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RE4DY

MANUFACTURING DATA NETWORKS

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Further Information

More information about the project can be found on project website: https://re4dy.eu/

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Project Partners

Num	Participant organisation name	Acronym
1	ASOCIACIÓN DE EMPRESAS TECNOLÓGICAS INNOVALIA	INNO
2	CHALMERS TEKNISKA HOGSKOLA AB	Chalmers
3	INTERNATIONAL DATA SPACES EV	IDSA
4	VOLKSWAGEN AUTOEUROPA, LDA	VWAE
5	ASSECO CEIT AS	CEIT
6	UNINOVA-INSTITUTO DE DESENVOLVIMENTO DE NOVAS TECNOLOGIAS-ASSOSIACAO	UNI
7	FILL GESELLSCHAFT MBH	FILL
8	AVL LIST GMBH	AVL
9	VISUAL COMPONENTS OY	VIS
10	UNIVERSIDAD MIGUEL HERNANDEZ DE ELCHE	UMH
11	ATLANTIS ENGINEERING AE	ATLANTIS
12	DATAPIXEL SL	DATA
13	CORE KENTRO KAINOTOMIAS AMKE	CORE
14	UNIVERSITETE I OSLO	UiO
15	GE AVIO AERO	AVIO
16	ENGINEERING-INGENIERIA INFORMATICA SPA	ENG
17	POLITECNICO DI MILANO	POLIMI
18	ATOS IT SOLUTIONS AND SERVICES IBERIA SL	ATOS IT
18.1	ATOS SPAIN SA	ATOS ES
19	KATHOLIEKE UNIVERSITEIT LEUVEN	KU
20	NETCOMPANY-INTRASOFT SA	INTRA
21	NOVA ID FCT - ASSOCIACAO PARA A INOVACAO E DESENVOLVIMENTO DA FCT	NOVA
22	INDUSTRY COMMONS FOUNDATION (INSAMLINGSSTIFTELSE)	ICF
23	ETHNIKO KENTRO EREVNAS KAI TECHNOLOGIKIS ANAPTYXIS	CERTH
24	GRUPO S 21SEC GESTION SA	S21SEC
25	UNIVERSITAT POLITECNICA DE VALENCIA	UPV
26	CONSIGLIO NAZIONALE DELLE RICERCHE	CNR
27	SOCIEDAD ANDALUZA PARA EL DESARROLLO DE LAS TELECOMUNICACIONES SA	SANDETEL
28	SWITZERLAND INNOVATION PARK BIEL/BIENNE AG	SSF
29	GF MACHINING SOLUTIONS AG	GFMS ADVMAN
30	FRAISA SA	Fraisa SA
31	SIEMENS SCHWEIZ AG	SIE

List of Acronyms/Abbreviations

Acronym / Abbreviation	Description
DoA	Description of Action
PoC	Proof of Concept
TEF	Testing and Experimentation Facility
WP	Work Package
DoA	Description of Action
PoC	Proof of Concept
TEF	Testing and Experimentation Facility
WP	Work Package
AI	Artificial Intelligence
ML	Machine Learning
GF	Georg Fischer Ltd
KPI	Key Performance Indicator
EIDS	European Industrial Data Spaces
CAD	Computer-Aided Design
RA	Reference Arichitecture
API	Application Programming Interface
PLM	Product Lifecycle Management

Executive Summary

The RE4DY project aims to create distributed value ecosystems based on previous demonstration that investments in digital manufacturing can lead to greater development and competitive advantage, laying the foundations for the embryonic European Industrial Data Spaces (EIDS).

The RE4DY pilot projects address both the resilience perspectives of machine tool builders and the resilience perspectives in product manufacturing, as well as the joint optimization of the smart product and manufacturing in both the engineering and operational phases. The use cases focus on European Industrial Data Spaces (EIDS), i.e. the sharing of data in anonymous format between different companies or within the same company to train AI models, with the aim of optimizing processing times and reduce material waste. These processes are potentially applicable to all sectors.

The objective of D5.1 is to provide a detailed overview of the pilot projects that constitute the "Large-Scale Trials of Resilient Smart Connected Factory 4.0 Process Operations" in the machine tool and aeronautics sectors, showing the different business cases and related requirements (business and technical). The main KPIs to be evaluated will also provided and a detailed description of the data sources to be used in each pilot.

In the pilot project led by +GF+, the three companies Fraisa, +GF+ and Siemens are strongly interconnected for this process. It starts from a CAD solution of SIEMENS which is communicating material, dimensions, tolerance, quantity etc. of a desired unit. With this information, +GF+ can decide which machine fits best to deliver that service. Further data from +GF+ like the cutting forces, the torque or the dynamics of the machine is exchanged and forwarded to Fraisa. The GF machine gets equipped with the appropriate tool and is ready to produce the parts ordered. While producing the parts, the machine is communicating to Fraisa if new tools are needed or if tools must be refurbished to guarantee the desired tolerances and quality, which are measured on machine with the Datapixel platform tools. The RE4DY project is intended to generate processes and adaptive workflows that stably run on different hardware and software platforms, are easy to adapt, are characterized by a high degree of standards, and reliably function.

The pilot project "Near real-time predictive quality on distributed manufacturing processes" conducted by Avio Aero will mainly address three objectives: (1) Support the operator in quality control thanks to the installation of an artificial intelligence software at the end of the line that is able to recognize defective parts and indicate whether they are waste or they are to be processed; this should allow to reduce quality control times. (2) The optimization of learning times so that an operator becomes autonomous in quality control thanks to the use of the AI Software; the possibility of the Junior operator to practice on an artificial intelligence system allows learning faster and without the need of the Senior operator to provide support. (3) The use of a Dataspace to implement Predictive Quality through an artificial intelligence system.

1 Introduction

1.1 Context and scope of this document

This Deliverable contains the presentation of the activities and studies carried out within WP5 (task 5.1). "Pilot set-up, responsive smart factory circular operations and value network data preparation".

T5.1 is divided into 2 main chapters: the first related to the pilot led by GF and the second one related to the pilot led by Avio Aero.

In both chapters the work done is divided into Pilots (4 Pilots for GF and 3 Pilots for Avio Aero. The report focuses on providing a detailed description of each of the two pilot projects. The description focuses on: (i) description of each business scenario within each trial explaining it in detail; (ii) Explanation of the current situation/scenario in the company; (iii) Directives and regulations; (iv) Description of the future scenario; (v) Business objectives; (vi) benefits expected; (vii) Company indicators.

The chapter on "Data Sources and Characterization" is intended to provide a means to gather information on the RE4DY pilot projects regarding their plans for the use of data standards, management and governance, as well as safety, security, privacy, trust and resilience.

Thanks to the partner companies, Avio Aero and GF were able to plan the development of Artificial Intelligence software systems. In particular:

GF will collaborate with the FRAISA company, its tool supplier, to improve the use and prevent breakages of its tools and avoid production machine downtime thanks to greater continuous monitoring. The collaboration involves GF sharing data relating to its machines and tools with FRAISA and analyzing them through an AI system developed by Siemens and Swiss innovation park which can make predictions on useful life of tools and machine monitoring.

Avio Aero will collaborate with the partner companies Engineering and Polimi and with CERTH for the development of an artificial intelligence system capable of supporting the operator in carrying out a quality control on the product at the end of the line, identifying, through a visual scan of the part, any defects. This will allow to speed up the quality control procedures on the part. The archiving of images of the parts analyzed by the software will allow the AI system to train and to test Junior operators by providing reports on their progress and making the learning process more efficient.

Avio Aero will also collaborate with the CNR to develop Predictive Quality algorithms thanks to the sharing of information between its plants. The data relating to the real-time monitoring of the EDM machines and those relating to the declaration of defective parts on the SAP portal will be cross-referenced in the search (again thanks to AI software) for a correlation between the anomalous behavior of the machine and the incorrect processing of the parts. The software will alert the personnel responsible for anomalous machine behavior and the possible release of defective parts.

1.2 Relationships among other deliverables

WP5 is a consequence of WP2 and WP3. So D5.1 will take the results of the previous Derivable as input:

• "D2.1 - Active resilience model of production and supply chain", which provides the first indications on the Pilots and contains a first draft of the structure of the digital continuum 4.0.

• "D2.2 - Digital 4.0 continuum reference framework_First Version" RE4DY Reference Architecture (RA) which aims to link AI/ML/data pipelines, Digital Twin workflows, digital threads and data spaces.

• "D3.1 - Resilient and sustainable data as an IT product and data space", which aims to build a set of European Test and Experimentation Facilities (TEFs) and data spaces with the aim of qualifying open systems of the digital continuum 4.0 and OSS tools.

D5.1 will be used as input for "D5.2 - 2 Proof of concept validation for connected factory 4.0 active resilient operations".

2 GF Pilot

Use-case sequence

From the 09. November 2022, we started with the design of the High-Level interface. There the architecture for the multi-cloud-interfacing must be designed. Furthermore, the exchange formats and structure should be described, and the different software solutions of the partners should be also briefly described and understood by every partner. In a next step, the detailed interface design should be ready. There are detailed specifications about the relevant data to use and data formats should be included. And once more, more detailed descriptions of the software solutions of the partners should be made. At the end of February 2023, the implementation plan for the pilot should be ready before Milestone 3 of the RE4DY project arrives. The details of the first pilot scenario should be clear and all implementation details for the OPEN API's should be specified. At the end of March 2023, the implementation of the first pilot scenario should be done. There it is the plan to implement a first setup at the SSF in a virtual environment. This is based on the Set-up of OPEN API's on the software solutions of the partners. The next step in future would be the testing of the first Pilot.

PoC definition

Current business scenario

The businesses of the three companies are somehow interacting but still very separated. Basically, all three companies have their own businesses and services (described in chapter 1 of the pilot trial handbook). In the context of the pilot project, the process is described from the perspective of the end user. E.g., An end-user is buying a milling-machine from GF. The hardware and software are either purchased once or billed periodically based on customer needs. To operate the milling-machine, the end-user must buy milling-tools. These tools are supplied e.g., by Fraisa. In addition to the milling-tools, Fraisa is also offering Software-parts, which are e.g., billed periodically, based on customer needs. The customer is therefore buying the milling-tool and the milling-machine from two different companies. The customer is responsible for checking the wear of the tool and must have it reworked or replaced by Fraisa. Furthermore, the user may use SIEMENS software to design the desired components and for Product Lifecycle Management (PLM). From his point of view, he does not benefit from a link between the three companies.

For the manufacturing and production of the products of GF and Fraisa, the companies are using hardware and software parts from SIEMENS. To produce tools, Fraisa is using GF machines. Vice versa GF may be using Fraisa tools for the manufacturing of their machines. This shows that the companies are already interacting together and are using products, hardware, and software of each other.

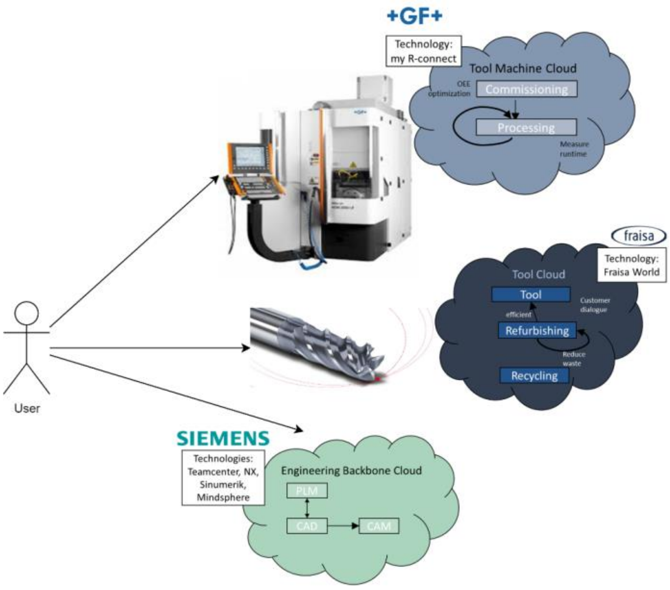


Figure 1, Current Business Scenario

Future business scenario

For the future business scenario, the three companies Fraisa, GF and Siemens are strongly interconnected for this process. It starts from a CAD solution of SIEMENS which is communicating the material, dimensions, tolerance, quantity etc. of a desired unit. With this information, GF can decide which machine fits best to deliver that service. Further data from GF like the cutting forces, the torque or the dynamics of the machine is exchanged and forwarded to Fraisa. The GF machine gets equipped with the appropriate tool and is ready to produce the parts ordered. While producing the parts, the machine is communicating to Fraisa if new tools are needed and if tools must be refurbished to guarantee the desired tolerances and quality. The quality of the process is verified through simulation in the Siemens virtual environment and the Datapixel application directly connected to the controller, which takes care also of the dimensional control and provides feedback to the CAM system. The RE4DY project is intended to generate processes and workflows that run stably on different hardware and software platforms, are easy to adapt, are characterized by a high degree of standards, and function reliably for our customers.

