Ref. Ares(2023)3112018 - 03/05/2023

AI·PROFICIENT

Artificial intelligence
for improved production efficiency,
quality and maintenance

Deliverable 2.6

D2.6: Smart components and local AI at system edge

WP2: Smart components and local AI at system edge

Version: 1.0

Dissemination Level: PU

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 957391.

Table of Contents

List of Figures

List of Tables

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Title: D2.6: Smart components and local AI at system edge

Lead Beneficiary:	TEK
Due Date:	30/04/2023
Submission Date(expected)	03/05/2023
Status	Final ~~Preliminary~~ ~~Draft~~
Description	Public summary report on AI edge technologies (WP2) developed and on application at the different demonstration scenarios within AI-PROFICIENT.
Authors	Aitor Arnaiz (TEK), Kerman Lopez de Calle (TEK), Alexandre Voisin (UL), Vassilis Spais (INO)
Type	Public - Report
Review Status	~~Draft~~ ~~WP Leader accepted~~ PC + TL accepted
Action Requested	~~Contribution from partners requested~~ ~~To be revised by partners~~ ~~For approval by the WP leader~~ ~~For approval by the Project Coordinator & Technical Leaders~~ For acknowledgement by partners

VERSION	ACTION	OWNER	DATE
0.1	First version released	AA	21/04/2023
0.2	Revision and suggestions	KL/AV/BI/(VS)	28/04/2023
0.3	Completed version	AA	30/04/2023
0.4	PMT review	AV	2/05/2023
1.0	Consolidated version /Upload	AA	3/05/2023

Executive Summary

This deliverable is a public report that summarizes the activities and achievements reached at WP2 within AI-PROFICIENT H2020 project. This WP has attempted to introduce local AI technologies at the system edge under the 'smart component' concept, close to the production lines, considering MEMS and PLCs information outputs. This differentiates from other technologies expected to work at 'cloud' level on most scenarios (and developed in other WPs)

The report offers a unified vision on the work performed at system edge and is based on previous deliverables already issued in relation with WP2, and in particular on the technologies and final applications of these technologies in use cases, already described in D2.2, D2.3, D2.4 and D2.5. As some of these previous reports are private, the integration will also provide a coherent and consolidated public vision of the work performed.

Therefore, the deliverable summarizes and explains the technologies researched and their application, that is aligned to 4 main technology applications, namely:

- AI pre-processing algorithms for raw data cleansing, aggregation, and filtering. More specifically the processing of image data and of dense 3D position data, i.e., point clouds, into low cardinality vectors to be used as input to industrial maintenance support systems.
- Self-diagnostics and component operating condition estimation: Diagnosis strategies that are used for asset monitoring and how the AI could be used to improve those strategies. … implying the monitored assets themselves could be updated so that they could produce their own diagnostic information.
- Prognostics, more specifically degradation-based prognostics, where projections are made over the future in order to predict not only the remaining useful life (RUL), but also the degradation trajectory of the asset in consideration, by blending AI-based techniques with more conventional approaches such a stochastic processes, trend, and time series models.
- Field automated control mechanisms to provide 'real time' response and adaptation to the current condition of the controlled asset.

The report also summarizes the application of these technologies within the pilot scenarios and the Industrial IoT environment deployed, which includes up to 7 different use cases, including a common structure that differentiates the technologies under research (section 3.x), the description of each use case (4.x.1), the solution proposed, based on the technological approach (4.x.2) and main details regarding the deployment of these solutions (4.x.3), that can be complemented with more in depth information included at deliverables already reported in WP2.

1 Introduction

This deliverable is a public report that summarizes the activities and achievements reached at WP2. This WP has attempted to introduce local AI technologies at the system edge under the 'smart component' concept, close to the production lines, considering MEMS and PLCs information outputs. This differentiates from other technologies expected to work at 'cloud' level on most scenarios (and developed in other WPs), as shown in figure below.

The deliverable composes an integrated view of the technological developments carried out and their current application status at different demonstration scenarios.

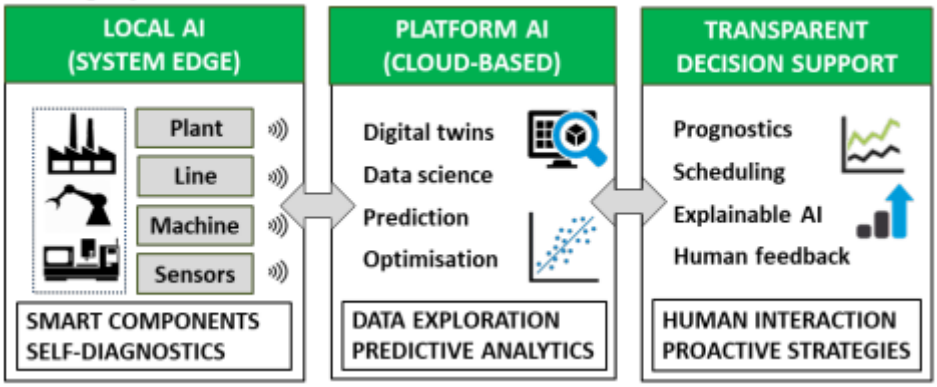


Figure 1. Main technology constituents of AI-PROFICIENT technologies.

As such, it is based on the previous reports already issued in relation with WP2, and in particular on the technologies and final applications of these technologies in use cases, already described in some reports. These are:

- D2.2: Data cleansing, aggregation and filtering at system edge (Algorithms deployed at the system edge for raw data cleansing, aggregation and filtering).
- D2.3: Predictive AI analytics for component self-diagnostics (Algorithms for component self-diagnostics and fault identification at system edge).
- D2.4: Local AI for proactive maintenance support (Algorithms for prognostics applied to manufacturing assets and components).
- D2.5: Local automated control for quality assurance (Algorithms for closing the control loop locally from the system edge).

As some of these previous reports are private, the integration will also provide a coherent and consolidated public vision of the work performed.

Regarding the rest of the content of this deliverable, it is organized as follows: **Section 2** presents a functional specification of the functional requisites each AI service must consider, stemming from initial requisites identified at WP1. In **Section 3** a conceptual approach is made regarding the field of AI application (monitoring, diagnostics, prognostics, field automation). **Section 4** shows the way these technologies are being applied into different scenarios (use cases), and **Section 5** summarizes the results achieved so far.

2 Functionality requisites

The technical developments carried out in this WP were envisioned to contribute to several of the functionalities, as specified in D1.4 deliverable (see Table 1 below).

Table 1: Functionalities to be provided by the AI-PROFICIENT project (from D1.4).

AI-PROFICIENT Functionalities	***ID***
Monitoring	**_MON**
Diagnostic and anomaly detection	**_DIA**
Health state evaluation	_HEA
Component prognostics	**_PRO**
Hybrid models of production processes and digital twins	_HYB
Predictive Production quality assurance	_PRE
Root-cause identification	_ROO
Early anomaly detection	_EAR
Opportunistic maintenance decision-making	_OPP
Generative holistic optimization	_GEN
Future scenario based Lifelong self-learning system	_LSL
Human feedback	_HUM
Explainable and transparent decision making	_ETD

As per the diagnostic service, the following tables contains an updated description of the specification of the services specified in D1.5. These functionalities have been reviewed taking into account a 'generalization' approach, agnostic from specific UC application:

Table 2: Updated S_DIA service description.

Service ID	S_DIA
High level service description:	The aim of this service is to check the assets are operating under normal conditions. When anomalies are detected, the service will raise an alarm. The alarms raised by the service will be then managed by other systems or operators so that catastrophic failures are avoided.
Service input and dependency on other services:	This service is developed taking as a basis the IIoT sensor installation and the acquisition & pre-processing steps carried out by the acquisition and pre-processing service.
Service output:	Depending on the diagnosis system: - Anomaly or OK conditions - Specific fault name or OK condition - Health Index representing current wear status.
AI-PROFICIENT Application Specifics:	It contributes to various of the UCs in which a diagnosis and anomaly identification of the assets is required on the edge. Besides the application of the service in tyre industries and chemical industries, it has been validated in other scenarios, such as, for example a fuse manufacturing industry. In each of the UCs slight variations of the diagnostics systems have taken place according to the complexity and need of the UCs. In that sense, anomaly detection, fault diagnosis and health index type systems have been developed.

Table 3: Updated S_PRO service description.

Service ID	S_PRO
High level service description:	The purpose of the service is to provide an estimation of the Remaining Useful Life (RUL) of the component. Depending on the use cases and component, the service may also provide the Health state future trajectory of the component.
Service input and dependency on other services:	The service should be implemented at the edge and requires at least as input from the system: - Component's sensors - Data from the supervision - Production planning It will also require some input from other services (if available): - Self-diagnostics output - Health state evaluation
Service output:	/
AI-PROFICIENT Application Specifics:	Degradation based prognostics is based on degradation models, mainly based on historical data, and may consider age, usage, and measurement of the equipment. Such a model is then updated depending on available current measurements. The degradation model makes projections over the future in order to predict the remaining useful life of the item in consideration. The model includes AI-based techniques but also more conventional approaches, such as stochastic processes, trend, and time series models. They may deliver not only the RUL but also the degradation trajectory. RUL prediction prognostics provides only the RUL of the component. The proposed deep neural networks used for this purpose exploit automatic representation learning to discover weak and complex correlations between sensors that may not be easily captured by domain experts and thus potentially increase portability of the prediction model to other configurations and environments.

As no UC required of control functionality, the definition of the control service was not presented in D1.5. The following Table 2 shows how a generic control service could be like.

Table 4: S_CON service description.

Service ID	S_CON
High level service description:	This service is the last link of the monitoring-diagnosis-prediction-actuation chain taking into account an 'edge' oriented 'real-time' automated actuation (To be differentiated from Decision Support Systems with recommendations to operators) The data is first gathered by the monitoring service and processed by the pre-processing one; later, insight is created from that data with the diagnosis and prognostics services; and, finally, this control service uses that insight to modify the operation of the system without requiring human intervention.
Service input and dependency on other services:	This service heavily relies on the output of other services. Most probably the following services are compulsory to allow a control service to work properly: *Monitoring service, Signal-processing service.* Additionally, these other services could also contribute to an AI based control service: *Diagnosis service, Prognosis service.*
Service output:	This service is in charge of managing and commanding the system which is being monitored. Given a set of signals this service will modify or maintain the operation of the production line/target machine without requiring the intervention of operators.
AI-PROFICIENT Application Specifics:	In the context of AI-PROFICIENT, this service uses the insight provided by AI algorithms (which describes the actual health condition or future expectations regarding the evolution of that condition) to optimize the operation of the assets in a more efficient way.

3 Concept definition and potential AI based approaches.

This section introduces the main concepts and challenges being researched as part of field/edge based intelligent functionalities (i.e., preprocessing, diagnosis, prognosis, and control/actuation) as well as different ways AI technologies could contribute to the efficient resolution of these challenges. On the other hand, as the topic is very broad, the final research has been focused on a subset of AI technologies that are more specific and of practical interest to be applied to existing AI-PROFICIENT use cases, as shown in each subsection.

3.1 AI approaches for edge image processing

Aggregating vision data to low cardinality feature vectors

In industrial settings sensors have a certain resolution and accuracy constrained by technical factors (instrument capability, noise) and economic limitations. At the decision level (e.g., good vs. not good part decision) traditional threshold-based decision making can also be limiting as it is quite often difficult to manually determine first principles or heuristic function that maps inputs to numerical values (or set of values) that can be compared against a reference threshold (or set of thresholds).

Modern AI **data-driven** methods such as Deep Neural Networks have been proven to be trainable to effectively approximate such mappings. However, image and point cloud data are rich data sources that can be difficult to *directly* convert into features via the expedient use of an AI model, *unless a large data set is available for training*. While exemplars of good parts can be readily obtained, bad parts are much rarer, and it is quite common to use surrogate models[1] to get inputs for model training. At the same time in industrial applications where the output of each production step is serially fed into the next steps, the acceptable false positive rate, i.e., the rate at which we detect good parts as bad, is quite low, which makes the use of surrogate models less effective. In the automotive industry the de facto *desired* standard is 1 in 10000 (or 0.01%) false positives. In practice this desired outcome is not always achievable, but what industrial users will accept is still significantly more stringent than what can be achieved using, for example deep neural network models operating directly on the available image data. This contrasts with the well-publicized and very successful applications of AI for consumer use. In such an application suboptimal model outcomes are generally acceptable. Examples would be missing a potentially interesting search result, getting a suboptimal translation of a phrase in a document, or having an AI agent misunderstand a question and having to repeat or rephrase. For industrial applications, the available options are Retry and Skip and must be explicit operator decisions, that as just mentioned should not have to be requested of the operator more than once per 10000 parts produced.

On the other hand, traditional **hand tuned heuristics** can be manually optimized to deliver useful performance in industrial applications, but they are specific to a particular application and hardly generalizable. This drives up cost and time to implement. Thus, this limits applicability of traditional approaches (lots of manual tuning of mathematical heuristics) to cases where the combination of the production volume (must be large enough) and consequences of an incorrect decision (must be significant enough) makes economic sense.

Having said this, it is postulated that a **hybrid approach** will offer the benefits of AI approach despite the constraints of the industrial environment. In this hybrid approach, a preprocessing step is used to **aggregate the vision data into low cardinality feature vectors**. This preprocessing step can be either a manually designed and parameterized heuristic or an AI model running at the edge.

As part of AI-PROFICIENT we have developed software to support both approaches:

[1] https://en.wikipedia.org/wiki/Surrogate_model

- The manually specified heuristics are based on traditional pattern matching[2]. This is approximately equivalent to a neural network consisting of a single 2D convolutional[3] layer followed by a summation layer applied iteratively over a larger input image, i.e., a combination of neural network and iterative search. The area of interest over which the iterative search is applied is manually constrained to increase performance. This runs at the edge and is applied as a data aggregation solution to CONTI UC7 – Tread packing. 2D images are converted into positions and distances from nominal positions at the edge.
- For AI based preprocessing, we support both supervised models (Deep neural networks) and unsupervised models (clustering type models). We will validate the application of a supervised model for classification of tread cuts in CONTI UC5 – Tread cutting. A preprocessing step converts the point cloud data from a scanning laser triangulation sensor into a depth map which is fed to the DNN that classifies the tread cut as good or not good.

Intelligent clustering in a bin picking application

This was a laboratory (out of factory) development to design, implement and test an intelligent clustering at the edge capability. A meta-adaptation operator in the form of a search heuristic is used to select parameters for the primary clustering operator that is a traditional machine learning approach. The bin picking domain was selected as we internally considered it a domain that would maximize exploitation opportunity based on customer requests. In the car industry, the standard approach for delivering small to medium sized, complex geometry components (e.g., car door hinges) for assembly, was to either to manually preposition them on a tray with fixed locations in the warehouse or do this manually just outside the assembly cell.

In the last five years, bin picking has matured enough that these components can be delivered mixed inside a bin and bin picked and positioned for assembly via robotic means. However, the approach is not highly reliable and in many cases the pick fails, and components are returned to the bin for re-picking. Also, the pick is inaccurate and an intermediate alignment and -as needed- orientation reversal step is required. While these approaches can work, they increase cell cost and lead to variable cycle time which means that the customer needs to design based on the worst-case cycle time.

Our approach tries to make direct picking and positioning possible, with no intermediate steps and without returns. We also deal with the challenging problem of mixed object bin picking where more than one kind of object is in the same bin as can be seen in Figure 2, as well as an intermediate result of the clustering. While it was originally intended to use a clustering approach to preprocess the image input of CONTI UC-7, it was not necessary for the final system.

