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TESIS DOCTORAL:

A NON-INTRUSIVE AND ADAPTIVE DIGITAL TWIN AS ENABLING LEARNING ECOSYSTEM FOR THE DEVELOPMENT OF PREDICTIVE MODELS IN MANUFACTURING ENVIRONMENTS

Presentada por Alvaro García García para optar al grado de Doctor en Informática
por la Universidad de Valladolid

Dirigida por:

Dr. D. Anibal Bregón Bregón
Dr. D. Miguel Á. Martínez-Prieto

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DOCTORAL THESIS:

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Presented by Alvaro García García for the Doctor's Degree in Computer Science
at the University of Valladolid

Directed by:

Dr. D. Anibal Bregón Bregón
Dr. D. Miguel Á. Martínez-Prieto

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"Your focus determines your reality."

Qui-Gon Jinn

For my family, I love you “cucus”.

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Abstract

Recent unpredictable world economy challenges, such as the coronavirus pandemic and global energy crisis, have impacted the manufacturing industry, forcing production plants to reduce costs and improve productivity and sustainability. The demand for disruptive solutions and specialised workers under the Industry 4.0 paradigm has become an increasingly important digital priority for the manufacturing industry, which pushes technological upgrades towards building new cyber-physical ecosystems and supporting the skills improvement of the workforce. Despite the rapid adoption of next-generation Information Technologies, the accomplishment of this cyber-physical convergence remains an open issue in traditional manufacturing. In this way, the evolution of digital twins leveraged by progressive cyber-physical convergence has provided smart manufacturing systems with knowledge-generation ecosystems based on new models of collaboration between the workforce and industrial processes. However, industry will need to face the challenges of building and supporting new technical and digital infrastructures, while workers' skills development eventually manages to include the increased complexity of industrial processes. Similarly, academia faces the challenges of providing technological research programs and experts in line with complex manufacturing life cycle processes. From the point of view falling between industry and academia, this PhD thesis is intended to reach a better understanding of human-machine learning opportunities offered by emerging Industry 4.0 digital twin ecosystems in manufacturing. To overcome knowledge acquisition barriers associated with traditional manufacturing, the proposed research activities have contributed to a set of incremental results obtained in industrial environments, which are summarised as follows: (i) understanding of the current enablers and challenges found in the digital twin cyber-physical convergence concerning human–machine collaborative ecosystems; (ii) original definition of Digital Twin Learning Ecosystem (DTLE) and presentation of its three-layer DTLE conceptual architecture; (iii) application of two case studies in traditional manufacturing to address both digital retrofitting and human-machine integration, without interfering in working conditions; (iv) development of a three-tier digital twin-based methodology and the knowledge modelling process focused on a non-intrusive cyber-physical twinned interaction between skilled workers and legacy systems, for building an adaptive DTLE in manufacturing; and (v) implementation and replication of a DTLE in two different traditional manufacturing Small and Medium-sized Enterprises (SMEs) under the actual human-machine work conditions.

The results derived from this research culminated in a compendium of three publications. Based on these findings, the research priorities presented in this PhD thesis are considered a recognised basis in industry, which should help digital twins with the objective of progressive integration as a future learning ecosystem.

Resumen

Recientes e impredecibles desafíos para la economía mundial, entre los que se encuentran la pandemia de coronavirus y una crisis energética global, han impactado directamente en la industria de fabricación, exigiendo a las plantas productivas una reducción de costes a la vez que se mejora la productividad y la sostenibilidad. La demanda de soluciones disruptivas y de perfiles especializados, bajo el nuevo paradigma de la Industria 4.0, se ha convertido en una creciente prioridad para la digitalización de la industria manufacturera, potenciando la modernización tecnológica como base para la construcción de nuevos ecosistemas ciberfísicos y la mejora de las competencias de los trabajadores. Pese a la rápida adopción de las Tecnologías de la Información de nueva generación, la ejecución de esa convergencia ciberfísica es todavía un tema no resuelto en la fabricación tradicional. De esta forma, la evolución del gemelo digital, impulsada por una progresiva convergencia ciberfísica, ha proporcionado ecosistemas de generación de conocimiento a los sistemas de fabricación inteligentes a partir de nuevos modelos de colaboración entre el conjunto de los trabajadores y los procesos industriales. Pero la industria se encuentra en la necesidad de enfrentarse a los desafíos que supone construir y soportar nuevas infraestructuras digitales y técnicas al mismo tiempo que el desarrollo de las capacidades de los trabajadores se adapta para dar respuesta a la creciente complejidad de los procesos industriales. De la misma manera, el mundo académico se enfrenta a los desafíos de proporcionar programas de investigación tecnológica y expertos formados en el conocimiento del ciclo de vida de procesos de fabricación complejos. Desde un punto de vista a caballo entre la industria y el mundo académico, esta tesis doctoral pretende conseguir una mejor comprensión de las oportunidades de aprendizaje hombre-máquina que ofrecen los ecosistemas de gemelos digitales emergentes de la Industria 4.0 en la fabricación. Para superar las barreras de adquisición de conocimiento asociadas a la fabricación tradicional, nuestro trabajo contribuye con un conjunto de resultados obtenidos en entornos industriales de forma progresiva, que se resumen a continuación: (i) comprensión de los habilitadores y retos actuales encontrados en la convergencia ciberfísica de gemelos digitales relativos a los ecosistemas de colaboración hombre-máquina; (ii) definición original de Digital Twin Learning Ecosystem (DTLE) y presentación de su arquitectura conceptual de tres capas; (iii) aplicación de dos estudios de investigación en entornos de fabricación tradicional para abordar tanto la modernización digital como la integración hombre-máquina, sin interferir en las condiciones de trabajo; (iv) desarrollo de una metodología basada en un gemelo digital de tres niveles y el proceso de generación de conocimiento centrado en una interacción ciberfísica, que aúna trabajadores expertos y sistemas heredados, para la construcción de un DTLE adaptativo en la industria de fabricación; y (v) implementación y reproducción de un DTLE en dos pequeñas y medianas (PYMES) diferentes de fabricación tradicional atendiendo a las condiciones existentes de trabajo hombre-máquina.

Los resultados obtenidos durante la investigación han dado lugar a un compendio de tres publicaciones. Sobre la base de estos resultados, las prioridades de investigación presentadas en esta tesis doctoral se consideran reconocidas en la industria y, como tales, deberían ayudar a cumplir el objetivo de la progresiva integración del gemelo digital hacia un futuro ecosistema de conocimiento.

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Abbreviations

AI	**A**rtificial **I**nteligence
AR	**A**ugmented **R**eality
CBM	**C**ondition-**B**ased **M**aintenance
CPS	**C**yber-**P**hysical **S**ystem
CPPS	**C**yber-**P**hysical **P**roduction **S**ystem
DDT	**D**eep **D**igital **T**win
DT	**D**igital **T**win
DTLE	**D**igital **T**win **L**earning **E**cosystem
HMI	**H**uman **M**achine **I**nterface
I4.0	**I**ndustry **4.0**
IoS	**I**nternet **o**f **S**ervices
IoT	**I**nternet **o**f **T**hings
IIoT	**I**ndustrial **I**nternet **o**f **T**hings
KETs	**K**ey **E**nabling **T**echnologies
MBSE	**M**odel-**B**ased **S**ystem **E**ngineering
PHM	**P**rognostics and **H**ealth **M**onitoring
PLC	**P**rogrammable **L**ogic **C**ontroller
PLM	**P**roduct **L**ifecycle **M**anagement
SM	**S**mart **M**anufacturing
SME	**S**mall and **M**edium-sized **E**nterprise
VR	**V**irtual **R**eality

Chapter 1

Introduction

1.1 Motivation

Digital twins, as one of the most promising Industry 4.0 enabling-technologies, are called to accomplish the integration of physical and digital worlds in manufacturing (Liu et al. 2021). In this regard, digital twins have the advantage of representing an abstraction of the reality of manufacturing systems, allowing for multiple interaction levels between processes, systems and workers within the virtual space (Semeraro et al. 2021). Therefore, digital twins build and connect new research environments, driving human-machine learning.

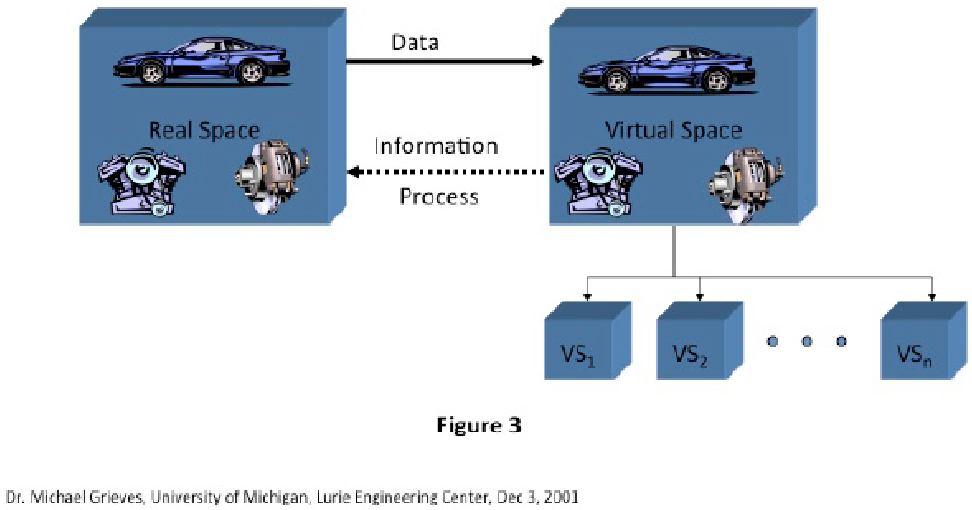

FIGURE 1.1: Conceptual Ideal for PLM (Grieves 2003)

However, the concept of digital twin is not new in manufacturing. Originally, Grieves (Grieves 2003) conceived digital twin on a conceptual level linked to Product Lifecycle Management (PLM). He defined a conceptual model containing three main parts, as depicted in Figure 1.1: (i) *Real Space* (physical products), (ii) *Virtual Space* (virtual products), and (iii) bidirectional data flow links between them, including virtual sub-spaces. Grieves (Grieves 2014) extended his own digital twin concept in manufacturing through Virtual Factory Replication, where the physical product and virtual product can be viewed and compared simultaneously in a closed loop. Moreover, in (Grieves and Vickers 2017) this definition was completed to rely on when referring to the digital twin and its different manifestations.

