The Digital Manufacturing and Design Training Network

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Deliverable 3.4

Self-contained and combinable services to support analysis of production performance, monitoring and optimisation activities

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Summary

This deliverable is centered on the development and deployment of a cloud-based service based on the architecture and requirements described in deliverable 3.3, with a specific focus on the implementation of a self-diagnosis service. This service is designed to continuously monitor, analyze, and detect potential faults or anomalies in real-time, facilitating predictive maintenance to minimize downtime effectively. The methodology employed involves a comprehensive mapping of the system components onto the established architecture, coupled with a thorough analysis of the predefined requirements for the self-diagnosis service. The OptiTwin project serves as a demonstrator, aligning seamlessly with the proposed architecture and providing valuable insights for future implementations. It is expected that the mapping process of the demonstrator contribute to the advancement of digital manufacturing and design practices.

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Foreword

DiManD aims to develop a high-quality multidisciplinary, multi-professional and cross-sectorial research and training framework for Europe. The purpose is to improve Europe's industrial competitiveness by designing and implementing an integrated programme in the area of intelligent informatics driven manufacturing, which will form the benchmark for training future Industry 4.0 practitioners. This will be done in compliance with the industrial requirements such revolutionary production systems will pose, and in particular this deliverable will provide a real-world demonstrator of one cloud-based service as described in the previous deliverable.

1 Introduction

In the modern industrial landscape, cyber-physical systems (CPSs) stand as a pivotal technological framework that integrates physical elements with advanced computing and communication technologies. This integration enables enterprises to increase their automation levels, enhance efficiency, and improve system adaptability to sudden changes [1, 2, 3]. Despite the potential CPSs show to reshape current and future industry practices, their integration into existing manufacturing environments still necessitates additional, proper guidance [4].

In the context of an increasingly globalized manufacturing landscape, the concept of customer-oriented manufacturing emerges as promising to elevate service quality and competitiveness, particularly for small and medium-sized enterprises (SMEs). Consequently, a new concept in the realm of advanced manufacturing, cloud manufacturing, has obtained global attention, which revolves around deploying CPS within a cloud computing environment [5]. Cloud computing is a model for enabling overall, convenient and on-demand network access to a shared pool of configurable computing resources (e.g. networks, servers, storage, applications, and services) that can be rapidly offered and released with minimal management effort or service provider interactions [6, 7].

Within the framework of the DiManD project, this deliverable (D3.4) represents a demonstrator of a cloud-based self-diagnosis service that adheres to the architecture and requirements previously proposed in the deliverable of this work package (**D3.3 Guide to develop and deploy CPS resources**). Thus, the main objective of this deliverable is to develop and deploy such a service, as a key component of the continuous improvement of machining processes. This service aims to monitor, analyze, and promptly detect potential faults in real-time, with the ultimate goal of enabling predictive maintenance to minimize downtime effectively.

To this end, this deliverable makes use of OptiTwin [8], a parallel project funded by the Provincial Council of Gipuzkoa, Spain, as demonstrator of self-diagnosis systems, aligning seamlessly with the proposed architecture. OptiTwin provides a tool condition monitoring (TCM) system based on machine learning (ML) and deep learning (DL) tool-wear prediction services. It is comprised of sub-systems (components) deployed in the machining laboratory of MGEP (asset and edge layers), as well as in the cloud.

This deliverable details the methodology, demonstrator, architecture mapping, and requirements fulfillment but also sets a blueprint for future developments. The planned integration of a fog layer, enhanced real-time capabilities, and the system's adaptability underscore its dynamic

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nature. As digital manufacturing continues to evolve, this deliverable reflects the ongoing pursuit of innovation and efficiency within the DiManD project.

The rest of this document is structured as follows. Section 2 describes the background concepts of machining and TCM, as well as related work. Section 3 presents the methodology (outlined in Subsection 3.1), which focuses on the comprehensive mapping of specific system features onto the established architecture, following a meticulous analysis of requirements. Subsequently, Subsection 3.2 describes the demonstrator, i.e., the OptiTwin project, as well as its components.

Section 4 maps the architecture of OptiTwin and its components with the proposed architecture of D3.3. This mapping underscores the capacity of the system for real-time TCM and tool wear prediction, showcasing its ability to capture, analyze, and deploy predictive models for optimized machining processes. Thereafter, Section 5 presents the requirements mapping, offering a comprehensive overview of the self-diagnosis requirements fulfilled by OptiTwin across the categories detailed in D3.3, i.e., connectivity, data managing, monitoring and analysis, planning, execution, and knowledge. Finally, Section 6 presents a discussion on the mappings, Section 7 as insights for future implementations, and Section 8 presents the conclusions of this deliverable.

2 Background

Machining is a cost-effective manufacturing process that produces high-precision parts with high-quality surface finishes. However, maintaining optimal machining conditions requires continuous monitoring of various parameters, such as force, noise, temperature, and vibrations, to identify tool wear that could lead to damaged parts and process disruptions [9]. Thus, accurate monitoring and prediction of tool wear stages, including initial, gradual, and failure wear stages, and remaining tool life are crucial in machining [10]. This has led to the development of TCM systems based on tool wear that aim to identify the appropriate time to replace cutting tools.

The TCM prediction cycle in machining processes, as depicted in Figure 1, is a continuous process that begins with the acquisition of signals from the machining process using various sensors. These signals are transmitted to a work station, where they are processed and analyzed to extract relevant features. Both the raw signals and the extracted features can be used to train predictive models, usually hosted in the cloud. These models, developed on datasets of historical data, predict the wear state or remaining useful life (RUL) of the tool. As the machining process progresses, the models are updated with new sensor data to improve prediction performance. Predicted tool wear states and RUL inform decision-making regarding machining process parameters, such as tool replacement or adjustment of processing conditions.

