Ref. Ares(2021)4251151 - 30/06/2021

IoTwins
BIG DATA OPTIMIZE INDUSTRY AND SERVICES

Grant Agreement N°857191

Distributed Digital Twins for industrial SMEs: a big-data platform

Deliverable 4.2 – First Digital Twin Version Delivery for the Manufacturing Test-Beds

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement № 857191

Document Identification

Project	IoTwins
Project Full Title	Distributed Digital Twins for industrial SMEs: a big-data platform
Project Number	857191
Starting Date	September 1st, 2019
Duration	3 years
H2020 Programme	H2020-EU.2.1.1. - INDUSTRIAL LEADERSHIP - Leadership in enabling and industrial technologies - Information and Communication Technologies (ICT)
Topic	ICT-11-2018-2019 - HPC and Big Data enabled Large-scale Testbeds and Applications
Call for proposal	H2020-ICT-2018-3
Type of Action	IA-Innovation Action
Website	iotwins.eu
Work Package	WP4
WP Leader	GCL
Responsible Partner	GCL
Contributing Partner(s)	FILL, BRI, BSC, ETXE
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File Name	D 4.2 – FIRST DIGITAL TWIN VERSION DELIVERY FOR THE MANUFACTURING TEST-BEDS
Contractual delivery date	M20 – 30 April 2021
Actual delivery date	M22 – 30 June 2021
Version	1
Status	Final
Type	DEM: Demonstrator, pilot, prototype
Dissemination level	Public
Contact details of the coordinator	Francesco Millo, francesco.millo@bonfiglioli.com

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1 Introduction

The main goal of Work Package (WP) 4 is the definition and implementation of four large-scale industrial testbeds in the manufacturing sector, according to the architecture for distributed and hybrid digital twins defined within WP2 and WP3. The available IT infrastructures were used to develop components linked to the deliverables D2.1 (Architecture and Technical/User Requirements (I)) and D3.1 (Requirements from large-scale industrial production and facility digital twins) and the milestone MS2 (IoTwins Platform and services – Requirements form large-scale industrial production, finalized platform specifications and facility digital twins available).

This deliverable reports on the work performed within the four large-scale industrial testbeds between M1 and M18 of the project.

1.1 Work package objectives

On-line data and off-line historical data from industrial plants and machinery will be used to generate an upstream flow of data to feed the developed components. To realize the required upstream of data, industrial control technology and IT solutions are implemented to the manufacturing testbeds.

By collaborating with WP2 and WP3, the concept of the first digital twin platform was defined by sharing the requested requirements. The architecture and the data flow are designed that every testbed can access the platform in a homogenous way.

This deliverable D4.2 focuses on presenting the first digital twin preliminary version delivery for the manufacturing testbeds.

1.2 Methodology

The testbeds exhibit several elements of heterogeneity in their IT infrastructure, also because they involve industrial processes and IT infrastructures partially implemented before the IoTwins project (extension of existing solutions and evolution of existing investments). In addition, each one is subject to different constraints/requirements due to the different industrial branches. In strict collaboration with WP2 and WP3, this work package has tried to adapt a general architecture and methodology for all the testbeds with tailormade specializations for the different cases, according to the general approach and methodology adopted within the whole IoTwins project.

The following sub-sections describe the generalized methodology to achieve the requested results.

1.2.1 Identification of the use case

At the first stage of the project the activity was to figure out the best scenario of connected machines to identify the use case for the pilot. The main goal was to provide a huge quantity of data to create models to be analysed in the following project phases.

1.2.2 Technical preparation

To allow industrial plants/machineries to upstream production data to IT services, it is often necessary to perform hardware- and/or software-sided upgrades. By collaborating with, e.g., suppliers and clients, the machines can be technically enhanced to fulfil the required features. Also, in some cases, laboratory setups are required.

1.2.3 Identification of sensors

Based on the specific testbeds, the requirements for the monitored events related to the machineries are slightly different. Such events can be, e.g., a breakdown to be avoided before it happens. A set of sensors monitoring the environment in each testbed has been identified.

1.2.4 Data processing

The processing of the data is executed in the dedicated infrastructures and/or applications defined in WP2 and WP3 for each testbed.

1.2.5 Digital twin

By defining the expectations of the usage of a digital twin for each testbed, the correct development of the first platform version is realized. In this subsection, testing and describing the behaviour of the digital twin is foreseen. The first digital twin preliminary version delivery for the manufacturing testbeds will be presented in the next sections.

1.2.6 Validation

The following points can validate the single and separated tasks:

- investigation of the correct collecting of data
- security aspects
- proper usage/upstream of data.

2. Testbed 1: Wind-farm predictive maintenance system, BRI

2.1. Objectives of the testbed

Wind Turbine Generator (WTG) generally operates 24/7 with a constant requirement of increasing Annual Energy Productivity (AEP) and reduce unexpected downtimes, (due to adverse weather conditions that cause excessive wear and tear of wind turbine components), that can cause important losses of energy production.

Although the yaw gearmotor represents the 1.25% of the entire WTG costs, the related costs to the unproductive or damaged WTG are higher. With corrective actions (after a failure occurs) the estimated costs of intervention/ repair vary from 60k€ to 200k€ per turbine; in addition, the cost of production losses during the intervention can vary from 2k€ to 4k€ per day.

Testbed 1 value proposition to be addressed to Customer Needs is finalized to have a higher annual energy production, to reduce Maintenance & operational costs, to have a reliable components' lifetime estimation and lower stocks of spare parts.

Our business model can offer additional services like: Smart yaw drive products, Predictive Maintenance services, Automatic spare parts ordering service (in future), Pre-installation / Run Time set-up simulation and parameter setting service

With the following benefits for end user: Reduced maintenance costs, Improved the WTG set-up, providing smart IoT-ized drives, Increasing AEP, reducing downtimes or optimize downtimes.

2.2. Presentation of the digital twin of the testbed

An initial version of a physics-based "virtual" twin of a wind turbine yaw drive system has been developed.

The physics-based model has been developed using SimulationX, I.e., the ESI proprietary system simulation tool, whose strength in multi-domain physics-based modelling lends itself very well to simulating complex cyber-physical systems such as WTGs. The model represents the control system, motors, and rotor of the yaw system of a turbine with a similar architecture to the target one, for which historical and manufacturer's data such as controller algorithms were provided by BRI and KKWind.

