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AI·PROFICIENT

Artificial intelligence for improved production efficiency, quality and maintenance

Deliverable 1.3

D1.3: Pilot specific demonstration scenarios

WP1: Pilot characterization reqs. and system architecture

T1.3: Follow up specs. of pilot demonstration scenarios

Version: 1.0

Dissemination Level: Public

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Executive Summary

The Deliverable D1.3 is a public document of AI-PROFICIENT project delivered in the context of WP1, Task T1.3 with regard to the specification of the use cases related to the different pilot sites. These use cases were initially described and reported at deliverable d1.1

This deliverable incorporates a specification of the demonstrator to be constructed per use case. This specification contains a description of the case, their potential solutions, and the requirements and preferences related to each solution: Expected datasets, existing experience coming from pilot, expected input and output parameters when demonstrator in execution, expected interaction with the operator, the ethic considerations that will be taken into account, the expected contributions from different partners and the link to appropriate task activities within development work packages WP2,3 & 4. The deliverable also states the relevance of these UCs for the demonstration of AI-PROFICIENT objectives.

Introduction

After the initial assessment of feasibility and ethical considerations conducted in Task T1.1 and reported in d1.1., this report summarises that work done in Task 1.3, where selected Use cases have been analysed from a technical point of view.

The reports analyses the 8 use cases finally selected in Task 1.1 and performs a specification of the demonstration to be constructed per use case. This specification contains:

- An expanded description of the d1.1. use case, e.g. including a problem statement from a technical point of view, to support better the expected demonstration workflow.
- Potential solutions to the problem statement. There might be more than one, complementary or even redundant.
- The expected datasets expected to be existing and reachable in order to develop the models. Additionally, if relevant, the existing experience coming from use case experts also embedded in the solutions.
- The expected input and output parameters when demonstrator in execution (including if relevant the frequency of execution, the connectivity to other systems – e.g. to MES, …)
- The expected interaction with the operators - the way AI will interact (human at command, on the loop, …)
- The ethics considerations that will be taken into account, specially regarding these interactions – understand whether any proposed solution may entail unexpected burden or risk to operators, and also how ethics may influence later low-level design and implementation.
- The links between each UC solution and the algorithms that may contribute to the solution: Where these AI constituents will be developed (specific tasks in WP2, 3 & 4) and which partner is expected to bring such constituent to the solution development, taking into account a collaborative approach in most of the UCs.

The report will include a last section where the relevance of these UCs for the demonstration of AI-PROFICIENT objectives will be assessed.

These use case specifications have been conducted by different people. Main contributors have taken the role of **use case (UC) leaders** to become main technical contact points for the UC technical specification regarding the interaction with UC providers (Continental and INEOS), with Ethics team and with the rest of the partners collaborating at each use case. Please find below the names of these UC leaders.

- UC Conti 2 - Restart Set up – **Kerman Lopez de Calle** (Tekniker)
- UC Conti 3 – Released extrusion optimization - **Alexandre Voisin** (University Lorraine)
- UC Conti 5 – Tread Blade wear - **Kerman Lopez de Calle** (Tekniker)
- UC Conti 7 – Tread alignment - **Vassilis Spais** (INOS Hellas)
- UC Conti 10 – Quality analysis - **Katarina Stankovic** (Institute Mihajlo Pupin)
- UC Ineos 1 – Reactor stability - **Sirpa Kalio** (VTT)
- UC Ineos 2 – Image recognition - **Alexandre Vasylchenko** (Tenforce)
- UC Ineos 3 – Rheology drift - **Dea Pujic** (Institute Mihajlo Pupin)

Also, it is worthy to mention the support provided in the development of these UC technical details by UC providers (**Paul Astiasarain and Antony Bella** from Continental, **Christophe Van Loock** from INEOS) as well as the support and multiple iterations made by the ethics team and in particular **Marc Anderson** (UL) with UC leaders concerning the identification of considerations to take into account when designing and developing each use case , and in some cases their mitigation or resolution at this first high detail approach.

CONTI-2 UC Specification: Restart Setup

UC description

Extrusion process is not continuous. Sometimes, the need to produce different types of recipes, or either scheduled or unplanned replacements require the production line to be stopped. As a consequence of the production stoppage, it is necessary to bring the production line back to the optimal production performance situation for which some adjustments (manual control of some setpoints) are carried out, which is known as the set-up process. Until this production-ready point is reached, the tread that is being produced tends to be of low quality and therefore not useful, for that reason, this low-quality tread (a.k.a. rework) is cut and sent back to the extruders.

It is well known that these stops of the production have a negative influence on the quality of the tread which is being produced, which impacts the tread weight stability or/and the tread geometries. However, the stops are unavoidable, as the repairs need to be done and it is also necessary to stop the production to change the type of product. Thus, the set-up process, the one in charge of bringing back the production to optimal conditions, is critical.

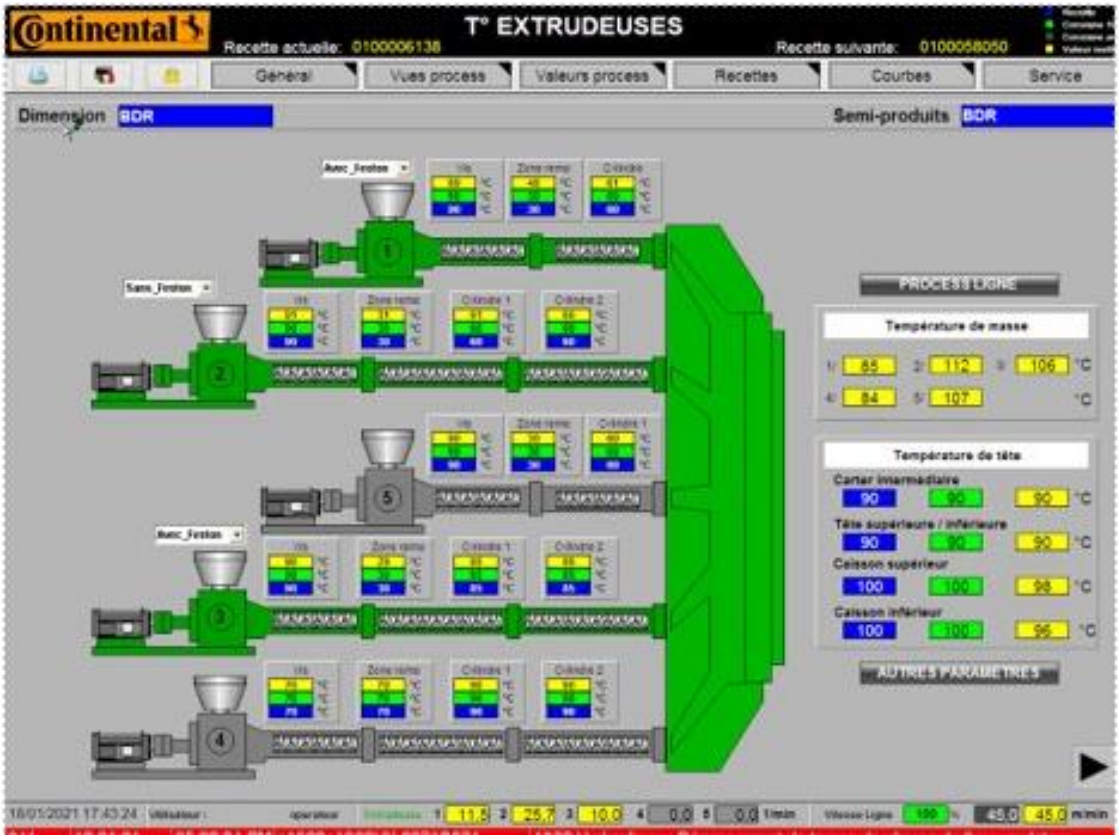


Figure 1: Extruder control and monitoring panel.

The duration of the set-up process determines the amount of rework that is created and brought back to the extruders (a.k.a. reintroduction) in order to not waste the raw materials. The longer the set-up the more rework that there will be.

The amount of reintroduction impacts the productivity, and, additionally, it creates the risk of getting the compound cured (appearance of curation particles) which is undesired.

Sharp setups produce some peaks and transitory states in process variables (such as in the pressure) that should be avoided.

In addition, it is noteworthy that currently extruder setpoints are considered in an independent manner (each extruder has its set point) and that the setup process is manually carried out by operators with the only help of their own experience. This leads to very different setup times, configurations and impacts on tread quality.

Proposed solution

From the technical point of view there are several ways to tackle this problem.

- **Best setup conditions detection:**
  Currently Conti's production line setup is carried out manually. From the historic data, it should be possible to associate the set-ups with their consequent rework quantity and detect which operation setpoint combinations have led to lower rework quantities and which temperature and viscosity conditions are optimal to begin the extrusion. This approach requires detecting the setups in the historic data, characterizing the curves and fetching some process related influential parameters and correlating these parameters with the quantity of rework.

- **Exploration of alternative and optimal setup conditions**
  Once an initial analysis of past data is carried out and having a more detailed knowledge of interactions and effects involved in the rework production, a Design of Experiments will take place in order to better determine the best startup settings that minimize rework creation. The results of this data will be processed with different techniques, such as surrogate models, that can enhance the identification of the optimal parameters for restart setup.

Main specifications & high level design

Required datasets for solution development

The datasets required for the detection of factors that affect the quantity of rework produced during the startup need to represent the speed of the conveyors after the extrusion, other factors that might be related to the rework production and, finally, the rework itself.

From this dataset each of the startups will be detected and processed so that the different speed stages can be detected. These stages will be related to the amount of rework that this start up created.

Rounded_date	DS_Conveyor1_Actual_V2	DS_Conveyor1_Setpoint_V2	EX_EX1_Screw_Setpoint	EX_EX2_Screw_Actual	EX_EX2_Screw_Setpoint	EX_EX3_Screw_Actual
2021-05-11 06:15:00	0.339321385	3.8809948	8.299560	0.386869222	10.396489	0.048289654
2021-05-11 06:16:00	0.403813157	4.6147822	8.299687	0.512746073	10.397507	0.056799876
2021-05-11 06:17:00	25.111700022	25.1365738	8.299781	0.605907337	10.398260	0.063098279
2021-05-11 06:18:00	26.941914273	26.0955696	8.299889	6.588609161	10.399127	7.930474025
2021-05-11 06:19:00	26.697798250	26.7155998	8.479769	10.635863664	10.644166	12.982512997
2021-05-11 06:20:00	33.960949750	33.9884184	10.737846	13.626456786	13.627094	16.053301417
2021-05-11 06:21:00	37.026275417	37.0188383	12.121993	14.742450714	14.629632	17.161235833
2021-05-11 06:22:00	37.356935583	37.3464435	12.328179	14.599000000	14.600000	17.401925083
2021-05-11 06:23:00	37.505614583	37.5167690	12.534364	14.599000000	14.600000	17.400003083
2021-05-11 06:24:00	37.580875833	37.5859363	12.740550	14.599000000	14.600000	17.403440000
2021-05-11 06:25:00	37.609472583	37.6341518	12.955066	14.598487333	14.600000	17.400664750
2021-05-11 06:26:00	37.546520417	37.5714752	13.363812	14.569947167	14.600000	17.363705000
2021-05-11 06:27:00	37.667852417	37.6577537	13.825508	14.594130775	14.600000	17.398320000
2021-05-11 06:28:00	37.681673500	37.6669506	13.959677	14.594643775	14.600000	17.398320000
2021-05-11 06:29:00	37.717509583	37.7179046	13.895161	14.595156775	14.600000	17.398320000
2021-05-11 06:30:00	37.726988583	37.7303051	13.830645	14.595669775	14.600000	17.398320000

CONTINENTAL has already provided a dataset which such characteristics. It is partners' duty, to process raw extruder speeds and other signals and correlate them to gain insight and develop algorithms.

Required input and output parameters for demonstrator execution

This solution will be based on two main components:

- Recommender system: This system will provide the operator with suggestions regarding the optimal instant to start the extrusion back again as well as the most beneficial speed curve that should be followed by the extruders. This way the system will aim to minimize the amount of rework that is created due to the low quality of the extrusion. Those recommendations will be given together with the explanation of the inference carried out by the AI in order to reach the conclusions.

- Retraining system: The retraining system deals with the lifelong learning capabilities of the recommender system. The aim of this system is to improve the recommender system based on the amount of rework that is created after following/not following the suggestions of the recommender system and the feedback provided by the operator.

The following figure represent the input/outputs of the proposed system in the context of the extruder.

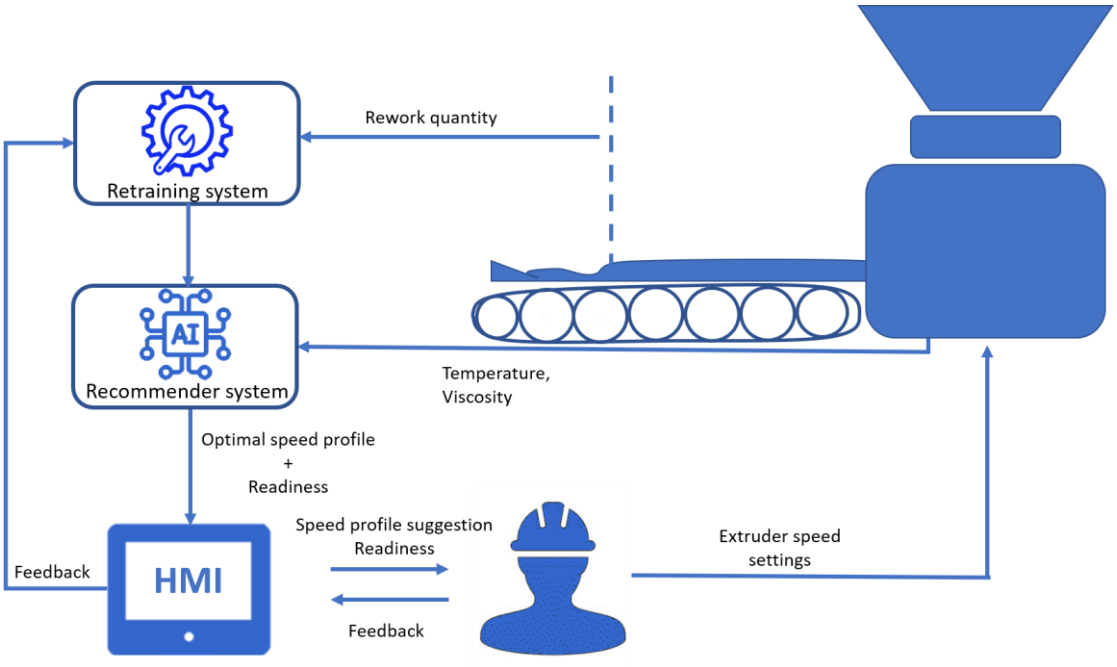


Figure 2: Schema of algorithm deployment.

For the deployment of said techniques it will be necessary to establish communication mechanisms among the components presented in the following table:

Model/System	Input(s)	Output(s)	Execution	Final user
Recommender system	• Temperature • Viscosity • Human knowledge	• Speed profile • Readiness	On event	Operator
Retraining module	• Operator's feedback • Rework cuantity	• Re-trained algorithms	On demand	Maintenance manager

Required interaction with the operator: ***What advantage do we provide to the final user?***

This use case provides valuable guidelines for the operators, as extrusion was merely adjusted based on experience. The guidelines the solution provides are meant to help less experienced operators on how to deal with the speed settings and, also, with the identification of the optimal instant to relaunch the extrusion process. In addition, it is expected that, by following the proposed guidelines, the amount of rework created as a consequence of the restart will decrease, which reduces the amount of waste.

In order to gain operator's trust and improve the AI systems, human knowledge will be employed during the development of AI algorithms. In that regard, during the initial deployments of the AI, more skilled operators will be requested to interact with the system and provide feedback so that it can be fine-tunned.

What do we expect from the operator?

Operators are expected to consider the suggestions provided by the recommender system and to carry out the actions that they consider appropriate. That is, the recommender system is provided as a guideline, not as strict order.

In addition, operators will have the means to provide feedback of the possible problems/errors that the AI might have caused. This is intended to provide robustness to the AI system, and hence, improve the operators trust on the recommendation system by improving its accuracy.

How is the interaction envisioned?

The adoption of a new system needs to be implemented while avoiding the friction that could cause with operators as much as possible. For that purpose, the solution will be implemented in various stages, each requiring different level of involvement, supervision, and trust by the operator.

In addition, considering the existence of various extruders and the desire to extend the use of the assistance system to all of them, besides the staged implementation, it will be initially carried out in a single extruder. The adoption process on the first extruder will be used to evaluate the overload/unload that might be caused to the operator and analyse the feasibility of extending the use of the aid system to other extruders.

Ethics considerations

Ethical Issues:

1) Human-in-command can be defined as the possibility of deciding when and how an AI will be used (or not used) combined with the capacity to supervise the activity of the AI in the broadest sense. According to this definition the operator has decision power over the AI use here insofar as the Continental request was for this Use Case to incorporate human-in-command.

   Given the above, there is some ambiguity in this Use Case regarding how the operator will use the AI proposals. Will the operator be expected to always use the proposal of the AI, or to judge the suggestions of the AI and decide when to use it based on his experience?

   It was suggested in Q&A (Jan 19th and Feb 16th) that the restart is based significantly on the feeling of the operator and the operator's experience. There are 20 parameters which the operator looks at and which must be nominal for restart.

2) Currently the operators only increase rpms for cap compounds (main extruder). It was suggested in Q&A (Feb 16th) that in future the operator will adjust rpms for all extruders, which will add further tasks for the operator.

Ethical Recommendations:

1) The default position about whether the driver operator is always expected to follow the AI proposal should be specified either overall, or for various phases of AI integration if there is a trial period. A trial period with phasing in of the AI integration in stages should be implemented.

   e.g. first 6 months – operator will consult AI proposals but use his own judgment whether to implement them; next 6 months – operator must always implement AI proposals unless it is clear that AI proposal causes some major problem

   Formally clarify at what stages the operator has command over the AI to the point of ignoring its suggestions if he chooses (according to the human-in-command definition)

2) It should be clarified at the beginning whether some time is envisioned when the operator can stop looking at the restart parameters. If so, clearly separate this period from a trial period to come before in which he must continue to monitor the relevant parameters.

   I.e. for building up trust in the robustness of the AI there should be a 'phase in period' in stages (combined with #1 above) where the operator's monitoring of the parameters is relaxed progressively (if it is going to be relaxed), rather than leaving it to be decided in an unplanned and ad hoc way.

3) There should be a protocol created to deal with the situation when the AI makes an error: Formally clarify who the operator is supposed to report it to.

   Formally clarify under what conditions the operator should report that the AI is in error (e.g. if the AI suggestion does not look right according to his previous experience)

4) The operator will be expected to adjust all extruders if AI is integrated. An estimate of how much more time this will take should be made. It should be determined whether the operator has enough time to do this added job and how much the added time to make adjustments will offset the reduced downtime in restarting the extrusion.

   The added time for the operator to make adjustments should be factored into the setup time component of the KPI and used to make a decision about a minimum success rate threshold above which the AI is worth deploying eventually.

Addressing ethical considerations:

- (1 & 2) There is a staged adoption of the solution planned, were the roles of the AI and the operator will be clearly defined. However, due to the level of maturity the solution has currently it is difficult to stablish those roles now.
- (3) Operators will be provided an HMI to provide feedback and handle AI errors. This HMI will be accompanied by a set of instructions/protocol on how to use the HMI and how to provide feedback.
- (4) With the inclusion of the AI, it is CONTINENTAL's desire to extend the manual adjustment of extruders from one to more, which might be an extra cause of overload. As a counter measure, during the adoption of the solution on the first extruder, it will be used to analyze the potential overloads or benefits and evaluate whether it is possible to extend the use of the AI to other extruders or not.

Technologies and links to WP

Currently, the following tasks are found to be related to the design, development and implementation of this use case.

WP 2 - This UC attempts to provide operators assistance, the algorithms developed for that purpose are based on data sources that are already existing, therefor there is no need of installing new sensors. However, there are some tasks to manage on edge level, covered in the following tasks:

- **T2.2 – Component level data acquisition and pre-processing.** From the signals that are currently recorded, new processing techniques will be needed to extract valuable information.

- **T2.3 Self diagnostics and production process anomaly detection & T2.4 Self prognostics and component operating condition estimation:** This use case tries to provide operators with guidance at edge level on

how to adjust certain parameters and, at the same time, identify optimal conditions are met (no abnormalities occur). To provide these suggestions, the solution will need to identify and detect anomalies in the process as well as being capable of prognosing the behaviour of the machine under different settings.

- **T2.5 Field-level automation and control from system edge**. In case the robustness of the algorithms is proven and validated, it will be extended to not just guide the operator during the restart, but to command the restart itself once the operators agrees the restart speed profile. This in turn would reduce the workload required from the operator, but will require of a great level of maturity of the algorithm.

WP3 - The UC is related mostly related to the edge systems. However, the retraining system will provide lifelong self-learning capabilities to the intelligent systems. For that reason, the following wp is linked to this UC.

- **T3.1 – Hybrid models of production processes and digital twins:** The solution requires of the integration of hybridization of a feedback system with a data-based model, that will take place inside this Task.

- **T3.5 – Future scenario based decision-making and lifelong self-learning:** In addition, the development of the retraining systems will be carried out on this task.

WP4 - WP4 deals with the analysis the identification of effective means for human-machine interaction. For this UC in particular, the following tasks might be of relevance in the development the final solution.

- **T4.1 – Human feedback mechanisms for AI reinforcement learning:** For the sake of an improved human-machine interaction, this task aims to provide mechanisms of interaction with the AI so that it can be improved. In addition, it gathers human knowledge in the development of AI algorithms.

- **T4.2 – Role-specific human-machine interfaces and data visualization & WP4.3 – Extended reality and conversational interfaces for shop floor assistance:** Depending on the technologies employed by the final feedback system, either (or both) of these tasks will take place in this UC.

- **T4.4 – Explainable and transparent AI decision making:** For the sake of a more reliable use of AI and greater involvement of operators, the AI systems will be designed adopting the cutting edge explainability techniques. This way decision will be easier to understand, trust or confront if the operators needs to do so.

Detail flowchart & partner/task involvement

Currently, due to the low maturity of this UC only the involvement of TEK is granted in this UC. It is expected, however, that other partners will get involved in this UC in the near future as specific tasks are started once the UC is more mature.

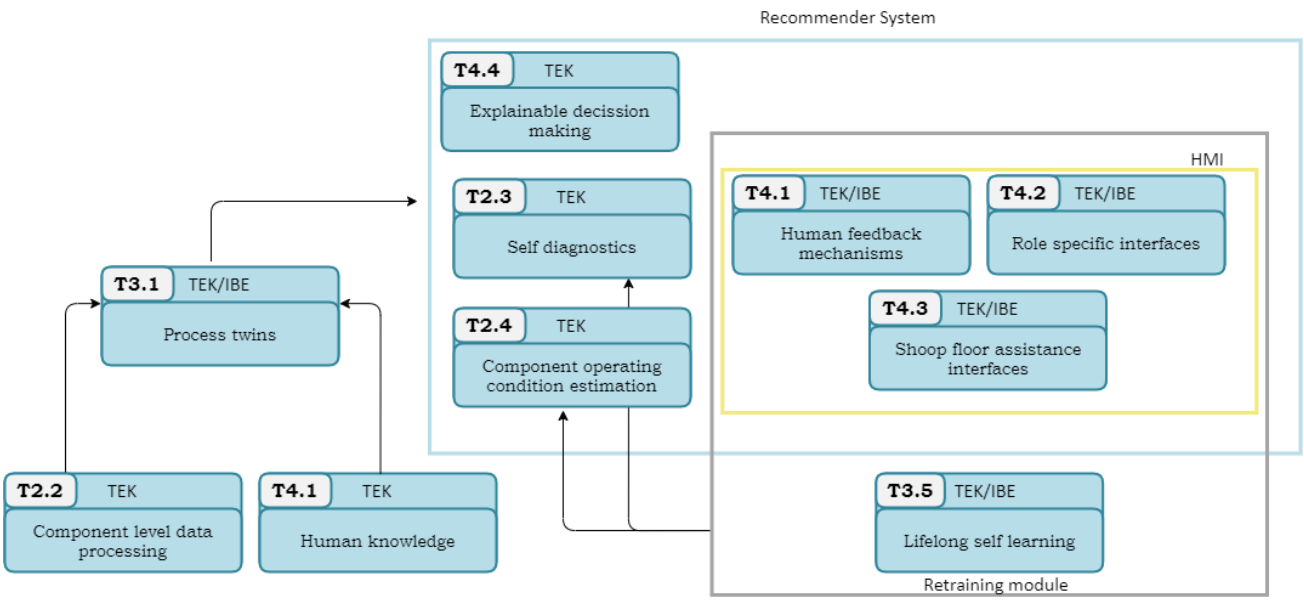


Figure 3 - High-level chart of the engaged tasks at CONTI-UC2

CONTI-3 UC Specification: Released extrusion optimisation

UC description

Relaxed extrusion is a concept to improve the quality of the semi products produced on the Combiline.

When extruding the objective is to have the minimum tension inside the product so that shrinkage effect after cutting is minimized to avoid length issue and bad weight repartition on the surface of the tire (RFPP deviations).

There are 3 factors to consider to minimize tension in the product:

- The visco-elastic phenomenon.
- The flow balancing in the die.
- The conveying of the product.

All those factors are followed via:

1. Check the cooling system of your extrusion line, i.e. the speed into the cooling bath must be larger or equal to the end of line speed, i.e. V2 > = Vend, Annex 2. Doing so you ensure that you have no stretch past the shrinkage area of the extrusion line.
2. Check that the line speed at the end of the shrinkage conveyor, V1 is larger or equal to V2, see See Annex 2. This will ensure that the total line is not pulling and that the loop between shrinkage conveyor and weighing table is not too deep and regulation is working.
3. Check that the material on the takeaway roll (Annex 3: pulled roll) has no slippage, i.e. material speed is +-2% relative to the surface speed of the take away roll. Take care that the shrinkage conveyor has at least 10% speed decrease.
4. All the speeds should be measured by tachymeter, don't take simply the numbers displayed on the control monitor. This to avoid an "invisible pull" though the line (invisible on the monitor).
5. Having adjusted all the areas from step 1 - 3 turn off the RMEA, reduce the line take away speed until the material develops ripples which disappear up to the end of the shrinkage conveyor, Annex 4. Then you have the best set up of the line for the "relaxed extrusion".
6. Keep these parameters, take tread samples past cutting and check the green tread profile (GTP) actual versus spec. If not within tolerance for the cross section adjust the die, not the line setting.
7. When new die is in use measure the residual shrinkage again. Compare also the areas of the die relative to the GTP from actual sample.

Problem statement (i.e. understanding and sharing problem definition)

Global objective: Understand, monitor and detect deviation of the process in order to control the tension inside the product (relaxation) that affects length, width and thickness of the tread after cutting. The summary of the UC is presented Figure 4.

- Usecase description :
  - Released extrusion needs high control of 2 exit conveyors to make perfect adjustment of the die and fast feedbacks from hot & cold profilometers + RMEA camera
- Conti request *(Human in command)*:
  - We want a proposal from IA about helping to define extrusion settings and alert when deviation happening before it gets critical
- Data required :
  - Conveyor speed (Existing)
  - Profilometry data & RMEA images (Existing)
  - Die specifications & product recipe (Existing)
- Influenced by :
  - Conv speed variations
  - Die geometry
  - Type of mix and recipe
- Affecting
  - Tread geometry
  - Setup change
- KPI
  - Tread quality

Figure 4: Summary of the use case from the Q&A session

Figure 5 and Figure 6 show the condition leading resp. to relaxed tread and non-relaxed tread. Despite the global phenomenon and condition are well understood from a process view point, it requires to be implemented technically on the Combiline.

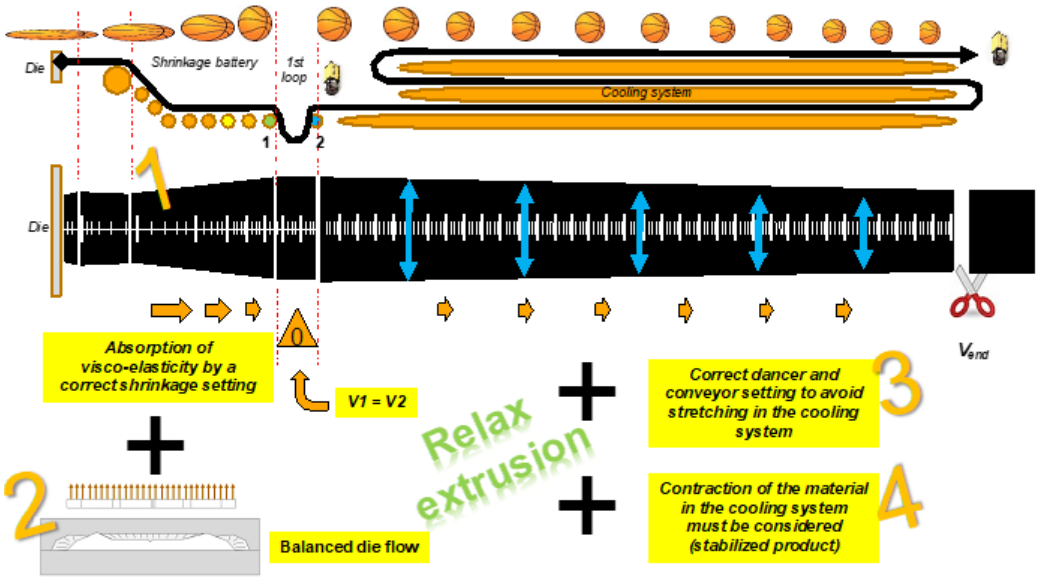


Figure 5: Summary of condition to ensure relaxed tread.