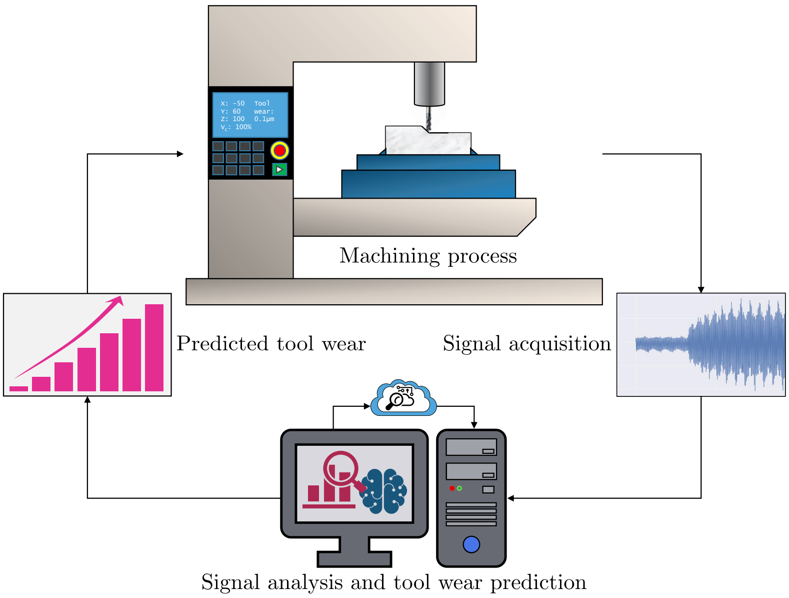

Figure 1: Tool wear prediction cycle in machining processes.

Several TCM systems based on artificial intelligence (AI) algorithms have been proposed and reviewed in literature. The algorithms implemented are usually based on machine learning (ML) or deep learning (DL) algorithms. For turning and drilling operations, TCM systems based on ML algorithms, e.g., decision trees, have been highlighted as effective approaches. For more

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complex processes, such as milling, more advanced algorithms, like ensembles and DL algorithms have been recommended [11].

Sofuoğlu et al. [12] developed models for turning using artificial neural networks, decision trees, and support vector machine models, with the decision trees showing superior prediction results. Bustillo et al. [13] compared various ML algorithms for turning, such as regression trees, artificial neural networks (ANNs), and ensembles. The study found that artificial neural networks had the highest accuracy but required complex tuning processes. On the other hand, ensembles such as random forest provided similar accuracy without tuning.

For milling, Cheng et al. [14] proposed a framework, which uses feature normalization and an attention mechanism for pre-processing. Then, a parallel convolutional neural network (CNN) followed by bi-directional long short term memory (BiLSTM) are used for TCM, and a dense residual neural network (ResNetD) is used for short-term and long-term tool wear prediction. Martínez-Arellano et al [15] presented a big data approach for TCM that uses Gramian angular summation fields for signal imaging and a convolutional neural network (CNN) deep learning architecture for tool wear classification, working directly with the signal images and avoiding statistical pre-processing or filtering. Finally, Sun et al. [16] integrated a LSTM network for forecasting multiple flank wear values based on historical data, and a ResNet for real-time TCM using raw signals.

Despite significant advancements, AI-based TCM have not yet fully reached technology readiness level (TRL) 9, indicating a lack of readiness for industrial applications. To achieve this level, three key factors need to be addressed: (i) Selection of key sensor signals captured from physical assets, (ii) efficient signals processing and analysis, and (iii) development of high-performing predictive models [17]. Relying on individual sensor signals can produce low quality process information. To address this, combining multiple sensor signals (sensor fusion) allows for monitoring various aspects of the process and enhances the effectiveness of TCM systems. Additionally, employing minimal and automated signal processing techniques and training AI models with diverse cutting conditions ensures adaptability to changing circumstances, reducing the gap between research and industrial applications [18].

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3 Methods

The primary objective of this deliverable within the DiManD project was to develop and deploy a cloud-based service within the established system environment and architecture formulated in the preceding deliverable. The chosen focus was the implementation of the self-diagnosis service, extensively discussed in **D3.3**. This service aims to continuously monitor, analyze, and detect potential faults or anomalies in real-time, enabling predictive maintenance to effectively minimize downtime.

In order to fulfill the deployment of this service, the OptiTwin project [8] was used as demonstrator. A comprehensive mapping was conducted, associating specific system features of the demonstrator onto different components of the architecture presented in D3.3. Additionally, a thorough analysis of the predefined requirements for the self-diagnosis service was undertaken. The following subsections detail the methodology followed to map the architectures and requirements and describe the OptiTwin project.

3.1 Methodology

The activities within this deliverable focused on the goals set in D3.3. Establishing a suitable demonstrator for the cloud-based self-diagnosis service needed a comprehensive evaluation to determine the alignment of the demonstrator with the architecture proposed in D3.3, depicted in Figure 2. The D3.3 architecture includes 4 layers: (i) assets layer, (ii) edge layer, (iii) fog layer, and (iv) cloud layer. In addition, the interaction between the layers and the self-diagnosis services are also depicted in the architecture. Additionally, the focus included a thorough analysis of the requirements, also described in D3.3, to establish which were fulfilled by the demonstrator. The full description of the system employed as a demonstrator for our implementation is provided in the following subsection.

The methodology followed in this deliverable was composed of two stages: (i) map the architectures and (ii) analyse the fulfilment of requirements. To map the architectures, several steps were followed. The equipment components were checked and data exchange flows and storage systems were identified. Thereafter, physical and digital connections between elements were determined and, finally, the elements of the demonstrator were mapped to the D3.3 architecture. This analysis can be seen in Section 4.

The requirements criteria list established in D3.3 was used to analyze and select the requirements fulfilled by the demonstrator based on its capabilities, as well as to highlight any requirements that were missed. As additional information, annotations were included for the requirements that were planned to be added in future improvements of the system. This mapping can be seen in Section 5

The mapping of the architecture and analysis of the fulfillment of requirements provided insights into the operational aspects of implementing self-diagnosis services. This case study not only presented a demonstrative model but also demonstrated the feasibility of integrating self-configuration services within a similar framework. Moreover, this assessment highlighted areas that require improvement, modification, or inclusion to achieve a fully functional cloud-based service configuration.