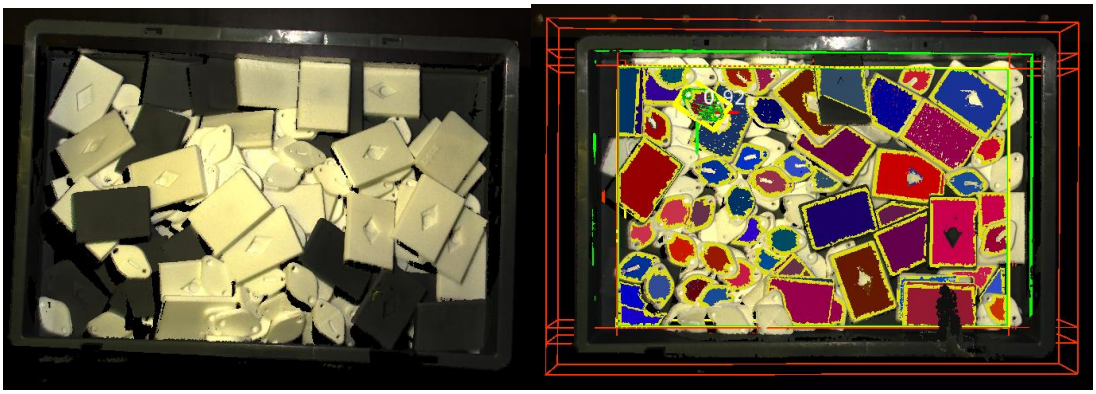


Figure 2: Point cloud input to the bin picking system(left). Intermediate clustering result with optimized clustering algorithm parameters (right)

[2] https://www.jot.fm/issues/issue_2010_03/column2.pdf
[3] https://en.wikipedia.org/wiki/Convolutional_neural_network

3.2 AI approaches for component self-diagnosis

Self-diagnosis in condition monitoring refers to the ability of a system to monitor its own variables and detect deviations that could indicate a developing fault. Depending on the degree of accuracy of the output of the self-diagnosis system, three different types of self-diagnoses can be distinguished:

- **Anomaly detection** refers to the process of identifying deviations from normal system behavior, which can indicate the presence of a fault or failure. This approach often involves the use of statistical analysis, machine learning algorithms, or other similar techniques to identify abnormal patterns in system data.

- **Health-index based** approaches, on the other hand, involve the use of a calculated health index that provides a quantitative measure of the system's health status. This index is typically based on a combination of sensor data, performance metrics, and other relevant information that can provide an overall picture of the system's condition.

- **Diagnostic based** approaches involve the use of explicit diagnostic models that are designed to identify the root cause of a fault or failure. These models are typically based on a detailed understanding of the system's components and how they interact with one another, and may involve the use of expert knowledge, fault trees, or other similar techniques.

Each of these approaches has its own strengths and weaknesses, and the choice of approach will often depend on the specific requirements of the application, the available data, and the desired level of diagnostic accuracy. In addition, it is also possible to combine various of the previous to develop more holistic solutions. This would be known as a hybrid approach.

On the other hand, when speaking about AI based self-diagnostics in most of the cases the focus is the construction of a ‘virtual’ model that can mimic the behavior of the physical asset. Whereas this modelling can be done through different approaches, such as physics-driven, data-driven or a combination (hybrid) based models, this work focuses in particular on data-driven based modelling, as physics-based approaches have been linked to cloud-based scenarios and are reported elsewhere (WP4).

Regarding these data-driven or data-based models, are created by means of modelling data coming from the system/asset. there mainly two branches of machine learning that contribute to the core of self-diagnostic models:

- **Unsupervised models** are used when there is no data that reflects the bad condition of the system (no labelled data exists). In such scenario, some other assumptions need to be made to model the existing data. Traditionally this is the case of the statistical process control (SPC) that assumes the data is normally distributed and detects deviations from that distribution. However, the limitations of the traditional univariate models have been overcome by more recent one-class support vector machines, isolation forests and other clustering algorithms. Unsupervised models are mostly used for **anomaly detection** as, typically, data related to faults is scarce.

- **Supervised models** are used when the data that is going to be modelled has a target variable or label. At the same time, this label can be of different nature. If it is a continues variable, we will talk about a **regression problem**; otherwise, if the target variable is categorical, it will be a **classification problem**. There is an extensive number of algorithms that serve for regression of classification problems. Typical classification algorithms include logistic regression, decision tree, random forest, and support vector machines. More recently, neural networks, Deep Learning models and boosted trees are gaining more attention on the literature. Most of the previous algorithms (but the logistic regression) have their counterpart version that are adapted to work on regression scenarios. Both **Health Index based,** and **diagnostic approaches** rely in supervised models, as they require to have signal data together with the labels (wear percentage or type of fault).

The most important factor in order to choose among the potential algorithmic approach is indeed the type of data that will be available for the development of the diagnosis system. When only good condition data will be available, unsupervised models will have to be chosen. On the contrary, if labelled data (faulty data, degradation evolution data, etc.) will be acquired, it will be better to opt for a supervised approach, as it will provide a higher degree of detail in the diagnosis.

3.3 AI approaches for data-driven edge industrial prognostics

Prognostics involves predicting the future health state of a system to anticipate potential failures before they occur (Jardine at al., 2006). This prediction can take the form of a forecast of the remaining useful lifetime or an estimation of the system's health for future operations. Prognostics relies on the features generated by the condition assessment step and the output of the diagnostics step.

As noted in the literature (Peng et al., 2010), prognostics can be broadly categorized into three main types: physics-based models, data-driven models, and hybrid models. Physics-based models make predictions based on physical laws and principles governing the system. Data-driven models rely on historical data to learn the system's behavior and predict its remaining useful life (RUL). Hybrid models combine both approaches. AI-PROFICIENT aims at leveraging AI techniques and as such the proposed approach relies on data driven techniques.

Machine learning has already been extensively used in system health prognostics, with promising results. In (Leukel et al., 2021) a systematic review has been conducted on prognostics of industrial systems using machine learning, which involves using data-driven methods.

One example of an advanced learning model that has been applied in different scenarios is the **long-short term memory neural network (LTSM)**, which is the basis of part of the work performed, as explained in (Chaoub et al., 2021).

In short, the approach relies in the combination of LSTM networks with Multi-Layer Perceptron (MLP) models, forming an architecture based on a Multi-Layer Perceptron (MLP) - Long Short-Term Memory (LSTM) - Multi-Layer Perceptron (MLP) structure. In short **MLP-LSTM-MLP**. This hybrid architecture combines the strengths of both MLP and LSTM networks, allowing the model to effectively learn and capture complex patterns within the data. MLP layers provide the capacity to learn non-linear relationships, while the LSTM layers enable the model to retain and process information over extended time periods. This specific architecture has been proposed in a prior study (An et al., 2020) and has exhibited encouraging outcomes for diagnostic purposes. Such architecture, should be able to overcome two main drawbacks:

- Introducing an initial feature selection phase can potentially hinder the modeling process by removing important information and subtle signals that experts may have missed or overlooked.
- Well-designed and uncomplicated neural networks often perform just as well as more intricate deep learning models. The latter requires extensive and energy-intensive experimentation to fine-tune their hyperparameters, which poses a technical obstacle for industrial applications.

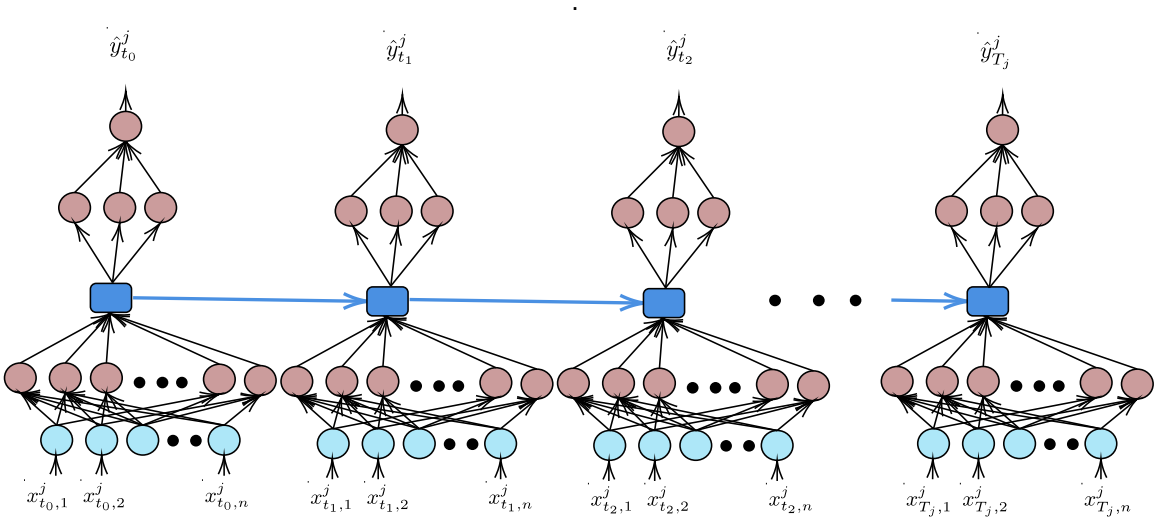


Figure 3: Architecture of the proposed model. To simplify the diagram, only one layer has been drawn for the MLPs.

There are different, complementary ways to take advantage of this architecture in order to develop effective prognostic systems: One of them (Chaoub et al., 2021) is to train on the well-known C-MAPSS dataset; this dataset is probably the most used for prognostics purpose. The C-MAPSS dataset has been generated using the simulation program by monitoring the degradation of multiple turbofan engines called commercial modular aero-propulsion system simulation (Saxena et al., 2008). In addition, it is possible to apply mechanisms to interpret these industrial data-trained deep learning models. This can be achieved through the application of mixture of experts, such as **Gated Mixture of Experts (GMoE)**. The combined structure of the model is presented in Figure 4. The first MLP layer of the previous model is replaced by a MLP GMoE.

This architecture has the advantage over MLP-LSTM-MLP if there is a scenario where different Operating Conditions (OC) are used to generate the data (For instance, previous Turbofan dataset C-MAPSS includes 6 different OC): It is expected that the first part of the model, i.e., GMoE, will be able to retrieve/discover that the turbofan measurement were done under several operating conditions (OC).

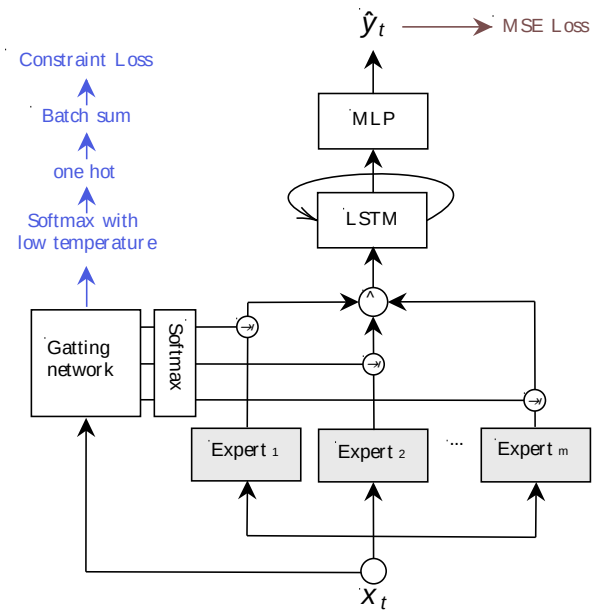


Figure 4: GMoE-LSTM-MLP architecture with m experts.

3.4 AI approaches for field automation control system engineering

Closed-Loop Control Systems are paramount for a correct adjustment of current process values to the desired references. The advances in control science are geared toward the improvement of the over/under shoots that are created by the controls, their settling time, and the oscillations. That is, bringing the control systems as close to theoretical optima (where system responses exactly match reference values) as soon and as smoothly as possible. And, in that sense, the use of Artificial Intelligence to enhance control systems is a promising yet not sufficiently studied topic.

In general, 14 steps can be considered during the development of a control system according to Skogestad & Postlethwaite (2005):

1. An in-depth study of the target system to understand the control objectives.
2. A model of the system.
3. Characterization of the model.
4. Deciding the controlled outputs.
5. Deciding the measurements (sensors) and manipulated variables (actuators).
6. Selecting the control configuration.
7. Deciding the type of controller.
8. Determining performance specifications in relation to the control objectives.
9. Designing the controller.
10. Analyzing if the controlled system meets the specification and adjusting if needed.
11. Simulating the controlled system.
12. Re-adjusting from the creation of the system model (2) to the simulation (11) if needed.
13. Choosing hardware and software to implement the controller.
14. Testing and validating the control system and tuning the controller on-line if needed.

These steps are depicted over the typical elements of the control system that are related to in the following Figure 5, which includes the groups suggested by AI-PROFICIENT work-team.

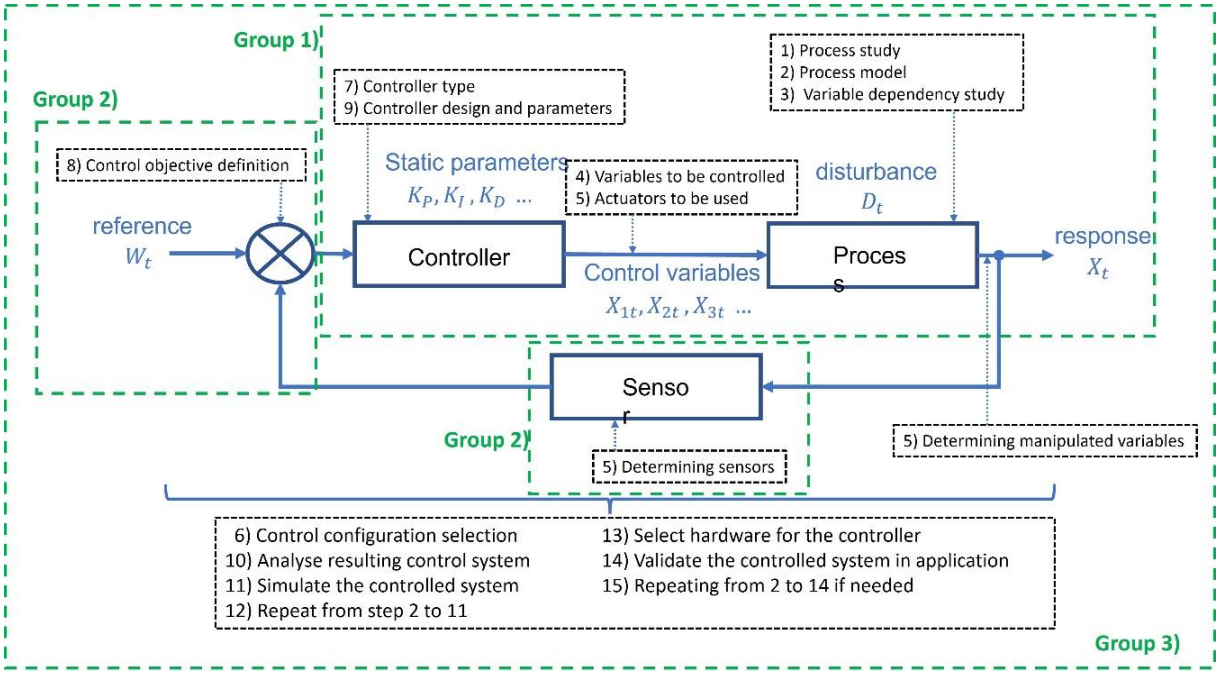


Figure 5: The different steps for the development of a control system. Adapted from (Schöning et al., 2022)

The question is, which of those steps could be improved using AI, and how this could be done. In that sense, the different types of AI enhanced control are elaborated in the following section.

The role of AI supporting control systems

Considering the elements of a control system and their development lifecycle, AI can be used with different purposes in order to enhance the overall control system. Some literature works distinguish among three types of AI enhanced control AI-based Process Modeling, AI-based Parameter Tuning and AI-based controller (Schöning et al., 2022). However, according to the experience of the partners collaborating in the AI-PROFICIENT project, this definition could be extended with two additional types: AI-sensed control and AI-referenced control. At the same time, these types can be categorized in the following three groups (which are depicted in Figure 5).

