifying the speed of response to change can be determined when using the demonstrator station by comparing the production time estimated in virtual reality programmes and the actual production time for that specific station.

The KPI range can be from 0 to 10, with:

- 10 := extreme indicating the ideal production rate for that station, estimated on the VR (plant simulator);
- 5 := current value of the production rate on a fully manual workstation;
- 0 := lower limit of the range, with the production time of a component on a lower station than the current one.

the KPI can be evaluated as the difference in performance obtained between VR and reality as following:

$$KPI\ 2 = \frac{1}{1 + e^{-5\Delta t\, -\, 1}}$$

$$\Delta t = \frac{Time_{Real} - Time_{VR}}{Time_{VR}}$$

In this way if $Time_{VR} = Time_{Real}$, the KPI will result in a score of ≈ 0.73, decreasing in case the real time is more and increasing in case it is less.

The production time is calculated from the positioning of the component to the removal of the assembly from the station. In the case of long waiting times (e.g. for curing adhesives), the time is calculated at the end of active operations. Initially, production times are expected to be in the range of 0-5, as there is an adaptation transition for the new operations to be carried out. Then, following training, times will decrease exponentially, tending towards the ideal time from the VR programme

KPI 3 - Configuration time for a new product.

While the process inside of the Prima Additive's IANUS cell is completely autonomous, an engineer must first decide on, determine, and design the reparation process. The current state-of-the-art process is structured in the following steps:

STEP Nº	STEP DESCRIPTION	ESTIMATED DURATION
1	Analyse defect	10 to 30 min
2	Decide on repair process: Prepare CAD/CAM file (separate original model) Decide on parameters (incl. flow rate, laser energy, speed, hatching distance, layer thickness) Select building strategy (coverage planning)	1 to 5 days
3	Check for singularities, collisions, etc., during additive process	1 hour
4	Remove defective part. Piece now has known geometry from step 2	1 to 5 days
5	Insert part into the IANUS cell	5 to 10 min
6	Calibration (alignment of the part) Verified using vision	5 to 30 min
7	Rehearse trajectories for additive process (sanity check)	10 to 40 min
8	Start deposition (additive process) Continuous quality check (visually)	Depends on part (no influence)
9	Stop deposition (additive process)	3h
10	Quality inspection	to be defined
11	Post processing	to be defined

The configuration of a new product includes steps 1 to 3, and it takes on average 21 hours (value provided by Prima Additive). In step 1, the engineer preforms a visual analysis of the part and the existing defect. As can be seen from the table, step 2 is the one that causes the biggest delay in the process. It is a purely manual task, in which the engineer uses a software to design the repair process. The design relies heavily on the experience and the decision-making of the engineer. For step 3, a simulation is used, without any influence from the engineer.

Fluently aims primarily to optimize step 2 (and possibly step 1, using a vision algorithm). The Fluently engine will assist the human engineer with the decision-making process. By learning from previous repair tasks, it will be able to recommend the best parameters and strategies. The engineer will retain the power of the decision, but this will help to streamline the process.

For KPI 3, the following 0 to 10 scale is introduced:

- **10:** With Fluently, the average duration for the configuration of a new product lowers to 8.4 hours.
- **5:** The average duration for the configuration of a new product stays the same at 21 hours.
- **0:** The new average duration for the configuration of a new product doubles to 42 hours.

KPI 4: Self-awareness

The degree to which a robot can accurately assess itself will have a direct impact on the ability of the human to efficiently interact with the robot. The less a robot is aware of its capabilities and the less it can recognize when it is having trouble, the more human monitoring and intervention is required. Self-awareness is particularly important when a robot must ascertain if involving the human is useful. Characteristics that express self-awareness are

- Understanding of intrinsic limitations (mobility, sensor limitations, etc).
- Capacity for self-monitoring (health, state, task progress) and recognizing deviations from nominal.
- Effectiveness at detecting, isolating, and recovering from faults (during both planning and execution).

This KPI can be evaluated considering the number of times the robot requires the human intervention in case of faults and deviations from nominal operation, instead of performing the operations autonomously.

Considering a binary score given by the human operator (i.e., needed/not needed) the KPI can be evaluated as:

$$KPI\ 4 = \frac{\#\ times\ the\ operator\ considers\ the\ human\ intervention\ necessary}{\#\ total\ number\ of\ human\ interventions}$$

KPI 5: Human awareness

The robot is sensitive to the human's presence and has knowledge about the human's commands needed to direct activities and any human-delineated constraints that may require command noncompliance or a modified course of action (e.g., go straight for 6 feet and there's a wall after two, so it stops at the wall). The level of "awareness" depends on the level of autonomy that the robot is expected to achieve, and the roles played by the humans. This capability can be dynamic and may include a user model that helps the robot recognize human behavior and react appropriately. Human-awareness can be identified as different tasks that FLUENTLY has to perform:

- Human-oriented perception (human detection and tracking, gesture, and speech recognition, etc.).
- User modeling and monitoring (cognitive, attentional, activity).
- User sensitivity (adapting behavior to user, measuring user feedback).

Most of the tasks that involved in the definitions of this tasks can be reduced to a classification problem (i.e., identify the human position, state and identity), therefore traditional metrics, such as accuracy, can be deployed.

The Human Awareness KPI can therefore evaluated as a weighted mean for the accuracy of the different tasks present in the context of human awareness, as following:

$$HA = \sum_{i=0}^{N} w_i Accuracy_i$$

with $\sum_{\mathrm{i}}^{\mathrm{N}} \mathrm{w_i} = 1$, i $\in$ {set of tasks T} and $Accuracy_i$ defined according to a metric specific to the task at hand. The correct definition of the set of task T will be developed in the context of the FLUENTLY project.

