A Digital Twin Driven Human-Centric Ecosystem for Industry 5.0

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***Abstract*— Industry 5.0 embodies the vision for the future of factories, emphasizing the importance of sustainable industrialization and the role of industry in society, through the key concept of placing the well-being of workers at the center of the production process. Building upon this vision, we propose a new paradigm to design human-centric industrial applications. To this end, we exploit Digital Twin (DT) technology to build a digital replica for each entity on the shop floor and support and augment interaction among workers and machines. While so far DTs in automation have been proposed for machine digitalization, the core element of the proposed approach is the Operator Digital Twin (ODT). In this scenario, biometrics allows to build a reliable model of those operator's characteristics that are relevant in working contexts. Biometric traits are measured and processed to detect physical, emotional, and mental conditions, which are used to define the operator's state. Perspectively, this allows to manage and monitor production and processes in an operator-in-the-loop manner, where not only is the operator aware of the state of the plant, but also any technological agent in the plant acts and reacts according to the operator's needs and conditions. In this paper, we define the modeling of the envisioned ecosystem, present the designed DT's blue-print architecture, discuss its implementation in relevant application scenarios, and report an example of implementation in a collaborative robotics scenario.**

***Note to Practitioners*—This paper was motivated by the problem of designing human-cyber-physical systems, where production processes are managed by concurrently taking into account operators, machines and plant status. This answers the needs of the novel Industry 5.0 paradigm, which aims to enhance social sustainability of modern factories. To this end, we propose an architecture based on digital twins that allows to develop a digital layer, detached from the physical one, where the plant can be monitored and managed. This allows the creation of a digital ecosystem where machines, operators, and the interactions among them are represented, augmented, and managed. We discuss how the proposed architecture can be applied to three relevant scenarios: remote training and maintenance, line operation and line supervision. Moreover, the implementation in a collaborative robotics scenario is presented, to provide an example of the proposed architecture can be implemented in industrial scenarios.**

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***Index Terms*— Industry 5.0, digital twins, human-centric automation.**

I. Introduction

IN RECENT years, technological progress and changes in the economy have significantly changed the manufacturing industry, in terms of processes, products and market needs, thus opening to new technological challenges and opportunities. In this challenging context, a significant change in the human operator's role has been observed. Low-skilled laborers who perform simple and repetitive tasks have been displaced, while the demand for higher-skilled labor has increased to manage the plant, coordinate flexible production and control complex and diversified technologies.

This has led to the introduction of the concept of Operator 4.0 understood as a smart, skilled operator who collaborates with machines and robots and can deal with human-cyber-physical systems, advanced interaction technologies and adaptive automation. In such a symbiosis, operators are assisted by automated systems, monitoring their biometric signals, and providing a sustainable relief of physical and mental stress and allowing them to utilise and develop their creative, innovative and improvisational skills, without compromising production objectives [1]. Moving along these lines, human-centricity of factories has been elaborated further in the more recent paradigm of Industry 5.0, where the wellbeing of the worker is placed at the centre of the production process and new technologies are used to provide prosperity beyond jobs and growth, while respecting the production limits of the planet [2], [3].

In this scenario, we envision a novel approach to design human-centric industrial applications by exploiting Digital Twin (DT) based technology [4], [5].

In Industrial Internet of Things (IIoT), the Asset Administration Shell (AAS) serves as a standardized representation of industrial assets and processes, bridging the physical and digital worlds. Through encapsulating relevant information in a standardized format, it enables seamless integration and communication across industrial components. Our work embrace this vision and the challenging goal of decoupling physical complexity from digital applications via structured and flexible intermediaries. We propose leveraging DTs as a Software approach to encapsulate AAS functionalities and extend its adoption in Industry 5.0 including cyber-physical relationships and interactions for human operators as well, as depicted in Figure 1 (left).

Our aim is to facilitate and make more efficient the interaction among human operators and technological systems in the plant, including information about the operator, such as their capabilities, their current status and workload, in the management of the plant. To achieve this goal, we resort to DTs, which allow to decouple the physical and the digital layers, solving the challenge of managing heterogeneous devices and data (e.g., associated with industrial equipment, wearable sensors, reality enhancement devices) through the creation of a new uniform and standard abstraction layer. Data collected by DTs can flow in a control room for the real-time analysis of production procedures to help operators in taking decisions and managing complex technologies depending not only on available information and measurements of machines, processes and productivity, but also an accurate model of human operators measured via wearable sensors. Hence, we build a blueprint architecture for the digital representation of operators and machines and the relationships among them through DTs, as discussed in Section III. We then discuss its application in the context of industrial automation in Section IV and propose an experimental implementation in a scenario of collaborative robotics (Section V).

A. Proposed Contribution

The proposed approach consists of the design of an ecosystem for industrial automation scenarios that supports and augments interactions among humans and machines, thanks to digital replicas of each agent, either human or technological, on the shop floor. Specifically, the proposed contributions of this work are the following:

- we propose a blueprint architecture for DTs in industrial automation and discuss its general application to operators, resulting in operator digital twin (ODT), and machines (machine digital twin, MDT);
- we combine ODTs and MDTs to shape an ecosystem for human-centric cyber-physical systems, where agents, either operators or machines, are abstracted, together with their relationships and interactions, thus allowing an orchestrated management of operations;
- we analyze the application of the proposed ecosystem in different automation systems, providing guidelines for its implementation in relevant scenarios.

Ultimately, the proposed ecosystem allows to comply with the increasing design complexity of the next generation of industrial human-cyber-physical systems, while taking the most out of technology and human capabilities. Thanks to the proposed approach, on the one side, the operator's role and peculiar characteristics (e.g., tasks, profile, behaviors, expertise, real-time condition) can be taken into account as a core input for production planning, process operation, productivity enhancement and the overall plant efficiency. On the other side, it allows to effectively handle and manage the massive heterogeneity and fragmentation of existing systems characterized by a plethora of different devices, platforms, communication protocols and data formats. The use of DTs turns out to be useful in this regard, as detailed in the next section.

II. State of the Art

With the advent of Industry 4.0, a striking feature of modern manufacturing systems is the focus on advanced automation. This combines technological progress and diversified needs of market, such as product customization and small batches production. As a result, physical and digital assets are integrated through the creation of smart products and processes capable of transforming the conventional value chains in cyber-physical systems [6]. To achieve this, the use of disruptive enabling technologies has been fostered, which include advanced autonomous and collaborative robots, IoT (Internet of Things) and IIoT devices, cloud computing and analytics, and artificial intelligence and machine learning. As a consequence, one of the challenges of this paradigm relates to the integration of these technologies. Reference architecture models have been proposed, that provide technical description and standards [7]. The main initiatives in this regard are the 5C Architecture [8], the RAMI model [9] and the IIRA model [10]. Although from different points of view, these models focus on technological systems and consider the human component in terms of technological management of human-machine interaction. However, one of the major requirements for such systems to work properly and efficiently is the presence of reliable human operators, who cooperate and work in symbiosis with advanced automated systems. Some works has been recently presented in this regard. For example, in [11] the authors have presented a human asset administration shell (HAAS) as an analogous to AASs for machinery and apply it to human-machine interaction and ergonomics. More recently, the work in [12] have extended this concept including a comprehensive understanding of an individual's cognitive state, physical wellness, and skill set in the HAAS.