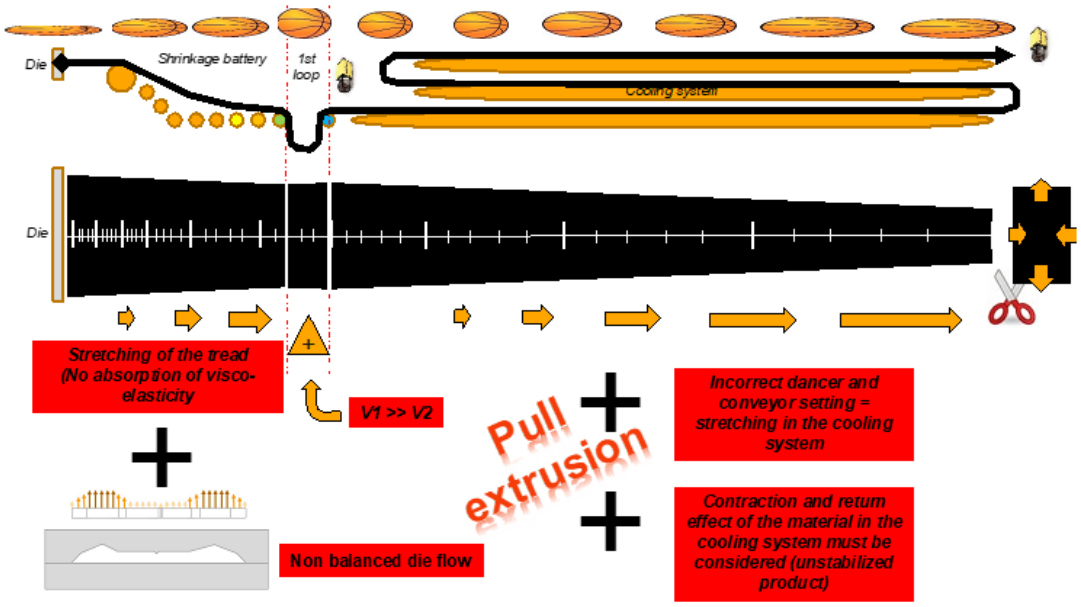


Figure 6: Summary of condition leading to non-relaxed tread.

The tread quality is followed on-line thanks to process measurement. 2 indicators are computed on-line:

- (V2-V1): difference between the speed of the first conveyor of the “cold” part of the Combiline and the speed of the last conveyor of the “hot” part of the Combiline;
- (hot width – cold width): difference between the width of the tread at the beginning of the cold part of the Combiline (hot width) and at the end (cold width). Both widths are measured at the same time; it means that the width do not correspond to the same part of the tread.

Figure 7 shows the objective function that is used to drive the Combiline.

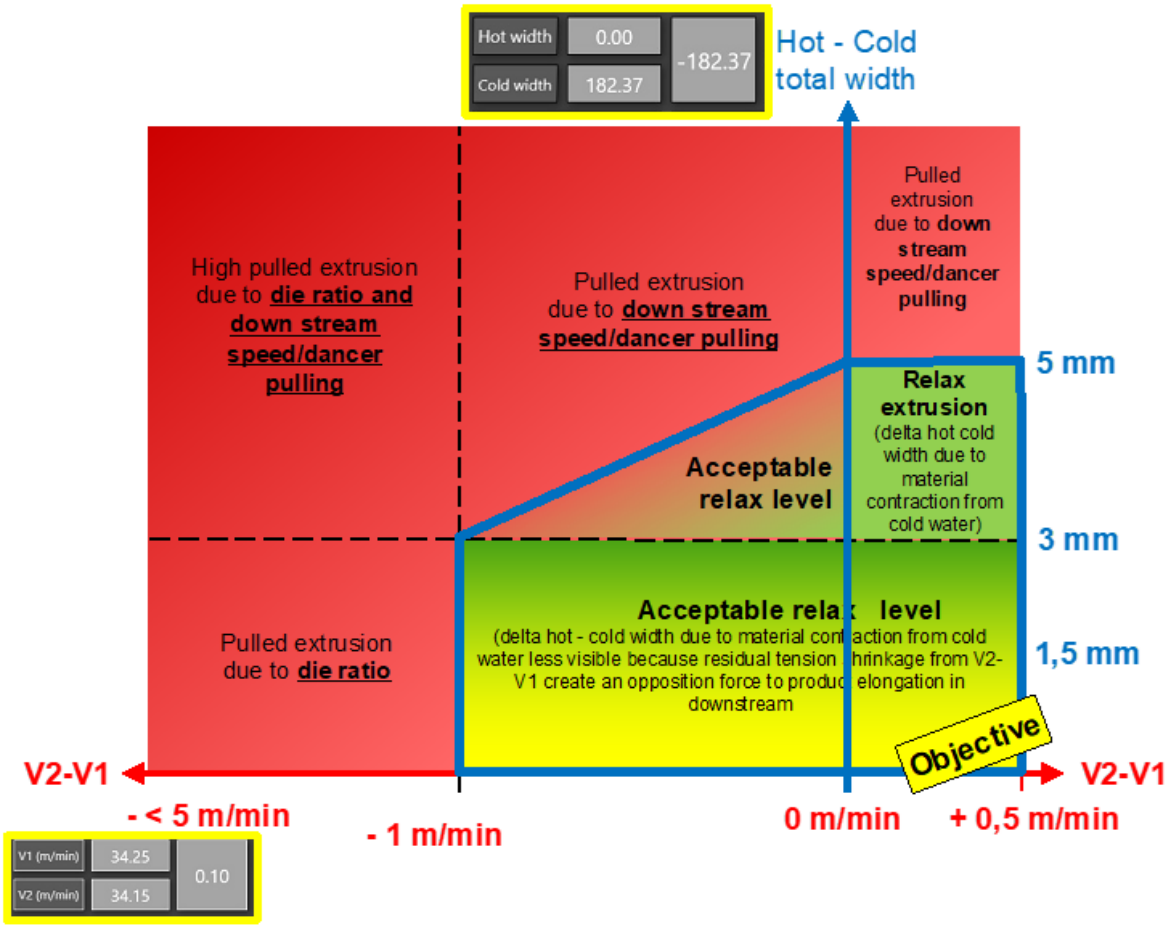


Figure 7: Objective function to drive the Combiline with respect to the 2 main tread quality indicators : (V2-V1) and (hot width – cold width)

From the Q&A session, Continental expresses the following requirements:

- AI must deeply analyze parameters which have an impact on the speed stability and length stability (cold side of the Combiline)
- AI must deeply study which parameters impact the relaxation level and make a proposal to reach a better relaxation level. (hot side of the Combiline)
- AI must alarm operators if the hot area isn't relaxed
- Target is to guarantee the relaxation of the product and then to use the velocity factor from the hot profilometer to predict the cold profile (project for reducing rework from Die trials and reducing time losses due to die development activities.)

Proposed solution

The analysis of the requirements leads to the following comments:

- The KPI related to tread quality (V1-V2) and (hot width – cold width) will be used as objective values as describe in the Figure 7
- The UC is related to the objective for the hot part of the Combiline. The objectives related to the cold part of the Combiline are part of another UC not selected yet.
- The last objective, i.e. predict the cold profile, is part of a Continental project and does not belong to the UC but is an extension of it.

As there already exists quite long historical of data available, the foreseen solution is to use deep learning models. Three steps are needed: analysis of the data, anomaly detection model, prognostic model.

Analysis of the data

A first step of analysis and understanding of the data is compulsory in order to determine what are the main influent parameters of the Combiline. While the phenomena influencing the relaxation of the tread are well understood, it is not clear how to monitor them on the Combiline, i.e., how to know which sensors are linked to these phenomena but also what range of the sensor values leads to either a relaxed product or a not relaxed one.

To reach this goal, we will use classical statistical analysis like PCA, correlation matrix, ANOVA. These statistical approaches will explicit the strongest correlations between the variables of interest. We will then further exploit Machine Learning approaches that may reveal weak and unexpected correlations between various sensors and the target measures (V2-V1 and Hot-cold total widths). These Machine Learning approaches may be of three types:

- First, well-known methods that may eventually lead to intuitive interpretations, such as decision trees, linear and logistic models.
- Second, more powerful models such as Support Vector Machines (SVM) that are equipped with fast convergence training algorithms, and may thus be used within outer loops of ablative experiments to identify relevant sensors and ranges of input values.
- Third, deep learning models, such as feed-forward, convolutions and transformers, that take more time to train but may leverage weak and unexpected correlation patterns. Interpretation of the models outputs in this case is however not guaranteed, because of the increased experimental time required that jeopardizes the number of probe experiments that can be performed in a reasonable amount of time.

The analysis of the data will be conducted considering that the aforementioned KPI's (V2-V1) and (hot width – cold width) are the target and their magnitude is representative of the magnitude of the quality of the tread as shown in Figure 7.

Further feedback and insight from UC 10 might also be of help.

Anomaly detection model

The aim of the anomaly detection model will be to alert the operator of the drift of some parameters that may lead to non-relaxed product. Depending of the findings of the data analysis the solution foreseen are of 2 types:

- Either to consider a model that may give some information, like "control chart", about the stability of the process in relation with its natural variations. Such kind of models are for instance Deep Learning one class models (e.g., Deep-SVDD). This kind of approach is mainly based on data representative of the nominal state of the process. This kind of model may be very sensitive and able to detect early drift.
- Either to consider a (or several) model(s) that will detect and diagnose which drift/degradation/anomaly is running and will alert the operator. This approach requires more data than the previous and furthermore data representative of the several kinds of drift. Moreover, the dataset has to be balanced with respect to the several drifts. This kind of model might be more difficult to train because of the several operating conditions of the process (several recipes for instance).

Both approaches are complementary and require different kind of data.

Prognostic model

Prognostic model aims to predict Remaining Useful Life (RUL) of components, i.e. the time remaining before the failure of the component. In this UC, if enough data are available, we will build a prognostic model that will predict the time before the drift of the parameters might lead to a non-relaxed product. Since the non-relaxed condition may come from several causes, one prognostic model has to be built for every cause.

For this aim we propose to tune an end-to-end approach with a MLP-LSTM-MLP model, which components include a first Multi-Layer Perceptron (MLP) to automatically extract relevant features, an LSTM to capture degradation patterns over time and a final MLP to predict the RUL. We have proposed and evaluated such a model for prognostics of turbofan RUL on a well known dataset. The results show that our proposed model obtains good performances compared to the state-of-the-art[1].

Main specifications & high level design

Required datasets for solution development

Continental has already provide expert knowledge about the process, the Combiline and the relaxation phenomena. As the foreseen approaches are based on ML, as much as possible data are required. The data must be segmented to get only the "stabilized" production phase. Furthermore, all sensors that might be related to the relaxation phenomena have to be included.

Continental has already provided a dataset with such characteristics. It is the other partners' duty, to process raw signals and correlate them to gain insight and develop algorithms. The list of sensors and the data are available on the PETA repository of the project.

Required input and output parameters for demonstrator execution

The output parameters delivered by the solution will be of 2 kinds:

- Anomaly detection model will provide an "alarm", i.e. a variable that will be set to 1, when condition drift to non-relaxed product situation will be detected.
- Prognostic model will provide either the RUL, in the sense defined earlier, or the KPI's trajectory. The selected kind of output will be selected regarding the data available for training the model as well as the models performances.

The inputs of both models, i.e. anomaly detection and prognostic models, are not known yet. They will be defined by the first step of data analysis conducted.

Required interaction with the operator: ***What advantage do we provide to the final user?***

The final user as far as we understand is the Combiline operator that drives the Combiline. We will provide 2 kind of output that will be of interest for the operator:

- Anomaly detection model will provide an "alarm", i.e. a variable that will be set to 1, when condition drift to non-relaxed product situation will be detected.
- Prognostic model will provide either the RUL, in the sense defined earlier, or the KPI's trajectory. The selected kind of output will be selected regarding the data available for training the model as well as the models performances.

[1] Alaaeddine Chaoub, Alexandre Voisin, Christophe Cerisara, Benoît Iung. Learning representations with end-to-end models for improved remaining useful life prognostic. PHME 2021. ⟨hal-03247997⟩

What do we expect from the operator?

Operators are expected to consider the alarm and RUL provided by the system and to carry out the actions that they consider appropriate. That is, the anomaly detection and the prognostic information are provided as a guideline, not as strict order.

How is the interaction envisioned?

Further insight with Continental as well as with HMI provider will be required in order to define what and how, at the end, will be delivered to the operator. For instance, one may think of using an "Andon" with 3 lights: green, orange and red to display anomaly detection information.

For the RUL, further insight has to be considered since the information is richer and not provided yet. Such information may lead to more cognitive load for the Combiline operator.

Addressing ethical considerations:

Following the recommendation provided by the ethics team on this use case, the following aspects have been clarified and discussed

- **Clarify formally who is getting the guidance to define extrusion settings and to what extent they will be expected to use that guidance:**

Voisin – AI may not propose setting points; There will be a simple alarm for the operator (0 or 1 status) and also the RUL

This is a clarification of the alarm but also a weakening of the initial proposal for Conti_3 (from the one pager) – to be re-visited if position on AI guidance changes.

Error protocol was mentioned but not addressed so far and has to be provided.

A. Bella – uncertain at this time whether AI guidance will go to technician or whether it will involve interaction with operator

Voisin – It will depend on the findings

Situation is evolving. Re-assess once it becomes clear through findings whether operator or technicians will get guidance. Error protocol and expectations for operator or technician still needed.

- **Recommendations for Die Making**:

Clearly define the two distinct projects/goals in the UC and separate them

Bella – there is no good way to measure AI guidance directed at die makers

Die making project relation clarified somewhat, but also bypassed due to technical difficulties

Voisin – die making is not within this use case. The feedback to the die making is not within the use case.

- **Recommendations for cognitive load**

As we assume the RUL prognostic will provide information continually and in real time regarding parameter drift and how much time remaining until un-relaxed product, the operator (or technician) will either have to 1) react as soon as possible to avoid degradation, or 2) wait until a certain limit of degradation is passed to react.

If 1) then his cognitive load will be increased considerably, he will be always checking the RUL to make sure everything is optimal

If 2) the cognitive load is increased less but the adjustment to get back to optimal may be more difficult to make than if he had reacted earlier

Cognitive load will be increased even more if the operator is getting feedback in real-time from his adjustments, e.g. if he makes a wrong adjustment while trying to correct, then the RUL will show that he is making things worse (that he has even less time to correct the problem)

Therefore, it is recommended that before implementing the RUL in live trial, proceed first by deciding with Conti – and based on operator experience if possible - on a reasonable limit of degradation/time remaining at which the operator will react by making adjustments. (it could be tied into the Andon system with a 4th light maybe)

Use this limit in a first stage of RUL implementation, then, if earlier reaction to RUL is necessary for better adjustment either 'move' the limit or remove it altogether after the operator (or technician) has become familiar with RUL based adjustments.

The idea is to prevent the RUL information from becoming a constant 'worry' for the operator (like obsessively checking emails) by giving some delineation to the acceptable relaxation level in operator centred terms (some boundaries of reasonable checking and reaction to the RUL)

Technologies and links to WP

Several work packages of AI-PROFICIENT are linked to this Use Case. Currently, at least the following ones have been identified. But this list might change (include more or reduce) as the more insight in the data analysis and use case are available.

This use case is in-between component/edge and system/cloud levels. Indeed, the decision (alarm and RUL) has to be provided at the (sub-part) machine level and may come from several components. As such in might involve task from WP2 (edge/component level) and WP3 (cloud/system level) as well as WP4 to interact with the users

WP 2 - Work package 2 deals with the edge system. This UC attempts to provide services at the edge in relation to components.

- T2.1 – IIoT environment deployment and set-up: Some additional sensors may need to be installed and their information sent to the servers for further processing and development of models. If the sensors information will be compulsory, the deep learning approach will be no longer valid for some of the anomaly (not all of them). In this way, more classical techniques will be explored.

- T2.2 – Component level data acquisition and pre-processing: Since new sensors may be installed, they will need of signal processing techniques to be brought to the edge to reduce the amount of data captured and provide answers efficiently.

- T2.3 – Self-diagnostics and production process anomaly detection & T2.4 – Self- prognostics and component operating condition estimation

These two tasks are the core of this UC. Primarily because the aim of this UC is to provide an edge system that allows anomaly detection and prognostic, secondly, because this system need to consider the different operating conditions for this purpose.

WP3 - As the use case is in-between component and system level, it will required also tasks from WP3.

- T3.3 – Proactive maintenance strategies at system/line level: This task will leverage the aggregation of components health/states and aggregate them in order to provide the status of the relaxation of the tread. Indeed, some dependencies and interaction might exists between the comonents and anomaly that must be considered in order to anticipate their combined impat on the relaxation of the tread.

WP4- WP4 deals with the analysis the identification of effective means for human-machine interaction. For this UC in particular, the following tasks might be of relevance in the development the final solution.

- T4.1 – Human feedback mechanisms for AI reinforcement learning: In this task we might be considered in the feedback of the operator to improve the AI. It should be part of the processing of the AI errors.

- T4.2 – Role-specific human-machine interfaces and data visualization & T4.3 – Extended reality and conversational interfaces for shop floor assistance: Depending on the technologies employed by the final feedback system, either (or both) of these tasks will take place in this UC.

Detail flowchart & partner/task involvement

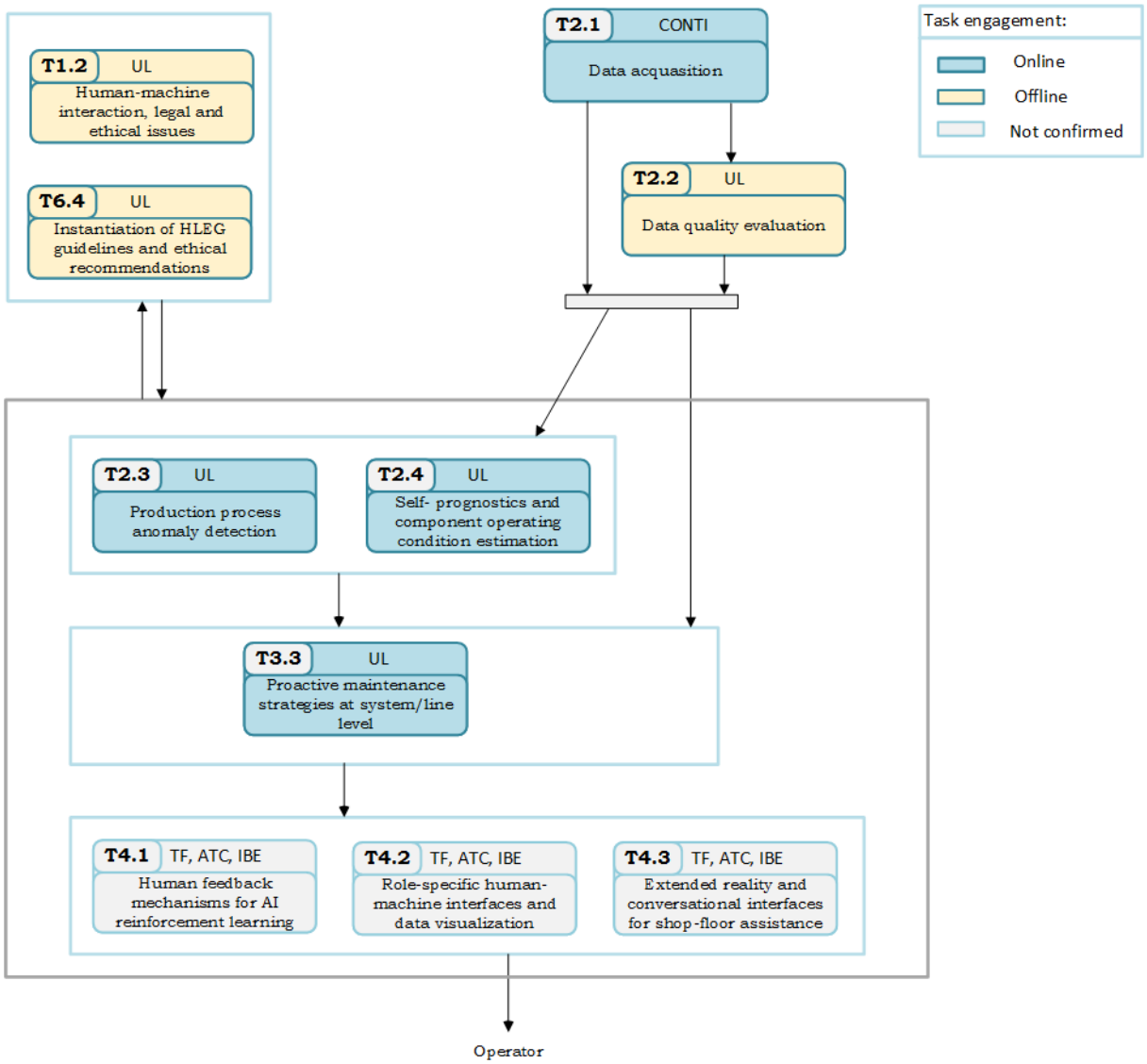


Figure 8 - High-level chart of the engaged tasks at CONTI-UC3

CONTI-5 UC Specification: Tread blade wear

UC description

After the cooling process takes place, the tread is almost ready to be stored in the trolleys. However, it needs to be cut first into single tyre units. This process is carried out in between the entry and exit conveyor as shown in the following figure.

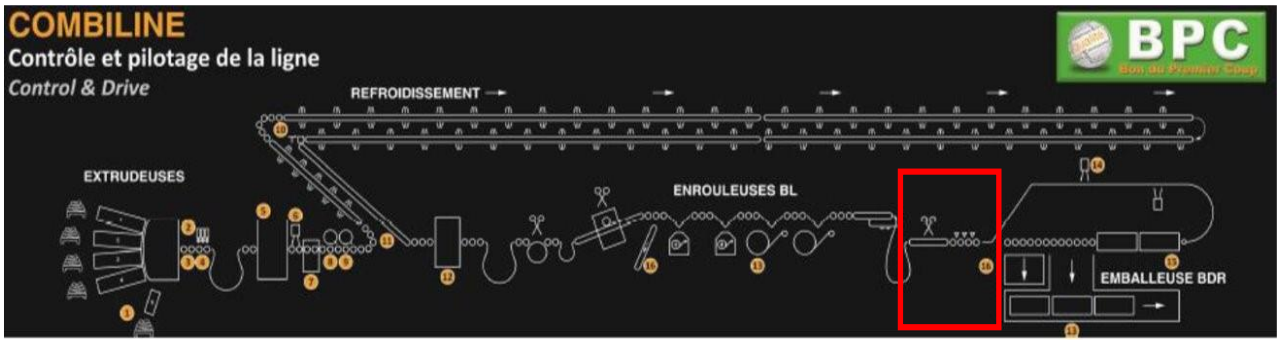


Figure 9: Location of the tread cutter in the production line.

In that point of the production line, the tread that comes in a single piece is cut into single tyre units of the same approximate length, following the tyre design specifications.

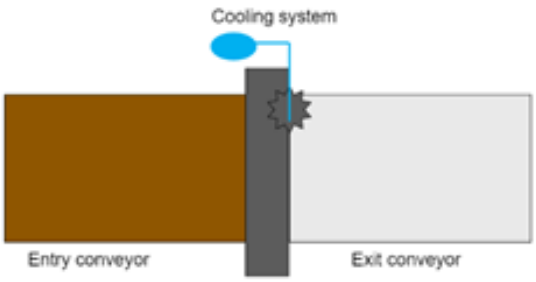


Figure 10: Upper schematic view of tread cutting system.

There are 3 main components involved in the tread cutting systems:

- Entry and exit conveyors
- Blade system
- Lubrication system

Entry and exit conveyors bring the uncut tread to the cutting systems and, once it is split into single pieces, they carry it to the next step in the production line. Blade system consists of a rotational blade that cuts the tread. It is the core of the cutting system, it performs cuts with certain angle that allow both sides of the rubber to be ensembled later.

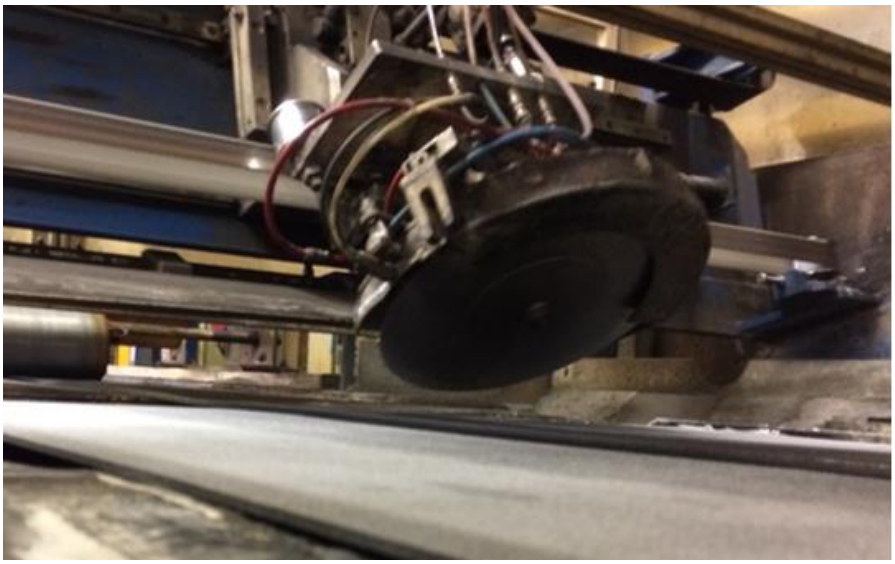


Figure 11: Blade system.

Problem statement

The blade performs a considerable amount of cuts each day. These repetitive cuts make the blade to be worn out and it needs to be replaced almost in a weekly basis. The blade changes are not regularly scheduled as the stiffness of the tread can vary from one tread type to another. In consequence, there is no standardised method to assess the blade status now.

Due to the stickiness and rigidity of the rubber, the blade needs to be in optimal conditions to perform accurate cuts that will not compromise the final quality of the tires. When the blade is worn, its' capability to produce good cuts is compromised leading to quality issues downstream the production line.

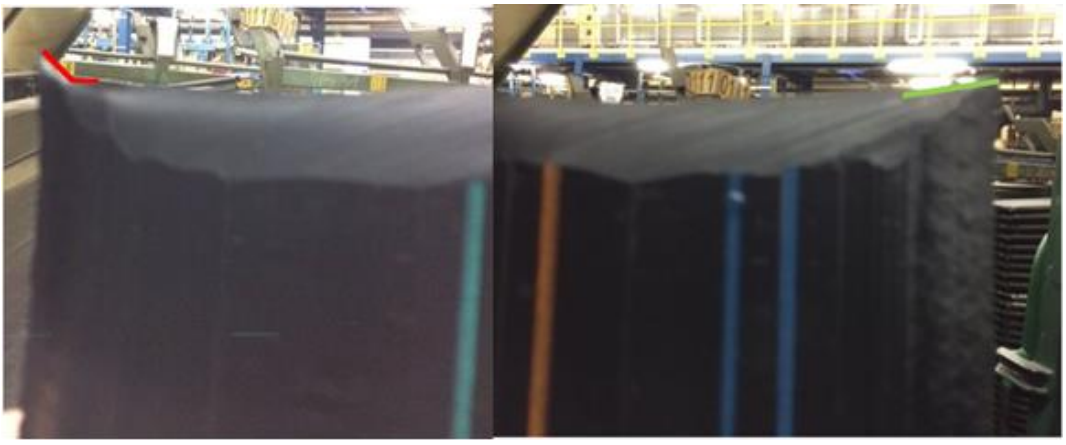


Figure 12: Left) Cut with imperfect geometry (in red). Right) Cut with desired geometry (in green).

Currently, assessing the degree of wear of the blade is a complex task, which is carried out by the operators. This implies visually checking the quality of the cut and adopting some corrective measures (such as slight modifications of the cutter setting parameters) in case some burrs appear in the tread or if the cutter is getting stuck during the cuts.

There is no system to transfer any information regarding the goodness of the blade from one shift to the next one. Consequently, on every shift the incoming operators need to check the blade again visually without having prior information regarding the state of the blade in the previous shift.

Blades are only changed when the cut quality is too bad or following some preventive maintenance schedules (the second rarely occurs).

Of course, increasing the blade change frequency could reduce the problems associated to the low quality on the cuts. However, the consequent production line stoppages may cause higher costs than a more corrective based maintenance approach.

It is also worthy to notice that there are three different actors that are involved in this UC related to blade changing. These are:

- **Operator:** Persons in charge of running the production line and ensuring the product is being created. When problems arise on the cutting system (faults, breakdowns etc.) they call maintenance craftsmen to fix them.
- **Maintenance craftsmen**: Persons in charge of fixing the maintenance problems created in the line. It might be due to scheduled maintenances or because of unplanned breakdowns. They repair the blade system or replace the blade. In case a blade replacement is carried out they keep a log of this change on the SAP.
- **Maintenance manager/engineer:** Person in charge of the supervision of all the assets and of the planification of scheduled maintenances. Currently they have no way of planning blade changes due to the lack of monitoring system of the blade.

Proposed solution

Given the current situation regarding the data affecting the tread cutting systems, it seems reasonable to follow an approach that starts from a basic dataset, i.e. with the data that is currently available, and adds layers of complexity and detail to the final solution as soon as new data (provided by new sensors) is available and it can be used to design more detailed algorithms.

In that sense the following complementary approaches are proposed:

- **Usage based approach for cut wear estimation**:

In a first stage, developing a model that approximates the wear of the blade based on the number of cuts made in each type of tread seems to be a good starting point. This model can be later complemented by the algorithms developed with the current measurement to disambiguate other faults or have a more precise blade wear detection measurement provided by the vision system.