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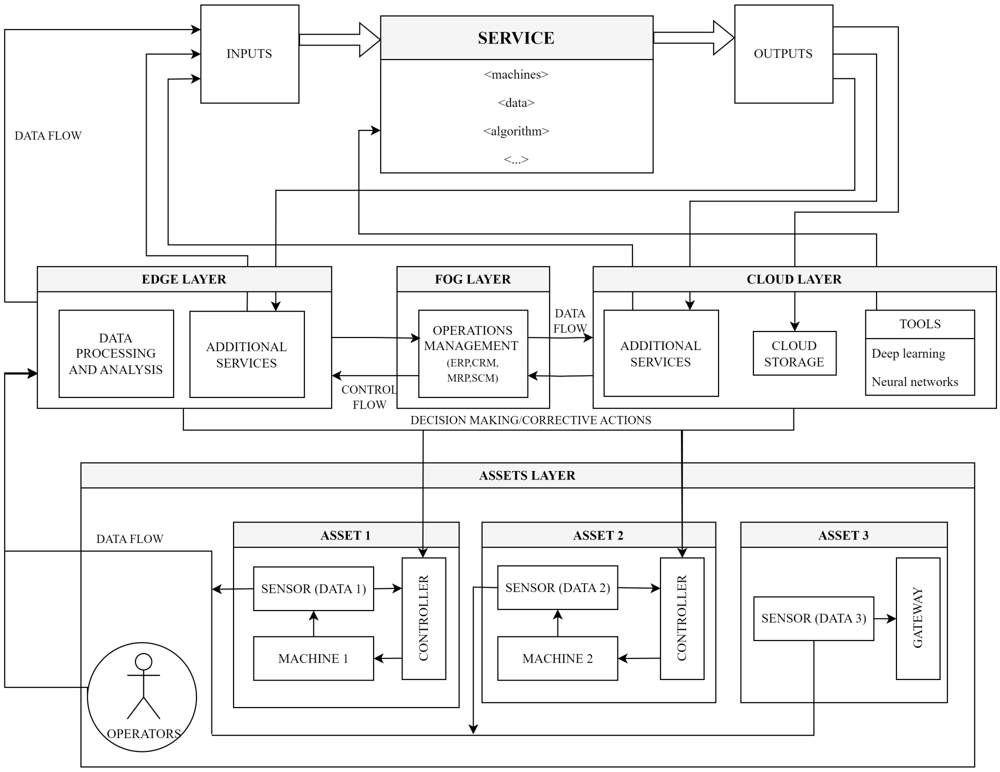

Figure 2: Architecture proposed in Deliverable 3.3.

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3.2 Demonstrator - OptiTwin

The system used as demonstrator for the methodology presented in the previous subsection is a result of the OptiTwin project. OptiTwin is a project funded by the Provincial Council of Gipuzkoa (Department of Economic Promotion, Rural Environment and Territorial Balance) in the 2020 call of the "Support Program for the Gipuzkoan Network of Science, Technology and Innovation". OptiTwin is situated within the field of digital manufacturing and has the objective of developing data-based models aimed at optimizing digital twins for machining processes. In particular, OptiTwin has focused on signal acquisition and analysis, as well as tool wear prediction.

OptiTwin is the result of the collaboration of three research groups: (i) high-performance machining [1], (ii) software and systems engineering [2], and (iii) data analysis and cybersecurity [3]. All these groups, belonging to the Higher Polytechnic School of Mondragon Unibertsitatea, have collaborated on the project focused on implementing machine learning models in the industrial environment. This has been done by integrating the cloud-based system into a computerized numerical controlled (CNC) machining center. The workflow of OptiTwin is presented in Figure 3 and involves three components:

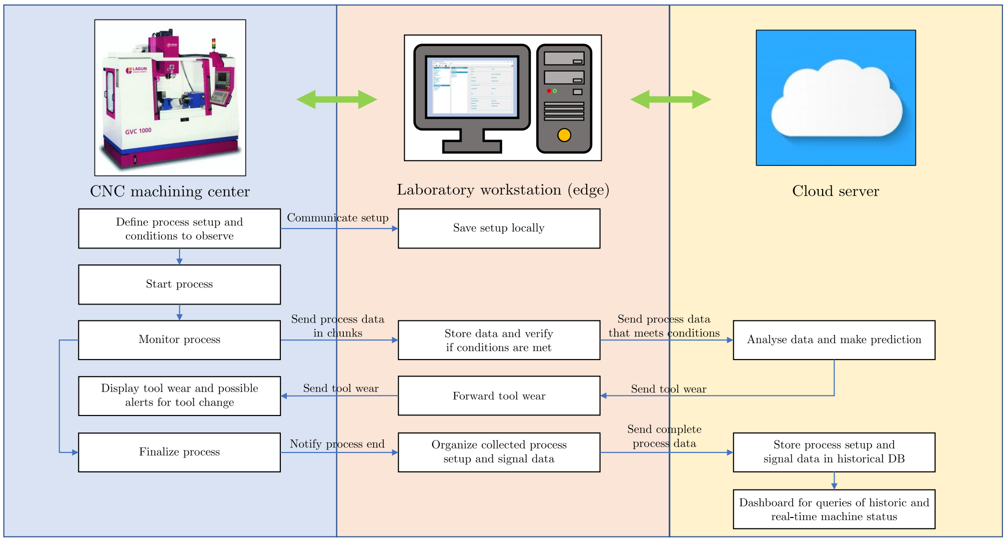

Figure 3: OptiTwin workflow.

