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A non-intrusive Industry 4.0 retrofitting approach for collaborative maintenance in traditional manufacturing

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Abstract

The recent COVID-19 outbreak impact on the world economy has boosted the increasing business needs to force manufacturing plants adapting to unpredictable changes and ensuring the continuity of industrial production. The demand for asset monitoring solutions and specialised support at the shop floor has become an increasingly important digital priority in industry that pushes human-machine technological upgrades leading to digital workforce skills assessment. In the case of traditional manufacturing, Small and Medium-sized Enterprises (SMEs) face the challenge of managing digital technologies and Industry 4.0 (I4.0) maturity models with a low adoption rate. In this digital context very few SMEs with traditional means have anticipated the latest advances in maintenance strategies impeded by technical and economical barriers. This work presents a human-machine technological integration solution in traditional manufacturing based on a non-intrusive retrofitting development with interoperable I4.0 tools. The method provides a common and rapidly deployable hardware and software architecture supporting an HMI-based legacy maintenance approach and addresses its evaluation focused on the physical-digital convergence of older industrial systems. A case study applying a digital pro-

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cess approach integrated with condition-based maintenance (CBM) techniques, has been carried out on a CNC milling machine and reproduced in an injection moulding machine during COVID-19 alert state. These already existing scenarios served to deploy digital retrofitting and communication strategies without interfering in working conditions. Patterns extracted from the machines were monitored in real-time interacting with the operational knowledge of the experienced staff. In this way, we provided an original contribution to confront human-machine challenges with improvements applied in traditional manufacturing, where workers and industrial systems were collaboratively updated with augmented digital strategies and proactive CBM environments.

Keywords: Digital retrofitting, Collaborative maintenance, Industry 4.0, Human-machine interfaces, Traditional manufacturing, Non-intrusive sensors

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1. Introduction

The advent of the Fourth Industrial Revolution [1] has accelerated the way traditional manufacturing faces digitisation challenges towards Industry 4.0 (I4.0) [2, 3]. Specifically, current changing business models [4] and recent major changes to manufacturing industry, such as the COVID-19 outbreak [5], have ignited the technological upgrades to develop remote maintenance services and workforce skills [6, 7]. Furthermore, the demand for asset monitoring solutions and specialised support has become an increasingly important digital priority in manufacturing, where maintenance represents a very significant function within the overall production environment and manufacturing overhead [8]. A paradigm shift for asset maintenance management [9] is emerging leveraged by I4.0 key enabling technologies (KETs) [10]. Some of these, such as industrial Internet of things (IIoT), cloud computing, machine learning, data analytics and augmented reality (AR), are being adopted in manufacturing to integrate new cyber-physical systems (CPSs) which have their digital twin (DT) counterpart [11]. By using CPSs, data operations can be real-time integrated in manufacturing plants on a holistic level [12, 13] where sensors and communication technologies interconnect data sources to a virtual world. Then, augmented data is available with the implementation of DTs and human-machine interfaces (HMI), where assets, workers and services are integrated in an interoperable environment based on specific, tailored information [14]. In this connected scenario, I4.0 arises as a wider concept that encompasses manufacturing in a new model of collaboration between workforce and industrial processes. Besides this convergent approach, I4.0 provides digital strategies to standardise and transform the entire manufacturing value chain [15]. As a result, connected human-machine ecosystems grow at the shop floor enhanced by digital-physical convergence models, taking advantage in real-time of I4.0 KETs and assets integration [2].

In the case of traditional manufacturing Small and Medium-sized Enterprises (SMEs), I4.0 transformation challenge is facing a low adoption rate of digital technologies and maturity models. At the European level, important barriers for I4.0 KETs adoption are the lack of skilled personnel [16] combined with its continuously increasing demand [17]. SMEs are also less ready due a lack of experience in new technologies [18], which leads to a slow initial stage of digitisation [19] and maturity [20]. Thus, the deployment of collaborative maintenance strategies is not always directly possible, being common to find SMEs without information connectivity models inherited from older manufacturing systems [21, 22].

On the other hand, SMEs' inherent difficulty to invest in economic or technical resources [23] may be a barrier to manage the system's maintenance [24]. However, the concept of retrofitting provides manufacturing with opportunities to connect traditional machines with I4.0 KETs [25]. Retrofitting process opens up a legacy way [26] for upgrading machines with the introduction of new digital features based on infrastructure and communication [27] at the shop floor while tailoring such assets with protocols [28], electronic data capture systems [29] and new HMI control applications [30], bringing also opportunities of sustainable manufacturing [31]. In the case of SMEs, it is a fact that retrofitting of existing assets reduce investment costs, while the reliability can be considerably improved and their lifetime extended, being a low-cost alternative to introduce sustainable strategies [31].

Recent outbreak impact on the world economy has joined the increasing business needs to force manufacturing plants adapting to unpredictable changes and ensuring the continuity of industrial production in real-time. In that way, smart monitoring [2] and new human-machine collaborative maintenance models are adding value to the improvement of the manufacturing processes [32, 12]. However, today the way forward for SMEs still has several challenges to overcome for the successful and timely reimplementation of the I4.0 concepts such as interoperability, virtualization, decentralization, real-time capability, service orientation and modularity [14]. Moreover, the workforce requires upgrading to the skills needed to cope with the upcoming digital technologies [4]. In this context, the development of a flexible and connected retrofitting approach may offer a rapid and reduced-cost alternative as a service for the deployment of a real-time collaborative maintenance in traditional manufacturing [28]. This "servitization" concept, based on standardised digital retrofitting techniques at the plant floor, is intended to provide specialized skills and tools to support SMEs' new collaborative business models, including service trends as remote maintenance [33, 34].

This work presents a solution for human-machine technological integration in traditional manufacturing based on a non-intrusive retrofitting development with interoperable I4.0 tools. It provides a common and rapidly deployable hardware and software architecture with the ability to support a HMI-based legacy maintenance approach and addresses its evaluation. For this purpose, the methodology described in this paper is focused on minimizing digital retrofitting barriers in real older non-digitised traditional manufacturing machines. To deal with practical applications for collaborative maintenance, based on common architectures, protocols and standards, a case study was carried out on a CNC milling machine and reproduced in an injection moulding machine during COVID-19 alert state. The propposed solution allowed workers and industrial systems to be updated with non-intrusive digital strategies and proactive condition-based maintenance (CBM) environments laying the foundation for collaborative methods. The machines were monitored remotely in real-time interacting with the operational knowledge of the experienced staff. Finally, behaviour models were extracted to support learning processes.

The remaining of the paper is organized as follows. Section 2 introduces a background for advanced maintenance in aged manufacturing machines. Next, Section 3 presents a methodology based on a non-intrusive retrofitted approach to support collaborative maintenance, and Section 4 describes the system architecture. Then, in Section 5, the retrofitting implementation and the evaluation models in the traditional manufacturing scenarios is detailed. Finally, Section 6 presents the findings and conclusions derived from the applied research.

2. A background for advanced maintenance in aged manufacturing machines

For decades, the manufacturing industry has populated its plants with supervisory control systems and, in some cases, advanced process control systems [35]. The development of diverse techniques in the field of maintenance management [36] such as Total Productive Maintenance (TPM), Reliable Centred Maintenance and CBM, has greatly improved the level of accuracy to reduce unplanned downtimes [37], thus optimising resources and productivity. However, the necessary integration of I4.0 requirements to address data management under the physical-digital convergence [38], introduces barriers [23] and compatibility challenges [21] ahead in SMEs traditional manufacturing systems [20]. On the basis of the findings reported by The Publications Office of the European Union [16] and publications by the U.S. National Institute of Standards and Technology (NIST) [22], these existing barriers in SMEs for adopting advanced manufacturing technologies and advanced maintenance technologies can be summarised as follows. In general, very few SMEs with traditional manufacturing means have kept up with the latest advances in maintenance strategies [22, 39]. Moreover, most of them use diverse commercial industrial systems that often own data sources with proprietary access [39] and heterogeneous communication interfaces for which the data architecture is unknown [40]. Despite maintenance trends (jointly with the communication and control architectures) have collaboratively evolved with I4.0 technologies [41], the most common use of the maintenance strategies inside the manufacturing industry is mainly reactive and preventive [42] without taking in consideration shop floor data [43].

In this section, we explore the evolution of convergent maintenance strategies in traditional manufacturing based on the integration of the physical and the digital worlds in order to contextualize our proposal. Retrofit is introduced as an emerging opportunity to address old hardware reconditioning methods [30] that facilitate traditional environments to benefit from predictive maintenance technologies based on sustainable and collaborative human-machine models [39, 44].

2.1. Non-intrusive convergent retrofitting technology for manufacturing

SMEs are opening up the possibility to adopt maintenance strategies based on CBM [39]. This approach provides a wider vision to control and monitor the actual condition of an asset in order to determine the specific maintenance needs to be done [45]. Under these requirements, the challenge of upgrading older machines to advanced maintenance in manufacturing, is facing very high economical costs and the lack of expert staff to address the I4.0 KETs [23]. However, adaptive retrofitting methodologies based on personalized data models and a non-intrusive digitisation, are for SMEs a more feasible alternative way to include updated features in older machines [28, 30]. Experiments made in two EU funded projects, presented the advantages of digital technologies to integrate the machines' real-time status and work orders implementing maintenance models. On the one hand, the BEinCPPS project (Business Experiments in Cyber Physical Production Systems) [19], implements a 3-layer architecture (of machine, factory, cloud) capable of supporting open standards to integrate existing legacy hardware and software systems installed on manufacturing SMEs in Europe. On the other hand, the MANTIS project (Cyber Physical System based Proactive Collaborative Maintenance) [32], involves 3 groups of SME users in Europe to provide a proactive maintenance service platform architecture based on CPSs capable of predicting and preventing imminent faults and scheduling proactive maintenance. Other experimental retrofitting use cases and methodologies based on I4.0 concepts for applying in SMEs' CNC machines are presented in [29, 31]. Also, [46] demonstrated in the laboratory that a traditional manufacturing system can be retrofitted in a non intrusive way using a standardized I4.0 implementation framework. The Reference Architectural Model for Industry 4.0 (RAMI 4.0) [47] is used in [27] to present the standardization of an industrial robotic arm prototype in order to validate a retrofitting process that transforms old industrial equipment into CPSs. Furthermore, digital technologies and sensors allow the integration of the data from different manufacturing sources using non-intrusive retrofitting methods to address monitoring conditions in manufacturing [48]. Some examples are: (i) a surface-mounting-system using a single current sensor to gather data from a power supply line [49]; (ii) an in-situ energy measurement for online identification of machine operation states in injection moulding machines [50]; and (iii) a CNC tool wear detection using an accelerometer at a remote location [51].

