



Human-AI Teaming Platform for Maintaining and Evolving AI Systems in Manufacturing

D1.1 Analysis report on human-AI teaming variants

Deliverable Lead	Profactor GmbH
Deliverable due date	30/06/2021
Actual submission date	30/06/2021
Version	1.0

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Document Control Page	
Title	Analysis report on human-AI teaming variants
Editor	Profactor GmbH
Contributors	PRO; IDEA, UMA, IDK, ITU, TYR, GOI, WU, TUD, SCCH
Work Package	WP1: Requirements and Prerequisites
Description	Report as output of Task 1.1 and 1.2, containing: (i) status-quo analysis of human-AI teaming in all phases of the AI system engineering lifecycle (at engineering time, set-up, maintenance and adaptations to changes); (ii) data and evidence-based elaboration of case study examples key performance indicators of Overall Equipment Efficiency (OEE) and Overall Labour Effectiveness (OLE).
Creation date	10/05/2021
Type	Report
Language	English
Audience	<input checked="" type="checkbox"/> Public <input type="checkbox"/> Confidential
Review status	<input type="checkbox"/> Draft <input type="checkbox"/> WP leader accepted <input checked="" type="checkbox"/> Coordinator accepted
Action requested	<input type="checkbox"/> to be revised by Partners <input type="checkbox"/> for approval by the WP leader <input type="checkbox"/> for approval by the Project Coordinator <input checked="" type="checkbox"/> for acknowledgement by Partners

Document History			
Version	Date	Author(s)	Changes
0.1	25/06/2021	Gernot Stübl (PRO); Maria Chiara Leva, Hector Diego Estrada Lugo, Aoife Burns (TU Dublin); Thomas Hoch, Bernhard Heinzl (SCCH);	Initial Version
0.6	28/06/2021	Gernot Stübl, Thomas Pönitz (PRO); Bernhard Heinzl (SCCH);	Integrated review of 0.1
1.0	28/06/2021	Sabine Stockinger (SCCH)	V1.0, PDF generated and submitted to EC portal

List of contents

1	Abstract / Executive Summary.....	4
2	Introduction.....	4
2.1	Description of the document.....	4
2.2	WP and Tasks related with the deliverable	5
3	Use Cases	5
3.1	Use Case 1 – FARPLAS	5
3.2	Use Case 2 – INDUSTRIAS ALEGRE	9
3.3	Use Case 3 – GOIMEK.....	12
4	Inter-Use Case Findings.....	14
5	Performance Indicators OEE / OLE	14
5.1	Overall Equipment Effectiveness (OEE).....	14
5.2	Overall Labour Effectiveness (OLE).....	14
6	Conclusions.....	15

List of Figures

Figure 1: Plastic injection moulding machine at FARPLAS.....	6
Figure 2: Current workflow of plastic injection moulding at FAR.....	6
Figure 3: Manual Quality Inspection of produced parts.	6
Figure 4: Selected product in UC1.....	7
Figure 5: Possible workflow of UC1 with Teaming.AI.....	8
Figure 6: Automated Quality Control setup.....	8
Figure 7: Current workflow at IAL.....	9
Figure 8: Process curves of "scientific moulding" process to setup the injection machine.	9
Figure 9: Selected products in UC2.	10
Figure 10: Possible workflow of UC2 with Teaming.AI.	11
Figure 11: (left) Milling Machine at GOI. (right) Mounting plate for wind turbine gearbox.	12
Figure 12: Selected product in UC3.	12
Figure 13: Possible workflow of UC3 with Teaming.AI.	13

List of Tables

Table 1 Assignment Use case providers and Use case responsible partners	5
Table 2 OLE distribution for UC1 and UC2	14

1 Abstract / Executive Summary

This document is part of the requirement analysis work package and describes the situation at the use case partners, states the problem definitions, and gives outlooks of possible integration of the Teaming.AI concept. Use cases 1 and 2 come from automotive suppliers, and cover the process of plastic injection moulding. In detail UC1 focuses more on fault analysis of defects and the derivation of injection parameters, while UC2 deals with injection parameter optimization itself. UC3 is from a completely different field, namely large part manufacturing. Here the interplay between AI-controlled machine tasks and manual human labour is in focus of optimization. The contrast of UC3 compared to the other use cases highlights the universality of the Teaming.AI platform.