- Process-safe storage, read-in and read-out of tool information on RFID
- Robust data transfer of the information in apps
- Fast, robust error-free and customer-friendly application and geometry data import into CAM software
- Secure but also flexible readout of application data from the Control

- Safe but also flexible readout of the process forces and spindle torques from the machine
- Robust cloud architecture to use data in different clouds
- Simple and robust installation of the service at the customer
- Maximum use of non-proprietary standards

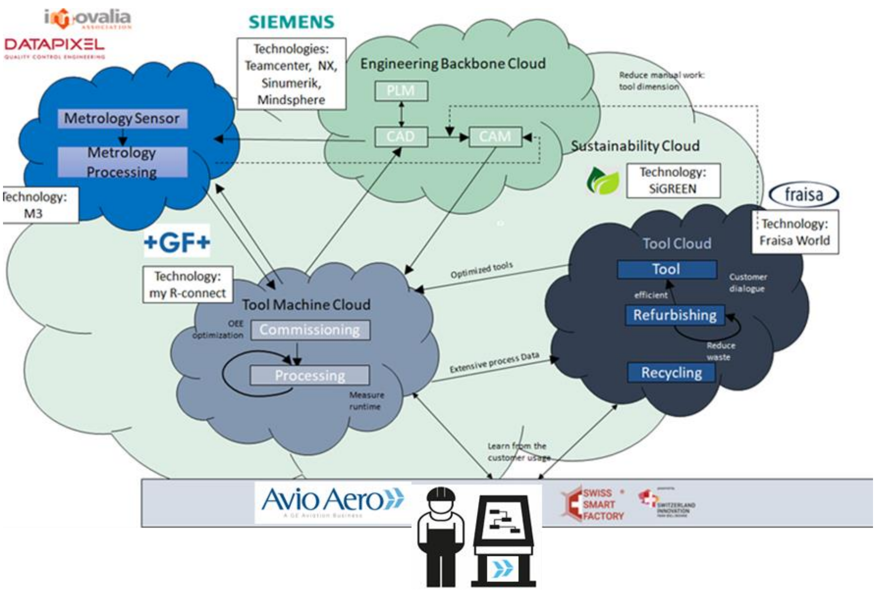
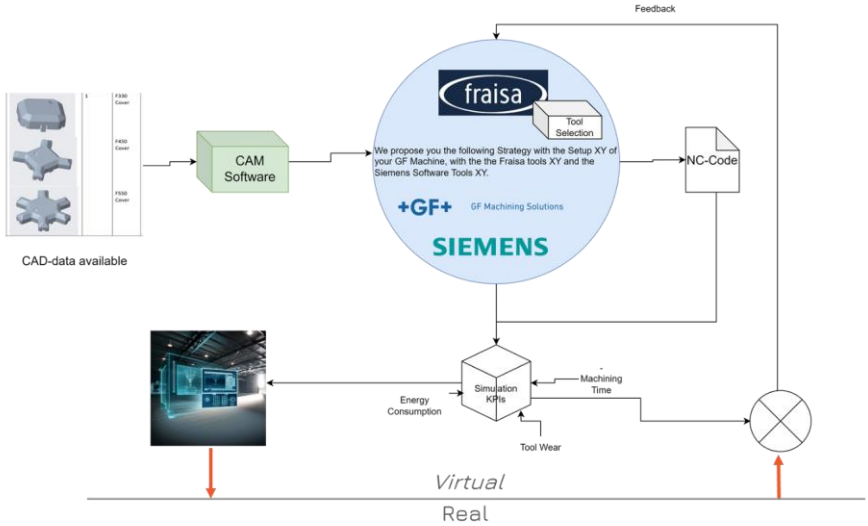


Figure 2, Future Business Scenario

First experimentation results

BP1 - Defining Milling Strategy, Tool selection (integrated in NX)



Business process in detail

<u>Current process (Customer; CAM Data)</u>

In the current process, the CAM operator receives the CAD model of the workpiece from the designer and imports it into the NX-CAM system. They then need to define the material of the workpiece and verify the required surface quality. Next, they utilize the FRAISA ToolExpert to filter all milling tools and select the ones recommended for this specific material. From this selection, the operator must decide which tool to use for milling the workpiece. It is also essential for them to be aware of the available tools in the company's stock. If the chosen tool is not in stock, they either need to order it from FRAISA or select an alternative tool. The operator now needs to determine the milling strategy for the workpiece, considering the various options available in the ToolExpert. Based on this choice, they obtain the cutting data recommended by FRAISA for the job, and they manually transfer these parameters to the CAM system. However, factors such as whether the selected tool is the ideal one for this particular workpiece, the effectiveness of the chosen strategy, the expected tool's lifetime, and the optimal time to send it for regrinding may still be unknown without prior experience.

Future process (Customer, CAM Data)

- The operator obtains CAD model and uses NX CAM with FRAISA tooling (FRAISA Tool Expert) interface for simulating a program that provides the best tool and optimized
- process parameters in terms of productivity, cost (and energy efficiency, with special add-in)
    - Inputs: CAD Model (including material, surface quality), machine
    - Selection of pockets, regions, then Jack gests recommendation of tools (better already knowing the stock of tools) and a strategy (spindle speed, depth of cut, machining speed)
    - Output: NC code from the CAM and KPIs (machining time, how many parts can be machined with the tool)
    - Tools are selected for the machining process based on the simulated time and wear information for the particular machining process, based on availability from tool stock and tool data available in FRAISA world
- The simulation tools provide also forces (possibly chatter) and simulated tool wear for such an optimized process (special add-in)
- The resulting KPIs are validated by the operator (timing, costs, energy consumption)
- The operator generates the code and goes to the virtual environment for simulation of the full process
- The process is simulated in the virtual machine and validated after verifying no potential collision

Current process (Customer, Reconditioning process)

Currently, the customer sends a used tool to the tool manufacturer for reconditioning. The tool manufacturer has no information on how the tool was used to make application recommendations based on wear. Due to the lack of data exchange, no process optimization is possible, which means increased tool and energy consumption and is therefore not very sustainable.

The lack of usage data also does not allow the tool manufacturer to design the tools to meet customer needs in the future, which in turn creates process inefficiencies.

Future process (Customer, Reconditioning process)

In the future, the customer will send used tools to the tool manufacturer to be reconditioned but with the tool's usage data stored on the RFID chip or stored in a cloud. Now the tool manufacturer has the possibility to correlate the tool wear with the usage data. If it turns out that the customer has not used the tool optimally, recommendations for use can be made. Thus, future tool use can be optimized with the result that costs and emissions can be reduced, and valuable resources can be saved.

The tool-specific usage data also enables the tool manufacturer to design tools to meet customer needs in the future, which in turn can generate process efficiencies.

Business indicators

ID	BUSINESS Indicators	DESCRIPTION	Unit*	Current value	Future expected value	Expected date of achievement**
1	Tool selection	Operator takes the right tool	Less failures	90%	99%	2025
2	ToolExpert in CAM	The ToolExpert is integrated in the CAM system	Less failures	5%	<1%	2024
3	Virtual environment for tool	Planning is easier because they know how many tools they need for XX workpieces	Less time to set up process h	100%	<20%	2025
4	Virtual environment for machine	Planning is easier because they know which machine fits the best for the workpiece	Less time to set up process h	100%	<20%	2025

**Provide the units, in which you measure the value of the defined indicator (%, people, €, Si, etc.).*

*** During the implementation / end of the implementation / before 6 months after implementation / before 12 months after implementation / before 24 months after implementation / more than 24 months after implementation*

Business Requirements

No.	BUSINESS OBJECTIVE	REQUIREMENT	AREA[1]	SUB HEADING[2]	FUNCTIONALITY[3]	PRIORITY[4]
1	ToolExpert (Fraisa Word) connected in CAM	The operator must be able to select the best tool in the available stock to design the process	Production	Technical	Functional	Critical
2		The operator should receive some recommendations based on available data	Production	Technical	Functional	Critical
3		The system must load the information from the CAD	Production	Technical	Functional	Critical
4		The operator must be able to enter the data manually	Production	User	Functional	Critical
5		The operator should receive some recommendations for the best milling strategy based on the production priorities (Productivity, production-safety, economy, ...)	Production	User	Functional	Preferred
6	Virtual environment	The machine simulation must know the detailed dynamics of the axis	Production	Technical	Functional	Critical
7		The spindle power- and torque diagram must be known	Production	Technical	Functional	Critical
8		The machine simulation must be detailed	Production	Technical	Functional	Critical
9	Tool Simulation	The wear development from each tool with the chosen milling strategy must be known	Production	Technical	Functional	Critical
10		The force development and maximum force must be known and matched to the	Production	Technical	Functional	Critical

		corresponding wear				
11		The tool lifetime must be known	Production	Technical	Functional	Critical

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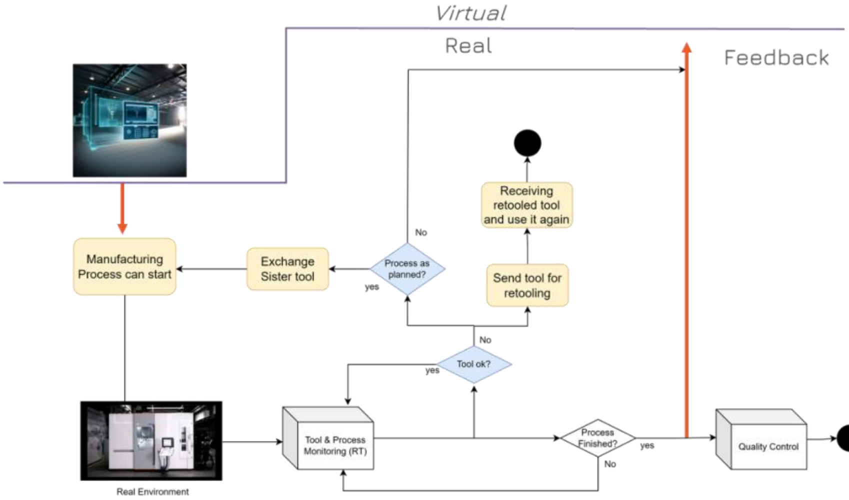
BP2 - Process-Management, Tool refurbishment & Recycling



Business process in detail

Active Resilience

The secure and fast reading of tool data via RFID significantly increases process reliability during data entry and makes the process significantly more robust against disturbance variables. The same applies to the import of application and geometry data into the CAM software. A cleanly programmed interface between ToolExpert and NX /Teamcenter forms the basis for this. The automatic storage of application data, cutting forces and torques in My r Connect provides a secure data basis for carrying out validated process optimizations. This not only increases productivity, but also process reliability, which is particularly crucial for autonomously running processes. Also, the link between the usage data and the tool wear leads to more transparency and a significant increase in the resilience of the process, while at the same time conserving resources. Finally, the use of non-proprietary standards will lead to a future data communication that is secure, fast, flexibly adaptable, but also robust.

Manufacturing Business Process Case: Customer

By combining tool data, cutting data, tool wear, process forces and component qualities, the customer can realize significant savings in his production. By comparing max. possible cutting forces and actually occurring cutting forces, the application parameters can be adjusted, the tools can be loaded higher and the process times can be reduced. This process optimization can easily save 20-30% of the process times. Today, it is not possible to make a statement about the remaining service life of the tools, and many tools are replaced with a new tool at an early stage as a precaution. By reading out the run time of the tools, this can now be summed up in apps and compared with the recommended service life of the tools. In this way, tools can be used longer in a process-safe manner in the future and valuable resources can be conserved. This process optimization can save up to 30% of tool costs. The link of component qualities and tool conditions is not yet installed today. In this project, however, the wear conditions of the tools are combined with the application data, process forces and the component qualities and ideal process parameters are derived from them to ensure maximum tool utilization, minimum process times and thus CO2 and resource-saving processes.

Data Value Chain

The perfect data value chain can be ideally described in the RE4DY project using the Fraisa ReTool process, which defines the management of the used tools after the tool is considered worn out and once recovered from the customer. All production-relevant data from a tool as well as specific data from a manufactured tool are already stored in an internal cloud at Fraisa and can be made available to the customer in the future, reducing measurement processes at the customer's site and simplifying logistics. The simple loading of tool information via RFID and the fast and process-safe upload of application data lead to fewer input errors and thus to higher productivity. Further linking of this data with machine data can lead to significant process optimizations, so that further cost and resource savings can be achieved. A further linking of this data with component data then leads to an almost ideal coordination between process, component quality and tool use, which in turn results in a cost reduction on the one hand and an increase in quality on the other. In order to close the Data Value Chain now, on the one hand a dialog must be established between the customer and the Fraisa Retool, so that the wear data of the tool can be compared with the application data of the tool, and on the other hand this data must also be mirrored in the tool development of Fraisa, in order to develop even more customer-oriented tools. Thus, numerous stakeholders are involved in the Data Value Chain (Fraisa tools, GF machines, e.g. Avio customer and Siemens system provider) that can map a complete data set of a tool life.