Nevertheless, during the last decade, the digital twin role has been improved with different approaches and definitions (Negri, Fumagalli, and Macchi 2017) and has focused on the manufacturing domain, considering that digital twin is gradually stepping out of its infancy (Liu et al. 2021). Consequently, the evolution of digital twins, leveraged by progressive cyber-physical convergence (Tao et al. 2019), has provided a manufacturing industry with connected ecosystems that are growing in factories enhanced by new models of digital collaboration and human-machine interaction (Cimini et al. 2022), as shown in Figure 1.2.

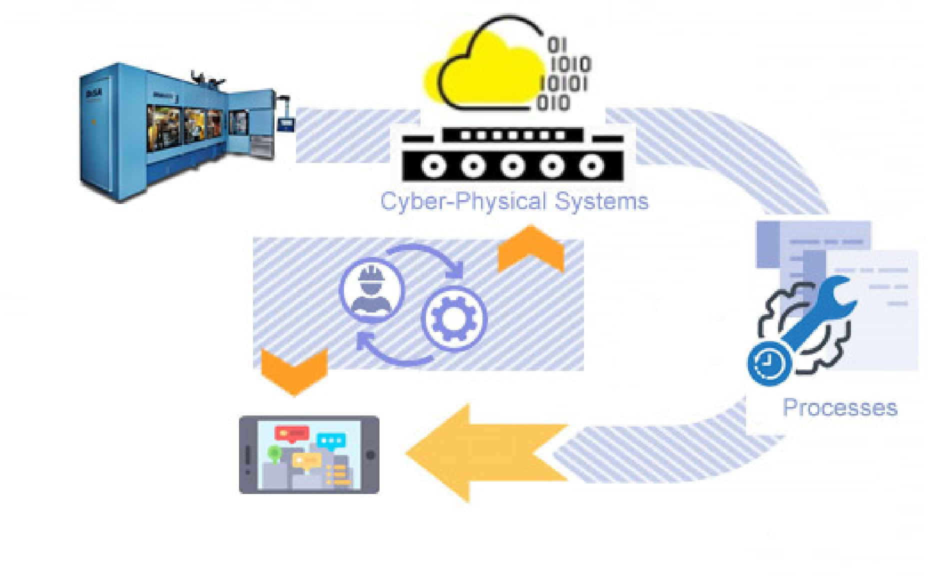

FIGURE 1.2: Human-machine interaction based on a Cyber-Physical System schema

Throughout the connection process, required to realise the potential of Industry 4.0, the paradigm shift advanced by Kagermann et al. (Kagermann, Wahlster, and Helbig 2013) in human-technology and human-environment interaction is tacking place in manufacturing plants by gathering data operations in real time:

"In the future, businesses will establish global networks that incorporate their machinery, warehousing systems and production facilities in the shape of Cyber-Physical Systems (CPS). In the manufacturing environment, these CPS comprise smart machines, storage systems and production facilities capable of autonomously exchanging information, triggering actions and controlling each other independently. This facilitates fundamental improvements to the industrial processes involved in manufacturing, engineering, material usage and supply chain and life cycle management".

Despite the significant impact of the rapid adoption of next-generation Information Technologies in the manufacturing industry (Raptis, Passarella, and Conti 2019), the achievement of cyber-physical convergence in manufacturing Small and Medium-sized Enterprises (SMEs) remains an unresolved issue (Mittal et al. 2018; Doyle and Cosgrove 2019; Li 2022). The integration of digital twin technology in production is still in its early stages, as it requires overcoming traditional machinery and specific technological barriers (Cimino, Negri, and Fumagalli 2019). Thus, it is undeniable that the traditional industry must confront the challenges of supporting legacy manufacturing systems and constructing new digital infrastructure while ensuring the skill development of workers to handle the growing complexity of industrial processes (Horváth and Szabó 2019). Under these considerations:

(i) The traditional manufacturing industry has relied for decades on skilled workers for supervisory control of systems and processes. On this basis, human knowledge is indispensable as part of the digital twin learning process to maintain and improve manufacturing systems, while the causes of the problems which may occur are identified and solved to prevent them in the future.

(ii) The recent COVID-19 outbreak impact on the world economy has joined business needs, forcing manufacturing plants to adapt to changes in a predictive way to guarantee the performance and continuity of industrial production in real-time. In this context, very few SMEs with traditional equipment have anticipated the latest human-machine technological upgrades impeded by technical and economic barriers.

With regard to the first challenge, the increasing business requirements motivated by enhancing factors over the entire manufacturing life-cycle, such as the maintainability of the whole production process, systems, and services, make highly skilled workers remain necessary for transforming legacy manufacturing systems into smart manufacturing systems (Burke et al. 2017). Nevertheless, the traditional manufacturing workforce requires upgrading to the skills needed to cope with upcoming digital technologies (Deloitte 2018). Furthermore, this is an important consideration when discussing lifelong learning and training in industry Li (2022), which are increasingly dependent on experienced workers and digital changes to improve working methods (Toivonen et al. 2018). In practice, the digital twin of the manufacturing system (Graessler and Poehler 2018b) can tackle the challenge of providing industrial workers with a deeper understanding and skills development, being a decision-making solution underpinned by real-time communication between humans, systems, and processes (Zhong et al. 2017). Thus, both the interaction of workers and the integration of digital information with the real environment provide the plant ecosystem with cyber–physical connections and digital twin data flows towards Human-in-the-Loop CPPS (Cimini et al. 2020), as shown in Figure 1.3.

FIGURE 1.3: Milling machine‘s worker provided with personalised digital twin support for training in maintenance tasks (Fundación Cidaut)

In this context, the potential of digital twins and their real-time cooperation between machines and human resources offer continuous learning opportunities to clear away obstacles in technological environments (Berisha-Gawlowski, Caruso, and Harteis 2021).

Regarding the second challenge, smart monitoring (Zhong et al. 2017) and new human-machine collaborative maintenance models add value to the improvement of manufacturing processes (Albano et al. 2018; Fantini, Pinzone, and Taisch 2020). However, the adoption of collaborative ecosystems implicitly requires a digital integration, connecting knowledge with management tools to benefit from predictive maintenance technologies (Baglee et al. 2017; Zonta et al. 2020). Thus, the progress that still needs to be made in SMEs for the successful and timely reimplementation of Industry 4.0 concepts has barriers to overcome, such as interoperability, virtualization, decentralization, real-time capability, service orientation and modularity (Hermann, Pentek, and Otto 2015). Furthermore, the integration of advanced Industry 4.0 strategies in manufacturing SMEs to monitor and enhance the actual condition of an asset, such as predictive maintenance and condition monitoring techniques (Albano et al. 2018; Baglee et al. 2017) is not always directly possible. It is common to find a lack of information connectivity models inherited from older manufacturing systems (Chesworth 2018). Similarly, (Cimino, Negri, and Fumagalli 2019) considers that digital twin in production environments faces many common scenarios where manufacturing systems are equipped with traditional machinery. This legacy approach means that digital twin services are limited without a bidirectional connection to interchange information between the virtual space and its physical counterpart. Conversely, the concept of retrofitting provides manufacturing with opportunities to connect traditional machines by applying Industry 4.0 key enabling technologies (Wan, Cai, and Zhou 2015; Lins and Oliveira 2020). The retrofitting process opens up a legacy method for upgrading machines with the introduction of new digital features based on infrastructure and communication at the shop floor (Orellana and Torres 2019), while tailoring such assets by using protocols (Contreras, Cano, and García 2018), electronic data capture systems and new HMI control applications (Quatrano et al. 2017; Ayani, Ganebäck, and Ng 2018). In the case of SMEs, such adaptive methodologies based on hardware and software provide a more feasible alternative to include updated features in legacy machines, as shown in Figure 1.4.

Figure 1.4: Human-machine integration based on hardware and software interfaces on a retrofitted legacy milling machine (Fundación Cidaut)

Due to the aforementioned challenges for workers and systems posed by Industry 4.0 in traditional manufacturing environments, this PhD thesis investigates a non-intrusive and adaptive twinned interaction between skilled workers and legacy systems for manufacturing SMEs.

Digital twins are expected to be a decision-making solution to provide manufacturing workers with a deeper understanding and skills development (Kokkonen et al. 2023). However, despite the fact that the advent of Industry 4.0 having provided SMEs with a new digital transformation movement (Han and Trimi 2022), it is not clear in the industry what features a digital twin should have or how it should work in different ecosystems. Both academia and industry are facing real problems in providing research programs, technological solutions and experts, in line with the predictive and complex requirements of newly evolving industrial processes (Onaji et al. 2022). This is the main reason why all research efforts have been focused on reviewing and understanding the implementation of an adaptive knowledge management process, which includes the cyber-physical convergence of both retrofitted legacy production systems and skilled workers. Thus, this convergence is considered the first step towards the building process of a connected **Digital Twin Learning Ecosystem** regardless of the level of digitisation.

1.2 Objectives

The motivation and research context outlined in the previous section determined the objectives of this PhD thesis. Although both investment in economic or technical resources and resistance to change can be obstacles to innovation in SMEs, the proposed hypothesis that introduces a non-intrusive and adaptive Digital Twin Learning Ecosystem in manufacturing is aimed at achieving a reasonable trade-off between workers and machines in traditional environments. As such, it explores diverse ways to cope with upcoming digital technologies and the required workers' skills at the shop floor, while closing to the minimum the lack of confidence of the workforce on them. Given this hypothesis, the global objective can be summarised as follows:

The integration of an adaptive human-machine Digital Twin Learning Ecosystem (DTLE) in a traditional manufacturing environment to facilitate the development of predictive models in a non-intrusive way, regardless of the level of digitisation.

