A Human-in-the-loop manufacturing control architecture for the next generation of production systems

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Abstract

In recent years, the introduction of Industry 4.0 technologies in the manufacturing landscape promoted the development of smart factories characterised by relevant socio-technical interactions between humans and machines. In this context, understanding and modelling the role of humans turns out to be crucial to develop efficient manufacturing systems of the future. Grounding on previous researches in the field of Human-in-the-Loop and Human Cyber-Physical Systems, the paper aims at contributing to a deep reflection about human-machine interaction in the wider perspective of Social Human-in-the-Loop Cyber-Physical Production Systems, in which more agents collaborate and are socially connected. After presenting an evolution of manufacturing control organisations, an architecture to depict social interactions in smart factories is proposed. The proposed architecture contributes to the representation of different human roles in the smart factory and the exploration of both hierarchical and heterarchical data-driven decision-making processes in manufacturing.

Keywords: Industry 4.0; human-in-the-loop; cyber-physical production systems; manufacturing control architecture.

1. Introduction

The Fourth Industrial Revolution, namely Industry 4.0, has emerged as a disruptive force in the manufacturing landscape, with significant impacts on supply chains, business models, and business processes [1]. Market requirements for a more tailored and customised production are pushing companies to face complex and fast-changing scenarios [2,3]. A wide set of technologies, such as Internet of Things (IoT), Cloud computing, and Big data Analytics, are used to provide devices with connectivity, interoperability and intelligence capabilities. However, among the potential opportunities for organizations and supply chains to innovate and create strategic advantage, an underrepresented area is the one related to the change of the role of humans in manufacturing, where technology can greatly enhance the human-machine integration[4]. In particular, Industry 4.0 technologies can support human work in several ways, augmenting the physical and cognitive capabilities of the operators [5], which are increasingly required to perform complex activities, such as conducting data-driven decision-making processes, instead of physical and routine tasks [6]. In this regard, big data and related technologies play a prominent, disruptive role in today's digital transformation that requires operators to extend their skill set.

Currently, Industry 4.0 vision is mainly reflected in the concept and development of *smart factories*, which represent the archetype of the next generation production systems, also referred to as *Smart Manufacturing Systems* (SMS) [7] and *Cyber-Physical Production Systems* (CPPS) [8]. In a smart factory, the physical and the digital worlds converge [9], and collaborative business processes take place [10]. Moreover, interactions between humans and machines in smart factories, often referred to as socio-technical interactions, take place continuously; therefore, proper conceptual socio-technical models should be considered to gain a complete understanding of this complex system [11].

In this scenario, understanding the role of humans in a smart factory is becoming a crucial topic. Indeed, many manufacturing systems are human-centred, where human operators interact with intelligent devices all around. Literature offers valuable contributions in this field, under the stream of research concerning Human-

In-The-Loop [12]. However, the new Industry 4.0 paradigm imposes a deeper reflection on the modes of interaction not only between humans and machines, but also in relation to the other smart objects which coexist, such as products, transport systems, and so on. Recently, the definition of optimal interactions between humans and non-human agents has been identified as a research gap in the literature about reference models and architectures for Smart Manufacturing as well [13].

1.1. Objective and structure of the paper

In consideration of the relevance of the socio-technical perspective and the role of the human work in smart factories, the objective of this paper is to explore the following research questions (RQ):

1. How are the roles of humans in a smart factory impacted by the implementation of Industry 4.0 technologies?
2. How does a human-centred perspective affect the integration of Industry 4.0 technologies and humans into next generation production systems?

In doing this, we aim at contributing to the theoretical development of Human-in-the-Loop Cyber-Physical Production Systems (HITLCPPS). To this end, the research adopts a human-centred approach, aiming at analysing the manufacturing system in relation to the humans that are involved. As a result, the scenarios discussed and the architecture proposed in the following sections fit the Human-In-The-Loop (HITL) research stream, representing humans involved in the actuation and decision loops of the production systems.

To address the topic, first, a review of the technologies that involve and change the role of human operator in the Industry 4.0 context is performed to identify the roles that human operators can play in a smart manufacturing system. Then, the interaction of several typologies of HITLCPPS is explored, discussing the evolutionary role of communication and control architectures that can be applied to regulate the decision-making processes in a factory. The focus on the human centricity in the manufacturing systems finally results in a scenario of a Social Human-in-the-Loop Cyber-Physical Production System, in which many agents collaborate and are socially connected both at the physical and cyber levels.