Further this document describes findings on the initially proposed KPIs Overall Equipment Efficiency (OEE) and Overall Labour Effectiveness (OLE).

It turned out that the OEE is a generally used KPI in industry. However, the OLE is treated as non-practical KPI and even cannot be given in all use cases. Deliverable 1.2 about Human Factors will treat this in detail.

2 Introduction

2.1 Description of the document

The content of this deliverable follows the original definition of the Grant Agreement, which is stated as:

To elaborate an evidence-based baseline for upcoming comparative studies regarding human-AI teaming regarding the scope of technology integration of WP6 (digital twins, decision support systems and agile production) and use cases WP7 (injecting moulding and high precision machining of large-size parts), containing:

- a) *status-quo analysis of human-AI teaming in all phases of the AI system engineering lifecycle (at engineering time, set-up, maintenance and adaptations to changes);*
- b) *data and evidence-based elaboration of case study examples identifying the key performance indicators (KPI) of Overall Equipment Efficiency (OEE) and Overall Labour Effectiveness (OLE).*

During the joint work with the use case partners, it came up that the description of point a) on all phases of the lifecycle is too broad for the use cases. For the use case partners, their biggest problems are mainly in the set-up and the execution phases. Improving these brings also the most cost savings for them. Therefore, this document is mainly dedicated to describe the status-quo of set-up and execution phase of the use cases.

The document structure is as follows: Chapter 3 is the main part and covers the use case descriptions. All descriptions follow the same pattern:

1. Current situation and selected products
2. Problem definition
3. Vision with Teaming.AI

Chapter 4 is about inter-use case findings, while Chapter 5 describes the gathered information about the Key Performance Indicators OEE and OLE. The conclusion chapter ends the document.

2.2 WP and Tasks related with the deliverable

Task T1.1 “As-is Analysis” has been the coordinating task for all actions in WP1: “Requirements and Prerequisites”. In a first technical meeting, every use case provider got an academic partner assigned, who serves as use case responsible and contact point for the partners for the whole project. The use case responsible academic partner is involved into each communication with scientific content, which should avoid uncoordinated double queries to the use providers. The assignment is the following:

Use case provider	Use case responsible
FAR	ITU
IAL	SCCH
GOI	PRO

Table 1 Assignment Use case providers and Use case responsible partners

As starting point, two initial meetings per use case have been held. In the first meeting the use case providers got the chance to introduce their problem, without being influenced in any direction of problem solving. The second meeting was dedicated to detailed questions of the academic partners, which they had to send in before. To guarantee an optimal information flow also leaders from other work packages have been invited. Additional meetings were optional. With this procedure a total of 7 meetings have been held. All of them have been recorded and are available in the MS Teams space.

All deliverables in this work package highlight a special view on these meetings. The present D1.1 is a description of the current situation, D1.2 focusses on the human aspects, D1.3 on the legal and ethical rules and principles, D1.4 on the data related view, and finally D1.5 the application of the teaming idea.

3 Use Cases

3.1 Use Case 1 – FARPLAS

Description of the current situation

The Turkish company FARPLAS offers plastic parts for the automotive industry. They produce these parts with plastic injection moulding machines, see Figure 1.



Figure 1: Plastic injection moulding machine at FARPLAS

Plastic injection moulding itself is a complicated process, with three major steps: (a) setup of injection process, (b) production, and (c) quality inspection. The whole workflow is visually described in Figure 2.