From a point of view falling between industry and academia, the proposed concept of DTLE is intended to support a holistic approach to the manufacturing environment based on an adaptive behaviour management of systems, workers and processes, regardless of the level of digitisation. Therefore, as shown in the thesis schema depicted in Figure 1.5, three partial and specific objectives are also defined below to attain the aforementioned global objective:

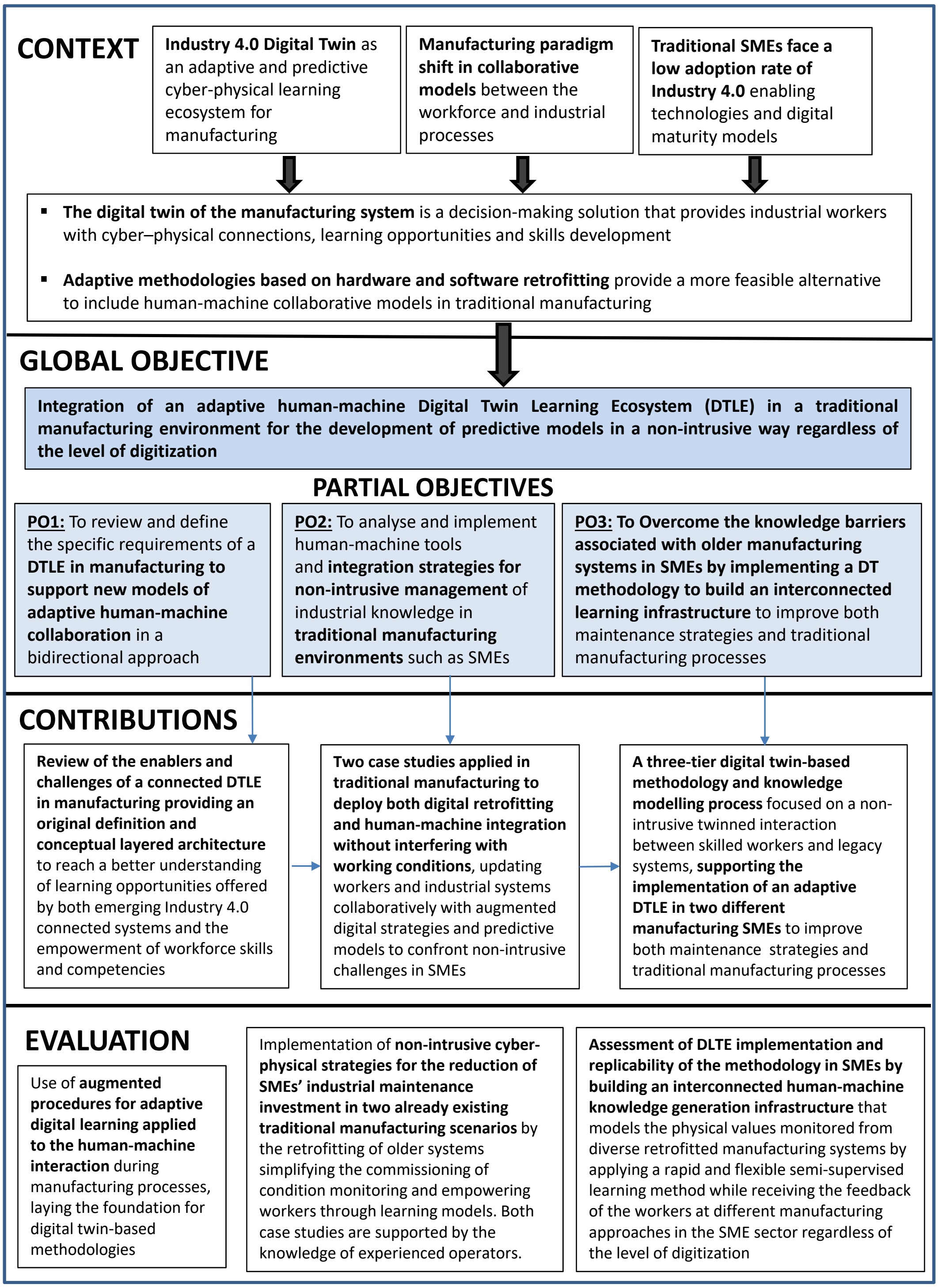

FIGURE 1.5: General overview of the context, goal, objectives, contributions and evaluation of the thesis

1. **To review and define the specific requirements of a DTLE in manufacturing, supporting new models of adaptive human-machine collaboration using a bidirectional approach.**

   This objective addresses knowledge-generation strategies based on new cyber-physical models of collaboration between the workforce and industrial processes. In this way, some of the main outputs explored concerning physical-digital learning are aligned with worker training programs oriented towards required digital skills. As a result, the objective includes three different phases:

   - Reviewing Industry 4.0 driven applications of digital twins, which offer human–machine cooperation opportunities in smart manufacturing ecosystems from both academia and industry.
   - Understanding emerging Digital Twin Learning Ecosystems, focusing the research topic on both theoretical virtual factories and real collaborative manufacturing ecosystems connected.
   - Reviewing the current enablers, challenges and research priorities in developing Industry 4.0 Digital Twin Learning Ecosystems.

2. **To analyse and implement human-machine tools as well as integration strategies that facilitate and support a non-intrusive management of industrial knowledge in traditional manufacturing environments, such as SMEs.**

   This objective considers the background for the advanced maintenance of old manufacturing machines and explores the evolution of non-intrusive convergent retrofitting technology applied in manufacturing. The approach aims to implement a human–machine Industry 4.0 integration, updating workers and industrial systems with digital strategies. In this way, it also facilitates traditional environments to interact with and benefit from predictive maintenance technologies based on sustainable and collaborative human-machine models.

3. **To overcome the knowledge barriers associated with old manufacturing systems in SMEs by implementing a digital twin methodology and building an interconnected learning infrastructure to improve both maintenance strategies and traditional manufacturing processes.**

   This objective aims to help SMEs build their own interconnected learning infrastructure at different manufacturing levels as a basis for the implementation of an adaptive Digital Twin Learning Ecosystem. For this purpose, it pursues a non-intrusive and tailored twinned interaction between skilled workers and legacy systems. It considers a knowledge modelling process based on three interconnected digital twin tiers as a way to enable adaptive learning in traditional manufacturing by characterising legacy systems and processes with the support of workers' expertise. As a result, this approach helps manage non-intrusive cyber-physical convergence in the SME sector.

1.3 Methodology

The approach of this PhD thesis is focused on understanding the interaction between humans (Social Science) and technologies (Computer Science) to implement a Digital Twin Learning Ecosystem. This mixed content is a suitable scenario for using the engineering method instead of the scientific method (Dodig-Crnkovic 2002). Therefore, the evolutionary paradigm of the engineering method proposed in (Adrion 1993) was considered adequate to successfully accomplish the objectives of our research: *"observe existing solutions, propose better solutions, build or develop, measure and analyse, and repeat until no further improvements are possible"*. For effective implementation, this method was applied following four different phases studied in (Glass 1995) based on the contemporary computing research. The four phases are described as follows:

1. **Informational**. During this phase, all information necessary to address the research process (literature review, technical articles, maturity level assessment of the technology, the workforce skill levels, etc.), is gathered and aggregated.
2. **Propositional**. During this phase, the scenario and different definitions, methods, models, or solutions are proposed to implement the concepts presented in the informational phase.
3. **Analytical**: During this phase, the analysis and exploration of the proposed approach are implemented in a proof of concept/case study to prove its operational capability in this respect.
4. **Evaluative**. During this phase, the proposed approach is evaluated through experimentation and observation to assess the effective implementation, replicability, and improvement of the methodology.

This research is motivated by the digital twin concept presented by Grieves (Grieves 2003) with a focus on a connected physical–virtual model in manufacturing. The methodological process addressed a systematic literature review to contribute with different learning approaches applying the digital twin concept in theoretical and existing manufacturing ecosystems, in line with Industry 4.0 physical–digital convergence. Diverse human–machine interaction methods based on applications, frameworks and collaboration models, which are used for decision-making and training in manufacturing, have been studied. Furthermore, the current enablers and challenges found in the literature concerning virtual replication factory have been explored from a point of view between academia and industry. On the other hand, the scenario to carry out the digital twin cyber-physical convergence, the digital twin research priorities and future trends in collaborative learning ecosystems are also proposed.

Under this approach, the analysis and exploration of the cyber-physical interaction in traditional manufacturing was studied in a CNC milling machine using a non-intrusive retrofitting development based on interoperable Industry 4.0 tools. This case study was built on a three-tier methodology supported on common architectures, protocols, and standards without interfering with working conditions and replicated in the manufacturing cycles of an injection moulding machine during the COVID-19 emergency. Workers and industrial systems were updated towards increasingly evaluative phases with human–machine digital strategies and proactive management environments, laying the foundation of the three conceptual layers proposed for a Digital Twin Learning Ecosystem model in manufacturing. This three-tier solution provided: (i) cyber-physical connections; (ii) smart human–machine interfaces; and (iii) cognitive skills, enabling the human–machine technological integration in a traditional manufacturing scenario and supporting the cyber-physical convergence of old industrial systems for non-intrusive human-machine learning.

Finally, the proposed Digital Twin Learning Ecosystem was evaluated in two industrial scenarios in the SME sector. The same CNC milling machine was used to achieve an interactive and adaptive Digital Twin Learning Ecosystem in a machining workshop by building an interconnected knowledge-generation infrastructure for maintenance strategies. To obtain a fully evaluative iteration, an induction furnace was used to replicate the Digital Twin Learning Ecosystem in a foundry plant with the aim of improving the efficiency of the cast iron process. In this way, the three-tier methodology for adaptive digital learning was implemented and replicated on a non-intrusive twinned interaction basis between skilled workers and legacy systems to overcome the knowledge barriers associated with old manufacturing systems.