Additionally, as new recipes are expected to be created in the future, the reliability system may be enhanced by means of semantic knowledge, so that initial wear-per-cut values can be inferred for new recipes that have not being cut before.

- **Current signature based cut efficiency estimation**:

Current sensors can be used to identify excess effort made by the machine when cutting (meaning either the blade is worn or other faults are occurring). Additionally, signal processing techniques can be used to distinguish other root causes of the faults by using frequency domain techniques which could become a fault diagnosis system.

- **Vision based cut quality assessment**:

Vision system can be used to provide an automated measurement of the goodness of the cut which is an objective by itself, but could additionally be fed in the blade wear estimation system, as the goodness on the cut is already a symptom of blade wear.

Main specifications & high level design

Required datasets for solution development

a) **Usage model:** The development of the model will require obtaining the following table:

Blade ID	Recipe A cuts	Recipe B cuts	Recipe C cuts	Recipe D cuts	Blade change info
1	0	25	800	90	EOL
2	150	0	0	1000	EOL
3	250	250	250	500	EOL
4	100	50	50	700	EOL
5	200	200	200	200	EOL
6	100	50	750	100	Others
...	x	x	x	x	Scheduled

Table 1: Example of required table for usage model design.

Each row represents the lifetime of a blade (which is identified with the Blade ID), additionally there will be a column for each different recipe/tread type. The value in this column represents the number of cuts that each blade has done to each type of recipe. Furthermore, the column Blade change info stores the reason for the blade change: EOL (End of Life), Scheduled (when the change is due to maintenance schedule) and other (When there are other reasons for the blade change). This info will be used to detect which blade observations should be considered for the training/re-training of the models. At a first stage, if no information regarding the blade change info is given, all the cases will be considered as EOL. Later, once the feedback system is operating, this information will be filled by the maintenance craftsmen.

The number of cuts can be inferred, for example, by getting the approximate dates of the blade changes and summing the production of tyres in between. As an example:

Blade change table:

Blade_ID	Date placed	Date removed
1	2020/05/10	2020/05/17
2	2020/05/17	2020/05/28
...	...	...

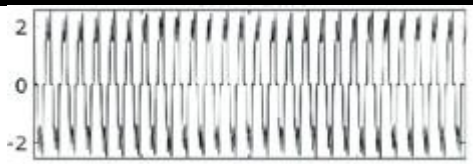
Tyre production table:

Date	Tyres_A_Produced	Tyres_B_Produced	Tyres_C_Produced	Tyres_D_Produced
2020/05/10	0	100	0	200
2020/05/11	50	150	50	20
2020/05/12	...	...		
...				

Finally, regarding the use of semantic technologies for the inference of new recipes, a table detailing the properties of each recipe will be needed. As the following example table shows:

Recipe_ID	Cut Surface (cm2)	Weight/meter	Compound_A	Compound_B	Compound_C	Compound_D	Compound_...
1	35	1,5	20%	70%	10%	0%	x
2	32	1,35	0%	10%	35%	55%	x
3	28	1,2	50%	5%	40%	5%	x
...	x	x	x	x	x	x	

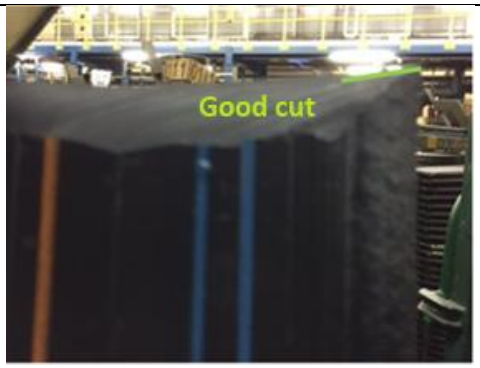
b) **Current model:** In comparison to the reliability model, current will be estimated from cuts (instead of from blades). For that purpose, the required dataset will need to include the following information:

Cut_ID	Blade_ID	Timestamp	Raw_Current (array/ time series)	Degradation (inferred)	Others (Faults, etc)
1	1	2020/05/		0%	None
2	1			1%	
3	1			5%	
4	1				Jamming on the blade.
5	1				
[…]	1				
1	2				
2	2				
3	2				
[…]	[…]				

Current measurements will be directly obtained from the sensors. Degradation can be inferred from the reliability model and, regarding the other faults, the different operator logs will need to be parsed and homogenised (if there are any available).

c) **Vision model:** The vision model will work similarly to the current model, having an observation per each cut the cutter does. For the development of the model, the following data will be required:

Cut_ID	Blade_ID	Image (matrix)	Label (Boxel/Binary/etc.)
1	1		Boxel: Region with bad cut. Label: Good/bad cut. Others.

2	1		

Images need to be labelled somehow, that is, someone needs to define which cut images represent good cuts and which does not. Additionally, it is necessary to define which will be the output of the model and bear it in mind during the labelling process: only good/bad cut, a region surrounding the extra or missing tread, etc.

D) **Feedback system:** Each model will have its own approach for feedback and retraining.
The feedback system will be in charge of keeping the human in the loop while ensuring the lifelong learning capability of the models.

The feedback system is comprised by the means provided to the maintenance craftsmen to provide feedback as well as the re-training system for the models.

Currently, maintenance craftsmen log the blade changes carried out with dates and other codes, ideally, this logging system will be extended to include information relevant for the retraining of the algorithms without increasing the time and effort carried out by craftsmen when logging.

In addition, maintenance managers will be provided with interfaces to monitor on quasi-real time the health status of the blade as well as to make different simulations on how the blade life will evolve in relation to the expected tread cuts in order to ease the scheduling of maintenance actions as well as type-of-product schedules. Furthermore, managers will be able to trigger the retraining of the algorithms based on the logs provided by the craftsmen.

In particular, this impacts the previous systems as follows:

- Usage model: As currently done during normal production conditions, craftsmen will need to provide a detailed log of when blades are changed. Additionally, they will mark either of the following options:
  - Blade end of life: The blade is changed because it was not cutting correctly.
  - Scheduled: The blade is changed following a maintenance schedule.
  - Others: Other reason for changing the blade.

  This reporting is carried out for auditability purposes and allows the maintenance manager to compare the wear values estimated by the algorithms with the real values. In addition, the cases marked as blade end of life will be used to retrain the reliability model, so that it improves its accuracy for wear estimation.

- Current model and vision system: For the case of monitoring algorithms (current, and vision system) managers will be able to request craftsmen to check the blade system based on the recommendation of the algorithms (such as too low tread quality or excess current consumption). If craftsmen detect the model is providing invalid suggestions, they will notify it in their logs. It will be manager's duty to retrain the algorithms by selecting the timespan where the models have provided invalid outputs; after, labelling the wrong records with the proper labelling (Example: Marking the correct shape of the cut); and, lastly, sending these records to server to allow retraining.

Required input and output parameters for demonstrator execution

The following table summarizes the inputs and outputs that the models will need for their correct operation:

Model/System		Input(s)	Output(s)	Execution	Final user
(A) Usage model	(A.1) On-line model	• Number of cuts per tread type	Degradation (%)	On event	Maintenance manager
	(A.2) Prognosis model	• (Estimated) Number of cuts per tread type	(Estimated) Degradation (%)	On demand	Maintenance manager
(B) Current model		• Current measurements (raw/features) • Degradation (%)	Anomalies/Efficiency	On event	Maintenance manager
(C) Vision model		• Images	Cut quality (binary/boxel/others)	On event	Maintenance manager
(D) Feedback system	(D.1) Feedback log system	• Maintenance Craftsmen's feedback	Logs	On event	Maintenance Crafstmen
	(D.2) Retraining system	• New labelled datapoinst	Re-trained algorithms	On demand	Maintenance manager

Essentially, maintenance managers will be the final users of the algorithms and systems. But they will rely on the feedback system, used by maintenance craftsmen, that will provide feedback to the recommendations provided by the AI.

Flowchart of model stacking

The sensors installed in the blade cutting system allow to send the information to the cloud. So that it can be processed.

Figure 13: Schema of sensors installed on the cutting system.

Essentially, 'on event' models, hosted on the cloud, are combined to provide assistance in the detection of blade wear and cut quality indications, without directly observing the cutter condition, and using advanced interfaces to warn maintenance crew about undesired behaviors.

In addition, the reliability model can be used with scheduling purposes. This 'on demand' use can be triggered by maintenance managers for the planification of schedules to avoid undesired blade changes by using other planned stoppages to change the blade before it reaches the end of its life.

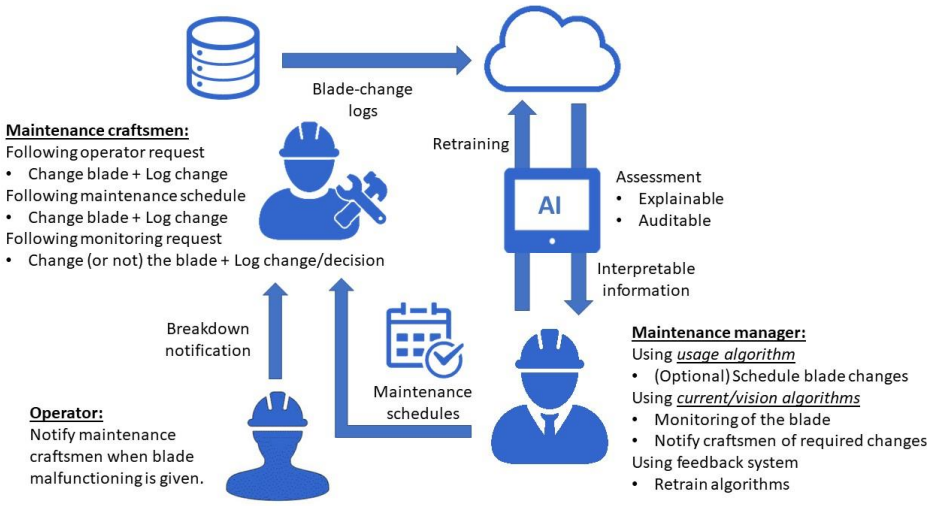


Figure 14: Interactions among involved personnel.

The models that operate 'on event' employ sensor inputs (current/image) to provide estimations once the necessary input is given. Note that the current model also employs the estimated reliability as an input. The outputs of the models are then presented to the maintenance manager by means of an AI taking advantage of the explainability capacities to add interpretability.

The manager can use the indications provided by the models in order to determine whether the blade needs to be changed or not.

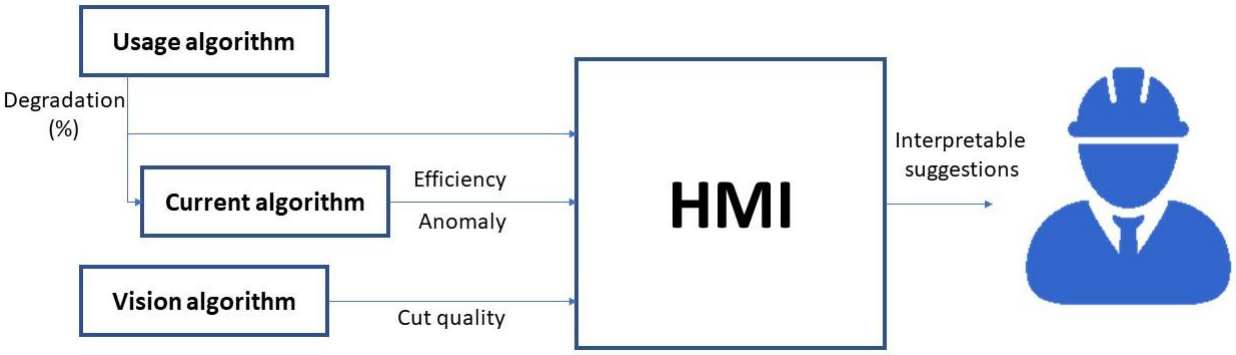


Figure 15: Models assisting maintenance manager

Furthermore, the craftsmen will use the feedback system that extends current logging procedure. This feedback system serves a double purpose. Firstly, it provides the chance to let the AI know when it has provided wrong estimations/suggestions. And, at the same time, the AI is improved with the feedback by re-training them.

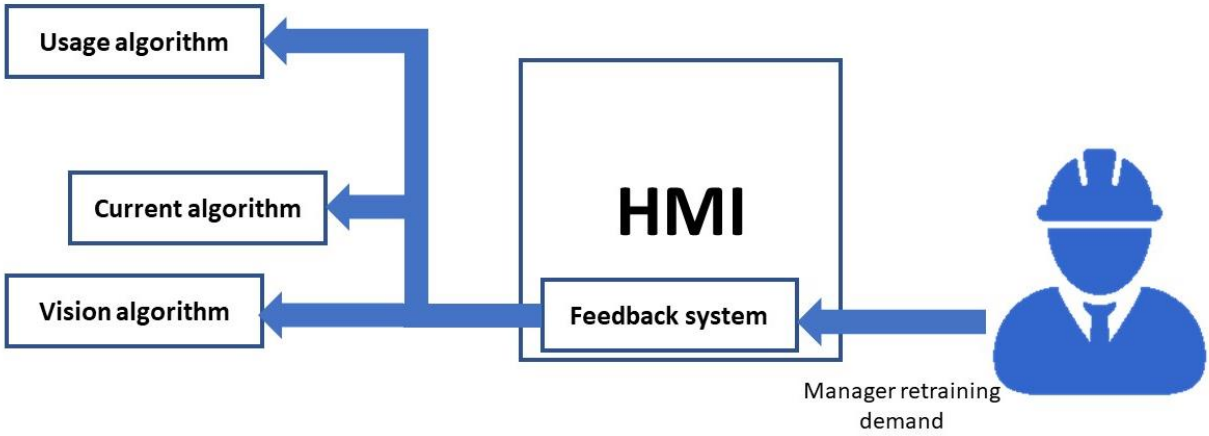


Figure 16: Maintenance Manager using feedback system to improve models.

In this way human and AI coexist and augment each other. Manager gains trust over the AI as it gets better in the suggestions and the AI improves with the help and supervision of the craftsmen.

Required interactions

Decision Support: Manager will be provided an HMI to improve their decision making. This HMI will reflect the health of the blade as well as the goodness of the cuts providing means for a better decision making.

Explainability: Model suggestions will be backed by their explainabitily. That is, models will be developed following explainable design techniques so that Manager is granted a "why" beyond the "what".

Feedback The craftsmen will act based on a decision system that is supported by the models. When the model provides bad estimations, they will provide feedback to the system, so that the models can be retrained and reinforced in their learning. This re-training will apply to the three models.

Addressing ethical considerations:

Following the advice provided by the ethics team, the following aspects will be considered:

1. **Define reach of the AI + Stagged implementation:** Models will be introduced in the production environment in a stagged way. Initially some training will be provided to craftsmen and manager. Additionally, at the first stages of the adoption of the IA, operators will be expected to have an almost full supervision over the models. With the help of the feedback systems and other tunings the models might need, they will be granted greater autonomy by the operators, bearing in mind that operator will always have the last word.

2. **Define a protocol for AI incorrect behaviour handling.** The feedback system will be developed to assist on providing feedback over the performance of the AI, so that the AI can be adjusted if needed and requested.

3. **Reduce operator overhead by using visual HMI (as a traffic light). Consider it over predictive maintenance.** Predictive maintenance approach will be based on the reliability model. Instead of seeking to interact with the operator, as it might be less accurate than the other on-line models, it will be provided to maintenance managers. The aim of providing this tool to managers is to approximate when the blades might need to be changed so that, if maintenance stoppages are planned for other reasons, they can be used to change the blade if it is close enough to the end of life.

4. **Include operator blade adjustment into the data. Additionally, use it to train operators if possible.** This suggestion has been disregarded: Even if currently operators tend to manipulate cutter settings, it should be avoided in the future (as per CONTIs request). For that reason, blade settings will not be considered.

5. **When visual management system is integrated, clarify operator's responsibility.** The need of visual management system is finally discarded, as managers will be in charge of requesting blade changes based on the support of the AI.

6. **Ensure proper integration of visual management system (readable, accessible, etc.)** There will be a specific task ensuring the proper installation and adoption of theHMI.

Technologies and links to WP

Several work packages of AI-PROFICIENT are linked to this Use Case. Currently, at least the following ones have been identified. But this list might change (include more or reduce) as the project progresses:

WP 2 Work package 2 deals with the edge system. This UC attempts to provide maintenance managers means to identify the wear of the blade at cloud level. However, part of the computation is carried out on the edge, at machine level.

- **T2.1 – IIoT environment deployment and set-up:** Given that some sensors need to be installed and their information sent to the servers for further processing and development of models, this task is key in this UC.

- **T2.2 – Component level data acquisition and pre-processing** Since some of the involved technologies include vision and current, the sensors installed will need of signal processing techniques to be brought to the edge to reduce the amount of data captured and provide answers efficiently.

- **T2.4 - Self-prognostics and component operating condition estimation** The usage model will need to be complemented by the inclusion of real operating conditions of the system, which will be based on the current and vision systems developed in this task.

WP3: As the models developed are used at a higher level to leverage the planning and scheduling of blade changes, cloud computation related tasks are very present in this UC.

- **T3.2 – Predictive AI analytics for production quality assurance:** Reliability model, a data-based model, will be used to provide predictions of the possible evolutions of the blade health.

- **T3.3 - Proactive maintenance strategies at system/line level & T3.5 – Future scenario based decision-making and lifelong self-learning** These tasks involve scheduling and decision making, which is one of the aims of the reliability model. As, besides its capability to estimate the degradation at real time, it can be used for making future estimations of how the blade will wear according to the recipes that need to be cut.

WP4: WP4 deals with the analysis the identification of effective means for human-machine interaction. For this UC in particular, the following tasks might be of relevance in the development the final solution.

- **T4.1 – Human feedback mechanisms for AI reinforcement learning:** As mentioned above, AI-PROFICIENT wants to include the operator in the production loop for the sake of a improved human-machine interaction. For that purpose, this task aims to provide mechanisms of interaction with the AI so that it can be improved.

- **T4.2 – Role-specific human-machine interfaces and data visualization** This use case will require the development of HMIs for data visualization..

- **T4.4 – Explainable and transparent AI decision making:** For the sake of a more reliable use of AI and greater involvement of operators, the AI systems will be designed adopting the cutting edge explainability techniques. This way decision will be easier to understand, trust or confront if the operators need to do so.

WP5. T5.2 Semantic knowledge graph for integrated digital twins: In case recipe compounds are made available, semantic knowledge techniques will be used to infer the possible wear associated to cut the different recipes.

Detail flowchart & partner/task involvement

Expected partners participations are shown in the chart below.

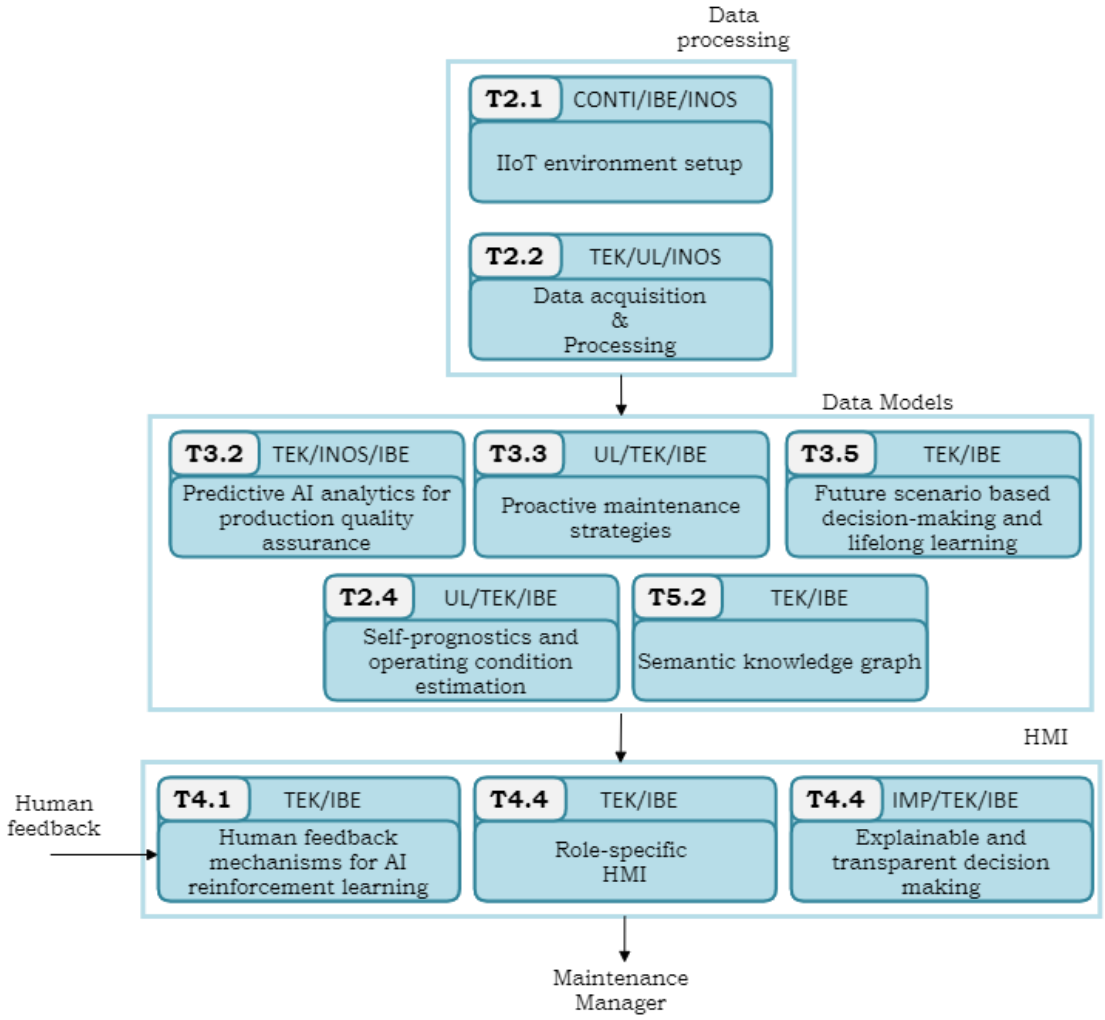


Figure 17 - High-level chart of the engaged tasks at CONTI-UC5

CONTI-7 UC Specification: Tread alignment

UC description

The tread when cut needs to be packed on trolleys to go to the next machine for tire building. All of this is made automatically on the packing unit of the machine.

The packing unit is made of multiple belts and the wear of some of them can create misalignment on the trolley. As the treads are managed via robots on the next steps the alignment needs to be perfect.

Good Alignment

Packing Unit Belts

Possible improvements

Currently this task is just monitored by operator, and most of the time we detect the variations when it is too late. The objective is to have AI managed vision sensors to detect slow deviations to avoid quality issues, prevent low robot utilization (efficiency) and give predictive maintenance advice.

Problem statement (i.e. understanding and sharing problem definition)

Global objective 1: Understand, monitor and detect deviation of the alignment (positioning) of the treads on the tray cassettes (leafs)

Global objective 2: Monitor and detect deviation of the tread motion along the cross feeder belt system

The summary of the UC is presented in Figure below.

- Usecase description :
  - The tread need to be perfectly aligned when packed
- Conti request *(Human in command):*
  - We want the IA to detect alignment deviation and compare it to packaging unit parameters and settings (amount of tread per level)
- Data required :
  - Belts Conveyor speed (1 point to be added)
  - Vision on the tread alignment (To be added)
  - Energy used for conveyors (To be added)
- Influenced by :
  - Mechanical problems
  - Settings
- Affecting
  - Packaging repeatability
  - Final product quality
  - Tire building automatization
- KPI
  - Tread quality
  - TBM robot usage
  - Breakdown rate

Figure 18: Summary of the use case from the Q&A session

General Overview of Layout

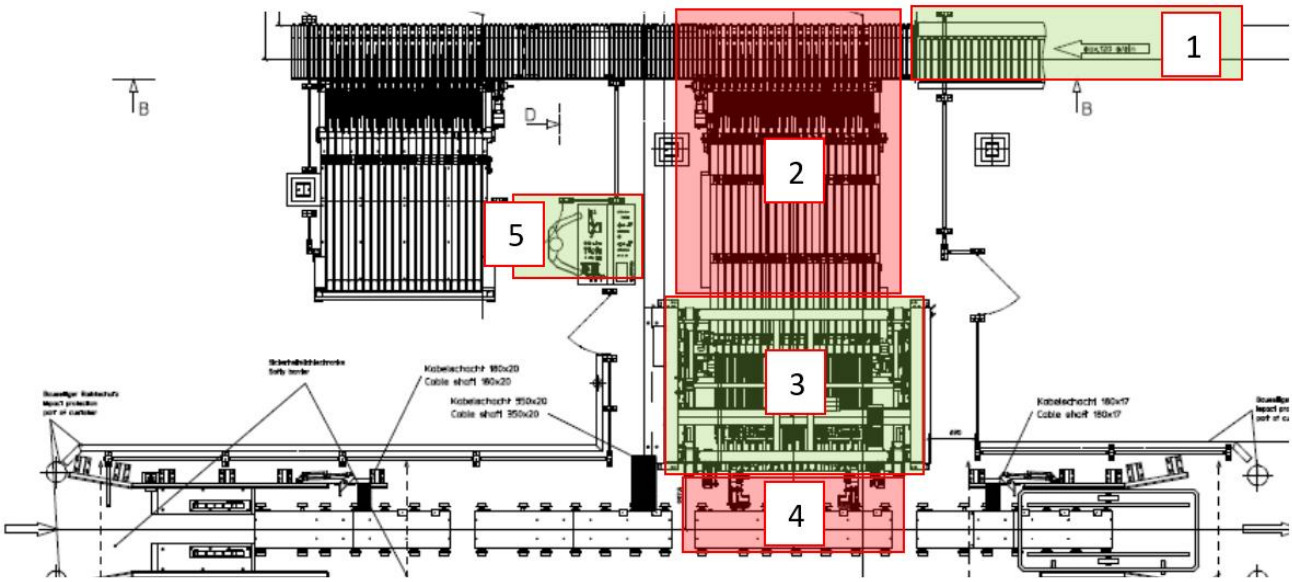


Figure 19: Top view of tread packing station layout

The tire treads are fed along a roller belt (1) and then are grabbed by multiple belts on a cross feeder (2) and fed to the loader (3) where they are raised to the correct height for packing into a tray (4) containing 30 cassettes (leafs). Two to four treads are packed per tray leaf. Due to variations in the process and particularly the wear condition of the belts it can happen that the treads are not correctly placed onto the leaf. If the treads are positioned on the leaf but this is done incorrectly, then the tray cannot be robotically unloaded and it has to be done manually. If the treads are not positioned on the leaf at all, further action may have to be taken in the packing station. The operator is currently stationed roughly in front of the belt cross feeder (5).

We need to detect the correctness of the tread positioning (alignment) on the leafs of the output tray (4) for tracking positioning quality variation (shorter timescale adjustments and longer timescale maintenance) and possibly for alarm purposes (alerting the operator, marking a tray as incorrectly packed).

We also need to track the motion of the tread along the belt cross feeder (2) for belt speed adjustment purposes (shorter timescale interventions) and for guiding machine maintenance (longer timescale).

A 3D drawing of the tread packing station was prepared where the drawing was simplified by showing the bounding boxes of the station major components and the areas of measurement. Different views of this drawing, including proposed positions for measurement sensors and cameras are shown in Figure below.

The tray is shown with the loading arm and sensors at the topmost leaf position.

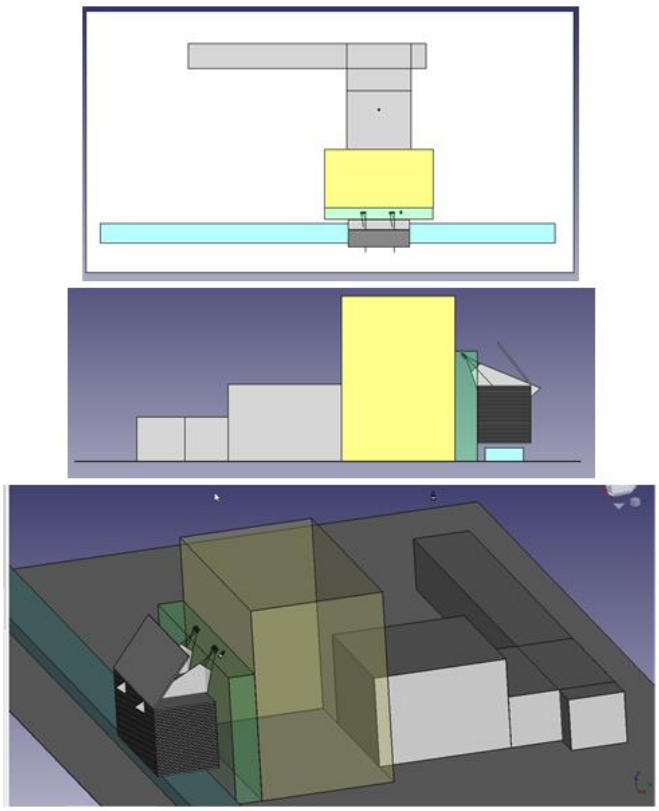


Figure 20: 3D views of the tread packing station

From the Q&A session, Continental expresses the following requirements:

- The vision system (with possible AI augmentation) must detect correct alignment of the treads on the tray and report the number of threads packed, the distances from the tray edges and the gaps between the treads. The tray leaf optical characteristics can vary. The treads are black.
- The vision system with AI augmentation must detect deviation of the tread motion on the cross feeder belt system and suggest to maintenance which driving belts are not behaving nominally.
- AI must alarm operators (and possibly the plant management system) if the tray leaf is not correctly packed
- The target is to guarantee that the trays are packed within the tolerances required for correct robotic unloading of the trays in following stations (KPI: TBM robot usage), to ensure that the tread transfer and packing process is within such tolerances that the tread quality is not affected (KPI: Tread quality) and to detect impeding drift of the packing process outside nominal operation (indicating need for adjustments) and longer term drift (indicating need for maintenance) reducing unplanned adjustments and maintenance (KPI: Breakdown rate)

Proposed solution

As there is no historical data available we need to create an installation and collect image data and convert them to position measurements.