The initial studies have focused on comparing the real and simulated data streams about speeds and torques of yaw motors. So far, the paucity of available environmental data (wind speed, wind direction, etc) for the test turbine have limited the fidelity of the model that was achievable. These limitations will ultimately be alleviated by the high-frequency data that will be generated by the target WTG. Furthermore, ongoing work using data-driven methods for time-series data (by ENSAM) will be applied to the yaw acceleration data as a precursor to classifying the health of the system. The goal is to integrate the two models (physics-based and data-driven) to construct a "Hybrid Twin" model that can be applied to predictive maintenance applications.

The linked video shows a simulation performed using the current version of the physics-based model, with comparison of the actual wind speed direction and the computed yaw direction of the nacelle model.

Yaw system simulation

2.3. Compliance with the IoTwins architecture

The aim is to merge two systems through an Edge Computer being capable of gathering data from these systems, both the turbine control system and the purpose-built multi-sensor platform system.

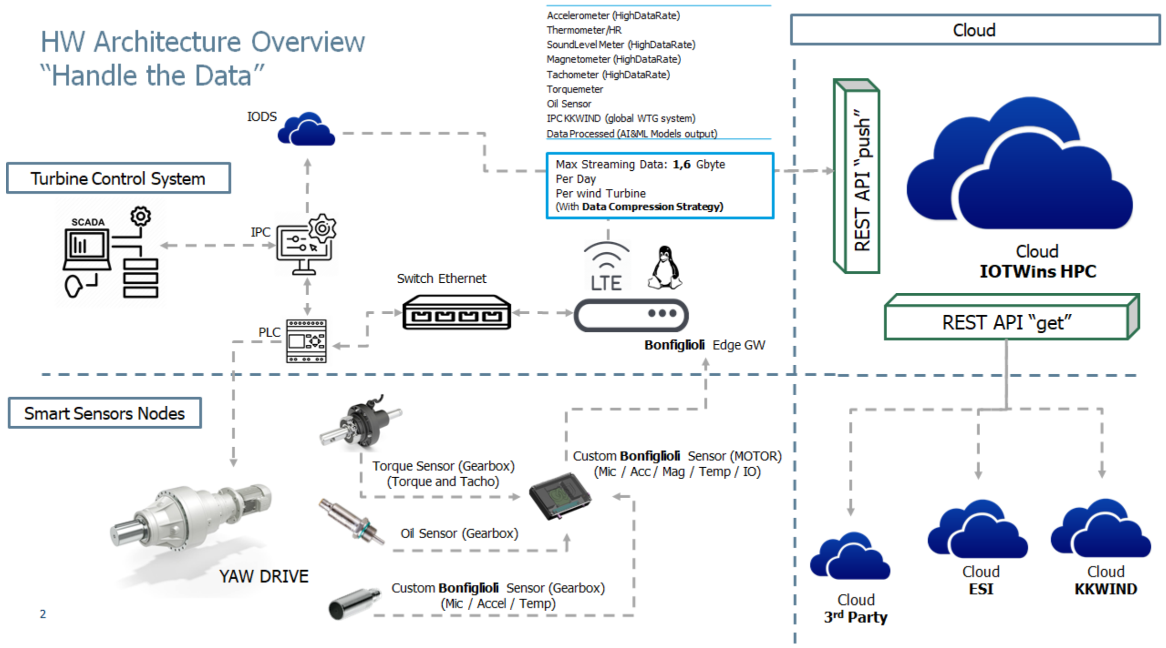

Figure 1: Hardware architecture overview

The two systems consist of smart sensors nodes from one side and on the other side the turbine control system plus the SCADA of the WTG.

The data stream that will be generated, based on team experience and know-how, will be based on both sensors applied on gearmotors and data coming from turbine control systems and possibly ecosystems.

2.4. Validation performed so far

Initial results show that the implemented model of the nacelle of the WTG correctly tracks the changing direction of the wind, Figure 2 for the low-frequency (every 15 minutes) environmental data that was available.

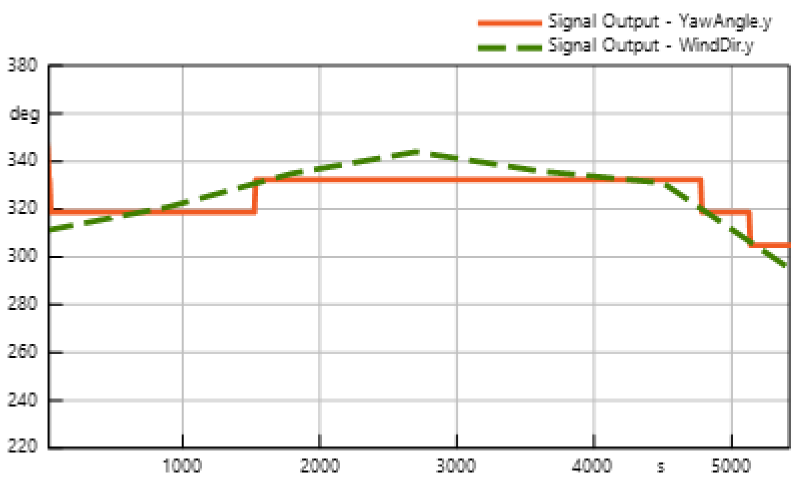

Figure 2: Simulated yaw angle (direction of WTG nacelle) vs actual wind direction

Ongoing work is focused on adapting this model to the target WTG. A first validation step will be to verify that the simulation model correctly predicts the yaw angle of the nacelle, even at higher sampling frequencies. In parallel, aerodynamic model components are being developed and integrated in the overall system model using data collected by the Edge Twin (instrumented yaw drive and SCADA systems), with the aim of improving the correlation between simulated and measured torque values.

Where system simulation approaches are not able to accurately capture the physical phenomena, e.g. in the high-frequency accelerometer data generated by the instrumented yaw system, complementary data-driven methods such as Topological Data Analysis will be employed. Currently, the approach is being tested using historical acceleration data provided by Bonfiglioli from an instrumented yaw drive of a WTG similar to the target one.

Both data-driven and system simulation models can be translated to lightweight executable components, thus enabling them to be deployed on the Edge machine, taking as input the necessary WTG sensor data to provide the operator with up-to-date estimates of the health of the system.