However, to the best of our knowledge, there is not a single data model and architecture approach that integrates heterogeneous manufacturing systems with an IT/OT convergence model addressed in a modular n-tier way. An adaptive development according to individual and specific manufacturing requirements is needed.

2.2. Human-machine collaborative maintenance models

Current challenges in a changing manufacturing industry, lead to developing methods to provide adaptive and sustainable strategies for systems maintenance in a continuous production life cycle [2]. That means allowing workers to move towards a new generation of human-machine systems to see and respond to problems more efficiently [15]. The development of these systems has been enhanced with the increasingly widespread use of distributed services with sensors and monitoring resources based on I4.0 KETs [52]. Also, production cycles and maintenance tasks become connected through a large amount of shared data making it easier to implement collaborative predictive platforms for smart maintenance [42]. These systems gather data from heterogeneous sources in order to implement predictive maintenance solutions. Some examples in [43] such as the Senseye company and the R2MPHM platform, introduce data analysis to alert workers when an abnormality is detected or to perform CBM and prognostics, helping the maintenance managers to predict critical impacts in the factories. In [39], a CBM-based method for SMEs focused on determining the current health level of an asset whilst the use of connected technologies provides more advanced decision-making in a collaborative way is presented. Moreover, HMI research has already come up with sophisticated HMI-solutions for DTs, that seek to adapt to the personal and situational context [53]. A few years ago, the digital coaching systems [54] got started as an answer to the demand of human operators able to manage advanced automated systems that can monitor and control complex and large industrial processes and systems. Nowadays, manufacturing as an industry has been pervasively impacted by the rapid adoption of information technologies. With the advent of smartphones, tablets and smart glasses, mobile HMI [55] has emerged as an example of the technological advances used at the shop floor. The increasing deployment in manufacturing of augmented reality (AR) and virtual reality (VR) technologies [56, 57] is changing the way operators visualize [58] and manage maintenance process monitoring [59]. The information can be virtually displayed overlapping the physical asset in real-time such as temperature changes, consumption trend, etc. [23]. This augmented interaction enables the understanding of real-time processes in order to improve CBM skills through non-intrusive technologies. However, the introduction of collaborative maintenance models in traditional manufacturing requires the development of a legacy human-machine-based data modelling approach. This perspective is crucial to integrate complex heterogeneous scenarios in manufacturing, where systems, processes and workers are involved in operations at the same time. The aim is to achieve a collaborative maintenance approach in a traditional environment where workers are allowed to perform their tasks while being part of the learning process. In that way, the deployment of advanced human-machine software tools extends the opportunity to simulate and understand human-system interaction. Online monitoring can display manufacturing key performance indicators (KPIs) to generate knowledge about systems and processes lifecycle with a wide perspective [32]. This interactive approach therefore provides a path to follow for maintenance in collaborative environments. Learned knowledge and skills are exploited for the incorporation of past experiences in root-cause analysis [60, 61]. Thus, human-machine collaborative models applied to maintenance enhance the development of skills 4.0, providing direct access to existing manufacturing-process knowledge.

3. Methodology

This section presents the methodology to support collaborative maintenance capabilities using a non-intrusive retrofitted approach in traditional manufacturing systems. In particular, a twofold objective is pursued: (i) To provide traditional manufacturing processes with decision support tools by linking workers' expertise with the health status of the machines; and (ii) To test and validate human-machine learning interfaces for collaborative maintenance.

To accomplish all the foreseen objectives, practical applications are built on a three-tier concept where workers, systems and processes are connected to collaborate at the same time. A hardware and software stack is proposed to provide SMEs with a three-tier solution supported by data streams, data models and knowledge models (Edge, Cloud and Business tiers, respectively). These tiers, in turn, are interconnected as shown in Figure 1.

Firstly, the **Edge tier** addresses standardised hardware and software interfaces following a non-intrusive paradigm. This paradigm allows to connect workers and systems without changes in the existing manufacturing infrastructure. A set of portable and flexible acquisition devices, interactive systems, and health status methods (for example, vibration analysis, energy consumption,

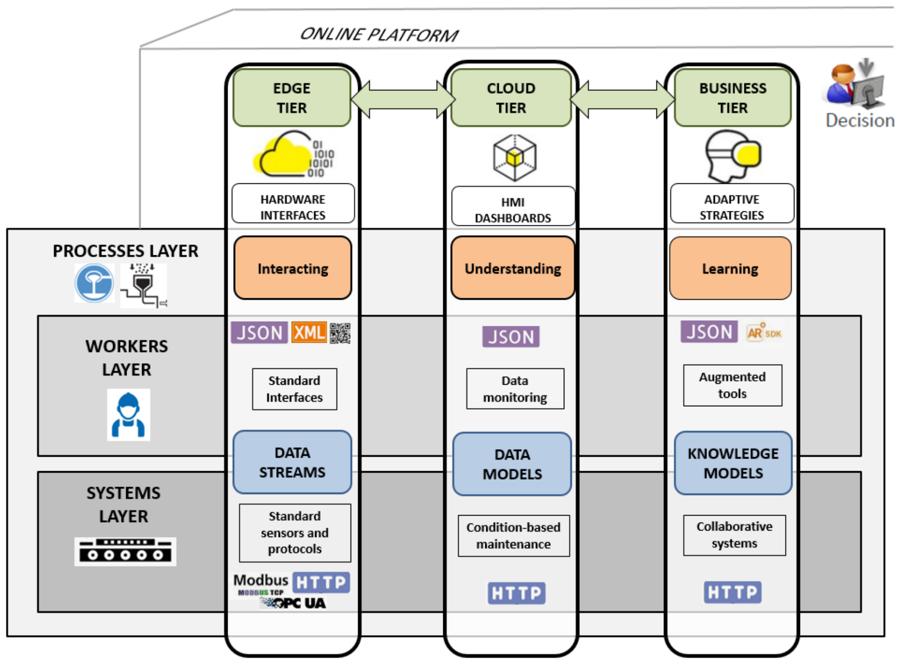

Figure 1: Three-tiers concept to support non-intrusive collaborative maintenance in traditional manufacturing.

and temperature control) are connected through secure and standard interfaces for data management in a non-intrusive way. This concept performs an interacting stage nearest to the sensors, machines and workers with a common communication layer. Data from the digital convergence of all shop floor actors is collected, structured and transferred to the next tiers. Under the umbrella of I4.0 KETs, this interoperability facilitates a common ISA95 5-level architecture that integrates information from multiple data streams (measuring devices, HMI devices, industrial automation middleware, process control systems or other software programs) based on standardised protocols (MODBUS TCP, OPC-UA and HTTP) and data formats (JSON, XML, QR).

Next, the **Cloud tier** addresses the distributed HTTP microservices located on the cloud with a focus on the development of manufacturing data models. This tier manages the cloud storage capabilities to gather and display data streams from different kinds of entities of the Edge tier (HTTP/REST). Also, Cloud tier provides workers with maintenance tools such as CBM for data monitoring and flexible processing, building a digital representation of operations and resources status. Thus, a convergent concept extracts valuable information about systems management, KPIs, historical data and anomalies. That information enables workers to get local or remote support in the maintenance process through a connected problem-solving approach. Collected data allows an understanding stage that eases monitoring, configuration and handling of the digitised systems in accordance with their specific needs. Using a set of HMI software tools, time series data, and widget-based Web dashboards, the exploration of the shop floor data models (work in progress, resources, assets, maintenance plans, etc.) to fulfil the manufacturing objectives towards collaborative systems, is boosted.

Finally, the **Business tier** addresses the whole retrofitted approach to manage collaborative systems in different traditional manufacturing scenarios. It performs the learning stage where workers are called to play an active role as part of the integrated manufacturing ecosystem [52], [15]. This tier incorporates augmented tools and data from interactive human-machine smart interfaces based on AR apps running over HTTP. Workers' experience is exploited by applying lessons learned to digital contents using AR SDKs, JSON data and QR codes. The fusion of adaptive procedures with real-time data is intended to improve the skills of workers. All that experience is converted into precise statements to support maintenance tasks and reinforce the processes knowledge. Thus, workers and systems are gradually connected to an interactive digital ecosystem. So this concept provides means to respond and maintain systems quickly and accurately within an alternative technological context of traditional manufacturing.

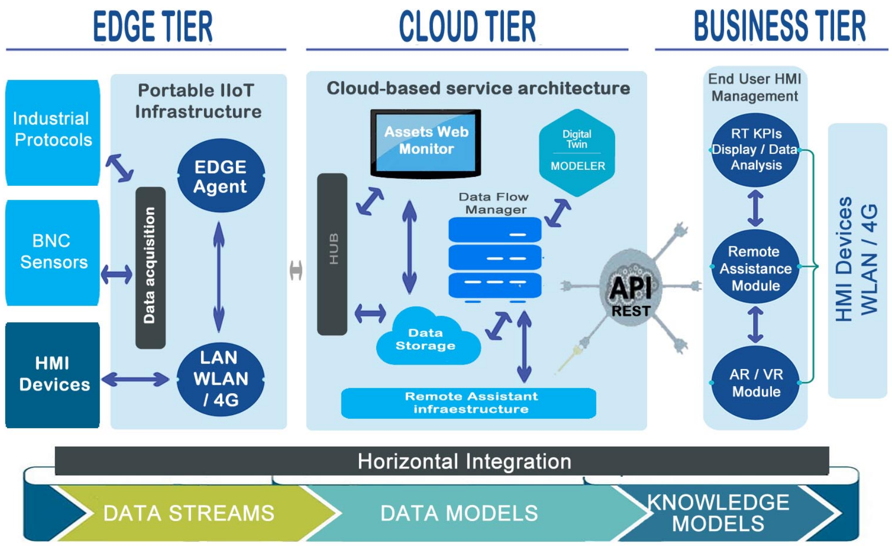

Figure 2: System architecture.