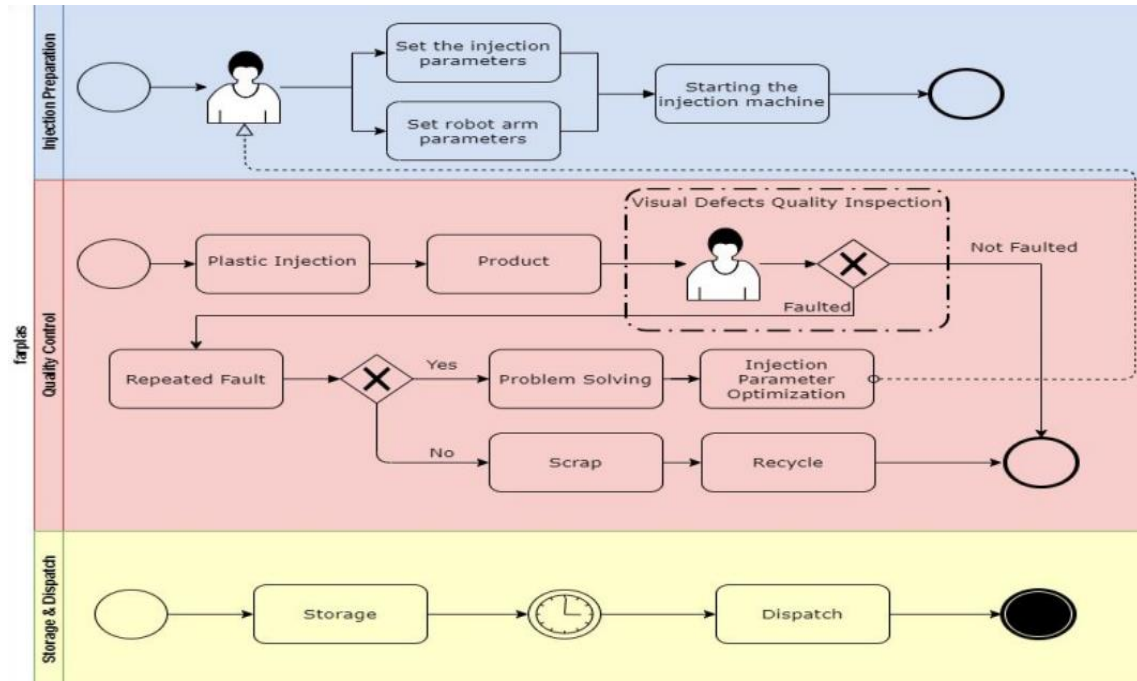


Figure 2: Current workflow of plastic injection moulding at FAR.

An Injection Process Engineer sets the initial parameters of the injection machine, and eventually robot arm parameters. All parameters are dependent on the actual produced part. After that, production starts and a robot arm takes the parts out of the machine. A controller manually checks if the parts are faulty, see Figure 3. In case of a good product, a protective coating is put on the surface.

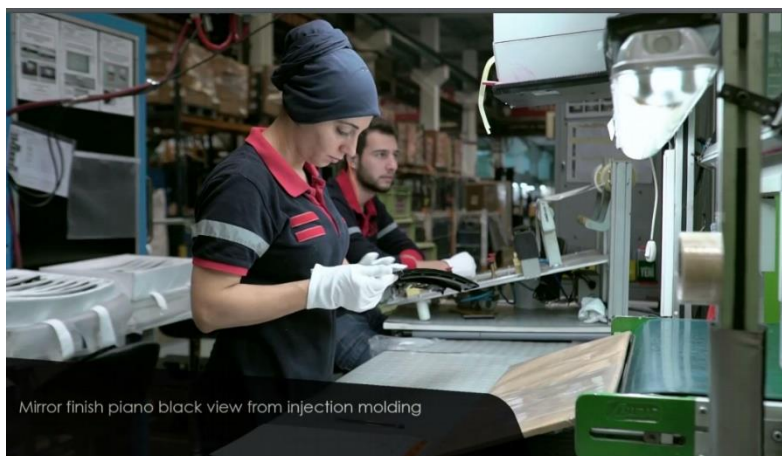


Figure 3: Manual Quality Inspection of produced parts.

If the product is faulty and it is a repeated fault (3-5 products), the Injection Process Engineer is called to optimize the parameter setting of the machine. During the setup phase, this cycle is repeated until the product can be produced without faults. Nevertheless, also during production a

fault can appear. In this case also the Injection Process Engineer is called and parameters are adjusted. All parameter changes are noted in a “parameter change sheet”.

FARPLAS sees two major areas of improvement, which are filed as sub-use cases:

1. introduce an Automated Quality Control (AQC),
2. support parameter optimization for injection moulding machine.

The selected product for the development and Evaluation of Teaming.AI in UC1 can be seen in Figure 4.



Figure 4: Selected product in UC1.

Problem Definition

The automated quality inspection should look for fault reasons and should link the fault reasons of the visual defects to parameters of the injection machine in order to support the human operator with the configuration. The main points are:

1. Automated quality detection system with a human in the loop,
2. Integrating new human data: The controller should have the chance to overrule and correct the decision of the AI system, e.g. by manually marking defected regions, if they were wrong classified,
3. Provide decision support for the injection parameter configurations. Helping to decide which of the 16 most common problems has occurred.