In this context, Romero et al. [1] introduced the term *Operator 4.0*, to refer to operators of human-cyber-physical systems who perform work aided by machines if and when needed. Building upon these ideas, this concept has evolved in the next industrial paradigm, namely Industry 5.0, which has put focus on the importance of human-centricity of the factories of the future [2]. Human operators are being placed in the center of attention, in the sense that automation is seen as a complement and enhancement of the cognitive capabilities of humans by advanced sensing and the higher precision of machines [13]. The idea of *Operator 4.0* has evolved into *Operator 5.0* defined as a smart and skilled operator who uses human creativity, ingenuity, and innovation, aided by information and technology, to develop new, cost-effective and sustainable manufacturing solutions [14], [15]. Additionally, Industry 5.0 has introduced the concept of *Healthy Operator* [16], such that it is necessary to consider the physical and mental well-being of skilled operators working in highly automated industrial settings. The aim and the results are more flexible, inclusive and safe workplaces, as well as better work conditions, increased productivity and improved quality. Moreover, this means increased worker satisfaction and wellbeing, more empowered and engaged workers and increased interest towards factory work as a career, attracting young talented people.

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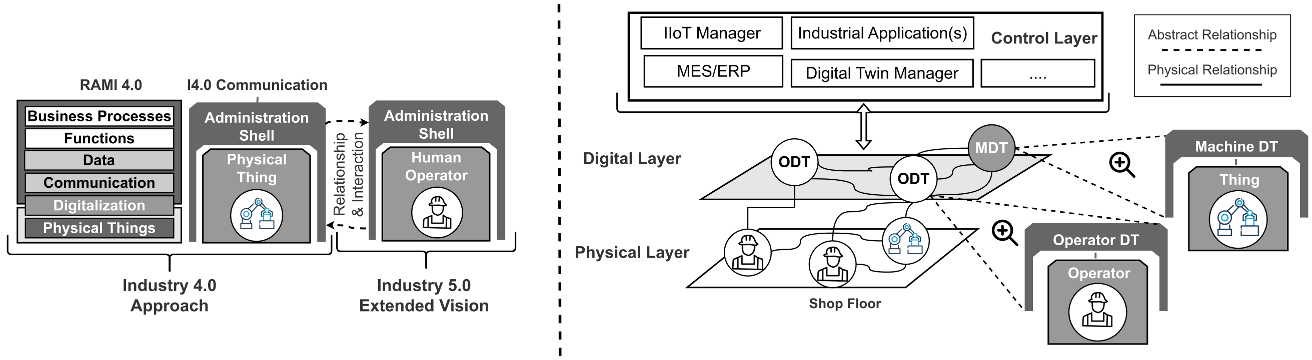


Fig. 1. On the left side a schematic representation of the extension of the Industry 4.0 vision toward the native integration of human operators. On the right side, the abstraction of the physical layer through the adoption of the Operator Digital Twin (ODT) and the Machine Digital Twin (MDT) as digitalization tools for administration shells.

To enhance human-machine interactions, the analysis of biometric information has been deeply analyzed in the state of the art in order to investigate and understand how physiological signals can be used to analyze affective states, focus, attention and intent. Physiological patterns and cognitive workload can be found in brain, cardiac, respiratory, electrodermal, muscular, skin temperature and eye (pupil dilation) signals [17]. An extensive review on methods for affect recognition, either emotions or stress, from the analysis of physiological signals has been recently presented in [18], with specific focus on wearable devices. While there has been recent exploration of biometric analysis from an architectural perspective [19], the application of these methods to create a comprehensive, synchronized representation of an operator by combining production, environmental, and biometric factors over time is a novel and interesting research opportunity. This approach could foster fresh collaborative models within industrial applications.

The scientific and industrial communities identified the role of DTs to enable new interaction forms between physical and digital layers [20], in particular in relation with IoT and IIoT [21]. Traditionally DTs have been massively adopted in different machine-oriented production stages and use cases [5], in particular related to manufacturing [22], [23], [24] and product design [25]. Only recently the idea of adopting DTs to build a human replicas has been investigated both as general concept in [26] and in specific domains such as industrial training [27], health [28], fitness [29] and ambient assisted living [30]. However, in current industrial applications, DTs are mostly considered as tools for high-fidelity simulations, thus not leveraging their potential to represent and augment physical assets [31]. In [32] the high level notion of human DT for Operator 4.0 has been discussed, while the work in [33] and [34] has introduced a meta-model for a human DT in the shape of a UML class diagram. Therein, the attributes of such DT are presented, including worker's medical, emotional and psychophysical condition, together with context and environment features. However, it is not discussed how the proposed human DT can interact with the surrounding automation setting, for a human-in-the-loop management of cyber-physical systems.

The current limitations of the existing approaches are related to the fact that they are mainly focused on the machine digitalization without investigating how DTs can be also effectively exploited to digitalize an operator and how it can cooperate and interact with equipment, colleagues and production processes. Furthermore, there is also the need to provide a comprehensive analysis and definition of how to characterize and build a model specific to the operator, taking into account not only static and production oriented information but also (and maybe primarily) biometric signals in order to build a realistic and adaptive representation. While some attempts in this regard have been proposed with human-centric AASs and HAASs [11], [12], [35], they have not been fully integrated with DTs. As a result, without the encapsulation and abstraction capabilities provided by DTs, managing this complexity within software systems becomes challenging. DTs provide a structured way to model, interact and augment physical assets, making it easier to handle the intricacies of industrial environments and providing a flexible way to enhance capabilities by adding new functionalities. Hence, we believe that the availability of a human-centric DT-based ecosystem would represent a concrete step into human-centricity of factories of the future.

III. The Proposed Digital Ecosystem

In the IIoT, the AAS plays a crucial role as a standardized representation of industrial assets and processes. It acts as a bridge between the physical world of industrial machinery, equipment, and processes, and the digital world of data analytics, automation, and control systems. As schematically depicted in Figure 1 (left), by encapsulating relevant information about industrial assets and processes in a standardized format, the administration shell enables interoperability, seamless integration, and efficient communication between different components of the industrial ecosystem, such as sensors, actuators, controllers, edge devices, cloud platforms, and software applications. In this work, we foster this vision by aiming for the effective decoupling between physical complexity and digital applications through a structured intermediary. We propose, on the one hand, DTs as an effective way to encapsulate AAS functionalities and potentially also submodelling [36], and, on the other hand, to extend in an Industry 5.0 vision the adoption of AAS through DTs for the comprehensive digitalization of industrial operators and

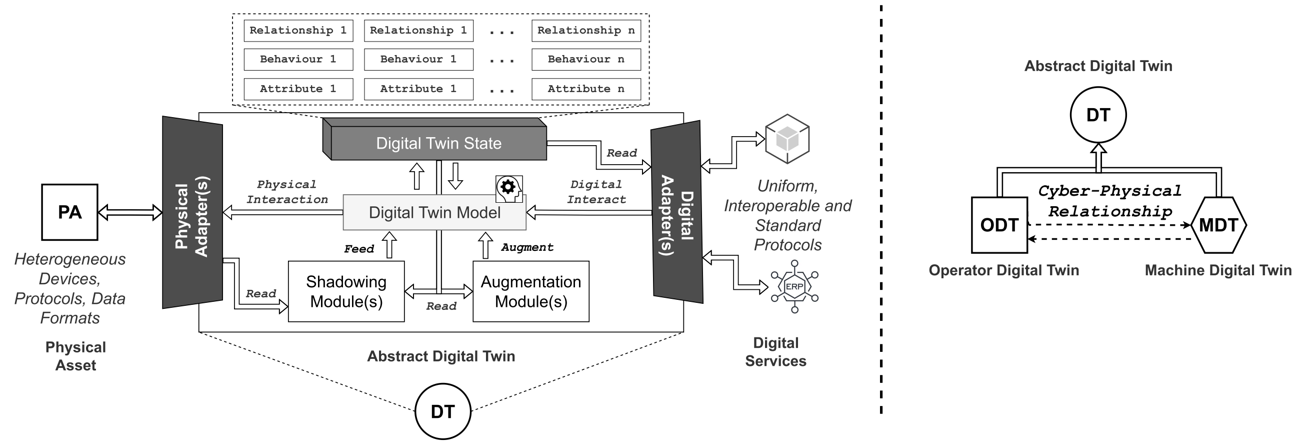


Fig. 2. The representation of the abstract blueprint architecture of a DT (left) and its hierarchical branching to ODT and MDT (right) with their cyber-physical relationships.

the enabling of simplified coordination between humans and machines in industrial environments.