1.4 Contributions

This PhD thesis encompasses several contributions. The methodology defined in the previous section was followed to accomplish the foreseen objectives.

First, a comprehensive literature review of existing technical articles and scientific research on digital twin ecosystems in Industry 4.0 manufacturing is provided. Based on this information, the current enablers, challenges and research priorities found in digital twin cyber-physical convergence concerning human–machine collaborative ecosystems are exposed (García, Bregon, and Martínez-Prieto 2022b). Therefore, all of them contribute to the understanding of learning opportunities enhanced by digital twin ecosystems in manufacturing. In that regard, this PhD thesis presents the original definition of the Digital Twin Learning Ecosystem and depicts the three conceptual layers that form the Digital Twin Learning Ecosystem architecture (see Figure 1.6), providing a cyber-physical scenario for assessing the learning ecosystems offered by both emerging Industry 4.0 connected digital twins and the empowerment of workforce skills.

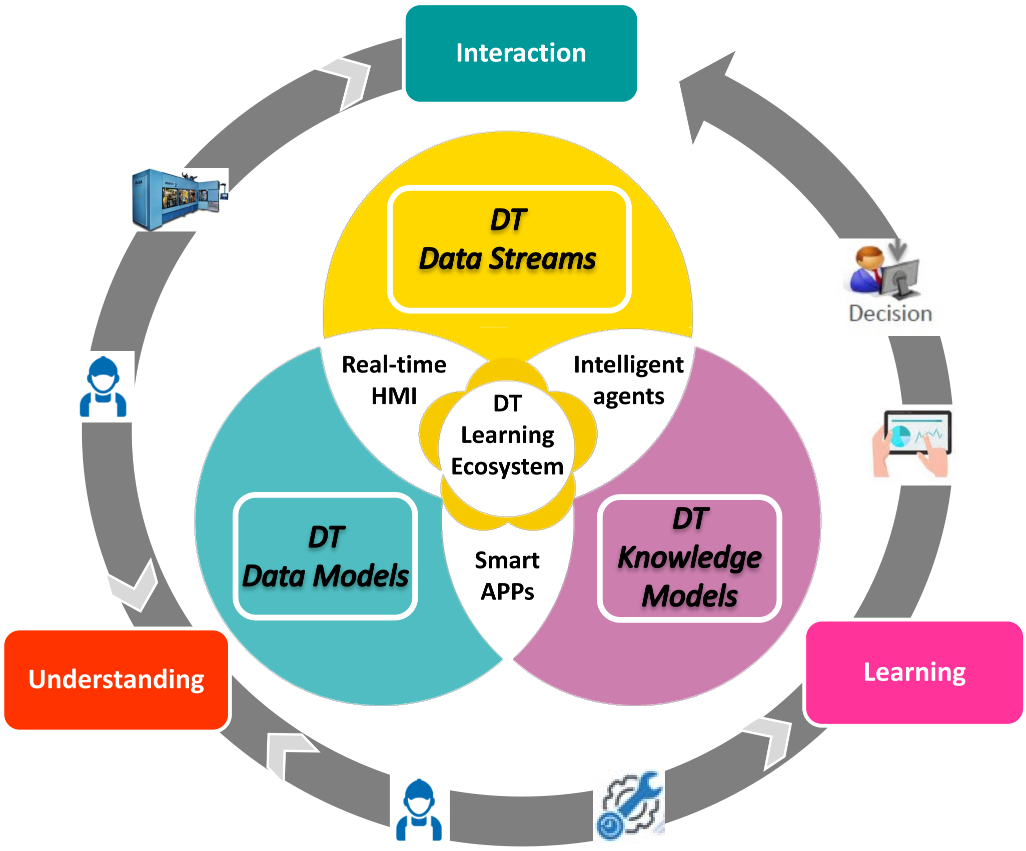

FIGURE 1.6: Three-layer Digital Twin Learning Ecosystem

With the objective of achieving a non-intrusive human–machine technological integration for learning in traditional manufacturing, this research also contributes with two case studies to deploy both digital retrofitting and human-machine interaction without interfering in working conditions (García, Bregon, and Martínez-Prieto 2022a). These studies demonstrate how it is possible to update workers and industrial systems collaboratively with augmented digital strategies and predictive models to confront the challenge of non-intrusive interaction in SMEs. Therefore, this work evaluates a methodology that pursues the reduction of SMEs' industrial maintenance investment, achieving two objectives: (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. The human-machine integration is built on the three-tier concept depicted in Figure 1.7, deploying a common system architecture to enable the modular communication of data between the three tiers (data streams, data models, and knowledge models), where workers, systems and processes are connected at the same time.

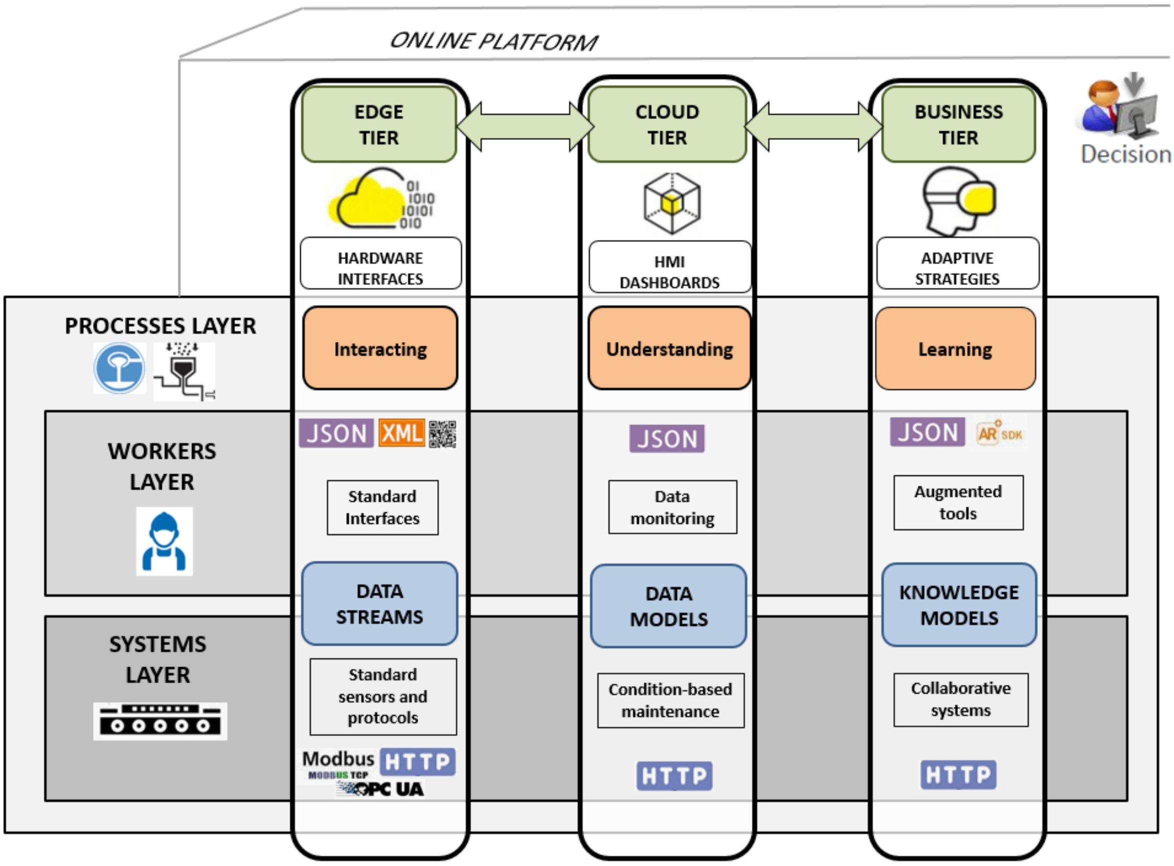

FIGURE 1.7: Three-tiers concept to support non-intrusive collaborative maintenance in traditional manufacturing

Finally, this PhD thesis contributes with both the assessment of the three-tier digital twin-based methodology, and the knowledge modelling process for building an adaptive DTLE in manufacturing. This approach has been implemented and replicated in two different manufacturing SMEs under actual work conditions (García, Bregon, and Martínez-Prieto 2024). It considers a non-intrusive cyber-physical twinned interaction between skilled workers and legacy manufacturing systems, thereby improving both maintenance strategies and traditional manufacturing processes. In particular, this methodology depicted in Figure 1.8 makes two significant contributions: (i) to provide the basis for the implementation of a DTLE in manufacturing SMEs, and (ii) to help SMEs build their own interconnected learning infrastructure towards the improvement of both manufacturing processes and maintenance operations.