Group 1) Controller tuning related:

- **AI-based Process Modeling**: The role of the AI in this situation is to build a model that represents the physics of the process so that the model can be used for the development of the control. In this sense some AI techniques are well known for their capability to model any measurable function making them particularly well suited for this purpose. For example, the artificial neural networks (ANN). As this technique requires collecting data first (to train the AI), it is sometimes used in combination with physical models that could represent extreme cases, that are more difficult to record. This field is known as physic informed AI.

- **AI-based Parameter Tuning**: Most of the industrial control systems rely on the use of PID (Proportional Integral Derivative) controllers. These controllers need the fine tuning of the PID parameters so that optimal control is reached. This is typically done by using some specific techniques such as Ziegler-Nicholas tuning, Kappa-Tau tuning or, more recently, heuristic tuning. However, these tuned parameters are static and may no more be optimal as the process drift due to change in ageing, operating condition… according to some authors, AI could be used to generate the parameter sets online. This would lead to a reduction on the computation complexity of the problem in non-convex optimization problems.

Group 2) Controller sensing related:

- **AI-sensed control**: This type of control consists of the use of AI to sense magnitudes without using additional hardware. This type of control is particularly interesting in cases where some magnitudes that affect the system are hard or expensive to measure. This type of technique is also known as virtual sensors.

- **AI-referenced control**: There are other cases in which AI is used to create references that are given to the control. For example, future estimations or other external aspects that cannot be directly measured by a sensor (for example, the presence or the absence of an object on a vision camera) that are used to modify the reference.

Group 3) Controller sensing related:

- **AI-based controller**: This type of controller is given in cases where the AI takes absolute responsibility of the control of the system. From the sensor readings to establishing the references. Reinforcement learning like techniques are popular for such situations. In those scenarios, AI algorithms learn control policies by iterating with the environment in an autonomous way.

Given the criticality and lack of supervision of many control systems, their robustness is paramount. In that sense, including in their development innovative technologies such as AI which that are considered “black-boxes” (with limited capability to trace and understand errors) is complex. For that reason, more conservative approaches (either the ones presented in Group 1 or Group 2) are more likely to be adopted in industrial environments, where any error that might occur has to be traced back and purged without any room for uncertainty.

4 Edge AI use case applications

Potential use case applications from existing pilots were thoroughly analyzed during WP1, and an initial best-case scenario of potential applications was reported at deliverable D1.3.

Table 5: Original excerpt of expected partners involvement in WP2 AI use cases (from D1.3).

Task	CONTI-2	CONTI-3	CONTI-5	CONTI-7	CONTI-10	INEOS-1	INEOS-3
Pre-processing			TEK/INOS	CONTI/INOS	**	**	**
Self-diagnostics	TEK	UL	TEK/UL/IBE	INOS			
Self-prognostics	TEK	UL	TEK				UL
Control	TEK		TEK*	INOS/TEK*			

(to be confirmed; ** contribution to preprocessing from multiple partners)*

Since the definition of those links, the project has matured and the content of D1.3 cannot be longer considered updated. Several considerations apply: Most important reason is that several use cases are better addressed from cloud perspective. This is the case for instance of CONTI-2: The complexity of the problem, including different data sources and the way operators must interact with the solution implies that the approach should be better tackled from a platform/cloud perspective than from a local one, and therefore the solution has been developed as part of the platform solution (WP3). Likewise, use cases CONTI-10 and INEOS-1 and 3 have included that pre-processing functionality at platform level. Last, the inclusion of field automation solutions at real working environments can jeopardise operation, so the consortia have taken advantage of test beds already existing at partners facilities to use them as additional demonstration workspaces, where AI-PROFICIENT outcomes have shown their relevance in edge-level manufacturing scenarios beyond the actual pilots. In particular, this applies both to the cases described as TEK-ADD and PHME21 below, that are explained as part of the implementation of AI technologies for self-diagnostics and field automation respectively.

Therefore, final application table includes the following use case scenarios:

Table 6: Final updated application table (Newly added Use Cases)*

Task	CONTI-3	CONTI-5	CONTI-7	TEK-ADD*	PHME21*
Pre-processing		INOS	INOS		
Self-diagnostics		TEK			TEK
Self-prognostics	UL	TEK			
Control				TEK	

A detailed description of each technology application of them follows.

4.1 Pre-processing UC1 (CONTI-UC5) - Cutting Blade image preprocessing.

4.1.1 UC description

The aim of CONTI-UC5 is to develop a solution that will allow the operators and maintenance managers know about the current wear state of the blade that is placed on the thread cutting system. In a daily basis, this blade keeps wearing until there is a point in which it produces bad quality cuts (hence, having to scrap the tread it cut) or it gets stuck, and the production line has to be stopped.

Given the current situation regarding the data affecting the tread cutting systems, it seems that an interesting way of identifying wear status can be through a visual assessment of the cut status. The tread cut quality is important in this process as the slanted cut is used to join the ends of the tread into the cylinder that becomes the outer surface of the tire in contact with the road. If the cuts are not correctly shaped, then the tires cannot be properly assembled, and the reject rate increases. An approach based on detecting the cutting quality could be done indirectly via the cutting motor current (which in turn depends on cutting blade condition and the material being cut), which is fast and

computationally efficient, but it should be complemented and verified by a direct cut shape-based approach.

Therefore, AI-PROFICIENT has proposed a vision system that can be used to provide an automated measurement of the goodness of the cut as an estimation objective by itself, that could be fed in a more complex blade wear estimation process with other indicators.

4.1.2 Proposed solution

Tread cut optical quality inspection of point cloud representations of tire treads with an edge deployed deep NN.

In CONTI UC5 an optical inspection method for tread cut quality control has been implemented. This is a **binary decision process, running at the edge**. The problem is ill defined as there are marginal cases where it is not immediately obvious whether the tread has been cut well or forced/snapped. To achieve this, we preprocess the 3D point cloud data into a depth map, which is a 2.5D representation, i.e., it is a 2D array where the value represents a height. This is a structured representation where neighboring locations (height "pixels") in the data structures map to neighboring sampled points on the tread.

An interface was developed to obtain a 3D point cloud from a KEYENCE LJ-V7300[4] laser triangulation profilometer as part of the existing INOS machine vision software. The GUI developed for configuring this interface is shown in Figure 6 below.

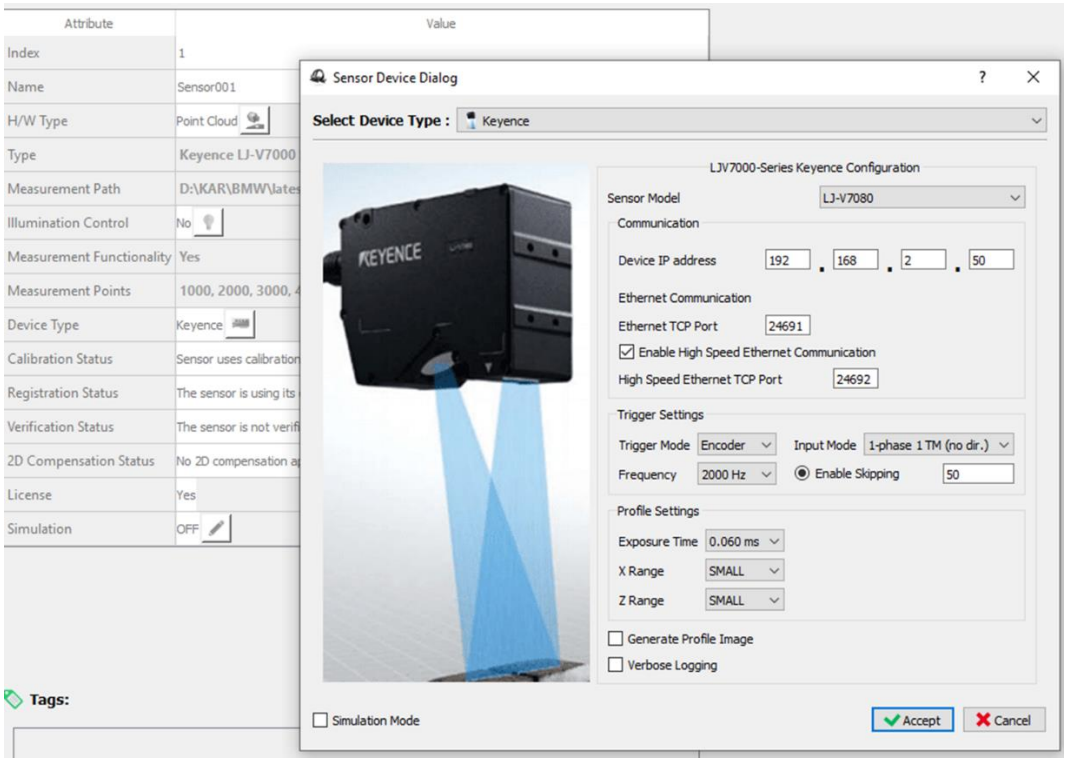


Figure 6: INOS Maestro configuration interface for the KEYENCE LJ-V300 profile sensor family

Once we have a point cloud, we convert it to a depth map where the value of each entry (pixel) corresponds to the height of the tread. Using this image equivalent input, we use TensorFlow 2.5 to train the model separating good from not good tread cuts. An example image of a depth map of a tread

[4] https://www.keyence.com/products/measure/laser-2d/lj-v/models/lj-v7300/

cut is shown next in Figure 7. On the left we display the 3D point cloud and on the right the 2.5D depth map.

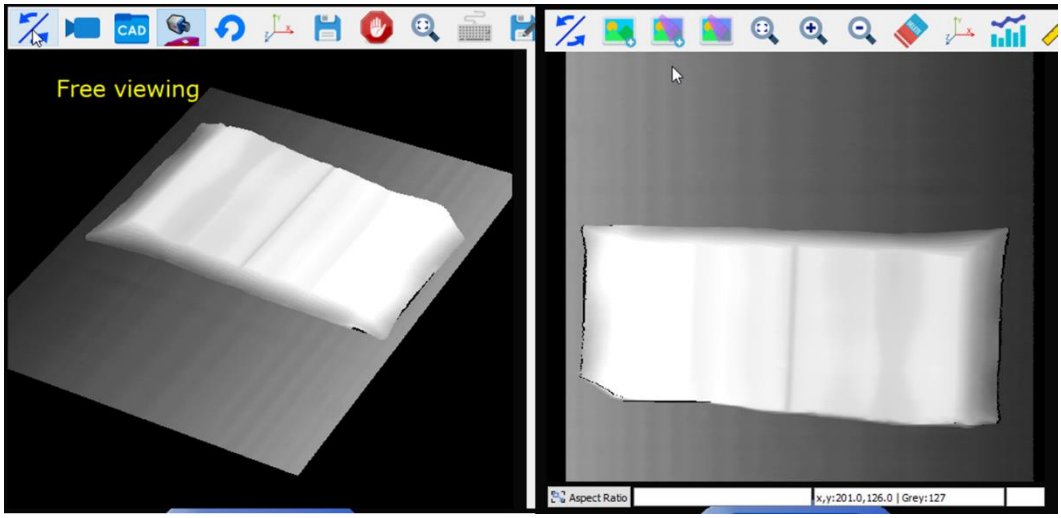


Figure 7: INOS Maestro view of 3D point cloud and 2.5D depth map of the end of a tread

Deep neural network used for defect detection in the automotive body shop.

Additionally, a concept and implementation validation test were used to verify the correct operation of the deep learning edge implementation and tune its user interface. We used an industrial dataset from an automotive body shop application. The body of a car is built from spot welded sheet metal. A large number of threaded studs (or bolts) is welded onto the self-bearing frame and is used to attach a large number of functional elements. The existence of these studs must be verified before the body is handed over by the body shop to the paint shop. As we had available a data set of such imagery, we used it to test the functionality and effectiveness of a deep neural network implementation for defect detection. The evolution of this algorithm was used for detecting tread cut quality as already described above.

An example of the above type of input is shown in Figure 8 below.

Figure 8: Example of stud defect detection with a deep neural network model

We also tested the same algorithm on multi-class classification applications for as built verification.

4.1.3 Deployment in AI-PROFICIENT platform

This AI service runs at the edge and a simple binary value is sent to the AI service in the AI-PROFICIENT VM (cloud). The results of the edge processing in an industrial PC (IPC) are then sent over an MQTT (IoT) interface to a MOSQUITO MQTT broker running on the AI-PROFICIENT VM and

a Telegraf[5] agent is the used to push them into an InfluxDB[6] database as shown in Figure 9. This is aligned with the technical solution adopted in D5.5 for measurement results from existing sensors, where the data from PLCs (Edge IPC layer) are made available via an OleDB server (MQTT broker) via the Telegraf middleware (common) to the InfluxDB time series database (common). This supports the use of historical measurements, which are required by the AI-services running in the cloud.

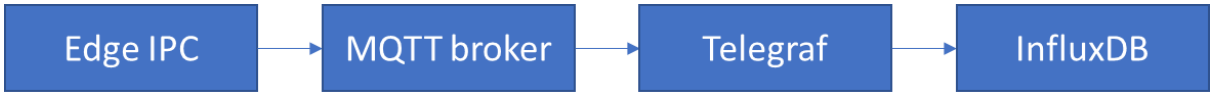


Figure 9: Sensor measurements database in Continental pilot – input from vision edge IPCs

4.2 Pre-processing UC2 (CONTI-UC7) – Tread alignment

4.2.1 UC description

Once the tread is cut it 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. Currently the task is just monitored by operator, and most of the time variations are detected too late. The objective for AI is to detect slow deviations to avoid quality issues, prevent low robot utilization (efficiency) and give predictive maintenance advice.

4.2.2 Proposed solution

As indicated previously, a **hybrid AI approach,** is proposed. A preprocessing step is expected to aggregate vision data into low cardinality feature vectors. This preprocessing step can be either a manually designed and parameterized heuristic or an AI model running at the edge. As part of AI-PROFICIENT we have developed software to support both approaches.

This runs at the edge and is applied as a data aggregation solution to CONTI UC7 – Tread packing. 2D images are converted into positions and distances from nominal positions at the edge. This leads to a reduction of input data from a few megapixels per tread over 4 detection locations to a feature vector of less than 20 real numbers which is forwarded to the AI services running in the AI-PROFICIENT VM (cloud).

Convolutional pattern search for measurement in noisy 2D images.

As already indicated the manually specified heuristics are based on traditional pattern matching. The area of interest over which the iterative search is applied is manually constrained to increase performance. Steps for configuring the operator are as follows:

1. The area of interest is graphically defined by the user on a nominal image.
2. The pattern of interest is selected by the user from the nominal image and a point of interest is defined in relationship to the pattern. This can be offset outside the pattern.
3. To get a repeatable and usable pattern we use directional artificial illumination that creates a shadow at the edge of the treads, enhancing contrast. At the software level exposure adjustment is used to maximize contrast while avoiding bleed-over of the bright tread top onto the edge shadow.
4. A detection threshold is defined corresponding to an argmax operator.
5. Subsampling of the input raster is supported to increase cycle time performance by sacrificing some accuracy.

[5] https://www.influxdata.com/time-series-platform/telegraf/
[6] https://www.influxdata.com/products/influxdb-overview/

6. The area of interest over which the iterative search (AOI) is applied is manually constrained to increase performance.

4.2.3 Deployment in AI-PROFICIENT platform

For CONTI UC-7, the packing area is divided into 3 zones of measurement, plus the tray area in which the treads are packed. In zones 1, 2 and 3 (see Figure 10) we use 2D cameras and very strong led illumination elements. In zones 1 and 2 with a larger standoff, the cameras and illumination are approximately collinear, and we rely on the true edge shadow to get high contrast for edge detection. In zone 3 the lights and cameras are in opposite orientations, and we use the enhanced edge shadow (due to larger light incidence angle) for the edge on the camera side. This installation approach was imposed by the available mounting height.