Figure 1 (right) depicts an overview of the proposed approach. More specifically, each human operator working on the shopfloor is represented in the digital space by an ODT responsible for building and maintaining a digital replica and interacting with both physical assets and colleagues. Each ODT collects the user's data and simplifies interaction with the physical environment, abstracting from the existing heterogeneity of deployed devices and processing all relevant data that may impact productivity, wellbeing and working behavior. As a result, it is possible to build a dynamic and evolving profile associated to operator's capabilities and physical, emotional and cognitive states. Additionally, technological agents, such as automatic machines, robots, tooling machines and sensors, are represented in the digital layer by MDTs, which collect relevant information and behavior and share them with the other agents. Relationships among operators and machines are not only reproduced in the digital layer, but are also actually supported by merging and processing information coming from the field. As a result, production processes can be managed by concurrently taking into account operators, machines and plant status.

In order to simplify and uniform the creation of ODTs and MDTs in the envisioned ecosystem, we have structured a common blueprint architecture (depicted in Figure 2) built on top of the recent state of the art principles [37], [38]. Thanks to such an architecture, ODTs and MDTs share a set of core abstract properties and modules that can be then characterized to digitalize operators and connected machines, together with their relationships over time. The first identified capability that we model into our reference DT architecture is related to the concept of *Representativeness & Contextualization*. Each DT should be independent and autonomous to model and represent as much as possible its physical counterpart within the context where it is operating, in terms of *attributes* (e.g. biometric information, assigned tasks, profile, etc …), *behaviors* (e.g., actions that can be performed by the operator or on one of its associated devices) and *relationships* (e.g., a coworker and a machine within the same production process). From a technical point of view, this fundamental capability has been associated to the core component denoted as *Digital Twin Model*. It is responsible to decide at the same time how and when variation of the physical world should be mapped into the digital replica or inputs and actions performed on the twin should be propagated to the associated physical entity. On the one hand, the model works side-by-side with the *Digital Twin State* with the specific responsibility to structure, store and expose to other components all the computed attributes and relationships, together with their changes over time. On the other hand, the model receives inputs from the physical layer through a set of *Shadowing Module(s)* in charge of implementing the second core DT's capability, called *Shadowing*. It refers to the accurate measurment of the physical counterpart over time. Each physical attribute (e.g., biometry from wearable devices) can be reflected from the physical environment without any changes or it can be transformed during the process in order to properly match the modeled state (e.g., re-sampling the signal or adapting its representations). Nevertheless, the shadowing process involves also the possibility to retrieve or automatically detect physical relationships involving the target DT with other external entities or DTs, as detailed in Section III-C (e.g., a robot inside a plant, belonging to a production line and used by an operator).

The capability of a DT to interact with the physical layers has been modeled through a set of *Physical Adapters* in charge of communicating with connected devices reading data and triggering actions according to the adopted protocols and data formats and following the behaviours implemented through the shadowing functionality and the internal DT's model.

Furthermore, since physical objects come with well-defined functionalities and services that are fixed for the entire life cycle of the object, the modeled abstract DT architecture can leverage its digitalization capabilities in order to modify, update and improve its representation over time by implementing the *Augmentation* capability. In other words, a physical asset can be functionally augmented through its DT (and a set of *Augmentation Modules*) extending its capabilities and defining new attributes or relationships that were not originally available on the physical counterpart.

Since the aim of a DT is to bridge the cyber and the physical worlds through a simplified digitalization process, an additional fundamental functionality for the designed DT's architecture is the possibility to interact with the digital layer (e.g., applications, services and other DTs) through multiple interoperable and standard interfaces, protocols and data formats at the same time in order to realize an effective DT-driven ecosystem. Following this principle, each DT can instantiate one or multiple *Digital Adapters* allowing at the same time the exposition of the current DT's state together with the possibility to receive commands to execute actions or dynamically adapt the implemented behaviours. Moreover, the combination of DT's augmentation capabilities with the structure of digital adapters offers a versatile approach to facilitate and empower the mapping of AAS submodelling [36], enabling the extension of functionalities, structure, and characteristics of the digital replica, as well as the representation of assets in the digital realm through an interoperable and standardized approach. This expansion is achieved without compromising the modularity of the software instance, which remains modular due to the architecture of the DT.

Relying on the presented abstract architecture, in the following sections we present its characterization for the definition of ODTs and MDTs. We provide a specific and detailed focus on the ODT and the interactions and collaboration between ODTs and MDTs, since MDTs have been already analyzed in the scientific literature and implemented in production solutions.

A. ODT Modeling

The ODT aims to represent those characteristics that are relevant from the point of view of interaction with complex systems, according to [39]. Other human characteristics and capabilities that do not affect the interaction with socio-technological systems and the operator's working scenario are out of the scope of the ODT modeling.

From a technical point of view, following [33] and [39], to implement the *Representativeness & Contextualization* capability of the ODT, the attributes of the ODT's state are:

- *Profile*: a set of static values associated to the operator, such as their role or training level.
- *Task*: the list of production related assignments or duties useful to check or identify the type of actions performed or detect anomalies and dangerous situations.
- *Biometrical*: attributes associated to biometric signals (e.g., electrocardiogram (ECG), electrodermal activity (EDA), electroencephalogram (EEG), eelctromyiogram (EMG), etc ...), collected through wearable devices worn by the operator.
- *Behavioral*: parameters related to actions performed by the operator, for example while interacting with a machine (e.g., driving a vehicle or using a specific tool) or with other colleagues through the production line.
- *Situational*: characteristics based on the current operator's context and the detected circumstances. These are typically represented by specific conditions computed through the analysis of multiple biometrics signals and associated to the detection or prediction of a specific operator status (e.g., an increase of fatigue while interacting with a machine).

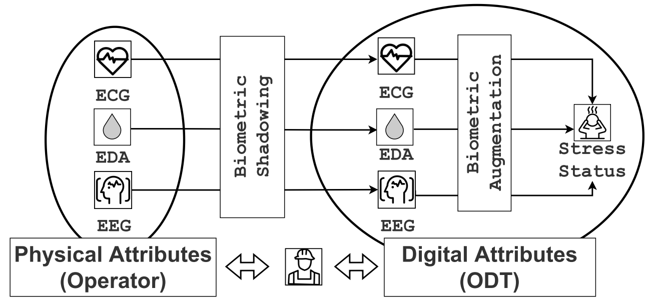


Fig. 3. A schematic mapping between physical and digital attributes through the shadowing process able to compute both biometric signals and enrich the ODT state evaluating additional situational attributes (e.g., the stress status).