KPI 6: Robot's Perceived Empathy

Empathy is defined as the capacity to understand and appropriately respond to the affective states of others (Złotowski et al., 2016). Empathy involves the consideration of others' affective states and the situation, leading to cooperation, prosocial behavior, altruism, and a positive relationship. To establish effective human-robot collaboration, it is critical for the robot to empathize with human partners. This includes recognizing human emotional states, thoughts, and situations and behaving accordingly (S. Park & Whang, 2022). The extent to which humans perceive robots as empathetic, can be described as a robot's perceived empathy, which is an emerging topic of interest in the fields of robotics and artificial intelligence.

Empathic capabilities can be divided into two analytic categories: (1) emotional capabilities, with the ability to share the affective experience of someone else; (2) cognitive capabilities, with the ability to represent and understand the mental states of someone else and their perspective (Charrier et al., 2019) Cognitive empathy has many subcategories, including empathic comprehension and empathic response (see Figure 19).

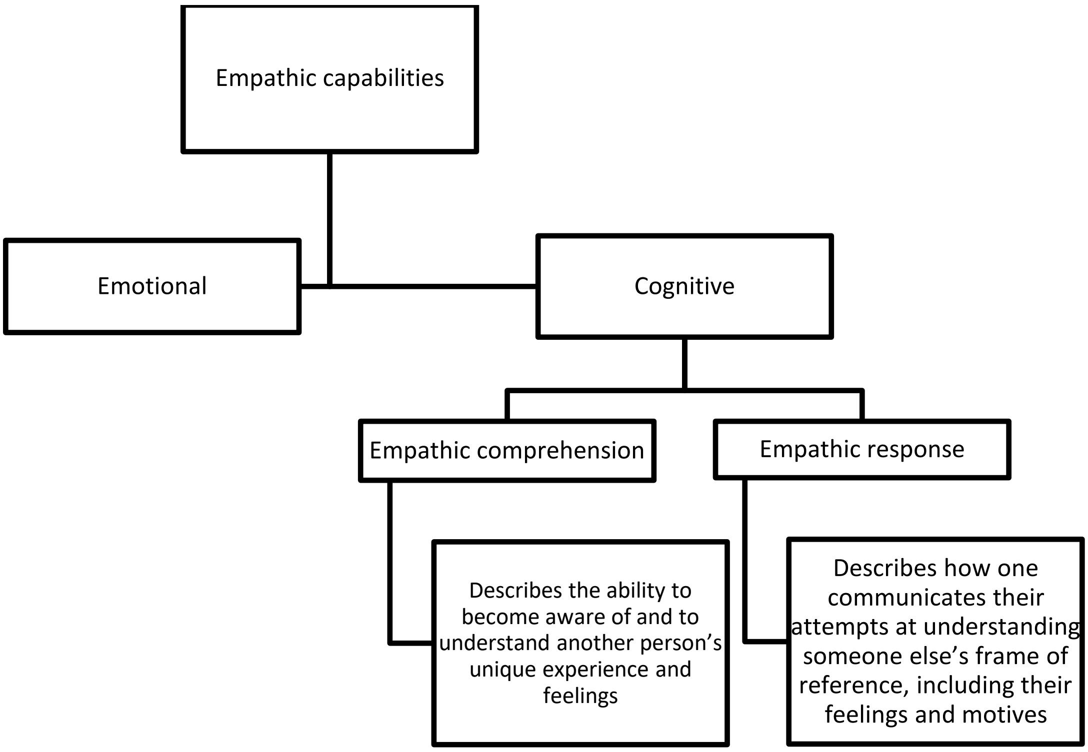


Figure 19: Emphatic capabilities in Human-Robot Interaction (based on Charrie et al., 2019)

Research has found that the way in which robots are designed and interact with humans can influence how their empathic capabilities are perceived (S. Park & Whang, 2022). The appearance of the robot plays an important role in this (Misselhorn, 2009). For example, in an experiment conducted by (Złotowski et al., 2016) a highly humanlike robot was perceived as less empathic than a more machinelike robot, suggesting that more machinelike robots might be more suitable as companions than highly humanlike robots.

Another body of research suggests that robots that are able to recognize and respond to human emotions are likely to be perceived as more empathetic. In addition, how robots communicate with humans also affects how empathic people perceive them to be. For example, robots that use more human-like language, such as first-person pronouns and empathetic statements, are perceived as more empathetic than those that use more robotic language (Kopp et al., 2022). Research also shows that human-like language and behavior as well as robot empathy can positively impact the level of trust human place on a robot (e.g., (Hancock et al., 2021; Sanders et al., 2011)). Thus, robot empathy, as well as robot characteristics that can increase perceived robot empathy, may positively impact trust.

All empathic interactions occur within a specific situational context or behavior. Therefore, the context in which robots are used also plays a role in their perceived empathy. In the HRI context, this indicates the type of robot's tasks and goals involving the empathic processes and where and when such interactions occur (S. Park & Whang, 2022). For example, robots used in therapeutic or caregiving roles are perceived as more empathetic than those used in more technical or mechanical roles.

Overall, research suggests that multiple factors influence robot perceived empathy, including physical features, communication style, and context of use. This has some practical implications for technology designers. By designing robots that are able to recognize and respond to human emotions, researchers can increase their perceived empathy and enhance the effectiveness of their interactions with humans.

The KPI can evaluated using the RoPE scale with a 4-item Likert scale and evaluating a normalized score for the perceived empathy.