Multiple convolutional operators (measurement actions) as described in previous subsection are used to detect the location of the treads in the three zones of the packing station feeder and in the current leaf of the packing tray.

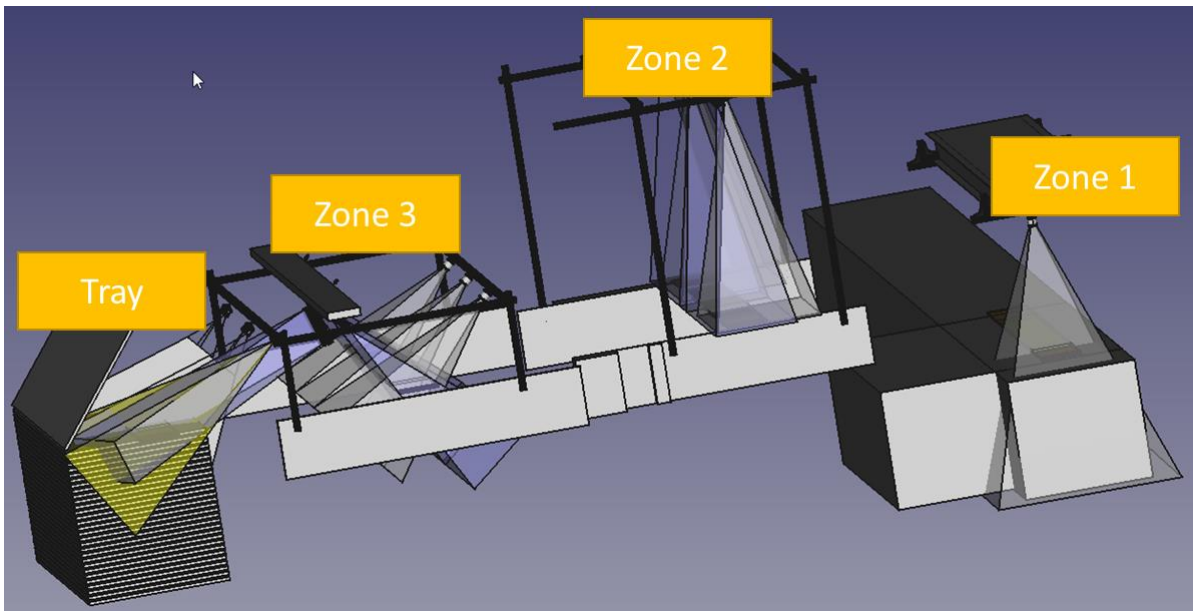


Figure 10: Measurement areas in CONTI UC7

Two high accuracy laser triangulation profile sensors are installed to provide the location of the tread long edges and the edge of the tray leaf. The sensors are factory calibrated and provide outputs in mm. Used in combination they are used to compute the location of the treads along the width (smaller dimension) of the tray and the rotation around the vertical axis (azimuth) of the tread against the longitudinal axis of the tray. Additionally, a high-resolution 2D camera is placed at an angle to the illumination to generate a high contrast shadow at the tread edge. This arrangement provides the location of the tread short edges against the short edge of the tray leaf. The final arrangement is shown in Figure 11. More details on the deployment are provided in D2.2.

Figure 11: Installed measurement system on the first zone of the belt transporter

4.3 Self-diagnosis UC1 (CONTI-UC5) - Cutting Blade wear diagnostics.

4.3.1 UC description

As indicated before, the aim of CONTI-UC5 is to develop a solution that will allow the operators and maintenance managers to know about the current wear state of the blade that is placed on the thread cutting system. In a daily basis, this blade keeps wearing until there is a point in which it produces bad quality cuts (hence, having to scrap the tread it has cut) or it gets stuck, and the production line has to be stopped.

In light of this, CONTI wants to develop an intelligent system that would let the user know the approximate wear status of the blade. This way the operators will be able to replace the blade before it starts to produce low quality cuts, or it stops the production line. At the same time, it is desired that the diagnostics system could, somehow, support the creation of scheduled replacements that would reduce the amount of curative mode changes of the blade. This UC solution focus is on the most available data source (reliability measures).

4.3.2 Proposed solution

The first challenge of this use case is the low availability of the data. In principle, there is no direct way of knowing the exact amount of cuts a blade has carried out before it wore out. In that sense, one of the major challenges of this UC relies on the “data-fusion”, that is, retrieving data from different databases and combining it to produce meaningful data that could be used by the algorithms.

First stages of algorithm development.

Given that the data-fusion process was challenging, the development of a potential algorithm was started with simulated data.

For that purpose, a literature review was carried out identifying works that had measured the wear development on similar blades. According to the Lopez et al. (2022) most of the works showed constant wearing speeds (see following Figure 12). However, this was not always the case, as some works showed varying wear speeds, tough less frequently, as in Figure 13.

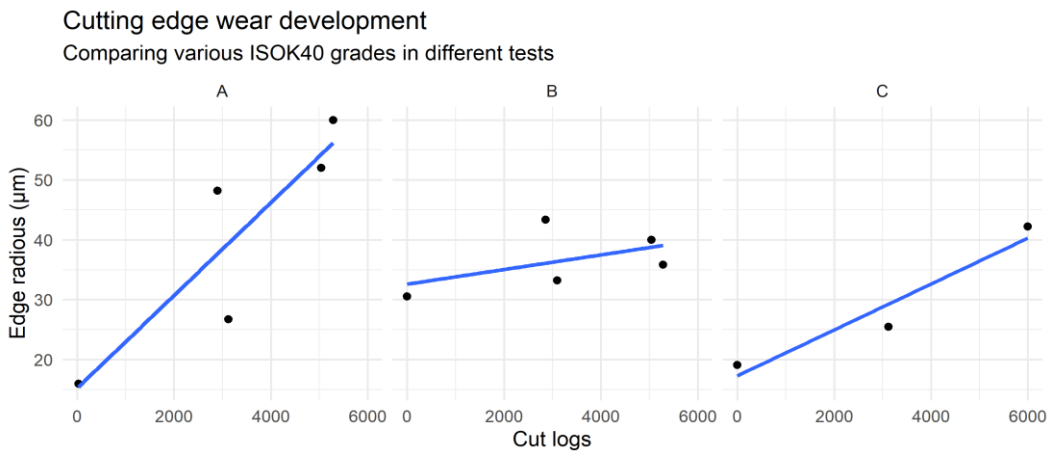


Figure 12: Example of cutting-edge wear development. Adapted from Ekevad et al. (2012)

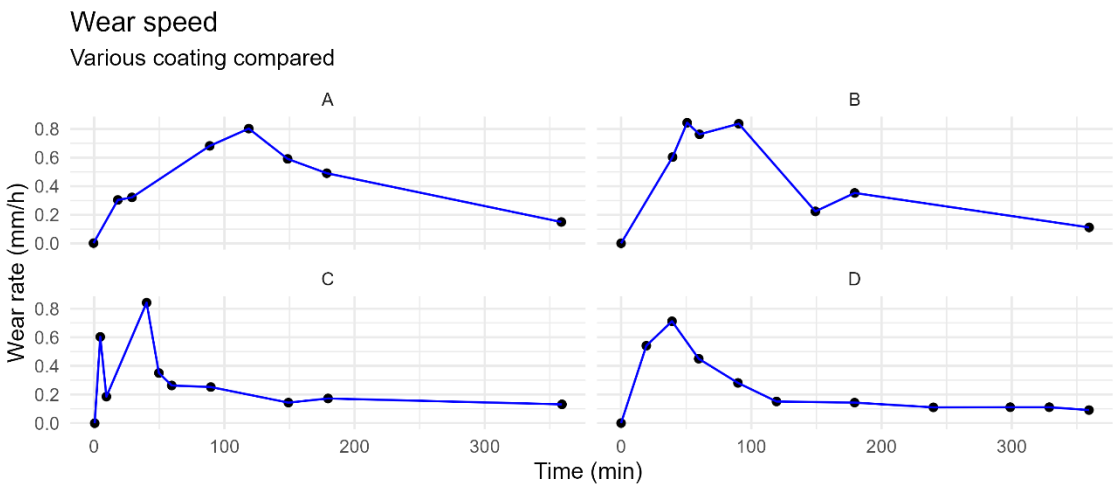


Figure 13: Another example of wear speed in blades with different coatings. (Lau et al. 2000)

Consequently, it was decided to design a model that would try to identify the wear-speed based on the data from the database. Different potential wear-speed patterns were tested and the one that best fits the database would be chosen. The following Figure 14 displays the different patterns that were tested on the synthetic data.

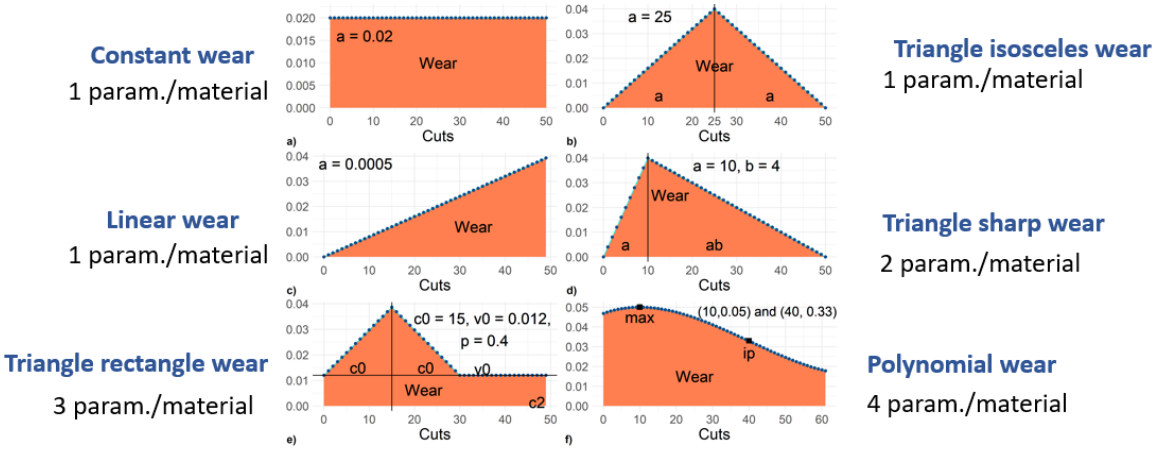


Figure 14: Different wear speed patterns tested on the synthetic data.

These wear-speed patterns would represent the health-index of the blade (inverse of the wear-index), that could let the operators know the approximate wear status of the blade. At the same time, each recipe (each different material to be cut) would have its own parameters, meaning the mechanical differences of the cut materials would be considered (which was one of the major sources of variability according to the literature survey).

The approach was validated by creating some synthetic data with noise from different distributions. Using some wearing patterns and the noise, a database was created (similarly to the one expected to have at CONTI-UC5), this database consisted of 200 blade lives, as the one presented Table 7.

Table 7: Example of a synthetic blade live.

Chronology	Recipe	Cuts
1	4	41
2	2	12
3	4	5
4	2	18
5	1	169
6	3	21
7	4	1

Once the database was ready, an optimization was launched to identify the different potential parameters that might have created the database, without knowing the exact wear profile used to create the database. According to the results, it would be possible to create a quite robust model that would represent the database data. However, the amount of noise on the original wear distribution would greatly affect the accuracy of that model. Further details on the approximation can be found in the work Lopez et al. (2022).

Real data retrieval.

In parallel to the theoretical validation of the proposed model, by cross-referencing data from different databases it was possible to build a dataset similar to the one required to test the approach. For that purpose, maintenance records (daily created free texts containing the maintenance actions carried out) were parsed so that the blade replacements were identified. At the same time, the signals representing the amount of good treads, the bad treads and the recipes were combined so that the total cuts per recipe and blade life could be computed. Nevertheless, it was detected that given the maintenance logs had low precision on the dates recorded (only the day and the shift could be known) the data had some noise.

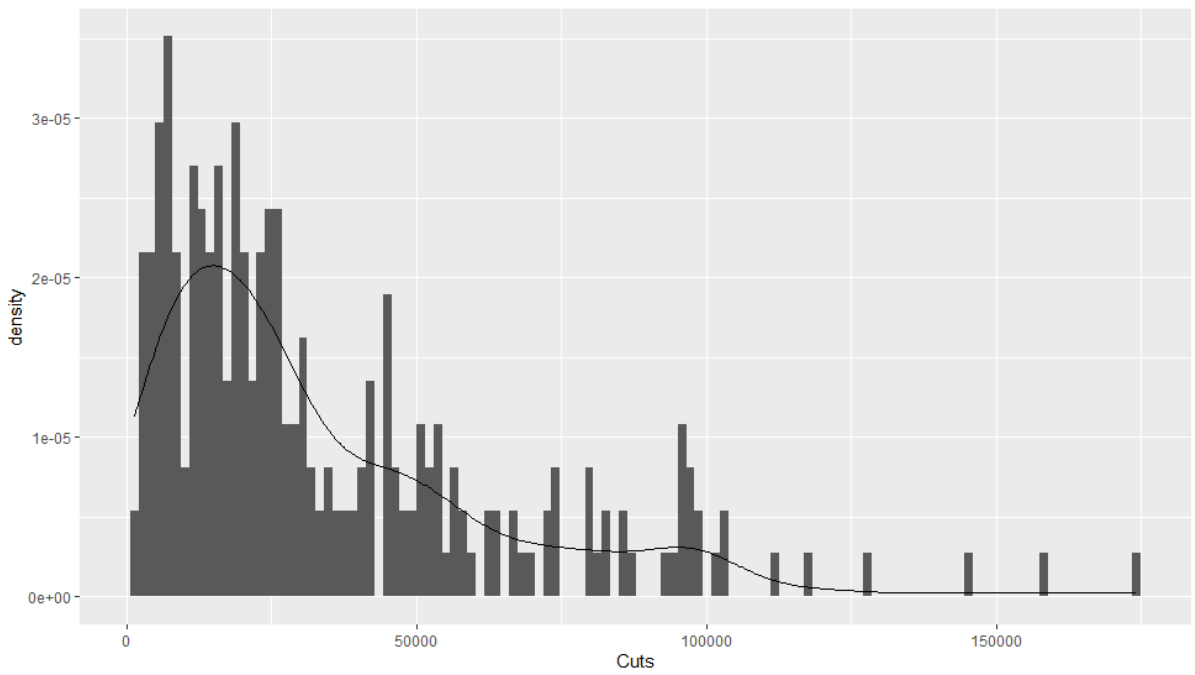


Figure 15: Histogram of final number of cuts of the blade life database.

As the previous Figure 15 shows, the blades recorded in the database follow a Weibull-like distribution. A total of 255 blades are available and there are some potential outliers that have “too many cuts” which could be caused by the non-robust data fusion system. At the same time, the existence of too many recipes is identified which, as it is greater than the number of blades, will mare the modelling through the proposed approach challenging (due to the number of parameters that need to be estimated).

Algorithms comparison.

To implement the best possible solution, the suggested approach was compared with more traditional approaches, such as Weibull based reliability and non-parametric Kaplan-Meier survival models. The problem of this kind of approaches is that their aim is different. Instead of modelling the wear that occurs on the blade, they try to approximate the survival function of the whole fleet, that is, the probability of an asset of being alive after certain number of time/cuts. One of the shortcomings of this kind of models is that they cannot be improved by additional information unless it through factors (not with many different values) or single continuous variables.

At the same time, it is well known that the cutting process is influenced by many external factors (Nasir & Cool, 2020) which, in an industrial scenario such as the one in UC5. On that regard, it could be considered that the major source of variability is the working-piece, that is, the mechanical properties of the material being cut. This kind of information could be transferred to a survival model by creating binary variables for the different materials (recipes) cut by a blade. But, given the vast amount of recipes and combinations, the number of samples per recipe is quite small. This would lead to a poor fitting of a big number of survival curves. Alternatively, the usage-based model requires a smaller number of parameters and can be fitted with less effort and data requirements.