- **CNC machining center**: This component is a LAGUN GVC 1000 CNC machining center equipped with a Fagor CNC. It includes the software of the CNC and the experiment designer of OptiTwin. OptiTwin extracts signals from the process via the API of the

[1] `http://www.mondragon.edu/mar`
[2] `http://www.mondragon.edu/ingsw`
[3] `http://www.mondragon.edu/danz`

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CNC and sends this data to the **laboratory workstation**, together with the experiment definition data. In addition, the tool wear obtained from the OptiTwin tool wear prediction services in the **cloud server** is displayed on the OptiTwin screen. In addition, condition ranges, such as tool position and cutting speed, are configured in this component to identify when to perform process diagnosis. Figure 4 illustrates the graphical user interface (GUI) of the OptiTwin experiment designer with two images: (Figure 4a) experiment definition and (Figure 4b) ongoing experiment tool wear prediction. The experiment definition screen includes fields to record process data, cutting conditions, and tool data. The ongoing experiment tool wear prediction presents the status of the connection to the laboratory workstation in the panels, followed by the selection of only collecting data or collecting data and predicting tool wear. The bottom right panel displays if there is connection to the CNC, if data is being transmitted, and if range conditions are met for predicting tool wear. In case range conditions are met, tool wear is displayed in real time in this panel. Finally, in the bottom left panel, an alert is displayed in case the tool needs to be changed due to its wear.

- **Laboratory workstation (edge)**: This component is a workstation in the edge of the network that hosts the OptiTwin experiment manager software, which records and stores the signals sent by the experiment designer of OptiTwin hosted in the **CNC machining center**. The workstation analyses the received signals and processes the data to extract key performance indicators (KPIs). These, and the complete process data, are sent in real time to the **cloud server** for storage and, if the condition ranges are met, to predict tool wear with the ML and DL models. Tool wear is received back from the cloud and sent to the CNC to be displayed on screen. Figure 5 illustrates the GUI of the OptiTwin experiment manager, where the process data is stored and can be queried. In this screen, the historical experiments can be selected, and the experiment definition data for the selected one is displayed in the right panel.
- **Cloud server**: This component is a cloud server where ML and DL models for tool wear predictions are hosted and historical process data is stored to retrain models or to further investigate additional aspects of the process, such as chatter or surface roughness. Process KPIs and raw data are received from the **laboratory workstation** and stored in databases. In addition, KPIs and process signals are processed by the ML and DL models for tool wear predictions. The predicted tool wear is sent back to the workstation and then forwarded to the **CNC machining center**. Tool wear prediction is performed based on the complexity of the machining process type. For drilling processes, which form simple circular shapes, a decision tree model is used, which receives the KPIs as input for the predictions. For milling processes, which form complex and varied shapes, an advanced DL ensemble is used, which uses the pre-processed signals as input for the predictions. In addition, the cloud server includes a dashboard for querying and displaying historical data from the CNC machining centre.

Based on the description of the OptiTwin project, it was determined that the system aligns with the architecture proposed and described in D3.3. Therefore, the mapping of the architecture and the fulfillment of requirements are detailed in following sections, as well as a discussion of the results.

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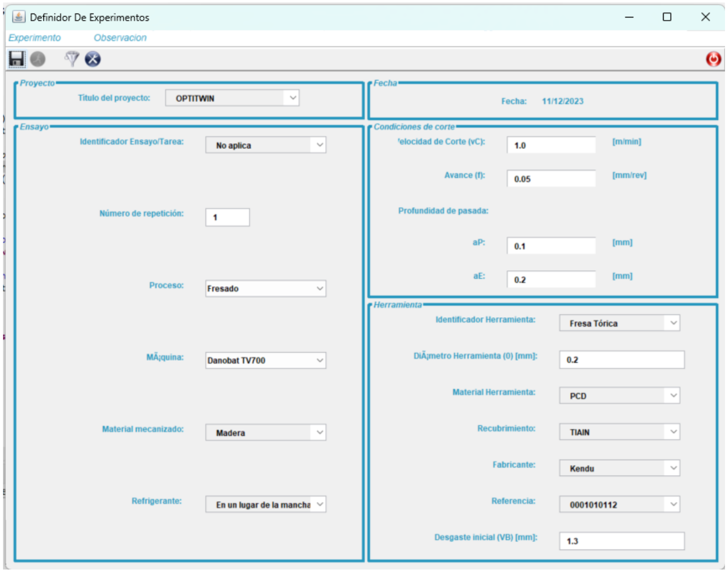
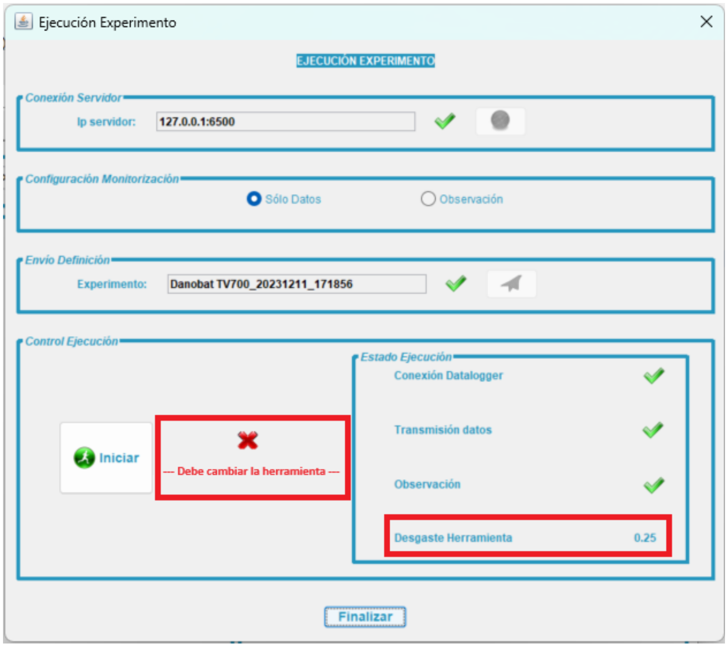


(a) Experiment definition.



(b) Tool wear prediction of ongoing experiment.

Figure 4: OptiTwin experiment designer hosted in the CNC machining center.