Business indicators

ID	BUSINESS Indicators	DESCRIPTION	Unit*	Current value	Future expected value	Expected date of achievement**
1	Tooling cost reduction	Due to optimized application parameters the tool can stay longer in operation	(€)%	100%	70%	2025
2	Longer tool life cycle	Cost reduction	(€)%	100%	130%	2025
3	Better designed tooling	Tool layout is tailored on the application	Life time h (%)	100%	120%	2025
4	Reduced CO2 footprint	Less energy consumption	kW (%)	100%	90%	2025

**Provide the units, in which you measure the value of the defined indicator (%, people, €, Si, etc.).*

*** During the implementation / end of the implementation / before 6 months after implementation / before 12 months after implementation / before 24 months after implementation / more than 24 months after implementation*

Business Requirements

No.	BUSINESS OBJECTIVE	REQUIREMENT	AREA[1]	SUB HEADING[2]	FUNCTIONALITY[3]	PRIORITY[4]
1	Linkage of tool wear and application parameter	The operator should receive some recommendations based on available data	Production	User requirements	Functional	Critical
2		The operator must be able to select the best tool in the available stock to design the process				
3		The system must load the information from the CAD				
4		The operator must be able to enter the data manually				
5	Identification of the remaining tool life for tools	The selected tool must be identified with the RFID reader and the tool data should be accessible in the system	Production	User requirements	Functional	Critical
6		The system should help to validate the right conditions of selected tools for the job				
7		The system should be able to inform the wear status of tools and warn if risk thresholds (forces over time) are surpassed or if tool is reaching end of life before expected time so a sister tool exchange is needed				
8	Validation of the geometric tolerances based on simulation	The system should be able to inform if the part is within tolerances based on the quality predicted from tool wear (dimensional tolerances), and the process stability indicators	Production control	Technical requirements	Functional	Critical

		(vibrations, for surface quality)				

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BP3 - Machine Maintenance

Business process in detail

GF Machine Maintenance and Refurbishing

The process focuses on the relationship with GF customers and closes the loop with respect to the other use cases. Data from machines and tooling integrate in a system that collects information through service calls about machine health, technical issues and potential component failures, and gives services to customers through manual processes. This includes refurbishing of key components like spindles and machine tables.

In a future RE4DY scenario, this information is shared with customers through the multi-cloud platform and allows implementing condition monitoring and predictive maintenance for just-in-time services for repairing as well as identifying possible refurbishing items. Diagnosis is facilitated and accelerated through the semantic framework and a complete connected service is implemented with tooling and critical component supply in order to increase uptime and enable resilience to component and tooling materials supply scarcity. The data and application integration will be implemented with end users as GE Avio, having their own cloud platform for managing their manufacturing processes.

Business indicators

ID	BUSINESS Indicators	DESCRIPTION	Unit*	Current value	Future expected value	Expected date of achievement**
1	Machine Uptime	Productive machine time with respect to total available time	%	80-90%	95%	2025
2	Remaining Useful Time of tool before refurbishing	Residual lifetime of tools with respect to total lifetime	%	30%	5%	2025

**Provide the units, in which you measure the value of the defined indicator (%, people, €, Si, etc.).*

*** During the implementation / end of the implementation / before 6 months after implementation / before 12 months after implementation / before 24 months after implementation / more than 24 months after implementation*

Business Requirements

No.	BUSINESS OBJECTIVE	REQUIREMENT	AREA[1]	SUB HEADING[2]	FUNCTIONALITY[3]	PRIORITY[4]
1	Tool Lifetime estimation and management	The operator must be able to select the best tool in the available stock to design the process	Production	User requirements	Functional	Critical
2		The operator should receive some recommendations based on available data	Production	User requirements	Functional	Critical
3		The system must load the information from the CAD. The operator must be able to enter the data manually. The CAD CAD system delivers the optimized code with simulation KPIs, in particular estimated tool lifetime.	Production	Technical requirements	Functional	Critical
4		When process starts the operator should be able to manage lifetime of tools and use them until end of life with no risks. In case of risk warning, the system should propose a sister tool exchange. The system finally gives feedback to the CAD CAM system about effective KPIs. The system informs that the tool should be recycled when it reaches end of life.	Production	Technical requirements	Functional	Critical
5	Component lifetime estimation and management	The system should provide the capacity of the machine to perform the job, given the estimated time and part-tool system. This capacity is defined in terms of residual lifetime of key machine components and other consumables (fluids, grease). The operator should be able to validate the job given the machine capacity	Maintenance	Technical requirements	Functional	Critical

		matches the corresponding requirements				
6		The system should be able to monitor in real time the main indicators of component health and provide historical thresholds which define normal operation conditions. In case the indicators fall outside the thresholds, a warning is given indicating a potential problem related to the component.	Maintenance	Technical requirements	Functional	Critical
7		A diagnosis stage is started once the warning is given, with specific pre-defined measurement cycles, and a specific analysis of the resulting indicators is displayed to the operator, providing failure probability and estimation of the residual lifetime, requiring service within a given timeframe.	Maintenance	Technical requirements	Functional	Critical
8		A link to service is provided where component exchange can be requested and exchange with a service engineer is activated in order to have detailed recommendations for the potential issue.	Maintenance	Technical requirements	Functional	Preferred

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BP 4 – Adaptative Digital Manufacturing

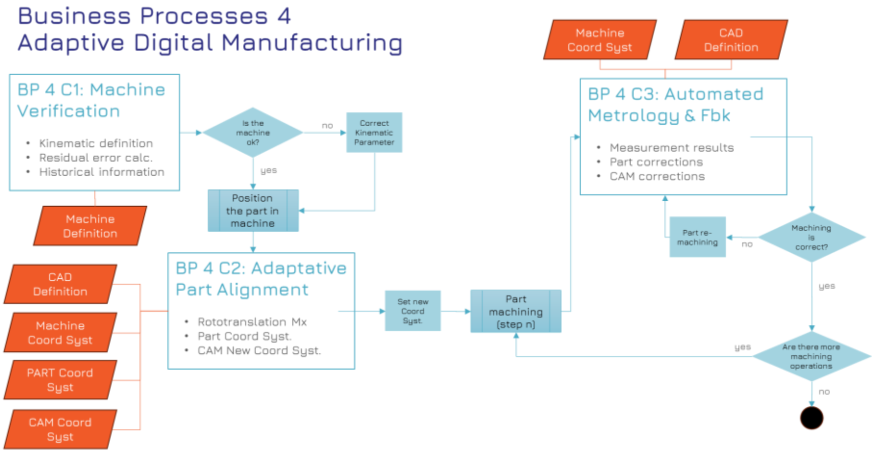


Figure 1: Business Process Components

Business process in detail

In the realm of advanced digital manufacturing, the integration of metrology into the machining process stands as a transformative approach to quality assurance and process optimization. By seamlessly integrating measurement and correction mechanisms directly into the machining cycle, manufacturers can achieve unprecedented levels of precision, efficiency, and cost-effectiveness. This integration marks a paradigm shift in manufacturing, enabling manufacturers to harness the power of digital technologies to revolutionize their production processes.

Traditionally, quality control and machine verification have been conducted post-machining, often leading to delays, rework, and increased production costs. However, advanced digital manufacturing embraces a proactive approach, incorporating metrology into the very heart of the machining process. This integration empowers manufacturers to monitor and optimize the machining cycle in real-time, enabling early detection of deviations and prompt corrective actions.

Machine Verification

In the traditional machine verification process, a technician manually conducts checks using high-precision measuring equipment, requiring specialized skills and disrupting production flow.

The new in-machine metrological solution revolutionizes machine verification by providing operators with the tools and capabilities to perform these checks independently. These solutions integrate sensors and software directly into the machine, enabling operators to capture precise measurements of the machine's axes and compare them to reference values.

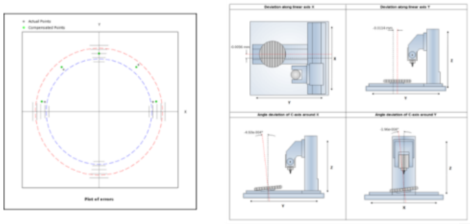


Figure 2 Metrology-based machine verification setup

While this approach involves operator-initiated verifications, it also incorporates a closed-loop control system for automatic error compensation. If the captured measurements deviate from the reference values, the software sends feedback to the machine controller. The machine controller then adjusts the machine's parameters based on this feedback, effectively compensating for smaller errors without requiring manual intervention. This real-time feedback and adaptation mechanism further streamlines the verification process, allowing operators to focus on more critical tasks and contributing to overall efficiency.

Adaptative Part Alignment

Traditional part alignment relies on complex fixtures and manual adjustments, often requiring specialized knowledge and expertise. This process can be time-consuming, labor-intensive, and susceptible to errors due to the complexity of the fixturing and manual measurement.

In this business process, the in-machine metrology solution will capture precise measurements of the part's position and orientation, comparing them to the digital model. Any deviations are detected and most of them can corrected before the machining process.

This real-time error detection and correction mechanism ensures that the part is positioned correctly for accurate machining, eliminating the need for time-consuming manual adjustments. If the deviation is small, the in-process metrology solution provides a roto-translation matrix to the controller of the machine, allowing it to adjust the machining program with a new coordinate system. This enables the machine to compensate for the minor misalignment and achieve the desired dimensional accuracy.

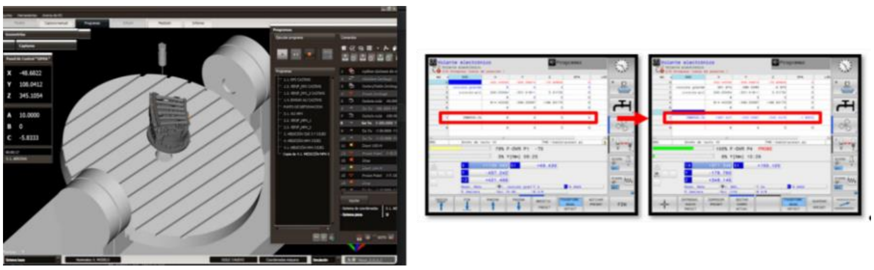


Figure 3 Adaptative part alignment supported by metrology results

For larger deviations, the in-machine metrology solution alerts the operator, who can then reposition the part to ensure accurate machining. This operator-guided approach ensures that the part is aligned correctly before any machining starts, minimizing the risk of errors and ensuring the production of high-quality parts.

In essence, ADM's in-machine metrology solutions transform part alignment from a manual, error-prone process to an automated, data-driven process that ensures precise positioning and accurate machining. This shift empowers operators to focus on more value-added tasks while maintaining the integrity of the machining process.

Automated Metrology and Feedback

Traditional quality control is conducted after the machining process is complete, often using CMMs or other off-line measuring devices. This approach is inefficient, as it delays the detection of issues and may lead to rework or scrap.

In-machine metrology elevates quality control to an in-sequence process. During sequential machining processes, the part is measured periodically at key stages. This strategic approach ensures that critical dimensions are assessed at milestones, minimizing the risk of undetected errors and allowing for timely corrective actions.

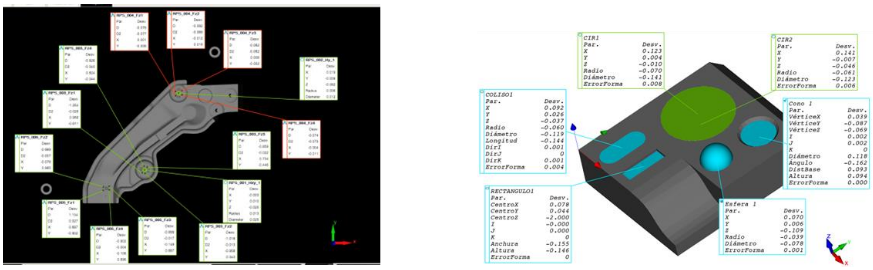


Figure 4 Metrological Quality Control Results

If the measured dimensions deviate from the specified tolerances, the metrology solution immediately alerts the operator and sends feedback to the CAM software. This real-time notification allows the operator to intervene immediately, either by re-machining the previous step to correct the error or, if necessary, discarding the part without delaying the overall process.