KPI 7: Process recipes acceptance index

To measure this KPI, once Fluently has been established and is aiding in the decision-making processes and suggesting strategies, the acceptance of the proposed recipes can be recorded. We will measure whether the operator accepts or rejects the proposed process developed in by Fluently on a scale between 0 and 10.

This will involve surveying those working with and training on the Fluently system to score how they would accept the solutions proposed compared to their current workflow. Additionally, the data can be obtained from the Fluently system recording stress, cognitive load and wellbeing to measure whether strategies suggested are accepted or not.

- 0 all suggestions not accepted
- 10 all suggestion accepted

In general, the expected grade to start with will be quite low, likely around 2, due to uncertainties over a novel process as such. Then over time this grade will increase as the database expands and learns new recipes. After integration of the robo-gym and the workers being trained in this, there will likely be more trust in the Fluently system, so the acceptance rate will increase to around 6 during the training process. It is expected that once Fluently is fully integrated and training has continued for a while to learn new process recipes and obtain information about the humans work style from the robo-gym, the grade will reach 9.
Each use case is expected to follow a similar progression in the process recipes acceptance index.

KPI 8: Available technical knowledge

To measure this KPI, a grade will be given to each use case from 0 to 10 to judge the amount of available technical knowledge there is on the process.

- 0 is no available technical knowledge.
- 10 is all technical knowledge is available.

It is expected that the technical knowledge needed by the worker will be high for most use cases to start with as the decisions rely on their knowledge. But since through the Fluently technology, interaction is facilitated through the use of speech and decision making instead of programming through touchpads and keyboards, workers can rely less on detailed but instead general project knowledge. Hence it is expected, that the amount and the kind of required knowledge changes. While the amount of knowledge required can be quantified, the kind of knowledge needs to be measured primarily by qualitative means such as interviews.

KPI 9-11 (workflow changes acceptance, loads level analysis, exogenous perception) address the resilience of users towards workflow changes which imply an increased cognitive load and hence potential stress for the users. Stress is not only causing health issues, in the long run, it can also lead to human mistakes resulting in items required to be redone or even scrapped if the error is irreversible.

KPI 9: Workflow changes acceptance

The integration of technologies into work processes can fundamentally transform employees' tasks and roles. Specifically, *workflows* are affected in that different task processing steps are changed (e.g., in terms of human skills required), or delegated to systems (e.g., (Berkers et al., 2022; Parker & Grote, 2022)). To identify these workflow changes, we have developed a taxonomy (partially based on (Endsley, 2017; Onnasch & Roesler, 2021)) that differentiates different task processing steps as well as associated user and collaborative requirements.

At the same time, *whether and to what extent employees accept these changes* is a central prerequisite of actual system use, and thus a central challenge for the development of Fluently.

The theory of planned behavior (Ajzen, 1991) explains when individuals are willing to accept such changes. The theory has been applied to general work related changes as well as to the implementation of technologies, suggesting a central role of user attitudes for the acceptance of technological change (e.g., Technology acceptance model; e.g., (Venkatesh & Bala, 2008). Central to these theories is the individual's intention to engage in a new behavior. Three central factors influence intention to engage in a new behavior:

(1) Employees or users need to see the new behavior or a new technology as favorable;
(2) Employees or users need to perceive the new behavior or technology as desired by their co-workers and managers;
(3) They need to believe that they can (i.e., are able to) perform the new behavior/interact with the new technology (e.g., how easy using the technology is).

For Fluently, this can be translated into three core objectives that need to be considered in measurements. First, users will need to recognize the potential of Fluently to ease collaboration with the robot (measure: perceived usefulness; (Davis & Venkatesh, 1996)). Second, the subjective norm relating to the use of Fluently needs to be communicated effectively for users to recognize the introduction of the system as desired by others (measure: communication strategy; user understanding, etc.). Third, users need to feel able to effectively use Fluently and engage in the new behaviors (measure: perceived ease of use; self-efficacy (Davis & Venkatesh, 1996; Ulfert-Blank & Schmidt, 2022)), highlighting the central role of training.

Next to the acceptance of the workflow changes, users will also have to adapt to the workflow changes. Theories of adaptive performance describe how employees change their task-directed performance behaviors in response to relevant (actual or expected) changes in their task (or workflow). The theory further suggests a range of predictors impacting adaptive behavior (see Figure 20).

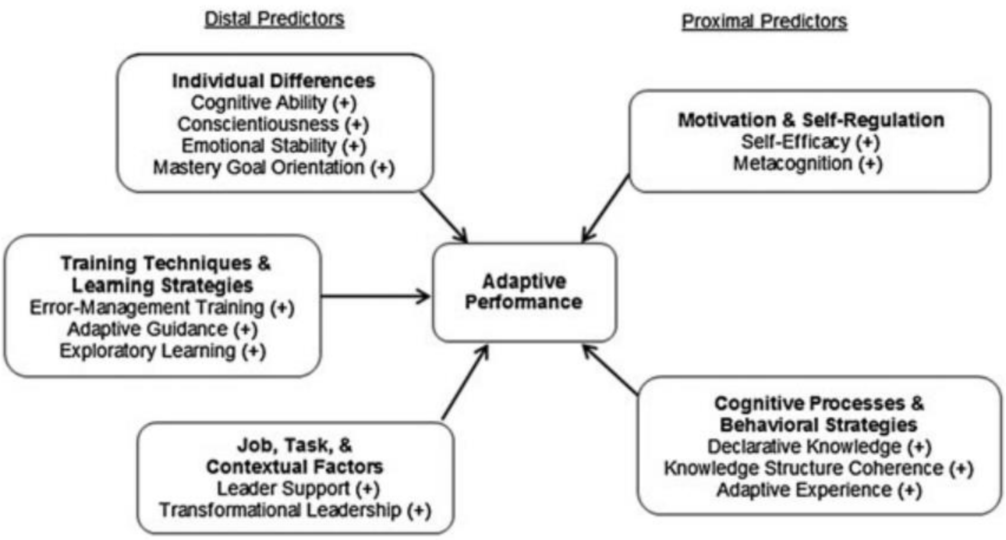


Figure 20: Predictors of adaptive performance (Jundt et al., 2015)

For Fluently, in order to guarantee a high level of job quality and employee wellbeing, these predictors are important considerations for the development of the training.