In order to compare the usage-based approach with the survival like modelling, defining out of the box metrics has been needed. With these metrics, the potential performance improvement of the usage-based models has been tested.

The underlying assumption of the tests is simple: “If cuts are not equivalent in reality (because the materials have different hardness), is it possible to provide an alternative measuring dimension (Equivalent Cuts) that considers the materials that were cut and improves the survival fitting?”. To test such assumption, a regular fitting to a Weibull Distribution is compared to a fitting of the same model

after the Cuts have been recomputed with the usage model. To validate the approach in a statistically meaningful way, the data is first split in train/test split.

The results of the fitting are compared using three different metrics:

- Kolmogorov-Smirnov Hypothesis Test, which gives a comparison of cumulative distribution functions, and the test statistic is the maximum difference D. The underlying assumption is that the data follows a certain distribution (in our case the Weibull distribution) – Null hypothesis. Thus, we compute:
    - p-value associated with the null hypothesis that the data follows a Weibull distribution.
    - $\mathrm{D} = \max_{u}\left(F_x(u) - F_y(u)\right)$
- Coefficient of determination (R^2) can be computed:
    - $R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$

Finally, three scenarios are compared:

1. Directly modelling through fitting a Weibull distribution on Cuts
    a. KS-Test
        i. p-value = 0.08256
        ii. D = 0.084735
    b. R^2 = 0.9683114
2. Recoding Cuts with Triangle-Rectangle wear-speed model and Weibull fit on the Equivalent Cuts
    a. KS-Test
        i. p-value = 8.042·10^-7
        ii. D = 0.18214
    b. R^2 = 0.8609486
3. Recoding Cuts with Constant wear-speed model and Weibull fit on the Equivalent Cuts
    a. KS-Test:
        i. p-value = 0.2468
        ii. D = 0.068624
    b. R^2 = 0.9742978

Better results with Equivalent Cuts computed using a Constant wear-speed model, i.e., we obtain fitting to a Weibull distribution after pre-processing the data this way. However, computation time and complexity of this model may result in complication in the deployment from a practical point of view. Thus, simpler models, which still offer good fitting results, provide an adequate initial solution to this particular problem.

4.3.3 Deployment in AI-PROFICIENT platform

Given the vast number of recipes that CONTINENTAL uses during the production, managing all that variety is needed to enable the usage model. However, at some point the potential improvement that could be achieved by implementing the usage model is eclipsed by the effort needed to manage the variability of the recipes correctly. As the clustering of the recipes requires additional pipelines in order to reduce the number of parameters that the usage model needs to fit.

For that reason, it has been decided to finally implement the survival like model on the AI-PROFICIENT platform. This model will be simpler (and hence more robust) and will equally benefit from the existence of the human reinforcement system so that it can improve over time.

4.4 Self-diagnosis UC2 (PHME-2021) Fuse production line fault diagnosis

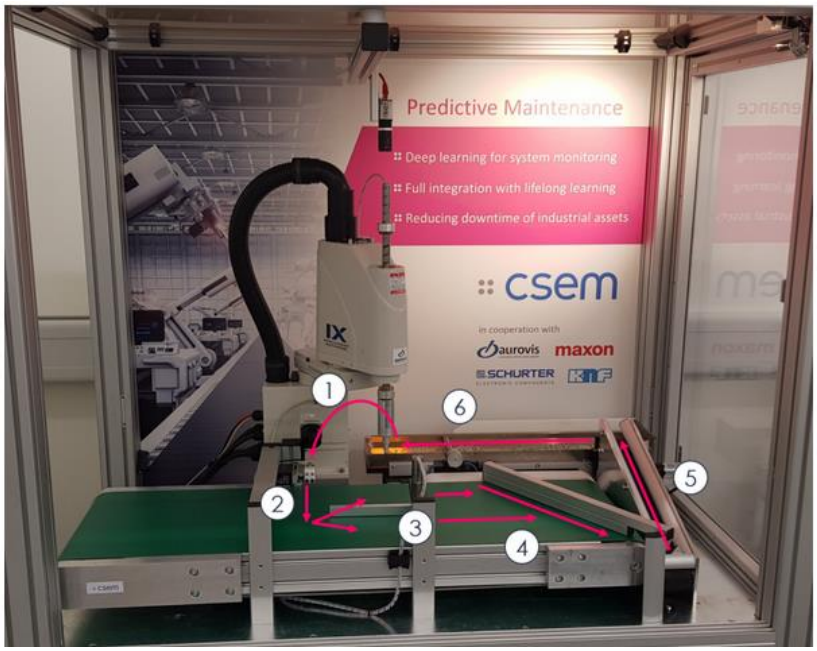
4.4.1 UC description

This use case is presented by the Prognostics and Health Management Society in Europe. This society wants to promote the development, growth, and recognition of prognostics and health management (PHM) as an engineering discipline and has worldwide recognition in that field.

In the year 2021, they organized a data-challenge, an engineering problem that consisted of building a diagnostics system for a fuse production line in which some faults occurred. This resembled a typical component of a large-scale quality-control pipeline of a production line. The experimental bed, courtesy of the Swiss Centre for Electronics and Microtechnology (CSEM), was used to generate data similar to a real-world industrial manufacturing line.

Besides the normal operating condition (class 0) 8 additional faulty states were recorded in the data. Participants were not given any clue regarding the type of fault that each different class could have, in fact, part of the challenge was identifying the signals related to each fault.

The following Figure 16 depicts the test rig used for the data generation.



Exp.	№
0	70
2	4
3	4
4	3
5	4
7	4
9	4
11	3
12	3

Figure 16: Left) Test rig used for data generation. Right) Number of tests provided for each faulty state.

The challenge had 3 different goals:

- Creating a diagnosis model that would correctly classify experiments.
- Provide diagnosis in the shortest time.
- Identify the root causes of the faults.

For simplicity's sake, only the diagnosis and the time consideration are explained in this deliverable.

4.4.2 Proposed solution

During the first exploratory analysis, typical issues occurring in industrial scenarios were identified. Including:

- **Missing values**: The sensor records had data that had to be dealt with.
- **Class imbalance**: As it occurs in most of the manufacturing/industrial scenarios, the target classes are imbalanced in favor of the nominal class, which is usually over-represented on the data.
- **Multi co-linearity**: Given the high number of signals and indicators, it is quite common that they are linearly correlated, which is a problem for certain algorithms and means some information is redundant.
- **High dimensionality**: As previously mentioned, the high amount of sensor and indicators leaded to a high dimensionality scenario, which can be challenging.
- **Experimental uncertainty**: Even if the test rig was the same, the sole fact of re-starting it leaded to different patterns on the signals. This variability was also something to take into consideration as some of the classes had only a couple of experiments.
- **Chronology in diagnosis**: Given that the goal was to provide a diagnosis in the shortest possible time, that meant to consider the sequences of observations which is not very common in the machine learning field.

In sight of the previous issues, different strategies were tested. Finally, it was decided to use Last Observation Carried Forward (LOCF) technique to deal with missing values. Class imbalance was tackled by using SMOTE-Tomek to resample the observations and balance the classification problem and tree models were chosen for the diagnostic system as they usually work better for scenarios with correlated variables. Overfitting over the experiments was fixed by using leave one group out validations scheme, where, each time, only data from the same experiments were taken for training and testing each time.

Different machine learning algorithms were tested and, in general, the performance did not change much from one to another. Nevertheless, some of the classes were difficult to identify regardless of the employed algorithm. To solve that matter feature engineering was used. With the inclusion of new features, it was possible to detect those difficult classes with a rather simple decision tree (DT). The final structure of the diagnosis pipeline is depicted in the following Figure 17.

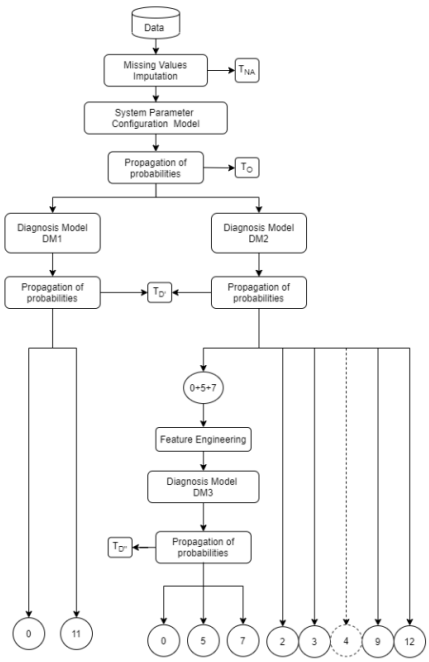


Figure 17: Diagnostics pipeline structure.

Regarding the shortening of the diagnostic time, it must be considered that the diagnosis algorithms was executed for each new observation, but the small changes in the signals could lead to completely different diagnosis values (see Figure 18: Left).

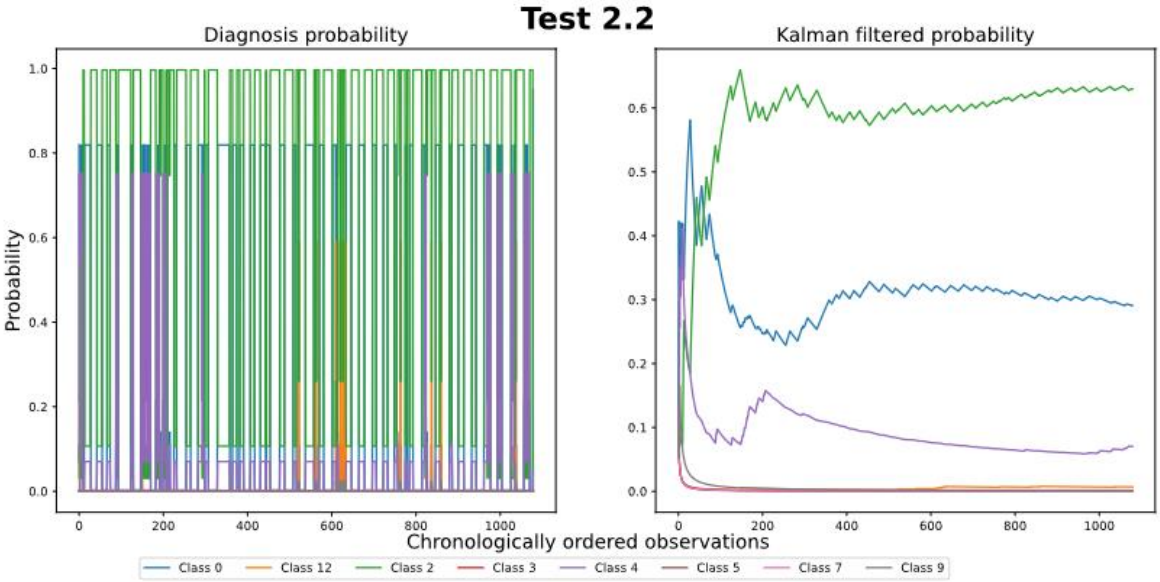


Figure 18: Evolution of diagnostic values over time with no filtering (Left). Diagnosis filtered with a Kalman filter (Right).

To avoid the oscillating behavior of the diagnosis algorithm a Kalman filter was fed with the probabilistic output of the algorithm. This filter would be able to identify the main trend of the diagnosis so that the prevailing diagnosis class could be detect, as Figure 18 Right) shows.

The solution here presented was the one that won the PHME-Data Challenge in 2021, proving the validity of the approach. More details can be found in Lopez et al. (2021), the journal paper where the solution was disseminated.

This solution belongs to a diagnostic type of problem were supervised algorithms (Decision Trees) have been used to build the diagnostic model that is able to distinguish among different faults. This is possible because the set of data contained fault related data. In such conditions, using supervised approximations was possible and preferred over unsupervised approaches that would be vaguer.

4.5 Prognostics UC1 (CONTI-UC3) – Extrusion drift prediction

4.5.1 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 effects after cutting are minimized to avoid length issues and bad weight repartition on the surface of the tire (RFPP deviations). There are 3 factors to consider minimizing tension in the product among which the easiest controllable during the production is the conveying, the 2 others being the flow balancing in the die and the visco-elastic phenomenon.

4.5.2 Proposed solution

In this use case, the service must predict the drift of the extruder that can lead to not relaxed product. When a not relaxed product is about to occur, some changes in the setting point of V1 need to be done. Such changes can occur manually or thanks to a control loop at the line level. Hence the goal of the model will be to prognosticate the remaining time before the V1 setpoint change.

Some data are available on PETA repository. Thank to discussion with Continental expert, we have defined some rules to segment the data into relevant segment. Indeed, this use case is focused on in-

production drift. Hence, all set-up time, stoppage, sidewall production, trials… have to be removed from the data. Only sequence of thread production have been kept.

The proposed solution is based on the MLP-LSTM-MLP model presented earlier. Furthermore, thanks to the analysis of the data and some initial trials, the use case has been reformulated as classification task for which the time frame remaining to a V1 setting point change occurs has to be predicted. Indeed, no other measurement of the relaxation of the product is available.

Initial development.

In this early development the class used as gold represents the number of half minutes remaining before change, this makes evaluating the performances of the model easier to understand and analyze. As shown in the Figure 19, when the time left to change is more than 5 minutes (before the green vertical line), the frames are considered to belong to a class that intuitively represents a relaxed product on the line.

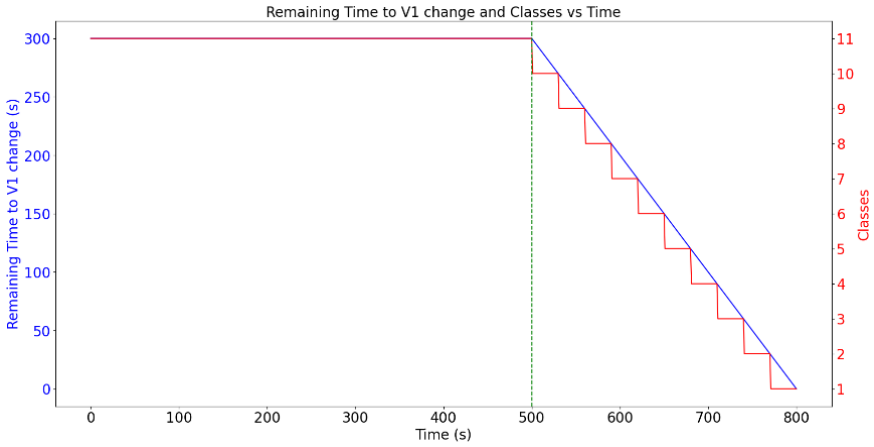


Figure 19: The remaining time to change with the true classes used for training the model.

In this development stage, we used only 1 month of data and did not fully optimize the model. The aim is more to agree on the objective of the model and the metric to evaluate the performances. Some results have been obtained and are shown in Figure 20.

As a conclusion, the proposed model can predict deviations in 60% of the trajectory, in the remaining 40%, the model always predicts a relaxed product (class 11). When deviations are detected, as shown in Figure below, most of the points are well predicted (they are around the diagonal), which provides proof of concept for the future development of the approach. When deviation is not predicted, it means the data doesn't contain relevant information and the V1 setpoint changes cause is not in the hot part of the Combiline.