The evolution of the deviations could also be analysed and, in some cases, some adjustments can be made to the machining program to compensate for the identified issues. This closed-loop control system enables the machine to adapt to the part's changing geometry and maintain dimensional accuracy throughout the machining process.

In essence, this in-machine metrology approach transforms quality control from a reactive to a proactive process, ensuring that deviations are detected and addressed early, minimizing rework and scrap, and maximizing part quality. This shift empowers operators to make informed decisions and optimize the machining process, while also reducing the need for post-machining inspections.

Business indicators

ID	BUSINESS Indicators	DESCRIPTION	Unit*	Current value	Future expected value	Expected date of achievement**
1	Machine Check Frequency	Tracks the number of machine checks performed per month	#chk /year	1	12	*before 12 months after implementation*
2	Machine Check Time	Monitors the time taken for each machine checking process	Min	120	30	*during implementation*
3	Misalignment Downtime	Monitors the downtime caused by machine misalignment	Hours	6	1	*before 12 months after implementation*
4	Production Error Reduction	Tracks the reduction in errors due to improved compensation of part alignment errors.	#err /month	20	10	*before 12 months after implementation*
5	Misalignment Scrap Rate	Tracks the number of parts scrapped due to part misalignment.	#parts /month	10	2	*before 12 months after implementation*
6	Defect Rate	This measures the percentage of parts produced that are defective.	%	10	5	*before 12 months after implementation*
7	First Pass Yield	Tracks the percentage of parts produced that meet quality standards without the need for rework or repair.	%	80	90	*before 12 months after implementation*
8	Rework Rate	Monitors the percentage of parts that require rework.	%	15	10	*before 12 months after implementation*

**Provide the units, in which you measure the value of the defined indicator (%, people, €, Si, etc.).*

*** During the implementation / end of the implementation / before 6 months after implementation / before 12 months after implementation / before 24 months after implementation / more than 24 months after*

Business Requirements

No.	BUSINESS OBJECTIVE	REQUIREMENT	AREA[1]	SUB HEADING[2]	FUNCTIONALITY[3]	PRIORITY[4]
1	Enhanced Accuracy	Integrated metrology equipment and software in the machine	Production	Technical	Functional	Critical
2		Implemented precise machine verification and part alignment systems using in-machine metrology solutions	Production	Technical	Functional	Critical
3		Provided comprehensive training to machine operators on the use of in-process metrology tools and procedures.	Production	Training	Non-functional	Critical
4		Provided real-time metrology data and insights directly to the machine's operator interface.	Production	Technical	Functional	Critical
5		Integrated metrology data into the machine's control system to dynamically adjust machining parameters.	Production	Technical	Functional	Critical
6		Automated alignment compensation based on metrology data, enhancing machining accuracy and consistency.	Production	Technical	Functional	Critical
7		Implemented real-time alerts and notifications to operators when machine alignment or compensation issues arise.	Production	Technical	Functional	Critical
8	Reduce waste	Implemented advanced part alignment supported by in-machine metrology	Production	Technical	Functional	Critical
9		Integrate the metrology process in between machining steps	Production	Technical	Functional	Critical
10		In-machine quality control solution should have a fast response time	Quality Control	Performance Requirements	Non-Functional	Critical
11		The solution should be robust and able to operate in a variety of	Quality Control	Performance	Non-Functional	Preferred

		environmental conditions.		Requirements		
12		The solution should have a high degree of precision to minimize false positives/negatives.	Quality Control	Performance Requirements	Non-Functional	Critical
13		Integrate metrology data with the production scheduling system to optimize production flow	Production Control	Performance Requirements	Functional	Preferred
14	Automated Quality Control	Implement in-machine automated part dimensional inspection.	Quality control	Technical	Functional	Critical
15		Automate the generation of quality reports and defect notifications.	Quality control	Reporting Requirements	Functional	Critical
16		Establish a centralized quality database to store and analyze metrology data.	Quality control	Reporting Requirements	Functional	Critical
17		The solution should have a user-friendly interface that requires minimal training.	Human Resources	User requirements	Non-Functional	Preferred
18		The solution should be scalable and able to handle increasing volumes of data as operations grow.	IT / Infrastructure	Performance requirements	Non-Functional	Critical
19		The solution should be reliable and have minimal downtime.	Maintenance	Performance requirements	Non-Functional	Critical
20	Improved flexibility	Enable real-time adjustment of machining parameters based on results of machine verification supported by in-machine metrology solutions	Production	Technical	Functional	Critical
18		Support rapid prototyping and customization of parts using in-process metrology feedback.	Production	Technical	Functional	Preferred
19		Develop tooling and fixtures that can be easily adapted to different part geometries.	Production	Technical	Functional	Preferred
20		Implement a centralized data	Production	Technical	Functional	Critical

		repository to store and manage metrology data for future use.				
21		Train operators to utilize in-process metrology data for improved decision-making.	Production	Human resources	Non-Functional	Preferred
22		Collaborate with design engineers to incorporate in-process metrology requirements into product designs.	Production, Design	Support	Non-Functional	Preferred

**See the ¡Error! No se encuentra el origen de la referencia. in Annex Chapter for a description of the columns*

System requirements

Drawing from the previous chapters related to the pilot business requirements, detailed system requirements are described in the following tables. The requirements cover the business processes for the preparation of the manufacturing process in the CAD CAM, with the selection of the appropriate tool for a given part machining, the tool matching application, the optimised tool management during the manufacturing process and the optimised machine component management using predictive maintenance components.

ID			SR-Pilot 3-BP_2
Business requirement reference			Tool identification, Remaining Tool lifetime identification and job feasibility verification
Overall Description			The system should be able to identify the remaining tool lifetime and tool specific data and verify process consistence
Rationale			Use each tool properly and check if the tool can do the job
Specific Requirements	*Feature*	*Introduction & Purpose of feature*	Reads the tool data and associates with CAM program data for verifying the job is feasible and displays operation times
		Stimulus Response Sequence	Input: tool data, CAM data Output: Tool data display, remaining tool life before and after operation
		Functional Requirements	The system shall get the tool data corresponding to a program and associate with specific operations, then display remaining tool life before and after each operation
	External Interface	*User Interfaces*	My rConnect application
		Hardware Interfaces	Smartphone or Qr code reader.

	Requirements	Software Interfaces	SW for reading Qr codes and associating data with tool holder reference and CAM data
		Communications Interfaces	API between Fraisa world, My rConnect and Siemens Teamcenter(Inight Hub
	Performance Requirements		XML file, < 1 MB, transferred within 5 sec
	Other non-functional requirements		…

ID			SR-Pilot 3-BP_2
Business requirement reference			Tool wear and remaining useful time prediction and monitoring
Overall Description			The system should be able to predict tool wear and monitor it with respect to threshold values
Rationale			The tool should be changed when it arrives to end of life without breaking
Specific Requirements	Feature	Introduction & Purpose of feature	Predicts tool wear and remaining lifetime for avoiding breakage and exchanging tool when needed
		Stimulus Response Sequence	Input: tool data, machine force sensors, AI models Output: Tool wear, remaining lifetime
		Functional Requirements	The system shall use AI models for calculating tool wear and remaining lifetime, display it in the application, monitor with respect to lilmits and exchange the tool when needed
	External Interface Requirements	User Interfaces	My rConnect application
		Hardware Interfaces	My rConnect HW user interface
		Software Interfaces	My rConnect application interface
		Communications Interfaces	Internal application communication links
	Performance Requirements		AI calculation within 1 sec
	Other non-functional requirements		…

ID			SR-Pilot 3-BP_3
Business requirement reference			Machine component remaining useful time prediction and monitoring
Overall Description			The system should be able to predict component residual useful time and monitor health with respect to functional values
Rationale			The component should be changed when it arrives to end of life without breaking
Specific Requirements	*Feature*	*Introduction & Purpose of feature*	Predicts component failure and remaining lifetime for avoiding breakage and plan exchanging when needed
		Stimulus Response Sequence	Input: Component sensor data, warning messages, AI and ontology models Output: Component health indicator, remaining lifetime
		Functional Requirements	The system shall use AI models for calculating health indicators and remaining lifetime, display it in the application, monitor with respect to limits and exchange the component when needed
	External Interface Requirements	*User Interfaces*	My rConnect application
		Hardware Interfaces	My rConnect HW user interface
		Software Interfaces	My rConnect application interface
		Communications Interfaces	Internal application communication links
	Performance Requirements		AI calculation within 1 sec
	Other non-functional requirements		…

ID			SR-Pilot 3-BP_1
Business requirement reference			Tool expert connected in CAM
Overall Description			The system should be able to recommend and import (with a few clicks) the right tool inclusive tool geometry and milling data
Rationale			Have the perfect matching tool and prevents careless mistakes
Specific Requirements	*Feature*	*Introduction & Purpose of feature*	Decides which tool is the best to mill the workpiece and gives the perfect milling data
		Stimulus Response Sequence	Input: CAD file of Workpiece with the corresponding material Output: Reccomended tool with the matching milling data directly imported in the NX CAM
		Functional Requirements	The system shall use direct connection to the ToolExpert
	External Interface Requirements	*User Interfaces*	NX
		Hardware Interfaces	Local Computer
		Software Interfaces	NX and ToolExpert
		Communications Interfaces	
	Performance Requirements		According to Siemens NX
	Other non-functional requirements		…

Data Sources and Data Characterization

The required data exchange specifications and sources are described in the following tables, following the definition of the pilot business processes and pilot objectives. The main requirements are related to the tool information, from Fraisa world platform, the NC program information, from Siemens CAM and Teamcenter PLM, and the process information, from the GF My rConnect platform.

Tool references

Parameter	Description	Unit	Format	Source	Example
Article Number	Serial number of the tool	Number	Int	Fraisa world	P46200450
Tool ID number	Unique ID number of the tool	Number	Int	Tool DMC/RFID	7613088486692

Tool geometry and material

Parameter	Description	Unit	Format	Source	Example
Tool Geometry	Simplified 3D file of tool with actual geometrical values, following manufacturing or reconditionning	NA	DXF	API CimSource	
Tool Material	Base tool material	NA	ASCII	API CimSource	HM-MG10
Tool Coating	Coating name or code	NA	ASCII	API CimSource	Polychrom

Tool lifecycle history

Parameter	Description	Unit	Format	Source	Example
Time	The time the tool has been in use	min	Float	(My rConnect) Fraisa world	60
Residual useful lifetime	The estimated time the tool can be used	min	Int	(My rConnect) Fraisa world	20
NumberOfParts	The total number of parts that have been produced	NA	ASCII	(My rConnect) Fraisa world	

NumberOf Usages	The number of process steps (milling sequences) this tool has been used	one	Int	(My rConnect) Fraisa world	
Feed Distance	The sum of the feed path covered by the tool and the workpiece relative to each other during machining	one	m	(My rConnect) Fraisa world	
Cutting Distance	The sum of the lengths that the cutting tool works in the workpiece.	one	m	(My rConnect) Fraisa world	
Lenght	The abraded length of the tool	one	µm	Fraisa world	23
Diameter	The abraded diameter of the tool	one	µm	Fraisa world	10

Process data

Parameter	Description	Unit	Format	Source	Example
Estimated Machining Time	The estimated machining time for the programmed machining process	h	Float	Fraisa world – CAD CAM	
Process Parameters	Feed speed, depth of cut, spindle rotational speed	m/s, mm, rpm	Float, float, int	Fraisa world – CAD CAM	

GF data sources

Data Source Name			**My rConnect**
Type			Database, OPC UA
Licence			NA
Data Owner			GF
Internal/External			NA
Details	*APIs*		SQL data access, OPC-UA server.
	Data	*Description*	• Milling Process Parameters: Forces, torques, Axes loads, Vibration, Axes positions, speed, acceleration, Acoustic emission • Process metadata (machine, program name, time,..) • •
		Format	• CSV files
Data Characteristics (if applicable)	*Data Source (distributed/centralized)*		• Centralised (machine)
	Volume (size)		• 100 MB/day/machine
	Velocity (e.g. real time)		• 10 Hz sample time
	Variety (multiple datasets, mashup)		• Single type
	Variability (rate of change)		• None
Other Data Science (collection, curation, analysis, action -if applicable)	*Veracity (Robustness Issues, semantics)*		• High
	Visualization		• My rConnect dashboards
	Data Analytics		• Statistical tolerances analysis
Data Source Name			My rConnect
Type			Database, OPC UA
Licence			
Data Owner			GF