We will be using optical sensors to measure the alignment (position) of the treads on the leaf tray and on the cross feeder belts.

We will (at least initially) store the sensor images on a local disk. These will be transferred out manually.

We will store (initially in a local relational database and by sending in JSON format) the positions of the treads on the tray leaf, tagged by timestamp and (tray ID, leaf ID).

We will store (initially in a local relational database and by sending in JSON format) the positions of the treads at specific time intervals on the cross feeder belt, tagged by timestamp. The start of the imaging and measurement sequence will be via photocell.

We will use traditional threshold based detection of incorrect positioning as a baseline.

We will attempt the use of an AI based approach for improving the false positive and false negative abnormal position detection rates.

We will attempt the use of an AI based approach for generating maintenance suggestions.

Measurement of the tray leafs

To measure the positions (alignment) of the treads on the tray leaf we will use a combination of two 3D profile sensors and a 2D camera.

Shown in Figure below are the positions of the sensors for measuring on the leaf, including the fields of view of the profile sensors. The field of view of the 2D camera can be adjusted by selecting a lens with a different focal length.

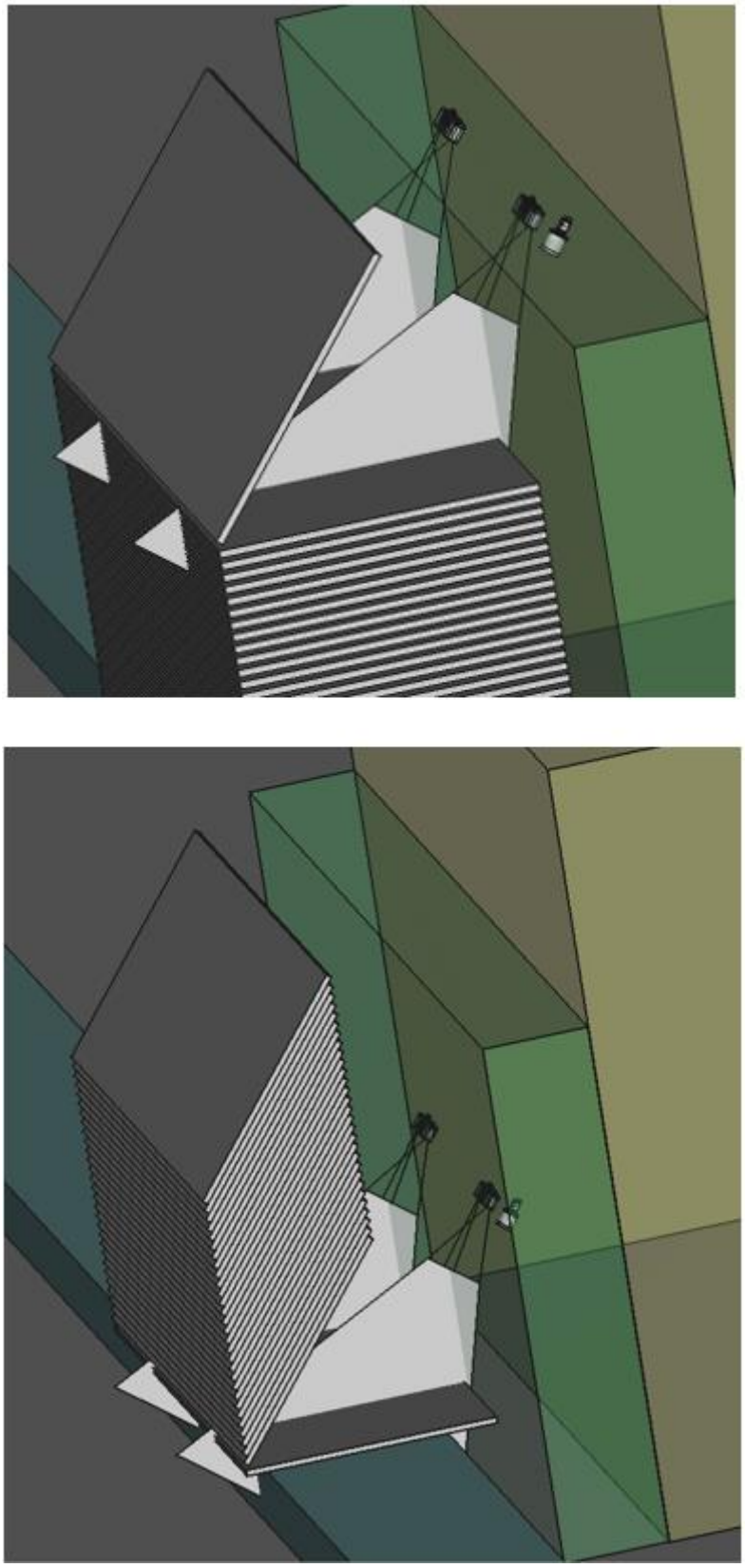


Figure 21: Measurement on the tray leaf, top and bottom leaf positions

The profile sensors are much less sensitive to environmental lighting conditions and will be used to measure the profile of the treads as they are positioned on the leafs. The profile will be measured at two positions along the length of the treads selected so that the shortest treads will be measurable. This measurement will include the number of treads, the position of the first tread with respect to the long edge of the leaf (at two points), the distances between the successive treads (at two points) and the widths of the threads (again at two points). Derived information includes the azimuthal angle of each tread on the leaf.

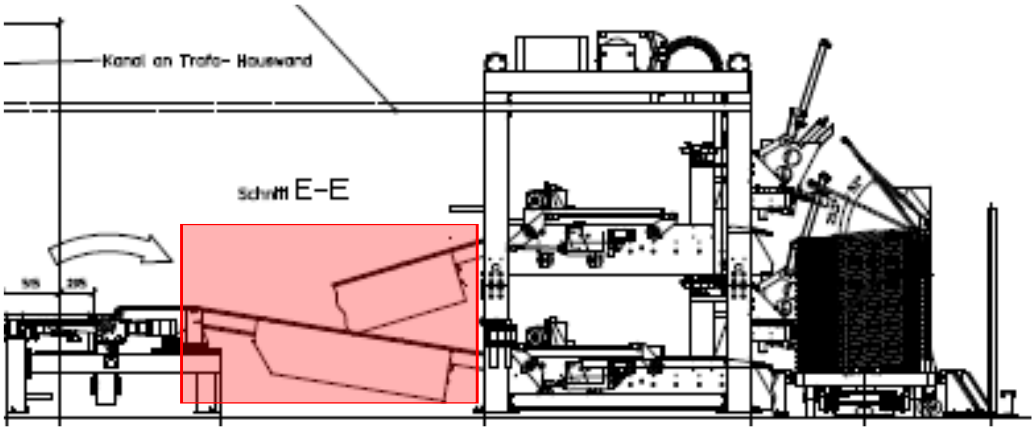
Note: It is possible to extract additional information from the profiles such as the thickness of the profile along the tread width (profilometry), with some error due to the angled position of the profile sensors.

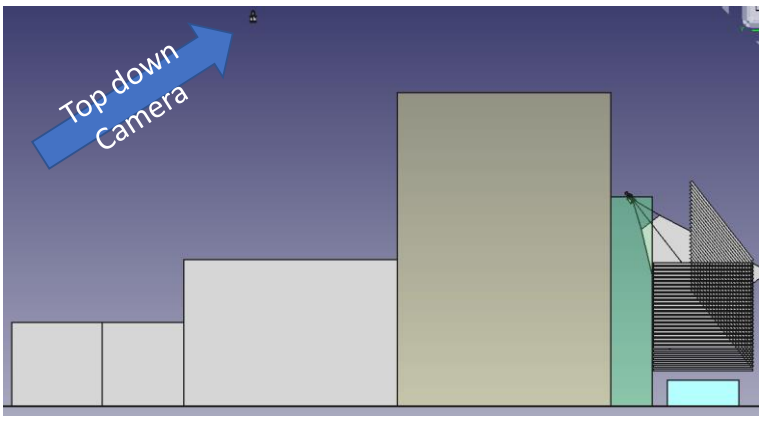
The 2D camera will be used to measure the position of the treads with respect to the short edge of the leaf. This is a less accurate and more noisy measurement but will measure all along the short side (width) of the tread.

The information from the 3 measurement sensors can/will be combined to generate more general indicators of tread alignment.

As shown in the drawing the sensors are placed on the moving loader arm so that the imaging field of view and standoff distances are (approximately) the same for all the tray leafs, irrespective of which leaf is being imaged. As the profile sensor measurements are relative with respect to the leaf long edge and the sensors are calibrated in 3D and the measurement scale does not depend on standoff, their measurements can be (if needed) used to recalibrate on the fly the measurements of the 2D camera.

Measurement on the cross feeder belts





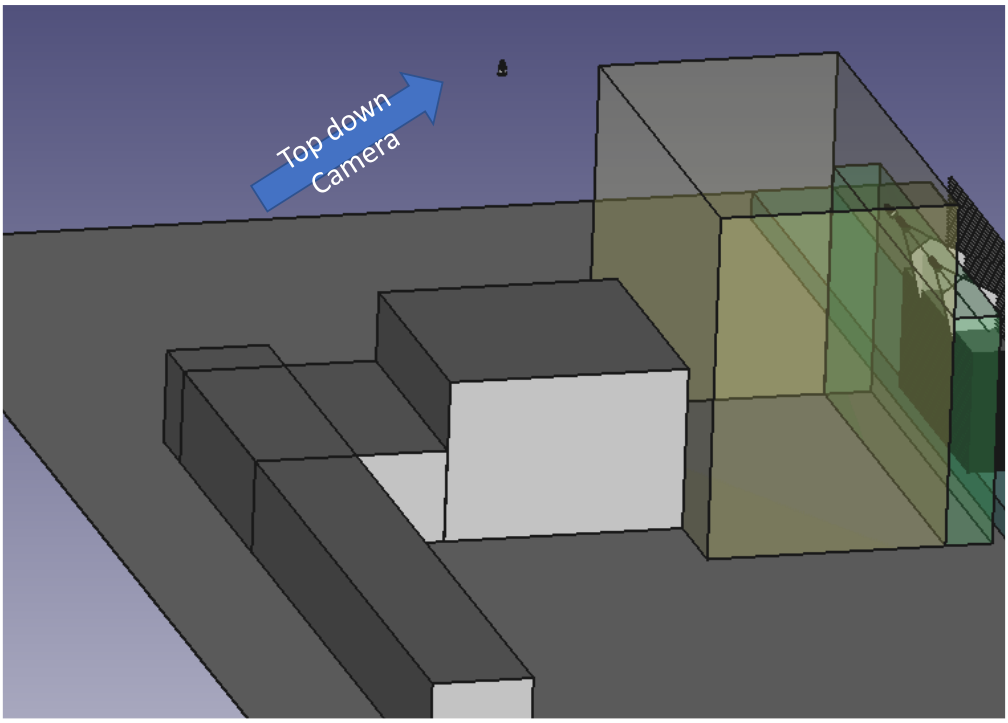


Figure 22: Measurement on the belt cross feeder

The cross feeder is shown in Figure above as a side view and in 3D. The sensor measuring on the cross feeder belts is a top down 2D camera. Initially only one camera is envisioned as if it works it will simplify construction. However part of the cross feeder belts is on a structure that has variable inclination (red/dark rectangle in side view) and therefore standoff with respect to the top down camera. This will be compensated by taking into account which leaf is being currently loaded and therefore the current position of the variable inclination belt segment. If this strategy proves inadequate, then a second camera could be added on a frame attached to the variable inclination part of the cross feeder with added construction difficulty.

Analysis of the data

Analysis of the data is not possible before a minimal set of images and measurements has been obtained.

Given a set of images we may need to manually label good and bad images for the major alarm use cases, i.e. total lack of expected tread.

The first set of images should have approximately 100 “good” images from normal production and about 20 “bad” images constructed by artificially introducing major packing errors.

We will then manually specify threshold for the baseline detection algorithms.

We can then collect data for fine tuning and deviation analysis based functionality.

As the baseline algorithm (not AI) is now running, we can collect sets of “bad” images from production. By temporarily specifying a too strict acceptance threshold for the baseline detector we will get a larger set of images that have been machine labelled as “bad” for the major alarm use cases. A large number of them are expected to be false positives. Inspecting them manually on the disk and deleting the false positives takes approximately 5 sec per image on a fast disk. The total effort to get a large sample of bad images (it can be

assumed that we will have a much larger sample of good images) by inspecting at least 2000 machined labelled bad images should not exceed a person day. Of course this depends on the actual ratio of false positives to machine labelled positives – the initial assumption is about 0.5 (in order to get about 1000 bad images). However it may be the case that "bad" images are so rare that we cannot collect 200 images to inspect within a reasonable amount of calendar time. The labelling will be performed off-line by the machine learning algorithm developer – no particular skills are required for detecting the total absence of treads.

The AI based processing of the data will follow, targeting the three KPIs:

1- TBM Robot use

- We will use the measurements on the leaf to identify correctly packed leafs.
- We will use trend data on the tread alignment on the leafs to identify impeding loss of tolerance compliance that will lead to manual unpacking
- We will use trend analysis on the cross feeder to identify belts that need to be adjusted or are worn and need to be replaced

2- Tread quality

- We will use the measurements on the leaf to track tread quality as positioned on the leaf.
- We will analyze the secondary profilometric measurements on the leaf for detecting deformation of the tread

3- Breakdown rate

- We will use trend analysis on the cross feeder to identify belts that are worn and need to be replaced
- We will use trend analysis on the leaf to identify the onset of drift on the loader arm and suggest to the maintainer the need to inspect and possibly repair

Anomaly detection model

Two anomaly detection model types are proposed:

- a baseline based on thresholds
- a non-linear classifier (SVM or deep NN) trained via manually labelled training sets or via autocorrelation based unsupervised NNs

The purpose of these models is to raise alarms, for immediate action or for informing follow on steps, i.e. tray unloading

Prognostic model

The prognostic model aims to predict Remaining Useful Life (RUL) of components, i.e. the time remaining before the failure of the component. In this UC, if enough data are available, we will build a prognostic model that will predict the time when a belt will need replacement.

Main specifications & high level design

Required datasets for solution development

The dataset is new and will be the results of the vision measurements and possibly (if they can be measured) the speeds of the different belt groups on the cross loader and the power consumption of the belt drive.

The positions of the treads on the leaf depend on the nominal number of treads that is to be loaded on the leaf and the width and length of the particular tread model. To be able to compare with the correct nominal values the packing station automation must inform the vision system with the number of treads being packed per leaf and the tread model being loaded (dimensional information of the tread model, i.e. width and length).

If we use profilometric information to check tread quality, then information about the nominal profile should also be made available to the vision system and AI. This information should be stored as part of the dataset (measurements and images) so that effective measurement and prediction are possible and it is an additional complexity (difficulty) that we should plan for. The measurement result length (number of measurement components) is also not of a fixed size as it varies with the number of treads on the leaf (2 to 4).

Required input and output parameters for demonstrator execution

The output parameters delivered by the solution will be of 2 kinds:

- Anomaly detection models will provide an "alarm", i.e. a variable that will be set to 1, when an off nominal situation is detected.
- Prognostic models will provide either the RUL, in the sense defined earlier, or the KPI's trajectory. The selected kind of output will be selected depending on the models' performance.

The exact inputs of both models, i.e. anomaly detection and prognostic models, are not known yet. They will be defined by the first step of data analysis conducted.

Required interaction with the operator:

What advantage do we provide to the final user?

The final user as far as we understand is the Combiline operator that drives the Combiline and the maintenance personnel. We will provide 2 kinds of output that will be of interest for the operator:

- Anomaly detection models will provide "alarms", i.e. variables that will be set to 1, when not nominal conditions are detected. The alarms addressed to maintenance will be complemented where feasible with indicators of possible sources of deviation, e.g. which belt or belt group is suspect.
- The system must include an adjustment mechanism for the alarm thresholds. The missing tread alarm should inform the operator that a tread is potentially missing from the leaf and is an informative message for the operator (no action expected) and can be switched off. This message that can be forwarded to the TBM area for their action, i.e. prepare to at least partially unload the tray manually – this is also an informative message. The off nominal alarm threshold for the operator alarm must also be adjustable to keep the cognitive load of the operator low and only raise the alarm when a critical threshold has been reached. Maintenance will get an informative message when a stricter tolerance threshold is violated.
- Prognostic model will provide either the RUL, in the sense defined earlier, or the KPI's trajectory.

What do we expect from the operator?

Operators are expected to consider the alarm and maintenance personnel the RUL provided by the system and to carry out the actions that they consider appropriate. The alarm does not need to be constantly monitored and does not stop production. When the operator notices the alarm she/he should perform a quick visual check and see that there is no major obvious fault in the machine and clear the alarm. That is, the anomaly detection and the prognostic information are provided as guidelines, not as strict orders.

How is the interaction envisioned?

Further insight with Continental as well as with HMI provider will be required in order to define what and how, at the end, will be delivered to the operator.

How to handle error and use it to improve the service?

Errors are better handled in the TBM area.

If technically efficient we will try to provide an informative message to the correct destination in the TBM area that a given tray is potentially incorrectly packed.

For every trolley that is found to be unloadable by robotic means we will record the fact and if possible additional information such as the leaf number that are incorrectly packed. This set of actually unloadable trays will be correlated with the measurements (and possibly images) of the set of trolleys that were detected as incorrectly packed by the vision system.

Differences between the two sets above will be used to improve the system.

Addressing ethical considerations:

1) *It appears to be implied that the operator will depend completely on the alarm (or depend upon it after it is proven reliable in a trial period), instead of manually checking tread alignment, but this is not clear.*

Currently the operator does not constantly check the layout on the leaf. The operator is expected to continue not checking every single leaf and depend mostly on the alarm for total (rather that periodic) checking of the tray packing result. The operator has the belt cross field within his field of view when at his station but may have other activities to attend to, i.e. the operator does not constantly check the belts. The alarms from the belt area are not addressed to the operator but to maintenance with the exception of a significant (critical) threshold violation. In every case the operator is advised by the AI and not obliged to follow its suggestions and retains primary responsibility for periodically (sample based) checking of the machine condition and overall packing quality. He will be assisted in this by tread data on the alignment measurements.

2) *Recommendation to clarify scope of human-in-command role (including who has this role) and establish error protocol remains unaddressed at level of Task 1.3.*

The operator remains in command for handling immediate alarms, and the maintenance personnel for handling drift type alarms. The machine is an information source at the pre-AI level and an advisor at the AI level. All alarms are advisory alarms (warnings, informative) and not production stop alarms.

3) *Regarding choice of approaches: AI based approach for generating maintenance suggestions will be used instead of statistical process control.*

Statistical process control will be the baseline against the performance of which the AI approach will be evaluated. Depending on the outcome a hybrid approach could be implemented to give the maintenance personnel and operator more information to make decisions as the system is designed as human in command.

Technologies and links to WP

WP2 - Work package 2 deals with the edge system. This UC attempts to provide services at the edge in relation to components.

- T2.1 – IIoT environment deployment and set-up: The machine vision software is being extended to support MQTT 5.0. It will be possible to post the measurements encoded as JSON messages to an MQTT broker. The measurements results will also be locally stored in a relational database and the images will be locally stored as files.
  Work on defining mechanisms for collecting the data from the MQTT boker and transferring the images from the edge to the cloud is ongoing.

- T2.2 – Component level data acquisition and pre-processing: A hardware and software system is being designed to address the measurement requirements of the use case. Additional facilities are being implemented to support blackboards over a Web interface that include system alarms.

- T2.3 – Self-diagnostics and production process anomaly detection & T2.4 – Self- prognostics and component operating condition estimation: The system will require implementation of related functionality for measurement and detection of anomalies, including a baseline statistical process control implementation for comparison (T2.3) and a more advanced AI approach for increased performance and benefit. Supporting the maintenance function entails using the measurements over time as input to a prognostics module (implemented as part of T2.4).

WP3 - As the use case is in-between component and system level, it will required also tasks from WP3..

- T3.3 – Proactive maintenance strategies at system/line level: The system interacts with the follow on TBM stations (eight in number). It will make available status information (good/not good) and per tray measurement information which can be subscribed to by the follow on TBM stations. The process improvement and error reduction strategy for the system implemented in the use case, requires feedback from the TBM stations, i.e. information about which trays were actually wrongly packed (and on which tray). This will enable improvement of the deviation detection system itself and allow adaptation to long term changes in the line behaviour. At the system level, the intent is to provide specific information of where to look for problems and suggestions for proactive component replacement (belts of cross feeder) due to presumed wear.

WP4 - deals with the analysis the identification of effective means for human-machine interaction. For this UC in particular, the following tasks might be of relevance in the development the final solution.

- T4.1 – Human feedback mechanisms for AI reinforcement learning: It is not initially expected to use Ai reinforcement learning in this UC. We plan to track the developments in T4.1 and if we find an opportunity to apply the results of the task we will consider it in the later stages of the project.

- T4.2 – Role-specific human-machine interfaces and data visualization & T4.3 – Extended reality and conversational interfaces for shop floor assistance: The UC has operator specific interfaces to address immediate alarm issues and maintenance specific interfaces to address deviation detection issues. The alarm issues will be mostly handled as part of WP2. The longer timescale analysis features addressing maintenance should be partly handled as part of T4.2 We do not currently plan for a conversational or ER interface as part of T4.3.

Detail flowchart & partner/task involvement

Additional to the current flowchart, UL will participate in this use case as part of T2.3, T2.4, T3.2 and T3.3 once data is available for establishing the models of anomaly detection, prognostics and maintenance decision making.

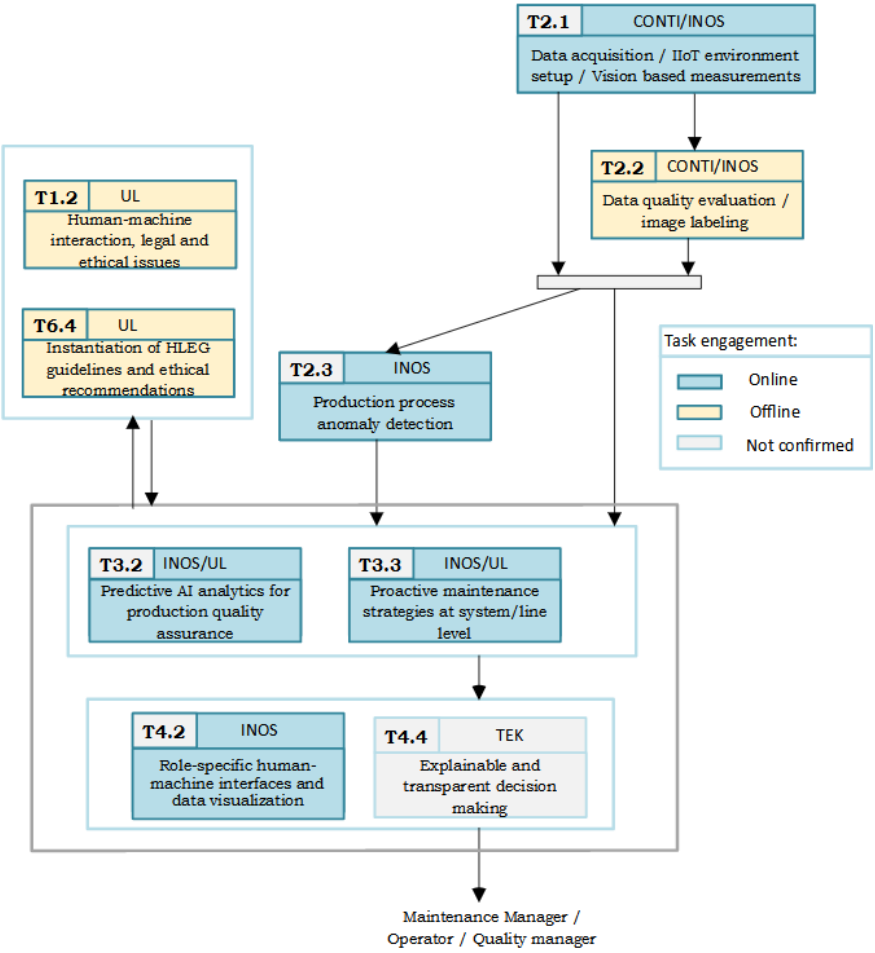


Figure 23 - High-level chart of the engaged tasks at CONTI-7

CONTI-10 UC Specification: Quality analysis tool

UC description

During production, occasional product deviations out of the desired scope are inevitable. When it happens, a quality team is obliged to manually compare all the parameters along the whole process line (Figure 25) influencing factors in general, in order to identify what caused the issue. As the forms of deviations that occur are numerous, and the influencing factors, even more numerous, it is clear how time-consuming this task could be. Therefore, the main aim of use case 10 is to automate this process of investigating the causes of quality deviations. In that way, support to the quality manager will be provided, in form of a quality analysis tool, and, consequently, the process of solving the issue will be accelerated. The plan is to go a step further and bring an assurance aspect in the tool (to be "Quality analysis and assurance tool"), including the decision support features in the system, about which more detail in following.

Problem statement

Briefly, different quality indicators (length, weight, profile thickness, wings deformation level, etc.) are affected by different process variables, machine settings, breakdowns, and certain operators' decisions. Some of those parameters are stochastic causes and, such that, not possible to be recorded, or, they could be just correlated with the deviation happening, but not directly causing the issue. The depicted table below, Figure 24, illustrates those relations derived from pilot site team experience and will be a great initial point to take up the UC activities.

Product characteristic	Influent factor 1	Influent factor 2	Influent factor 3	Influent factor 4	Influent factor 5	Influent factor 6	Influent factor 7	In
Weight	Machine speed	Screw speed	Base mix storage time	Final Mix storage time	% of remill in mix	Mix viscosity	Screw pressure	T
Detection Zone	Supervision pilot	Supervision pilot	Mixing room	Mixing room	EWM	QDV	Supervision pilot	C
Cold width	Conveyor speed	Screw speed	Mix viscosity	Tool wear	Tool conformity	Mix temperature	Tool position	%
Detection Zone	Supervision pilot	Supervision pilot	QDV	Visuel opérateur	Check info CGRS	Supervision pilot	Operator visual check	
Profile thikness	Machine speed	Screw speed	Conveyor speed	Base mix storage time	Final Mix storage time	% of remill in mix	Mix viscosity	S
Detection Zone	Supervision pilot	Supervision pilot	Supervision pilot	Mixing room	Mixing room	EWM	QDV	Su
deformation of wings	Screw speed	Mix viscosity	Base mix storage time	Final Mix storage time	Raw material dealer	Mix temperature	Tool position	%
Detection Zone	Supervision pilot	QDV	Mixing room	Mixing room	Mixing room	Supervision pilot	Visuel opérateur	
Length	Conveyor speed	Cut length	Machine speed	% of remill in mix	Mix viscosity	Cooling unit temperature		
Detection Zone	Supervision pilot	Operator visual check	Supervision pilot	EWM	QDV	Supervision pilot		
Base thickness	Pression mélange	Base screw speed	Base mix storage time	Final Mix storage time	% of remill in mix	Mix viscosity	Tool wear	M
Detection Zone	Supervision pilot	Supervision pilot	Mixing room	Mixing room	EWM	QDV	Check info CGRS	Su
blocked CCB	Screw pressure	Tool cleaning	Tool conformity	Mix temperature				

Figure 24 – Product characteristics reflecting quality and their influential factors

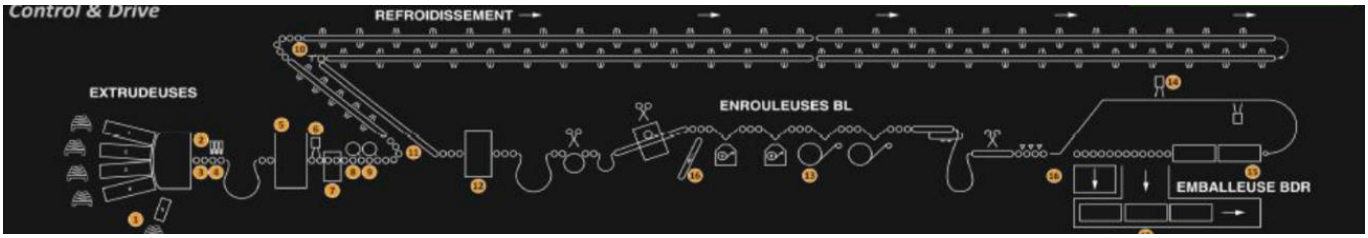


Figure 25 –Combiline – the tread production process (UC10 as the system-level use case)

Proposed solution

As it was previously stated, among numerous control parameters, generally influencing factors, some subset of them mainly affects the quality of the final product (precisely, tread quality). Initial work on the UC10 assumes:

- *Performing experiments and analysing in that way obtained data set*
  Clearly, not all the patterns will be visible from the historical data. Therefore, performing specially designed experiments will be needed. Basically, different combinations of measurable control parameters have to be applied in a well-designed time sequence, and information about caused product characteristics stored.

- *Data quality evaluation and pre-processing*
  Early phases of the use case-related work will imply applying different analytical components, used for evaluation, improvement, and exploration of collected data.
  Historical data pre-processing and testing sensitivity of signals in low quality, those associated with product characteristics out of desired range, will be the very first step.