4. Architecture of the system

This section introduces a common system architecture to enable the modular communication between the aforementioned three tiers for collaborative maintenance in traditional manufacturing. As previously stated in Section 3 (see Figure 1), three conceptual tiers manage the collaborative digital retrofitting solution in a non-intrusive way: the Edge tier, that interacts with the sensors, machines and workers using retrofitting strategies; the Cloud tier, that provides SMEs with means to understand the maintenance needs; and the Business tier, that generates collaborative maintenance knowledge for workers and processes. The proposed system architecture (see Figure 2) consists of three separate modules horizontally integrated to provide interoperability between all tiers: (i) a **portable IIoT infrastructure**, providing non-intrusive sensors, software interfaces and heterogeneous data streams to the Edge tier; (ii) a **cloud-based service architecture**, hosting a common information connectivity layer and data models to the Cloud tier; and (iii) an **end user HMI management**, that contains interactive human-machine software tools and assets health condition-based strategies providing knowledge models to the Business tier.

This modular infrastructure is composed of different microservices to store and process data (based mostly in Web apps and open source tools such as Elasticsearch, Kafka, etc.). All information from the different tiers is connected using Web APIs. The system components and the relations between all actors as shown in Figure 3, are intended to represent a common industrial scenario where different conceptual levels are presented in order to support the system architecture.

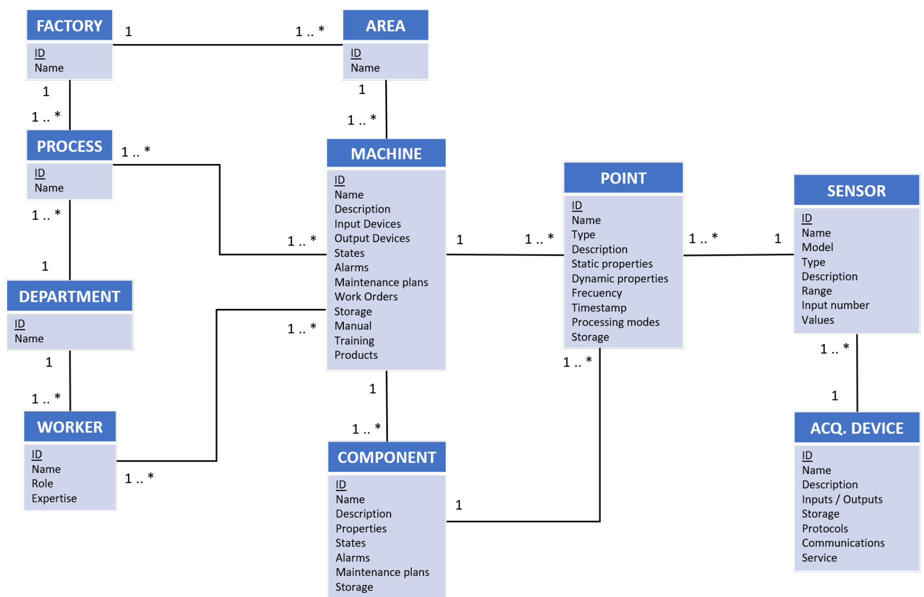

Figure 3: Conceptual model.

4.1. Portable IIoT infrastructure

The first module of the architecture proposes a portable IIoT infrastructure including a customisable industrial acquisition hardware device, industrial communication protocols, industrial common sensors and software interfaces as described below. It provides the lowest level of digitisation services to the Edge tier, necessary to implement retrofitting techniques. In traditional environments it may be desirable to use a condition monitoring framework regardless of the nature of the machines and their level of digitisation, providing the hardware interfaces with standard types of sensors. At the same time, a common communication layer is required to enable the necessary software services integration for the physical-digital convergence of all actors involved at the shop floor. On the other hand, the incorporation of HMI devices and linked AR apps to old systems it is now increasingly used to provide workers with augmented data of industrial scenarios in a collaborative digital ecosystem. Our work is based on an IIoT infrastructure that consists of four main components as shown in Figure 2:

1. A **data acquisition module** (TWave T8-L model with mobility case[2]) used for condition-based monitoring and failure mode identification. The system includes twelve external BNC inputs that accept static and dynamic signals from sensors and tachometer signals. Eight of them are high speed inputs with a sampling rate from 512 to 102400 Hz, and the other four are auxiliary inputs with a sampling rate up to 200 Hz (one sample for each capture). These four static signals have been adapted to measure 4-20 mA current loop signals for analog sensor data transmission. This kind of current loops is an industry standard commonly used in many applications and equipments. All captured signals are stored in an internal database for further processing following the conceptual model presented in Figure 3.
2. A **wireless Wifi/4G router**. It provides an external Ethernet connector attached to a WAN entry to give the system direct access to the Internet. Additionally, the mobile GSM 3G/4G connection allows gaining remote access to the IIoT infrastructure in places where Ethernet access to the Internet is not available. Wifi connection is used to generate the wireless local network for management.

[2]https://www.twave.io/products.html

3. **Sensors and coaxial cabling** intended for applications requiring a non-intrusive retrofit monitoring solution in a very short time using "plug and play" BNC connectors:
   - A three-phase AC current transducer to convert input voltage from three open-ended Rogowski coils to a 4-20 mA DC output.
   - One Pt100 magnetic resistance temperature detector (RTD) sensor suitable for high temperature measurements on ferrous surfaces up to a maximum of 300°C to a 4-20 mA DC output.
   - Two PCB Piezotronics 603-Series accelerometers with magnetic mounting base to install in ferrous magnetic surfaces.
4. **Embedded web-based and Edge communication agents**. TWave includes a user interface to the acquisition hardware that can be accessed from any browser. The configuration interface provides a dashboard to set up the system: assets definitions, sensors, points, measurement parameters, etc. The dashboard application also provides access for monitoring the data recorded by the acquisition hardware where a static point corresponds to analog or digital readings. Also, the system can work in a standalone mode or communicate these scalar measurements to other systems using Modbus-TCP, OPC-UA protocols and HTTP (REST API). The architecture converts all digitised shop floor environments into individualised objects characterised by type and properties. All of them are associated with the selected machine.

4.2. Cloud-based service architecture

The second module of the system proposes a cloud-based service architecture to store and understand the data from different assets connected to the Edge tier. This module (see Figure 4) consists of five cloud-services: (i) Apache Kafka hub, (ii) Elasticsearch data storage, (iii) data flow management (DFM) module, (iv) data modeling and visualization in a Web monitor, and (v) augmented data sources management (sensors, machines, and other software solutions such as

AR SDK integration). This module includes information on which alarms have been triggered in one asset, systems configuration, systems status, real time data snapshots of all measurement points, data analytics, augmented contents and dashboards.

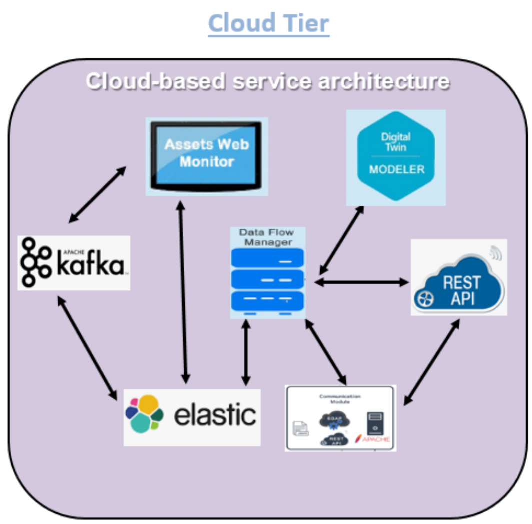

Figure 4: Cloud-based service architecture.

Each measurement input is a source of data that brings information to the Cloud tier about the machine that is being monitored. Using the edge communication agent, an authenticated API which allows access to the data recorded in the retrofitted objects is provided. To gather all this information from the shop floor, a hub module using REST API with Apache Kafka ingests JSON data (see Figure 5) from the portable IIoT system to the Elasticsearch cloud database. Different types of REST calls can be done by Cloud tier microservices to return a specific JSON. This allows DFM to customise Web monitor dashboards according to a configurable flow defined by three main components: inputs, logic and actions.

Data visualization includes alarms triggered from individual objects and data models related to the health status of the assets. A user-friendly dashboard interface allows users to define and configure their own data through

```
{
 "points": [
  {
   "error": <ERROR_NUMBER>,
   "error_msg": "<ERROR_MSG>",
   "id": <ID_POINT>,
   "proc_modes": [
    {
     "id": <ID_PROC_MODE>,
     "params": [{"id": <ID_PM>,"tag": <TAG_PM>,
                "unit_id": <UNIT_ID_PM>,
                "value": <VALUE_PM> }]
   "tag": "<SENSOR_NAME>"
  },
  {
   ... (MORE PROG_MODES)
  }
 ],
 "t": <TIMESTAMP>,
 "tag": "<MACHINE_NAME>"
}
```


Figure 5: Formatted JSON data used to ingest a measurement input.

drag-and-drop widgets containing several different out-of-the-box graphics and data tables. The analytic dashboard system integrates a unified framework of interactive data representation for condition-based maintenance methods and engineering graphic interfaces, to understand behaviour models and support predictive data. These features include real-time data analysis, anomaly detection, behaviour fault model and advanced system monitoring to alert the operator about some incidents like overheating, decrease in the manufacturing rate, trend changes, etc. Augmented services manage all the data handling logic for the AR apps, displaying the information processed at the shop floor in the devices of the workers. REST APIs deliver the data processed by the platform to the Business tier and enable the interaction between the workers and the different platform modules. In addition, the Cloud tier enables connection with third-party systems through API connection.