The KPI can be evaluated as the sigmoid of the regression score used in (Edwards & Parry, 1993) where the covariates of the regression will be chosen in the context of the project FLUENTLY.

KPI 10 Loads level analysis

When interacting with technologies at work, employees can experience a variety of loads (e.g., physical, cognitive). In the following we first discuss the underlying mechanisms that explain when users may experience overload before describing how loads levels are analyzed.

The Person-Environment Fit Model (P-E fit model) of stress is one of the most widely used models in stress research (Cooper et al., 2001; Edwards, 1991; Edwards & Cooper, 2013). This model is based on the premise that there is an equilibrium relationship between people and their environment (the context around the individual). When this relationship is out of equilibrium, it results in strain. This simple but powerful idea of P-E fit holds a central position in stress research and is reflected in other frameworks of stress (Edwards et al., 1998; Eulberg et al., 1988). Specifically, the lack of fit or the gap between the characteristics of the person and the environment could lead to unmet individual needs or inability to deal with job demands that may result in strain (Cooper et al., 2001). This view emphasizes the subjective evaluation of the P-E fit (i.e., how the individual perceives the situation) or misfit. This is particularly the case for the demands a certain environment poses to the individual and how well the individual's abilities fit these demands (H. I. Park et al., 2012). A misfit between the individual's abilities and the environment/ demands can lead to psychological strain and overload.

(Ayyagari et al., 2011) further emphasize the central role of technology characteristics in inducing stress in individuals. Building on the P-E model, they argue that usability, intrusive, and dynamic features of a system are linked to different stressors (i.e., role ambiguity, job insecurity, or workload).

In the context of FLUENTLY, both the environment and the demands posed by the technology and task need to be considered in relation to users' abilities. One important aspect being considered is the pace of change (understood as the degree to which an individual perceives the changes in their technological environment to be rapid; also see section on workflow changes). When changes are introduced quickly, the ability of an individual is reduced due to uncertainty regarding management of work and learning demands. In this context, new learning demands and increases in effort are triggered by the implementation of the system or by changes triggered by the interaction with the technology. A misfit between demands and resources (like abilities) leads to stress because of work overload, role ambiguity, and job insecurity. Further, aspects, such as system characteristics relating to privacy (e.g., due to monitoring) should also be considered.

Different measures have been developed to investigate technostress or technology demands and resources (see e.g. (Ayyagari et al., 2011; Day et al., 2012). To measure cognitive workload and stress of operators working with various human-machine interface systems, a variety of validated measures, such as the NASA-Task Load will be used Index (Frantz & Holmgren, 2019; Ouwehand et al., 2021).

The KPI can be evaluated with the NASA-TLX total score in case of the different tasks of the workflow. In addition, we could add a stress metric (i.e., STAI-Y1) and then perform a weighted mean.

KPI 11: Exogenous perception

Exogenous perception is defined as an automatic, transient form of attention that can be triggered by sudden changes in the periphery (e.g., shapes or color (Chica et al., 2011; Fuller & Carrasco, 2006)). Exogenous perception is particularly important for guaranteeing smooth collaboration between the human user and the system, as users have to detect and interpret system behaviors and intentions while also being aware of changes in the environment. As workflow change is a central aspect in Fluently, it needs to be measured whether users can identify and understand these changes. Since exogenous perceptions are automatic, observation studies have been suggested as the most valid measure (see e.g., (Fuller & Carrasco, 2006)). Observers are trained to observe whether users react to specific peripheral cues as well as their behavioral responses. We further suggest that the observation should be accompanied by self-report questionnaires investigating users' conscious perception of the changes (e.g., did users see the cue?) and their understanding (see, e.g., (Chica et al., 2011)).

In line with the proposed KPIs, research has shown that for the changes to be implemented successfully, employee acceptance, workload, and stress are central elements to be considered. To prevent negative employee outcomes (such as stress) and enhance acceptance, it is important to provide employees with enough guidance and training and to develop management strategies/policies to relieve technology-related pressure.

KPI 12: Process efficiency index

In this KPI, we measure the amounts of scrap and waste as well as the energy used in the process and the retrieved source material. This KPIs is particularly important for the MEM-use case, which nowadays is solved based on very energy demanding chemical processes which in addition deliver sub-optimal separation of material, which results in the less recovered raw material and more waste. Besides, for the Prima Additive use case, we expect improvements through the optimization based on knowledge of earlier processes, leading to less mistakes and re-addition, which results in less wasting of additive material.

7 Conclusion

In this deliverable, the three Fluently use cases have been investigated in detail according to the processing steps performed today. In addition, blueprints for the application of Fluently technology that demonstrate the transformation of the use cases to new workflows that are more efficient as well as more user- and environmental-friendly than the currently performed processes have been defined. The provided twelve KPIs will allow to measure the consequences of the changes that Fluently technology will cause.

Interestingly, it was found that, although the end users are very competitive in the market, the level of automation present in their processes is close to zero. In the CIM's use case, the process is done purely manually. While in the PA use case the robotic cell is autonomous, the programming and the decision process is completely preformed by the operator. The success of the processes is based solely on the experience and capabilities of the operator, which can be taxing in the long run. During the visits it was possible to converse with the operators, which were, on average, interested in and open to the possibilities that will arise from Fluently.