Vision with Teaming.AI

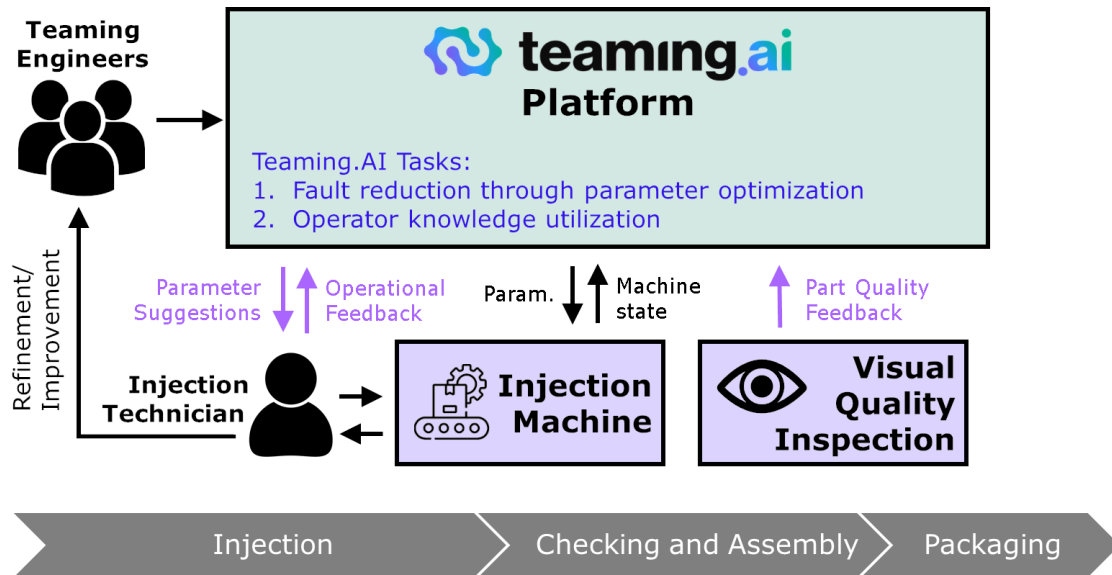


Figure 5: Possible workflow of UC1 with Teaming.AI.

One possible workflow of UC1 with Teaming.AI is depicted in Figure 5. An Automated Quality Control based on deep neural networks is utilized to support Visual Quality Inspection. An initial detection software and the hardware setup can be taken from pre-work, see Figure 6.

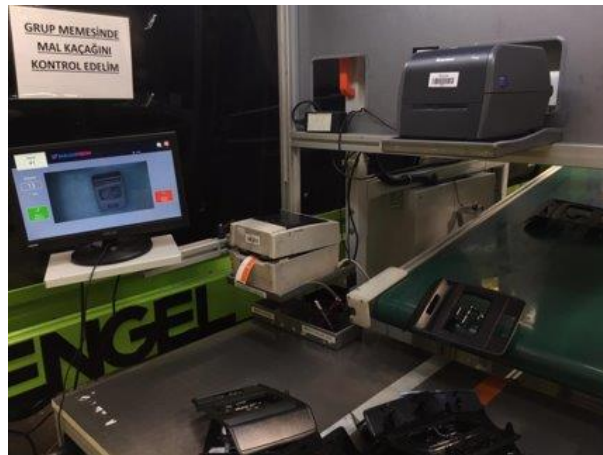


Figure 6: Automated Quality Control setup.

Together with the machine data, the Teaming.AI platform is then able to support the Injection Technician with parameter selection. The main focus is how visual quality inspection data (context information) can help to derive fault reasons which is the main information the Injection Technician needs for parameter adjustment.

3.2 Use Case 2 – INDUSTRIAS ALEGRE

Description of the current situation

The Spanish company IAL also produces plastic parts for the automotive industry (but is in no competition to FAR). On a high level, their workflow is similar to UC1 and can be seen in Figure 7.