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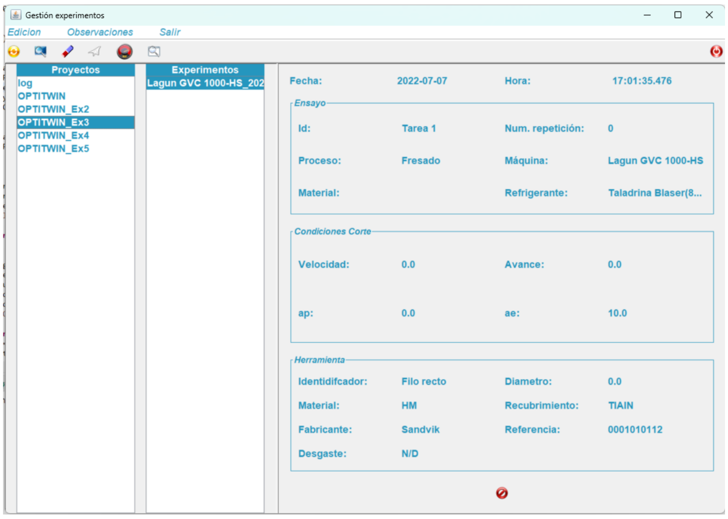

Figure 5: OptiTwin experiment manager hosted in the edge.

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4 Architecture mapping

This section presents a description of the architecture of the OptiTwin demonstrator, a real-time monitoring system developed for optimizing machining processes. The architecture is mapped to the previous architecture proposed in D3.3, highlighting the alignment of the components and services provided by OptiTwin.

Figure 6 presents the mapping of the architecture of the OptiTwin demonstrator to the architecture proposed in D3.3. The components outlined in Section 3 are marked in the figure using the same color scheme used in Figure 3. The components and service provided by OptiTwin are mapped as follows:

- **Assets layer**: There is one main asset in the OptiTwin demonstrator, a Lagun GVC 1000 CNC machining center with a Fagor CNC controller. The CNC measures several signals from the machine via a CNC API. The signals measured include:
  - the real RPM
  - position of the spindle (S) in degrees
  - position of the spindle in the X, Y and Z axes in mm
  - RMS current feedback and active power of the spindle (S)
  - RMS current feedback and active power of the X, Y and Z axes motors
  - torque feedback in the X, Y and Z axes

  The signals measured are acquired from the CNC API by the OptiTwin experiment designer and are transmitted in real time to the **edge layer**. In addition, process information is transmitted as well to the edge layer.

- **Edge layer**: The OptiTwin laboratory workstation component is hosted in the edge layer. Data pre-processing and analysis are performed on the raw signals acquired in the **assets layer**. These services include signals de-noising using a moving-average filter and z-normalization. Furthermore, feature extraction is performed, obtaining KPIs of machining processes that include statistical features of the time, frequency, and time-frequency domains. Two additional services are provided by OptiTwin: (i) Local storage of process information, raw signals, and KPIs in the edge file storage and (ii) observation of predefined condition ranges in the pre-processed signals and KPIs. When the conditions are fulfilled, the data is transmitted to the **cloud layer** for tool wear prediction.

- **Fog layer**: A fog layer is not currently implemented in the OptiTwin project, as it is in an early stage of development, where focus is given to establishing core functionalities of tool wear prediction system and to ensuring accuracy and reliability. As the OptiTwin project matures, a fog layer will be considered to enhance real-time capabilities, providing integration with production and logistical systems, such as material requirements planning (MRP) and supply chain management (SCM) systems.

- **Cloud layer**: OptiTwin provides cloud storage in two formats: time-series storage using InfluxDB and a file storage using Dropbox. The tools provided by the OptiTwin cloud

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layer include DL models for tool wear prediction for milling and drilling processes, as well as a Grafana dashboard for querying historical and real-time data. The DL models are used by the tool wear monitoring **service** when the edge layer sends data for tool wear prediction.

- **Services**: A tool wear monitoring service is provided by OptiTwin. The service uses the pre-processed signals and extracted KPI features obtained from the **edge layer** as inputs, when condition ranges are met. The DL models hosted in the **cloud layer** perform the prediction, and the output, i.e., tool wear prediction, is sent to the cloud layer for storage. The cloud layer then forwards the prediction to the **edge layer**, which in turn forwards it to the CNC controller in the **assets layer**. The tool wear prediction is displayed on screen in the CNC controller and a warning is emitted when the tool wear exceeds a predefined tool wear value.