3. Testbed 2: Machine tool spindle predictive behaviour, FILL

3.1. Objectives of the testbed

This testbed is aimed at creating multiple target-oriented digital twins of machine tools (Syncromill) in a shop floor (esp. automotive series production). By deploying simulation and ML models of machine tools, drives and spindles for detecting the condition and behaviour of the spindle manufacturing-relevant and quality-influencing parameters (load, forces, vibrations etc.) are predicted. This enables the reduction of unexpected rejects, breakdowns and downtime by optimizing load and performance indices.

A machine tool was set-up for this testbed in the Fill Future Zone, which is illustrated in Figure 3.

Figure 3: Syncromill for Testbed 2 set-up in Fill Future Zone

3.2. Presentation of the digital twin of the testbed

The digital twin of Testbed 2 aims at creating multiple target-oriented digital twins of machine tools in a shop floor by deploying machine learning models for detecting the condition and behaviour of the machine tool, drives and spindles.

This is done in four steps:

1. Iotizing data from the machine and processing and storing them on edge
2. Data transfer to the cloud
3. Data Analytics and training Machine Learning models
4. Extension of the testbed

The architecture on edge has been designed according to the IoTwins reference architecture, with a local messaging bus as central component. Data has been collected by performing experiments and analyzing the data to identify the important features. The edge device itself is managed by the Nerve platform developed by Testbed 2 partner TIAG.

The current version of the digital twin collects all relevant data from the controllers of the machine and extracts the important features to distinguish the milling inside the material from milling outside the material to detect the behaviour of the spindle. As part of the IoTwins project, the complete data recording pipeline was set up, the most important features for predicting the behaviour of the spindle were identified and a first version of the digital twin was developed. Furthermore, the data is transferred to the cloud. Future work will exploit cloud computing resources to extend the current digital twin model to include more use cases.

3.3. Compliance with the IoTwins architecture

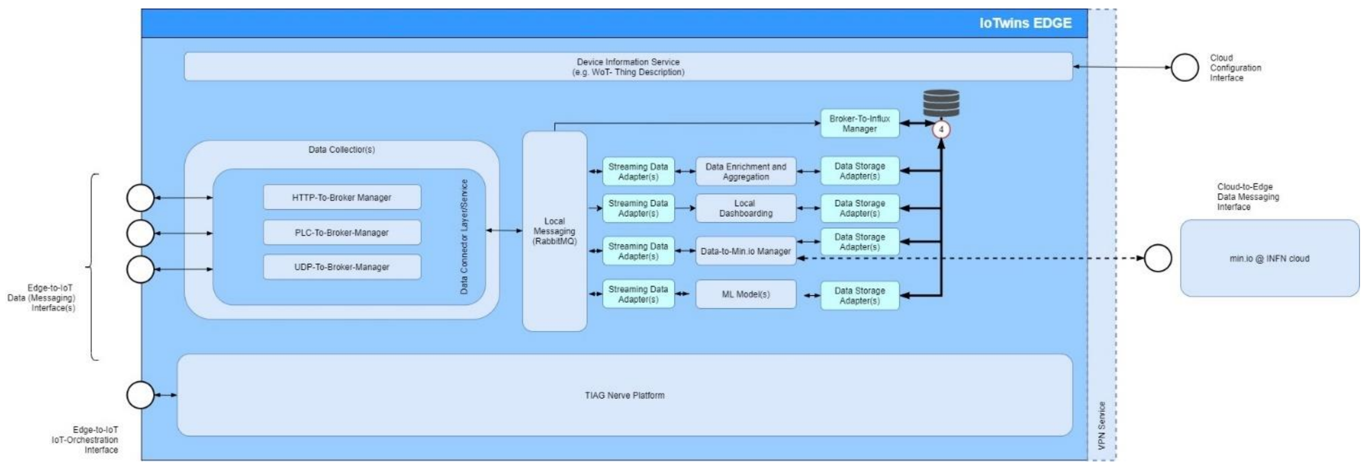

Figure 4: Architecture Overview

3.4. Validation performed so far

To validate the work developed so far in Testbed 2, the system, the data and the machine learning model were considered.

Intensive test runs were made to successfully test the system for its robustness with regard to possible machine malfunctions, and the plausibility of the data was checked. The identified features for the predictions of the spindles were clarified with the domain experts and the results of the machine learning models were checked. All these tests were performed in-house and will be enriched with data coming from production as soon as the testbed is enlarged.

4. Testbed 3: Crankshaft manufacturing system predictive maintenance, ETXE

4.1. Objectives of the testbed

High throughput crankshaft manufacturing system, the principal product of ETXETAR, is a semi-autonomous Computer Numerical Control (CNC) machine that produces an average of 1.000 crankshafts per day (a picture of such machine is provided in Figure 5). Downtime and breakdown reduction improve the productive efficiency of the whole line and consequence increase revenue. For instance, one of the main customers of ETXETAR estimates 50,000 €/hour for the cost of downtime in its production lines. Obviously, this figure would strongly depend on the process and on the type of company, but it seems necessary to work on it to contribute to the reduction of costs due to machine failures.

Figure 5: Etxetar's crankshaft manufacturing system

Within the IoTwins project, we studied the failure mode and effects analysis to identify the element with the highest Risk Priority Number (RPN). Having the highest RPN means that an unexpected failure in this element will stop the complete machine, affecting the complete production line. Therefore, the machine's element with the highest RPN is the frontal ball-bearing of the spindle head (see Figure 6). Frontal ball-bearing will be the focus for the testbed, producing high amount of data to generate a digital twin that will enable data-based maintenance, reducing the downtimes related to this part of the machine.