Fraisa data sources

Data Source Name			**Fraisa World**
Type			Database
Licence			NA
Data Owner			Fraisa
Internal/External			NA
Details	*APIs*		SQL data access
	Data	*Description*	• Tool data (geometry, substrat, coating, etc.) • Recommended cutting data (spindle speed, feed, deep of cut, etc.)
		Format	• CSV files
Data Characteristics (if applicable)	*Data Source (distributed/centralized)*		• Centralised
	Volume (size)		• 1 MB / day / tool
	Velocity (e.g. real time)		• 1 Hz
	Variety (multiple datasets, mashup)		• Multiple datasets
	Variability (rate of change)		• No
Other Data Science (collection, curation, analysis, action -if applicable)	*Veracity (Robustness Issues, semantics)*		• High
	Visualization		• Tool geometry in CAM and My rConnect
	Data Analytics		• Predicted wear and Residual Useful Lifetime

Siemens data sources

Data Source Name			**Teamcenter**
Type			Database, Digital Twin
Licence			NA
Data Owner			Siemens
Internal/External			NA
Details	*APIs*		SQL data access
	Data	*Description*	• CAD CAM and Manufacturing Process data • Machine and part references •
		Format	XML files
Data Characteristics (if applicable)	*Data Source (distributed/centralized)*		• Centralised (PLM)
	Volume (size)		• 1-10 MB
	Velocity (e.g. real time)		• 1 sec
	Variety (multiple datasets, mashup)		• Multiple datasets
	Variability (rate of change)		• High
Other Data Science (collection, curation, analysis, action -if applicable)	*Veracity (Robustness Issues, semantics)*		• High, controlled
	Visualization		• Standard representation
	Data Analytics		• NA

Comentado [MF1]: For the fields that are not applicable we have to mention it

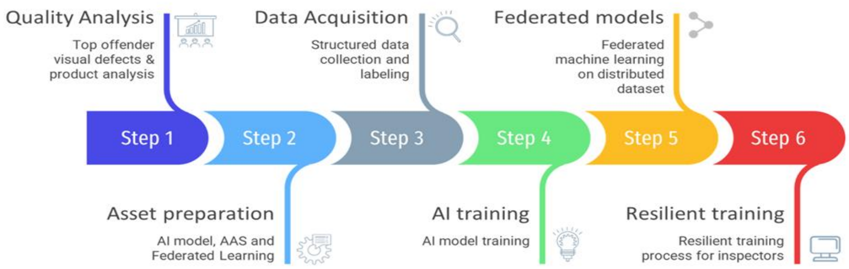
3 AVIO AERO Pilot

3.1 Use-case sequence

3.1.1 Business Scenario 1 and 2

The implementation of the future scenario starts from a study of the main visual defects which appear to be the top offenders of the production process, for a given observation period. The analysis can be based on the Quality Notifications that came out from the visual inspection process in the final phase of the production cycle (over inspection), but also by crossing the customer's escape data on defects not identified during the over inspection phase. Similarly, the analysis can be extended by identifying the top offender part numbers on which the majority of QNs related to visual defects occur.

Training AI algorithms involves a structured and properly labelled image dataset on defects. Therefore, a structured data acquisition is necessary to proceed with the implementation of an AI-based solution to support operators in the visual inspection phases of the parts. In order to enable interoperability of the trained AI algorithm, the concept of Asset Administration Shell (AAS) will be exploited. There will be an AI AAS dedicated to the AI algorithm which represents the AI algorithm as an asset which can interact with datasets obtained from various sources to train the AI algorithm. The advantage of this AI AAS model is the Common Information Model (CIM) of the algorithm which later can be shared and extended on products with the similar quality defects, furthermore, the AAS model equips the AI model with a common structure leading to training the model more effectively and efficiently. Considering the training on multiple part numbers, with different geometries but with similar types of defects, it is possible to consider the introduction of the Federated Learning concept.Once the required image datasets have been acquired, it will be possible to start to design, develop and train a machine learning model specifically conceived to visually inspect the produced pieces and identify defects. Thanks to Federated Machine learning approach it will be possible to perform a distributed training of the model by leveraging a set of data sources even related, when possible, to different part numbers and to the same type of defects. Being the training performed federally, it is not required to move the datasets outside Avio Aero's domain of control. As a result, the training will be more robust, accurate, and corporate data security not threatened by this process. Once the machine learning model has been trained, it will be possible to deploy it on the inspection pipeline, where it will support the operator in identifying defects on images taken for the newly produced pieces. Finally, the association of the defect - identified by the algorithm and confirmed by the operator - with the serial number of the part and the associated work order will allow a completely digital management of the Quality Notifications.



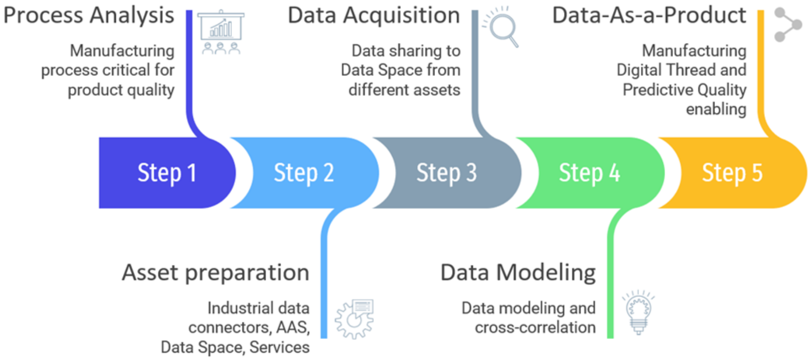
3.1.2 Business Scenario 3

The implementation of the use case implies the identification of a series of assets that currently generate useful data for the product quality process. In the vision of implementing a Data Space that implements the Data-as-a-Product concept, it is important to define the parts of a process that generate data that are suitably cross-correlated with each other, with other sources coming from digital twins and other customers of equipment suppliers may be able to predict some characteristics of product quality. Data sources will be interconnected to factually establish a Manufacturing Digital Thread, creating the foundations on which Predictive Quality algorithms will be developed and operated to generate unprecedented insights into the Avio Aero's manufacturing processes.
An example could be to identify a dedicated manufacturing process such as the EDM one and analyze with the manufacturing engineers which process parameters can influence the quality of the product.

Within this process, the opportunity of implementing the concept of Asset Administration Shell (AAS) could be evaluated in order to represent assets such as EDM process consisting of various operational parameters and data that could affect the quality of the machined part with the aim of gathering of the parameters in a structured manner so that it can be shared and used by other stakeholders having similar quality problems or products.

Implementing the IIoT solution to capture and expose this data externally, enabling the sharing of data residing in other systems and related to the same process (e.g. measurements through SPC).

The RE4DY Data Space, its components and the underlying IDS principles will support, where needed, the physical exchange of data. The adherence to the IDS principles will ensure that the exchange occurs while the end user always maintains sovereignty over the datasets being shared and how they are used, also allowing for the participation of additional value chain players. When possible, these principles will also allow for a safe and sovereign exchange of data across multiple geographically distributed Avio Aero's plants.



3.1.3 PoC definition

3.1.3.1 Business Scenario 1 and 2

CURRENT BUSINESS SCENARIO:
The visual inspection process is present in different parts of the production process of the parts (MAKE) and in the final phase before the delivery to the stock warehouse (over inspection). It turns out to be a crucial phase which certifies the correct execution of the mechanical processing operations of the official processing cycle. It also opens up scenarios for evaluating the production process, in the event of defects.

This process is now completely manual without any help from IT tools for the identification and categorization of defects. The instrumentation used is linked to the sensitivity of the operator who, depending on the type of defect, can resort to the use of probes to evaluate the surface defect.

The report of the non-conformities found during the visual inspection process is on paper and requires the operator responsible to insert a series of information on the identified defect (type, position, categorization) for each serial number inspected. Product quality team manages non-conformities through the company management system (ERP) by opening quality notifications (QN) and defining which of these defects are acceptable or need rework operations. It also has the entitlement to define if a serial number is not compliant from the point of view of quality and issue a rejection. Therefore, in this process, the IT infrastructure only focused on the management of quality notifications by the quality engineer who manually traces the non-conformities relating to a processing batch before deciding whether the part can move on to the assembly phases (in the case of over inspection) or subsequent work operations.

FUTURE BUSINESS SCENARIO:
Within the future business scenario, a Machine Learning model specifically trained for the purpose of identifying and highlighting areas of the produced parts where defects can be found will be added to the inspection loop. In particular, the part will reach the quality control station where several pictures of it will be taken. Dedicated working stations (similar

to photo booths) will be put in place, ensuring a standardization in the way images are captured. Lighting conditions, framing and other technical characteristics are extremely important to ensure that data provided to the algorithm is consistent.

Starting from the acquired pictures, the ML algorithm will then proceed with the identification of areas that potentially contain defects. Such areas will then be highlighted and notified to the quality inspector who will proceed with further manual checks. From this point on, the inspection and non-conformities registration process can continue as per the existing version. Thanks to the introduction of the aforementioned machine learning model, it will be possible to speed up the entire inspection process, make it safer reducing the number of false negatives and customers escapes and also allowing the creation of a digital and structured knowledge base.

3.1.3.2 Business Scenario 3

CURRENT BUSINESS SCENARIO:
The over-inspection process identifies a series of defects, which after appropriate evaluation by the product quality and manufacturing areas, are managed as Quality Non-Conformances. The documentation relating to the serial numbers associated with the production batch is managed and updated in the company ERP. Similarly, customer complaints and quality escapes are managed through the ERP system, from which the process analyses required by product and quality engineers start.

The production process of a part number goes through a series of operations which are formalized on the company Product Lifecycle Management (PLM) system. On that system, all the official technical information related to the life cycle of the product, from design to market recall, can be found and managed.

Within the machining process, certain operations performed on specific equipment make available a process dataset related to the product quality of the specific machining in progress. Data is collected using IIoT solutions and sent to cloud-based applications. In the current business scenario, raising a quality notification (also known as a non-conformance) implies a reactive business process, meaning that problems and defects are identified after they occur. The only exception to this scenario is represented by the adoption of a Statistical Process Control (SPC), where the constant acquisition of dimensional data provides information on whether the process is deviating from the nominal conditions. It is worth noting, however, that even in this case the approach is very limited considering that we are only monitoring the dimensional data at the end of each single job. In the current approach, therefore, there is no correlation between the data residing in different IT systems and related to the quality of the production process. An example is represented by the EDM (Electric Discharge Machining) machines supplied by +GF+, which carry out the EDM process on parts for which the normal milling process is not recommended or possible. The quality of the process depends on a series of parameters related to the electrode which are currently not related to the defects found in the over-inspection phase and then managed with QN.

Furthermore, the processes themselves do not benefit from the knowledge gained from similar processes in the supply chain of other sites and/or customers of the plant supplier.

FUTURE BUSINESS SCENARIO:

From a current scenario where quality notifications are managed in a reactive way and various shop assets are generating data that is not captured or leveraged, the goal of this trial is to enable new predictive capabilities for identifying quality issues across the manufacturing process.

The trial will collect data from a variety of assets (CNC machines, other shop devices, CMM machines, the ERP system, a central data warehouse aka data lake, inspection stations) with the goal of extracting valuable insights through the definition of one or multiple localized Digital Twins. Leveraging a set of open connectors as defined by the IDSA specifications, we'll also share data into a specific data space, to enable data exchange towards and from other company plants or other players across the extended supply chain.

In particular, we could train the localized Digital Twin with a broader set of data and at the same time provide a subset of the dataset generated by our assets to the machine OEMs for example. At the same time, the OEM could provide additional data on the usage of that asset by other customers, on similar parts or on similar materials. This dataset, protected and anonymized using the data space principles, could be beneficial for our local Cognitive Digital Twins.

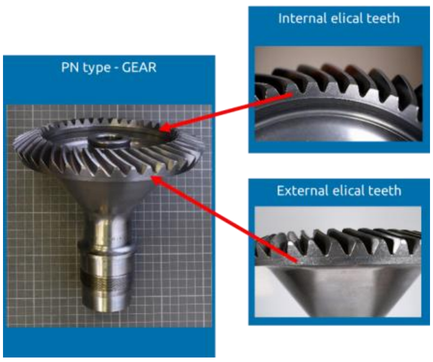
In this new scenario, we can envision new business processes generated by the new predictive capabilities. For example, a "forecasted" quality issue could generate a specific business object in the company ERP and trigger a set of tasks assigned to a quality or manufacturing engineer like for example evaluating which corrective actions have to be put in place to avoid the occurrence of the defect.

3.1.4 First experimentation results

For Pilot 1, related to Business Scenario 1, the first experimentation has been focused on problem analysis and data collection definition on the Gear product.