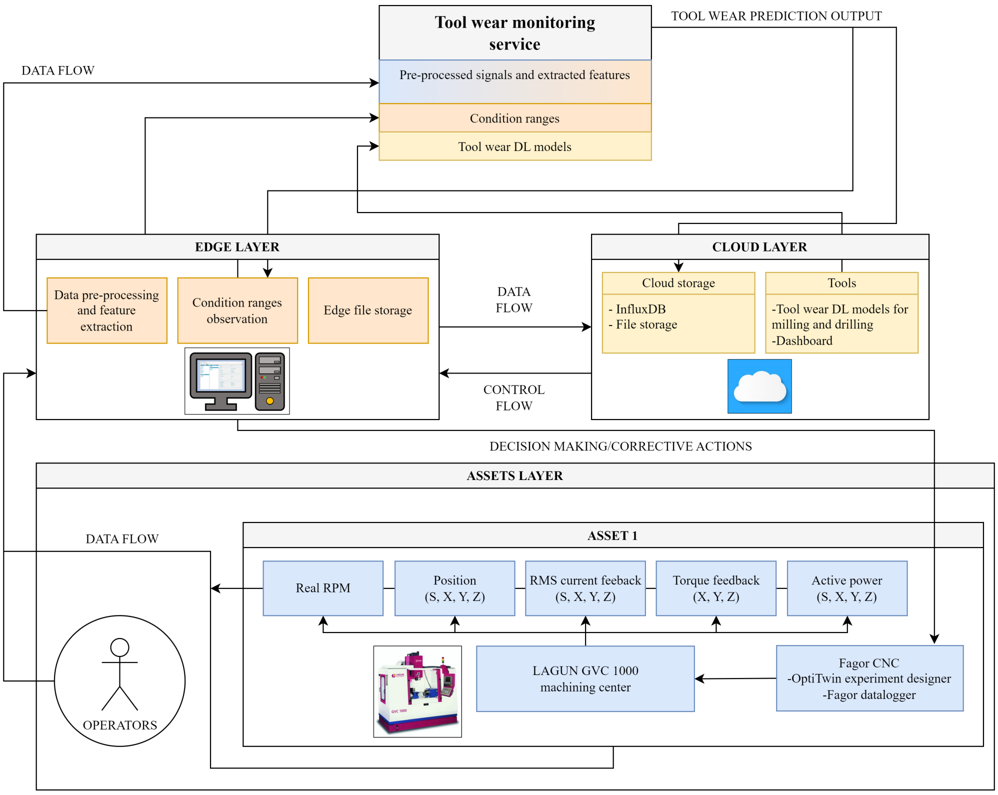

Figure 6: Mapping of OptiTwin architecture to the architecture proposed in D3.3.

The OptiTwin architecture provides an implementation aligning to the architecture of D3.3 for self-diagnosis, enabling real-time tool wear monitoring and prediction for improved machining efficiency. The system captures and analyses sensor data, extracts relevant features, and

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deploys predictive model, ensuring accurate and real-time tool wear insights. While the current implementation lacks a fog layer, plans are in place to integrate it in future developments to enhance real-time capabilities and to facilitate seamless integration with production and logistical systems. The following section will further map the requirements for self-diagnosis presented in D3.3, providing a more thorough assessment of the suitability of OptiTwin as demonstrator of self-diagnosis systems.

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5 Requirements mapping

In this section, the requirements mapping process is performed by associating specific requirements for self-diagnosis behavior derived from D3.3 with elements and features within the OptiTwin platform. Table 1 provides an overview of the requirements and components associated with the presented architecture and illustrates how these requirements are mapped into the implementation of the OptiTwin system in a manufacturing environment. Requirements are organized into categories such as Connectivity, Data Management, Monitoring and Analysis, Planning, Executing, and Knowledge. The table outlines sub-requirements for each of these categories, including the fulfillment status, OptiTwin resources, inputs received by OptiTwin, and OptiTwin outputs.

The **connectivity** requirement fulfillment highlights the diverse array of signals acquired from the CNC machine, such as real RPM, position, and current feedback, showcasing the ability of the system to monitor various parameters. Several application protocols, including MQTT and HTTPS, and an Ethernet communication protocol ensure efficient data transfer between the CNC machine and the other components of OptiTwin system, promoting seamless connectivity.

For the **data management** requirement, the system fulfills the sub-requirements. Data collection and storage, with specified sampling frequencies and storage capacities, are defined as outlined in D3.3. Security measures, such as firewalls, OAuth access tokens, and TLS security, ensure the confidentiality and integrity of the collected data. This section also emphasizes the importance of securing the data during its transfer from the edge to the cloud and maintaining user authentication for access control.

The **monitoring and analysis** requirement unveils the robust capabilities of the system in the data pre-processing and analysis aspects. Various techniques, including moving average filters and z-score normalization, are employed for noise reduction. Moreover, deep meta-learning models and decision trees are applied for data analysis, showcasing the system's adaptability to different machining processes. It was identified that fault detection and performance analysis features are yet to be implemented. However, the lacking sub-requirements do not hinder the implementation of the core functionality of the system that implements elf-diagnoses tool wear.

For the **planning** requirement, OptiTwin fulfills one of the sub-requirements. The system effectively handles alerting and accessibility requirements, as evidenced by the on-screen alarm feature, ensuring that relevant stakeholders receive timely notifications. However, there are still gaps in fulfilling the fault assessment and the recovery plan sub-requirements. The absence of a fault assessment mechanism prevents the system from generating reports based on expert knowledge and root cause analyses, hindering a comprehensive understanding of failures. Additionally, the lack of a recovery plan suggests a potential gap in addressing issues and implementing corrective actions systematically. Regarding policies adjustments, the system has a well-defined strategy to be implemented in upcoming versions, incorporating standards like ISO 8688-1:1989 and manual adjustments as well. The planned implementation of continual learning techniques for fine tuning of DL models when new data becomes available showcases the adaptability potential. Adjusted policies and model weights serve as valuable outputs, contributing to the system's resilience and adaptability.

Similarly for the **executing** requirement, the system faces challenges in plan execution and fault correction. This is anticipated considering the absence of fault assessment and recovery

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plans in the planning phase. However, the reporting sub-requirement has been fulfilled, with the use of Grafana dashboards to effectively visualize failure reports to stakeholders,

Finally, the **knowledge** requirement underscores the system capability to manage information effectively. In the context of the OptiTwin framework, the subrequirements are fulfilled. For historical data, the system successfully captures measurements and tags related to CNC machine variables in an Influx database, while storing and managing user information in a PostgreSQL database. Additionally, historical experiment data is stored in Dropbox and on the edge. Policies, in adherence to ISO 8688-1:1989 and observation condition ranges, are systematically managed and updated within the databases. Symptoms and conditions are monitored through a tool wear log, supported by machine learning models that contribute to generating logs and alarms. Lastly, the information sub-requirement encompasses the generation of information from data, where KPIs are extracted from cutting conditions and signals.