- *Environmental*: attributes associated to the environment where the operator is working and useful to support both local awareness (e.g., current detected temperature) and interactions patterns (e.g., the presence of an actuator to control a functionality).
- *Time & Location*: attributes useful to support the contextualization of the ODT, properly tag received data and computed attributes and enable both historical and future analysis (e.g., predict the value of a stress condition).

Figure 3 depicts this idea. On the one hand, it illustrates the relationships between physical and digital attributes through biometric shadowing, which is responsible to mirror the current state of the operator through measured signals. On the other hand, the same attributes can be used and processed to evaluate new augmented attributes enriching the ODT's state and the awareness of its counterpart.

B. MDT Modeling

The design and development MDTs has been massively studied in the literature and recently revamped following both industrial specifications and scientific contributions [40], [41], [42]. In this section, we analyze, on the one hand, how the proposed DT's architecture is aligned with existing requirements and, on the other hand, how it is able to extend MDTs supporting the collaboration with operators through their ODTs.

The fundamental responsibility of an MDT is to digitalize its industrial machine's physical counterpart through a mapping over time of its core attributes and properties, with respect to the target operational context (e.g., rotation speed, joint position, or operational parameters). At the same time, the MDT is responsible for the management of incoming actions from the digital layer (e.g., reducing robot speed or changing target task) and the associated actuation on the physical machine. Furthermore, each MDT can augment original physical attributes and capabilities by integrating new data coming from external data sources (e.g., production scheduling information from the manufacturing execution system or details about maintenance procedures) or extending provided functionalities (e.g., introducing anomaly detection skills or increased interoperability with the support of multiple application protocols).

An MDT exploits the same blueprint architectural modules adopted in the ODT. As weel, it builds its behaviors through

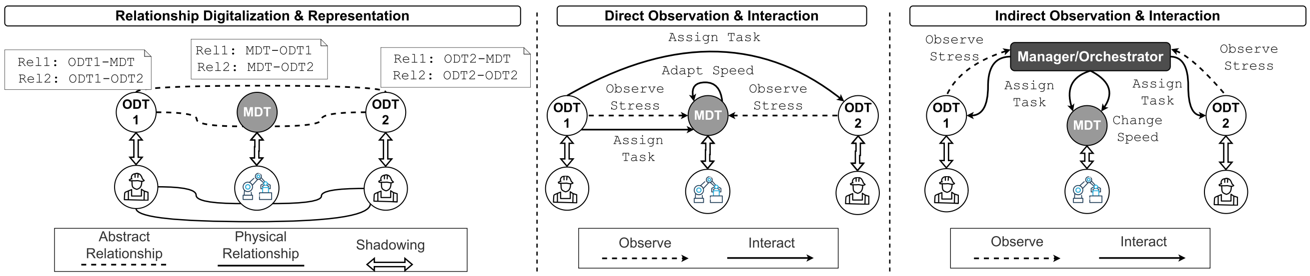


Fig. 4. An illustrative representation of the digitalized relationships between operators and machines through their DTs counterparts together with their exploitation supporting direct and indirect interactions.

the combination of the internal DT's model and the interaction with the *Shadowing* and *Augmentation* components. Communication with the physical and the digital worlds are enabled and supported through the dedicated adapters. Such adapters enable the management of the massive fragmentation of deployed IoT and IIoT devices and allow a uniform and interoperable interaction with digitalized machines through standard protocols and data formats.

The exploitation of this homogeneity and interoperability, combined with a structured characterization of ODTs and MDTs, represent the pillars for the envisioned Industry 5.0 extension, where machines and operators can effectively collaborate by means of DTs.

C. ODT & MDT Relationships and Interaction Patterns

A fundamental contribution of the proposed DT-based approach is the possibility to map and keep updated the knowledge of the relationships between operators and machines. This information can then be leveraged to improve intelligent and secure cooperation while simplifying coordination, thus alleviating the challenges linked to directly managing physical assets. Figure 4 schematically illustrates both the digitalized knowledge maintained by each DT together with direct and indirect *observation* and *interaction* patterns among active entities.

On the one hand, in its internal state, each DT maintains a structured digital representation of the list of all the relationships coming from the physical world in which it is involved. Relationships can involve at the same time both ODTs and MDTs according to the nature of the tie and are stored on the two sides of the link. For example, the use case of an operator working with a robot on a specific task (t) generates a relationship between ODT (e.g., ODT-1) and MDT (e.g., MDT-1) that is mapped at the same time on the two independent DTs modeling the following associations: i) on ODT-1: *working with MDT-1 for task t*; and ii) on MDT-1: *used by ODT-1 for task t*. On the other hand, the knowledge of the existing relationships in the physical environment combined with the uniform interaction capabilities provided by DTs enables the simplified cooperation between operators and machines, achievable both directly and indirectly according to the use case.

In a direct approach, ODTs and MDTs can observe and interact with each other without any intermediate component to retrieve specific properties (e.g., the stress/fatigue level of an operator or the telemetry of the robot's joint) and/or to invoke target capabilities or behaviors (e.g., reduce robot speed or assign a new task). For example, with reference to the middle panel of Figure 4, considering a simplified use case with a robot (MDT-1), a senior operator (ODT-1), and a junior operator (ODT-1), we can easily enable a scenario where: i) ODT-1 assigns tasks to both MDT-1 and ODT-2; and i) MDT-1 is aware of the collaboration with ODT-1 and ODT-2, observes their stress level to automatically reduce its execution speed if an anomaly condition is detected.

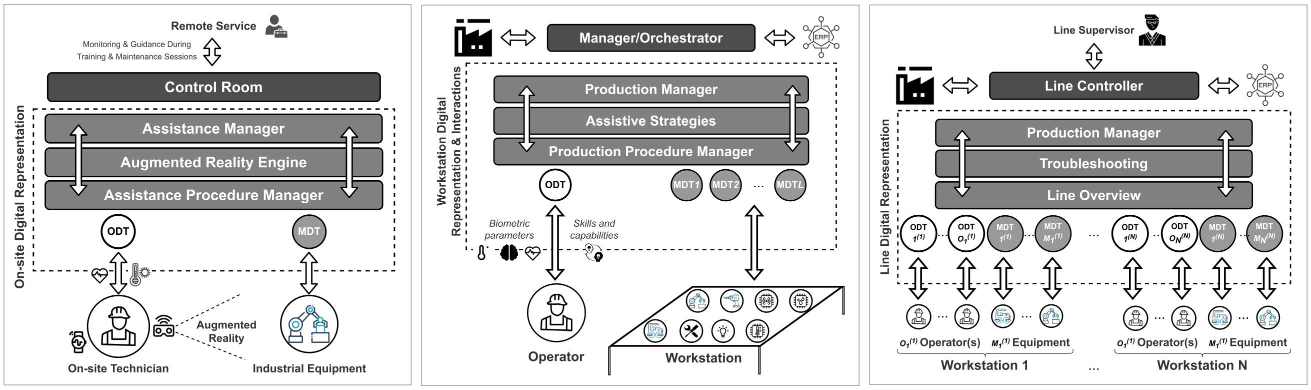
On the opposite side, observation and interaction can be managed by adopting one or more intermediate entities that are aware of deployed DTs and their relationships and are in charge of managing and orchestrating the deployment, while keeping a centralized and synchronized view. With respect to the same illustrative example, in the right panel of Figure 4 we introduce a *Manager/Orchestrator* responsible for observing stress levels and task execution of ODTs and interacting with the MDT to change the target assigned task or modify the machine's speed according to the detected context (e.g., reduce speed in case of a detected stress condition involved operators). Direct and indirect patterns are not meant to be necessarily independent but they can be combined and adopted following application scenario specifications, security targets, and autonomy requirements while preserving the same abstraction capabilities on top of the physical layer.