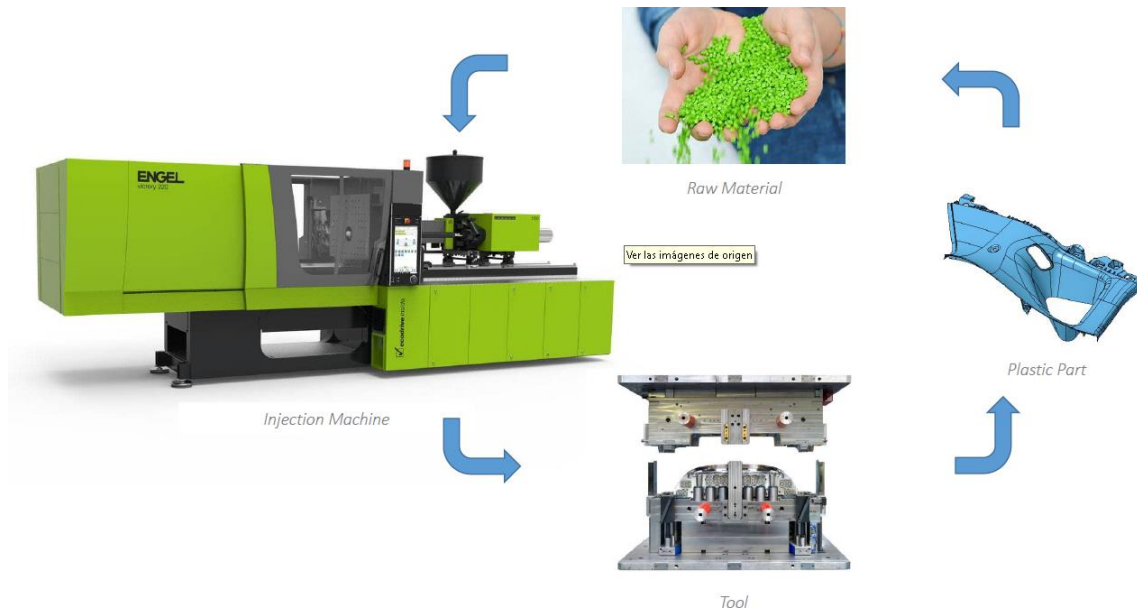


Figure 7: Current workflow at IAL.

The differences are on a detail level. The setup of the injection machine is done with a process called “scientific moulding”. Here a process curve has to be in a defined parameter tube for proper working, see Figure 8. Parameter changes are again stored in change sheets.

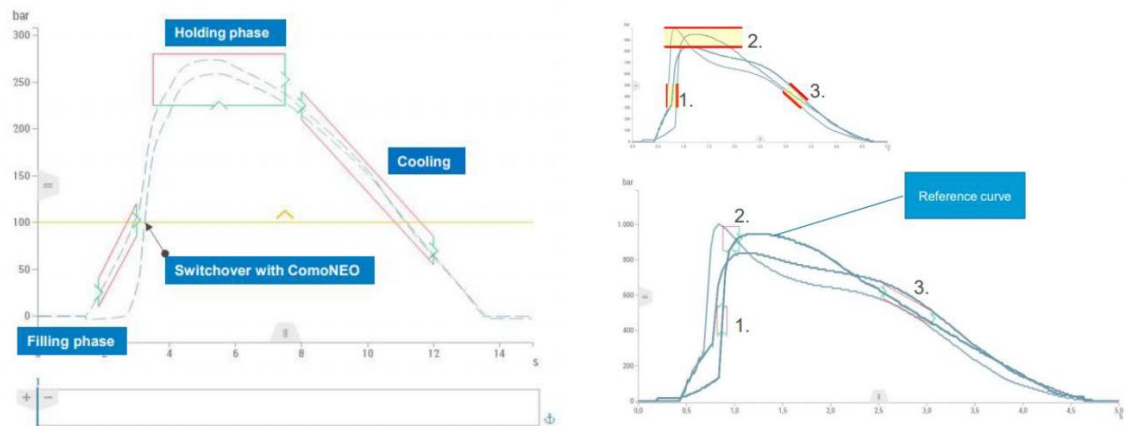


Figure 8: Process curves of "scientific moulding" process to setup the injection machine.

The selected products for the development and evaluation of Teaming.AI in UC2 can be seen in Figure 9.