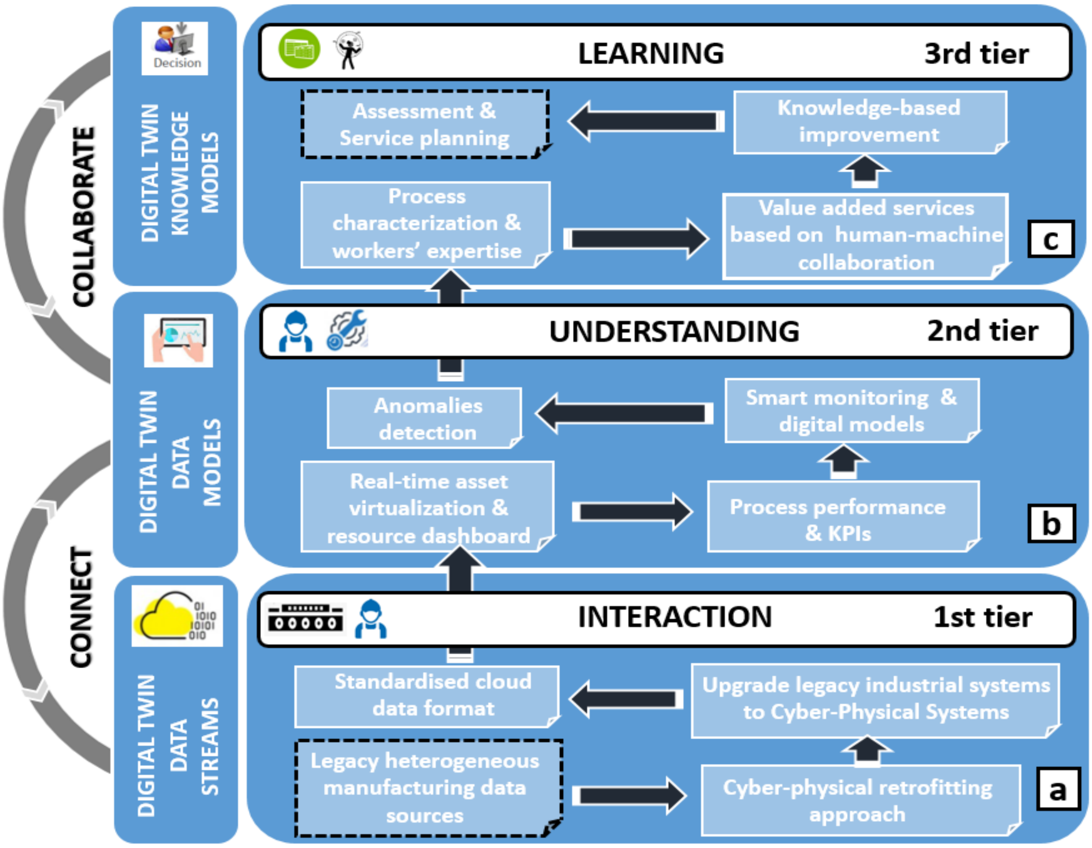

Figure 1.8: Three-tier Digital Twin-based methodology

1.5 Thesis Structure

This PhD thesis is a compilation of three publications. Before its presentation, Chapter 2 provides the background on which the proposed research is based, that will help to better understand the contextual framework including the understanding of Industry 4.0 digital twin learning ecosystems in manufacturing, and the human–machine interaction challenges in traditional scenarios to enable a non-intrusive learning approach. Chapter 3 then gather the three publications and their addressed contributions that constitute this PhD thesis. Finally, Chapter 4 presents the conclusions of the PhD thesis and the open lines of research left for future work.

Chapter 2

Background

2.1 Introduction

Advancements in the proposed field of research related to digital twin can not be regarded without a common understanding between academia and industry. Industry 4.0, presents opportunities for enabling Digital Twin Learning Ecosystems in academic and industrial scenarios. On the one hand, industry faces the challenges of building and supporting new technical and digital infrastructures, while workers' skills development eventually manages to handle digital change. On the other hand, academia faces the challenges of providing technological research programs and experts in line with complex manufacturing processes. In both cases, a change in the fundamentals of the manufacturing systems and operations is required. All these challenges, focusing on the physical–digital convergence and digital skills development, are explored below.

2.2 Digital Twin and Industry 4.0

At the beginning of 2015, the vision of the German manufacturing industry, named "Industrie 4.0", and its main design principles (*interoperability*, *virtualization*, *decentralization*, *real-time capability*, *service orientation*, and *modularity*) were presented in (Hermann, Pentek, and Otto 2015) as a "how to do" Industry 4.0. This vision as *"a new level of value chain organization and management across the lifecycle of products"* is based on four key components: *CPS*, *IoT*, *IoS* and *Smart Factory*. The integration of these components was standardised in the "Reference

Architecture Model Industrie 4.0" (RAMI 4.0) as a service-oriented architecture for the development of Industry 4.0 applications and the development of models for smart manufacturing ecosystems (Adolphs et al. 2015). Also, in 2015, the term "Smart Manufacturing" (SM) was introduced in the United States to deploy the new technologies in manufacturing, such as IIoT and AI. The National Institute of Standards and Technology (NIST) defined SM as *"fully-integrated, collaborative manufacturing systems that respond in real time to meet changing demands and conditions in the factory, in the supply network, and in customer needs"* (Tantawi, Fidan, and Tantawy 2019).

Currently, the most representative terms for these definitions and technologies have been adopted globally by industry and academia. Overall, their key characteristics and technologies (Mittal et al. 2019) serve as a guide to the implementation of Industry 4.0-enabled manufacturing systems. In a scenario led by the cyber-physical convergence of Industry 4.0 ecosystems (Qi et al. 2018b), the concept of digital twin emerges as one of the most disruptive innovations to exploit industrial data enabling technologies (Raptis, Passarella, and Conti 2019). Owing to its growing relevance, the Gartner Hype Cycle (Dedehayir and Steinert 2016) named digital twin as one of the "Top 10 Strategic Technology Trends" from 2017 to 2019 (Qi et al. 2019). In this process, there has been a paradigm shift from traditional product-oriented manufacturing to service-oriented manufacturing (Moghaddam, Silva, and Nof 2015). Therefore, this landscape allows value to be added through connected services, specialized skills and learning tools to support new collaborative business models, besides hybrid digital twin data-driven approaches such as monitoring, diagnostics, and prediction (Lu et al. 2020).

Regarding current studies on realising digital twins in Industry 4.0, (Tao et al. 2019) summarises state-of-the-art of digital twin research and its application in different industries as a reference guide. In addition, the paper poses many pressing issues, such as a unified digital twin modeling method, which should be addressed to enhance rapid digital twin evolution in practice. In a different work, (Lu et al. 2020) reviews the connotations, application scenarios, and research issues of digital twin-driven smart manufacturing in the context of Industry 4.0. It presents some digital twin aspects focused on manufacturing assets, people, factories, and production networks, as they play a crucial role in the vision of smart manufacturing. However, even though the digital twin concept has been refined in system theoretical terms for learning, optimization, and control (Cronrath, Ekstrom, and Lennartson 2020), it is certainly true that the research outcomes for digital twins in the manufacturing domain are mainly at the conceptual level.

In general, academia and industry have different visions on how to understand and apply digital twins as a tool of knowledge responding to dynamic changes in manufacturing processes (Parrott and Warshaw 2017). Thus, the advent of connected digital twin models in manufacturing has enhanced the development of collaborative skills 4.0 and training capabilities (Fantini, Pinzone, and Taisch 2020), providing workers with direct access to existing plant-process knowledge to perform technical tasks or use their inputs as part of the learning process (Graessler and Poehler 2018b). Furthermore, enabling technologies such as augmented reality in digital twin ecosystems derives added value for human-machine interface integration, visualization, and learning of digital twin data (Zhu, Liu, and Xu 2019) for all the observable manufacturing elements.

2.3 Digital Twin learning applications in manufacturing

New digital twin learning applications are emerging in the virtual space to provide the reality of manufacturing ecosystems with an additional knowledge layer. From this perspective, a connected digital twin enables different applications and ways to collaborate between humans and automated production systems. Moreover, distributed learning provides opportunities for modelling multiple interactions between processes (Kunath and Winkler 2018), systems (Reid and Rhodes 2016), and workers' skills (Graessler and Poehler 2018a). Therefore, the following three categories are considered to discuss diverse learning opportunities in academia and industry.

2.3.1 Human-machine interaction applications

Towards the concept of a learning ecosystem (Burke et al. 2017), digital twin offers bidirectional interaction in real-time dealing with different data sources to transform information into valuable knowledge (Uhlemann, Lehmann, and Steinhilper 2017). The use of human-machine interfaces is therefore promoting the implementation of digital twin applications oriented to collaborative environments. Applications based on context-aware and adaptive digital twin models (Hribernik et al. 2021) offer complex human-machine interactions in an intelligent data space related to manufacturing processes. In this collaborative context, a social-based framework of interconnected manufacturing systems of workers, assets, and services also takes place. Virtual, physical, and social worlds are integrated around a Cyber-Physical-Social System (CPSS) approach based on the concept of social manufacturing (Leng et al. 2020).

When applied in manufacturing, collaborative learning models present strategies for evaluating workers‘ skills in CPS environments and provide intuitive augmented applications for monitoring and controlling industrial processes, as well as enabling local or remote interaction services. For example, in studies such as (Graessler and Poehler 2018b) a conceptual approach of a digital twin application is shown involving workers and CPS devices in an experimental assembly station of a production laboratory in fully automated decision-making processes. In addition, there are other studies focused on the usefulness of augmented interfaces. (Padovano et al. 2018) presented a digital twin-based application designed to enable a knowledge as a service approach in a real factory floor that produces carton packaging boxes. The digital twin prototype provides workers with a real time CPPS-based 4.0 knowledge navigation service linked to an Android application with a QR code. Workers can use this application, a screen interaction or a vocal message to request specific knowledge, keeping their attention directly on the physical system. Another collaborative scenario, based on an AR human-machine interface for the visualization of digital twin data, is presented in (Zhu, Liu, and Xu 2019). In this case, an AR application was used to provide workers with comprehensive information to monitor and control a CNC milling machine in a real manufacturing environment. The connected framework also allows the worker to interact and manage digital twin data to improve process efficiency through an augmented approach.

2.3.2 Training applications

Workers’ knowledge is improved by different backgrounds and outcomes in training processes (Berisha-Gawlowski, Caruso, and Harteis 2021). Likewise, experienced workers need to guide others with little experience. Nevertheless, training applications of digital twin in manufacturing require a collaborative learning framework as the basis for generating knowledge for decision support systems. In this way, learning factories offer a path towards Industry 4.0 in an academic context while promoting the integration of learning systems in the workplace. In this approach, lessons learned are transferred to knowledge-based manufacturing through convergence with the real world. In addition, training in virtual environments encourages cognitive processes when working in immersive and multi perception environments with augmented learning.