4.3. End user HMI management

The third module of the system architecture proposes human-machine visualization services, contents and augmented maintenance models to the Business tier (see Figure 6). These maintenance models are oriented on how users on traditional environments can be supported when interacting with the manufacturing systems. Thus, workers are assisted with the visualization of the assets status and KPIs monitored from the sensors deployed in the machine. Also, the incorporation of AR components to the system architecture provides workers with new capabilities to access real-time advanced visualization of complex data, expert-guided remote assistance, and supervised training.

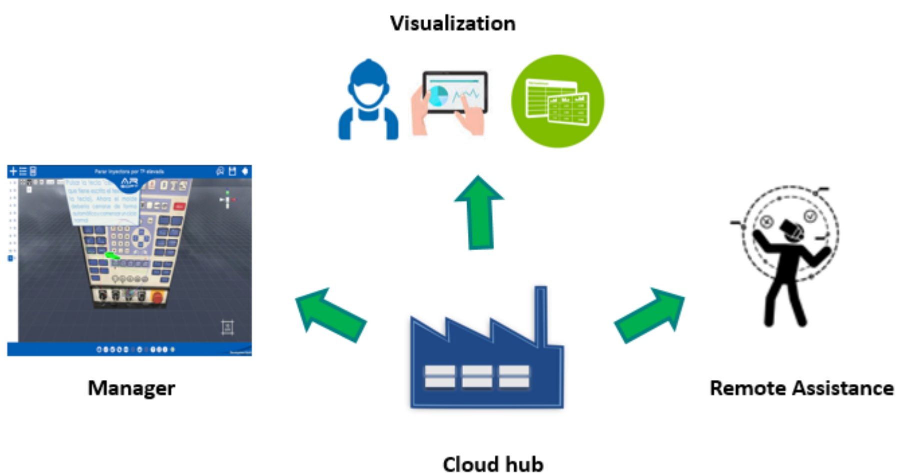

Figure 6: Business tier human-machine management and visualization services.

The End User HMI Management module defines the augmented infrastructure consisting of four components: (i) **Cloud hub** is already integrated with the cloud-based services architecture using REST APIs (see Figure 4). It includes the management logic for all data stored in the cloud as well as the integration of Web services to facilitate the communication over a secure socket layer; (ii) **Manager component** provides the creation and management of manuals with 3D models, 3D indications in many languages, images, videos, etc.; (iii) **Visualization component** allows industrial operators to see all the instructions of a process with AR, using AR Glasses or just a smartphone or tablet; and, (iv) **Remote Assistance component** provides three-dimensional render instructions on a machine about how to replace a component, and remote contact with an expert in the same system to get immediate assistance.

5. Digital retrofit case studies

In order to be able to illustrate and evaluate the applicability and overall performance of our proposal, a non-digitised production milling machine with more than 25 years old, is used for the deployment and assessment of collaborative maintenance approaches. Then, to illustrate the generalisation and applicability of the solution, we applied the same architecture to an injection moulding machine. The development, focused on the physical-digital convergence between workers and older industrial systems regardless of their level of digitisation, was tested in the Research and Development Centre facilities[3].

Figure 7: Nicolas Correa CF20 CNC milling machine at the R&D facilities.

[3]Due to the requirements for anonymized manuscript submissions at Computers & Industrial Engineering, the name of the research center is not mentioned in this version of the paper

Table 1: List of tools used in the CNC machine.

tool	code	tool	code
edge finder	1	shell mill carring Ø32 with 8 cutting edges	2
shell mill carring Ø63 with 8 cutting edges	3	shell mill carring Ø80 with 8 cutting edges	4
shell mill carring Ø50 with 4 cutting edges	5	shell mill carring Ø80 with 4 cutting edges	6
drilling endmills APKT Ø65	7	endmills Ø18	8
drilling endmills APKT Ø20 large	9	drilling endmills APKT Ø16	10
drilling endmills APKT Ø18	11	drilling endmills APKT Ø30	12
endmills Ø16	13	endmills Ø30	14
endmills Ø32	15	endmills Ø52	16
mandrel	17	head mandrel	18
tool holder Ø0-3	19	tool holder Ø3-14	20
morse taper drill bit	21	90º countersink bit Ø12	22
90º countersink bit Ø22	23	turbo face milling	24
dial indicator	25	tool holder Mickey type	26
tool holder	27	endmills Ø12	28
endmills Ø18 large	29	indexable insert drill	30
endmills Ø20	31		

5.1. Development of the solution

The case study was carried out on a three axes milling machine Nicolas Correa CF20 with Touch Numerical Control (TNC) HEIDENHAIN TNC-407 (Figure 7). This milling machine is a machine tool typically used to shape slots and drill solid material work pieces with a rotating cutter. The cutting tool is mounted in a spindle housed in the milling head moving vertically along the Z axis. The machine is controlled by an old SIEMENS SIMODRIVE 611 PLC embedded in the electrical panel, however all historical information during its life cycle is not accessible for monitoring. Maintenance strategies are preventive or corrective while the milling machine is started and stopped every working day. On the shop floor all the manufacturing orders with the production plan are on request under different CAD designs. One experienced operator prints each part design and manages manually the associated milling operations. Specifically, this machine tool is developed for shop floor programming by the operator using conversational programming.

The operator has to generate part programs at the machine with the part design in hand, but it is required a manual change of cutting tools (see Table 1

Figure 8: Milling machine cutting tools.

and Figure 8) for a different milling operation (milling, contour milling, face milling, bore milling, drilling, etc.) (see Table 2). The manufacturing strategies for programming and cutting tool changes depend on the criteria of the operator or any unplanned events. Thus, all the aforementioned non-digitised strategies are setting the terms of the whole manufacturing process-time and resources, where it is not possible to predict future decisions based on the performance and the health condition of the CNC milling machine.

Table 2: List of milling operations and materials used in the CNC machine.

milling operation	code	material	code
zeroing milling	1	plastic	1
face milling	2	aluminium	2
contour / form milling	3	steel	3
bore milling	4	316 stainless	4
milling	5	other	5
drilling	6		
special	7		

To address this case study, a first phase is proposed for the deployment of the Edge and Cloud tiers described in the system architecture. First of all, the portable IIoT infrastructure is used to develop retrofitting approaches on the CNC milling machine without interfering in working conditions. Next, the cloud-based service architecture deploys a common connectivity layer with the status information of the manufacturing processes based on CBM and human-machine software tools. Then, a second phase is proposed to deploy the Business tier for testing and validation of human-machine collaborative maintenance models such as monitoring services, remote maintenance and training tools, applied to real traditional manufacturing scenarios.

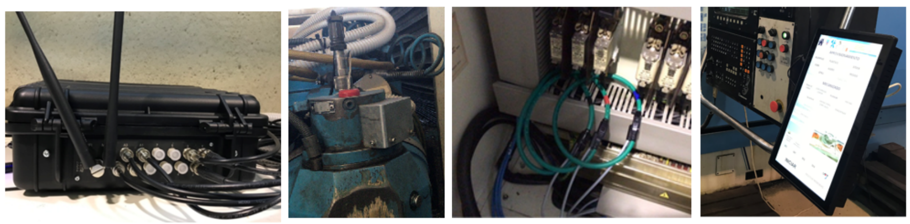

Figure 9: a) TWave with mobility case b) Accelerometers and RTD sensor c) Three-phase current transducers, d) HMI panel PC.

Figure 10: Milling machine dashboard detail in AWM cloud platform.

The TWave case (Figure 9a) provides CNC with the hardware acquisition device to enable sensor-based non-intrusive digital retrofitting techniques. Common industrial sensors detailed in Section 4.1 are used to get CNC's attributes from different measurement points: (i) two accelerometers and one RTD sensor with magnetic mounting base placed in the spindle of the CNC's milling head (Figure 9b); and (ii) three-phase current transducers with open-ended Rogowski coils connected in the electrical panel to the three-phase circuit wiring (Figure 9c).

All sensors and coaxial cabling can be easily guided from the spindle and the electrical panel to the portable hardware control case and plugged to the BNC inputs. A Web browser is used to connect with TWave's embedded dashboard interface (see Figure 10). All CNC's measurement inputs plugged to the data acquisition system can be configured in the dashboard and assigned to a new created asset object associated with the milling machine. Then, each input point in CNC's machine is associated with one of the different sensor types (for example, accelerometer, RTD or three-phase current). Also, labels with the names (for example, "Acel1", "Acel2", "Temperatura", "Fase1", "Fase2" and "Fase3"), properties (processing mode, input range, units, etc.), and operation mode (static, dynamic), are set (see Figure 10). The dashboard application also provides workers with CNC's data monitoring on HMI tools. Additionally, one HMI panel PC with capacitive touch screen (Figure 9d) for real-time monitoring of data and operator's interaction, is used in our case study. The standalone HMI device allows workers to interoperate with a software interface right next to the CNC's TNC and is capable of accessing both forms of data visualization, local network client and cloud services, as described below.

Once the data acquisition system is ready, the mobile GSM 4G module gives the hardware's edge communication agent access to the Internet. Data streams resulting from the measurement points are linked with DFM cloud services. Milling machine asset object registered in the Cloud platform (Figure 10), en-


```
{
 "points": [
  {
   "id": 30,
   "proc_modes": [{"id": 35,
                  "params": [{"id":96,
                             "tag":"val",
                             "unit_id":25,
                             "value": 0.23827815}]
    }
   ],
   "tag": "Fase1"
  },
  {
   .........
  }
 ],
 "t": 1580989890.22308,
 "tag": "CNC_CF20"
}
```


Figure 11: Specific JSON data format including "Fase1" measurement values.

ables the interconnection of the physical-digital common layer for remote monitoring and CBM tools. The system uses HTTP protocol and REST calls returning JSON data to customise the inputs, logic and actions of the asset in the monitoring dashboards. Figure 11 shows a specific JSON data (based on the structure proposed in Figure 5) with values recorded by the current transducer of the sensor labeled as “Fase1”.