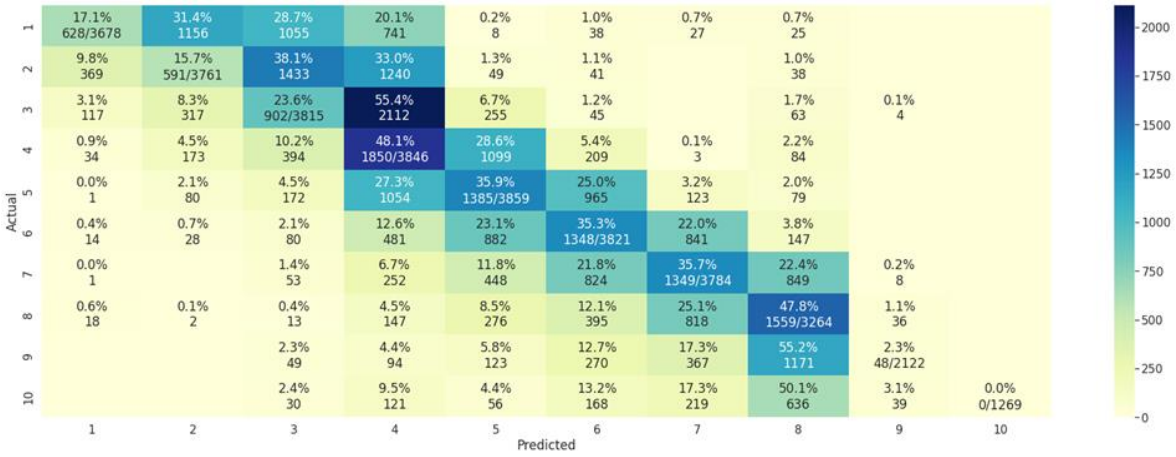


Figure 20:Confusion matrix between actual and predicted classes without the final class that represents the relaxed product.

The next steps for the models are to consider external factors that have some influence as reported by the process engineer and the Combiline driver, such as Air Temperature, type of compound… It is also planned to consider the whole dataset (over the 1,5 years) to train the model.

We are thinking of what must be delivered to the operator and as such, Continental and the ethic teams have been put in the loop. A preliminary ethical issue has been raised regarding how the operator's perception of the accuracy of the AI suggestions will affect the operator's trust and subsequent use of them. The issue can be partly addressed by making the operator's use of AI suggestions facultative, but attention to the format in which the suggestions are presented will also be needed.

Service development.

In order to further develop the prognostic model, we utilized data from the year 2021, as train and validation sets, and the first quarter of 2022, as test set, to assess the model's generalization capabilities. This was done to ensure the model's accuracy and relevance in predicting outcomes based on real-world production data. To simplify the predictions and make them more accessible for operators, we reduced the output classes from 11 to 6. Instead of using half-minute increments for measuring the time remaining for set point V1 change, we opted for a one-minute frame. This decision was driven by the need for clear visualization and easier interpretation, as depicted in Figure 21.

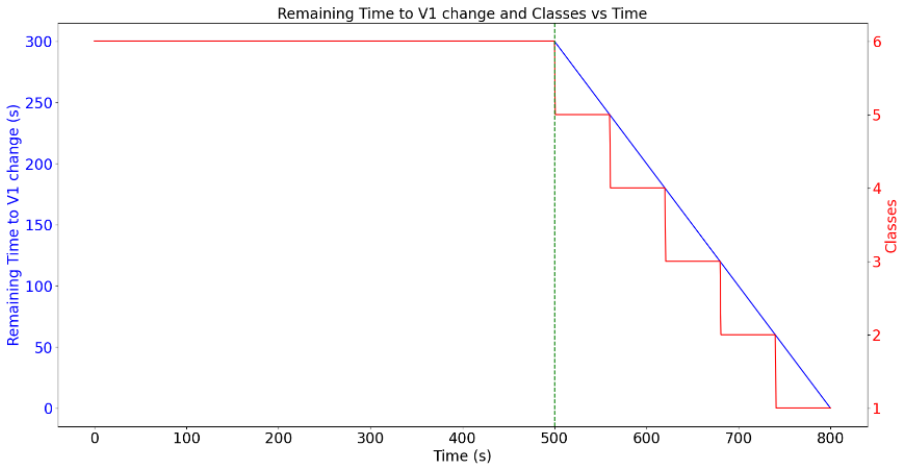


Figure 21: The remaining time to change with the new gold classes used for training the model.

For the development of this model, we used data collected during the production process in 2021. The initial step involved clustering production times, which yielded multiple trajectories representing various

production phases. In order to build a model capable of predicting changes in the V1 setpoint, we only considered trajectories that exhibited this change. This meant excluding stable productions from our dataset, leaving us with approximately 60% of the total trajectories.

The performance of the prognostic model, based on MLP-LSTM-MLP is illustrated through confusion matrix heat maps generated using multiple trajectories from the first quarter of 2022. These heatmaps display the predicted values against the true values (see Figure 22).

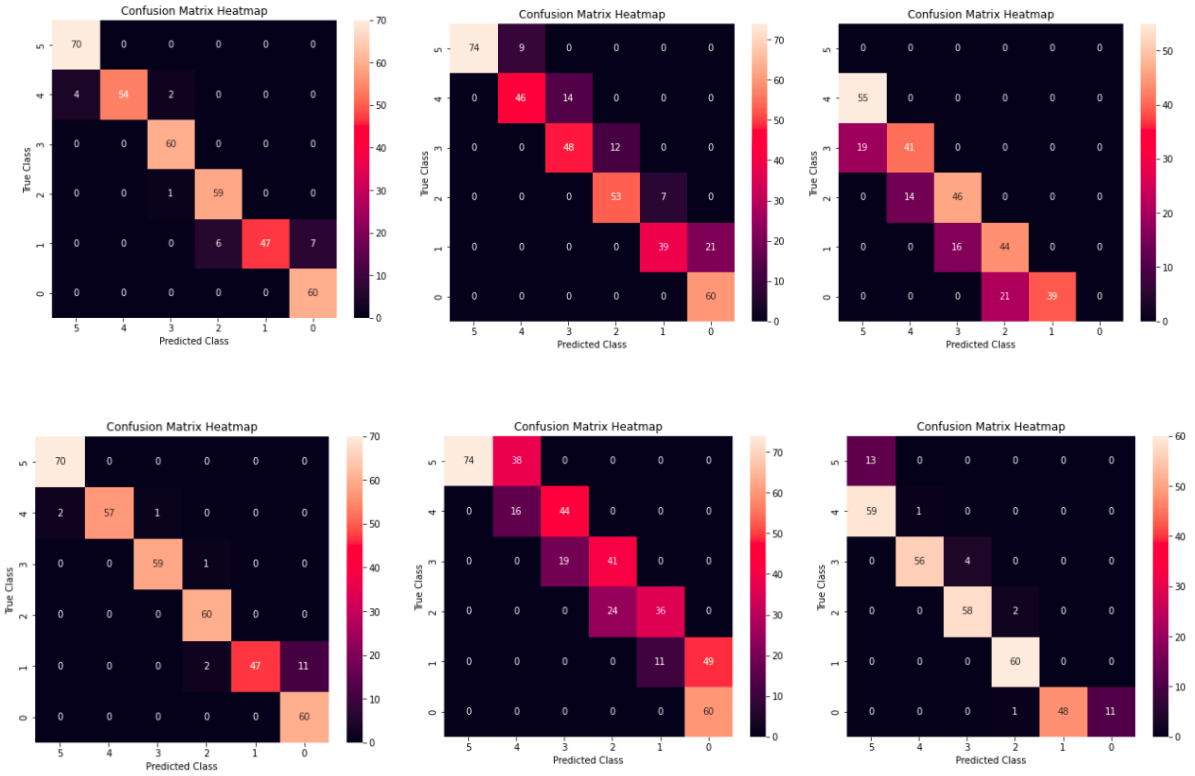


Figure 22: MLP-LSTM-MLP results

While the overall accuracy of the model exceeds 60%, it is important to note that the previously encountered issue of only predicting one class has been resolved, enabling the model to predict deviations more effectively. The relative loss in accuracy can be attributed to some values not being situated directly on the diagonal, indicating that there may be occasional discrepancies between the predicted and true values. However, these discrepancies are generally minor, with predictions often being slightly early or late compared to the true values. The overall results are still considered to be satisfactory, as the model is capable of capturing the essential dynamics and changes in the V1 setpoint.

4.5.3 Deployment in AI-PROFICIENT platform

The goal was to develop a model specifically designed for prognostics. This model would be preceded by another model specializing in diagnostics, making the learning process more efficient and resulting in smaller, more manageable models. The implementation of such models on the edge would enable real-time monitoring and analysis, ultimately improving the overall production process. By employing a two-stage approach, with separate models for diagnostics and prognostics, we can effectively identify issues in the production process and predict potential changes in the V1 setpoint. This streamlined system will not only enhance the accuracy of predictions but also facilitate easier implementation and interpretation for operators in a production setting. Figure 23 presents the corresponding architecture.

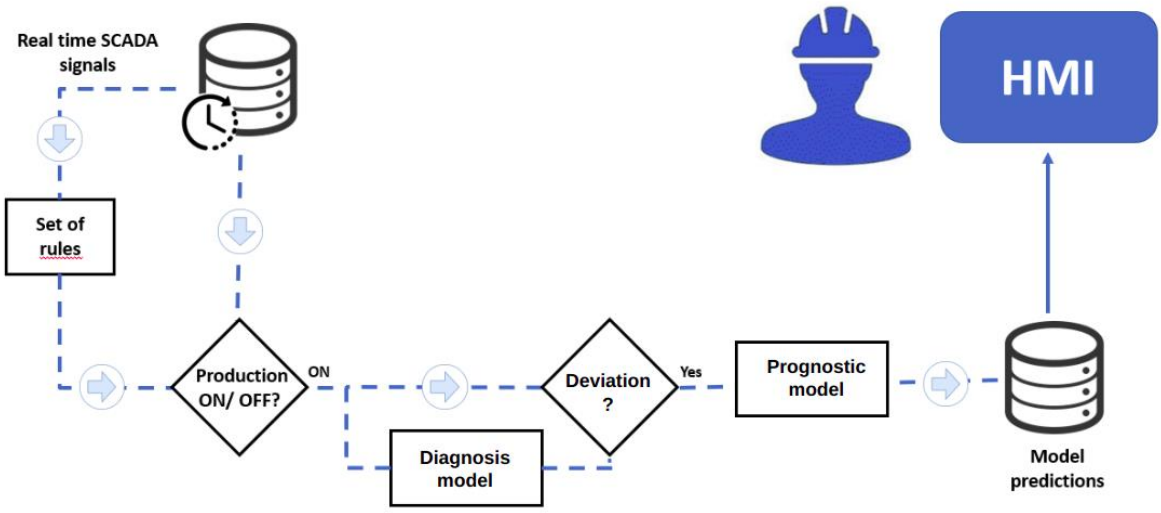


Figure 23: implementation architecture of the CONTI-3 prognostic service.

At some point during the deployment of the prognostic algorithm it was detected that the V1 values were not truly representative of a relaxed product on the production line. This finding led to the reconsideration of the prognostic/diagnostic model's utility, as the V1 values may not be a reliable indicator of the product's actual state or quality during production. Consequently, any model built upon these values would not be able to deliver accurate assessments or predictions regarding product quality or potential issues within the production process. Under such circumstances, and, considering the potential harm that providing misleading predictions could produce to operators, it was decided to cease the deployment of the algorithm in the AI-PROFICIENT platform. In any case, the prognostic algorithm and its value have been validated and would produce satisfactory results under good data quality conditions.

4.6 Prognostics UC2 (CONTI-UC5) - Cutting Blade wear prognostics.

4.6.1 UC description

The aim of CONTI-UC5 is to develop a solution that will allow the operators and maintenance managers to know about the current wear state of the blade that is placed on the tread cutting system. In a daily basis, this blade keeps wearing until there is a point in which it produces bad quality cuts (hence, having to scrap the tread it cut) or it gets stuck. Consequently, the production line has to be stopped and the blade replaced incurring in the consequent downtime costs.

The first steps towards the development of the algorithms that would enable CONTINENTAL deciding when to change the blade according to wear estimations are detailed on deliverable D2.3 - Predictive AI analytics for component self-diagnostics (for further details, please refer to this deliverable's chapter 3.1). As stated in D2.3, survival-like models try to model the probabilities of an asset being alive after certain usage/cuts. Yet, from the operator point of view, this information is not easily applicable on the production line and its counterintuitive, as the survival value of 0.95 does not mean that the blade that is currently working is at the 95 % of its live, instead, it means only 5 % of the blades do that number of cuts. For that reason, a workaround that will allow the users have a more understandable algorithm as well as to give some prognostic capabilities is needed.

4.6.2 Proposed solution

Considering the previous, it is decided to produce a Health Index that will to reflect the health condition of the asset that implicitly considers the probability shown by the survival function. This Health Index (HI) rescales a certain number of cuts to a 0-1 scale. This way, the algorithm can be used not just for diagnosis purposes but for prognosis purposes, as, the estimated remaining HI can be known based on the expected future cuts.

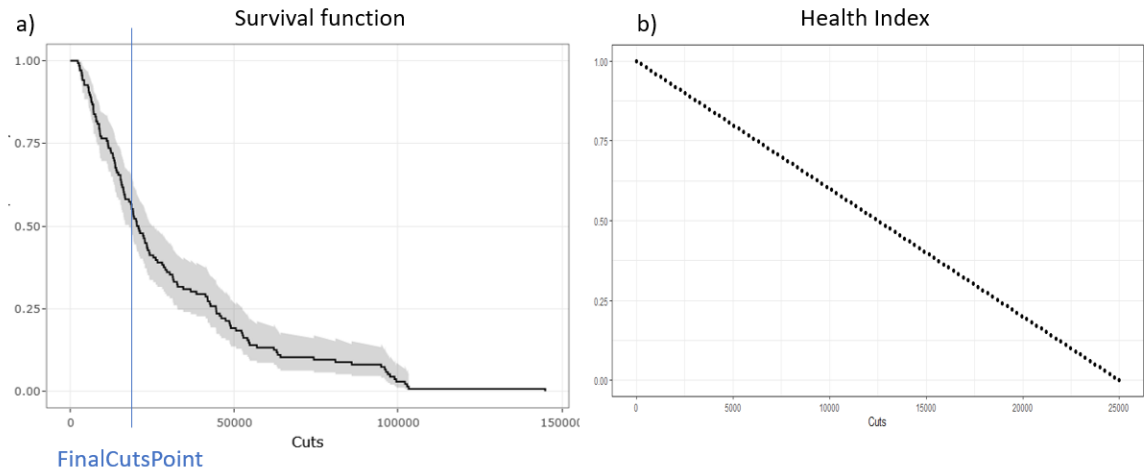


Figure 24: a) Survival function with a potential FinalCutsPoint. b) Example of a Health Index based on that Final Cutting Point.

Following such an approach the key point is determining the value of the Final Cuts Point, that is, identifying the amount of cuts that does not incur in too high cost caused by unplanned stoppages because of worn blades; or a point in which too many blades are changed early without considering the replacement cost. For the optimization of this point these two factors are considered:

- Cost of unplanned blade change
- Cost of a regular blade change

Given that using exact values to these factors is complex, different scenarios are simulated using the survival function and considering different quantiles of the survival function as Final Cutting Point. In each simulation, certain simulation parameters are considered:

- Monthly Cuts (MC): The average number of cuts carried out during a month, which is fixed value.
- Planned Final Cut Point (PFCP): The value of cuts that will be used by operator to replace the blade, which is varied in each simulation.
- Unplanned Blade change cost (UBCC): The cost associated to an unplanned blade change.
- Planned Blade change cost (PBCC): The cost associated to a planned blade change.