Some studies in the literature show that the Learning Factory concept is evolving in manufacturing to support Industry 4.0 enabling technologies (Baena et al. 2017) and practical learning activities (Prinz et al. 2016) as a promising training and research environment where digital twin combines both industrial scenarios and academic applications (Abele et al. 2017). The communication and interaction between teams of engineers and researchers establishes two-way knowledge bringing real industrial environments to teaching programs and research laboratories to factories. In a Learning Factory context, the digital twin concept offers learning opportunities for representation and visualisation through the mapping of real processes in digital and virtual models (Tvenge et al. 2020). Moreover, augmented reality/virtual reality technologies provide workers with enhanced interaction frameworks and augmented interfaces (Ke et al. 2019).

2.3.3 Data-driven applications

(Kunath and Winkler 2018) defines digital twin *"as the sum of all available data, i.e. engineering data and operational data, of all elements of the manufacturing system that reflect the historical and actual state of the system in realtime"*. In the context of industrial applications, therefore, digital twins provide a connected data infrastructure able to help with the generation of data-driven models in proactive decision making and transfer results learned from simulations in the virtual space to the physical space, without training the model from scratch.

Different data-driven learning applications in real-time can be found in the literature based on the digital twin approach. For example, in (Leng et al. 2019) a systems engineering-based approach of a digital twin to co-create personalised products is presented. A demonstrative implementation scenario is characterised by a digital twin-driven manufacturing CPS for parallel control of a smart manufacturing workshop. Through the analysis of a dynamic process execution, a digital twin provides workers with the status of manufacturing operations and enables continuous improvement with an intelligent optimisation engine. Another solution was proposed by (Liu et al. 2019) using a digital twin-based process planning evaluation method with real-time data status. The implementation is addressed in a manufacturing workshop of key parts of the marine diesel engines, where planning evaluation is required to ensure consistency in the processing quality of the manufactured parts. Internet of things and digital twin technologies allow the improvement of the machining efficiency by using dynamic cyber-physical information about the process status. On the other hand, data analysis enables behaviour-based applications focused on CPS. For example, a digital twin-assisted fault diagnosis method for real-time monitoring and predictive maintenance was presented in (Xu et al. 2019). The case study is implemented in a car body-side production line, where a PLC allows for data interconnection and interaction. Through a two-phase process using deep transfer learning, the application of digital twins in virtual and physical spaces transforms fault diagnosis patterns in knowledge for both the development and maintenance phases, thus reducing the risk of accidental breakdowns.

2.4 Digital Twin-based adaptive human-machine interaction

An important consideration when discussing lifelong learning and training in the industry is that they are increasingly dependent on highly skilled workers and digital changes to improve working methods (Toivonen et al. 2018). In this context, the potential of digital twin and their real-time interaction and cooperation between machines and human resources offer continuous learning opportunities to clear away obstacles in technological environments (Berisha-Gawlowski, Caruso, and Harteis 2021). Through the combination of factors presented previously such as human-machine learning (Ansari, Erol, and Sihn 2018) and the concept of Learning Factory (Tvenge et al. 2020), physical and virtual environments that include all processes, products, resources, and categories of people in different manufacturing activities are set to improve the skill set of the future workforce, regardless of age, gender, and social status.

In addition, the emergence of connected platforms supporting digital twin frameworks provides manufacturing with a learning ecosystem oriented towards exploiting knowledge from the integration of physical and digital worlds. In the literature, we can find some Digital Twin Learning Ecosystems based on frameworks. These frameworks are well known for providing learning features that enable effective competence (David, Lobov, and Lanz 2018), enhanced skills (Caldarola, Modoni, and Sacco 2018), more efficient engineering solutions (Yildiz, Møller, and Bilberg 2020), improved human-asset interaction (Kong et al. 2020), synchronous modeling (Zhuang, Gong, and Liu 2021), human-robot collaborative systems (Malik and Bilberg 2018), improved quality and resources (Qamsane et al. 2019) and support fault diagnosis (Mi et al. 2021). Consequently, Digital Twin Learning Ecosystems enable a distributed approach focused on achieving a connected learning model of a product (Tao et al. 2018), process or industrial service (Tao et al. 2019). It is thus necessary for a real-time replicated representation of the physical world to be built for understanding purposes, while technological frameworks offer their own digitised data and fully bidirectional interaction capabilities (Qi et al. 2019). As noted above, these digital twin learning approaches can also be studied in Learning Factories that combine academic applications and demonstration scenarios. In this way, virtual factory replication and the Learning Factory concept also allow the implementation of complex scenarios and frameworks for testing and training in a diversity of human-machine interactive levels as

Digital Twin Learning Ecosystem enablers. Researchers and experts in the use of next generation information technologies and industries, are already working together to develop learning platforms for research and demonstration (Ansari, Erol, and Sihn 2018), experiential CPPS environments for training and learning (Uhlemann et al. 2017), immersive environments for different applications and sectors (Eyre and Freeman 2018), collaborative software (Brenner and Hummel 2017), collaborative factory environments (Grube, Malik, and Bilberg 2019) and new Industry 4.0 learning approaches in manufacturing (Raza et al. 2020).

Nevertheless, Industry 4.0 requires workers to be better prepared to meet the increased complexity of industrial tasks in dynamic working environments. The integration of digital twin information within the real environment of the worker is therefore crucial to connect and define all real-time relationships and behaviour between systems, users and processes. In this way, a context-aware digital twin can use learning capability and the ability to adapt to changing environments (Hribernik et al. 2021) to improve the knowledge of the processes and workforce. Another example of integration is VR applications that allow workers to interact with production processes through non-intrusive technologies that improve their skills. This guided approach makes training tasks more flexible and attractive by using virtual digital twin contents (Tvenge et al. 2020). Visualisation interfaces of digital twin data, driven by human-system interaction in manufacturing, have become one of the ways of enabling better support for workers in learning and training processes. A digital twin powered by AR/VR technologies can be used to build autonomous and highly-efficient training environments for workers (Egger and Masood 2020). Moreover, augmented interfaces enable collaborative environments that allow a physical object to be modelled and dynamically adjusted based on instructions learned from a virtual model (Tao et al. 2019). Thus, the role of the workforce is changing because of the use of user-facing technologies (Ras et al. 2017), leading to agile production and improved products and processes qualities.

Figure 2.1 describes an example of a connected digital twin learning framework at Cidaut Research and Development Centre labs, which was designed and tested for the proactive collaborative maintenance (local and remote) of manufacturing assets. The framework is focused on the generation of a non-intrusive and fully two-way adaptive human-machine collaborative ecosystem, supporting workers' training and enhanced learning. In addition, the proposed real-time AR and VR augmented frameworks for visualising digital twins enable the development of skills 4.0, while providing direct access to existing manufacturing-process knowledge bridged through smart sensors.

FIGURE 2.1: Example of a Digital Twin framework to enable learning ecosystems at Fundación Cidaut

2.5 Cyber-physical convergence challenges in SMEs

How to bring about the future and effective interoperability, managing different types of human-machine ecosystems, and enabling the intelligent operation of cyber-physical convergence, is still an open challenge towards Smart Manufacturing (Qi et al. 2018a).

Traditional environments, which are still common in manufacturing SMEs, are facing a substantial increase in the use of advanced technologies to improve the learning capability of the workforce. In that sense, a human-machine integration is necessary to lead the learning process and knowledge management in organisations (J. Kaivo-oja et al. 2020). At the European level, the adoption of Industry 4.0 key enabling technologies faces important barriers, such as the lack of skilled personnel (Kroll et al. 2016) compounded by its continuously increasing demand (Glass et al. 2018). Additionally, SMEs are also less ready because of a lack of experience in new technologies (Stentoft et al. 2019), which leads to a slow initial stage of digitisation (Doyle and

Cosgrove 2019) and maturity (Mittal et al. 2018). Some operations required to handle cyber-physical changes are conducted manually, and operational data are incomplete or missing owing to a lack of acquisition systems. Therefore, the use of fully automated techniques to support planning processes is not considered a common practice, while the information and timing with regard to manufacturing business planning (long run) comes up against manufacturing operations management (real-time) (Cimino, Negri, and Fumagalli 2019). In addition, (Hu et al. 2021) considers that the integration of sensors and data acquisition technologies to achieve two-way connections must be achieved to ensure real-time data. It is also considered that data accuracy and building models in virtual space with high fidelity of physical objects are fundamental issues. Particularly concerning digital twins, (Uhlemann, Lehmann, and Steinhilper 2017) shows that a widely used manual data acquisition of motion data, and hence the lack of data availability in real-time, compromises it for the evaluation and analysis of production systems. In this manner, (Semeraro et al. 2021) considers that the process of modelling reality in a digital twin is a complex task, especially when using traditional approaches involving sensors and different kinds of sources, models, and services. With regard to digital twins construction, a minimum level of data quality and a consistent data stream for efficient use are required (Fuller et al. 2020), while another challenge resides in determining the optimal level of detail to create a digital twin model (Parrott and Warshaw 2017). Nevertheless, a major challenge arises when digital twin comes up against organizations and workers and must verify that the generated models work as expected, in addition to ensuring that they know its benefits (Fuller et al. 2020).

2.6 Enabling a new generation of human-machine systems in SMEs

The development of a new generation of human-machine systems in the manufacturing industry has been enhanced with the increasingly widespread use of distributed services, adding sensors, and monitoring resources based on Industry 4.0 KETs (Cimini et al. 2020). Under these requirements, the challenge of upgrading older machines in manufacturing SMEs is facing very high economic costs and the lack of expert staff to address Industry 4.0 enablers (Horváth and Szabó 2019). However, adaptive retrofitting methodologies based on personalized data models and non-intrusive digitisation are for SMEs a more feasible alternative way to include updated features in older machines (Contreras, Cano, and García 2018; Ayani, Ganebäck, and Ng 2018). Digital technologies and sensors allow for the integration of data from different manufacturing sources. Non-intrusive retrofitting methods are used to address the monitoring conditions in manufacturing (Lins et al. 2017). Some examples are: (i) a surface-mounting-system using a single current sensor to gather data from a power supply line (Suzuki, Kohmoto, and Ogatsu 2017); (ii) in-situ energy measurement for online identification of machine operation states in injection moulding machines (Chee et al. 2011); and (iii) CNC tool-wear detection using an accelerometer at a remote location (Herwan et al. 2019).