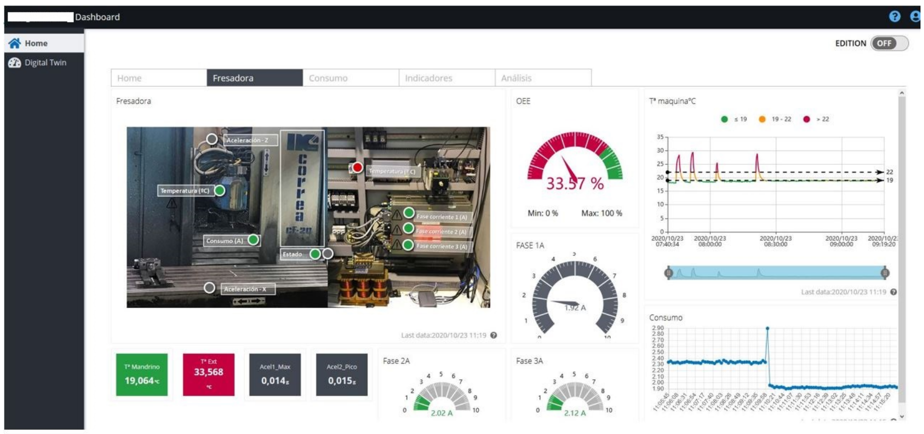

Figure 12: Dashboard detail in the Cloud platform.

Figure 13: a) CNC’s HMI software to interact with the operator. b) Real-time AR app installed on a Samsung tablet.

A Web service API has the advantage of providing a visual status of the monitoring system in real time for workers. On the other hand, cloud-based dashboard systems allow for remotely access to information, including customisation of individual alarm triggers and information related to the health status of specific milling machine points (Figure 12). Moreover, the HMI panel device (Figure 13a) can be used to install software applications to provide operators with workflow information connected to the IIoT communications layer. A graphical user interface empowers the operator to take an active part in CNC's work orders analysis and maintenance processes. By matching some parameters monitored (for example, vibration, temperature and power consumption) with the human-data gathered, can be enabled the extraction of additional CNC's maintenance indicators in order to validate manufacturing models with the support of the machine operator skills. In this way, the work provides additional interactive HMI tools such as AR systems to enhance workers' skills. Due to the AR layer incorporation to our proposal, workers are enabled with new capabilities accessing augmented data of the milling machine in real-time and receiving expert-guided assistance as well as remote training.

A test was carried out aiming to introduce collaborative maintenance strategies based on a CNC's process learning approach. During the learning stage, human-machine knowledge models were built to formalize insights (Business tier) from data streams (Edge tier) and data models (Cloud tier) in order to

Figure 14: CNC's human-machine integration based on hardware and software interfaces.

evaluate the impact of new collaborative maintenance technologies in traditional manufacturing. The opportunities for digitising workflows enable the analysis of production cycle times and how performance losses and downtimes impact them in real-time. Besides the aforementioned milling machine retrofitted infrastructure to deploy the digitisation layer, the collaboration of the machine's operator was required. A software interface was installed in the HMI panel right next to the CNC's TNC to facilitate the extraction of manufacturing process knowledge (see Figure 14). New digitised contents provided the operator with a real-time interaction to classify specific milling operations and their duration, enhancing the learning process with additional featured data.

Table 3: Detail of milling work orders processed by the machine's operator.

work order	op.	start	end	mat.	cutting tool
fab-0305-19-12002	2	2020/13/01 09:41:34	2020/13/01 12:07:38	4	6
fab-0305-19-000	3	2020/13/01 12:08:06	2020/13/01 15:28:15	4	14
fab-0305-19-000	2	2020/13/01 15:28:20	2020/13/01 15:43:46	4	6
fab-0305-19-000	7	2020/14/01 07:20:46	2020/14/01 08:57:51	4	23
fab-0305-19-000	3	2020/14/01 08:57:56	2020/14/01 12:22:16	4	5
fab-0305-19-000	5	2020/16/01 08:43:49	2020/16/01 09:19:13	4	27
fab-0305-19-000	3	2020/16/01 09:19:18	2020/16/01 09:31:30	4	5
fab-0305-19-000	7	2020/16/01 09:31:35	2020/16/01 09:34:55	4	22
fab-0305-19-000	6	2020/16/01 09:34:57	2020/16/01 09:54:51	4	20
fab-0305-19-000	3	2020/16/01 09:54:43	2020/16/01 10:02:59	4	5
fab-0305-19-000	6	2020/16/01 10:03:02	2020/16/01 10:37:25	4	20
fab-0344-19-000	2	2020/16/01 12:01:58	2020/16/01 15:59:51	2	5
fab-0344-19-000	3	2020/17/01 07:42:07	2020/17/01 12:53:24	2	5
fab-0305-19-12004	3	2020/22/01 07:22:58	2020/17/01 07:47:25	3	5
fab-0305-19-12004	5	2020/22/01 07:47:27	2020/22/01 08:06:01	3	27
fab-0305-19-12004	6	2020/22/01 08:06:03	2020/22/01 08:28:27	3	20
fab-0305-19-12004	2	2020/22/01 08:28:35	2020/22/01 09:21:08	3	6
fab-0316-19-000	2	2020/22/01 09:21:29	2020/22/01 09:42:13	3	6
fab-0316-19-000	6	2020/22/01 09:42:16	2020/22/01 09:57:54	3	20
fab-0266-19-11392	3	2020/23/01 14:37:24	2020/23/01 15:00:40	3	5
fab-0266-19-11392	6	2020/23/01 15:01:09	2020/23/01 15:28:21	3	30
fab-0266-19-11392	7	2020/23/01 15:28:26	2020/23/01 16:00:58	3	22

In this particular case, manufacturing orders consist of: (i) printed CAD drawings, (ii) milling operations, (iii) kinds of material parts, and (iv) cutting tools. These features were labeled and identified by a numerical code to facilitate further data processing (see Table 3 for an example of milling work orders). Moreover, using triggers with monitored parameters such as vibration and current consumption values it was possible to automatically detect CNC's process downtimes. This is especially common whenever the CNC machine finishes a milling operation or a cutting tool change is needed. Once a change status is detected, the HMI system prompts the operator to enter the next milling operation or to describe an unplanned event. Thus, the execution time for each individual milling operation, used material and cutting tool is classified by the operator and sent to the cloud services. On the other hand, when the operator detects an anomaly with this machine, the data is reported to enhance maintenance orders. Data is reinforced with a non-intrusive condition monitoring strategy. The avail-

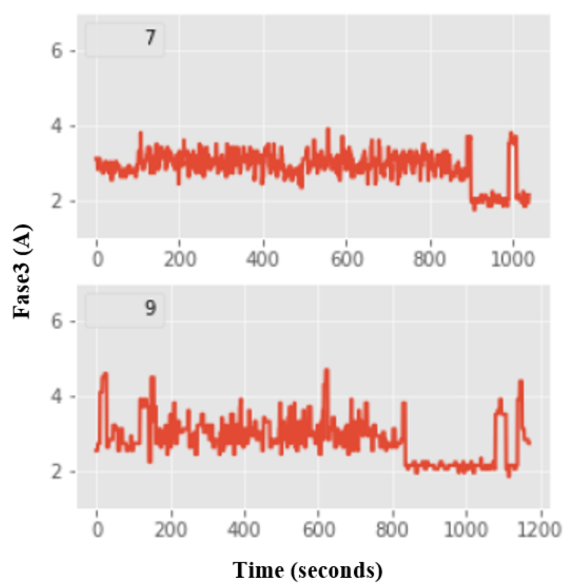

Figure 15: Example of energy consumption registered in two CNC's face milling operations on steel.

ability of tasks execution time from data gathered for the whole manufacturing process facilitates the implementation of adaptive maintenance plans by matching milling machine operation patterns with CNC's parameters monitored. The experienced operator of the milling machine contributed to the identification of valid patterns characterising single milling operations (Figure 15). The estimated duration of processed milling operations was calculated based on average values. A proof of concept to validate this learning approach in production cycles was conducted using an initial threshold-based model with maximum and minimum measurement values registered in the CNC machine. The details of milling operations were considered. Also, alert messages triggered by initial threshold limits were configured.

Figure 16: a), b) Personalized AR software apps. c) QR code.

To provide the operator with an interactive overlapped visualization of CNC's digitised data in real-time, an AR software app was deployed on an Android tablet model Samsung Galaxy S3 (Figure 13b). The system uses REST APIs to interconnect real-time data of the retrofitted milling machine with the AR cloud infrastructure, as described in Section 4.3. The software is used to test the worker interaction guided by augmented contents coupled to the CNC's health-condition status. The aim of this system is to achieve a digitised learning environment for workers who interact with manufacturing processes that depend on the asset condition. The mobile device eased the operator's movements on every part of the milling machine at the shop floor. Personalised QR codes located on the CNC machine (door, TNC and electrical panel) served to match physical points with digital contents (Figure 16a and Figure 16b). In this scenario, AR allows the operator to simply point the tablet to a QR code placed on the milling machine (Figure 16c) and directly show customised information about it. This collaborative approach has a twofold objective: firstly, to minimise downtimes with a fully digitised context-aware environment for workers. Secondly, to guide workers step by step with AR technology applied to practical skill training.