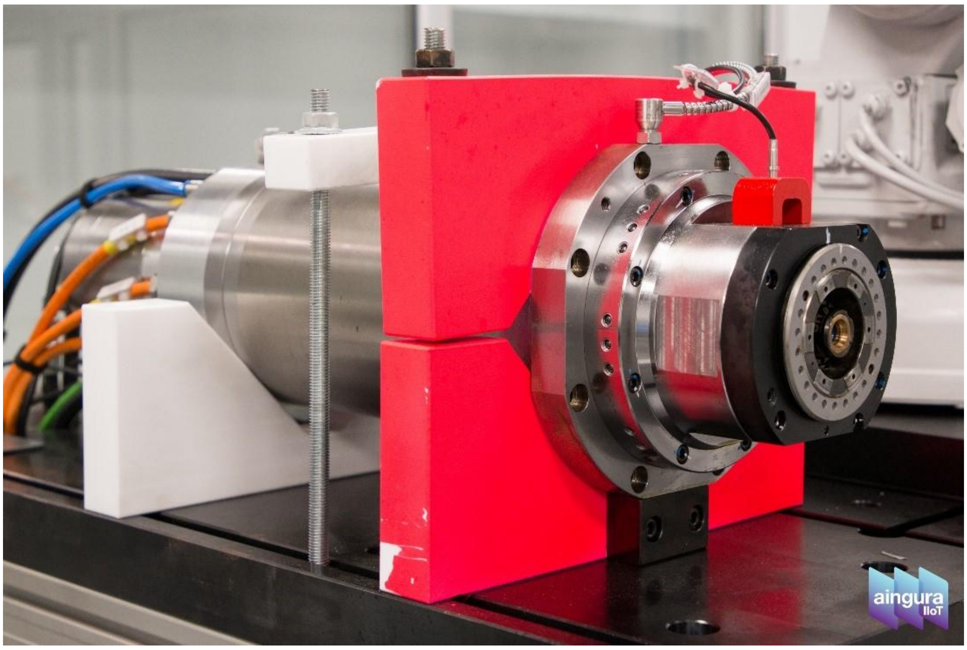

Figure 6: Crankshaft manufacturing spindle head (lab environment)

4.2. Presentation of the digital twin of the testbed

This testbed is certified by Industrial Internet Consortium[14] (IIC). The Industrial Internet Consortium brings together the organizations and technologies necessary to accelerate the growth of the industrial internet by identifying, assembling, testing and promoting best practices. Members work collaboratively to speed the commercial use of advanced technologies. The testbed provides part of the infrastructure needed at three different deploying levels:

1. Lab: a synthetic setup with an infrastructure similar to the one deployed on the commercial products;
2. Factory-lab: a setup deployed on a real product when still in the factory (before deployment);
3. Production line: the actual final setup on the field and at scale.

These three scenarios will help to communicate, isolate (the ball-bearing analysis), test and validate all the required infrastructure related to data acquisition, pre-processing, and processing.

Therefore, at different deployment scenarios, the Aingura Insights (AI) edge computing node (see Figure 7), from our Linked Third Party, Aingura IIoT, S.L. will be used to extract different variables related to the frontal ball-bearing. Additionally, the AI will be used to run feature subset selection over those variables to send only the require variables, avoiding redundant and not related that will compromise posterior data analysis algorithms.

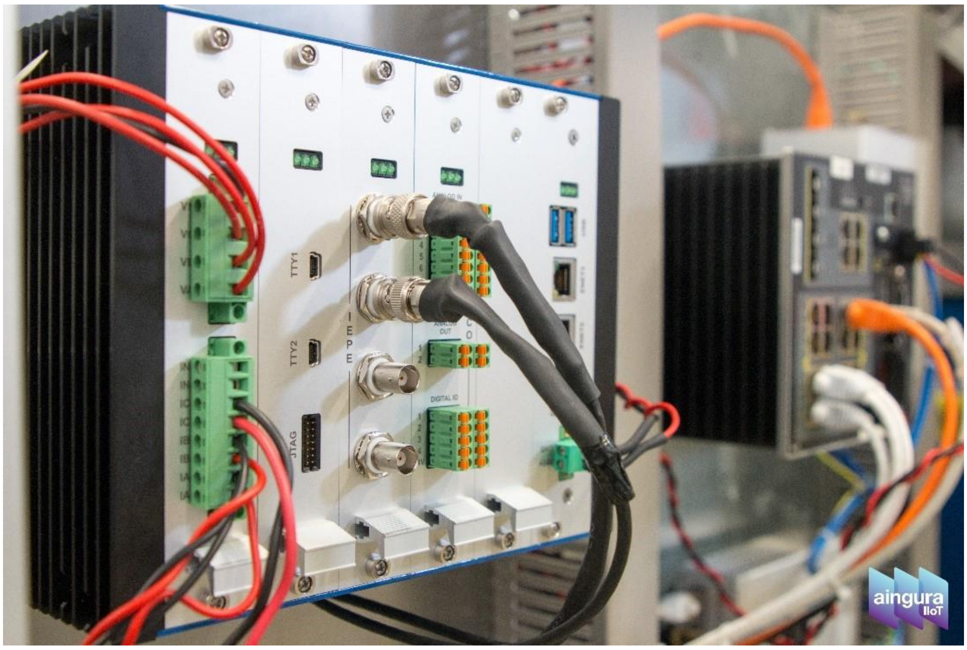

Figure 7: Aingura Insights (AI) edge computing node

Additionally, a specific testbench to extract data from ball-bearings has been built. From this testbench and the spindle head, the extracted data is mainly from accelerometers, thermocouples and CNC data (power, torque, current, winding temperature). The ball-bearing testbench is shown in Figure 8.

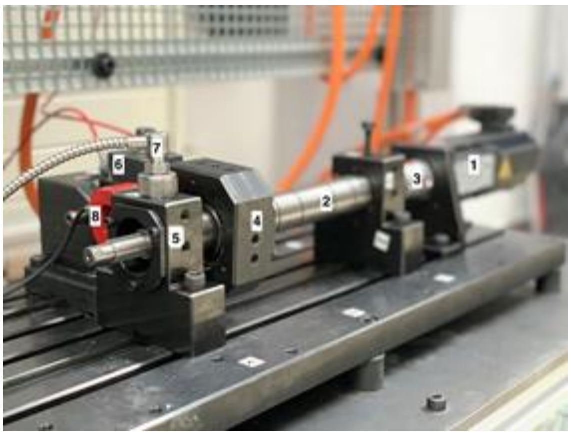

Figure 8: Ball-bearing testbench. (1) CNC servomotor, (2) rotary axis, (3) elastic coupling, (4) axial force heavy duty ball-bearing, (5) ball-bearing to be tested, (6) force actuator, (7) accelerometer, (8) thermocouple.