Experiments conducted in two EU-funded projects presented the advantages of digital technologies in integrating the machines' real-time status and work orders by implementing maintenance models: (i) the BEinCPPS project (Business Experiments in Cyber Physical Production Systems) (Doyle and Cosgrove 2019) implements a 3-layer architecture (machine, factory, and cloud) capable of supporting open standards to integrate existing legacy hardware and software systems installed on manufacturing SMEs in Europe, and (ii) the MANTIS project (Cyber Physical System based Proactive Collaborative Maintenance) (Albano et al. 2018) involves three 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.

To address the current manufacturing challenges in a new changing industry, workers should also become "Operators 4.0" to respond to problems more efficiently (Romero, Stahre, and Taisch 2020). 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. Therefore, the deployment of advanced human-machine software tools extends the opportunity to simulate and understand human-system interactions. Learned knowledge and skills are exploited to incorporate past experiences in root-cause analysis (Bokrantz et al. 2017; Gaham, Bouzouia, and Achour 2015). Thus, human-machine collaborative models applied to maintenance enhance the development of skills 4.0, providing direct access to existing manufacturing-process knowledge. In this sense, some examples in the literature, such as the Senseye company and the R2MPHM platform (Cachada et al. 2018), 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 (Baglee et al. 2017), a CBM method for SMEs focused on determining the current health level of an asset is presented, where the use of connected technologies provides more advanced decision-making in a collaborative way. Moreover, existing research on human-machine interaction has already developed sophisticated HMI-solutions for digital twins that seek to adapt to the personal and situational context (Josifovska, Yigitbas, and Engels 2019). A few years ago, digital coaching systems (Carlsson 2018) started as an answer to the demand of human operators to manage advanced automated systems that can monitor and control complex and large industrial processes and systems. Nowadays, as an industry, manufacturing has been pervasively impacted by the rapid adoption of information technologies. With the advent of smartphones, tablets and smart glasses, mobile HMI (Qasim et al. 2020) has emerged as an example of the technological advances used at the shop floor. The increasing deployment in manufacturing of AR and VR technologies (Liu et al. 2017; Damiani et al. 2018) is changing the way operators visualize (de Souza Cardoso, Mariano, and Zorzal 2020) and manage maintenance process monitoring (Longo, Nicoletti, and Padovano 2017). The information can be virtually displayed by overlapping the physical asset in real-time, such as temperature changes, consumption trends, etc. (Horváth and Szabó 2019). This augmented interaction enables an understanding of real-time processes to improve workers' 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 for integrating complex heterogeneous scenarios in manufacturing, where systems, processes and workers are simultaneously involved in operations at the same time.

2.7 Digital Twins for knowledge-based improvement

The advent of Industry 4.0, has also provided factories with new enhanced HMI and Artificial Intelligence (AI)-driven technologies. In particular, the potential for cyber-physical convergence has closed the loop between systems and workers' interactions (Fantini, Pinzone, and Taisch 2020). When coupled with expert knowledge in maintenance operations, the interaction between workers and the production environment can provide a digital twin with a context-aware approach for supporting decision-making and learning. Owing to the cyber-physical connection process, digital twins have attracted the interest of industries regarding maintenance strategies. Specifically, the manufacturing industry is the sector on which most research on the implementation of digital twins is focused (Errandonea, Beltrán, and Arrizabalaga 2020). Moreover, (Tao et al. 2019) states that the ability to offer seamless integration between the cyber and physical spaces enables their implementation to improve the performance of products and processes in the physical space. In this context, the work also defines a digital twin as *"a digital representation that can depict the production process and product performance"* and summarises the state-of-the-art of digital twin research and its application as a reference guide in different industries such as aerospace engineering, electric grid, car manufacturing, petroleum industry, healthcare, etc. Concerning digital twin use in manufacturing, (Fuller et al. 2020) identified a range of publications with particular growth in the health of machines and predictive maintenance. In particular, (Madni, Madni, and Lucero 2019) considered maintenance to be a major contribution area for digital twins, both helping organisations transition from schedule-based to condition-based maintenance and reducing system maintenance costs while also enhancing its availability. In a different paper, (Kritzinger et al. 2018) provides a categorical literature review of digital twins in manufacturing. The review, which is broader in scope, describes maintenance as a main discipline of production systems with a common target to increase competitiveness, productivity and efficiency, supported by four applications of the digital twin:

- State changes on production systems.
- Anticipatory maintenance measures.
- Condition based maintenance.
- Machine's health condition.

To this end, several authors have presented papers in the literature concerning the applicability of maintenance strategies based on digital twins and focused on manufacturing: (i) integration of manufacturing data into developing "digital-twins" virtual machine tools for the health status of a milling machine (Cai et al. 2017); (ii) a methodology for advanced physics-based modelling to enable the digital twin concept in predictive maintenance applications (Aivaliotis et al. 2019); (iii) a digital twin-driven cooperative awareness and interconnection framework to improve the accuracy of fault diagnosis, prediction, and support, creating a maintenance plan with higher accuracy and reliability (Mi et al. 2021); (iv) a digital twin-driven online anomaly detection framework for an automation system based on edge intelligence for the early detection of potential failures in industrial systems and proactive maintenance schedule management (Huang et al. 2021); (v) an overall vision and rationale for incorporating digital twin technology into model-based system engineering (MBSE), including updated performance, maintenance, and health status data throughout the physical system's life cycle (Madni, Madni, and Lucero 2019); (vi) a two-phase digital-twin-assisted fault diagnosis method and framework to achieve smart manufacturing using deep transfer learning, which realises fault diagnosis in both the development and maintenance phases (Xu et al. 2019); and (vii) a Deep Digital Twin (DDT) for prognostics and health monitoring (PHM), which is used for the automation of predictive maintenance scheduling directly from operational data (Booyse, Wilke, and Heyns 2020).

The use of connected platforms in manufacturing enables digital twin frameworks for learning. (Mi et al. 2021) presented a specific working framework to support the sharing of digital twin data, knowledge, and resources, for predictive maintenance and decision-making. A similar solution, focused on predictive maintenance techniques and performance monitoring frameworks, was presented in (Tantawi, Fidan, and Tantawy 2019) as valuable human-machine interfaces for continuous improvement. Thus, the promotion of digital twin tools for continuous improvement can help in process planning (Liu et al. 2019), which would further improve the work cycles of existing systems and ensure that each associated maintenance task can be carried out in an adaptive manner. Nevertheless, the integration of advanced strategies into manufacturing SMEs (Baglee et al. 2017) such as predictive maintenance techniques and condition monitoring are facing a digital transformation challenge in legacy production systems.

2.8 Digital Twin Learning Ecosystems and current challenges in manufacturing SMEs

As a future trend in the industry, production factories will be presented with multiple digital twins representing their complete production system (Suuronen et al. 2022). By promoting the digital twin areas of research already under way, new approaches for transforming existing production and control methods may emerge towards intelligent cyber–digital interfaces and smart decision support models. This is the case of the interaction between skilled workers and the production environment, allowing digital twins to offer a context-aware approach for supporting decision making and learning (Hribernik et al. 2021). A standardized framework to develop a digital twin in manufacturing, such as ISO 23247, which partitions a digital twin system into layers, can facilitate the acceptance of the digital twin concept (Shao 2021). However, Shao and Helu (Shao and Helu 2020) remarked that there remains much confusion about digital twins and how different solutions can be implemented in real manufacturing systems, especially among SMEs. Furthermore, digital twins depend on the context and viewpoint required for a specific use case and require a good understanding of the scope and constraints of the use case to avoid enormous costs.

Digital Twin Learning Ecosystems based on frameworks provide learning features for manufacturing. Nevertheless, most processes still depend on human intervention and expert knowledge, and data are highly dependent on the specific goals of the system in place. Some challenges are: (i) enhancing the workforce skills and competencies in manufacturing, (ii) managing adaptability under different tasks in manufacturing systems, (iii) understanding process and data science, and (iv) the need for expert knowledge in the extraction of the corresponding simulation models. In particular, in the case of SMEs, despite the development of Industry 4.0-enabling technologies, digital twins face a lack of digital resources concerning data acquisition Uhlemann, Lehmann, and Steinhilper (2017), while workers' skills development eventually manages to include the increased complexity of industrial processes Mittal et al. (2018). It should be noted that SMEs are generally less prepared to adopt digital technologies Horváth and Szabó (2019) and maturity models Semeraro et al. (2023). Although collaborative human-machine models Zonta et al. (2020) and maintenance trends have evolved collaboratively Bokrantz et al. (2020), only a few SMEs have the capacity to implement the latest advances in maintenance strategies Dolatabadi and Budinska (2021).

Focusing on digital twins convergence, some studies have presented solutions to augment legacy-based production equipment without incurring expensive resources. For instance, Orellana and Torres (2019) proposed a retrofitted method using monitored sensors within cyber-physical systems to upgrade legacy production systems while reducing costs. Similarly, Lins and Oliveira (2020) focused on reusing existing equipment with the addition of new technologies installed independently of the system, upgrading to cyber-physical production systems as a rapid and low-cost solution. Pantelidakis et al. (2022) considered a cost-efficient digital twin ecosystem used to provide legacy equipment with digital twin capabilities, collect historical data, generate analytics, and establish an ecosystem with bidirectional information flow in a simulated virtual environment.

However, digital twins convergence can be improved by following adaptive development according to productive and specific manufacturing requirements, thereby generating an adaptive learning framework that seamlessly integrates workers, systems, and processes into knowledge modeling.