The schema of the simulation is depicted in the following Figure 25:

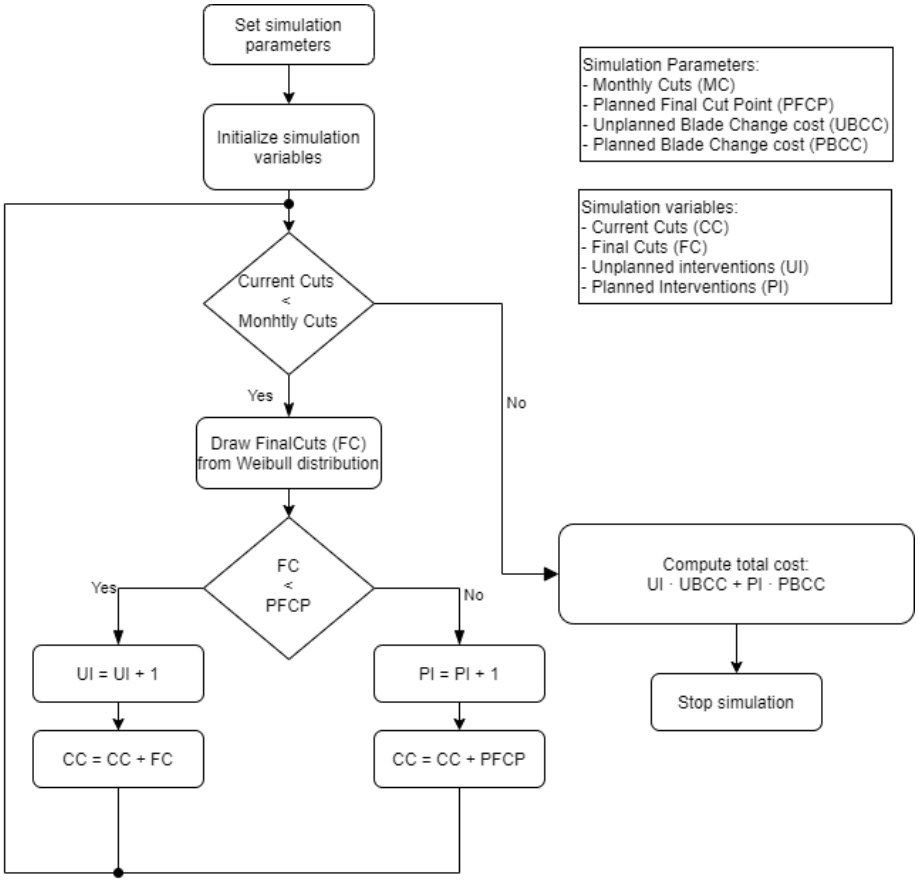


Figure 25: Schema of the simulation.

The simulation was run various times, with different PFCP values and considering different UBCC/PBCC ratios. The following Figure 26 depicts the results of the simulation, where bars represent the quantile values (or PFCP, which is equivalent).

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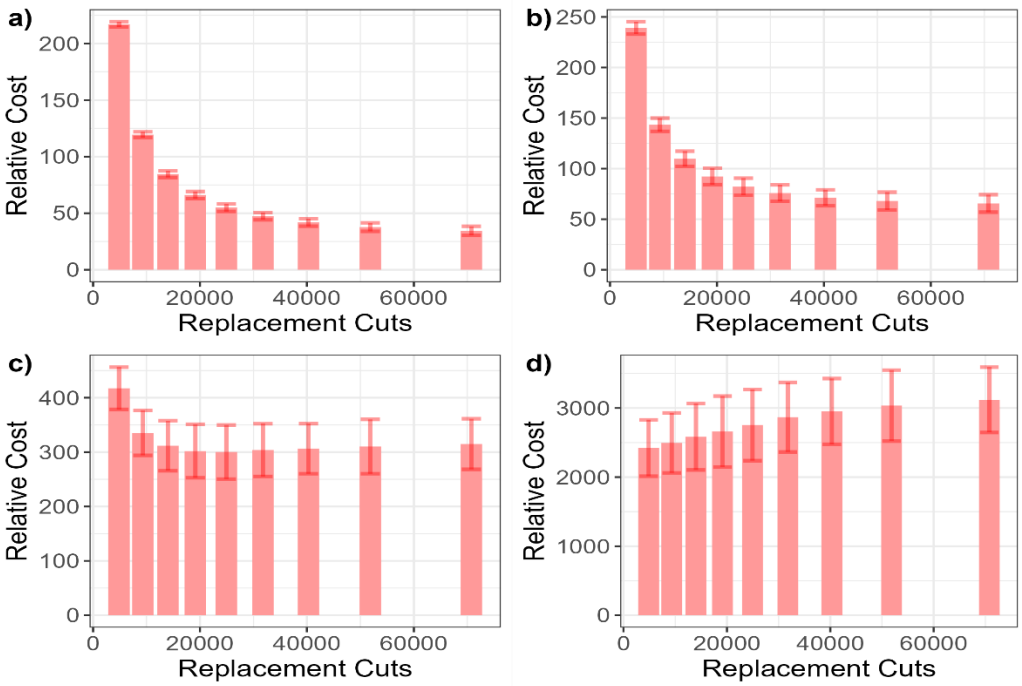

Figure 26: Simulation results under different UBCC/PBCC ratios. a) ratio=1, b) 2, c) 10, d) 100.

Given the distribution of the data and, considering the results of the different UBCC/PBCC scenarios, it is clear that, unless the incurred cost when the blade change is unplanned is much greater (more than ten times the cost of a planned one), there is no economic incentive to replace the blade before it breaks. This could be partly caused due to a bad quality of the data (which comes from the scrapping of free text) as it has very long tails on the distribution (see the following Figure 27). However, it is not possible to trace back or to acknowledge if the data records are actually valid.

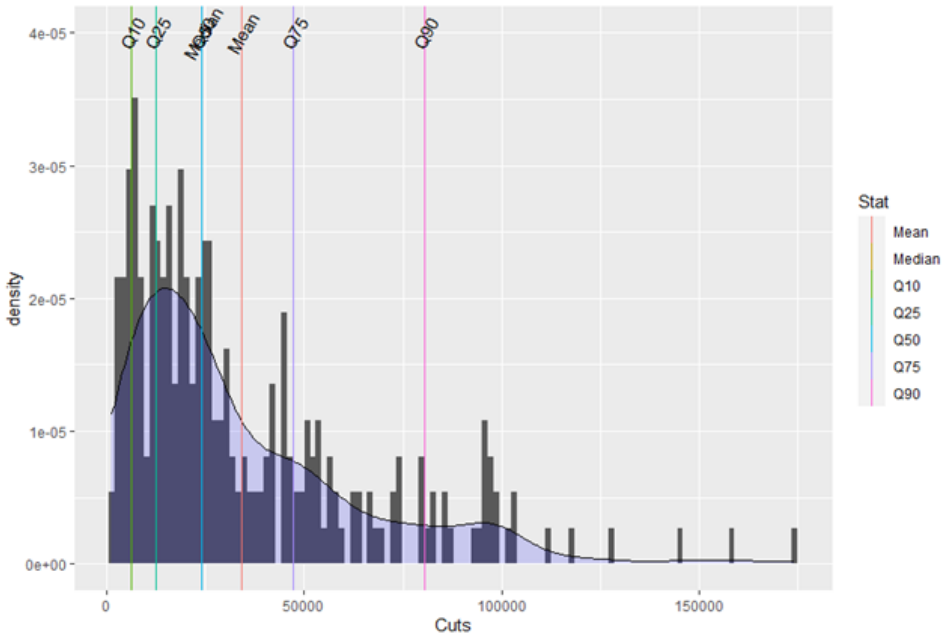

Figure 27: Density plot of the number of cuts carried out by the blades on the dataset.

At the same time, it is difficult to quantify the actual estimations of a planned and an unplanned blade change. In addition, there are other aspects (such as the stress felt by the operator when an unexpected production line stoppage occurs) that could be improved regardless of the economic justification. For that reason, the end-to-end approach is developed.

For that purpose, the Health Index values of the different scenarios are computed. In each of them, the final cutting point is considered the point at which the most economical benefit would be reached according to the simulation. Then, the intersecting point between the FinalCutsPoint and the Survival curve is used, this intersection point is then rescaled to 1-0 scale. This way the cuts consider the probability of being alive and do not just increase gradually till reaching the FinalCutsPoint. The different Health Indexes are depicted in the following Figure 28.

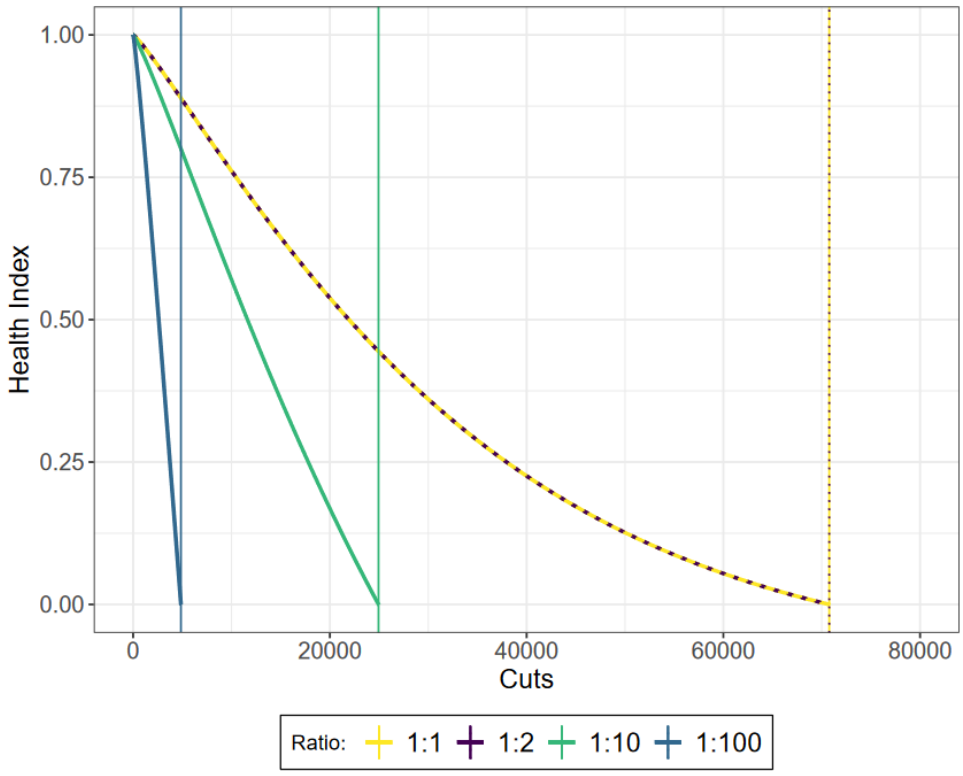

Figure 28: Health Index development for different Final Cutting Points.

It is noteworthy that, in practice, the Health Index is almost equal to the survival curve. If the Final Cutting Point is close to the point at which the survival function reaches 0, then, the Health Index will be exactly equal to the survival function. However, this is not how the Health Index is meant to be used. Ideally, the FinalCuttingPoint is reached way before the survival probability is 0, and, in such circumstances, the curves will differ. In such scenario, the user will have a more intuitive indicator that better reflects the potential condition of the blade, instead of having to interpretate the probability of the asset of being alive.

4.6.3 Deployment in AI-PROFICIENT platform

At the writing of deliverable, some changes have been made on the data pipeline on AI-PROFICIENT platform as described in D3.5. The aim of these changes is to guarantee an improved quality of the data that is stored on the databases. With these changes it is expected that, as the models will be periodically retrained in the future, the outcomes of the models will be more accurate.

For more details of the deployment of this algorithm please refer to D3.5: Future scenario-based decision making.

4.7 Control UC1 (TEK-LMD-ADD) Laser Metal Deposition Field Automation & Control

4.7.1 UC description

This use case deals with a Laser Metal Deposition (LMD) additive manufacturing process. In contraposition to traditional manufacturing processes (i.e., milling) that remove the excess material from a piece of raw material, the additive manufacturing process grows the piece by continuously adding the material, in the form of powder or metal wire, and melting it with an energy source, creating the part. This results in a reduction of waste and the ability to create more complex structures with internal cavities that can hardly be created by means of traditional machining.

During the additive manufacturing process, the tip of a metal wire is melted and deposited following certain profiles to create layers. After a layer is finished, the next layer is built over the previous one, following the same procedure: move, melt, deposit. If the process goes smoothly, all the layers will be created and after the piece is built some polishing of finish machining will be carried out to improve the surface finish of the piece[7]. The diagram in Figure 29 depicts the elements that take part during the LMD process.

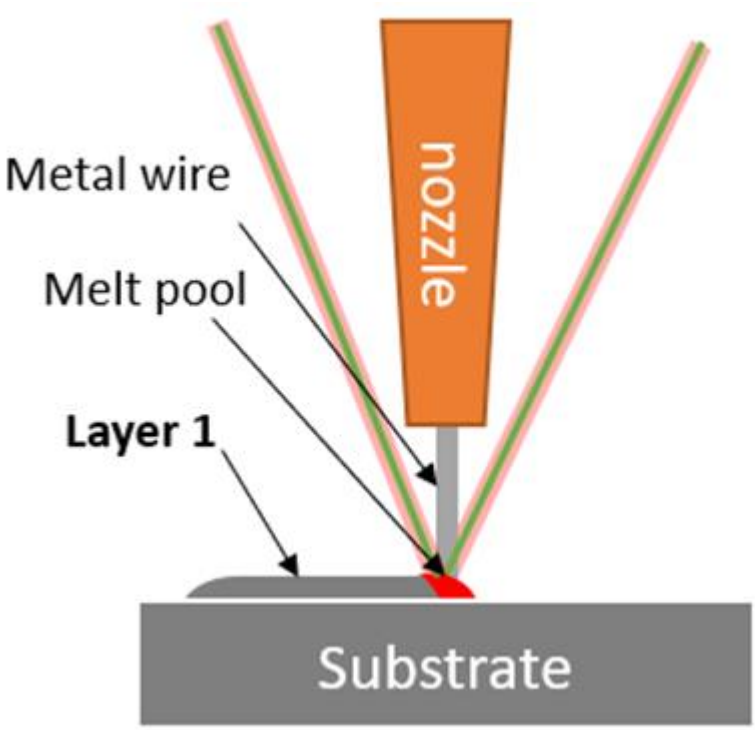

Figure 29: Schema of the elements of the LMD process.

Nevertheless, the process is delicate and small variations on the deposition from the target surface as well as other external conditions (temperatures, humidity, etc.) can lead to undesired situations in which the control of the process is lost and, in many cases, the piece that is being built must be discarded.

[7] An example of additive manufacturing process at Tekniker's lab: https://www.youtube.com/watch?v=n6M-EOX0QXI

According to the experience that Tekniker has acquired in the field of LMD based manufacturing, there are two major sources of failure related to LMD processes: Drop creation and hitching.

- Drop: Excessive melting of the molten material splits the melt pool and breaks the contact between the wire and the base surface. The wire continues feeding in and melts in the air until it falls by its own weight on the surface or gets attached to the nozzle (see Figure 30).
- Hitch: The energy introduced is not sufficient to melt both the base material and the fed material, so the melt pool solidifies while the wire is being fed. The additive manufacturing process is interrupted, and the wire gets stuck to the surface, which impedes the movement of the robot.

The following Figure 30 depicts several RGB images taken during normal, dripping, and hitching situations during a LMD process.