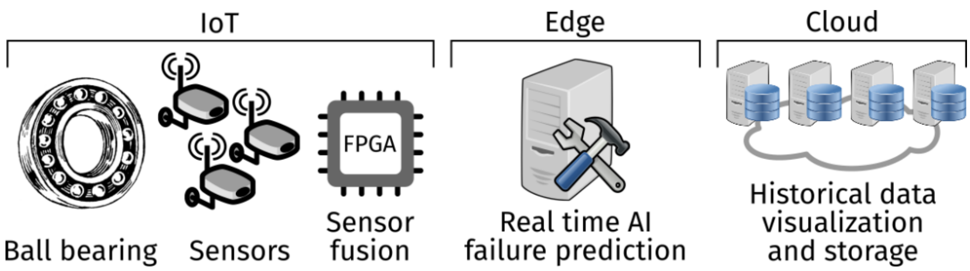

Figure 9: Dataflow of the testbed

The data collected by the sensors introduced in the previous sections are cleaned and fused by an FPGA-based IoT device (Aingura Insight). They are processed on the edge with AI techniques improving failure prediction. The testbed leverages the Cloud layer for storage and visualization of historical data. Figure 9 summarizes this dataflow.

4.3. Compliance with the IoTwins architecture

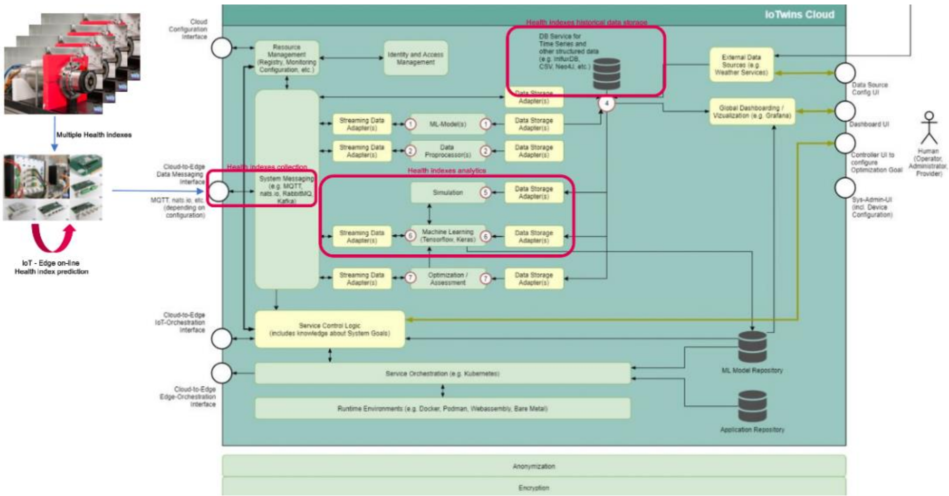

Figure 10. Integration with IoTwins cloud architecture

4.4. Validation performed so far

Testbed 3 is illustrated in this video (link). The testbed is divided into three different scenarios: (1) lab, (2) factory, and (3) production facility. The video describes in order the first two scenarios, as the last one is performed inside customer (automotive OEM) facilities, where video recording is forbidden.

The first scenario is the lab, where a specific ball-bearing run-to-fail testbench is working 24/7 producing different types of datasets where the ball-bearing useful life is accelerated under different conditions. These datasets are used to simulate data streams from ball-bearings, in order to validate the Edge algorithms ideas, where no training is needed to estimate the remaining useful life. That is why, different failures modes: different forces (variable forces, temperatures, speed, …) are used, with the aim of creating broad scenarios of validation. This dataset also has the objective to be used when the full integration with the complete IoTwins platform is done, in order to validate ML based estimations done on the RUL. This testbench has being built exclusively for the IoTwins project.

Figure 11: Accelerometer signals configuration on the Aingura IIoT computing node

This lab scenario also has a spindle test facility, a larger machine, with all the systems and subsystems that make possible to run spindle heads. This machine has all the lubrication, refrigeration, control systems, and power to operate a spindle head in dry cycle (no machining) as long as needed. This machine mimics the spindle head behaviour found in real machines, giving the testbed to extract real datasets with all the contextual variables found in CNC production machines. Although is not possible to perform a run-to-fail test on the spindle heads, as these are really expensive elements, and the design useful life is around 2 years under working conditions, real-time monitoring can be done to showcase real operation and insight production in controlled and 24/7-available environment.

The second scenario shown is the video is the factory. When Etxetar produces CNC machines to its customers, those machines have to be tested and validated prior delivery. In fact, these machines need to perform a "production capacity" test, where around 200 real workpieces (real crankshafts) are manufactured. During this pre-production tests, Etxetar is able connect Aingura IIoT computing nodes to extract, test and validate different elements. As it is real production, this is the most controlled environment that is available to finally test different applications. As these types of data-based monitoring systems are highly sensitive to noise (huge amount of pre-processing is oriented to clean this noise), the scenario is highly useful to test the robustness of the solutions.

At this time, there is no associated code already distributed on the IoTwins gitlab repository, as the integration with the IoTwins platform has only recently started. TB3 will upload selected datasets once the testing process is finished. It is important to say that only datasets coming from run-to-fail testbench can be uploaded.

5. Testbed 4: Predictive maintenance and production optimization for closure manufacturing, GCL

5.1. Objectives of the testbed

OEE (Overall equipment effectiveness) is a measure commonly used in manufacturing processes to evaluate the optimal usage of a resource based on its full capacity and potential. OEE is a function of Availability, Performance, and Quality, thus including the effects of downtime and scraps on the expected productivity of a machine or process. Downtime, in terms of machine stops, includes both macro-stops for maintenance and format changeovers, and micro-stops due to jams and temporary failures along the entire process. On the other hand, the percentage of scraps represents the quality of the produced parts. It is clear how both of these factors affect OEE.

This testbed will focus on stoppages caused by the failure of certain critical component of an injection moulding machine. This failure, if repeated several times, degrades the health of the entire machine, ultimately causing its complete breakdown. This breakdown has a high impact on the company, given the high cost of the asset itself, the induced repairs, and the loss of production it causes.

5.2. Presentation of the digital twin of the testbed

Within the scope of the IoTwins project, it has been added some critical ball bearings sensors on an injection moulding machine, measuring its vibration speed, acceleration and temperature. Between all variables, it has been identified which one are the most responsible for indicating the overall health of the machine. Then, following the ISO 10816-3 regulation, it has been defined thresholds for these measured values, where each threshold corresponds to one of four bearing statuses – normal, pre-warning, warning, alarm.