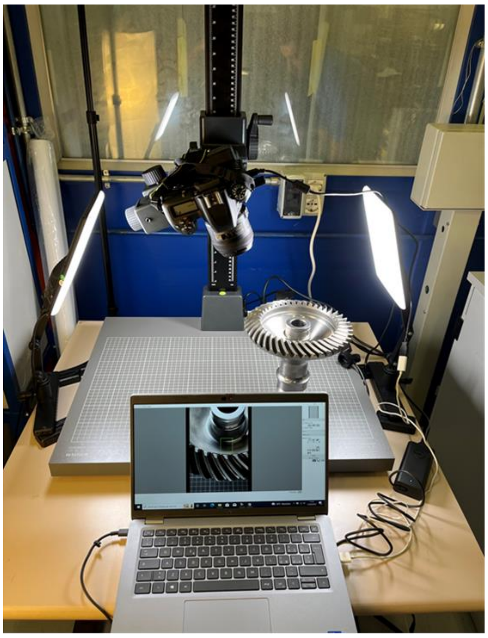
In the Figure below are shown the areas of a component identified on Gears affected by defect.

Gear component



Below the Figure shows the equipment definition for data acquisition on Gears part number and finalization of Points of Acquisition.

Data acquisition set-up for Gear



The manual defect identification and labelling phase through bounding boxes has been provided to prepare the training dataset for AI models, as shown in the below Figure.

Defect Labelling for Gear

The labelling activity includes the images organization through .csv file with the attributes about filename, number of defect presented (region_count) and bounding boxes coordinates of the defect (region_shape_attributes), as shown in the below example of table including attributes. The labelling procedure requires the involvement of a specialized operator.

Example of .csv file

filename	file_size	region_count	region_id	region_shape_attributes
Img0805.jpg	8924335	1	0	{"name":"rect","x":4850,"y":1449,"width":627,"height":293}
Img0806.jpg	8920253	1	0	{"name":"rect","x":4488,"y":1454,"width":711,"height":283}
Img0807.jpg	9031723	1	0	{"name":"rect","x":4307,"y":1477,"width":632,"height":232}
Img0808.jpg	9077052	1	0	{"name":"rect","x":4121,"y":1463,"width":627,"height":242}
Img0809.jpg	9036821	1	0	{"name":"rect","x":3926,"y":1473,"width":646,"height":223}
Img0810.jpg	8959847	1	0	{"name":"rect","x":3656,"y":1487,"width":678,"height":232}
Img0811.jpg	8927272	1	0	{"name":"rect","x":3545,"y":1491,"width":562,"height":223}

The next steps will include the data acquisition finalization on Gear part number in order to start the model training. In addition, the evaluations on Airfoil part number will start defining the areas of interests, the equipment design for data acquisition and the data collection process. The Federated Learning will be tested between the different models trained on different dataset.

For Pilot 3, related to Business Scenario 3, the experimentation phase has been focused on EDM production machines selection in the shop floor and process data analysis, enabling the data collection of signals.

Below the table shows some of EDM process data and the technical evaluation on availability in the Numeric Control of the machine, done with +GF+ support as machine provider. In particular, the "Level 2" define the signals available on EDM machines in Avio Aero facilities.

EDM machines signals

	Requested Parameter	Additional Description	Availability	Parameter	Source	Level
1	Cycle time	Time of working phase	Yes	Machiningtime	MT-Connect	2
2	Erosion speed (mm/min)		Yes	Machiningspeed	MT-Connect	2
3	Management and modification of tool offset and piece		Yes		eTRUE solution	
4	Orbit modification	Gap value (U-mm) in the tool table (orbiting strategy not imposed)	Yes	U	eTRUE solution	
5	Abnormal discharges, short circuit, instability		Yes	Arcvoltage, delay, good, shortcicuit, arckill, instability	MT-Connect	2
6	Amperage and voltage recording		No		Internal process recorder	

Below the internal dashboard to show the dataset available from EDM machines present in Avio Aero site.

The further steps will include the enabling of more EDM machines on data transmission and the predictive model development and training depending on crucial process characteristics could have an impact on the product quality.

3.2 BP1 & BP2 - Mitigate the impact of Human Factor

3.2.1 Business process in detail

In the current scenario the visual inspection activities are completely manual and managed by a specialized operator within the "Inspection Unit".

The "Inspection Unit" receives the production lot and after authorization by the area manager, the inspection phase begins. The specialized operator cleanses the parts to be inspected, makes sure he/she has the right lighting and proceeds with the inspection phase.

The inspection phase is based on the operator's knowledge of all known defects in the quality procedures. The operator has the procedure available for consultation and inspects the entire geometry of the part for possible defects. During the inspection, he/she can change the position of the part under the light source, to more easily visualize the presence of a defect. For some suspected defects, the operator can use a 40x enlarger to see the defect enlarged and be able to analyze it.

Once the defect has been identified, the operator can also use small devices to scrub the defect to understand the real entity of the defect and proceed to the correct categorization of the same, based on specific quality acceptance criteria.

The defect identification phase therefore is heavily dependent from the experience in correctly recognizing the types of defects acquired by the specialized operator.

The use case implementation impacts two business processes. The first concerns the objectification of the defect by the operator, who shifts his competence from "operator" to "supervisor" of the inspection phase.

The implementation of AI algorithms, after a learning phase on known defects, would make it possible to suggest to the operator which defects are present on the part with an initial categorization of them. The trained machine learning model will therefore support the operator in the visual identification of defects. The operator, however, will always be supervising this process, providing feedback on possible "false positives" and improving the accuracy of the algorithms.

Moreover, the model being developed to identify a class of defects, it will also be possible to reuse the same model or at least the knowledge base constituting the model for other applications. A similar visual inspection process performed on different part numbers affected by the same type of defects could benefit using the same model with some specific tuning.

Likewise, the recognition of the same types of defects could be extended to completely different products, through the implementation of the Federated Learning concept. This approach makes it possible to exploit the knowledge acquired in identifying a defect on a particular product, on other products present on the same site or on other production sites.

3.2.2 Business indicators

Business Indicators Summary

ID	BUSINESS Indicator	DESCRIPTION	Unit*	Current value	Future expected value	Expected date of achievement**
1	Reduce quality control time on the final product	The use of the software will speed up the quality control process	Minutes dedicated to quality check	TBA	-10%	End of implementation
2	AI Software recognizes the same defects the operator does	To help to operator the software must has a good reliability	Numbers of defect recognized by the software	NA	85%	Before 12 months after the implementation
3	Reduce the number of trainings hours	Using learning software could simulate higher volume production	Hours needed for training	480	-10%	End of implementation

**Provide the units in which you measure the value of the defined indicator (%, people, €, Si, etc.).*

*** During the implementation / end of the implementation / before 6 months after implementation / before 12 months after implementation / before 24 months after implementation / more than 24 months after implementation*

3.2.3 Business requirements

Business requirements are statements of what a system should do rather than how it should do it. They are instructions describing the functions the system should provide and the characteristics the solution should have. They answer the question: "what does the business want to do?"

When developing or implementing a new IT solution, business requirements serve a number of important purposes. For example:

- Help a business understand and articulate what they are looking for and provide a framework for them to make an informed decision
- Help manage the scope of an IT development or purchase
- Provide a mechanism to communicate to a technology service provider what the solution needs to do to satisfy the business' needs
- Inform cost and product pricing decisions

No.	BUSINESS OBJECTIVE	REQUIREMENT	AREA[1]	SUB HEADING[2]	FUNCTIONALITY[3]	PRIORITY[4]
1	Mitigate the impact of Human Factor	The tool should support inspectors in identifying defects	Production	User requirement	Functional	Critical
2		The tool should be able to learn from manual inputs and collect the operator' expertise	Production	User requirement	Functional	Critical
3		The tool should be able to automatically go through specific training sessions of the algorithm, without requiring activities from the end users.	Production	Support requirement	Non-functional	Preferred
4		The tool should achieve an adequate level of accuracy in identifying the defects, at least aligned with the state-of-the-art defined by the literature.	Production	Performance requirement	Functional	Critical
5		The tool should provide a dedicated interface for supporting training sessions for the junior inspectors	Production	User requirement	Functional	Preferred
6		The activities required to the operator to acquire images should be approved by EHS and Unions	Production	EHS requirement	Non-functional	Critical
7		The activities required to the operator to acquire images should have minimal impact in terms of time	Production	User requirement	Functional	Preferred
8		The tool should be easily applicable to different parts or product lines	Production	User requirement	Functional	Critical
9		The tool should ensure IP protection as per the internal policies	Production	Security requirement	Non-functional	Critical
10		The tool should fulfill the applicable cybersecurity procedures and international regulations	Production	Security requirement	Non-functional	Critical
11		The images acquired should be archived in such a way that the labeling information and other relevant metadata is always available regardless of the tool	Production	Security requirement	Non-functional	Preferred

*See the GLOSSARY in Annex Chapter for a description of the columns

3.3BP3 - Enhance quality process stability

3.3.1 Business process in detail

Avio Aero's processes currently include a series of information that resides in different IT systems. The management of non-conformities on the corporate ERP takes place by the quality engineer following the identification of defects in the over inspection phases, and therefore in the final parts of the production process. The opening of a Quality Notification (QN) implies a series of backward actions focused on identifying the problem or operation that generated the non-conformity. This impacts several actors in the supply chain, depending on the type of problem identified, including manufacturing engineers, process engineers, quality engineers and process technologists. The management of a non-conformity with respect to the official process, declines the process as a reaction to the non-conformity itself: in other words, the corrective actions of the process are identified and implemented downstream of a non-conformity that has already had an impact on the quality of the product.

The implementation of the use case would make it possible to transform the logic of the process, shifting from reactive to predictive. The sharing of datasets related to different parts of the production process of a part and the correlation with measurement data and process data would make it possible to analyze the trends of significant characteristics of the part quality process. The implementation of models that correlate these signals would make it possible to predict their trend by identifying on which characteristics it is needed to operate to avoid process deviations.

The second process impacted by the implementation of the use case is related to the industrialization and validation phases of a production process for new products (New Product Introduction). In fact, this requires a series of evaluations and statistics in order to identify the main characteristics of the process and the optimal values of the individual operations which ensure the conformity of the process from the point of view of product quality.

To date, this process is often based on past knowledge and experience made on similar products, or limited to the most critical operations or even with studies that generate statistics on a limited number of test parts that go through the single operations of the production cycle. The approach is somehow limited by the need of containing costs and production times. This results in a series of approximate assessments, which could lead to the introduction of non-conformities in the over inspection phase.

The implementation of the use case would improve and optimize this process in the most critical operations, benefiting from results deriving from similar processes present in other plants and from services made available by the plant manufacturer which in turn can optimize the quality parameters of the process based on data retrieved from other distributed digital twins.

3.3.2 Business indicators

Business Indicators Summary

ID	BUSINESS Indicators	DESCRIPTION	Unit*	Current value	Future expected value	Expected date of achievement**
1	Efficiency of OEE on EDM machines.	Data collection could implement both Predictive Quality and Predictive Maintenance by intervening on 2 of the 3 indices that calculates OEE	OEE	75%	+1%	Before 24 months after the implementation

**Provide the units in which you measure the value of the defined indicator (%, people, €, Si, etc.).*

*** During the implementation / end of the implementation / before 6 months after implementation / before 12 months after implementation / before 24 months after implementation / more than 24 months after implementation*

3.3.3 Business requirements

Business requirements are statements of what a system should do rather than how it should do it. They are instructions describing the functions the system should provide and the characteristics the solution should have. They answer the question: "what does the business want to do?"