It is expected that – as the discussion in the consortium will go on – the blueprints will be further refined during the coming months as well as the KPIs. This will be reported in deliverable 5.1 and other deliverables. However, the specifications of the targeted workflows – as done in this deliverable – provide already a suitable basis for the further developments in the Fluently project.

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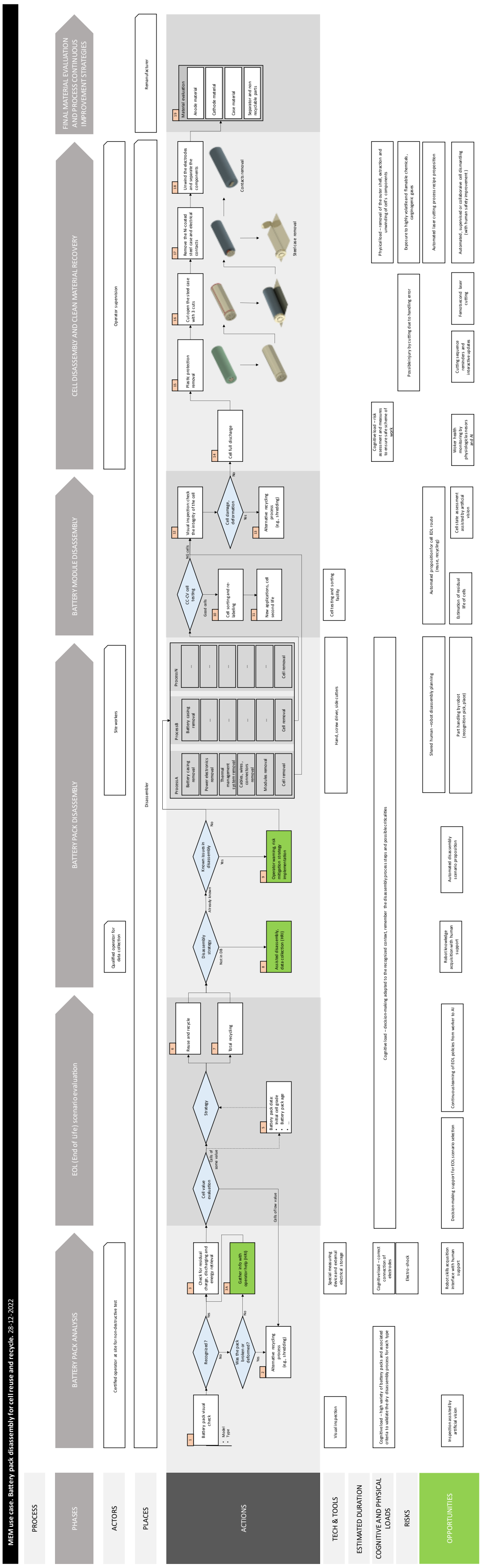
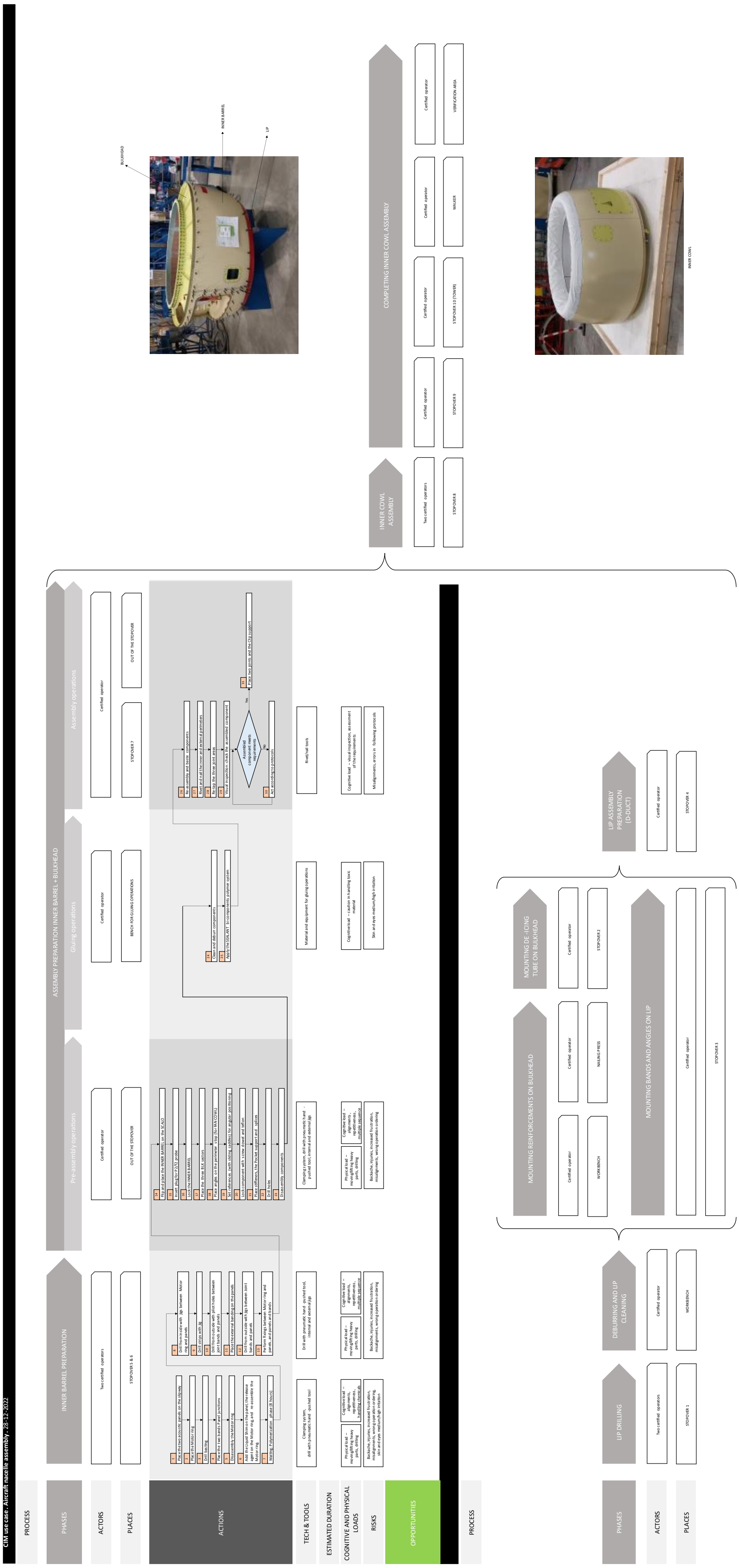
9 Appendices