IV. Relevant Scenarios

In this section, we discuss three relevant scenarios where to apply the proposed digital ecosystem. These scenarios have been selected since they are representative of different interactions among agents on the shopfloor. In particular, while the use of DTs in such contexts has been largely explored (see, e.g., [43]), here we discuss how the concept of ODT and the whole proposed digital ecosystem can be applied to shopfloor organization, information management, and operator's task assignment. We provide guidelines about how the ecosystem can be instantiated in the different scenarios, presenting the corresponding functional modules to be implemented in the digital layer.

A. Remote Training and Maintenance

In this first scenario, we refer to training and customer service provided by manufacturers to remote plants and machinery at customer's premises. Remote service allows manufacturer's expert engineers and technicians to provide remote assistance and training for troubleshooting in the event



(a) (b) (c)

Fig. 5. Analyzed Use Case are the following: (a) Application of the proposed ecosystem to remote training and maintenance.; (b) Application of the proposed ecosystem to line operation.; and (c) Application of the proposed ecosystem to line supervision.

failures, periodic maintenance and continuous monitoring. While some services can be provided automatically and fully remotely, on-site presence of an operator for local intervention is often required. In addition, remote service can be leveraged to train local operators.

In this context, real-time decision support, remote monitoring, and training capabilities can be provided through the use of DTs and interactive display technologies, such as Augmented Reality (AR) and Virtual Reality (VR).

Figure 5(a) schematically illustrates the scenario. A technician interacting with the industrial equipment is supported in real-time by an AR system, which provides contextualized information, such as visual feedback (e.g., real-time data from the machine or production specifications) and operational instructions (e.g., videos, 3D models). Displayed information and data are dynamically generated and adapted according to the type of technician and their experience and a set of biometric and environmental parameters (e.g., eye activity, fatigue, ergonomy assessment, room temperature, etc.) collected from the field.

Training and maintenance can be remotely controlled and supported by a remote service manager who guides the technician, validates their actions, provides customized AR feedback, and prevents wrong or dangerous operations. Interaction between on-site technician and remote service can be managed at an abstract digital layer, which contains a digital representation of the on-site scenario and where the technician's ODT, MDT, and training material lie. With reference to Figure 4, the considered remote assistance scenario can be seen as an example of hybrid observations and interactions patterns, since the interaction between ODT and MDT is not direct but is managed by the remote service support, through a *Control Room*, which has the role of *Manager/Orchetrator*.

As shown in Figure 5(a), the architecture of the digital representation of on-site relationships can be organized into three different modules. First, the *Assistance Procedures Manager* (APM) module defines each step of training and maintenance processes. Such steps can be completely autonomous and handled by the industrial machine or require manual intervention or configuration from the operator. The *Augmented Reality Engine* (ARE) module is responsible for the interaction with any AR wearable device worn by the technician. By communicating with the associated ODT, it provides real-time multimedia content supporting the operator during each phase of training or maintenance. It can also interact with the *Assistance Manager* (AM) module to receive feedback and contents from the remote specialist in order to adapt the AR behavior with respect to the selected procedure, the status of the equipment, and the actions of the technicians. AM provides an interface to design and execute AR-driven training or service sessions through a remote expert operator and a technician in the plant. Each training can be associated with one or more procedures defined through the APM module. AM interacts also with ARE and ODT in order to dynamically adapt contents and information for the AR module and to support a bidirectional effective communication with the operator.

B. Line Operation

This scenario refers to an operator responsible for a single production step. To keep the discussion general, we consider an operator working at a collaborative workstation, where different pieces of equipment, such as sensors, automatic machines, and/or robots, are installed. The workstation receives input (i.e., raw material or preprocessed pieces) from previous cells and provides processed pieces as output to the following workstation.

By applying the proposed ecosystem to this scenario, we envision the workstation represented at the digital level as the collection of the ODT and the MDTs of the M IoT devices in the workstation, and their relationships. Operator's interactions can be sketched as 1 ODT $\rightarrow$ $\{M$ MDT$\}$. Workstation operation is, then, managed considering not only events occurring in the physical layer, but also augmented information brought in the digital layer by each DT. The production process can be then orchestrated to seamlessly account for any specific request or need coming from human and technological agents. Examples in this regard are atypical sensor readings, lacking or queuing input materials, and machine failures. In the presence of any of these events, their effect can be mitigated by reprogramming the way the workstation operates. Additionally, information about the operator's state, extracted from biometric measurements and processed by ODT biometric shadowing, can be included to workstation management. As discussed in Sec. III-A, information about fatigue, discomfort, posture or user's skills is made available by the ODT and can be used to influence the behavior of the workstation, as well. Workstation operation and management can be then optimized including such information and leveraging the operator's skills and compensating for any (temporary) decline. When needed, appropriate assistive strategies can be implemented to meet operators' needs and relieve their discomfort.

A possible architecture for this scenario is shown in Figure 5(b). The operator and the workstation are mapped in M MDTs and an ODT and the way they collaborate and interact is managed by a *Manager/Orchestrator*. Specifically, the *Manager/Orchestrator* takes into account information regarding the operator's status (mapped in the ODT), workstation operation (mapped in the MDTs), production planning (coming from industrial digital services, such as ERP), and other workstations in the same line. These pieces of information are merged to manage the production of the workstation, through a *Production Manager* (PM) module. This module defines the sequence of production processes for the operator and the workstation, with the details of operational steps. To this end, PM interacts with the *Production Procedure Manager* (PPM), which stores production recipes and instructions. PM interacts also with the *Assistive Strategies* (AS) module, where the assistive strategies are defined as algorithmic policies that determine the abstract behavior of each agent in the workstation. Such policies consist of hardware and application-independent rules and methods that describe how the workstation can be adapted to the current situation and measured the operator's state. Each agent's MDT is then in charge to instantiate them depending on the specific physical features of its agent. Implementing any of these strategies requires collecting information from ODT and MDTs and coordinating the operator and the agents in the workstation to reconfigure the production process according to PPM.

With reference to Figure 4, this architecture implements an indirect observation and interaction pattern, since the collaboration among agents is managed by the *Manager/Orchetrator*, which observes them and coordinates their interactions.

C. Line Supervision

Another use case where we envision the proposed ecosystem refers to the supervision of production lines. The typical setting for this scenario consists of an operator responsible for overseeing the operation of a production line. The line is operated by several operators, each assigned to a specific production step, as in the case discussed in Subsec. IV-B, and is composed of different interconnected workstations. High variability can be found among operators and equipment: this last often includes devices from different manufacturers, while operators have different expertise, skills, and plant knowledge. Line supervisor's responsibilities consist in coordinating operations, ensuring that all workers are doing their jobs correctly, machinery is operating as expected and production goals are met. To achieve this, supervisors rely on a control panel, which runs on a dedicated human-machine interface (HMI) and is connected to equipment in the line. Specifically, while monitoring production processes, the supervisor's role is to take proper intervention when displacement from nominal behavior occurs, isolating causes, identifying strategies to solve them, and reorganizing the line in the short term. To this end, different pieces of information are needed: on the one side, an overview of line status is constantly required, to monitor production processes. This includes raw and/or processed data about the availability of input materials, line throughput and other key performance indicators, and major equipment status. On the other side, a detailed view of each stage of the line might be necessary, especially in the presence of alarms or specific needs of the corresponding operator.