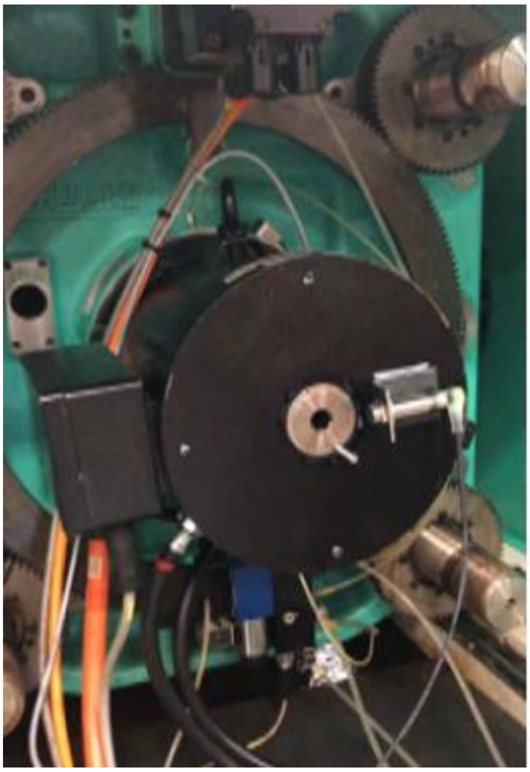

Figure 12: Moulding Machine testbench

Goal of this TB is to predict the occurrence of the “alarm” status during normal production runs. This will be done by developing, with the help of our project partners in WP2, validating and testing a machine learning model, based on deep learning, capable of predicting the remaining useful life (RUL) of the ball bearing. The model outputs the RUL in the form of a survival probability, with values ranging from 0 to 1, where 1 indicates that no failure will occur within now and a given time window, and 0 indicating the certainty that a failure will occur within now and a given time window.