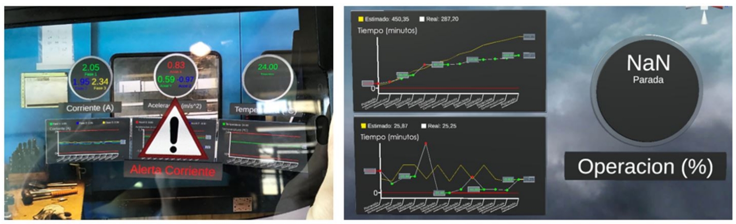

Figure 17: a), b) AR apps to display virtual manufacturing information.


```
{
"Time_Stamp":{"timestamp":<VALUE>,"zone":<TAG>},
"Temperatura":<VALUE>,"Temperatura_Min":<VALUE>,"Temperatura_Max":<VALUE>,
"Acel1_Valor_Global":<VALUE>,"Acel1_Valor_Global_Min":<VALUE>,"Acel1_Valor_Global_Max":<VALUE>,
"Acel2_Valor_Global":<VALUE>,"Acel2_Valor_Global_Min":<VALUE>,"Acel2_Valor_Global_Max":<VALUE>,
"Fase1":<VALUE>,"Fase1_Min":<VALUE>,"Fase1_Max":<VALUE>,
"Fase2":<VALUE>,"Fase2_Min":<VALUE>,"Fase2_Max":<VALUE>,
"Fase3":<VALUE>,"Fase3_Min":<VALUE>,"Fase3_Max":<VALUE>,
"Operation":"<TAG>","Estimated_duration":<VALUE>,"Progress":<VALUE>,
"Alert":"<TAG>"
}
```


Figure 18: Specific AR JSON data format.

Figure 17 shows how the virtual manufacturing process information was displayed with the AR app overlapping the physical asset. All the manufacturing information was previously considered in the IIoT infrastructure and integrated with AR cloud-based services using a JSON data format as shown in Figure 18. On one hand, graphic displays with fixed thresholds defined to alert on detected anomalies during milling operations, such as temperature and consumption trend, provided the operator with a visual representation of the parameters monitored at the same time that the milling machine works (Figure 17a). On the other hand, production cycle time from tested work orders was calculated using the total run time from individual estimated operation times. These values were compared using each single operation real progress time (Figure 17b).

Finally the milling machine operator was provided with personalised AR manuals for training and to guide in maintenance tasks. The application displays an interactive manual with a step-by-step guide overlapped on the CNC machine (Figure 19). This way the maintenance operator, regardless of his experience and knowledge of the machine, can carry out the intervention in a supervised and safe way.

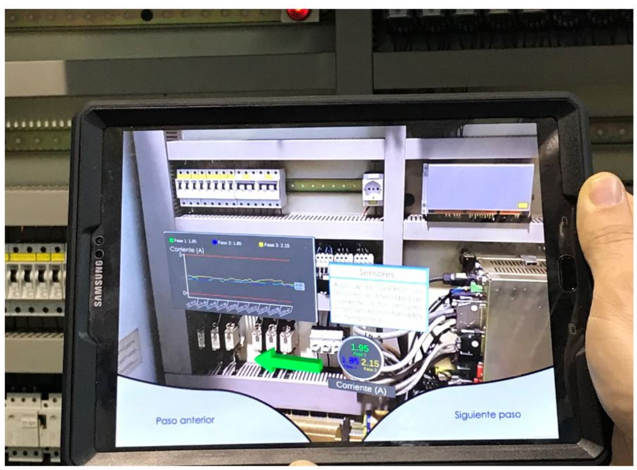

Figure 19: AR guide step-by-step applied to maintenance tasks in the electrical panel.

The use of augmented procedures and digital contents applied to the milling manufacturing process turned out useful to save time and gain improved performance and advanced diagnosis using real-time information about KPIs monitored. As a result, milling machine behaviour models were monitored interacting with the operational knowledge of the experienced operators. Workers and industrial systems were updated, at the same time, with human-machine digital strategies and proactive management environments laying the foundation for a collaborative maintenance methodology.

5.2. *Generalisation of the solution*

The COVID-19 pandemic has changed industrial work. New practices to allow social distancing and provide remote access capabilities during confinement, created a digital dependence in industry. At the same time, the production of protective face shields during the worst weeks of the COVID-19 emergency became a national health priority. The Spanish Federation of Technology Centres (FEDIT[4]) made all its members' resources available to the fight against the

[4] https://fedit.com/

Figure 20: Two-component injection moulding machine Krauss Maffei 200-700 C2 and protective face shields at the R&D facilities.

COVID-19. In particular, The Research and Development Centre[5], contributed for the manufacture of protective face shields visors for health staff (Figure 20). An injection moulding machine was used starting from the last week of March 2020. At the beginning of April 2020, the global multi-energy company Repsol donated 1,500 kilograms of polypropylene to the R&D Centre. In this way, it was possible to increase the daily production from 4,000 up to 5,700 units on a 2-component injection moulding machine Krauss Maffei 200-700 C2 (Figure 20). Maximising the overall equipment effectiveness based on that increase of production, presented a great challenge to support 24 hours a day a non-digitised asset. Maintenance was highly important in response to machine unplanned breakdowns without previous digitised historical data.

Injection moulding is a high-precision manufacturing process used for plastic parts production. Krauss Maffei 200-700 C2 injection machine consists of four main modules: a clamping unit, an injection unit, an electrical panel and a control panel. A custom mould design is required to the injection of the particular plastic part or product whilst an hydraulic system controls the moving parts of the clamp unit where the mould works (Figure 21a). The cooling system is one of the most important points for both, hydraulic system and mould, affecting the total cycle time and the quality of final products. The temperature measured at the mould area during the injection moulding process is a key parameter, but it requires an expensive equipment, technical experts and additional interfaces configuration on the machine's control panel. Moreover, the moulding injection cycles can work in an intensive unattended mode for several hours in the night shift. Therefore, monitored relevant changes in the machine's health condition status such as overheating, performance or unexpected breakdowns, need to be supported through remote management. Thus, to test the generalisation capacity of our proposed architecture, the portable solution used in the milling

[5]Due to the requirements for anonymized manuscript submissions at Computers & Industrial Engineering, the name of the research center is not mentioned in this version of the paper

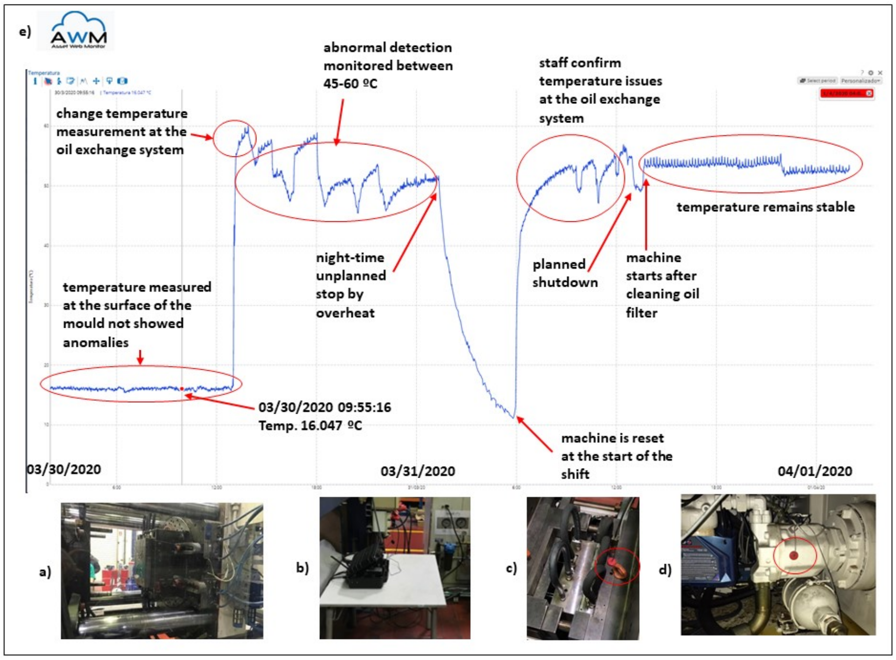

Figure 21: Injection machine detailed diagnosis and maintenance process using retrofitting and AWM monitoring dashboard.

machine (Figure 21b) was deployed on that moulding machine on March 30th, replicating the non-intrusive digital retrofitting concept: (i) mobility case with the hardware acquisition device; (ii) measurement points consisting of two accelerometers and one temperature sensor deployed in the injection mould area, and three-phase current transducers with open-ended Rogowski coils connected in the control cabinet; (iii) coaxial cabling to connect sensors to the BNC inputs in the portable hardware control case; and (iv) embedded communication agents to enable remote monitoring with cloud-based CBM tools.

Temperature and vibration changes at the surface of the mould, and the registration of abnormal current consumption patterns, were monitored in AWM dashboard and supervised by production and maintenance staff. Registered data under continuous production conditions showed unplanned breakdowns in the injection moulding machine. In order to respond to this particular unexpected operating condition, experienced operators recommended to register temperature measurements at a different location.

Remote assistance was provided to maintenance staff, moving the temperature sensor from the mould cooling circuit - with cooling rate stable values around 16ºC as shown in Figure 21c -, to the oil heat exchange system (Figure 21d). This move was intended to determine a better temperature variation during the injection moulding process. As shown in AWM monitoring dashboard (Figure 21e), a few hours later on March 31th, a night-time unplanned breakdown was registered in the dashboard and notified by email to the production and maintenance staff to alert them at the start of the morning shift. The abnormal pattern was confirmed as an overheat problem, and fixed that morning after a maintenance planned shutdown. A dirty filter in the oil heat exchange unit was the detected cause. After cleaning the filter the injection process of face shields manufacturing was restored quickly to a stable behaviour.

In this particular case, it was a digitisation challenge to give full mainteinance services due to confinement, providing workers with real-time trend data and remote assistance in a few hours. The proactive CBM solution implemented, in

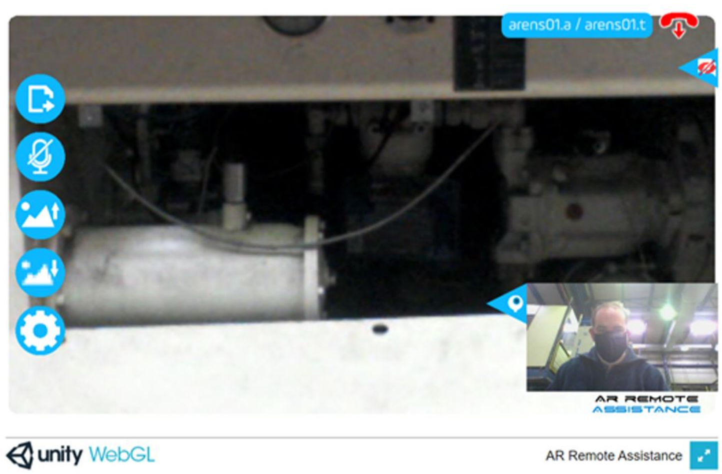

Figure 22: AR app used to provide maintenance staff with interactive support during COVID-19 confinement.

a non-intrusive way, provided knowledge about the machine behaviour to operate it under changing conditions with limited staff in place. Moreover, it was possible to alert maintenance staff during unattended labour in the night shift and to deploy and validate an interactive (see Figure 22) and remote collaborative maintenance strategy based on I4.0 KETs, to avoid the injection machine overheating and its subsequent breakdown during COVID-19 confinement.