Applying the proposed ecosystem to this scenario results in the architecture depicted in Figure 5(c). Therein, we consider the general case where the line is operated by N workstations, and the $i-$th workstation has O_i operators and M_i pieces of equipment, where $i = 1, \ldots, N$. Line management is enabled by a digital layer, where a replica of the line is represented in the *Line Overview* (LO) module. In such a replica, each agent is mapped in the corresponding DT, and relationships among agents (e.g., who is working with each piece of equipment) are mapped as well. In other words, LO presents a functional hardware-independent abstraction of the production line and provides access to raw or processed information of each agent operating the line, through the *Shadowing* and *Augmentation* modules of each ODT and MDT. Line management is enabled through a *Line Controller* (LC) module that provides an interface to the line supervisor. LC interacts with LO and coordinates all the workstations assigning them production tasks depending on information coming from PM about production scheduling. Additionally, LC allows to tackle of faults and undesired events: these are shadowed in LC and can be detected by either LC itself, through the *Augmentation* module of DTs or PM. Once detected, the *Troubleshooting* module provides instructions and procedures to solve them. In terms of the interactions patterns in Figure 4, this scenario can be implemented in either direct or indirect mode, since the line supervisor might interact directly with each single DT or with the *Manager/Orchestrator* of a workstation (not shown in Figure 5(c).

D. Security & Privacy Considerations

The direct management of raw biometric signals and personal information by the ODT potentially opens to privacy and security critical issues and threats. Although the aim of this paper is not directly related to these challenging aspects, we believe that a few considerations on the topic are fundamental in order to better contextualize the role of DTs with respect to the security of their physical counterparts.

A DT (and in our specific case an ODT) defines a trusted relationship and a strong linkage between a physical object and its digital replica. Extending this concept, we can envision the DT as the unique digital gateway allowing the communication between the two worlds. In our application scenario, this means that a connected operator can exploit their own ODT as the unique entry point for any connected digital services in the factory; on the other hand, those services

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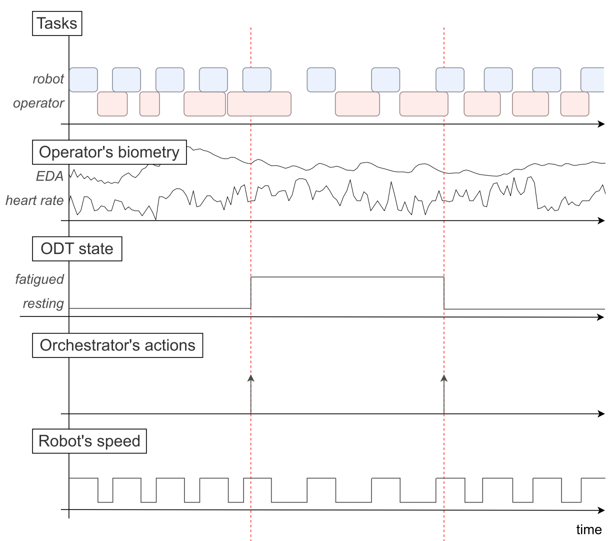
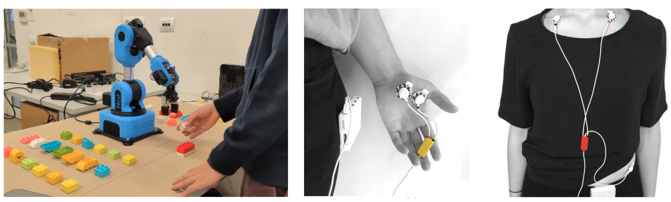


(a) Timeline for the considered experimental case study.



(b) Experimental setup: assembly scenario with Nyrio Ned collaborative robot (left) and BITalino (r)evolution Plugged Kit BLE/BT board (center and right).

Fig. 6. Timeline and setup of the considered case study.

can observe and interact with the operator only passing through its digital replica. Therefore, the ODT is in charge of securely communicating with the operator and their devices (e.g., wearable and augmented reality headset), processing incoming information and directly controlling who car read or modify available attributes, or invoking specific methods according to their role and authorization level. Side by side with secured communication technologies, the ODT can also introduce data anonymization and obfuscation techniques to support interoperability and guarantee service operation while preserving privacy. Exchange of operator's data and their interaction with machines and cyber-systems can be then managed implementing security protocols and following formally specified and analyzed security ceremonies [44], [45].

Relying on these considerations, the extension and detailed definition of ODT security modules and behaviours are currently out of the scope of this work and will represent an appealing research opportunity of next future activities.

V. Case Study

We implemented the proposed ecosystem in a collaborative assembly use case, where a human worker and a collaborative robot work together in a shared workspace. With reference to the relevant scenarios described in Sec. IV, this use case is a laboratory implementation of line operation, where, for the sake of simplicity, we considered $L = 1$ machines, namely the robot. Considering a prototypical scenario, the robot is in charge of presenting different pieces to the worker, who is in charge of assembling them. We assume that the parts to assemble are variable and, hence, human cognitive flexibility is required to assemble the final pieces. As a consequence, it can be expected that the task induces mental fatigue and a decrease in cognitive capabilities during the shift. Consequent adaptation of the robot's behavior is beneficial for the worker if the robot is informed when the worker feels tired and slows down the pace of the assembly task, as an assistive strategy.

The timeline of the experiment is shown in the left panel of Figure 6. The upper panel shows robot's and operator's engagement in picking pieces and assembling them, respectively. At the beginning, they are synchronized and the operator is ready to assemble any new piece just provided by the robot. In this condition, the operator is not fatigued and the robot moves with nominal speed. However, after some time (left red dashed line in Figure 6(a)), the task requires longer assembly time to the operator, who is no more able to keep robot's pace. This reflects in an increase in operator's fatigue, which is detected by the corresponding ODT, as presented in Sec. V-A. As a result, the *Manager/Orchestrator* is informed and commands the MDT to reduce robot's pace as an assisitve strategy. In the following assembly tasks, the operator is, then, given more time to assemble new pieces and, as a resut, their fatigue is decreased. When this is detected by the ODT, the *Manager/Orchestrator* commands the robot to restore its nominal pace (right red dashed line in the figure).

The scenario was reproduced in a laboratory setting, as shown in Figure 6(b). To this end, we used the Nyrio Ned[1] collaborative robot and operator's fatigue was detected with the BITalino (r)evolution Plugged Kit BLE/BT device,[2] shown in the right of Figure 6(b). It is a wearable device specifically designed for recording several different biosignals, namely ECG, EMG, EEG, and EDA, together with accelerations. The device supports Bluetooth connection and can be arranged in a modular manner with different configurations. As a consequence, its digitalization in a DT allows it to deal transparently with multiple configurations and provide a standard output to any consumer agent.

In the rest of the section, we first discuss how the ODT was implemented with specific focus on mental fatigue detection (Sec. V-A). Then, the implementation of the MDT is presented (Sec. V-B), together with an analysis of how physical complexity can be reduced by resorting to the proposed DT based framework (Sec. V-C) and the implementation of the digital orchestration layer (Sec. V-D).