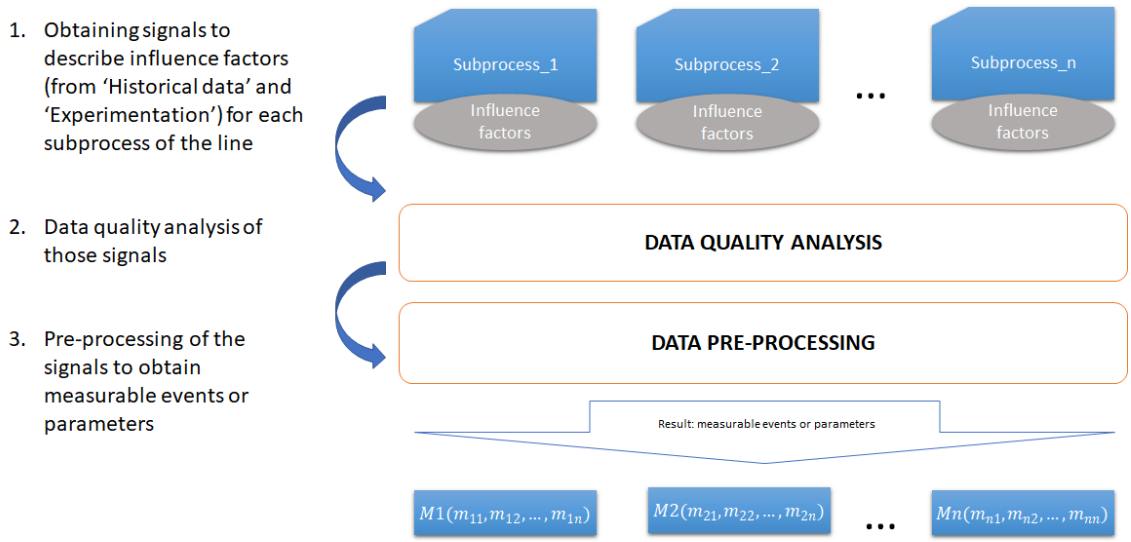


Figure 26 - Diagram of the Information flow to obtain the final dataset to be analysed (1)

The results obtained after the pre-processing will be saved in a final dataset (database) for future exploitation to perform the root cause analysis.

The main objective of data pre-processing, both historical and experimental, is to study the correlations and cause-effect relationships among parameters and quality characteristics.

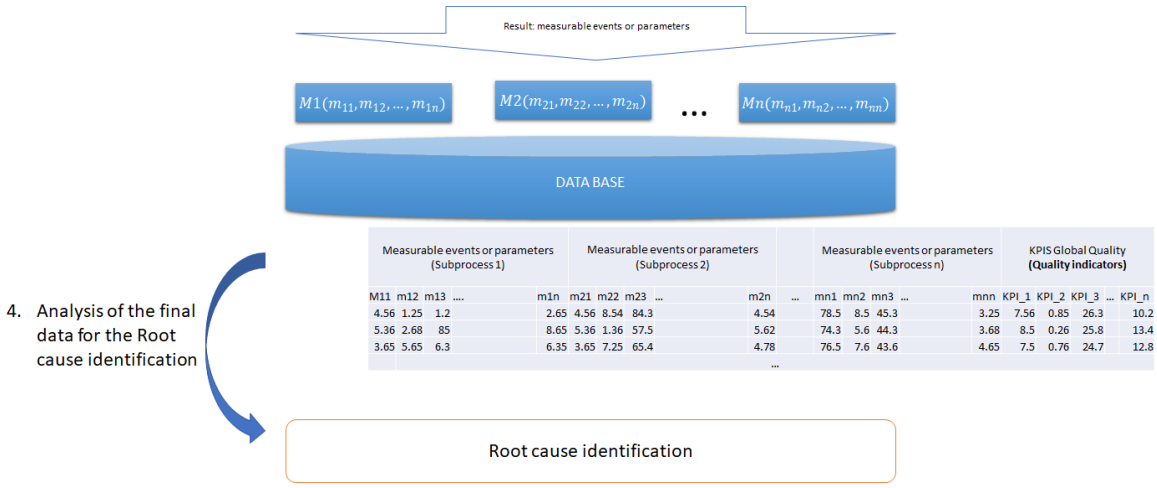


Figure 27 - Diagram of the Information flow to obtain the final dataset to be analysed (2)

- *Correlation analysis and features extraction*
  Approaches are numerous and within the UC, several techniques will be examined in order to extract the most influential parameters, factors in general, affecting each product characteristic (which defines its quality), from those simple, interpretable models and easily transferable to rules, to the Causality Hypothesis Generation via Neural Network Rate Convergence comparison, Figure 28.

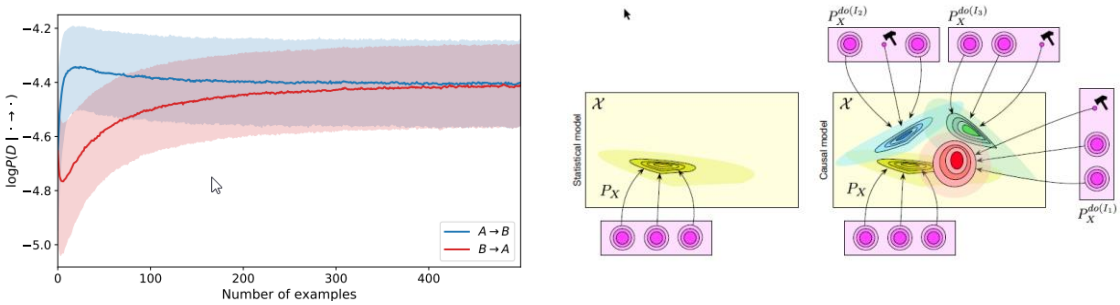


Figure 28 – Causality Hypothesis Generation via Neural Network Rate Convergence Comparison

The result of such a pre-processing unit could be integrated into the Root Cause Identification module explicitly and/or used to generate Data-Driven surrogate models, which approximate the functional dependencies of product characteristics, affecting parameters and time. Those models are especially interested for superior optimization, where it is of utmost importance to reduce the dimensionality of search space.
Additionally, different techniques of data visual display will be considered, which will be challenging due to the multivariable nature of the problem to be solved.

- *Early anomaly detection module*
  The use case will gladly consider outcomes of edge services, especially those focused on early anomaly detection.

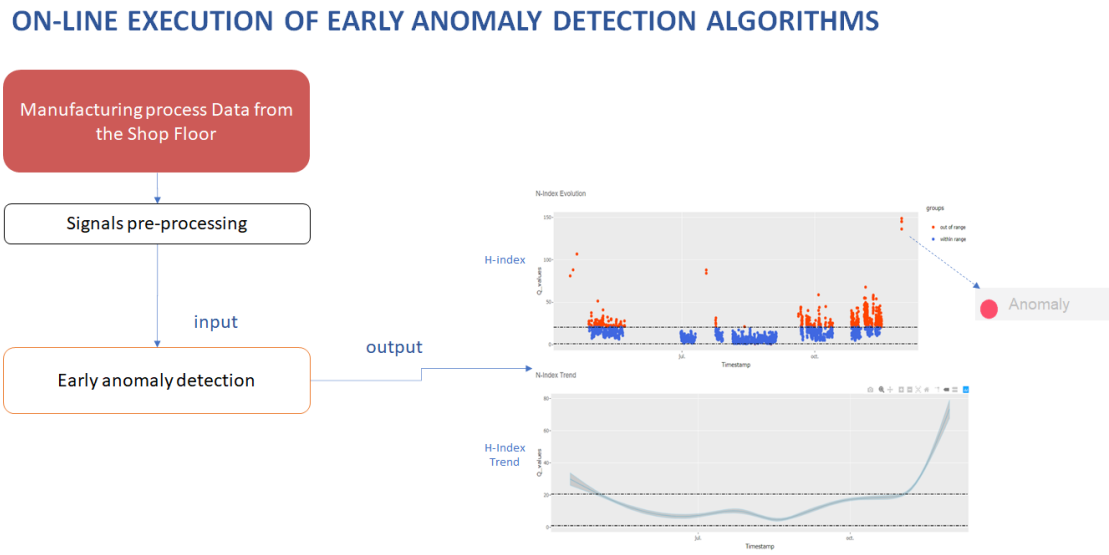


Figure 29 – Deployment of early anomaly detection

The tool will comprise not only the root cause identification, but it will go beyond the scope, providing the operator with suggestions regarding the optimal settings of parameters (at least crucial, detected ones) by means of multiple-alternative recommender, so that production of tread out of the desired specifications, is maximally reduced, Figure 30. For those purposes, several alternatives will be offered for selection, as sub-optimal solutions. The optimal number of alternatives will be defined during the development phase, and the decision on that will be made according to the objective of the minimization of the operator's cognitive load and time needed for the review of those recommendations.

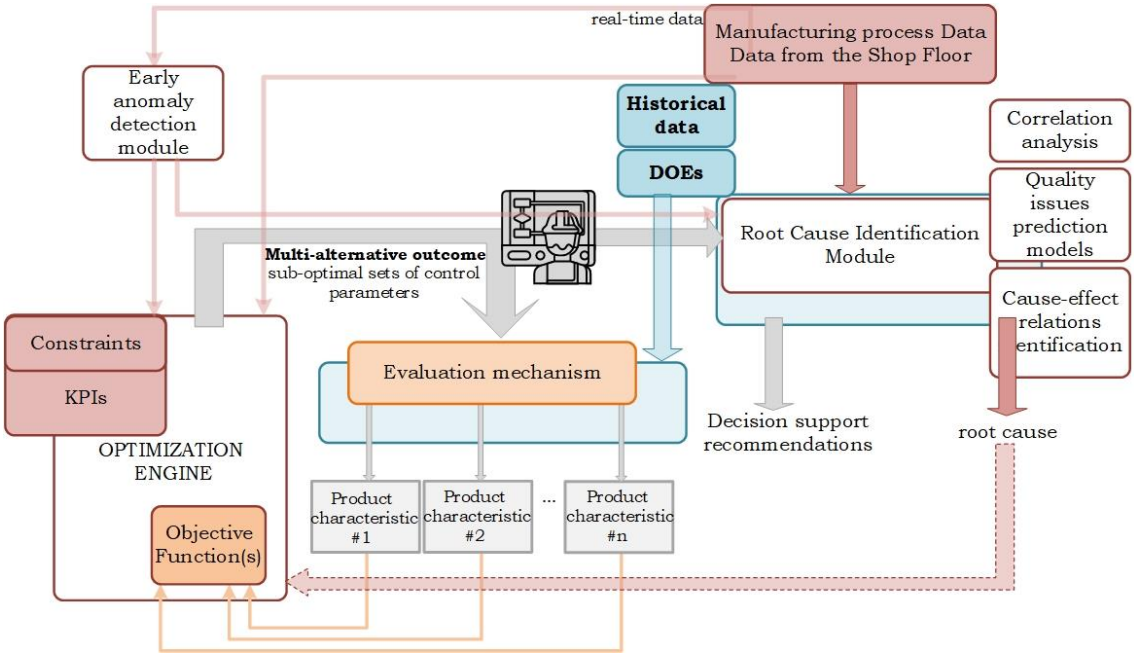


Figure 30 – The analytical techniques foreseen within the proposed solution

- *Optimization engine*
  Namely, the idea is to bring holistic generative approach for improved production, Figure 31.
  It will combine different AI techniques and multi-objective or single-objective optimization methods based on evolutionary algorithms. The approach will differ depending on the availability of the process model or digital twin.
  The process modelling task is naturally connected with any kind of optimization platform taking into account the benefits of the optimizer which is carried out upon predictive models. However, the chances are that something like that won't be conducted within this UC. In absence of it, surrogate modelling will be applied, resulting in surrogate-assisted optimization. Namely, each product characteristic will be approximated as a function of a certain number of the most influential factors, using historical and/or experimental data, and it will represent system response to be optimized properly setting the influential factors.

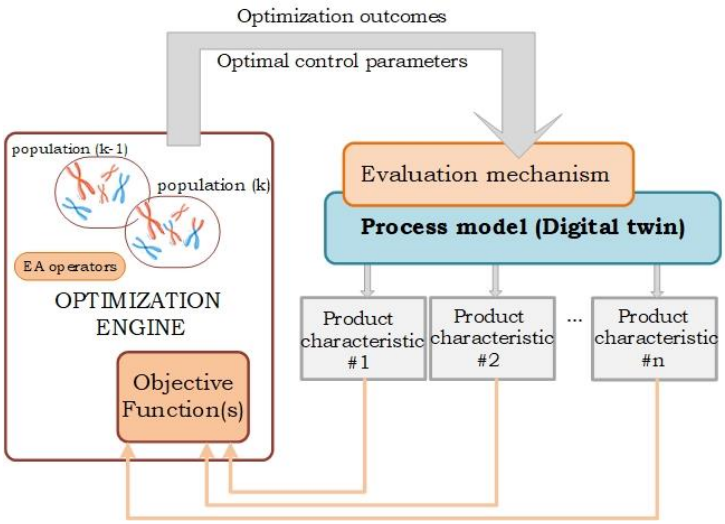


Figure 31 – Optimization based on process model (initial framework)

Remark A: As it is known that within UC2, optimization will be deployed as well, and considering that a significant number of issues could be inherited from the improper setting of that part of the system line – extrusion subsystem, the question of those activities possible overlapping should be thoroughly considered. Currently, it seems that those problems are decoupled in time, where UC2 dedicated optimization is primarily focused on the transient regime, while UC10 optimization aims to improve quality in regular operating (steady-state regime), similar e.g. to UC3. Additionally, optimization criteria are different. Still, this issue has to be thoroughly considered regarding their integration in a unique recommendation system, for the sake of consistency.
Remark B: Many-objective manufacturing problems such as this are challenging, by default. An alternative solution is to parse the product characteristics into few meaningful units and perform analysis separately, dividing the problem into few multi-objective subproblems.

- *Feedback system (Reinforcement learning concept)*
  Human feedback mechanisms consideration is crucial for bringing human-in-the-loop and human-in-command concepts to life. Expert human knowledge could make the system robust and improve its performances in the long run. In the concrete case of Quality analysis tool, AI models will be developed as an integral part of Root Cause Identification module and/or of Optimization module that could be refined thanks to the feedback branch, Figure 32. On the other side, the operator/ the quality team could benefit from a well-trained analysis-assurance system such as this. Namely, such

a system will provide the user with decision support and the results of the algorithm will be afforded in an interpretable manner.
Still, in absence of the feedback, precisely the operator's interaction with the system, the solution could be realized as an autonomous tool, with the operator out of the structure, obtaining a human-on-the-loop concept, which is a feasible solution, but quite deprived of the highest performances at the pure beginning.

- *Explainable and transparent AI models*
  Mentioned explainability and interpretability of the results provided by the AI is truly important for the operator to achieve trust in the AI-based system. Namely, explainable AI enables the creation of standalone solutions or it could interpret outputs of the independently developed models. The current point of view includes explainable AI approach within the surrogate data-driven models of the product characteristics and within the Root Cause Identification module while giving the estimation of the root cause of quality deviation to the user, Figure 32.

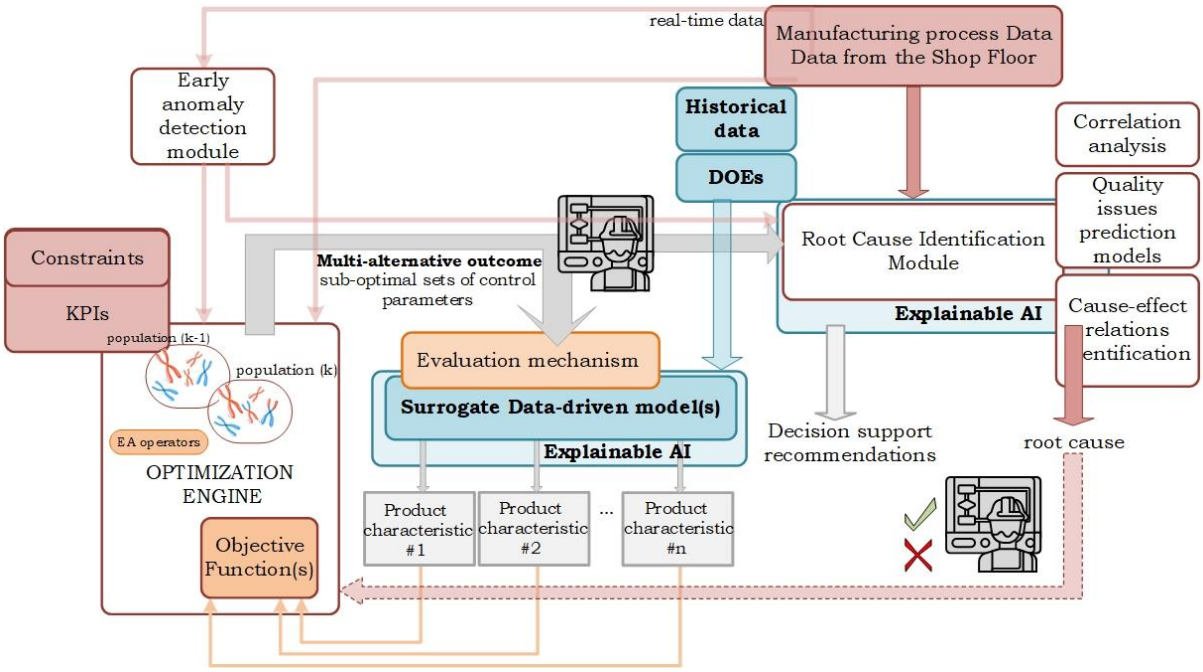


Figure 32 – Detailed overview of the proposed solution

Main Specifications and high level design

Required datasets for solution development ***What data is needed for the approaches chosen, how does it look like?***

Considering the compulsory information, for solution development are required:

1) *historical data with labelled those snapshots associated with characteristics out of range (and data points mapping on the process diagram would be desirable)*
2) *more details regarding the process itself*
   Questions of this type (additional clarifications) will arise on the fly, and occasional consultation with the pilot would be important and beneficial for development activities.
3) *specification of ranges of tolerance assigned to each product characteristic*

If those characteristics differ product-to-product (actually, a specific type of product/ recipe), more detailed data considering different types of products, needed as well. Alternatively, those ranges could be approximated using the historical training data.

4) *Data generated in experiments (experimental set), planned for design and execution*
   Not all the control parameters will be varied, but just those stated as the preliminary most influential, after pre-analysis based on historical data is completed. Proper design of experiment will ensure a limited number of trials with maximized obtained information.
5) *Quality of service - feedback system*
   To be able to test human in command concept, AI models will require, at least, operators' and/or quality managers' tentative feedback, in the training phase. By user's interaction with the tool, through a certain mechanism, improper tool recommendations/suggestions could be reported, and, finally, those models retrained (fine-tuned in the final scenario).

Required input and output parameters for demonstrator execution ***What does our solution/model need for its correct operation?***

Proper operation of real-time optimization-based tool implies the requirement of being almost constantly fed by data from the shop floor. Under "shop floor data", it is assumed necessary and sufficient subset of machine settings and readings from certain sensors. Still, it is too early to give a concrete specification of the parameters needed for the tool operating.

Optional but beneficial would be to have real-time logs of product quality estimation, having in mind those out of range. Precisely, logs of treads produced out of specification would contribute to fine-tuning of the AI models engaged in tool structure (reinforcement learning concept, self-learning models).

Finally, the outcome of the feedback system is optional, as well. By that is meant to have the operator's evaluation of provided decision support - recommendations, which are generated as the result of optimization.

Required interaction with the operator: ***What advantage do we provide to the final user?***

The final advantage is obvious - the Quality analysis tool will facilitate operator's and quality manager's work and reduce scrap rate, in the long run. Going beyond the scope of the pure Cause analysis tool, making it intelligent in the way to be capable of suggesting future actions in order to avoid undesired operating conditions, the final objective of reduced scrap rate will be achieved. Generated suggestions could reduce the set of possible actions the operator would usually consider and thus save his/her time.

What do we expect from the operator?

The mentioned mechanism for providing support to user's interaction with the tool can be achieved, by means of an HMI, for instance. This interaction is bidirectional, implying:

- decision support to the operator enriched by explainability, and
- mechanisms for feedback obtaining.

Precisely, decision support is meant to be provided in form of multiple suggestions regarding machine settings, a critical segment of the process to be specially monitored, etc., while feedback regarding recommendations to the operator, could be estimated in two compliant ways:

- user's selecting of one of the suboptimal set of parameters as an indicator of his/her agreement

- user's selecting of “not accepted” option, as the indicator of opposite opinion that there is no appropriate suggestion, derived from expert knowledge,
- it is allowable not to provide a reaction, as well, it just won’t bring improvement in models' performances.

Probably more suitable approach is to include natural interaction mechanisms such as dialogue-based voice interaction, but it is still under consideration.

When it comes to the primal purpose of the tool – root cause identification, feedback could be collected through the quality manager's selection of the following scenarios:

- “Recommendation not correct; the cause is improper setting of _____”
- “Recommendation not correct; but the cause still unknown to the operator and/or to the quality manager”
- “Recommendation correct”

In order to reduce working overload, the selection feature, probably will be reduced to not include any typing, just to require a choice of predefined options, including the “none of the above” choice. It is worth stressing out that this interaction is desirable, but not completely compulsory after the AI models training phase is completed.

Addressing ethical considerations: ***Answer the issues and suggestions made by the ethics team. How does the chosen approach answer/consider them?***

While exposing the solution and mechanisms for human interaction with the AI system, general ethical recommendations have been taken into account. By that, the following aspects are meant:

1) *Possibility of solution implementation in staged manner*
   The approach of finding a solution will be gradually made complex and more comprehensive. Results of collected data pre-processing will give a sense of how to tackle the problem, primarily considering the apparently influential control settings, and expanding the set of influential factors to be tested. There is, as well, a possibility to separate the set of factors into several categories and to solve the problem as the compilation of several sub-problems, with the final aim of their summarizing. Finally, identified time scales of different parts of the process will give a clearer insight into the staged implementation.
   The operator will be gradually involved, with high respect to his/her understanding of the performed experiments needed for thorough cause-effect relations analysis.

2) *Consideration of operator’s workload caused by AI system integration in the overall manufacturing process*

3) *The ease of the operator interaction with proposed AI interfaces*
   When it comes to these two tasks, the interfaces dedicated to the operator's monitoring and control capabilities over the AI operating will be made in accordance with already existing features of primal automation units (i.e. HMI stations). Precisely, they will be made not to be redundant, but to provide the operator with necessary information regarding the results of the AI services, understandable and transparent, giving the sense to the operator where such a solution comes from.
   There is a potential of including the natural interaction mechanism such as dialogue-based voice interaction, which is surely facilitating condition for the workers.
   Throughout this design process, the pilot and the ethics team will be involved in order to meet the requirements arising from different aspects of AI integration into a production process like this.

4) *The scenario development considering the human side of the process*
The considered use case as the final aim has the product quality improvement and operator's and quality manager's higher understanding of the root causes of quality deviations. It is meant to be a decision support system and takes the operator as a significant link in an overall chain. At the same time, it will leave an option to the operator to stay restrained, if he/she is not able to interact with (provide feedback to) the AI tool.

Technologies and links to WP ***Which technologies will be adopted in this UC, which WP/tasks are involved in the development of those technologies?***

This use case belongs to the class of covering use cases, given that it tends to look at the whole process line and such that, aims to maximize the impact of the solution through the collaboration of different services, intended to be developed, under the pilot site. Therefore, the solution workflow depends on the availability of remaining services, developed within the whole pilot site. Namely, the considered use case probably would benefit from the outcomes of services developed within the subordinate use cases. Precisely, UC10 could be concatenated on UC2, UC3, UC5 both edge- and system-level platforms, and re-use the information generated in that way to boost tool performances. By giving an example at the task level, the optimization task can profit from the results of edge services, introducing that information and re-directing the search of the multidimensional space toward more beneficial combinations of control parameters. For instance, if it is concluded that the blade is worn, probably tread cut goodness will be affected and, consequently, product disposal in scrap material caused by this issue. This edge service could bring the capability of predicting a degradation caused in this way in real-time. So, it is not needed to run the optimization to search the whole space, when the cause is almost obvious, by which more efficient work guaranteed. Therefore, all the tasks included in the listed use cases could be indirectly subsumed under this use case. For those purposes, we are bearing in mind WP2 tasks or, in other words, edge services (concretely, **T2.3 – Self-diagnostics and production process anomaly detection**).

When it comes do those tasks directly involved, Figure 33, they are at a high level:

- **T1.2 – Human-machine interaction, legal and ethical issues**
- **T2.3 – Self-diagnostics and production process anomaly detection**
  This task is related to the development of algorithms and models that allow the early detection of anomalies. The proposed approach is based on the modelling of the nominal behavior of those measurable events or parameters (calculated during Task 2.2. from the influence factors identified in Figure 26) that affect quality indicators. Statistical techniques and computational algorithms will be used. The algorithms will generate the normality index for measurable parameters that influences the quality of the product, upper and lower limits.
- **T3.2 – Predictive AI analytics for production quality assurance**
  This task involves the use of data-driven methods to predict the quality of the process. To this end, some statistical techniques and machine learning algorithms will be used for correlation analysis and cause-effects identification between quality indicators and the measurable events or parameters, extracted from the pre-processing (Task 2.2) of the most influencing factors (described in Figure 26). Once the most influential parameters and their relationship with the quality indicators of the final product have been identified and quantified, the models for early detection of anomalies (obtained from Task 2.3) will be used to predict the final quality of the product.
- **T3.3 – Proactive maintenance strategies at system/line level**
  As the Task 3.2, this task is closely related to the analysis-nature of the tool, to be developed. Namely, different AI models will be examined in order to check existing correlations and cause-effect relations

among variables, where each product quality indicator (characteristic) will be associated with the subset of most influencing features/parameters/factors.

- **T3.4 – Generative optimization for improved production execution and scheduling**
  The proposed solution relies on the optimization engine, which delivers an approach comprised of the conceptual idea of this task. This task brings a step forward to the primal aim of the use case, which is the identification of the cause of quality degradation. Its engagement tends to bring decision support to the operator, in form of a multi-alternative recommender.
- **T4.1 – Human feedback mechanisms for AI reinforcement learning**
  The AI can be improved by human engagement in the evaluation of tool outcomes - by being fed with expert knowledge. For the complete application of the reinforcement learning concept and the creation of self-adaptable models, it is necessary to consider those mechanisms.
- **T4.2 – Role-specific human-machine interfaces and data visualization**
- **T4.3 – Extended reality and conversational interfaces for shop floor assistance**
  The above two tasks' involvement in the UC10 has not been specified yet, but the need for its taking part is obvious as the way of interfacing human and decision system.
  T4.4 – Explainable and transparent AI decision making
  The proposed solution emphasizes the role of explainable AI models, as they have to achieve transparency and interpretability of AI outputs, make the decision support more understandable for the user and finally, increase their usability in the eyes of the operator.
- **T6.4 – Instantiation of HLEG guidelines and ethical recommendations**

1. **Detail flowchart & partner/task involvement**

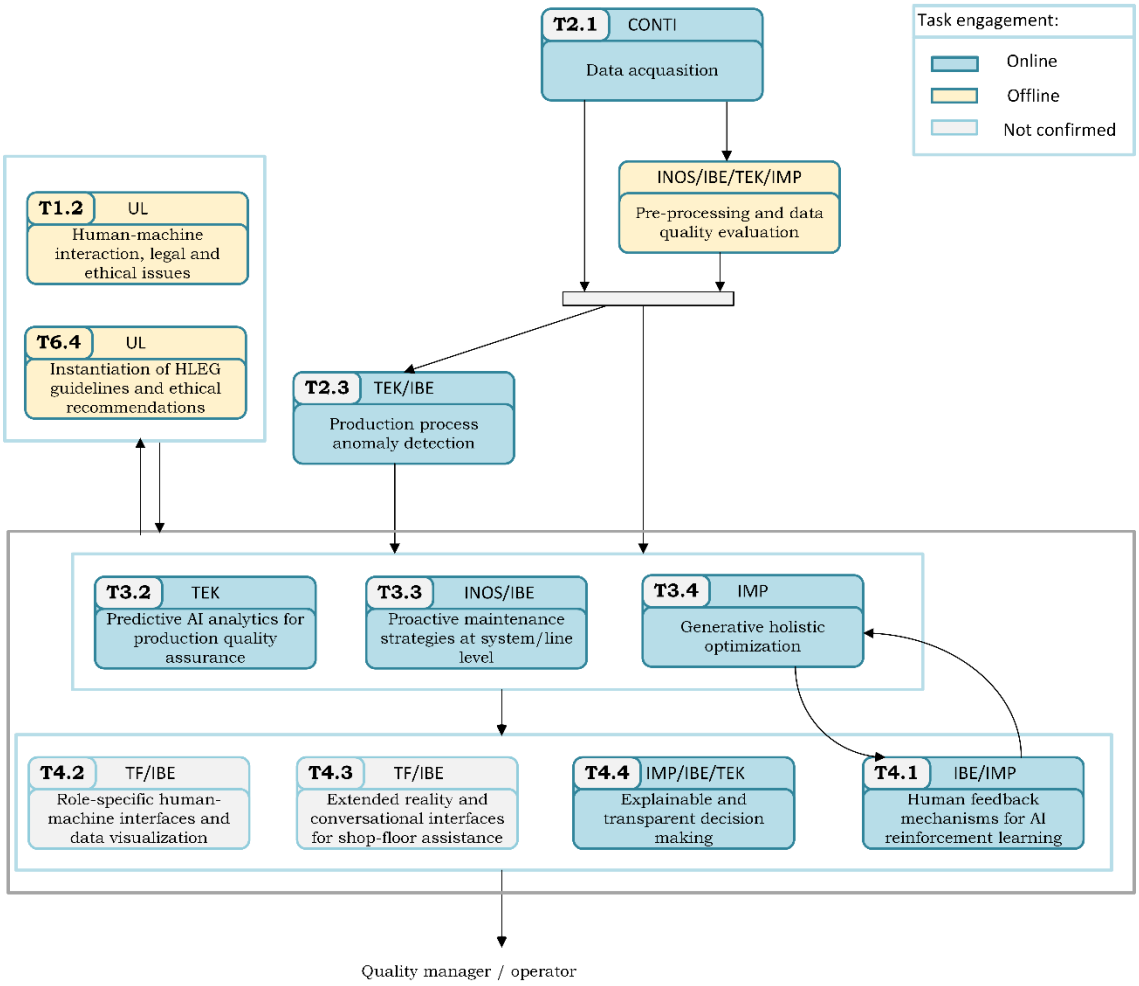


Figure 33 - High-level chart of the engaged tasks

INEOS-1 UC Specification: Reactor stability

UC description

The target process in INEOS UC1 is the first of the two continuous-flow stirred-bed reactors in the gas-phase propypropylene polymerization unit in Geel. A Ziegler-Natta catalyst, co-catalyst and modifier are fed from one end of the continuous-flow reactor. Production rate is controlled by the catalyst feed rate.