6. Conclusions and future work

The costs of maintenance have a great competitiveness impact in the manufacturing industry. In this context, traditional manufacturing faces the challenge of adapting older machines to advanced maintenance strategies with a low adoption rate of the new I4.0 KETs. Digital barriers and expensive hardware compatibility issues are known in the way to accomplish the physical-digital convergence in SMEs. Recent unpredictable world challenges, such as COVID-19, have impacted on the maintenance services of legacy assets as well. Remote maintenance certainly offer the possibility to provide substantial added value to the enhancement of operating resources. However, the adoption of collaborative maintenance ecosystems implicitly requires a digital integration connecting knowledge management tools. Collaborative models also mean that human-machine interaction is needed in order to analyse and characterise a proactive management of assets and workers through a limited number of maintenance windows. This will continue even more as the I4.0 interaction with traditional manufacturing environments requires workers' skill development and different asset maintenance strategies from those now prevailing.

This work presented a methodology and architecture to bring older physical assets with digitised scenarios in a non-intrusive way. The integration between systems and workers was described to support CBM technologies linked to supervised collaborative maintenance processes. Practical applications were built on a three-tier methodology based on common architectures, protocols and standards for collaborative maintenance in traditional manufacturing. Then, they were applied in milling operations and replicated in manufacturing cycles of face shields during COVID-19 emergency. Both the non-intrusive retrofitted approach and human-machine support systems were studied together with the knowledge of experienced operators. As a result, an original contribution to confront collaborative maintenance challenges in SMEs, including emergency situations such as social distancing, was provided.

Our solution proposed a connected infrastructure to store data and extract patterns about the failure probability of the critical components. Moreover, means to communicate a large amount of data from different industrial systems and assist the workers via augmented HMI tools, were tested. Already existing manufacturing traditional scenarios served to validate these digital retrofitting and communication strategies without interfering in working conditions. To sum up, the results of our work presented means to reduce SMEs' industrial investment by simplifying the commissioning of condition monitoring systems. At the same time, a collaborative maintenance approach for condition monitoring proved to be valid in traditional manufacturing environments in a very short time. In that way, the status of legacy systems was improved using a portable system characterised by standard sensors and industrial protocols, connected to cloud-based tools such as dashboards for global data analysis and trends. Finally, augmented tools were tested during maintenance processes to empower and support workers through learning models complemented with remote assistance.

As seen in the case study, there is room for improvement to test practical applications in traditional manufacturing. In the future, we plan to study a suitable human-machine interaction to improve results while the operator is involved during decision-making situations. So one of the further research lines will be to integrate a DT methodology based on these human-machine models in traditional manufacturing, generating an adaptive learning framework from the three levels that act at the same time in a manufacturing plant: processes, systems and workers.

References

[1] K. Schwab, The Fourth Industrial Revolution, Crown Publishing Group, USA, 2017.

[2] R. Y. Zhong, X. Xu, E. Klotz, S. T. Newman, Intelligent Manufacturing in the Context of Industry 4.0: A Review, Engineering 3 (5) (2017) 616–630. doi:10.1016/J.ENG.2017.05.015.

[3] M. Xu, J. M. David, S. H. Kim, The fourth industrial revolution: Opportunities and challenges, International Journal of Financial Research 9 (2) (2018) 90–95. doi:10.5430/ijfr.v9n2p90.

[4] Deloitte, Preparing tomorrow's workforce for the Fourth Industrial Revolution. For business: A framework for action, Global Business Coalition for Education (2018) 1–58.

[5] G. Czifra, Z. Molnár, Covid-19 and Industry 4.0, Research Papers Faculty of Materials Science and Technology Slovak University of Technology 28 (46) (2020) 36–45. doi:10.2478/rput-2020-0005.

[6] E. G. Caldarola, G. E. Modoni, M. Sacco, A Knowledge-based Approach to Enhance the Workforce Skills and Competences within the Industry 4.0, in: eKNOW 2018: The Tenth International Conference on Information, Process, and Knowledge Management, 2018, pp. 56–61.

[7] D. Mourtzis, F. Xanthi, V. Zogopoulos, An adaptive framework for augmented reality instructions considering workforce skill, Procedia CIRP 81 (2019) 363–368. doi:10.1016/j.procir.2019.03.063.

[8] S. Gallego Garcia, M. García, Industry 4.0 implications in production and maintenance management: An overview, Procedia Manufacturing 41 (2019) 415–422. doi:10.1016/j.promfg.2019.09.027.

[9] A. de la Fuente, V. González-Prida, A. Crespo, J. F. Gómez, A. Guillén, Advanced Techniques for Assets Maintenance Management, IFAC-

PapersOnLine 51 (11) (2018) 205–210. doi:10.1016/j.ifacol.2018.08.260.

[10] B. Chen, J. Wan, L. Shu, P. Li, M. Mukherjee, B. Yin, Smart Factory of Industry 4.0: Key Technologies, Application Case, and Challenges, IEEE Access 6 (2018) 6505–6519. doi:10.1109/ACCESS.2017.2783682.

[11] Q. Qi, F. Tao, T. Hu, N. Anwer, A. Liu, Y. Wei, L. Wang, A. Nee, Enabling technologies and tools for digital twin, Journal of Manufacturing Systems 58 Part B (2021) 3–21. doi:10.1016/j.jmsy.2019.10.001.

[12] P. Fantini, M. Pinzone, M. Taisch, Placing the operator at the centre of Industry 4.0 design: Modelling and assessing human activities within cyber-physical systems, Computers and Industrial Engineering 139 (2020) 105058. doi:10.1016/j.cie.2018.01.025.

[13] S. Bergweiler, Intelligent Manufacturing based on Self-Monitoring Cyber-Physical Systems, in: The Ninth International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies (UBICOMM-15), 2015, pp. 108–113. doi:10.13140/RG.2.1.2762.9281.

[14] M. Hermann, T. Pentek, B. Otto, Design Principles for Industrie 4.0 Scenarios: A Literature Review, Technische Universitat Dortmund 1 (1) (2015) 4–16. doi:10.13140/RG.2.2.29269.22248.

[15] D. Romero, J. Stahre, M. Taisch, The Operator 4.0: Towards socially sustainable factories of the future, Computers & Industrial Engineering 139 (2020) 106128. doi:10.1016/j.cie.2019.106128.

[16] H. Kroll, G. Copani, E. Van de Velde, M. Simons, D. Horvat, A. Jäger, A. Wastyn, G. PourAbdollahian, M. Naumanen, An analysis of drivers, barriers and readiness factors of EU companies for adopting advanced manufacturing products and technologies, European Union, 2016. doi:10.2873/715340.

[17] R. Glass, A. Meissner, C. Gebauer, S. Stürmer, J. Metternich, Identifying the barriers to Industrie 4.0, in: 51st CIRP Conference on Manufacturing Systems, Vol. 72, 2018, pp. 985–988. doi:https://doi.org/10.1016/j.procir.2018.03.187.

[18] J. Stentoft, K. W. Jensen, K. Philipsen, A. Haug, Drivers and Barriers for Industry 4.0 Readiness and Practice: A SME Perspective with Empirical Evidence, in: Proceedings of the 52nd Hawaii International Conference on System Sciences, Vol. 6, 2019, pp. 5155–5164. doi:10.24251/hicss.2019.619.

[19] F. Doyle, J. Cosgrove, Steps towards digitization of manufacturing in an SME environment, Procedia Manufacturing 38 (2019) 540–547. doi:https://doi.org/10.1016/j.promfg.2020.01.068.

[20] S. Mittal, M. A. Khan, D. Romero, T. Wuest, A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs), Journal of Manufacturing Systems 49 (2018) 194–214. doi:10.1016/j.jmsy.2018.10.005.

[21] D. Chesworth, Industry 4.0 Techniques as a Maintenance Strategy (A Review Paper) (January 2018). doi:10.13140/RG.2.2.18116.32644.

[22] X. Jin, B. A. Weiss, D. Siegel, J. Lee, Present Status and Future Growth of Advanced Maintenance Technology and Strategy in US Manufacturing, International Journal of Prognostics and Health Management 7 (Special Issue on Smart Manufacturing) (2016) 012.

[23] D. Horváth, R. Z. Szabó, Driving forces and barriers of Industry 4.0: Do multinational and small and medium-sized companies have equal opportunities?, Technological Forecasting and Social Change 146 (March) (2019) 119–132. doi:10.1016/j.techfore.2019.05.021.

[24] D. S. Thomas, The Costs and Benefits of Advanced Maintenance in Manufacturing, Tech. Rep. 100-18, National Institute of Standards and

Technology, Advanced Manufacturing Series (NIST AMS) (2018). doi:10.6028/NIST.AMS.100-18.

[25] J. Wan, H. Cai, K. Zhou, Industrie 4.0: Enabling technologies, in: Proceedings of 2015 International Conference on Intelligent Computing and Internet of Things, 2015, pp. 135–140. doi:10.1109/ICAIOT.2015.7111555.

[26] F. Orellana, R. Torres, From legacy-based factories to smart factories level 2 according to the industry 4.0, International Journal of Computer Integrated Manufacturing 32 (4-5) (2019) 441–451. doi:10.1080/0951192X.2019.1609702.