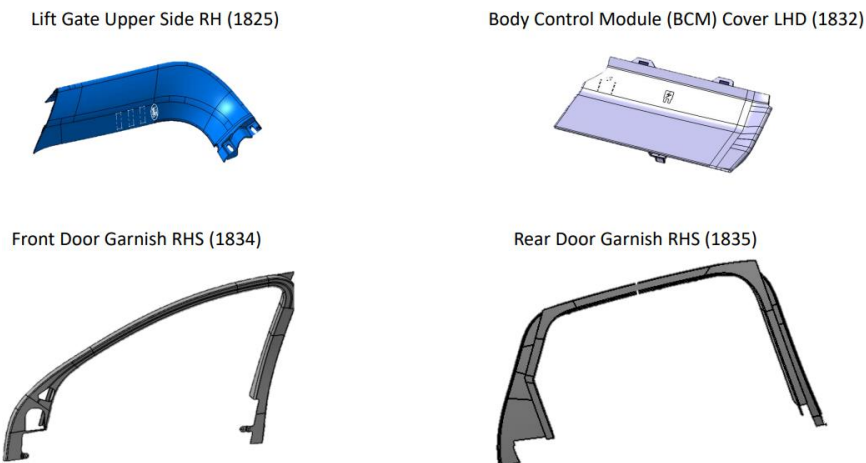


Figure 9: Selected products in UC2.

Problem Definition

Teaming.AI should support prediction of possible process deviations and the identification of likely root causes by identifying process parameters that deviate the most from their expected values. If there are detected visual issues with the parts produced, an AI-algorithm can help to detect the process parameters to be changed for adjusting the process curve to be as close as possible to the one considered to be optimal. Currently there is no knowledge about what should be an optimal process curve, therefore an AI algorithm can be designed to help identifying this shape by comparing the curves for the ok parts with the ones that are available for the defected parts. This includes the following:

1. Find the expected area where the curve describing the injection process should lie, to get an estimate about the optimal shape.
2. This should help to determine and already predict which parts are ok and which may not be ok (as the curve may be differing from the expected shape, or lie outside the expected area).
3. Additionally, the AI algorithm can find out what parameters are differing from expected values and therefore being likely to be the ones linked to possible root causes. Weight and dimensional checking should be done AI-supported. Vision check is performed by an Assembly Operator.
4. Decision support on root causes and likely interventions to correct the issues based on the capability of an AI algorithm to detect the expected shape of the injection process curve and the deviations and also the capability to link those deviations to parameters values that are differing too much from their expected values.
5. The parameters differing from their expected value may not provide enough information to help operators gain situational awareness regarding the root causes of process deviations, therefore the process parameters deviations could be linked to possible root causes using the information already captured in the FMEA study developed for the injection process failure modes identified.

Vision with Teaming.AI

As stated above, the Teaming.AI should support prediction of possible process deviations and help to identify likely root causes by discovering process parameters that deviate from their expected values. Further it should provide a decision support on root causes and likely interventions to correct the issues based on the capability of Teaming.AI to detected the expected

shape of the injection process curve. A possible workflow combining the different data sources is depicted in Figure 10.