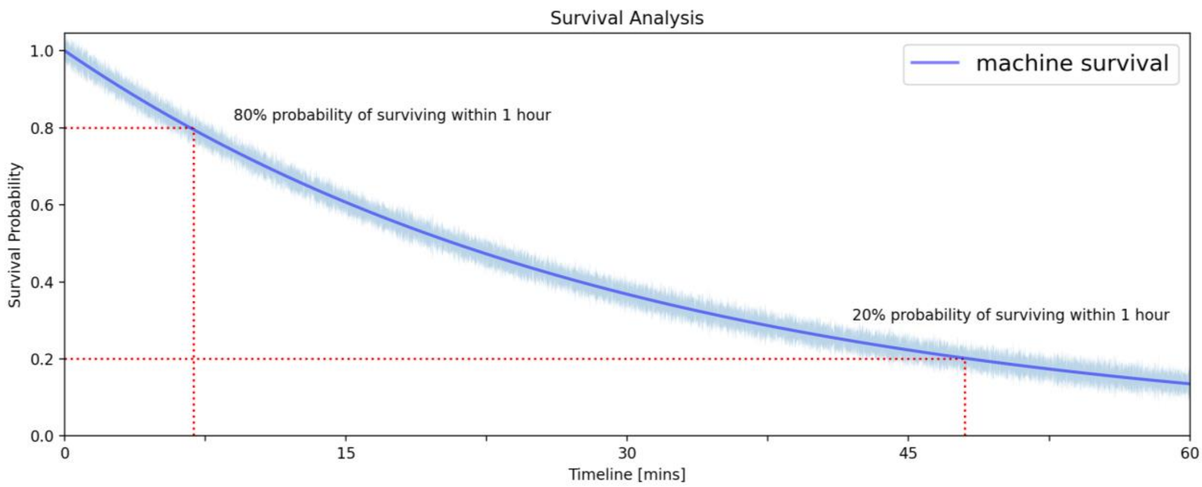

Figure 13: Survival Probability Model Outputs

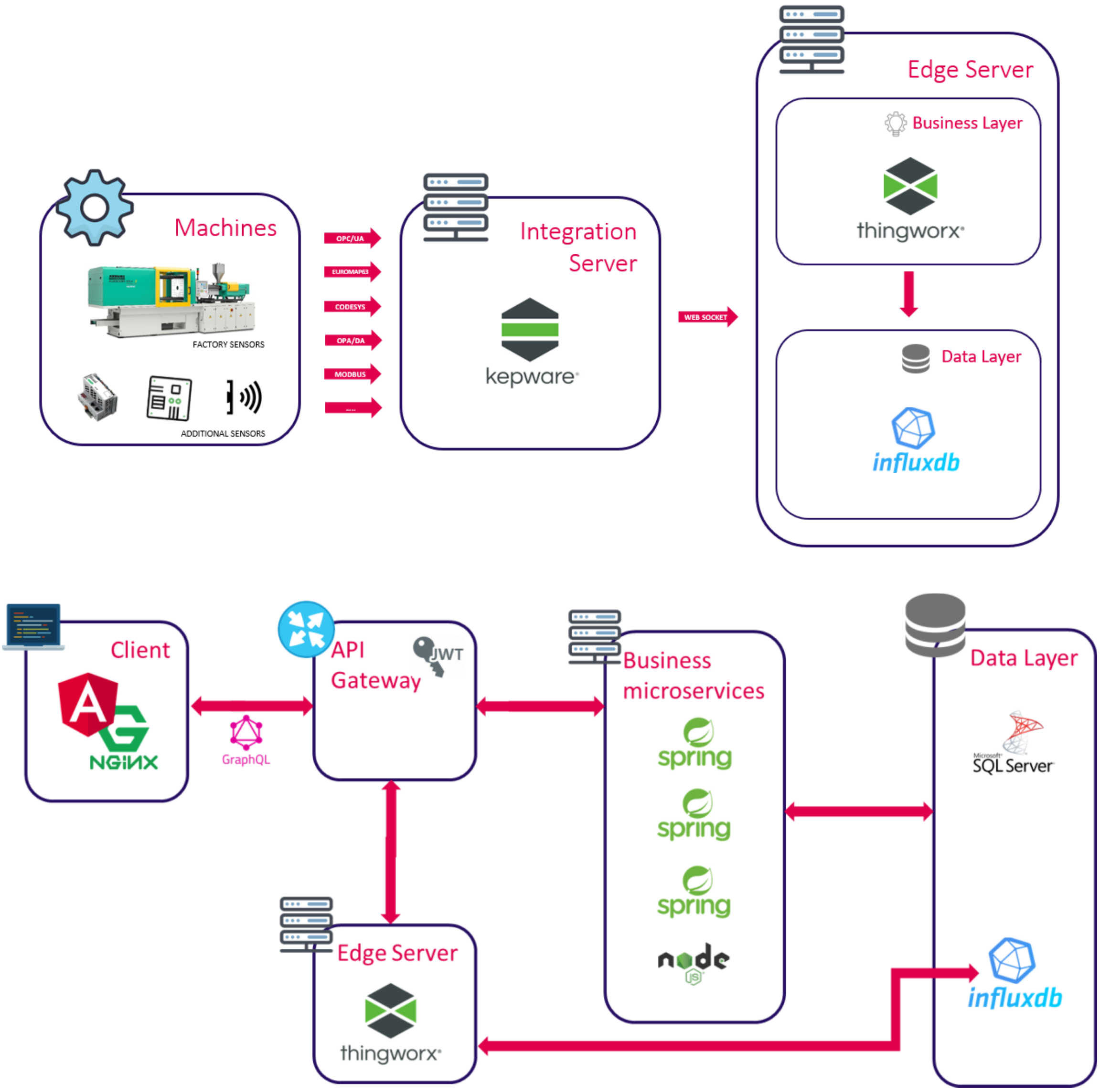

Figure 14: Machine Learning Model

5.3. Compliance with the IoTwins architecture

This model has been developed using the state-of-the-art tools/libraries and code has been build using TensorFlow as backend for ML tasks. The architecture of the model is based on recurrent neural network for time-series (CNN-LSTM). Interpretations of the model probability helps the production managers to plan a preventive maintenance to avoid any failures in the machine operation. Following is the link for demo videos.

https://liveunibo.sharepoint.com/:p:/r/sites/test603/Shared%20Documents/WP4/Deliverables/D4.2/Testbed4_Demo_videos.pptx?d=wabcfd985c43a4eb99298fb946f33eeed&csf=1&web=1&e=0pflMv

EDGE side it has been developed an architecture that uses components from an external partner to collect, normalize and store data from machine sensors. It has been developed a middleware platform based on microservices that will provide, among other things, connectivity with IoTwins cloud to consume its services to create, train, validate and run ML model.

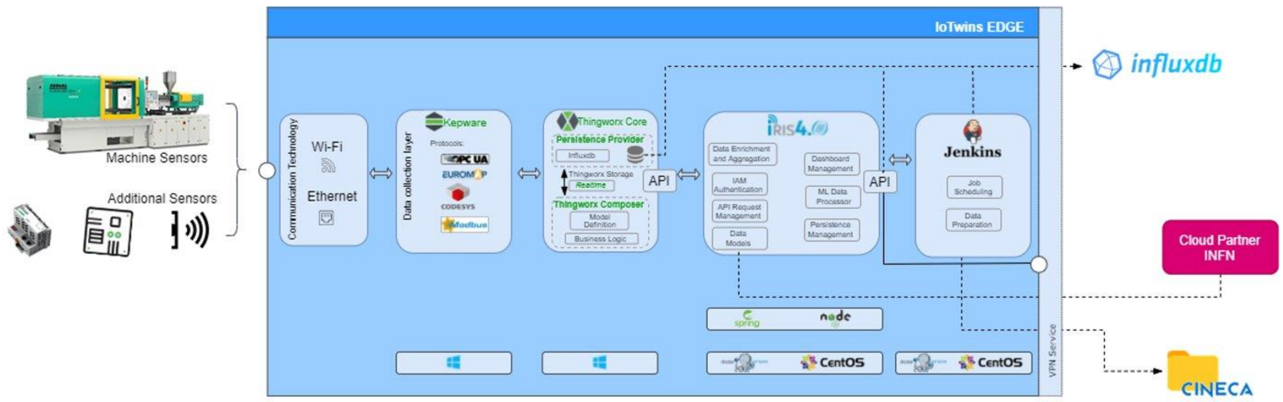

Figure 15: Architecture Overview

5.4. Validation performed so far

The validation aspect is done in one specific plant in Italy. To break down the overall goal to a limited number of machines in a controlled environment is reducing the complexity to understand the full behaviour of an injecting molding machine. The validation step is the comparison of the physical data to the behaviour model output and correct detection of a breakdown.

Input data for the model is a multivariate time-series sampled every 500ms with 49 input features. Data is then grouped in batches of 15 minutes for model training. The features include:

- the electric current consumption of the machine,
- the temperature in each of the cavities of the mould,
- the velocity of the vibration of the bearing
- the acceleration of the vibration of the bearing.

The figure below illustrates the sample input data.