[27] T. Lins, R. A. R. Oliveira, Cyber-physical production systems retrofitting in context of industry 4.0, Computers & Industrial Engineering 139 (2020) 106193. doi:10.1016/j.cie.2019.106193.

[28] J. D. Contreras, R. E. Cano, J. I. García, Methodology for the Retrofitting of Manufacturing Resources for Migration of SME Towards Industry 4.0, in: Florez H., Diaz C., Chavarriaga J. (eds) Applied Informatics. ICAI 2018. Communications in Computer and Information Science, Vol. 942, Springer, 2018, pp. 337–351. doi:10.1007/978-3-030-01535-0_25.

[29] A. Quatrano, M. C. D. Simone, Z. B. Rivera, D. Guida, Development and Implementation of a Control System for a Retrofitted CNC Machine by Using Arduino, FME Transactions 45 (2017) 565–571. doi:10.5937/fmet1704565Q.

[30] M. Ayani, M. Ganebäck, A. H. Ng, Digital twin: Applying emulation for machine reconditioning, Procedia CIRP 72 (2018) 243–248. doi:10.1016/j.procir.2018.03.139.

[31] T. Stock, G. Seliger, Opportunities of Sustainable Manufacturing in Industry 4.0, Procedia CIRP 40 (2016) 536–541. doi:10.1016/j.procir.2016.01.129.

[32] M. Albano, E. Jantunen, G. Papa, U. Zurutuza, The MANTIS Book Cyber Physical System Based Proactive Collaborative Maintenance, River Publishers, 2018. doi:10.13052/rp-9788793609846.

[33] M. Tauqeer, K. Bang, Servitization: A Model for the Transformation of Products into Services through a Utility-Driven Approach, Journal of Open Innovation: Technology, Market, and Complexity 4 (4) (2018) 60. doi:10.3390/joitmc4040060.

[34] J. Gao, Y. Yao, V. C. Y. Zhu, L. Sun, L. Lin, Service-oriented manufacturing: a new product pattern and manufacturing paradigm, Journal of Intelligent Manufacturing 22 (3) (2011) 435–446. doi:10.1007/s10845-009-0301-y.

[35] B. Rohée, B. Riera, Advanced supervisory control for manufacturing systems: from concepts to a separated monitoring system, International Journal of Intelligent Systems Technologies and Applications 6 (3-4) (2009) 381–401. doi:10.1504/IJISTA.2009.024266.

[36] A. Garg, S. G. Deshmukh, Maintenance management: Literature review and directions, Journal of Quality in Maintenance Engineering 12 (3) (2006) 205–238. doi:10.1108/13552510610685075.

[37] K. Fraser, H. H. Hvolby, T. L. B. Tseng, Maintenance management models: a study of the published literature to identify empirical evidence: A greater practical focus is needed, International Journal of Quality & Reliability Management 32 (6) (2015) 635–664. doi:10.1108/IJQRM-11-2013-0185.

[38] T. P. Raptis, A. Passarella, M. Conti, Data Management in Industry 4.0: State of the Art and Open Challenges, IEEE Access 7 (2019) 97052–97093. doi:10.1109/ACCESS.2019.2929296.

[39] D. Baglee, U. Gorostegui, E. Jantunen, P. Sharma, J. Campos, How Can SMEs adopt a new method to advanced maintenance strategies?: A case

study approach, in: 30th International Conference on Condition Monitoring and Diagnostic Engineering Management, 2017, pp. 155–162.

[40] M. Helu, T. Hedberg, A. Barnard Feeney, Reference architecture to integrate heterogeneous manufacturing systems for the digital thread, CIRP Journal of Manufacturing Science and Technology 19 (2017) 191–195. doi:10.1016/j.cirpj.2017.04.002.

[41] J. Bokrantz, A. Skoogh, C. Berlin, T. Wuest, J. Stahre, Smart Maintenance: a research agenda for industrial maintenance management, International Journal of Production Economics 224 (2020) 107547. doi:10.1016/j.ijpe.2019.107547.

[42] Z. Balogh, E. Gatial, J. Barbosa, P. Leitão, T. Matejka, Reference Architecture for a Collaborative Predictive Platform for Smart Maintenance in Manufacturing, in: IEEE 22nd International Conference on Intelligent Engineering Systems (INES), 2018, pp. 000299–000304. doi:10.1109/INES.2018.8523969.

[43] A. Cachada, J. Barbosa, P. Leitão, C. A. Geraldes, L. Deusdado, J. Costa, C. Teixeira, J. Teixeira, A. H. Moreira, P. M. Moreira, L. Romero, Maintenance 4.0: Intelligent and Predictive Maintenance System Architecture, in: IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, 2018, pp. 139–146. doi:10.1109/ETFA.2018.8502489.

[44] T. Zonta, C. A. da Costa, R. da Rosa Righi, M. J. de Lima, E. S. da Trindade, G. P. Li, Predictive maintenance in the Industry 4.0: A systematic literature review, Computers & Industrial Engineering 150 (2020) 106889. doi:10.1016/j.cie.2020.106889.

[45] M. Albano, L. Lino Ferreira, G. Di Orio, P. Maló, G. Webers, E. Jantunen, I. Gabilondo, M. Viguera, G. Papa, Advanced sensor-based maintenance in real-world exemplary cases, Automatika 61 (4) (2020) 537–553. doi:10.1080/00051144.2020.1794192.

[46] J. D. Contreras, J. I. García, J. D. Pastrana, Developing of Industry 4.0 Applications, International Journal of Online and Biomedical Engineering (iJOE) 13 (10) (2017) 30–47. doi:10.3991/ijoe.v13i10.7331.

[47] P. Adolphs, H. Bedenbender, D. Dirzus, M. Ehlich, U. Epple, M. Hankel, R. Heidel, M. Hoffmeister, H. Huhle, B. Kärcher, et al., Reference Architecture Model Industrie 4.0 (RAMI4.0), ZVEI and VDI, Status report, 2015.

[48] R. G. Lins, B. Guerreiro, R. Schmitt, J. Sun, M. Corazzim, F. R. Silva, A novel methodology for retrofitting CNC machines based on the context of industry 4.0, in: 2017 IEEE International Systems Engineering Symposium (ISSE), 2017, pp. 1–6. doi:10.1109/SysEng.2017.8088293.

[49] R. Suzuki, S. Kohmoto, T. Ogatsu, Non-intrusive Condition Monitoring for Manufacturing Systems, in: 25th European Signal Processing Conference (EUSIPCO), 2017, pp. 1390–1394. doi:10.23919/EUSIPCO.2017.8081437.

[50] X. M. Chee, C. V. Le, D. H. Zhang, M. Luo, C. K. Pang, Intelligent identification of manufacturing operations using in-situ energy measurement in industrial injection moulding machines, in: IECON 2011 - 37th Annual Conference of the IEEE Industrial Electronics Society, 2011, pp. 4284–4289. doi:10.1109/IECON.2011.6120012.

[51] J. Herwan, S. Kano, O. Ryabov, H. Sawada, N. Kasashima, T. Misaka, Retrofitting old CNC turning with an accelerometer at a remote location towards Industry 4.0, Manufacturing Letters 21 (2019) 56–59. doi:10.1016/j.mfglet.2019.08.001.

[52] C. Cimini, F. Pirola, R. Pinto, S. Cavalieri, A human-in-the-loop manufacturing control architecture for the next generation of production systems, Journal of Manufacturing Systems 54 (2020) 258–271. doi:10.1016/j.jmsy.2020.01.002.

[53] K. Josifovska, E. Yigitbas, G. Engels, A Digital Twin-Based Multi-modal UI Adaptation Framework for Assistance Systems in Industry 4.0, in: Human-Computer Interaction. Design Practice in Contemporary Societies, Springer International Publishing, 2019, pp. 398–409. doi:10.1007/978-3-030-22636-7_30.

[54] C. Carlsson, Decision analytics mobilized with digital coaching, Intelligent Systems in Accounting, Finance and Management 25 (1) (2018) 3–17. doi:10.1002/isaf.1421.

[55] I. Qasim, M. W. Anwar, F. Azam, H. Tufail, W. H. Butt, M. N. Zafar, A Model-Driven Mobile HMI Framework (MMHF) for Industrial Control Systems, IEEE Access 8 (2020) 10827–10846. doi:10.1109/ACCESS.2020.2965259.

[56] C. Liu, S. Cao, W. Tse, X. Xu, Augmented Reality-assisted Intelligent Window for Cyber-Physical Machine Tools, Journal of Manufacturing Systems 44 Part 2 (2017) 280–286. doi:https://doi.org/10.1016/j.jmsy.2017.04.008.

[57] L. Damiani, M. Demartini, G. Guizzi, R. Revetria, F. Tonelli, Augmented and virtual reality applications in industrial systems: A qualitative review towards the industry 4.0 era, IFAC-PapersOnLine 51 (2018) 624–630. doi:10.1016/j.ifacol.2018.08.388.

[58] L. F. de Souza Cardoso, F. C. M. Q. Mariano, E. R. Zorzal, A survey of industrial augmented reality, Computers & Industrial Engineering 139 (2020) 106159. doi:10.1016/j.cie.2019.106159.

[59] F. Longo, L. Nicoletti, A. Padovano, Smart operators in industry 4.0: A human-centered approach to enhance operators' capabilities and competencies within the new smart factory context, Computers & Industrial Engineering 113 (2017) 144–159. doi:10.1016/j.cie.2017.09.016.

[60] J. Bokrantz, A. Skoogh, C. Berlin, J. Stahre, Maintenance in digitalised manufacturing: Delphi-based scenarios for 2030, International Journal of Production Economics 191 (2017) 154–169. doi:10.1016/j.ijpe.2017.06.010.

[61] M. Gaham, B. Bouzouia, N. Achour, Human-in-the-loop cyber-physical production systems control (hilcp2sc): A multi-objective interactive framework proposal, in: T. Borangiu, A. Thomas, D. Trentesaux (Eds.), Service Orientation in Holonic and Multi-agent Manufacturing, Springer International Publishing, 2015, pp. 315–325. doi:10.1007/978-3-319-15159-5_29.