A. ODT

As regards the ODT, the proposed validation focused on the *Shadowing* and *Augmentation* modules of biometric attributes. Such modules are responsible for receiving and processing the operator's activity and estimating their current status, as depicted in Figure 3. In particular, we here focused on estimating mental fatigue, which is the condition that typically arises over prolonged working shifts. The use of physiological markers is an established tool for the quantitative and objective detection of mental fatigue. In particular, variations in electrodermal and cardiac activity can be observed during

[1]https://niryo.com/product/ned-education-research-cobot/
[2]https://bitalino.com/products/plugged-kit-dual-mode-ble-bt

either moderate and intense cognitive load [17], [46]. To record such physiological activites, sensors were placed as shown in Figure 6(b), considering standard positions used in clinical practice.

The ODT was implemented leveraging the open source project WLDT,[3] a modular Java software stack to effectively implement DTs through their communication capabilities, shadowing procedures, and augmentation functionalities [47]. The library was also extended to introduce a BITalino *Physical Adapter* to retrieve data from the board via Bluetooth Low Energy (BLE) and properly parse the adopted proprietary data format. Furthermore, a specific module was introduced to run Python scripts within the DT logic to support the execution of data analysis algorithms and machine learning models and support the estimation of mental fatigue conditions. Specifically, the *Augmentation* module of the ODT was in charge of data filtering, feature extraction, and affect estimation. It can be implemented according to the methodology presented in [48], which consists of an unsupervised machine learning pipeline to discover patterns and groups in physiological signals recorded under the different fatigue conditions. However, in the considered experimental validation, fatigue occurrence and estimation (second and third panels in Figure 6(a)) were simulated. A *Digital Adapter* was also created and integrated into the ODT with the aim to expose the computed state to the external world and to allow a simplified observation of monitored stress conditions. The designed adapter uses the MQTT protocol [49] for asynchronous Pub/Sub communication and implements a traditional IoT topic structure composed by the following topic: i) *Info*: publishing the description of the ODT with its structure and capabilities; *Telemetry*: notifying any variation of the state's properties (e.g., raw biometric signals); *Event*: sending messages and notification when a specific situation occurs (e.g., a detected stress condition); and *Action*: supporting the reception of incoming messages associated, for example, with alert notification for the operator or the variation of the execution task (visualized on its personal or wearable device). Outgoing and incoming messages were also uniformed and standardized through the adoption of SenML data format [50] and serialized through the JavaScript Object Notation (JSON) [51].

B. MDT

In the considered case study, the MDT has the responsibility to digitalize the collaborative robot allowing bidirectional communication by reading the telemetry (e.g., joints position, execution speed, and effector status) and enabling the execution of specific actions on the machine (e.g., task assignment, speed variation, and movement coordinates). This physical interaction was designed and implemented on the MDT through the creation of a dedicated *Physical Adapter* in charge of mapping the communication with the robot through the Robot Operating System (ROS)[4] protocol by using the Niryo Ned custom library PyNiryo2[5] together with RosLibPy[6] and ROSBridge module[7] allowing clients to publish or subscribe to ROS topics and call ROS services through a variety of transport layers, including WebSockets and TCP. The developed adapter has been integrated into the WLDT library with the aim to use the same code structure adopted for the ODT and focus on the peculiarities of the MDT only.

A dedicated *Digital Adapter* was designed and integrated into the MDT in order to expose the computed state and to enable the external digital invocation of actions on the robot related to changes of its operational speed (e.g., when a stress condition has been detected). Following the same approach adopted for the ODT, this adapter uses the MQTT protocols for an asynchronous and Pub/Sub communication approach and is aligned with the same topic structure (*info*, *telemetry*, *event* and *action*). Nevertheless, both outgoing and incoming messages are homogeneous and based on the SenML data format serialized through JSON.

C. Physical Complexity

In our experimental evaluation, we also estimated the impact of digitization and decoupling of responsibilities by estimating the scenario's complexity with and without the adoption of DTs. In order to assess the effectiveness of the management of physical heterogeneity and complexity according to the proposed approach, we exploited the indicator denoted Physical Complexity Indicator (PCI) presented in [52].

The PCI measures the perceived complexity associated with an application working with the physical layer (e.g., the coordinator of the production line) and considers criteria such

TABLE I
DETERMINING THE PCI FOR THE SPECIFIC USE CASE ASSESSING THE ADVANTAGES, ACHIEVED THROUGH THE VARIOUS IDENTIFIED PARAMETERS AND THEIR CORRESPONDING CIF VALUES

Criteria	CIF	w/o DT	w/o DT-CIF	w DT	w DT-CIF
Requ. Protocols (p)	2	2	4	1	2
Comm. Patterns (c)	1	2	2	1	1
Data Formats (d)	3	2	6	1	3
Inter. Points (n)	2	2	4	1	2
Aggr. Points (a)	3	2	6	0	0
Results	-	10	22	4	8

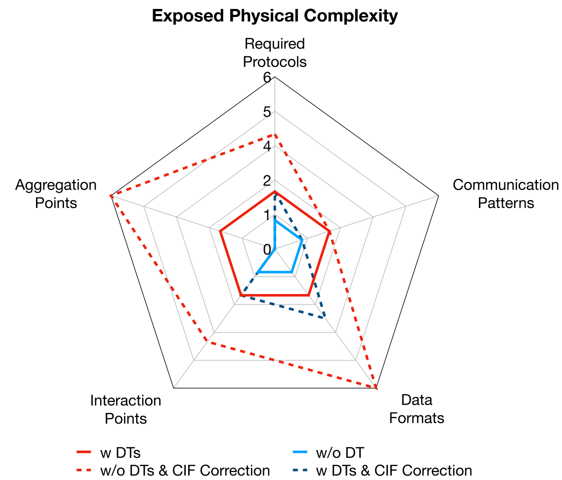


Fig. 7. Schematic representation of the physical complexity in the target use case considering results with and without the adoption of DTs and the Importance Factor (IF).

[3]White Label Digital Twin - GitHub - https://github.com/wldt.
[4]ROS - The Robot Operating System - https://www.ros.org/.
[5]PyNiryo2 - https://docs.niryo.com/dev/pyniryo2/v1.0.0.
[6]Python ROS Bridge library - https://roslibpy.readthedocs.io/en/latest/.
[7]ROS Bridge Suite - https://github.com/RobotWebTools/rosbridge_suite.

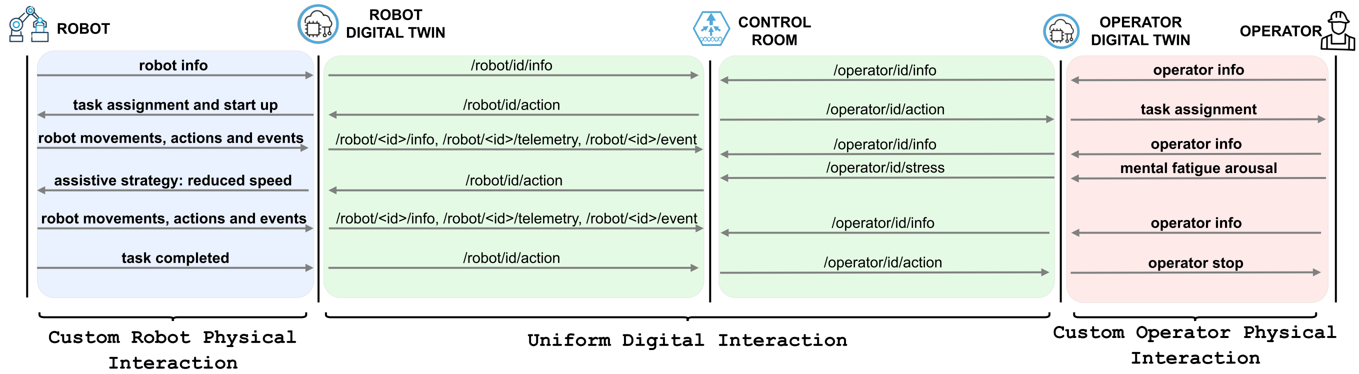


Fig. 8. Sequence diagram of the considered case study where physical and digital world are bridged through DTs, which are exploited by the control room to orchestrate operations.