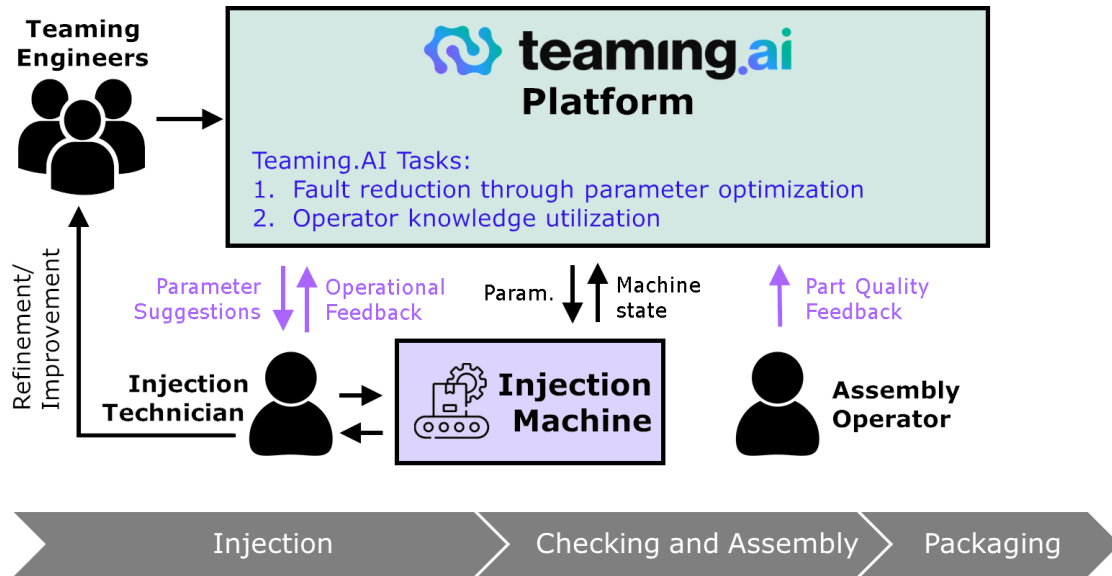


Figure 10: Possible workflow of UC2 with Teaming.AI.

The main focus in this use case is on the injection parameter optimization. The Teaming.AI platform can orchestrate the interplay between the Injection Technician and the AI-based process curve analysis. Through a decision support system, findings of the AI-system can be explained and the quality of men/machine cooperation will improve.

3.3 Use Case 3 – GOIMEK

Description of the current situation

GOIMEK is a large part manufacturer in Spain. They use a huge milling machines to manipulate metal, see Figure 11.



Figure 11: (left) Milling Machine at GOI. (right) Mounting plate for wind turbine gearbox.

The selected process is milling of large parts, which is a time-consuming process with execution times over 10 hours. This process intermixes automated and manual tasks. While the automated tasks can be precisely timed, the manual tasks have a huge variability in execution time (multiple hours).

The selected product for the development and evaluation of Teaming.AI in UC3 can be seen in Figure 12.

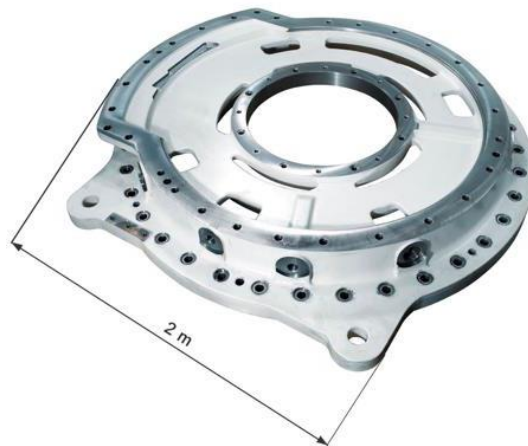


Figure 12: Selected product in UC3.

Problem Definition

In this use case on the one hand the used AI of the machine is blind regarding the actions of the human and on the other hand the machine does not give feedback about upcoming human interactions. Therefore, automated as well as manual tasks happen mutually exclusive, as none of the partner dares to interrupt the other. Teaming.AI should support to orchestrate the interplay between human and AI and optimize their joint outcome.

For this the following steps have to be accomplished:

1. Map out manual tasks associated to milling operations of large parts (gearbox) and collect information about estimated times for manual tasks. In detail:
 - a. Collect visual image information about the task (e.g. visual tracking software) and, if possible, perform ergonomic risk assessment of the tasks (e.g. forces or EMG recordings).
 - b. In this phase, the operators are asked to describe the manual tasks they carry out and what is happening in between milling steps, to provide missing information.
 - c. The information may be collected also using the IDECO-GOIMEK software system used to log information about work orders on the worker tablets.
2. Improve the machine to human communication as milling machines can also inform operators about approx. time they have between the milling automatic sub steps and therefore how much time they have to do something else before they need to attend to the next manual task.
3. Improve task scheduling to consider the combination of automatic milling expected time and manual tasks to see if an operator can attend to two simultaneous tasks (AI optimization problem).
4. Ergonomic risk assessment of the two simultaneous tasks in terms of static loads and repetitive strains.
5. Feasibility study on possible AI for visual recognition of possible real time Ergonomic risk assessment for musculoskeletal disorder exposure and also idle time recognition (teaming with operators on reporting issues).

Vision with Teaming.AI

The AI should map out manual tasks associated to milling operations of large parts and collect information about estimated times for manual tasks. By this it should

- improve the machine to human communication,
- improve scheduling to consider combination of automatic milling expected time and manual tasks,
- do an ergonomic risk assessment of the two simultaneous tasks in terms of static loads and repetitive strains.

A possible workflow can be seen in Figure 13.