The polymerization reaction taking place in the reactor is exothermic and for that reason cooling is provided by feeding most of the propylene monomers in liquid form through nozzles in the upper part of the reactor. Cooling takes place as the liquid vaporizes. Hydrogen is added to the reactor to maintain a specific hydrogen-to-propylene ratio. The average polymer molecular weight is controlled by hydrogen feed rate. Produced solid polypropylene particles are taken out from the end of the reactor. These solids in the reactor are mechanically mixed. The amount of solids in the reactor is controlled by measuring bed surface height and tapping polymers out of the reactor when necessary.

The reactor is divided in four zones for monitoring and control purposes. Temperature measurements are obtained from–multiple measurement points. Temperature in each zone can be controlled separately by adjusting the amount of liquid fed to the different zones.

Problem statement

The temperature control loop of the polymerization reactor is key to allow normal run rates (production capacity). In addition, sometimes also lumps of polymers are produced indicating that somewhere in the reactor, the local temperature has exceeded the melting temperature of the polymer.

To bring the temperatures back to stable conditions the operator needs to reduce the production rate and hence production capacity is lost. Thus the temperature profile stability has a direct influence on maximum production rate.

What is requested by the Geel production unit is to develop an improved understanding of what causes the oscillations and to develop an algorithm which can advise the console operator how to avoid oscillations (which process parameters to adjust). In addition, the goal is to optimize the current temperature control loop so that the DCS system automatically adjusts process parameters to avoid oscillations.

Proposed solution

it is not known, where the temperature oscillations are initiated. Fluctuation of the measured temperatures is recognized as a problem at maximum production rate but it is not known how large the fluctuations are inside the reactor and where the highest temperatures are located. The temperature distribution is affected by several controlled variables and thus it is even possible that operation data does not fully cover the whole range of possible operation options. Thus any analysis method based solely on analysis of process data will give only limited information. For that reason, the following complementary approaches that combine first principles modelling with data driven modelling as basis of the solution are proposed:

1) Collection of data and assessment of the quality of the data to determine the suitability of the different signals for data driven modelling. Pre-processing options will also be considered.

2) Data driven modelling. Multivariate regression analysis is carried out to evaluate correlations between measured reactor temperatures and process inputs. Main process inputs in this analysis are flow rates and properties of inflows to the reactor and conditions in adjacent process units that can influence the reactor. Data analysis will also include assessment of periodicity of measured fluctuations and the role of e.g. possible hysteresis (free play) in the valve actuators. Additionally, causality predictions based on DL network convergence rate are explored.

3) First principles modelling with CFD. Computational fluid dynamic (CFD) modelling of different sections of the reactor is carried out to analyse heat and mass transfer effects on the temperature distribution. The CFD model will describe transport of gas phase and its components, transport of solid particles, transport of the liquid in the spays, evaporation of the liquid, polymerization reactions, particle size distribution of the polymer particles, and energy transport phenomena. Fluid dynamic description is based on an Eulerian-Eulerian approach with the kinetic theory of granular flow and description of frictional forces. The general kinetic scheme for polymerization using a Ziegler–Natta catalyst comprises a series of elementary reactions including the following:
   a) activation of potential sites, the reaction through which a potential site is converted into a reactive vacant site.
   b) chain initiation, a new polymer chain is being built.
   c) chain propagation, the mechanism step in which the polymer chain grows.
   d) chain transfer, a type of reaction that terminates a ‘‘live’’ chain, producing ‘‘dead’’ polymer and a vacant site (hydrogen as transfer agent)
   e) site transformation, produces an empty ‘‘live’’ site (of a different type), unlike the previous chain-transfer reactions that produce an initiated site, and a ‘‘dead’’ polymer chain.
   f) site deactivation, the reaction step generally accepted as the explanation for the activity loss experienced during polymerization.
      - Both occupied and vacant sites are assumed to deactivate

   Even simplified reaction descriptions are considered.
   Results from analysis of the process data will be used to validate the CFD model. Adjustments to submodels may be also done based on comparison to measurements and on basis of observed correlations.

4) A simplified first principles dynamic model for the reactor is developed by describing the reactor as interconnected stirred tank reactors. The results from the CFD analysis will determine how the reactor will be split into separate numerical reactors and how mixing is described in these reactors. The goal is that this simplified dynamic model is fast enough to be run online so that it can serve as the basis for a digital twin.

5) CFD results and results from data analysis will be used to derive closures to improve the submodels of the simplified reactor model. Specifically, CFD results will be used to correlate temperatures at the walls with internal temperatures which should allow the model to predict temperature distribution inside the reactor in different process conditions. The hybrid model that combines correlations derived from 3D CFD modelling results and data analysis with the simplified reactor model constitutes the digital twin that will also include adaptive properties (mainly reaction parameters will be adjusted to fit the model prediction to measured data).

6) Based on the information that can be obtained by means of the digital twin, an advisory tool is developed to support operators to avoid oscillations.

7) A tool will be developed to optimize the current temperature control loop so that, if the tool is considered reliable, the DCS system automatically adjusts process parameters to avoid oscillations. The optimizer utilizes the digital twin to evaluate optimal solutions. Multi-objective or single-objective optimization methods based on evolutionary algorithms will be utilized.

8) Incorporating operators experience in the advisory and optimization tools will be an important means to guarantee that the tools don't recommend operation modes that are known to be risky or non-optimal. The tools should be first tested by the operators off-line with actual process data to collect their suggestions and comments on basis of which the tools are updated. The tools to be implemented on-line will also include human-in-the-loop or human-in-command concepts. The extent to which the developed tools are used without human intervention is decided based on the off-line testing and running the tools on-line first only as advisory tools in human-in-command mode.

9) The solutions will be installed on the common platform.

Main specifications & high level design

Required datasets for solution development

Different forms of information and data are required for solution development:

a) Drawings of the process internal geometry, including drawings of nozzles and locations of measurements. Photos to help to interpret the drawings and to fill any possible gaps in the information given in the drawings.
b) PI diagrams of the reactor and adjacent process units that feed materials to the reactor.
c) Operation data from long enough time during which no major changes have been made to the process. This data should include (but not be limited to) available measurements of the flows to and from the reactor and between auxiliary process steps, measured phase compositions, pressures, temperatures and bed height in the reactor. Data on process control and valve operation is also required. Any data that the operators and plant engineers consider potentially relevant should be included. One-minute process data from 2018-2021 is already available for the project.
d) Laboratory data on measurement of the properties of the polymer particles as they exit the reactor (bulk density, particle size distribution, other measured properties).
e) Data on the reaction mechanism and chemistry to the extent that is known to Ineos.
f) Operator experiences/conclusions.

Required input and output parameters for demonstrator execution

Process online data (similar to group c above) including but not limited to flow rates, compositions, temperatures, pressures, and bed height are required for demonstrator execution. Exact variables that are required will be determined during process modelling. In addition, laboratory data (similar to group d above) is required.

Required interaction with the operator:

Advisory tools based on the digital twin will help the operators to make decisions on the process control actions that the operators are doing manually. The optimization tool will tell what the recommended optimal actions would be to prevent temperature fluctuations. If the models prove reliable enough for automatic

control actions, decisions on part of the control actions can be made automatically thus reducing the operators work.

Operators should give feedback on the actions that the tools recommend. Operators should also feed information to the tools if some raw material change has taken place. For example, if the catalyst is changed, the model parameters need to be adjusted and for a period, it will be necessary to run the tools without utilizing their recommendations in process control to allow adjustment of model parameters to measured conditions.

Addressing ethical considerations:

Following the advice provided by the ethics team, the following aspects will be considered:

Recommendations (VTT Leading):

1) Recommendation to clarify chain of responsibility remains unaddressed at level of Task 1.3.

2) Recommendation to address secondary issues first remains unaddressed at level of Task 1.3.

3) Recommendation to address human limitations of operator in making adjustments remains unaddressed at level of Task 1.3.

4) Addressed preliminarily in proposal to have the operator test the advisory and optimization tools in offline mode as a first stage. (see further recommendation below) Recommend that this testing stage also include gradually adjusted limits beyond which the operator will disregard AI suggestions,

5) Exploratory approach will be followed in testing tools in offline stage.

6) Recommendation of training period partially addressed in incorporating offline testing stage.

Additional Recommendations, Task 1.3 Specific:

1) Recommend clarifying in a preliminary way with INEOS, some ranges, etc. within which AI adjustment suggestions will be considered reliable.

2) Recommend that you clarify who will decide when the tool is considered reliable, e.g. process engineers, operators, or both.

3) Recommend that you implement recommendation #4 of Ethical Recommendations Version 1.0 already in the off-line stage of testing, by specifying adjustment range limits for the operator, and conditions under which operator would override AI suggestions. I.e. expand the digital twin approach to include the human action with regard to a limited range of adjustments as part of integrating Human-in-Command approach through the whole process, from testing/training to real life trials. In other words, use the offline stage to train the operator in Human-in-Command approach.

4) Offline testing is a separate task from on-line use of the AI service. It adds extra work for the operators and plant engineers on top of their usual work. Recommend that you estimate how much extra time this will add to current operator and engineer tasks, (e.g. hours per day/per week?)

5) Recommend that you clarify how/in what format the operator experiences/conclusions will be gathered.

Technologies and links to WP

One of the core tasks in INEOS UC1 is T3.1 where a digital twin is developed for the process to analyse the reasons behind observed temperature fluctuations. The work in T3.1 can be linked to a large number of

tasks, listed below, that provide input to T3.1 or help to utilize the results of T3.1. Some of the listed tasks may have a minor role and even tasks that are not listed can contribute to the use case.

- **WP1: Pilot site characterization, requirements and system architecture** In WP1, the demonstration scenario and KPIs are identified which defines the basis for selection of the technologies
- **T2.2: Component level data acquisition and pre-processing** Collection of data for all process components and pre-processing the data such that it is usable for data analysis
- **T3.1: Hybrid models of production processes and digital twin** Both data-driven and first principles modelling techniques will be applied on different process scales and the results will be gathered in a hybrid model that, with added adaptive capabilities, will serve as the digital twin.
- **T3.2: Predictive AI analytics for production quality assurance** Predictive analytics utilizing process data and information from the digital twin may be considered to complement and utilize results of T3.1
- **T3.4: Generative optimization for improved production execution and scheduling** Process optimization utilizing results of T3.1 and T3.1
- **T3.5: Future scenario based decision-making and lifelong self-learning** Integration of results of WP3 in a decision-making support tool, with integration of human feedback
- **T4.1: Human feedback mechanisms for AI reinforcement learning** Integration of operator feedback to the AI solution
- **T4.2: Role-specific human-machine interfaces and data visualization** This may be included since data visualization might make it more attractive to end users
- **T5.1: Smart component integration and IIoT interoperability** Data management and communication
- **T5.2: Semantic knowledge graph for integrated digital twins** Data fusion and storage
- **T5.3: Data privacy, protection and security measures**
- **T5.5: AI-PROFICIENT platform deployment** Integration of the platform
- **T6.2: Use case validation analysis and reporting**
- **T6.3: Qualitative evaluation of user experience and feedback**
- **T6.5: Impact assessment and lessons learnt**

Detail flowchart & partner/task involvement

High level chart with a clear identification of the tasks and the partners that will be involved in their completion.

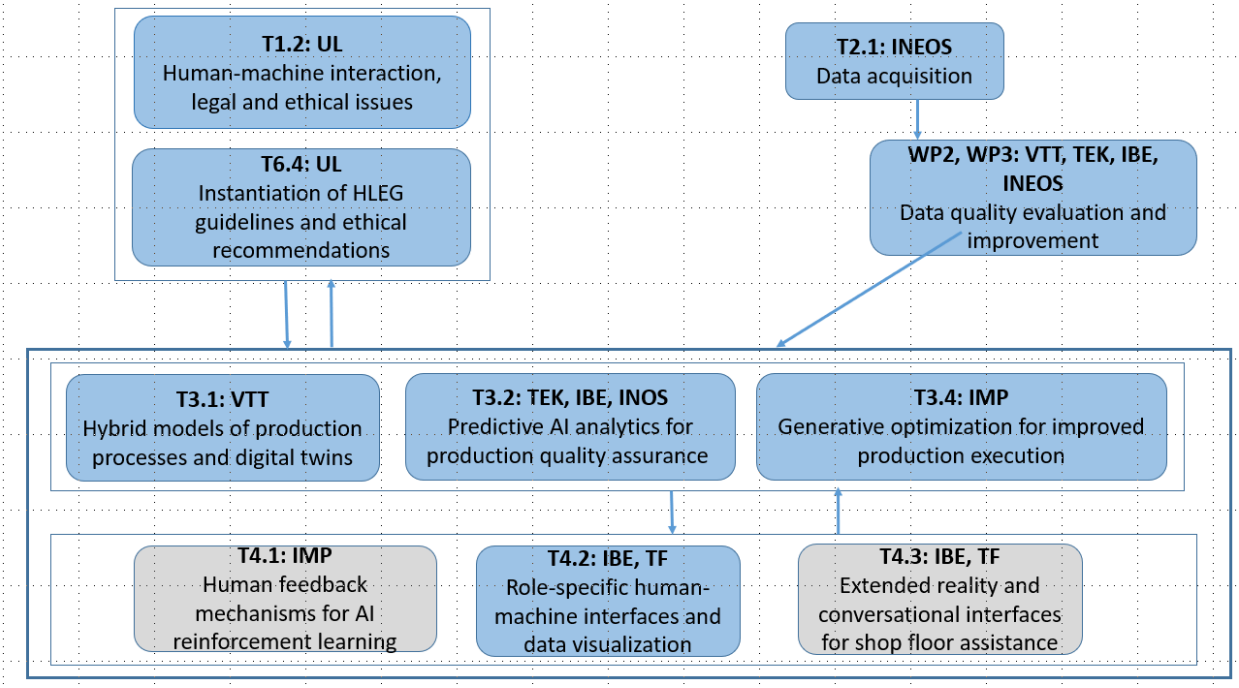


Figure 34 - High-level chart of tasks and activities regarding INEOS UC1

INEOS-2 UC Specification: Image recognition Geel plant

Problem statement

In process manufacturing, additives are required to ensure the base products are purified or enhanced for the market's requirements (food, pharma, textile, etc.) Since this is not a fully automated process yet, operators need to add big bags or other containers for additives to the feeders of the production line, which will take it when the previous batch is ending. As a result, the product grades or composition needs to change to the next batch. Human errors of operators putting the wrong additive on the feeder cannot be excluded.

With processing capacities of 50-tons per hour and no pro-active test at the start of the production line, a mistake can easily result in a production loss of 100 tons of prime product. For example, an operator needs to replace regularly a 500kg additive big bag in the extrusion section of the INEOS Geel plant. A human error of adding the wrong additive can occur due to a lack of uniformity on big bag labelling delivered from multiple suppliers. Therefore, this labelling diversity requires human intervention to decide on selecting the right additive big bag for the factory line process. Real-time quality control should support this human decision. Unfortunately, the back office quality control system currently relies solely on the operator manual inputs of the picked additive name into the terminal. Additionally, a mistake in the feeder number can also happen when the big bag is connected to the wrong one. Then, the additive name is cross-checked with the planned reactor process. The back office quality system notifies the operator whether the chosen additive is correct and connected to the correct feeder. A second feedback loop occurs when the Quality Assessment lab detects such an error that the product produced with the wrong additive is downgraded to a so-called "off-grade" (a low-value product).

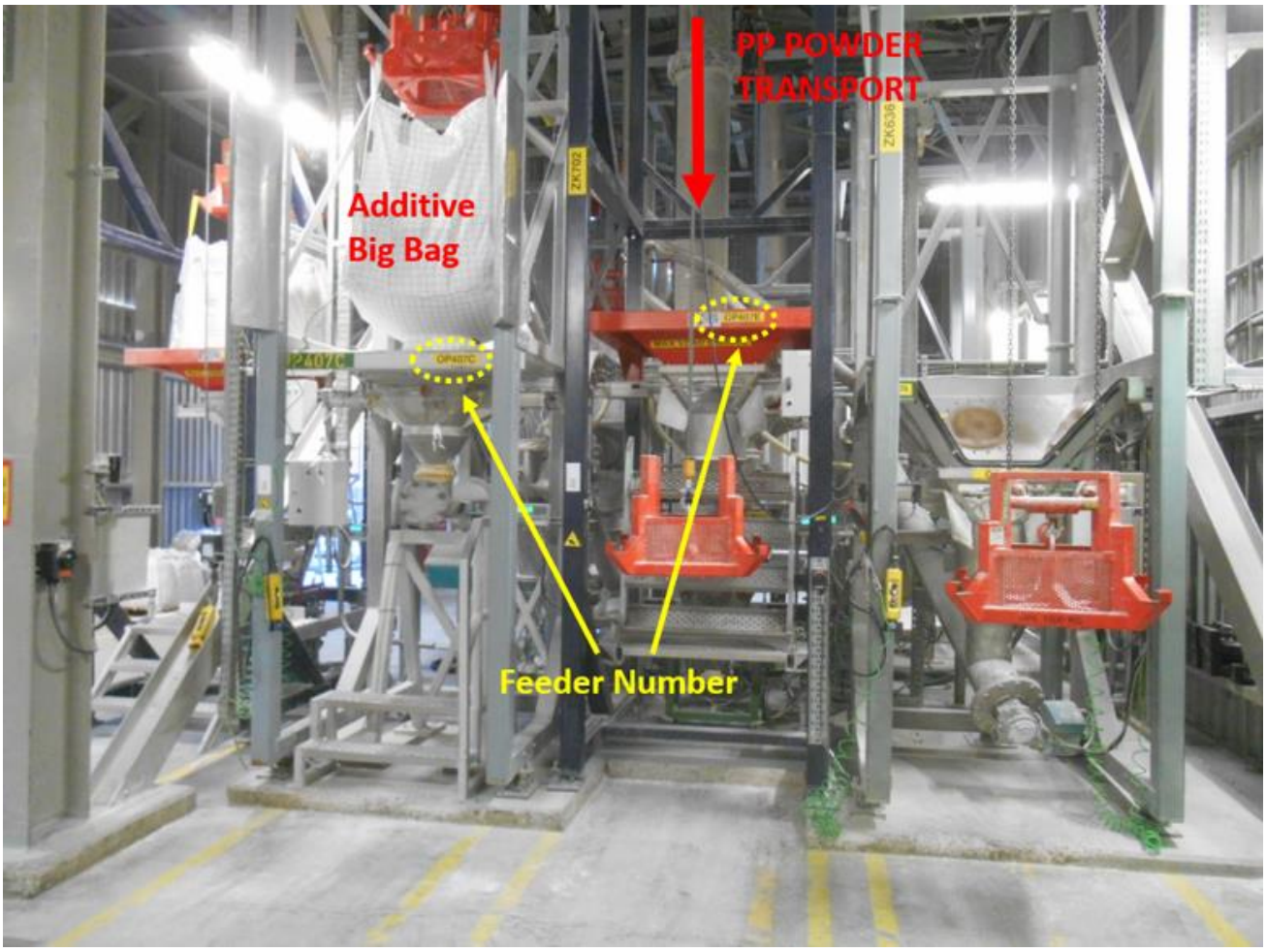


Figure 35 Feeder area

The need for the control of continuous monitoring and feedback of labels and feeders selection is apparent. Operators' errors related to a manual data input must be minimized and streamlined in a linear scenario. Figure 35 details the operational environment at the feeders, where the feeder numbers are highlighted. The complexity of choosing a correct label with the additive is multiplied by the fact that different additive suppliers have different additive name variants, which means the same additive. Some additives have one name adopted by all the suppliers, and some have up to eight different names that the suppliers print on their labels. Figure 36 demonstrated the diversity of label formats (the exact information is blurred for confidentiality reasons). The labels are often covered by a plastic foil which sometimes decreases the readability of the text. Using optical recognition support would aid the operator's job.

Initial solution request

The operator currently checks 'additive name' and 'lot number when he has returned to the control room. By then, the console operator might have put the additive already in use. INEOS would like a user-friendly and fully reliable tool to read the label on the additive's big bag and check immediately with the control system if the right additive is used. Challenging is the wide variety and poor quality of the data to be recognized.

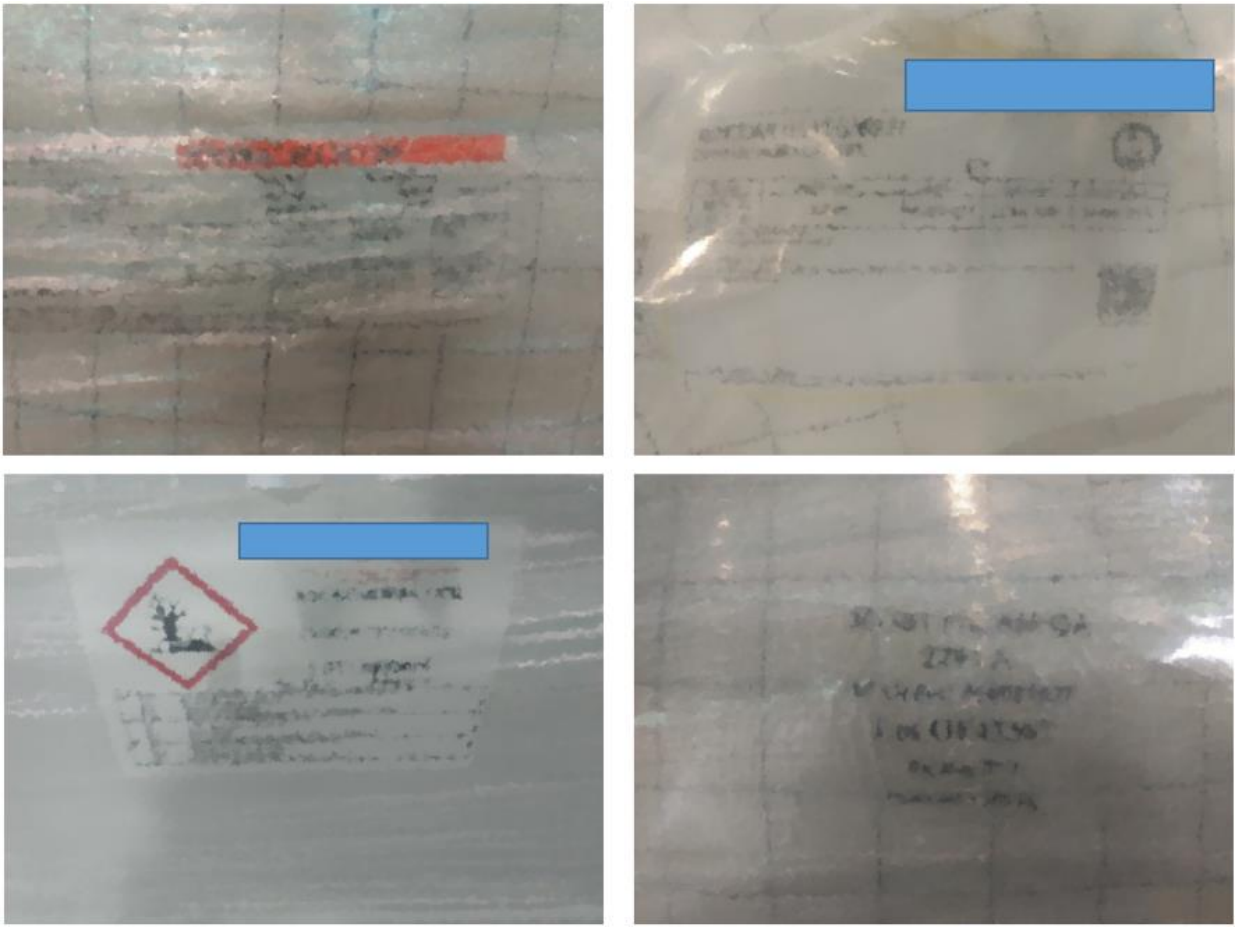


Figure 36 Examples of big bag labels

Proposed Solution

AI-PROFICIENT can develop a solution combining the capabilities of the operators' production-ready module augmented with the visual recognition and AI-enabled algorithm. Preferably it should be a mobile terminal such as a tablet or wearable device that can reliably read and analyze the label and verify if the combination lot number and additive name. The solution should apprehend the visual information within the context of the production process and give immediate feedback to the outside operator in case of the wrong additive.

The solution can be run on different systems. However, the initial focus will be on a mobile implementation and integration with TenForce. Equipped with the mobile terminal, the operator can scan QR/bar codes or directly text labels to identify the equipment or feeder. Additionally, the operator will take a picture of the big bag or container with the additive. The operator submits this form or inspection data to the system, the system will run an OCR-scan, and the AI/ML algorithm extracts the relevant data from the label. If needed, the scanned data can be further enhanced and then recorded in the database.

From the moment the data is in the system and the AI analysis has run, there are different options for closing the loop and processing the next steps.

The first choice or option is to integrate or not a validation step before further processing. Let's go through a detailed breakdown of those two options:

1) The system can present the processed information of the QR-code and the label photo to the operator for validation and only send the data to the next step in the processing after his/her approval:

Advantages	Disadvantages
• An extra visual and manual validation of the processed information • The approval is, in fact, a way to add quality and learning to the algorithm • With these steps, the accuracy of the processed data will increase over time.	• Requires extra work from the operator; • Reliance on human interpretation • In case the processing takes too long, this can lead to some extra frustration and less attention. • In case the data is always correct, it will be considered as an unnecessary step

2) We can skip the step above and immediately send the data further downstream.

Advantages	Disadvantages
• Allow avoiding additional human processing and handling	• We lose the opportunity to train the system with additional information

The step-by-step flow using a handheld terminal is proposed as follows

1. Setup the mobile terminal – operator initiates the tablet;
2. Registering the feeder by scanning the feeder's QR-code
3. Scanning big bag labels
4. OCR labels content
5. AI parses the text fields and recognizes the LotNr and AdditName information
6. The operator confirms "Send to DCS" (quality management system)
7. The INEOS DCS verifies the LotNr and AdditName
8. If the big bag data matches the requirements, the operator receives confirmation

The handheld iSafe tablet has been selected for field investigation and pilot testing. The selected IS930.1 tablet model is certified for industrial use compared to more widespread consumer home gadgets such as iPad, Samsung, etc. The iSafe IS930.1 tablet can be used in ATEX Zones 1/21 and 1/CI I Div1. It is an 8-inch tablet that is highly robust, equipped with a high-resolution camera, and has a long-lasting 8.400 mAh battery. In addition to the conventional WiFi, the tables it SIM card ready to support 3G data communication in low coverage areas. Figure 37 shows the selected device.

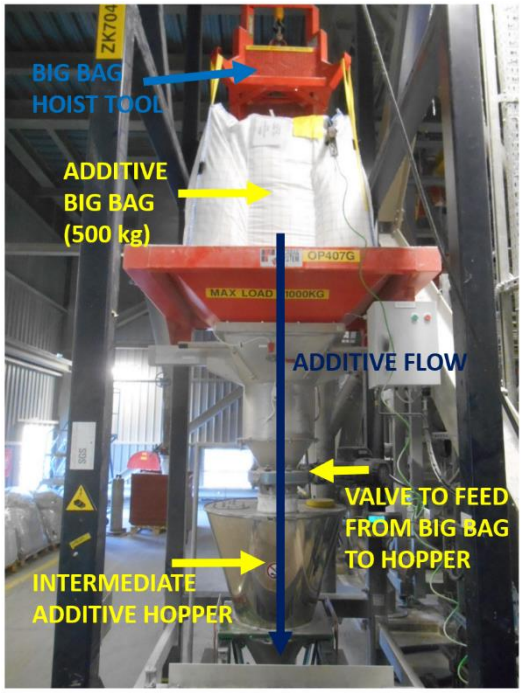
Figure 37 iSafe tablet selected for the Pilot implementation

Solution edge cases and optimization

Optical Character Recognition (OCR) is one of the earliest areas of artificial intelligence research. Today OCR is a relatively mature technology, and it is not even called AI any more. However, OCR provides outstanding results only on particular use cases. In most practical applications, it is still far below human-level accuracy. Modern OCR applications are inferior in processing documents with poor image quality; some alphabets like less commonly used Arabic fonts, handwriting, and cursive handwriting.

The limitation that prevents OCR tools from reaching 100% accuracy is look-alike characters: Some characters look so similar that OCR tools may not distinguish between them. For example, it is hard to differentiate between the number "0" and the letter "O" or a capital "I" letter and a small "l" (L) letter. A specific Use Case 2 diagram details on this problem in Figure 39. To reach higher accuracy levels, the AI-PROFICIENT solution will make use of human intervention to check for potential errors. These interventions will feed into the AI algorithm training data. After some iterations, the AI augmentation of the OCR will be handling the error-free processing related to the characters combinations used at the INEOS facilities. TF is provisionally estimating the optimal number of learning iterations that are required to reach a satisfactory training level of the AI.