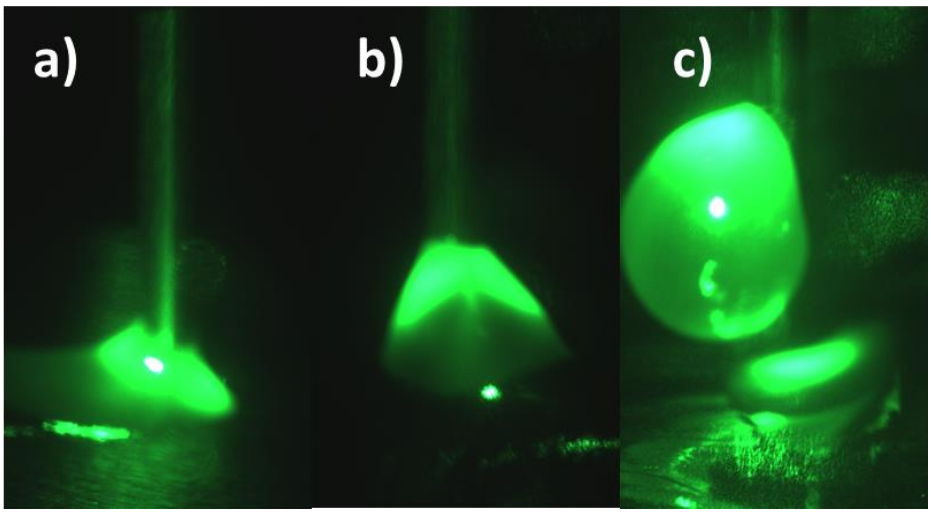

Figure 30: Example images taken during LMD process. a) OK condition, b) Hitch occurring, c) Drop formation.

The appearance of these two phenomena is undesired, as they require to stop the process, and, in some cases, the manufactured piece needs to be fixed (machined or/and polished) or discarded (depending on the severity of the fault) prior to continuing or restarting the process.

Current situation and role of the operator.

Tekniker does not follow a mass production schema. The additive manufacturing cell is used to produce a particular type of parts that have usually expensive raw materials and complex shapes. Those parts are too difficult or costly to produce by traditional machining, and, for that reason, they are produced by means of additive manufacturing.

Given the frequency at which drop and hitch occur in the process, an operator is usually supervising the images of the camera and manually stops the process if hitch or drop have occurred. In some cases, the operator can foresee some of the faults based on the images and try to take corrective actions before the faults occur, but this rarely happens.

With the actual process control system, there are some slight differences between the hitch and drop fault situations:

- Hitch: When the hitch happens, the movement of the robot is hindered, this is detected by the control system and hence, it is able to stop the process. Then the operator needs to cut the wire and relaunch the process.

- Drop: The drop starts to get bigger and, depending on how early the operator detects the drop formation, three scenarios may arise:

- Early detection: Operator detects the drop early (small size drop) the operator stops the process, cuts the wire and restarts the process.
- Late detection: Operator does not detect the drop early enough. Stops the process after the size of the drop is too big.
  - Stuck nozzle: If drop becomes too big and gets stuck on the Nozzle, the Nozzle becomes useless and has to be replaced by the operator. After the replacement, the process is restarted.
  - Drop fall: If the drop falls due to gravity over the part, the operator needs to: either try to compensate the non-uniformity of the drop on the surface by changing the trajectories for next layers in an attempt to maintain the flat growth of the part layer-by-layer; to machine or/and polish the part to remove the drop; or, if the effect of the drop is too severe, discard the part.

In either case, the longer it takes the operator to detect the drop the more destructive the impact is on the whole process and the part.

Services present on the Use Case.

To tackle this UC the following services presented in Figure 31 are needed. Some of the services were developed prior to the start of the AI-PROFICIENT, others, are new or have been improved during the course of the project.

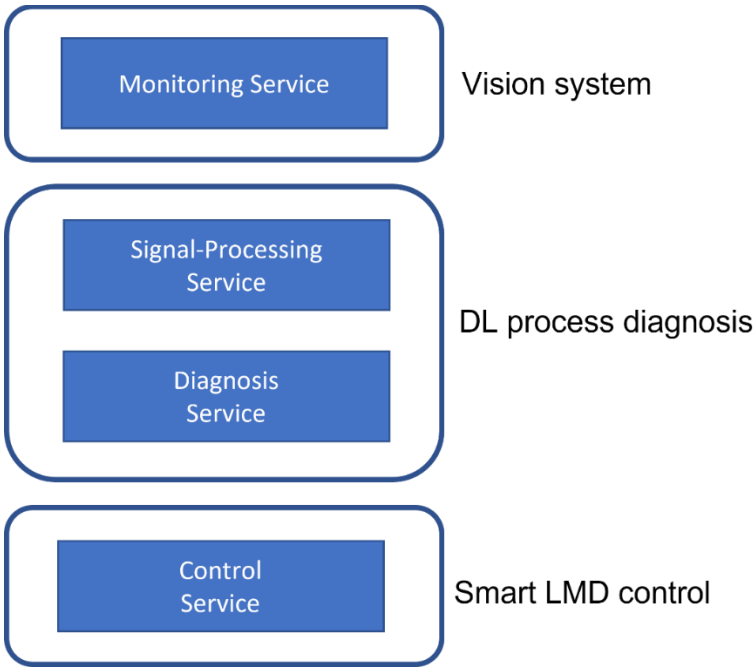

Figure 31: Module and service schema of Tekniker Additive Use Case.

4.7.2 Proposed solution

The solution proposed for this UC relies on the use of AI to determine if the process is running smoothly or not based on the images that are being actively taken and processed, in order to act on the process if required. As depicted in Figure 31 there are essentially four services building the three modules of this UC.

- **Vision module**: Which is provided by the monitoring service, a CMOS vision camera that is capturing images at 30 Hz illuminated by a green laser. The camera is equipped with a narrow band-pass filter at the illumination laser wavelength to eliminate the high light emission induced in the fusion zone.

- **DL process diagnosis module**: In which the Signal-processing service and the Diagnosis Service are used. This module takes the images captured by the vision module and returns a probability vector that classifies the image into 6 different classes: OFF, when the process laser is switched off; OK, when the process is running well; DROP RISK, when there is some small droplet on the tip and might become a drop; DROP, when it is already a harmful big drop; HITCH RISK, when there is not enough energy to melt the fed material and it starts moving relative to the molten bath, and HITCH, when the melt pool solidifies and the wire gets stuck.

  To develop the diagnosis module, transfer learning technique has been utilized to benefit from an existing Deep Learning neural network. EfficientNet-B3 network was taken and making a comparatively small training with a much smaller dataset generated at Tekniker it was improved to diagnose LMD process conditions. The dataset consisted of around 20.000 images taken during the fabrication processes of 9 blocks as the one shown in Figure 32. By using the transfer learning technique in combination to various image augmentation strategies the process diagnosis module was created. This module provides a diagnosis signal at approximately 11Hz.

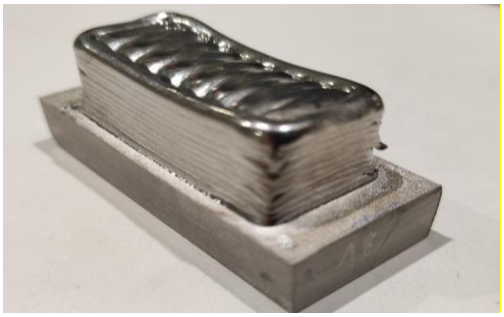

Figure 32: Example of block built by means of LMD.

- **Smart LMD control module**: This module is in charge of using the output of the DL process diagnosis module to stop the process before it is too late. This way the efficiency of the additive manufacturing process is improved. It integrates the process diagnosis signal in the control logic so that when a set of consecutive risky situations are detected, the system is stopped. When 3 consecutive frames are considered to be on Drop or Hitch, the control stops so that the piece need not be discarded.

The whole solution is running on the local PC that is used to control the manufacturing process, so that the use of AI sensed control is enabled. The following Figure 33 displays a caption of the DL process diagnosis module outputs. This interface can be displayed also during the control, but it is usually switched off as it reduces the computing capability of the system (increasing the latency) and does alter the control logic. This interface is used only for illustrative purposes, as it is not actually used by the operator, as only the camera image of the process (figure right) is.

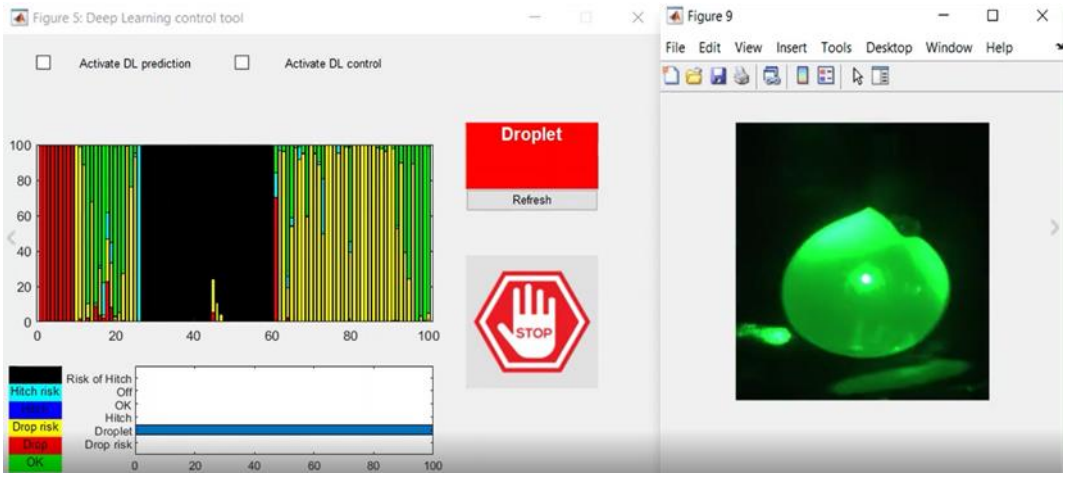

Figure 33: Interface developed to visualized DL process diagnosis module outputs.

According to the final results, the whole system is now resilient against fatal drops, as the system detects them in early stages. Hence, the new control logic stops the process early and the operator can remove scrap from the nozzle and restart the process. Furthermore, since the adoption of this solution no new manufactured pieces have suffered from severe drop problems that have required discarding the workpiece. Nevertheless, hitch detection remains an open problem as the phenomenon is too spontaneous and harder to detect. Additionally, it has been detected that small changes in the setup of the LMD system have a big impact on the accuracy of the diagnosis system. Some of these changes are the positioning of the camera with respect to the melt pool; the challenging robot trajectories that influence the acquired image; or changes in the laser head set-up. This needs to be further studied and understood to provide a fully satisfactory control system.

It is expected that, in the future, risky situations (drop risk & hitch risk) and hitch detection will be improved. In this way the control will evolve to not only stop the system but to adapt its operation so that failure can be avoided without needing to stop the production. Measures to reduce the impact of setup variability will be also taken to improve the robustness of the diagnosis algorithm.

4.7.3 Deployment in AI-PROFICIENT platform

The outcome of this task operates on the edge, and, given that the UC scenario is placed at Tekniker facilities where no AI-PROFICIENT cloud platform exists, there is no actual data flow between the system and the AI-PROFICIENT cloud. The process, the different services and the references occur in quasi-real-time in the same hardware that is used for the control and their design follows the AI-PROFICIENT service schema.

For that reason, it can be considered as an isolated edge instantiation of a system developed under AI-PROFICIENT guidelines. If needed, the data retrieved by this system could be sent to the cloud AI-PROFICIENT platform so that additional features (such as human reinforcement) could be provided. However, this is out of the scope of this project.

5 Conclusions

This deliverable summarizes the activities and achievements reached at WP2 within AI-PROFICIENT H2020 project. This WP has attempted to introduce local AI technologies at the system edge under the 'smart component' concept, close to the production lines, considering MEMS and PLCs information outputs. This differentiates from other technologies expected to work at 'cloud' level on most scenarios (and developed in other WPs)

Therefore, the deliverable firstly reports (Section 3) the **technologies researched**, divided in 4 different application areas. These have been:

- AI pre-processing algorithms for raw data cleansing, aggregation, and filtering. More specifically the processing of image data and of dense 3D position data, i.e., point clouds, into low cardinality vectors to be used as input to industrial maintenance support systems.
- Self-diagnostics and component operating condition estimation: Diagnosis strategies that are used for asset monitoring and how the AI could be used to improve those strategies. … implying the monitored assets themselves could be updated so that they could produce their own diagnostic information.
- Prognostics, more specifically degradation-based prognostics, where projections are made over the future in order to predict not only the remaining useful life (RUL), but also the degradation trajectory of the asset in consideration, by blending AI-based techniques with more conventional approaches such a stochastic processes, trend, and time series models.
- Field automated control mechanisms to provide 'real time' response and adaptation to the current condition of the controlled asset.

The report also explains the **AI technologies implementation** in real world use cases. Even though the research withstood the adverse conditions produced by the side effects of COVID as well as the global chip shortage from late 2021 to late 2022, the application has been conducted in similar terms as it was initially foreseen, it has led to redesign of parts of the system to use alternative components that could be sources, especially regarding image processing.

Even tough current application of these technologies is still undergoing, initial results are positive and have led to a thorough revision of several use case application potential, to withstand the challenging conditions of robustness and human interaction required to move **from demonstration to product integration,** where, among others, **ethical issues** are reviewed as part of this movement.

This applies for instance on the revision of the interaction with operators where providing assets with diagnostic capabilities is perceived as an interesting improvement as this ability leads to a reduction of both downtime and repairment times, as the root causes of the faults can easily be known and addressed. However, in many cases (i.e., CONTI UC5, TEK-LMD-ADD) fault detection may still depend partially upon the operator. This is a main ethical problem in most AI systems: the human is expected to make up for the errors in the machine, but this is rarely considered when evaluating the success of the machine. Following the recommendations given by the ethics team, some modifications have been carried out in some services, so that to simplify the logic behind the identification or diagnosis of events, together with specific training.

For instance, in TEK-LMD-ADD the operator can trust the AI to predict drops but not hitches. So, in part, the operator will still have to carry out a process watching as before as well as keeping an eye on the fault detection system. If this happens it would be a doubling of attention, working against the goal of the service. Ethical modifications included a simplified logic that only considers consecutive DROP diagnoses as a reference to stop the control system. In addition, LMD process operators have been trained adequately to understand the way AI works.

Last but not least, the fulfillment of this work package is resulting in their **dissemination** in different scientific publications and conferences, which serves as a further validation of the results already obtained. This dissemination is still ongoing and includes at least the following papers:

Chaoub, A., Voisin, A., Cerisara, C., & Iung, B., (2021) Learning representations with end-to-end models for improved remaining useful life prognostic, *European Conference of the Prognostics and Health Management Society*, Jun 2021, Virtual event, Italy

Chaoub, A., Voisin, A., Cerisara, C., & Iung, B., (2022) Towards interpreting deep learning models for industry 4.0 with gated mixture of experts. 30th *European Signal Processing Conference, EUSIPCO* Aug 2022, Belgrade, Serbia.

Flores J., Garmendia I., Gutierrez A., Lopez K. Real-time diagnosis and control of the wire to melt pool transfer mode for the w-LMD process using a Deep Learning approach. *Journal of Intelligent Manufacturing. pending*

López de Calle-Etxabe, K., Gómez-Omella, M., & Gárate-Perez, E. (2021) Divide, Propagate and Conquer: Splitting a Complex Diagnosis Problem for Early Detection of Faults in a Manufacturing Production Line, *PHM Society European Conference*, vol. 6 (1), doi: 10.36001/phme.2021.v6i1.3039

López de Calle-Etxabe, K., Garate-Perez, E., & Arnaiz, A. (2022). Towards a Circular Rotating Blade Wear Assessment Digital Twin for Manufacturing Lines, *IFAC-PapersOnLine*, vol. 55, n.º 2, p. 566, doi: https://doi.org/10.1016/j.ifacol.2022.04.253

To sum up, it is clear that edge level AI will play a key role on the industry as enabling technology for improved manufacturing systems. It is important to understand that the application of these technologies is still under validation and therefore final results and conclusions will add additional information on the validation process and also to conclusions on edge AI potential (This will be part of final WP6 outcomes to be reported at several D6.x deliverables). In any case WP2 team expects that the technologies explained and their application in very different scenarios will speed the spread of these technologies, in cooperation with other research topics also addressed in other WPs of AI-PROFICIENT.

6 References

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Acknowledgements

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 957391.