When developing or implementing a new IT solution, business requirements serve a number of important purposes. For example:

- Help a business understand and articulate what they are looking for and provide a framework for them to make an informed decision
- Help manage the scope of an IT development or purchase
- Provide a mechanism to communicate to a technology service provider what the solution needs to do to satisfy the business' needs
- Inform cost and product pricing decisions

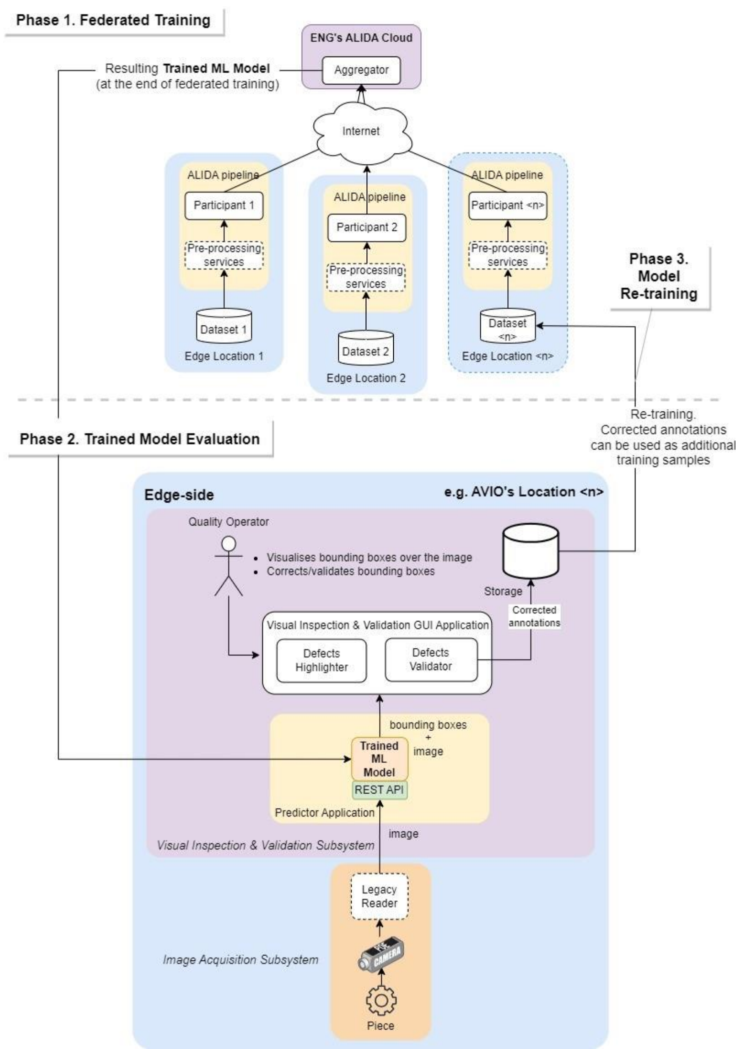
No.	BUSINESS OBJECTIVE	REQUIREMENT	AREA[1]	SUB HEADING[2]	FUNCTIONALITY[3]	PRIORITY[4]
1	Enhance quality process stability based on cross-correlation between process datasets	The solution should monitor process data and highlight potential quality issues on a given part	Production	User requirement	Functional	Critical
2		The solution should be able to collect data from different data source in a scalable way, based on data availability and relevance	Production	Technical requirement	Functional	Preferred
3		The solution should be able to automatically go through specific training sessions of the algorithm, without requiring activities from the end users.	Production	Support requirement	Non-functional	Preferred
4		The solution should achieve an adequate level of accuracy in identifying potential issues, at least aligned with the state-of-the-art defined by the literature.	Production	Performance requirement	Functional	Critical
5		The solution should provide a dedicated interface for visualizing the possible issues	Production	User requirement	Functional	Optional
6		The solution should provide an appropriate notification mechanism and reporting tools to inform and involve the right actors	Production	User requirement	Functional	Critical
7		The connection with the data space should ensure full control in terms of data	Production	Security requirement	Non-functional	Preferred

		exposed and should be easily maintainable and adaptable				
8		Data exchange should be monitored and tracked with an appropriate level of logging for auditing purposes	Producti on	Security requirement	Non-functional	Optional
9		The tool should be easily applicable to different parts or product lines	Producti on	User requirement	Functional	Critical
10		The tool should ensure IP protection as per the internal policies	Producti on	Security requirement	Non-functional	Critical
11		The tool should fulfill the applicable cybersecurity procedures and international regulations	Producti on	Security requirement	Non-functional	Critical
12		The data acquired should be archived in such a way that the labeling information and other relevant metadata is always available regardless of the technological platform adopted	Producti on	Security requirement	Non-functional	Preferred

*See the GLOSSARY in Annex Chapter for a description of the columns

3.4 System requirements

Pilot 1



ID			SR-Pilot_1-BP_1-1
Business requirement reference			Mitigate the impact of Human Factor #2, #8, #9, #11
Overall Description			Federated training for the visual inspection AI model
Rationale			Training the AI model for visual inspection by leveraging multiple distributed data sources reliably, efficiently, and trustingly through Federated Machine Learning techniques.
Specific Requirements	*Feature*	*Introduction & Purpose of feature*	Introduction & Purpose of feature Distributed datasets related 2 different products (Gears and Blades) with similar subset of kind of defects. Federated training of an AI model for visual inspection by using ALIDA.
		Stimulus Response Sequence	INPUT: • Aggregation pipeline (Aggregator) • Local training pipeline (Participant) including to-be-trained AI model for visual inspection • At least two data sources/datasets offering images of parts produced. OUTPUT: • Trained AI model for visual inspection
		Functional Requirements	Functional requirements: • Analytics Developer will access the ALIDA user interface on a dedicated cloud environment. • Analytics Developer will define – either by using the already available BDA service blocks or custom blocks – the two Aggregation and Local Training pipelines. • Analytics Developer will export from ALIDA the Local Training (Participant) pipeline and deploy it at each edge node where training datasets are available. • Analytics Developer will configure the Local Training pipeline to interact with the local data sources/datasets. • Analytics Developer will launch, on the ALIDA cloud, the execution of the Aggregator pipeline. • Analytics Developer will execute, on each edge node, the Local Training pipeline. • ALIDA (on cloud) and the Participants (on edge) will autonomously interact to

			carry out the training process automatically requiring no user intervention. • ALIDA will output the trained model.
	External Interface Requirements	*User Interfaces*	The ALIDA graphical user interface to graphically design the pipelines. The docker-compose yaml file specifying the Aggregator and Local Training pipelines can be customized to point to the specific data source.
		Hardware Interfaces	• Participant host machine should have at least 16GB of RAM • Participant host machine should have a GPU (NVIDIA with CUDA support) with at least 8GB of memory • Participant host machine preferably with a Linux OS
		Software Interfaces	N/A
		Communications Interfaces	
	Performance Requirements		N/A
	Other non-functional requirements		N/A

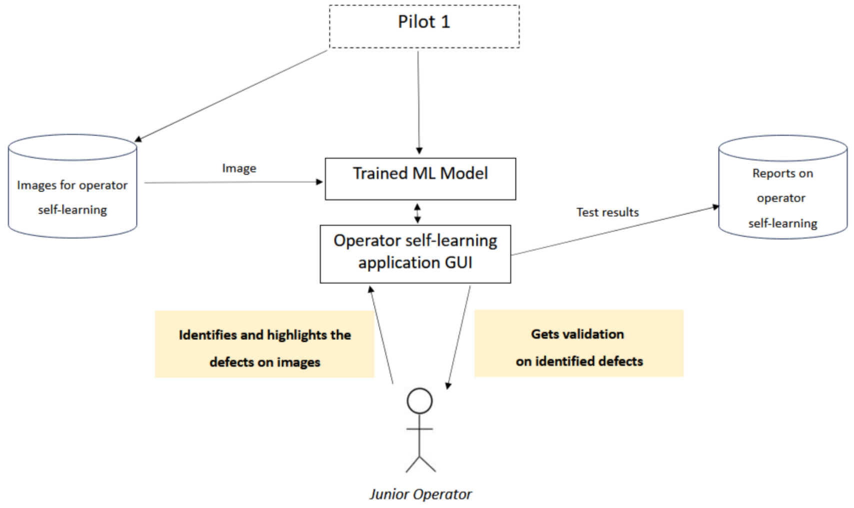
ID			SR-Pilot_1-BP_1-3
Business requirement reference			Mitigate the impact of Human Factor #1, #2, #4, #6, #8, #9
Overall Description			Visual inspection through AI model (Visual Inspection Subsystem)
Rationale			The software helps the operator defect recognition on parts, avoiding human errors and speeding up the process. Errors generate high reworking costs and branding costs.
Specific Requirements	*Feature*	*Introduction & Purpose of feature*	Pilot 1 is going to involve two plants with similar production lines where the AI model for visual inspection of parts will be installed. The purpose is to improve the precision of the inspection of the operator and reduce escapes.
		Stimulus Response Sequence	INPUT: Image(s) of the produced Part being inspected. OUTPUT: Image(s) of the Part where the areas containing defects have been highlighted by Bounding Boxes.
		Functional Requirements	Functional requirements: • The system will receive an Image of the Part from the Image Acquisition Subsystem • The system will identify, through the Trained AI Model, Bounding Boxes within the Image that contain (or might contain) defects. • The system will show to the Quality Operator an image obtained by combining the Image of the part with an overlay of the Bounding Boxes identified by the AI Model. • The Quality Operator visualizes the Image plus Bounding Boxes and carries out any other additional check on the physical Part.

	External Interface Requirements	User Interfaces	• The interface can be an image of the part with the bounding boxes returned by the AI model in overlay.
		Hardware Interfaces	N/A
		Software Interfaces	REST API
		Communications Interfaces	REST API
	Performance Requirements		
	Other non-functional requirements		• The system must be deployable at the edge. • The activities required to the operator to acquire images should be approved by EHS and Unions • The tool should ensure IP protection as per the internal policies

ID			SR-Pilot_1-BP_1-4
Business requirement reference			Mitigate the impact of Human Factor #2, #4, #11
Overall Description			Collect feedback from the Quality Operator
Rationale			Feedback from the Quality Operator about the AI model outcomes can be used to improve the model itself.
Specific Requirements	Feature	*Introduction & Purpose of feature*	The corrected output (plus original images) can be used to retrain the AI model.
		Stimulus Response Sequence	INPUT: • For a given image, a set of bounding boxes has been returned by the AI model for visual inspection. OUTPUT: • The updated (confirmed or corrected by the Quality Operator) set of bounding boxes for the given image
		Functional Requirements	Functional requirements: • The system will show to the Quality Operator the image of the part with the overlay of Bounding Boxes as identified by the AI Model. • The Quality Operator will be able to modify (correct) - through a GUI - the Bounding Boxes. In particular, he/she should be able to: 1) Fix false negatives: the Quality Operator adds a new bounding box in lieu of a not detected defect. 2) Fix false positives: the Quality Operator removes an untrue Bounding Box. The System will store the corrected Bounding Boxes on a storage service alongside the corresponding images.
	External Interface Requirements	*User Interfaces*	• "Corrector"/"Labeler" GUI show image of the part plus Bounding Boxes overlay to the Quality Operator through a Screen. The Quality Operator can then interact via mouse or keyboard to add, remove, adjust the graphically shown Bounding Boxes.
		Hardware Interfaces	• (Computer) Screen, Mouse or keyboard (workstation)

		Software Interfaces	N/A
		Communications Interfaces	
	Performance Requirements		Not specifiable
	Other non-functional requirements		N/A

Pilot 2

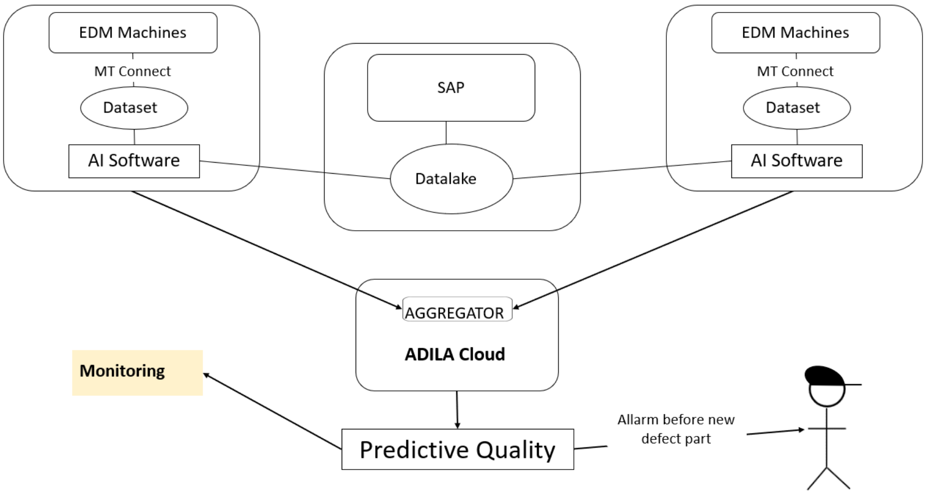


ID			SR-Pilot_2-BP_2-1
Business requirement reference			Mitigate the impact of Human Factor #1, #3, #5, #6, #10, #11
Overall Description			Quality Operators Training Use the software of Pilot1 to accelerate the learning and certification process of the quality operators.
Rationale			Currently, the numbers of hours needed to teach a junior operator to become senior is very high. This makes a few senior operators take part of their time to teach the junior ones.
Specific Requirements	Feature	*Introduction & Purpose of feature*	Purpose of the Pilot is to have some help in teaching the junior operators. With the agreement of the airworthiness authorities, it is possible to reduce the training hours, improve the teaching method and create more senior operators.
		Stimulus Response Sequence	INPUT: 1. Images of the manufactured items to be inspected. 2. Bounding boxes entered by the trainee junior operator (by drawing them on the screen around the defected parts). OUTPUT: 1. Bounding boxes (automatically drawn on the screen) suggested by the AI Model (it can be the BS-1 model retrained based on the senior visual inspector's collected feedback) that the junior inspector can compare with the ones drawn/entered by himself.
		Functional Requirements	Visual Inspection Simulation Tool The same software described for Pilot 1 will be used. In this case however, the Visual Inspection/Corrector tool of Pilot 1 will run in a Training Mode preventing junior operators from visualising the AI outcomes beforehand. • The Simulation Program shows an image of a manufactured item with no defects identified (no bounding boxes) • The Simulation Program allows the junior operator to draw - on the original image of the item - bounding boxes where he believes defects are present. • The AI Model for visual inspection independently detects the defects and highlights them as bounding boxes on the same image to allow the trainee to make a comparison. • From the comparison (drawn bounding boxes made by the AI and the ones from the trainee will be different) the junior operator can learn as in a "simulation game".
	External Interface Requirements	*User Interfaces*	Web-based graphical user interface
		Hardware Interfaces	None
		Software Interfaces	To be defined