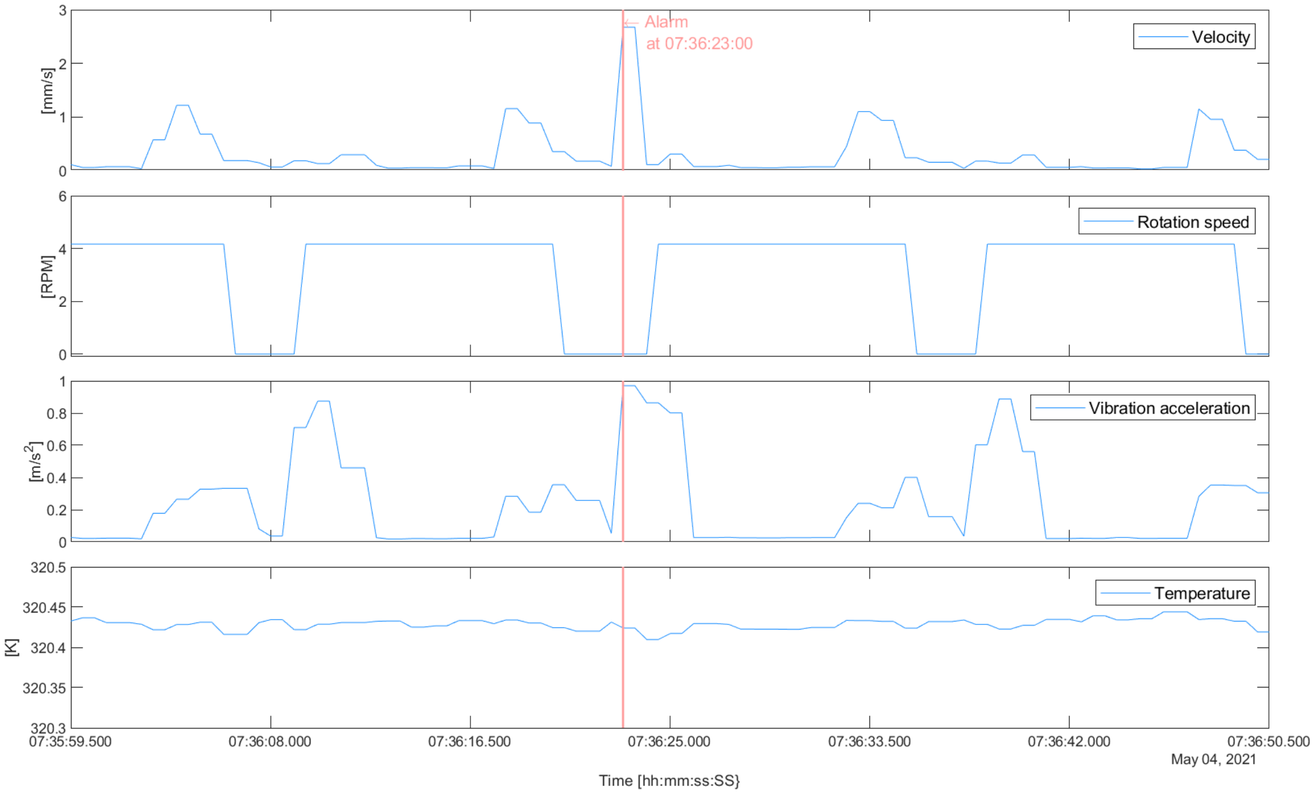

Figure 16: Multivariate Features by time

Preliminary results, illustrated below, indicate that the model predictions are in accord with the real data. Given a day in which the machine had one critical alarm at around 14:15, the model correctly begins predicting this failure at 13:30. This is illustrated in the figure below, showing a gradual decrease in model output value p from 13:30 (p = 0.8642) until 14:30 (p = 0.0353). Once the failure is resolved and the machine status goes back to Normal, the output value computed by the model increases and stabilises itself around approximately 1.

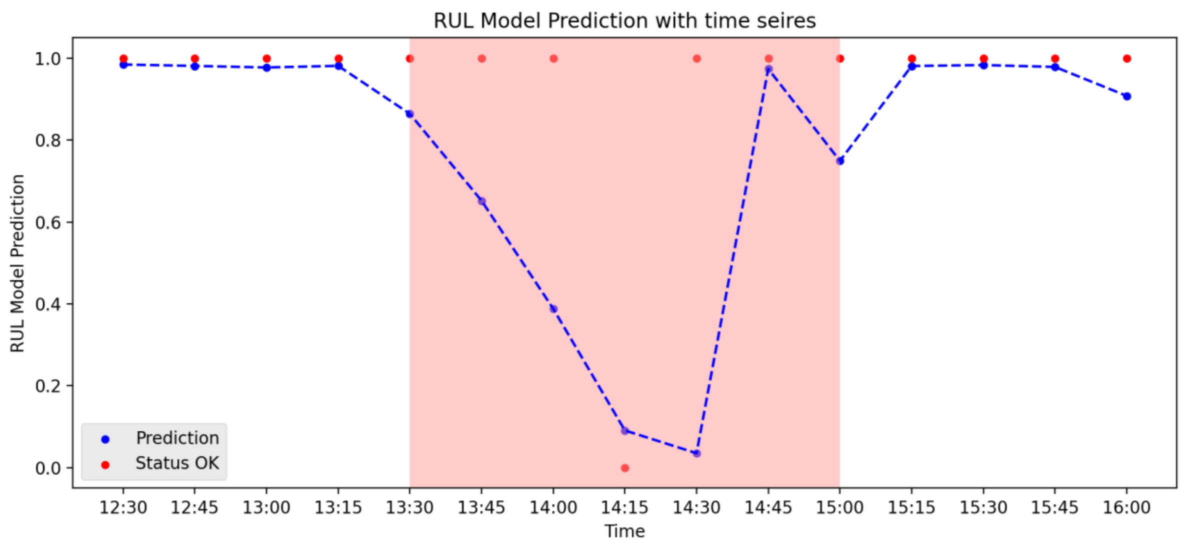

Figure 17: Model Prediction following Bearing Status

6. Conclusion

This deliverable reports the outcome of the work done within subtask 4.1.1, 4.2.1, 4.3.1 and 4.4.1 to smartify or sensorize the systems related to the testbeds and data acquisition. In addition, D4.2 concentrates on presenting the first digital Twin version delivery for all the manufacturing testbeds.

To summarize the primary results already achieved testbed per testbed:

Testbed 1 (BRI)

An **i**nitial version of a "virtual twin" (physics-based) model of a wind turbine yaw drive system has been developed. Limitations have been observed in the simulation model due to the paucity of environmental data (wind speed, wind direction etc) available. Future evolutions will exploit the high-frequency data acquired from installed WTGs to remove these limitations. Furthermore, complementary ML models will focus on analysis of acceleration data (ENSAM).

Testbed 2 (FILL)

The edge architecture was designed as microservice architecture based on Docker containers. In the first version, the data processing and data collection of the machine tool has been fully implemented. The data is transferred to the cloud using the min.io service of INFN. Furthermore, first local models have been established to distinguish milling inside from milling outside the material.

Testbed 3 (ETXE)

The 3 different scenarios are completely deployed to serve as data source to test RUL estimation and future system validation. AR-AsLG-HMM algorithm is being tested under the data coming from different testbeds. Right now there is available data from lab, factory and production facility that is being used to validate different steps towards actionable insights, i.e., data acquisition, pre-processing and Edge processing. Data is being recorded as a data stream to also test the platform processing done at the IoTwins platform.

Testbed 4 (GCL)

A Machine Learning model to estimate the remaining useful life (RUL) of a critical bearing in Plastic injection moulding machine is developed. This model will help to perform required preventing maintenance in advance to avoid any failures during production on the machine.