as: i) *Required Protocols (p)*: the number of protocols required by a digital application or service to interact with the deployed physical devices to collect data and to send commands; ii) *Communication Patterns (c)*: the number of communication patterns needed to interact with involved devices and platforms (e.g., Publisher/Subscriber or Request/Response); iii) *Data Formats (d)*: the number of different data formats, serialization, and information representation techniques required to read and send data from and to deployed devices; iv) *Interaction Points (n)*: the number of different modules, services, or platforms that an application should interact with to retrieve all the target data or consume services; and v) *Aggregation Points (a)*: the number of aggregation or composition levels required to abstract the physical world into the right level of complexity with respect to the observers' typologies and their application goals (e.g., merging information and telemetry data from machines in the same production line). Each parameter is then associated with a specific Criteria Importance Factor (CIF) ranging from 1 (lower) to 3 (higher), used to weight specific criteria considering their impact on the development, deployment, and maintenance of the solution. The current CIF values draw from established scientific references employing similar principles [52], [53], as well as from the experience in the IoT and IIoT domains, emphasizing reliability and relevance in assessing application complexity interacting with the physical layer. Specifically, they underscore the technological complexity's impact and the associated management costs regarding communication protocols, data formats, and interaction/aggregation points. In the current IoT and IIoT landscape [54], [55], characterized by ongoing standardization efforts, these interoperability aspects remain the most challenging to navigate, demanding specialized knowledge of the physical world and dedicated implementations for bidirectional information disambiguation with physical entities. While these values may vary in well-structured, interoperable deployments, the prevalent fragmentation in real-world scenarios makes such homogeneity currently unlikely.

The evaluation of physical complexity for our experimental use case, taking into account the identified PCI and comparing the exposed physical complexity with and without the use of DTs (reported in Table I), is presented in Figure 7. We have assigned a high significance level ($CIF = 3$) to effectively manage diverse data formats (criterium d) and determine the number a of aggregation points required for constructing robust data structures. These factors play a critical role in enabling distributed coordination between operators and robots. On the other hand, a medium level of impact ($CIF = 2$) has been attributed to the adoption of heterogeneous data protocols (p) and engagement with multiple active entities (n). This assessment is due to their potential influence on overall complexity, especially in scenarios involving an increased number of active entities. We have assigned a lower level of importance ($CIF = 1$) to simultaneously adopting multiple communication patterns (c). This is because, in contemporary applications, it is quite common and widely accepted to utilize various communication techniques concurrently, particularly within intricate distributed environments. As regards PCI values, in our application scenario, on the one hand, we have the physical robot communicating using ROS and custom data formats and communication patterns (Pub/Sub with Nyrio topics), and, on the other hand, a BITalino device connected through low energy Bluetooth connectivity and using platform-specific messages and interaction flows monitoring the operator ($p = c = d = 2$). An intelligent industrial orchestrator should directly handle this fragmentation in terms of protocols and data structures and also manage the interaction with active entities together with the associated required modules (ROS architecture and Bluetooth adapter). This results in a scenario with $n = a = 2$ and an overall PCI equal to $PCI = 10$ and $PCI_{CIF} = 22$, considering the correction of impact factors. On the opposite, the introduction of DTs allows the creation of a uniform digital layer where a single protocol (MQTT), communication pattern, and a unique data format (the standard SenML [50] with JSON serialization) are adopted. As a result, $p = c = d = n = a = 1$ and PCI reduces to $PCI = 4$ and a final $PCI_{CIF} = 8$ applying identified impact factors.

The depicted values demonstrate how DTs can effectively reduce physical complexity, enabling an intelligent service to interact with a uniform digital interface and focus solely on data processing and generating intelligent insights. Provided advantages can be limited in the simplified reference use case while can be significantly augmented by taking into account complex production lines with multiple robots and operators cooperating together on the same task through different technologies, implementations, and communication approaches.

D. Digital Orchestration

The coordination between the operator and the robot is managed by a digital *Orchestrator* responsible for synchronizing, scheduling, and monitoring the robot's and operator's actions, tasks, and conditions. Thanks to the availability of a homogeneous digital layer hosting ODT and MDT, for the *Orchestrator* it is not relevant on the one hand if the robot is from a specific manufacturer or connected through a target required protocol or on the other hand if operator's wearables and HMI assets belong to a specific group of supported devices. The only requirement is that there are DTs responsible for the robot's and operator's digitalization and for maintaining the same agreed level of abstraction and interaction.

The implementation sequence of the proposed coordination is depicted in Figure 8, which shows how information about the process is shared between the robot and the worker, through their DTs. They initially authenticate to the *Orchestrator*, which starts the process of assigning tasks and publishing them on the topics $/operator/id/action$ and $/robot/id/action$. Task assignment can be managed by matching the operator's capabilities and the robot's characteristics (retrieved from their topic id) with production planning. During task execution, the *Orchestrator* is constantly informed about robot movements, actions, and events since the robot publishes such information on the corresponding topics. When the *Augmentation* module of the ODT detects arousal of mental fatigue, this information is forwarded to the *Orchestrator* on the topic $/operator/id/event$. Hence, the *Orchestrator* commands the robot to adapt its behavior and implement proper assistive strategy, by changing task execution features through the topic $/robot/id/action$. If mental fatigue decreases to normal workload, this information is shared again through the topic $/operator/id/event$, and assistive strategies are deactivated through $/robot/id/action$ to restore the nominal behavior of the robot. When the task is completed, the robot (in the case of Figure 8) or the operator informs the *Orchestrator* through the corresponding topic $action$ and the information is forwarded to the other agent.

VI. Conclusion

In this paper, we introduced a novel human-centric approach for human-cyber-physical systems in industrial scenarios. The proposed architecture relies on the concept of DTs to develop a digital layer, detached from the physical one, where the plant can be monitored and managed. This allows the creation of a digital ecosystem where machines, operators, and the interactions among them are represented, augmented, and managed. A pivotal component of such an architecture is the ODT. This is a digital replica of each human operator working in the plant and collects relevant human attributes that affect, or are affected by, interactions and collaborations with the automation system. Specifically, the ODT includes static features, and most importantly, dynamic features that summarize the current condition of the operator. Among such features, biometric traits allow to have a detailed understanding of their affect, such as attention, physical or mental fatigue, and engagement in working tasks. The ODT allows collecting such data directly handling the heterogeneity and fragmentation of the physical layer and augmenting them to get an objective, broad and implicit estimate of the operator's state. Ultimately, this allows to manage, operate and monitor the plant in an operator-in-the-loop approach, thus contributing to the creation of human-centric factories of the future. In the paper, we presented a blueprint architecture for MDTs and ODTs, where cyber-physical relationships among machines and operators are mapped among DTs. We discussed the application of such an architecture to typical scenarios of industrial automation. Additionally, we experimentally validated the proposed approach in a collaborative robotics application, showing how physical complexity can be reduced by resorting to the proposed architecture.

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