2.9 Summary

With the empowerment of workers' digital-based skills in manufacturing environments, human–machine collaborative ecosystems supported by digital twins will ultimately be a trend. Thus, the interaction of workers and the integration of digital information with the real environment provide the plant ecosystem with cyber–physical connections and digital twin data flows. During this time, the manufacturing industry took advantage of the digital twin learning opportunities presented by the development of a new generation of information technologies applied to physical–digital convergence. However, in the case of traditional manufacturing SMEs, the transformation challenge of Industry 4.0 is facing a low adoption rate of digital technologies and maturity models. In this digital context, very few SMEs with traditional means inherited from older manufacturing systems have anticipated the latest advances in maintenance strategies impeded by technical and economic barriers, while the workforce requires upgrading to the skills needed to cope with upcoming digital technologies.

To this end, this research presents literature findings that provide details on new adaptive models of collaboration between the workforce and industrial processes. The aim is to meet the human-machine challenges posed for knowledge acquisition in manufacturing SMEs, where there are plenty of outdated systems.

Chapter 3

Articles Published

3.1 Towards a connected Digital Twin Learning Ecosystem in manufacturing: Enablers and challenges

(García, Bregon, and Martínez-Prieto 2022b)

Title: Towards a connected Digital Twin Learning Ecosystem in manufacturing: Enablers and challenges

Authors: Alvaro García García, Anibal Bregon Bregon, Miguel Angel Martínez Prieto

Journal: Computers & Industrial Engineering

Impact factor: 7.900 (2022). Q1: COMPUTER SCIENCE, INTERDISCIPLINARY APPLICATIONS (17/110), ENGINEERING, INDUSTRIAL (10/50)

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This paper has been cited 24 times (See Appendix A.1).

Abstract

The evolution of digital twin, leveraged by the progressive physical–digital convergence, has provided smart manufacturing systems with knowledge-generation ecosystems based on new models of collaboration between the workforce and industrial processes. Digital twin is expected to be a decision-making solution underpinned by real-time communication and data-driven enablers, entailing close cooperation between workers, systems and processes. But industry will need to face the challenges of building and supporting new technical and digital infrastructures, while workers' skills development eventually manages to include the increased complexity of industrial processes. This paper is intended to reach a better understanding of learning opportunities offered by emerging Industry 4.0 digital twin ecosystems in manufacturing. Diverse learning approaches focused on the potential application of the digital twin concept in theoretical and real manufacturing ecosystems are reviewed. In addition, we propose an original definition of Digital Twin Learning Ecosystem and the conceptual layered architecture. Existing key enablers of the digital twin physical–digital convergence, such as collaborative frameworks, data-driven approaches and augmented interfaces, are also described. The role of the Learning Factory concept is highlighted, providing a common understanding between academia and industry. Academic applications and complex demonstration scenarios are combined in line with the enablement of connected adaptive systems and the empowerment of workforce skills and competences. The adoption of digital twin in production is still at an initial stage in the manufacturing industry, where specific human and technological challenges must be addressed. The research priorities presented in this work are considered as a recognised basis in industry, which should help digital twin with the objective of its progressive integration as a future learning ecosystem.

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

(García, Bregon, and Martínez-Prieto 2022a)

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

Authors: Alvaro García García, Anibal Bregon Bregon, Miguel Angel Martínez Prieto

Journal: Computers & Industrial Engineering

Impact factor: 7.900 (2022). Q1: COMPUTER SCIENCE, INTERDISCIPLINARY APPLICATIONS (17/110), ENGINEERING, INDUSTRIAL (10/50)

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This paper has been cited 17 times (See Appendix A.2).

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 process 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.

3.3 Digital Twin Learning Ecosystem: A cyber-physical framework to integrate human-machine knowledge in traditional manufacturing

(García, Bregon, and Martínez-Prieto 2024)

Title: Digital Twin Learning Ecosystem: A cyber-physical framework to integrate human-machine knowledge in traditional manufacturing

Authors: Alvaro García García, Anibal Bregon Bregon, Miguel Angel Martínez Prieto

Journal: Internet of Things

Impact factor: 5.9 (2022). Q1: COMPUTER SCIENCE, INFORMATION SYSTEMS (35/158) and Q1: ENGINEERING, ELECTRICAL & ELECTRONIC (53/275)

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Abstract

As Industry 4.0 enablers, digital twins of manufacturing systems have led to multiple interaction levels among processes, systems, and workers across the factory. However, open issues still exist when addressing cyber-physical convergence in traditional manufacturing small and medium-sized enterprises. The problem for both traditional operators and the existing infrastructure is how to adapt knowledge to the increasing business needs of manufacturing plants that demand high efficiency, while reducing production costs. In this paper, a framework that implements the novel concept of Digital Twin Learning Ecosystem in traditional manufacturing is presented. The objective is to facilitate the integration of human-machine knowledge in different industrial cyber-physical contexts and eliminate existing technological and workforce barriers. This adaptive approach is particularly important in meeting the requirements to help small and medium-sized enterprises build their own interconnected Digital Twin Learning Ecosystem. The contribution of this work lies in a single digital twin learning framework for different traditional manufacturing scenarios that can work from scratch using a light infrastructure, reusing the knowledge and common condition-based methods well-known by skilled workers to rapidly and flexibly integrate existing legacy resources in a non-intrusive manner. The solution was tested using real data from a milling machine and a currently operating induction furnace with a maximum power of 12 MW in a foundry plant. In both cases, the proposed solution proved its benefits: first, by providing augmented methods for maintenance operations on the milling machine and second, by improving the power efficiency of the induction furnace by approximately 9 percent.

Chapter 4

Conclusions and Future Work

4.1 Conclusions

The evolution of the digital twin concept, leveraged by the onward cyber-physical convergence, has provided manufacturing ecosystems with knowledge-generation opportunities based on new Industry 4.0 models of collaboration between the workforce and industrial processes. Conversely, digital barriers and expensive hardware compatibility issues are obstacles known in the way to accomplish the cyber-physical convergence in traditional SMEs. This will continue even more, as the interaction of Industry 4.0 with traditional manufacturing environments requires the development of workers' skills and different digital strategies from those currently prevailing. To this end, the rationale behind this PhD thesis has been to better understand the enablers and challenges involving the digital twin implementation in a non-intrusive way regardless of the level of digitisation. In particular, in manufacturing environments that include multiple interaction levels between processes, systems, and workers within the virtual space.

Considering the benefits of working in an R&D centre where I am leading Industry 4.0, this work has successfully addressed the research and development of Digital Twin Learning Ecosystems for manufacturing SMEs based on both cyber–physical convergence and adaptive human–machine collaboration models. In the course of this research, we have contributed with a trilogy of publications and incremental results obtained in industrial environments, which have made it possible to achieve the proposed objectives. These results include:

- **An original proposal of the system architecture and knowledge-modelling process to meet the requirements of a tailored DTLE for SMEs**. This approach has achieved a common understanding of human–machine interactions and their associated learning processes in manufacturing. In addition, a novel methodology based on the adaptive application of three interconnected bidirectional digital twin tiers has been developed, providing an augmented and interactive learning ecosystem between processes, legacy production systems and skilled workers.

- **The implementation of non-intrusive cyber-physical strategies in traditional manufacturing SME scenarios to reduce industrial maintenance investment**. An adaptive approach supported by the retrofitting of old systems and the support of experienced operators has been followed, simplifying the commissioning of condition monitoring techniques and empowering workers through learning models. Thus, the physical values monitored from diverse retrofitted manufacturing systems, regardless of the level of digitization, have been modelled by applying a rapid and flexible semi-supervised learning method while receiving feedback from workers using different manufacturing approaches.

- **The assessment of DTLE implementation in SMEs**. The validation of the proposed methodology, by building an interconnected human-machine knowledge generation infrastructure, has been conducted in a machining workshop, and then it has been successfully replicated in a foundry plant.

Moreover, the research has considered the implications of some unpredictable world economy challenges during the last five years, such as the coronavirus pandemic and a global energy crisis, which have impacted the manufacturing industry forcing production plants to reduce costs and improve productivity and sustainability. The demand for disruptive solutions and specialised workers has become an increasingly important digital priority for the industry, which pushes technological upgrades towards building new cyber-physical ecosystems and supporting the skills improvement of the workforce. Therefore, academia has used the opportunity to transfer knowledge from laboratories to real factories by implementing training ecosystems that comprises researchers, Industry 4.0 specialists and teaching programs.

As a final reflection, the research priorities presented in this PhD thesis are considered a recognised basis in industry, which should help digital twins with the objective of progressive integration as a future learning ecosystem.

4.2 Future work

Despite the progress made in the past five years, much remains to be done to ensure the adoption of digital twin for learning in production environments. It is not clear in the industry what features a digital twin should have or how it should work in different ecosystems.

In the near future, we plan to develop a hybrid framework infrastructure focused on the characterisation of virtual reality models of industrial processes while physical values are gathered from manufacturing systems. This approach provides a digital twin model of the target system connected through a mixed-reality immersive framework, where a worker can be trained and both monitor the physical parameters and interact with augmented devices such as AR/VR glasses and haptic gloves, setting a real configuration. It can also be applied to the field of industrial cybersecurity by building hybrid testbeds of industrial control systems. Therefore, a characterisation of a critical system replicating the real infrastructure as much as possible will allow researchers to develop a Digital Twin Learning Ecosystem in a non-intrusive way under safe execution, including cyber-physical systems and virtual processes of the industry.

An additional line of future work is oriented towards lifelong learning and training in the manufacturing sector. Digital twins have proved effective in enhancing the empowerment of workers' skills 4.0 to avoid technological exclusion risks. This approach is especially important for learning plant-process knowledge related to complex tasks, which are usually owned by highly skilled operators and difficult to replace at retirement. On the other hand, the removal of older workers from their jobs due to a lack of knowledge of new technologies poses a risk to their employment. As reflected in our research findings, the available knowledge from workers and their work methods could be implemented in a Digital Twin Learning Ecosystem and introduced into teaching programs to improve digital skills.

Appendix A

Citation list of published papers

A.1 Towards a connected Digital Twin Learning Ecosystem in manufacturing: Enablers and challenges

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