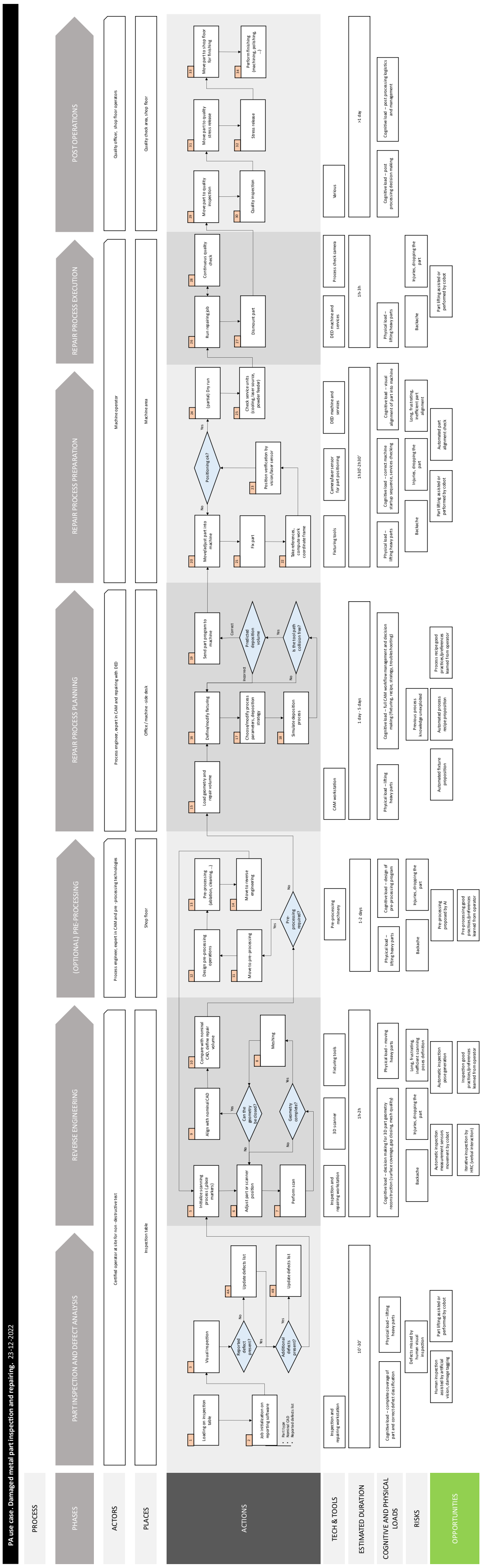
9.1 Workflow UC1 – MEM



9.2 Workflow UC2 – CIM

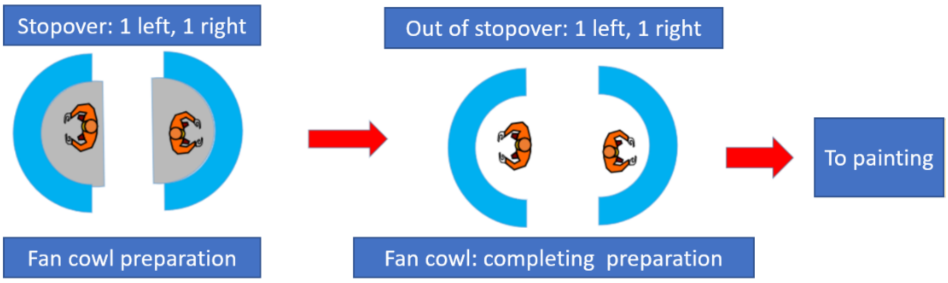


9.3 Workflow UC3 – PA

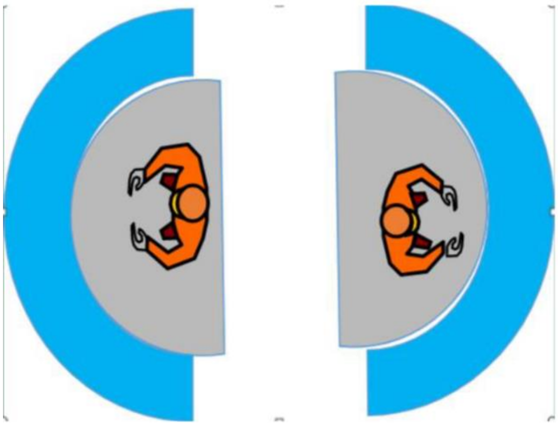


9.4 Additional background material for the UC2 – CIM

Scheme: process flow fan cowl: lip + front bulkhead + de-icing tube + minor parts