Requirements	Sub-requirement	Fulfilled (Yes/No/ Partially)	OptiTwin resources	OptiTwin inputs	OptiTwin outputs
Connectivity	Sensor selection and placement	Yes	CNC sensors: - RPM - Spindle position (X, Y and Z axes and angle of the spindle) - RMS current, torque and active power	Tool wear	Raw sensor data
	Sensor data and historical data	Yes	- Edge: CSV files - Cloud: Dropbox and InfluxDB	Machining data	Raw and historical data
	Application protocol	Yes	- Dashboard: MQTT (CNC-to-cloud data collector) - Data collection: CNC API (CNC to edge) - Tool wear: HTTPs (edge to cloud)	MQTT 3.1, CSV, HTTPS	Formatted data
	Communication protocols	Yes	Ethernet	IEEE 802.3	
Data managing	Data collection and storage	Yes	- Sampling frequency: 250 Hz for internal signals (tool wear prediction) and 0.1 Hz for energy consumption (dashboard) - Storage capacity: Unlimited for Dropbox, 50 GB for InfluxDB, and 500 GB for edge file storage.	Machining data	- Edge: CSV files - Cloud: Dropbox and own InfluxDB server
	Security and anonymity of data	Yes	- Firewall for CNC API. - OAuth access token for automated saving in Dropbox and InfluxDB. - User authentication for Dropbox file access, MQTT, InfluxDB administration, and dashboard access. - TLS security for MQTT.	OAuth 2.0, TLS 1.2, and IP and port screening through domain firewall	Secured data

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Monitoring and analysis	Data pre-processing	Yes	Moving average filter, z-score normalization, feature extraction: - Time domain: RMS, variance, maximum, skewness, kurtosis, peak-to-peak - Frequency domain: Spectral skewness and spectral kurtosis - Time-frequency domain: Max wavelet energy of wavelet coefficients	Raw signals	Normalized and noise reduced signals, as well as statistical features
	Data analysis	Yes	- Deep meta learning model for milling - Decision tree for drilling	Pre-processed data	Tool wear value
	Fault detection	No			
	Performance analysis	No			
Planning	Alerting and accessibility	Yes	On-screen alarm	Tool wear	Alarm indicating tool change
	Fault assessment	No			
	Policies adjustments	Planned for future implementation	- ISO 8688-1:1989 for maximum tool wear value - Manual adjustment of the maximum acceptable tool wear value to suit specific requirements - Continual learning techniques for fine tuning of DL models as new data becomes available	Machining data	Adjusted policies and model weights
	Adaptation plan/Recovery plan	No			
Executing	Plan execution	No			
	Fault correction	No			
	Reporting	Yes	Dashboards (Grafana)	Machining data and energy consumption data	Stakeholders
Knowledge	Historical data	Yes	- Measurements and tags, related to the variables captured by the CNC machines and stored within the InfluxDB database - Users and roles within django app are stored in a PostreSQL - Historical experiment data, stored in Dropbox and edge	Machining and experiment data	Dashboards

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Policies	Yes	- ISO 8688-1:1989 for maximum tool wear - Observation condition ranges	- Maximum tool wear - Condition ranges	Updated policies
Symptoms and conditions	Yes	Tool wear log	ML models	Logs and alarms
Information	Yes	- Cutting conditions - Statistical KPIs	- Signals - Cutting speed (S) - Feed rate (F) - RPM (Rotations Per Minute) - Radial depth of cut (a_p) - Axial depth of cut (a_e)	KPIs: - Time domain: RMS, variance, maximum, skewness, kurtosis, peak-to-peak - Frequency domain: Spectral skewness and spectral kurtosis - Time-frequency domain: Max wavelet energy of wavelet coefficients

Table 1: Self-diagnosis requirement analysis for OptiTwin.

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6 Discussion

This study aimed to present a self-diagnosis service to support production analysis, monitoring, and optimization complying with the CPS architecture proposed in D3.3 of the DiManD project. The selected service was a cloud-based TCM service deployed in OptiTwin to help improve machining processes. Based on the architecture and requirements for self-diagnosis services proposed in D3.3, the following points are worth discussing:

- OptiTwin is currently under development, and its structure is consistent with the CPS architecture outlined in D3.3. Although certain elements, such as the fog layer, are yet to be implemented, the primary function of the TCM service is fulfilled. Thus, future implementations will focus on enhancing features and benefits for the production system.

- The TCM service of OptiTwin operated independently of other functions of the CNC machine (asset), its controller, or other services that monitor the production system, becoming a self-contained service. As seen in Figure 6, the data acquisition, processing, storage, and results do not interfere with the main process execution (in this case, machining) and provide stand-alone results.

- Due to its modular structure, the TCM service could be easily scaled to include other assets or to increase its functionalities by combining its outcomes with other self-contained services. As seen in the architecture mapping, the machining center, CNC, and sensors correspond as to a single asset instance. As more machines executing similar machining process are added, service elements in the edge and cloud layers remain the same, due to the modular approach of OptiTwin.

- Regarding the fulfilment of requirements for self-diagnosis services, the valuable role of the connectivity, data management, monitoring and analysis, planning, executing, and knowledge requirements was demonstrated. Although the main service (tool wear prediction) is part of the monitoring and analysis requirement (data analysis), the successful execution of this service relies on the fulfillment of the other requirements.

- As shown by the current state of OptiTwin, the system does not need to fulfill all sub-requirements. However, the sub-requirements which are lacking should be assessed according to the needs of the target system, considering that the more sub-requirements are fulfilled the more trustworthy the service becomes. In this sense it is also important to balance the expected outcomes and current and future business demands, with the investment needed for its implementation.

Based on this demonstrator, it is possible to state that a self-diagnosis service complying with the architecture proposed in D3.3 and its requirements can be a self-contained service able to support process improvement. The benefits resulting from successfully implementing self-diagnosis services can contribute to the fast adoption of CPS in industrial environments.

The contribution of this work extends beyond outlining requirements and sub-requirements; it provides the blueprint for analyzing and implementing a self-diagnosis system within machining processes. By detailing every facet from connectivity to knowledge management, it serves as a road map for researchers, engineers, and practitioners in the field.