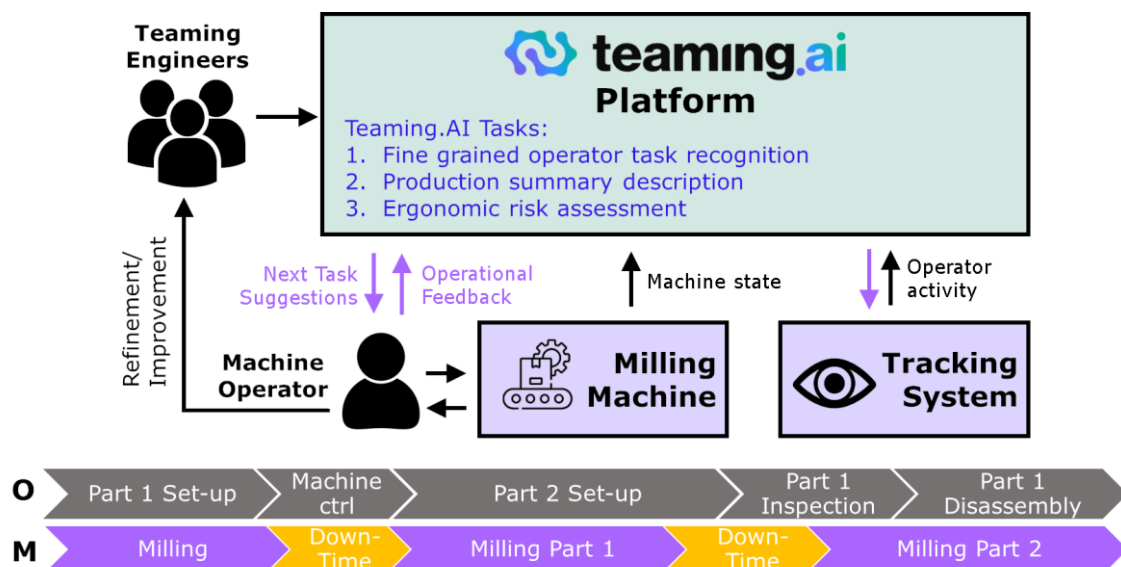


Figure 13: Possible workflow of UC3 with Teaming.AI.

In contrast to the current state, both the Machine Operator and the Milling Machine can work optimally together. The Teaming.AI platform can perceive the position of the human worker with its tracking system. The platform combines this with context information, e.g. machine data, and acts as mediator between the machine AI and the Machine Operator.

4 Inter-Use Case Findings

On the first view there seems to be large overlap between the plastic injection Use Cases 1 and 2. However they differ in the details, especially in the approach used for the set-up phase. Nevertheless, the similarities can be utilized in order study Transfer Learning capabilities of the Teaming.AI approach.

Another finding regards the human interaction in the use cases. It seems that human interaction in UC1 and UC2 can almost fully be captured by Graphical User Interfaces on tablets. In UC3, additionally to the tablet, an advanced tracking technology for the human operator is needed, which has been foreseen and will be provided by a consortium partner.

5 Performance Indicators OEE / OLE

5.1 Overall Equipment Effectiveness (OEE)

OEE is a measure of how well a manufacturing operation is utilized (facilities, time and material) compared to its full potential. This measure is fully known in all use cases through the machine data.

5.2 Overall Labour Effectiveness (OLE)

OLE measures the utilization, performance, and quality of the workforce and its impact on productivity. For the Assembly Operator this measure is given, almost equal, for UC1 and UC2 as the following:

Operations	% distribution
Visual self-control	16%
Assembly	60%
Final control	9%
Packaging	15%

Table 2 OLE distribution for UC1 and UC2

The above operations make 85% of the cycle time. Therefore, 15% are idleness which can be used to e.g. replace components in the machine. For other staff, e.g. Injection Technician, the values are unknown. For UC3 the OLE is unknown for the whole use case, as stated above, the manual tasks have to be first perceived through Teaming.AI.

However, missing OLE numbers are no problem for the further progress of the project, see alternatively proposed KPIs in D1.2.

6 Conclusions

This deliverable gives a thorough overview on the current situation in the use cases. Detailed aspects follow e.g. in D1.2 for the human factors and D1.4 for the available data.

The joint elaboration between research and use case partners results in the conclusion that all use cases have been proper selected and perfectly fit to demonstrate different aspects of the Teaming.AI approach.