Some static labelling which is entirely controlled by INEOS, like the feeders' labels, will make use of a conventional QR-code coding. Figure 38 shows how the name of a feeder "OP407G" is encoded into a QR-code, which will be stuck at a visible place for the operator's optical recognition. QR-code has the error correction capability to restore data if the code is dirty or damaged. Four error correction levels are available for users to choose from according to the operating environment. Raising this level improves error correction capability but also increases the amount of data QR-code size.



OP407G

Figure 38 Introduction of QR-codes marking feeders

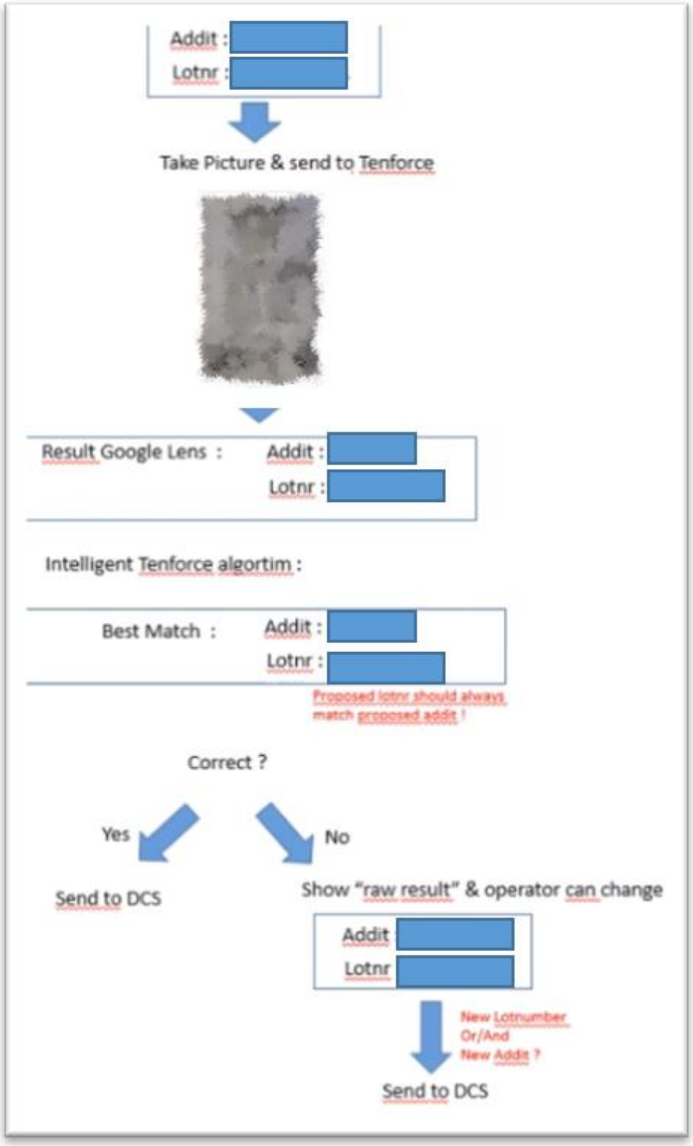


Figure 39 Initial process flow with OCR edge cases work around

Solution success measurement KPIs

- The tool requires less than **1%** manual adjustment, meaning for all actions ('times a big bag is scanned), 99% of the time, the quality of the label recognition is satisfactory, and the operator does not need to apply a **manual** override.
- For a maximum of **5%** of the actions, a second photo needs to be taken.
- The ultimate goal: **no** polymer product downgraded due to use of the wrong additive

Main specifications & high level design

Required datasets for solution development

Operators take photos of big bag labels at unloading sites and feeder sites as part of the quality control feedback loop. An OCR system reads the text on the label and matches it against the quality control database. This way, a product name and lot number are extracted. The operator can manually correct the recognized

text before submitting it to the quality control system. The system confirms whether the right big bag is used in the right place.

The described above user flow defines the purpose of data collection as follows. Because the data is submitted beforehand by the supplier, almost always, the product name and lot number are in the database. This facilitates text recognition greatly. However, in the rare case that the data is missing, the OCR system will return an incorrect name or number without warning. To give measurable feedback to the operator, the AI derives a confidence score from 0 to 100%. The operator can set up a threshold level of the confidence score to say 92%. As soon as the score is lower than this threshold, the operator is warned. The higher confidence allows the user flow to go uninterrupted. A blurry image could also result in incorrect recognition. When it happens, the operator is prompted to take another photo of the label. Real-world examples are needed to build an OCR model that can assign a confidence score to its recognition. It can warn the operator when manual correction is needed or when the data is missing in the quality control system. The training stage requires operators' feedback in case the recognition or the AI matching went wrong. TenForce estimates about one-year data for the Geel plant operational data for reaching a consistent AI scoring.

Photos paired with structured text will define the types and formats of data in question. All these data originate from the images taken at Ineos unloading sites and feeder sites, paired with OCR data that is manually corrected when needed.

The data can be reused in some instances, like the OCR of the text on big bag labels is informed by data in Ineos's quality control system, which contains text that is expected to be found on the labels. Other approaches to use-case-specific OCR can be developed using the same data. There are several OCR services comparable to Google OCR. Should the Google OCR service be replaced by an alternative, the accrued image data will necessary for calibration and potential AI retraining.

Expected data sets size is the range of Megabytes or gigabytes, which will be stored on HD of a TenForce server. This will be non-open data with a storage duration of a few years.

Required input and output – and operator interaction

A series of sequence diagrams illustrates de expected interaction

Additive Feeder Check Flow Diagram

The sequence diagram of the five system stakeholders is presented in Figure 40. The typical scenario assumes the use of the TenForce AI server in the cloud. However, the possibility to run the AI module on premises of the INEOS IT infrastructure will be evaluated to minimize communication overheads while improving the cybersecurity resilience of the whole setup.

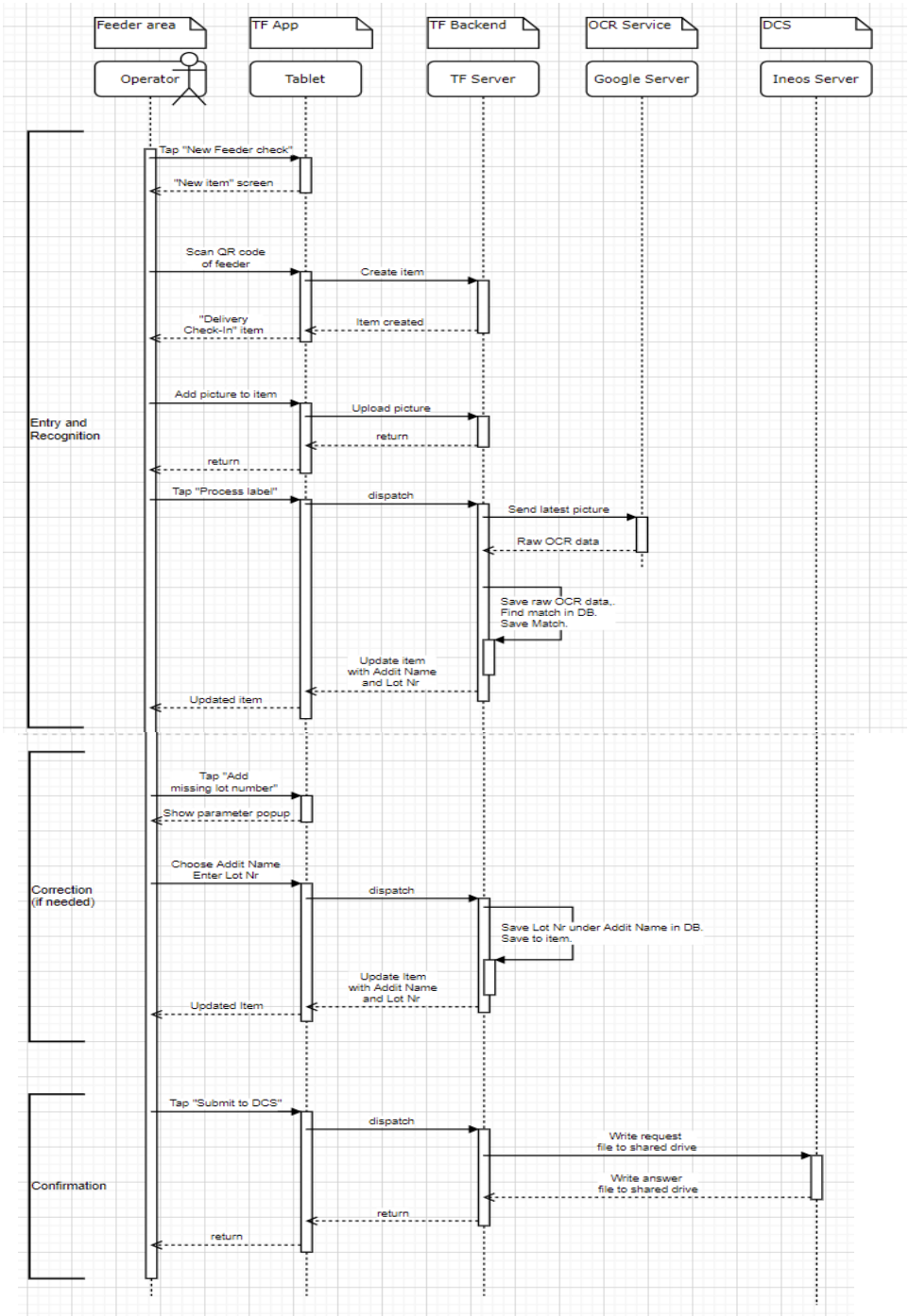


Figure 40 Sequence diagram of the proposed solution

Preventive Scope for Better Additives Registration

Sometimes the bags arrive at the INEOS plant without being registered in the quality management system. There is a need to check in the delivered big bags using the TF app. If Step 2 in the main additive feeder check is done, the Control System can verify the additive bags at the feeders even if there was no conventional registration of the delivery using invoices or suppliers input documents. In this case, the mobile app remains the same as for the original Additive Check Process. The only difference is with an additional step in the backend where the AI derives the CONFIDENCE SCORE.

Figure 41 details on the product entry and recognition in the additive acceptance flow. This flow is finalized by the interaction events shown in Figure 42

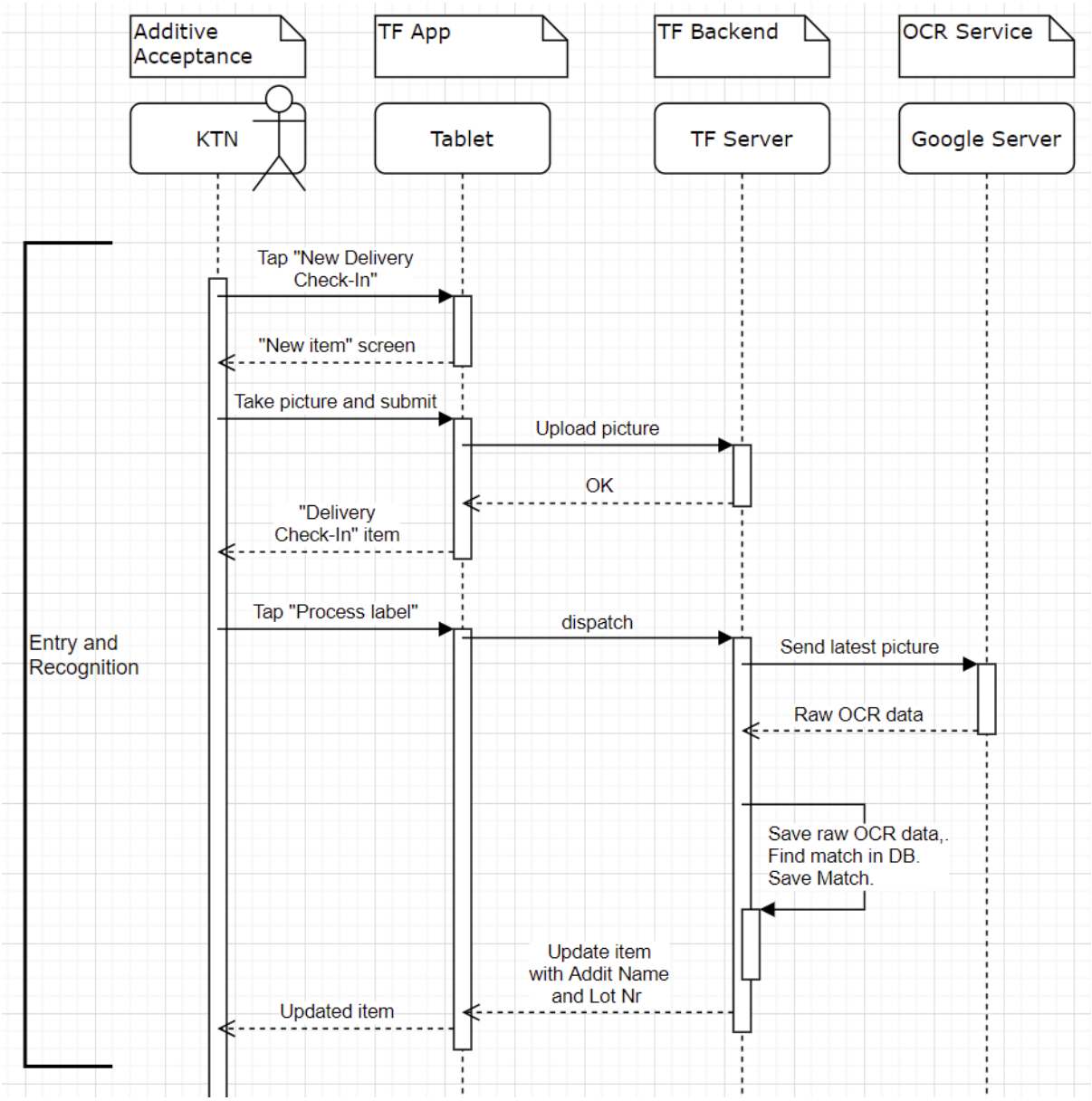


Figure 41 Additive Acceptance and Check Flow (part 1)

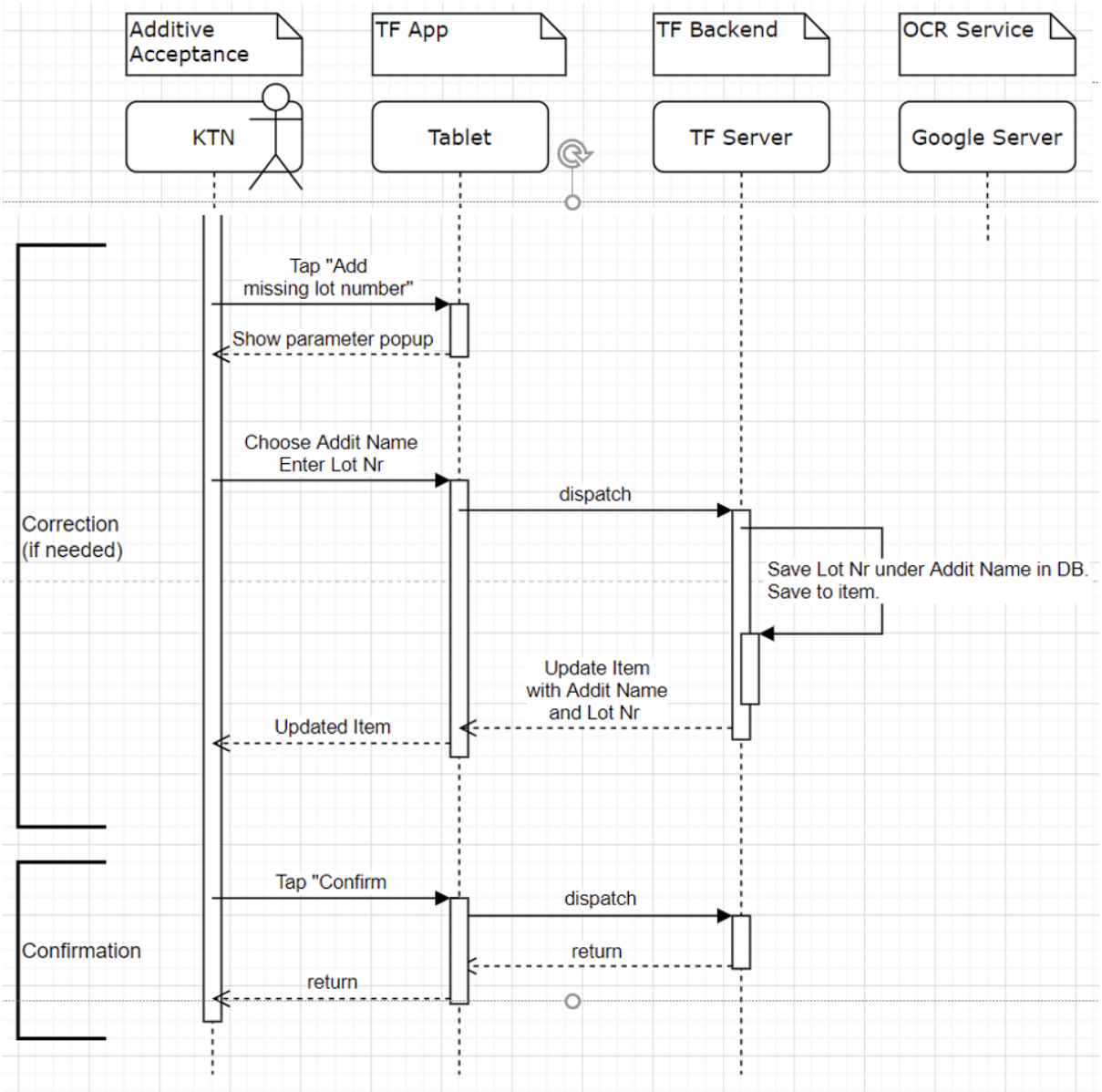


Figure 42 Additive Acceptance and Check Flow (part 2)

The user flow in the preventive Scope Process Steps During the Bags Delivery will be devised to the following steps:

1. Operators photographs the labels of the arrived big bags;
2. Their labels photos are OCR-ed
3. The recognized strings set is matched against the historical data of the AdditName and LotNr;
4. The AI assigns a CONFIDENCE SCORE;
5. If the CONFIDENCE SCORE is above the threshold value (e.g., 98%), the AdditName and LotNr are considered to be recognized correctly.
6. The operator gets the OK notification
7. If at STEP 5 the SCORE is below the threshold value, the operator is prompt to type in the AdditName and LotNr in the text edit field manually.
8. The operator pushes Send to DCS after verifying her manual entry of AdditName and LotNr.

TenForce will gather general operator feedback regarding the Preventive Scope Process Steps, in the example gathering/trial stage, to address particular difficulties the operators may have and incorporate any improvements they can suggest, i.e. develop the system with them. Additional estimation on different operations flows and their need (in time or manual operations) in operators' interventions will be conducted. These insights will feedback to the AI parametrization and the UI/UX improvements.

Ethics Considerations

The use of a relatively heavy (iSafe is 980 gram) handheld device can be continuous. The pilot implementation should foresee a dedicated carry-on bag for unloading the physical strain of the operator.

The operator will be increasingly relying on AI support as the algorithm's data auto-filling, and recommendation is improving. There is an anticipation of decision-making fatigue when the operator is getting used to just the confirmation of the AI-prepopulated data. In case of erroneous input, the operator can neglect the careful review and just confirm by a habitual default.

The last but not least concern is an increased risk of digital dementia when the overuse of digital technology ultimately results in the breakdown of cognitive abilities. The ethics challenge of the influence of digital devices and increase screen time has to be considered when it is proven that short-term memory pathways will start to deteriorate from underuse if we overuse technology.

Technologies and links to WP

With a heavy emphasis on image recognition and shop-floor human-machine interaction and collaboration, this use case will be directly supported by Work Package 4. Namely:

- **T4.1 – Human feedback mechanisms for AI reinforcement learning**
  While the final solution might not necessarily use reinforcement learning, INEOS-2 UC may still benefit from some of the outcomes of T4.1, such as the approaches for exploiting the human knowledge (know-how and expertise) and obtaining feedback (which will be fed into the learning cycle of the AI service) from the plant personnel on the shop floor through human-machine interaction and collaboration.
- **T4.2 – Role-specific human-machine interfaces and data visualization**
  This task will help develop the frontend solutions that will give the plant personnel direct and actionable insights into the process planning, status, and feedback, providing control room operators with the means to easily oversee plant operations even before the data reaches the INEOS DCS, and remote personnel in the field to timely respond to real-time data and notifications. Additionally, AI-PROFICIENT will aim to extend the capabilities of the TenForce platform to strengthen the loop between the worker and the system.
- **T4.3 – Extended reality and conversational interfaces for shop floor assistance**
  Even though the initial focus is on tablet devices, this task will aim to enable AI-driven assistance to the frontline workforce via extended reality solutions and possibly other wearables. In addition to providing process-critical information such as work instructions and immediate feedback from the image recognition services and the TenForce platform, input from alternative data sources, such as the semantic knowledge graph (for context-specific decision support), will also be considered. Also, this task will seek to establish a feedback loop between the augmented plant and the worker, placing the emphasis on the concept of the “connected worker”.s

INEOS-3 UC specification: Rheology drift Cologne plant

UC description

The INEOS Cologne plant applies a high level of automation in process of Polyethylene (PE) production, which assumes the production of 31 sorts of products. The pilot applies similar technology as the INEOS Geel plant, with some differences (number of reactors, chemical reactions etc.,). However, even though the pilot is featured by modern assets, the traditional process control and automation find its limits in an attempt to improve product consistency beyond current levels.

Quality is evaluated within the polymer laboratory (Figure below), which performs analysis of intermediate and final batch samples for three PE production units. Analytical methods are numerous, and one of them will be considered within this Use Case – Rheology (ECTP 23)[2].

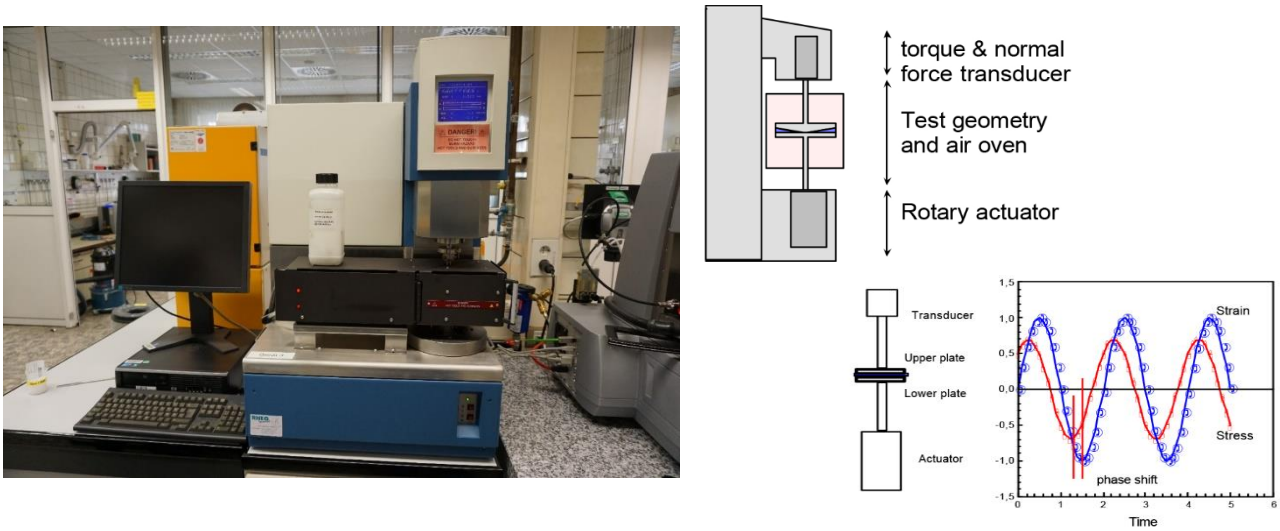


Figure 43– The polymer laboratory with rheometers (left); the illustration of procedure of rheological analysis (upper right) and the oscillatory test whom the material is exposed (lower right)

Materials need control of the rheological parameters within the tight intervals of tolerance, in order to achieve good replicability and usability.

For this use case, there are two key rheological parameters, zero shear viscosity and G-prime. Consistency of the product produced can be characterised by the mean and standard deviation of a certain batch. By adjusting process parameters, the operator can influence and steer these values. Finally, the aim of this use case is to identify additional options the operator has to further improve consistency of the product, through the AI techniques, in the first place. Additionally, this tool will be enriched by decision support features dedicated to the operator, with interpretable AI multiple-choice recommendations regarding process production settings/process parameters adjustment.

[2] Rheology is a branch of physics, which deals with the materials deformation and flow, both solids and liquids. Represents a standard in the polymer industry for materials characterization.

Control parameters whose adjustment is the responsibility of the operators have yet to be specified in detail, and for the sake of illustration, those could be partial pressures, the ratio of ethylene and hexane, the ratio of the hydrogen and ethylene, pellet shape, speed of pelletizer, etc.

Problem statement

Identification of further options to improve product consistency seems to be challenging due to various reasons and they will be mainly addressed through the proposed solution elaboration, with a certain review of them through the ethics point of view, as well. The main concerns could be summarized as follows:

- *Time distribution uncertainty*
  A lagging effect exists between production of a specific batch, and the relevant results of the quality analysis. This makes it challenging to make the needed process adjustments as fast as possible.

- *Non-existent patterns within the historical data (process constraints)*
  This issue is thematically related to the previous one, but just on the syntax level. Actually, this statement is meant to represent the question of constraints that the operators respect while operating the plant, with the cautiousness not to provoke instability of the polymerization reaction. For those reasons, they do not change control parameters beyond the region between a tight set of limits or even at all. The certain partial pressures, feeding ratios, and some temperature set-points are varied, but just slightly. Consequently, the AI-based tool will have modelled the process behavior only at a concrete part of the control parameters space at its disposal. Having said that, it could be concluded that some AI system's outputs will be hardly accepted, or even restricted by the low-level automation unit in the first place. The main issue behind this is the cost of testing beyond the common scenarios from practice, i.e. when certain parameters, which are set to fixed values (even if they have an influence on the final outcome and could lead to an improvement), should be varied in order to achieve more extensive design space exploration (always with respect to the process constraints).
  In order to indicate the risk of their variance beyond the usual scope, the very first step is the categorization of data points. In that sense, the proper constraints will be included in the AI reasoning and unexpected result derivation will be significantly reduced.

- *Uncertainty on potential levers to further improve consistency*
  According to the current understanding, potential areas of improvement could not be related to a certain part of the production process with high probability, or in other words, the whole production process should be considered: reaction stage, degassing phase, powder storage, or extrusion and palletization stage.

- *The cause relation to the extrusion part of the process*
  Namely, the rheology parameters are recorded with the timestamp of the product silo filling up, so it is difficult to correlate process parameters with the final product quality. The problem solution highly depends on the aforementioned aspects and consideration should be performed in two directions: ***do the quality deviation causes originate from the extrusion part of the process or have their roots in earlier phases of the production process?*** In case, it is extrusion related correlation between the rheological parameters and process parameters will be much easier, since extrusion lasts for approximately 1 minute.

Proposed solution

Challenges that have been presented previously imply performing the following steps under the planned activities on the Use Case:

- *Data quality evaluation*
  Collected historical data will be thoroughly analysed applying certain extensive analytical techniques, and, the result of this early phase will bring estimation of the additional, needed information, which is not an integral part of the patterns contained within the historical data.

- *Performing experiments and analysing in that way obtained data set*
  Conduction of specially designed experiments will be needed. Basically, different combinations of measurable control parameters will be applied in a well-designed time sequence.

- *Additional measuring points introduction*
  Determination of the critical part of the process is truly important for making decisions on future steps and the final instantiation of the methodology. Besides DoE techniques, another approach to enrich the information available in form of historical data is to introduce additional measuring points of the rheology parameters of intermediate products. It will help in the determination of the importance of the extrusion part of the line for the final product deviations.
  It will be beneficial to assess the production rheological property stability in order to assess the representativeness of the single measurement for a whole batch. To this end, for some batches, some sample every 30 minutes should be analysed. In that way, the variability of rheological properties over whole bathed could be determined.

- *Correlation and causality analysis*
  When it comes to the observed correlations, there are only some clues of conclusions regarding ZSV functional dependence of melt-flow properties of intermediate products, but correlation does not imply cause-effect relation among those variables. There might be some other variables truly causing the spotted pattern in behaviour of all those rheological parameters and that should be investigated. On the other hand, for the G-prime variations there are no findings. Therefore, planned data pre-processing assumes study of the correlations and cause-effect relationships (e.g. Causality Hypothesis Generation via Neural Networks) among process parameters and rheology parameters, with the alternative of additional data points introduction.

- *Reactor drift models: anomaly detection*
  Apart from the offline preparation work which will be inevitable and significant part of solving problems in this use case, AI enabled services will be the core. The first of them is reactor drift model, which is intended to detect if some parameters of the reactor are drifting so that the rheological properties of the product will no longer be in the requirement. According of the findings of the analysis, serval parts of the process may cause the rheology properties drift. Therefore, several models, one for each part of the process, wills be designed to monitor and alarm. This information, i.e. alarm and location, will be exploited by other services in order to reduce space in which cause of rheology drift should be found.

- *Process model (Digital twin) development*
  This task engagement depends on the results of the offline data analysis. Namely, if it is concluded that the core part of the production line which causes the issue is not located in the extrusion process section, or in other words, has deeper roots within the production line, there are two main consequences to be addressed. The first one is the significant multiplication of the time constant, which introduces considerable and hardly controllable delay in the system. The second one is somewhat more favourable and it concerns the availability of the process model. In that case, the cause should be investigated within the chemical reaction part of the production line, and focus will be translated to the reactor modelling and optimization of that part of the process. So, in the case that the extrusion part of the process is not

the critical one, the problem becomes more similar to the one we have in case of INEOS UC1: Reactor instability and will include the modelling activates.
Concerning concrete modelling techniques, the model could be solely data-based or supported by the first principles modelling.