1) Notes Stopover and equipment:



Each Stopover is in 2 parts, right and left (2 Stopovers in Total)

- Fixed internal platform. There is a step for internal processing
- Perimeter support surfaces, with lower and upper rebate probes. (Fan vertical sides)
- Fixed masks (casting + NC machining)
- The Stopover (scalo, in italian) simulates attacks on the 'Pylon' and closing brackets
- 3 Mobile Tools Damage Relief for Assembly Hinges on Top
- 3 Hinged Tools on Tool Damage Strikes below
- Drilling with pneumatic hand-pushed tool (operator training)

1) PREPARATION FAN COWL RIGHT: MACRO-OPERATION

- Positioning of Composite PANEL on the ladder ("Noble" side against Teflon dowels); fix with the destaco;
- The "h" is checked; any small trimmings (tenths) are permitted
- Perimeter locking from the centre outwards to prevent springback; perimeter probe in the header
- Length" on opposite side to reference stop is checked; 5 mm probe must pass.
- Masking Shiming Areas (Hinges, Keeper and Hor Rod Supports)
- With Panel in aerodynamic support on Mask, load 3 HINGES supports (different) on tools Ref.Mobile; attach tools to Mask
- Perform measurement with probe to determine METAL SHIM STD + LIQUID (tot. Max. 1.52 mm., of which max. 0.76 mm. Liquid)

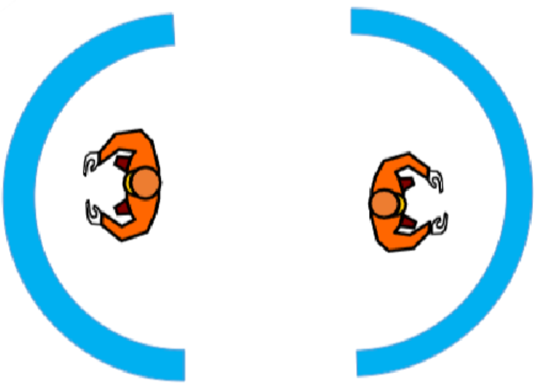
- Load KEEPER (RIGHT) or LATCHES (LEFT) Solid Shims on Ref. Hinged on the other side Mask
- Perform measurement with probe to determine METAL SHIM STD + LIQUID (tot. Max. 1.52 mm., of which max. 0.76 mm. Liquid)
- Load Machined Elements for HOR Rod
- Perform measurement with probe to determine METAL SHIM STD + LIQUID (tot. Max. 1.52 mm., of which max. 0.76 mm. Liquid)
- Trace and remove masking.
- Dismantle parts. Prepare surfaces, with release agent on demountable surfaces, degreaser on surfaces in contact with liquid Shim
- Reassemble the prepared parts; wait for curing 6-8 h
- Once cured, drill 6.35 full external HOLE on HINGES
- Once cured, drill 6.35 full holes from inside the slipway on KEEPER (LATCHES to LEFT)
- Once cured, perform complete DRILLING from inside shaft on HOR Rod Couplings
- While waiting for curing, position the PINNA with holes, DRILL, spread with Sealant and secure with prescribed organs
- Position the PLATE Conductor with holes, DRILL ?? spread with Sealant and secure with provided organs
- Unlock and move Cpls. Fans on Out of Stopover

--> Quality

[For the LEFT fan cowl repeat the same operations as for the right fan cowl, in addition: Mount 7 Brackets ....005 (Fadec Lid Support); Glue with MC Sealant... (also feasible on Offshore)]

2) PREPARATION FAN COWL DX- OUT OF LADDER

Notes: STOPOVER AND EQUIPMENT



Each Stopover is in 2 parts, Right and Left (2 Stopovers in Total).

- Use of simple 'saddles' to hold the Fans on the Vertical side
- Place Cpls. Fans with Hinges and Keeper Supports on Offshore Supports
- Perform on bench, with mask, DRILLING 2.5 pilot of Edge Protectors
- Position EDGE Protectors with reference pins and countermark pilot holes on Fan Panel
- Position the conductive STRIP ....151 with spring-loaded ratchets (1 for every 3 holes). Re-drill