	Communications Interfaces	REST API
	Performance Requirements	None
	Other non-functional requirements	None

Pilot 3

Comentado [PG2]: Remove red underlining from picture



<table>
<tr><td colspan="3">ID</td><td>SR-Pilot_3-BP_3-1</td></tr>
<tr><td colspan="3">Business requirement reference</td><td>Enhance quality process stability based on cross-correlation between process datasets
#1, #2, #8</td></tr>
<tr><td colspan="3">Overall Description</td><td>Federated algorithm training through ALIDA</td></tr>
<tr><td colspan="3">Rationale</td><td>The transition from a reactive quality to a predictive quality allows to identify some deviation of the process, that has an impact on the product quality, in advance</td></tr>
<tr><td rowspan="3">Specific Requirements</td><td rowspan="3">Feature</td><td>Introduction & Purpose of feature</td><td>Pilot3 involves the dataspace where companies and plants can share data. The purpose is to collect data from the plants and from other companies and cross correlate them to implement the predictive quality.</td></tr>
<tr><td>Stimulus Response Sequence</td><td>INPUT:
the specification of the local training pipeline (Participant pipeline) composed either of ready-to-use BDA service blocks or custom blocks. Such specification can be created on ALIDA. This pipeline also includes the ML model.
the specification of an Aggregation pipeline
OUTPUT:
the trained model/algorithm</td></tr>
<tr><td>Functional Requirements</td><td>Functional requirements:
Analytics Developer will access the ALIDA user interface on a dedicated cloud environment.
Analytics Developer will define – either by using the already available BDA service blocks or custom blocks – the two Aggregation and Local Training pipelines.
Analytics Developer will export from ALIDA the Local Training (Participant) pipeline and deploy it at each edge node where training datasets are available.
Analytics Developer will configure the Local Training pipeline to interact with the local data sources/datasets.
Analytics Developer will launch, on the ALIDA cloud, the execution of the Aggregator pipeline.
Analytics Developer will execute, on each edge node, the Local Training pipeline.
ALIDA (on cloud) and the Participants (on edge) will autonomously interact to carry out the training process automatically requiring no user intervention.
ALIDA will output the trained model.</td></tr>
</table>

	External Interface Requirements	User Interfaces	• The ALIDA graphical user interface to graphically design the pipelines. • The docker-compose yaml file specifying the Aggregator and Local Training pipelines can be customized to point to the specific data source.
		Hardware Interfaces	N/A
		Software Interfaces	•UI •Database
		Communications Interfaces	N/A
	Performance Requirements		N/A
	Other non-functional requirements		…

ID			SR-Pilot_3-BP_3-2
Business requirement reference			Enhance quality process stability based on cross-correlation between process datasets
Overall Description			Predictive quality on the parts in Avio plants using a machine learning model and a dataspace
Rationale			The transition from a reactive quality to a predictive quality allows to identify some deviation of the process, that has an impact on the product quality, in advance
Specific Requirements	Feature	Introduction & Purpose of feature	Pilot3 involves the dataspace where companies and plants can share data. The purpose is to collect data from the plants and from other companies and cross correlate them to implement the predictive quality.
		Stimulus Response Sequence	Input: • Process data from machine • Transitional data from SAP (e.g., quality notifications) Output: • Forecasting the deviation of product quality
		Functional Requirements	System shall: • Collect data from other machines • Collect data • Show future trends of quality data
	External Interface Requirements	User Interfaces	• Show trends of quality data • Show predictive quality • Show collected data
		Hardware Interfaces	
		Software Interfaces	
		Communications Interfaces	

	Performance Requirements	
	Other non-functional requirements	…

ID			SR-Pilot_3-BP_3-3
Business requirement reference (ref. TH Ch. 2 - business reqs table)			Enhance quality process stability based on cross-correlation between process datasets #6
Overall Description			Notifying the right actors about possible issues resulting from the analysis carried out by the predictive quality algorithm
Rationale			The results of the analysis done by the algorithm must be communicated to the right actors for them to be able to act
Specific Requirements	*Feature*	*Introduction & Purpose of feature*	This feature aims at enabling the due communication of the data analysis result to the right actors.
		Stimulus Response Sequence	INPUT: predictive quality algorithm output OUTPUT: An action needed to be implemented by the operator
		Functional Requirements	Functional requirements. • System will receive the algorithm output either by exposing an endpoint that the alg. will contact or accessing the output directly (e.g., if store on a storage service) • System will show the results obtained from the algorithm.
	External Interface Requirements	*User Interfaces*	N/A
		Hardware Interfaces	N/A
		Software Interfaces	N/A

3.5Data Sources and Data Characterization

Pilot 1

Data Source Name			Manufactured items images
Type			Several image files organized in a private corporate box repository.
Details	*APIs*		Not available. Data will be uploaded and made available to the RE4DY platform through the solution implemented for the pilot.
	Data	*Description*	Images of manufactured items.
		Format	JPEG
	Data Source (distributed/centralized)		Rivalta factory Bielsko-Biala factory
Data Characteristics (if applicable)	*Volume (size)*		GB
	Velocity (e.g., real time)		Not required. Data for batch analysis.
	Variety (multiple datasets, mashup)		2 products (gears and blades) with a subset of defects
	Variability (rate of change)		N/A
Other Data Science (collection, curation, analysis, action -if applicable)	*Veracity (Robustness Issues, semantics)*		N/A
	Visualization		N/A
	Data Analytics		Data will feed FML based algorithms being developed for the pilot.

Data Source Name			Coordinates of the defect regions on parts
Type			Several CSV files are organized in a private corporate box repository.
Details	*APIs*		Not available. Data will be uploaded and made available to the RE4DY platform through the solution implemented for the pilot.
	Data	Description	Set of coordinates of each image region where a defect is detected by human operator. Each defect region set of coordinates is coupled with the corresponding item image file where the defect is detected.
		Format	CSV, XLSX
	Data Source (distributed/centralized)		Rivalta factory Bielsko Biala factory
Data Characteristics (if applicable)	*Volume (size)*		GB
	Velocity (e.g., real time)		Not required. Data for batch analysis.
	Variety (multiple datasets, mashup)		2 products (gears and blades) with a subset of defects

Other Data Science (collection, curation, analysis, action -if applicable)	*Variability (rate of change)*	N/A
	Veracity (Robustness Issues, semantics)	N/A
	Visualization	N/A
	Data Analytics	Data will feed FML based algorithms being developed for the pilot.

Detailed description

Manufactured items_images: initially, this dataset comprises images captured during the visual inspection process in Avio Aero factory, accompanied by labeling data (see §2.4.2). This data is intended for the initial training of machine learning algorithms. The resulting trained ML models will be employed in Pilot 1 to infer, based on newly captured images, whether they exhibit defects.

Coordinates of the defect regions on parts: the dataset contains the coordinates of regions within each image where an expert Visual Inspector has identified defects in items, subsequently labeling them. The records of this dataset are mapped to the ones in "Manufactured items images" dataset (§2.4.1) using the name of the image file as "foreign key".

Pilot 2

This pilot may be regarded as an extension of Pilot 1, aimed at harnessing its data outputs to a greater extent, although with a different objective, within the context of the same quality inspection process. As such, starting from intermediate results, it doesn't leverage directly on already existing/available data sources, which are therefore not listed in tables. The data source necessary for this pilot will be instead a consolidated trained machine learning model of identified defects in manufactured items that puts together machine learning power and the human senior professionals' expertise collected within Pilot 1.

Pilot 3

Data Source Name			CNC machine data
Type			Low frequency time series
Details	*APIs*		MT Connect
	Data	*Description*	Electro Discharge Machining process
		Format	XML
	Data Source (distributed/centralized)		Distributed
Data Characteristics (if applicable)	*Volume (size)*		GB
	Velocity (e.g. real time)		Real time, low frequency
	Variety (multiple datasets, mashup)		Single dataset per machine
	Variability (rate of change)		Static, defined by the CNC version
Other Data Science (collection, curation, analysis, action -if applicable)	*Veracity (Robustness Issues, semantics)*		N/A
	Visualization		Graphana, NodeRed
	Data Analytics		N/A

Data Source Name			Quality Notifications
Type			Relational data on company datalake
Details	*APIs*		N/A
	Data	*Description*	Transactional data related to quality notifications
		Format	Postgres
	Data Source (distributed/centralized)		Centralized
Data Characteristics (if applicable)	*Volume (size)*		GB
	Velocity (e.g. real time)		Daily
	Variety (multiple datasets, mashup)		Single dataset
	Variability (rate of change)		Quarterly
Other Data Science (collection, curation, analysis, action -if applicable)	*Veracity (Robustness Issues, semantics)*		Based on actual level of detail manually reported in the QN by the shop operator
	Visualization		SAP reports and Business Intelligence dashboards
	Data Analytics		Based on Business Intelligence dashboards and company datalake

Detailed description

CNC machine data: The Database is populated in real time by the data that is sent from the machine in XML format. The data includes a series of parameters that describe the machine at a given moment and the way in which the part is working.

Quality Notifications: The database is a set of characteristics of the defective parts produced which are downloaded directly from SAP. In case there are new defects the DB is updated daily

In aeronautics the quantity of parts produced is very low compared to other industrial sectors; even the number of defects produced by a single machine on a single component in a year is very low and rarely exceeds ten units.

Consequently, making an artificial intelligence program operational and highly efficient based on real data will take a long time. The objective of re4dy's project is to develop AI models that can find process patterns enabling predictive quality despite the low quantity of data.

4 Conclusions

D5.1 provided a detailed overview of the pilots' characterization, business scenarios impacted and expected KPIs in tool machinery and aeronautical manufacturing fields. In particular, the pilots' setup and value network data preparation have been shown for pilots led by +GF+ and Avio Aero, focusing on the description of each business scenario within each trial and providing the future scenario description, business and benefit expected by the RE4DY's trial scale-up.

The deliverable combined the contributions addressed in Chapters 1, 2 and 3 of the Trial Handbook, by an iterative process. The relationship between the deliverables from other work packages are presented, highlighting the dependencies with next deliverables of the project.

The use-cases sequences have been detailed for +GF+ and Avio Aero, focusing on current and future industrial business processes impacted. Starting from future business scenario, the system requirements are defined with partners for each pilot in terms of functional requirements, user interface, hardware/software interfaces, communication protocols and performances expected.

Finally, the Data Characterization has been provided for all kind of data and assets involved in each pilot, listing the details in terms of data sources, data format available, volume and velocity of generation and gathering the information needed for the use of data standards, management and governance in RE4DY pilot projects.

Next activities will be focused on pilots' implementation and on-site validation using the technological components provided by RE4DY, measuring KPIs and revising them if needed.

5 Annex

Below the Glossary referred to the Business requirement tables is show.

GLOSSARY BUSINESS REQUIREMENTS

Comentado [MF3]: This should have been provided earlier or in and annex referenced before the first table

1 – Indicate to which area the requirement is addressed to:

Management
Marketing
Production
Production Control
Financial
Quality Control
Logistics
Human Resources
Sales & Purchases
Maintenance
Others: (Indicate)

2 – Choose the adequate from the following list:

User Requirements
Technical Requirements
Infrastructure Requirements
Reporting Requirements
Access Requirements
Security Requirements
Privacy Requirements
Performance Requirements
Support Requirements
Others: (Indicate)

3 – Choose one of the following:

- Functional Requirements: These describe how a solution should function from an end user's perspective. They describe the features and functions of the system required by the user.
- Non-Fuctional Requirements: These describe the operational characteristic of the system. These could relate to availability, accessibility, performance, scalability, auditability, etc.

4 – Choose the adequate from the following list:

Critical	This are those types of requirements without which the business objective are achievable
Preferred	This requirements are those without which, the business objectives are achievable but not in the most efficient and effective way.
Optional	This requirements although desired do not affect the business objective defined.