- *Optimization engine*
  As one of the UC's main goals is to provide a decision support system to the operator while bringing improved production execution, it is expected that behind such a system one holistic generative optimization task will be engaged. The envisaged approach is hybrid and combines different AI techniques and multi-objective or single-objective optimization methods based on evolutionary algorithms. The approach will differ depending on the availability of the process model or digital twin, and its flowchart diagram is given in Figure 44.

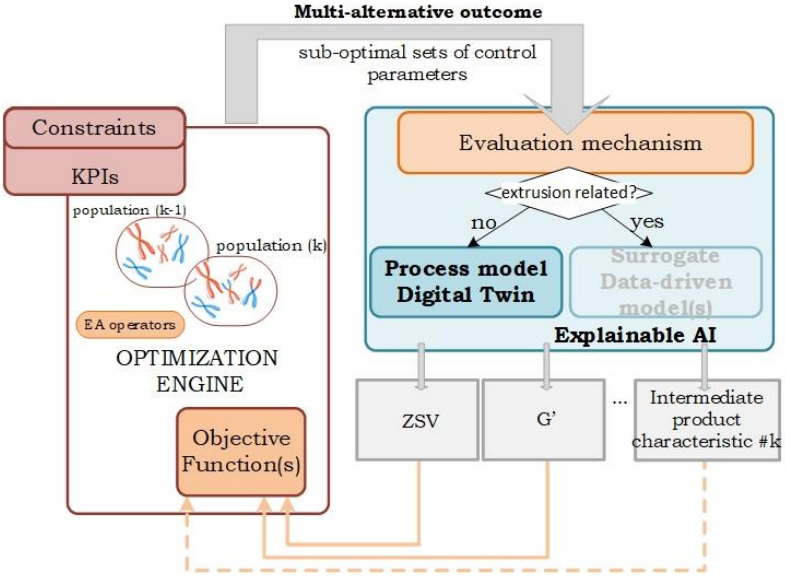


Figure 44 – Optimization based on process model (initial framework)

The resulting rheology parameter will indicate the benefit of beholding such an individual in the population. Otherwise, as the alternative, pure data-driven models will be developed in order to approximate rheological behaviour dependence on control settings within the plant. If it is concluded that an analogy could be made between rheology characteristics of the final product and certain properties of the intermediate products, for which cause-effect relations with control parameters are easier to be established, hence, their values will be considered as the indirect targets.

- *Feedback system (Reinforcement learning concept)*
  As it has already been mentioned, involving operator's feedback to the system via human-in-the-loop or human-in-command concepts would be beneficial for improve quality of the recommendation and additional specialization of the proposed AI-PROFICIENT platform. It that way, models will be trained during the running process, and will adapt themselves in accordance with the operators' experience. Additionally, feedback branch would enable control over process. Namely, due to various security and safety issues it will not be possible to allow this platform to act completely automatically and control the process itself. However, if operator would be included in the loop, AI-PROFICIENT platform would be able to indirectly control the process. Nevertheless, in case that operator's feedback is not present, system would be able to work and provides suggestions regarding the causes of the unsatisfactory rheological parameters, together with the recommendation of the parameter setting which are supposed to improve current state.

- *Explainable and transparent AI models*
  Having in mind process complexity and operator's responsibility when changing process parameters, it is expected that operators will not accept any recommendations without providing accompanying explanation. Therefore, within this use case, explainable and interpretable AI services will be included. Their particular utilization is twofold. On the one hand they could be exploited for root Cause Identification, whilst they could be utilized for providing understandable surrogate data driven model in case of digital twin absence. The particular XAI methodologies will be determined in the next phase of the use case development, when historical data is clean and ready. When particularities regarding XAI approaches are determined, the form which will they take at the operator end will be defined in agreement with the pilot and the ethical team.

  All of previously elaborated approaches and their interconnections in the context of this use case are given in Figure below.

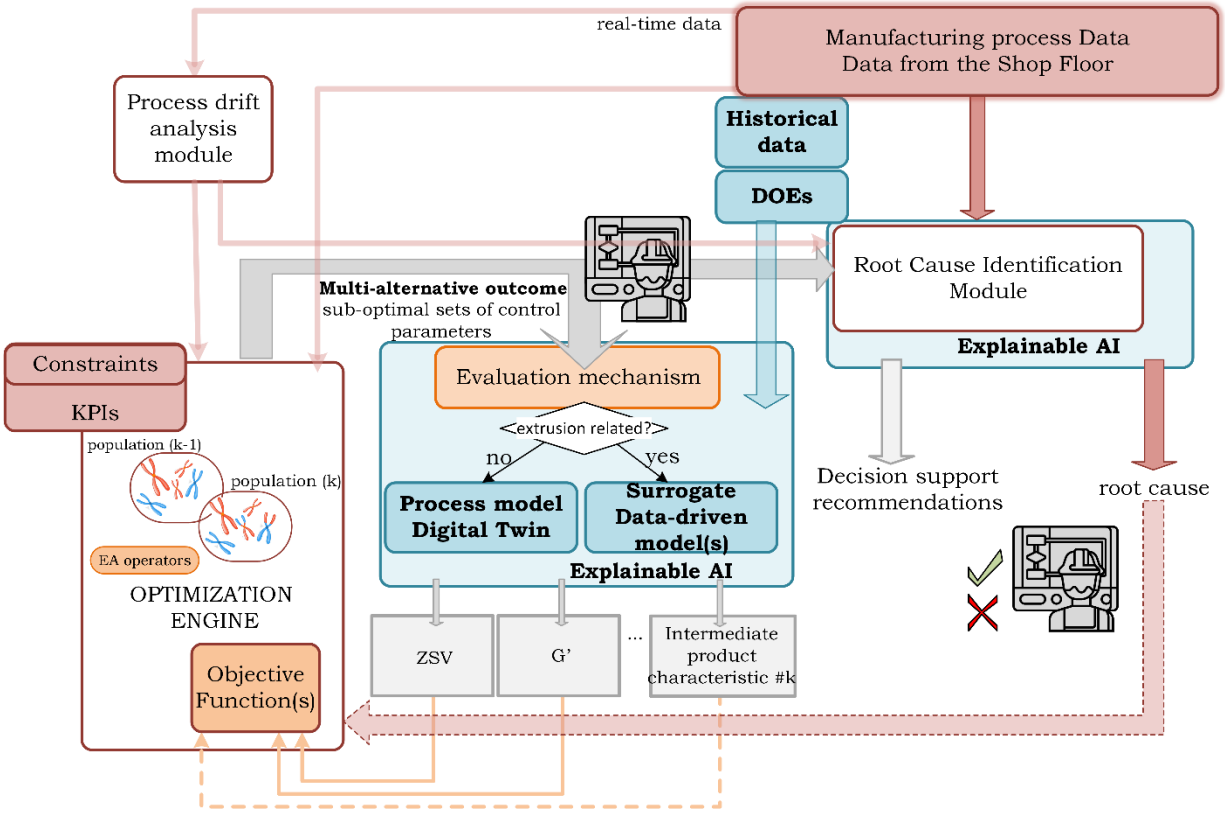


Figure 45 - Detailed overview of the proposed solution

Main Specifications and high level design

Required datasets for solution development ***What data is needed for the approaches chosen, how does it look like?***

Taking all of previous into consideration, the following data sets will be required:

1) *Process description and operator's experience* will be crucial in the starting phase of the development of the services. Namely, in order to be able to provide performable solutions, it will be necessary to

understand the process and its main characteristic. Similarly, heuristics that are proven to be effective would be valuable as the initial guidelines for the decision support tool.

2) *Historical process data from the extrusion part of the process* will be necessary in order to analyze correlation between the rheological parameters and adjustable process parameters. Additionally, if it is confirmed that cause of parameter deviation is in the extrusion process, this data will be utilized for the serves development, as well.
3) *Historical process data from reactor and degassing parts* will be required in case rheology parameters deviation is not caused by extrusion part of the process. In that case, this data will be exploited for the development of various services explained in section 2, including reactor digital twin.
4) *Historical rheological parameters measurements* will be utilized both in phase of data analysis and exploration and for service development. This data set is highly important in order to be able to detect critical behavior and provide performable models.
5) *Experimental data* would be beneficial in order to additionally enrich already present historical data. Namely, there are no much of example of the irregular behavior, thus it would be beneficial generate additional examples. Furthermore, testing process behavior in new conditions would be profitable for the modeling purposes.

Required input and output parameters for demonstrator execution ***What does our solution/model need for its correct operation?***

The main input which will be required in order to provide solution for this use case will be real time process measurements. At the point of writing this deliverable final list of those variables is unknown, especially taking into consideration two potentially different scenarios – one in which only extrusion part is considered and the other one in which the whole process should be tackled. Nevertheless, temperature, pressures, type of product etc. will be considered.

Apart from those, as already explained, feedback from the operator regarding the quality of the provided suggestion could be integrated within the system. In this way, system performance will improve with time and system would adapt much easier in case of change in product recipe. Furthermore, in case operators are included in the loop, suggested process parameter setting could be applied on process itself.

Required interaction with the operator: ***What advantage do we provide to the final user?***

This use case is quite specific in comparison with others. Namely, on contrary to many others, for example Continental 10 regarding quality analysis and assurance tool, where the main goal is to facilitate operator's work, from this one, plant itself should benefit primarily, rather than operator. Namely, the current state is that complete product batch for which rheological parameters are unsatisfactory has to either sold with lower price, due to lower quality, or to be completely discarded. Therefore, current monetary loses for the plant are high and UC3 solution should decrease them. However, with this tool, operator would be able to improve process management, as they would obtain the relevant information regarding the cause of the rheology deviation problem, together with the suggestion for the parameter setting in order to overcome this issue.

What do we expect from the operator?

In order to adequately complete this use case, suggestions provided from the AI-PROFICIENT system should be applied on a real process. However, it is highly unlikely that project platform will be allowed to control the process without supervision of the operator. Therefore, his main role would be accepting or refusing proposed suggestion. Taking into consideration that platform would provide a couple of potential solutions, it is desired that operator chooses one of the following:

- Approve one of the proposed solutions.

- Refuse all the solutions, due to the fact he finds them inadequate.

Nevertheless, the option for not responding on the system recommendation will be left, al well, in case it is not possible to obtain operator's feedback.

Bearing in mind the importance of involving the operator in the problem of detecting cause of parameter deviation, it is intended to provide simple interface for the feedback, so that a lot of extra effort should be put in. In case it is accepted that operator is included in the loop, interface will be designed in collaboration with the pilot representative and ethics teams.

Addressing ethical considerations:

challenges listed within the Problem statement, should be addressed from the ethical point of view as well. Received ethical issues and recommendations, stated by the Ethics Team and made to be use case-specific, respectively, are:

Ethical issues:

1) *Ambiguity of the role of Artificial Intelligence*
   This issue will be solved through the following steps of data analysis, when it will be easier to proceed work with some conclusions. The fact, that there is the mutual influence of several parameters on the rheological parameters of interest, has been expected, due to a multi-variability of the process/production system. The Use Case objective is to bring a higher understanding of the possible causes – to perform root cause identification, and, to bring alternatives for overcoming.

2) *Override-permissions (production instructions/guidance versus AI service)*
   The priority will belong to the expertise, or production instructions/guidance, with a tendency to fine-tune the AI tool to be able for standalone operating in the future. This issue is considered as well in following within "*Question of priority between future AI system suggestions and existing production instructions generated by the process engineers*".

3) *Traceability issue related to the ignorance of critical part within the production chain*
   This issue has been already addressed as a technical issue (chapter about Proposed solution).

4) *Reduced freedom left to the AI*
   As was the case previously, the issue has been considered within the Problem statement, "*Non-existent patterns within the historical data (process constraints)".*

Ethical recommendations:

1) *Pointing out the exploratory nature of the UC and benefits of organizing the work into several stages*, which will gradually involve the operator, with high respect to his/her understanding of the performed experiments needed for thorough cause-effect relations analysis. This staged approach surely will be satisfied, as the work on the AI services development progress. In the beginning, a limited subset of control parameters will be varied in order to conclude their influence. Afterward, results of data pre-processing will bring additional knowledge related to the crucial and critical parts of the process - a critical subset of influencing parameters affecting each of the rheology parameters of interest. The final step of DCS integration with the AI services on the communication level has to be considered further, giving the priority to the more mature system and taking into account process engineers' attitude in that regard. Currently foreseen approach assumes a human-at-command rather than a human-on-the-loop concept.

2) *Question of priority between future AI system suggestions and existing production instructions generated by the process engineers*
   This issue actually has its mapping in technical features already considered. The operator and process engineer will be afforded interpretable and explainable solutions/recommendations. Therefore, they will be familiar with the way how AI derives such a result and will be able to evaluate it by means of a feedback system, with the possibility to not listen to the recommendations, but, preferably, to leave feedbacks related to it. Clearly, the priority will be given to the expertise (operator's, process engineer's word), as long as the tool matures, at least.

3) *Recommendation regarding the schedule of exploratory activities with respect to the production time line*
   This statement is already covered within the proposed solution elaboration and it is in complete accordance with it. Surely, the research at the very beginning will be focused on the production procedures, which are close in time to the moment of product finalization/rheology analysis, firstly conducting analysis related to the extrusion segment of the line. If the issue is not related to it, the research will switch to the earlier phases of production.

4) *The possible resistance of manufacturing working environment to the changes AI will bring*
   When it comes to this aspect, the system-level which this Use Case stand requires extensive experiments in order to bring improvement in later phases. So, those experiments will be designed according to the all beneficial results of pre-processing and they will comprise necessary and, hopefully, sufficient set of trials. The operator workload will be respected and those activities will be planned and organized in a timely manner (when the time comes for it). Finally, taking into consideration that this system is intended to provide information which is crucial for improving product overall quality and is operators are currently incapable of obtaining in in any other way, it is expected that system will be well accepted.

Technologies and links to WP ***Which technologies will be adopted in this UC, which WP/tasks are involved in the development of those technologies?***

The Use Case represents a system-level problem to be approached, concerning the fact that the root cause of the rheology parameters drifts of the final product, could originate from almost any point of the production process line. As it has been stated, the tasks' engagement slightly depends on the results of pre-processing of collected data, when some preliminary conclusion will be made. Precisely, localization of the main causes on a certain part of the production process will redirect the final workflow and task interconnection. So, the following list includes the extended version and will be reduced and/or enriched with more detail, after conducting the initial analysis:

- **T1.2 – Human-machine interaction, legal and ethical issues**
- **T2.4 – Self-prognostics and component operating condition estimation**
  Different AI models will be examined in order to check existing correlations and cause-effect relations among variables, especially focusing on the reactor operating conditions research. Some Anomaly detection models will be designed to alarm when a drift happens at sub-system level of the process occurs. This task will build the edge models that will be used in the Reactor drift analysis module.
- **T3.1 – Hybrid models of production processes and digital twin**
  The model of the reactor will be developed if it is conducted that the root cause comes from the reaction part of the production line and if collected data quality is at a satisfactory level. This modelling will comprise a data-driven approach or first principles modelling techniques, and concrete choice will be made on the fly.
- **T3.2 – Predictive AI analytics for production quality assurance**
  Different AI models will be examined in order to check existing correlations and cause-effect relations among variables, especially focusing on the reactor operating conditions research. The goal will be detecting reactor's drift from the process view point based on the output of the edge drift detection models (T2.2). The result will be further exploited by generative optimization for improved production execution (T3.4 & T3.5).
- **T3.4 – Generative optimization for improved production execution and scheduling**
  Its engagement tends to bring decision support to the operator, in form of a multi-alternative recommender. It will tend to exploit the results obtained within the tasks T2.4, T3.1, and T3.2.
- **T3.5 – Future scenario based decision-making and lifelong self-learning**
  The multi-alternative recommender, in a second time, will exploit the results obtained within the tasks T2.4, T3.1, and T3.2 in order to refine the propose alternative. The results with and without the help of other services will be compared in order to show the added value of making the services work together.
- **T4.1 – Human feedback mechanisms for AI reinforcement learning**
  Coupling with the operator could bring some benefits to the AI-based platform, making it adaptable and self-learning. For the complete application of the reinforcement learning concept and the creation of self-adaptable models, it is necessary to consider those mechanisms.
- **T4.2 – Role-specific human-machine interfaces and data visualization**
- **T4.3 – Extended reality and conversational interfaces for shop floor assistance**
  If we talk about the support provided to the operator and hopefully, their engagement in the training and re-training process of the AI models, the interfacing of human and decision system has to be realized through certain visualization and/or conversational assets.
- **T4.4 – Explainable and transparent AI decision making**
  When it comes to the mutual reliability between the operator and the recommendation system based on the AI techniques, clearly, transparency and interpretability of the system outcomes are of the utmost importance. Therefore, this task surely will accompany data-driven models and the optimization engine, intended to be developed.

- **T6.4 – Instantiation of HLEG guidelines and ethical recommendations**

Additionally, the possibility of involving some extra tasks will stay open, especially bearing in mind edge services (WP2) which are not integral part of the technologies subset within this UC, but whose outcomes could be exploited by the INEOS UC3 platform services.

Detail flowchart & partner/task involvement

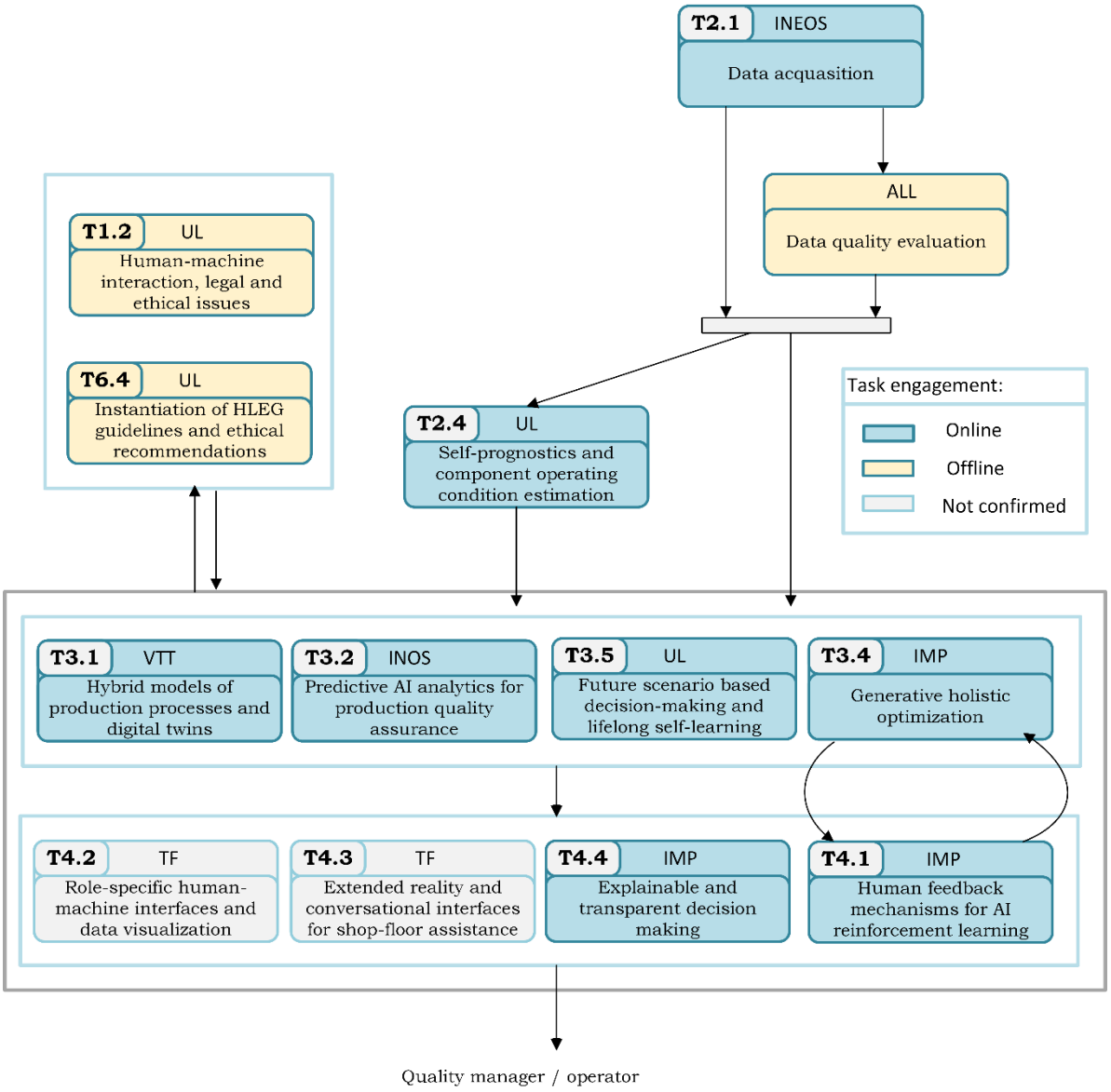


Figure 46 – High level detail of UC INEOS-3

Pilot UC specifications relevance for AI-proficient objectives

This report details the specification of 8 different use cases linked to three different pilots that will have a clear impact as described at the introductory 'description' of each Use Case. Whereas the impact of the Use Cases with respect to the General Objectives (GO) and Scientific and Technical Objectives (STO), as expressed in the Description of Work, will be later assessed in WP6, this section can advance the potential of the use cases in order to understand their alignment with respect to accountable GOs and STOs. This section will also summarise the task involvement with respect to the different use cases.

Relevance of Use cases for AI-proficient objectives

STO1- Integration of advanced AI technologies with production processes in IIoT environment. *Leveraging the Industrial Internet of Things (IIoT) environment and digital retrofit of existing assets, AI-PROFICIENT will integrate the self-learning and self-prognostic AI services with the manufacturing systems and processes.*

This STO is linked to almost all use cases: CONTI-2/3/5/7/10 as well as INEOS1/2/3. On the one side it is expected the deployment of new edge components in most use cases, also including HW (e.g. vision and current systems in CONTI-5/7, vision/wearables at INEOS-2). On the other hand it is expected that all use cases will behave similarly as online services connected to each pilot through AI-PROFICIENT IIoT data platform (currently under definition at task 1.5). As targeted metrics, we might foresee:

- AI services integrated with existing assets and production lines – *It is expected that at least 7 of 8 use cases will behave at the end as online services linked to the shared IIoT data platform (INEOS-2 probably as independent service)*
- Demonstrated interoperability with existing information systems (ERP/MOM) in 3 production sites – *all the three pilot sites will demonstrate interoperability: CONTI-2/3/5/7/10(Sarreguemines), INEOS-1(Geel) & INEOS-3(Cologne)*
- Communication mechanisms validated in 3 operating conditions – *The operation conditions present at each pilot site are quite different. Moreover – CONTI 2 includes different operation conditions (e.g. normal tyre production vs. set up of new products)*

STO2: AI for early detection of the process anomalies and provision of fault diagnostics. AI-PROFICIENT will embed the deep learning techniques and complex event processing capabilities for early-stage fault detection and diagnostics to improve OPE and product quality, and provide failure prevention capabilities.

This STO is also clearly liked to CONTI-2/3/5/7/10 as well as INEOS1/3. Most of these cases expect to develop prescriptive and predictive AI analytics for FDD and deployment AI services for early-stage anomalies detection (e.g. CONTI-3/5/7, INEOS1/3); Additionally, an empirical data exploration, and even different design of experiments to incorporate specific data sets for robust AI modelling (e.g. CONTI-2 & INEOS-3) are expected. As targeted metrics, we might foresee:

- At least 50% of anomalies predicted depending on the production process – *expectations in certain cases (e.g. in CONTI-5) are higher as a predictive approach is expected to anticipate up to 70-80% of the potential thread cutter anomalies, depending of the technologies implemented.*
- Increase in production availability during process reconfiguration (by more than 10%) – *This affects for instance to CONTI-2 (& partly CONTI-3), where the correct product set-up between changes regarding process stabilisation is a key concern.*
- Improved OPE between 5% and 10% (availability, performance & quality) – *For instance, combined interaction of CONTI-2/3, CONTI-5/7 & CONTI-10 are expected to reach this objective. Also, CONTI-10 use case will allow the assessment of this metric as will be able to collect performance data as well as condition and operational data regarding the impact of the other use cases.*

STO3: AI-based decision support for proactive maintenance at component and system level. To extend the Remaining Useful Life (RUL) of production assets, AI-PROFICIENT will provide a maintenance decision support by combining the predictive AI analytics with physical process modelling and digital twins.

This STO is also linked to use cases such as CONTI-2/3/5/7 and INEOS-1/3: On the one hand, there is a clear maintenance focus that includes CONTI-3/5/7 where thread conveyor, cutting and guiding components should be maintained. On the other hand, CONTI-2 and INEOS-1/3 represent the need of combination of big data analytics and digital twin modelling, either related to physical or to semantics-based knowledge models. Specific targets metrics of this STO are as follows:

- At least 50% reduction of false alarms and NFF scenarios. *This is particularly important in CONTI-3/5/7, and in particular linked the engagement of operators with the proposed solutions, that will be changing they way of working (from reactive/predictive to predictive).*
- Increase in asset lifetime and component reusability (by more than 25%). *Also related to CONTI-3/5/7, it is expected a targeted lifetime increase in at least one of these cases (e.g. CONTI-5).*

STO4: Joint human-machine approach to improved production planning and execution. AI-PROFICIENT will deliver a multi-objective generative optimisation approach, leveraging the human knowledge and feedback for reinforcement AI learning, in order to improve the production execution and scheduling.

All UCs are related to this STO, tough in some of them Human AI collaboration could be stronger, as decisions involve a more interactive approach. This is the case for instance of CONTI-2/10 and INEOS-2. As specific targeted metrics for this STO, we might foresee:

- Reduced time for lines to reach full rate production (by approx. 12.5%). *This will be a very clear focus e.g. regarding CONTI-2 UC, where the expected reduction set-up time will impact not only in a reduction of rework, but also in a faster stabilisation of line production after each product change (much related to the agile production requirements of the line, which involves from 40 to 60 product changes per day).*

Summary of Task involvement

An initial review between the expected involvement of the technologies to be developed at different tasks – in particular from WPs 2-3-4 where technology development will take place - and their expected contribution to the UCs shows the following:

WP/Task	CONTI-2	CONTI-3	CONTI-5	CONTI-7	CONTI-10	INEOS-1	INEOS-2	INEOS-3
WP2– Smart components and local AI at system edge								
2.1 IIoT environment		X	X	X	X	X		X
2.2 pre-processing	X	X	X	X	X			
2.3 Self diagnostics	X	X		X	X			
2.4 Self prognostics	X		X	X				X
2.5 Field Automation	X		O			O		
WP3- Platform AI analytics & decision making support								
3.1 Hybrid models/twins	X					X		X
3.2 Predictive AI			X	X	X	X		X
3.3 Proact. Maintenance		X	X	X	X			
3.4 Generative optimization					X	X		X
3.5 lifelong self learning	X		X			O		X
WP4- HMI, explainable AI and shop-floor feedback								

4.1 Feedback/reinforc.	X	O	X		X	O	O	X
4.2 role specific HMIs	X	X	X	X	X	X	X	X
4.3 XAI and conversational	X	O			X	X	X	O
4.4 Explainable AI	X		X	O	X	O		X

Figure 47 – Summary table with expected Task involvement per UC
(X- partner & technology already identified & matched to the UC; O- to be confirmed)

It can be concluded that there is a clear interaction between use cases and main development tasks, where all tasks will have the opportunity to demonstrate their support to one or more UCs, which shows a variety of needs. Anyway there are two remarks to highlight:

First, in some cases (i.e. WP4 activities) the potential involvement of some tasks/technologies is still to be confirmed once it is clearer the extent of WP2 & WP3 technologies and once it is verified the real interaction that can be feasible with the operators at both INEOS and Continental pilots.

Also, there is a specific task (2.5) whose technologies have a low demand within the use cases, as the control is always linked to the operator interaction (human on command, or human in the loop, rather than supervisory automated roles related to human-on-the-loop approaches) and it is difficult to foresee such automated solution within the project timeframe apart from CONTI UC2. In order to maximize the demonstration of these technologies, it is expected to have a review of certain UCs that might result on the application of field automation technologies, as indicated above (e.g. INEOS UC1). On the other hand, as it happens with other AI-PROFICIENT technologies, it is expected that some test beds already existing at partners facilities may serve as additional demonstration workspaces, where AI-PROFICIENT outcomes show their relevance in manufacturing scenarios beyond the actual pilots and can also be validated and demonstrated. In particular, it is expected to include a potential demonstration related to an *additive manufacturing* testbed (Tekniker) where Task 2.5 technologies can also be tested and will serve to demonstrate the applicability of the results beyond initial Pilots.

Conclusion

This deliverable summarises the work done during Task 1.3 regarding the specification of Pilot demonstration scenarios, that are focused in 8 different use cases.

This deliverable has served to support a wide exchange of information between technical partners and use case providers, by developing a common understanding of the challenges behind each use case, and it is expected to serve as a guideline for the expected interaction and collaboration among partners at all tasks, where low-level design, development and integration of relevant technologies will take part (WPs 2, 3 & 4).

The document also provides important clues concerning the way ethical aspects should be handled: Even though many ethical aspects will be relevant at development phase, it has been important to take them into consideration here, as it has led indeed to several modifications in the planning & design of proposed solutions.

It is expected that some of these issues will be re-visited, fine-tuned or even modified (e.g. ethics, task and partner interactions, AI4EU repositories, etc.), during project development and integration (WP5) as well as during use case evaluation later within WP6

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