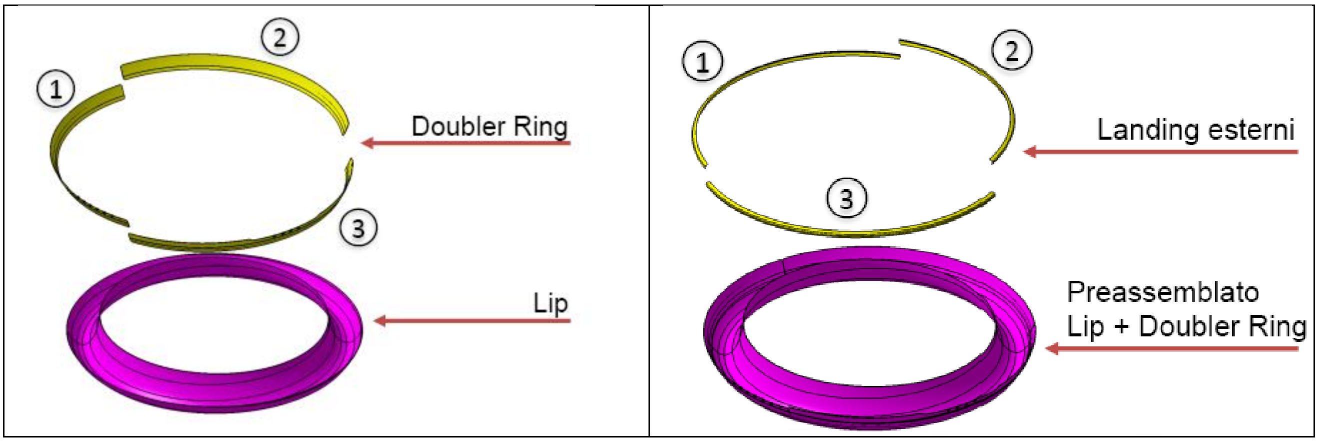
holes

- Remove Strip. Apply Sealant, reassemble.
- Reposition the STRIP ....185, after placing Sealant in between; reassemble
- Position 3 different goose necks (HINGES), after applying sealant and possibly drilling holes
- Fasten with elem. Supplied, 6 + 6 + 5: Fasten Nut with torque (approx. 10 Nm)
- Position 3 equal KEEPERS (LATCHES on the LEFT), after spreading sealant and possibly drilling holes
- Fasten with elem. Supplied, 14 + 14 + 14: Fasten Nut with torque (approx. 10 Nm)
- Position AIR INLET on panel compartment (existing finished holes); check centring; trim if necessary
- DRILLING Holes Panel
- Coat SHIM Liquid EA... and Release Agent on Air Inlet and Screws, secure with 14 Screws
- Position 1 + 1 HOR pole brackets on panel compartment (holes previously drilled?) after applying sealant.
- DRILLING Holes Panel
- Fasten with 2 + 4 screws
- Position 1 + 1 ANGULAR on panel compartment; drill Pilot holes.
- Coating SHIM Liquid EA... and Release Agent on Corners,
- After curing DRILLING 4.05 on Panels
- Wet nailing 7 + 7 Fixings
- Positioning and wet nailing (?) 1 + 1 Retainer Seal ....152 – 153
- Place 1 Conductive Seal ...143 using pilot holes Panel and 1 Cond. Seal ....142 using Edge protector holes.
- BASTING, DRILLING 3.25 , DISASSEMBLY, DEBUDGING for rivets; Reassembly
- Stamp and place LABEL identif. ; paste with SHIM Liquid EA... (can also be mounted after verifier)
- Protect Screws on Mass Parts with Sealant; Draw 'Faith' Lines on Nuts and Screws
- Mount ASTA HOR on supports, with 1 + 1 Bolts

[PREPARATION FAN COWL LEFT: Repeat all the operations made for the right fan]

3) TO PAINTING

Parts: further assembly scheme



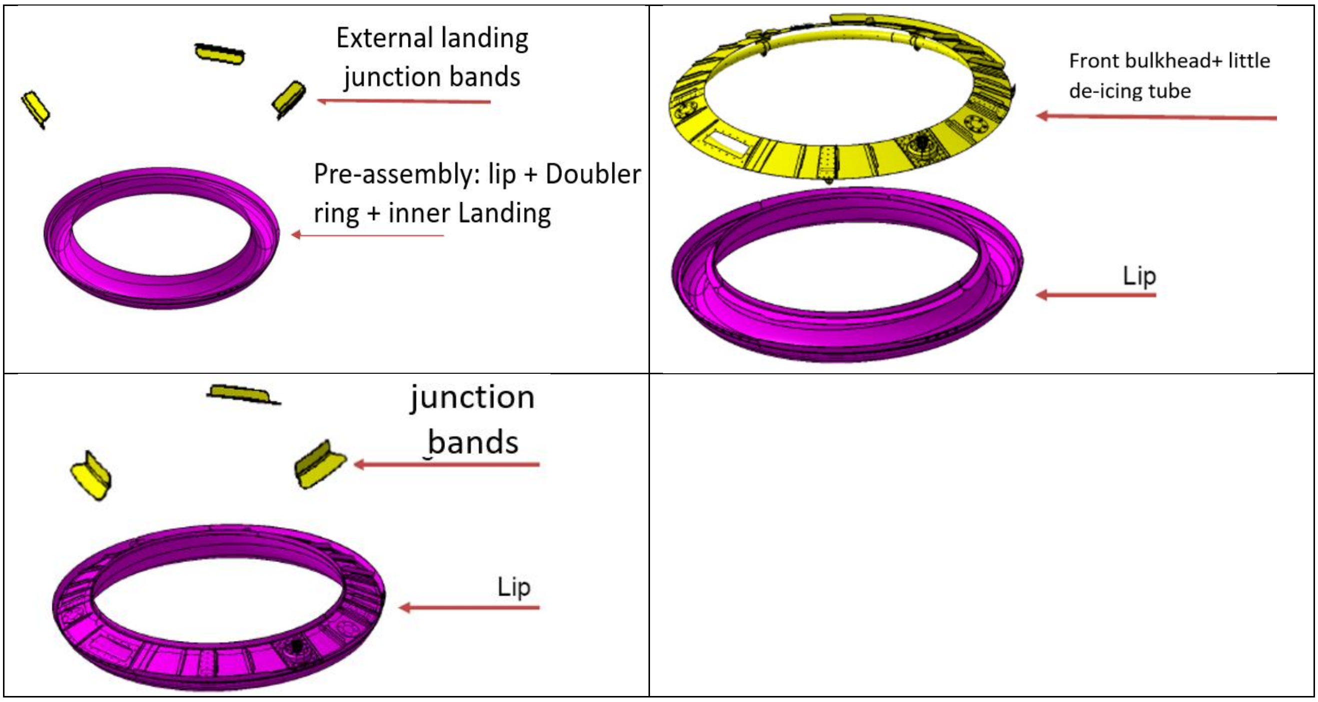


Figure 21: Compoments used for the assembly of theinner lip and front bulkhead