7 Insights for future implementations

The implementation and analysis of the self-diagnosis service using the OptiTwin project as a demonstrator, as outlined in this study, revealed significant insights. The potential for supporting production analysis, monitoring, and optimization within the context of the CPS architecture proposed in D3.3 of the DiManD project has been shown to be an effective approach. The following are the insights drawn from the results and discussion presented in the previous sections, regarding OptiTwin and its potential to improve machining processes.

- Improving and fulfilling the planning requirements within the self-diagnosis service is a promising opportunity, especially considering the service's current capability to predict tool wear.
- The system's ability to forecast tool wear against the designated useful lifespan of a CNC machine's tools acts as a vital trigger to improve machining processes. This alert system, signaling the necessity for tool replacement, becomes pivotal to prevent potential damages or substandard product manufacturing.
- Integrating a fault assessment function is a required implementation for self-diagnosis services like OptiTwin. This system complements the existing predictive capabilities, allowing the system, operators, and machinery to identify and address potential tool wear issues.
- Including an adaptation/recovery plan to manage tool wear represents a fairly easy additional step for the current service. Initially, manual intervention by operators for tool replacement and a system reset would be required for a seamless production cycle. Subsequently, automating the tool retrieval process from the machine's internal warehouse and executing the tool change while preserving fixture setup and manufacturing precision would represent a desirable progress to increase the autonomy level of the cell-service system.
- While OptiTwin may not fulfill all sub-requirements in its current state, there is a need to assess these gaps based on the target system. A balance is crucial, considering that the more sub-requirements fulfilled, the higher the trustworthiness of the service.
- It is essential to weigh the expected outcomes against current and future business demands and the required investment for implementation, providing a practical perspective for decision-makers.

In a more general scope, using OptiTwin as demonstrator of a self-diagnosis system has revealed additional insights:

- The work extends beyond outlining requirements and sub-requirements, offering a blueprint for analyzing and implementing self-diagnosis systems within machining processes. By detailing aspects from connectivity to knowledge management, the architecture and requirements of self-diagnosis services serve as a valuable roadmap for researchers, engineers, and practitioners in the field, facilitating the adoption of CPS in industrial environments and contributing to the advancement of process improvement.

- OptiTwin uses a pragmatic approach, in which not all components need to be implemented simultaneously. Recognizing that fault assessment and adaptation hold secondary but crucial significance, the implementation strategy can be subdivided in phases to address primary functionalities first while ensuring the essential aspect of fault assessment and adaptation are not overlooked. This adaptive approach would allow for more manageable and efficient deployments, accommodating the intricacies of system development and ensuring that critical elements are incorporated as the system evolves.

- The concept of incremental functionality is highlighted as a key strategy for implementing self-diagnosis services. By adopting this approach, stakeholders can witness tangible results and potential benefits at each stage of implementation. This not only provides a sense of progress but also allows for iterative improvements based on practical feedback and evolving requirements. This incremental strategy is particularly valuable in the dynamic field of self-diagnosis services, where the evolving nature of technology and industry demands can be accommodated seamlessly, ensuring the system remains adaptable and responsive.

- The modularity embedded in the architecture facilitates the seamless integration of self-diagnosis services but also enhances their scalability. The modular design allows for the independent development and deployment of specific components, ensuring that the implementation process can be tailored to the unique requirements of different industrial settings. This scalability is particularly advantageous in dynamic manufacturing environments where the scale and complexity of operations may vary. This modular scalability not only streamlines the initial implementation of self-diagnosis services but also positions the system for ongoing adaptability.

- The methodology presented in this deliverable provides the steps to map other systems to the architecture and requirements of self-diagnosis services. This not only facilitates a streamlined integration process but also enhances the interoperability of diverse systems within an overarching framework. In addition, this systematic approach contributes to the scalability and universality of the self-diagnosis service, potentially extending its application across various industrial contexts.

It is to note that this document does not discuss the specifics of implementation, as it should be preceded by an in-depth feasibility study and an evaluation period to assess system performance. Prior to deployment, a comprehensive analysis needs to be performed to validate the efficiency of predicted improvements.

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8 Conclusion

In this deliverable, a practical case study has been showcased, highlighting the implementation of self-diagnosis within a cloud-based platform. Specifically, the focus was on integrating the self-diagnosis architecture into the OptiTwin project, mainly on services related to diagnosing tool wear. The study involved a comprehensive two-stage process to align self-diagnosis specifications, ensuring coherence with the entire architecture and the requirements stipulated in the WP3.3 guidelines.

In the first stage, by mapping the architecture of OptiTwin with the D3.3 architecture, the self-diagnosis component were verified, enabling real-time monitoring and predictive analysis of tool wear to significantly enhance machining efficiency. This system actively collects and analyzes sensor data, identifies critical parameters, and employs predictive models, thereby providing accurate and immediate insights into tool wear conditions. Although the present configuration lacks a fog layer, plans are underway to integrate this component in future iterations, to reinforce real-time capabilities and facilitate seamless integration with production and logistic systems. In the second stage, the assessment involved benchmarking the connectivity, data management, monitoring, planning, execution, and knowledge-enabled components against those outlined in the guidelines. Through this process, it was demonstrated that OptiTwin fulfils all essential self-diagnosis requirements as defined in the guidelines.

This demonstrator of the self-diagnosis service using the OptiTwin project has revealed key insights for enhancing production within the CPS architecture proposed in D3.3 of the DiManD project. Noteworthy opportunities identified for OptiTwin include adding a fog layer and integrating fault assessment functions. In addition, the implementation of adaptation/recovery plans for tool wear management is seen as a feasible step towards increased autonomy.

Emphasizing a phased deployment strategy, incremental functionality, and the scalability of the modular architecture, it has been concluded that the architecture and requirements presented in D3.3 are suitable for implementing self-diagnosis services in industrial settings. It is crucial to note that specific implementation details necessitate a thorough feasibility study and evaluation period to ensure the efficiency of predicted improvements before deployment.

It is expected that this deliverable will provide a blueprint for the successful integration of self-diagnosis capabilities in industrial scenarios, emphasizing real-time monitoring and predictive analysis.

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