The paper is structured as follows. Section 2 presents the research methodology. In Section 3, Industry 4.0 enabling technologies are described and statistics about their adoption in the Italian and European manufacturing landscapes are reported. The analysis of technologies according to the physical and cognitive support to humans is presented as well. Section 4 discusses the socio-technical scenario of smart factories, focusing on the modelling of their objects in the light of multi-agent and holonic architectures. In particular, the modelling of human agents is discussed, according to different human roles in CPPS. Section 5 addresses the topic of the interaction of humans in Cyber-Physical Production System with a twofold objective, aiming at answering to the two research questions: understanding the ways of a single human-machine interaction and exploring the social interaction of many human and machine agents in a smart factory. For this purpose, further, in Section 6 an architecture for a Social Human-in-the-Loop Cyber-Physical System is proposed. Section 7 concludes the paper with limitations and further developments of this research.

2. Research methodology

To properly address the above-mentioned research questions, our study is built on a deductive research approach in which, starting from a well-founded knowledge represented in this paper by extant literature mediated by the authors' direct experience in interacting with companies, a generalisation is established, in order to be tested afterwards [14].

For this purpose, we deeply explored the research topics concerning human integration in manufacturing processes. The theoretical underpinnings at the basis of our study are manifold. First, we founded our research on the socio-technical systems theory, which aims at analysing the interaction and interdependencies between humans and technology to explain the behaviour and performance of a complex system, such as organisations [15]. According to this theory, to design and promote the implementation of the next generation manufacturing systems, parallel researches about technology and human aspects need to be considered. For this reason, an exploration of Industry 4.0 technologies affecting the human work turned out to be essential and provided the background to define the different roles of humans in a smart factory.

Finally, the theoretical concepts of multi-agent and holonic manufacturing systems have been used to represent the dynamic behaviour of human-technology integration in the operational control mechanisms of a Cyber-Physical Production System.

2.1. Research process

The first step of our research is the analysis of the literature about Industry 4.0 in relation to human work, focusing on case studies reported in academic and industrial papers. Secondary data have been used to provide more robustness to the research as well. We referred mainly on extant literature in order to leverage on a broader and diverse body of knowledge that, due to the relative recency of the topics discussed in this paper, would have been hard to gather only from direct experience. The literature review provided the basis for the analysis of the support that Industry 4.0 technologies provide to operators, which is presented in Section 3. The analysis of Industry 4.0 potentials allowed for the identification of the new roles of humans in the smart factory, and depicts how the evolution of technology is affecting the human-in-the-loop manufacturing control, thus addressing RQ1. Moreover, the second research question (RQ2) has been investigated and conceptualised in the form of a theoretical architecture for Social Human-in-the-loop Cyber-Physical Production Systems, in which humans play a central role in actively collaborating with machines and social interactions among humans and all the other agents in the smart factory occur.

3. Industry 4.0 key enabling technologies

Current literature offers different descriptions of Industry 4.0 [1,16–18]. According to Pereira and Romero (2017) [19], Industry 4.0 is a complex technological system that embraces a plethora of technologies (e.g., Cyber-Physical Systems, Internet of Things, Robotics, Big data), whose implementation allows the development of intelligent manufacturing processes, composed by devices able to exchange information, perform actions, and control each other.

In fact, Industry 4.0 implies the implementation of advanced technologies that, in most cases, are already embedded in conventional manufacturing systems. However, new ways of using and integrating technologies result in fully flexible and integrated manufacturing systems [20]. At the basis of the ongoing Industry 4.0

paradigm, there are many foundational innovations involving not only machines but also sensors, work pieces, and IT systems connected throughout the entire value chain. Standard Internet-based protocols enable real-time interaction between devices, thereby supporting data analysis to avoid and predict failures, as well as reconfiguration and adaptability capabilities [21].

In literature, different technologies are identified as the pillars of Industry 4.0 and Smart Manufacturing. For instance, the work of Mittal et al. (2017) [22], based on a systematic literature review analysis, lists 38 enabling technologies, further clustered in 12 groups, according to similarities. For the purpose of this study, the most cited technologies, labelled in literature as "Enabling Technology of Industry 4.0", have been considered and reported in Table 1, with a short definition and the sources that identify them as an enabling technology.

Technology	**Definition**	**Source**
Cyber-Physical Systems	CPS integrate physical processes with computation capabilities and are able to operate in changing environments, maintaining robust behaviour against unexpected conditions and failures	[19,22–28]
Internet of Things (IoT)	Internet of Things integrates various devices equipped with sensing, identification, processing, communication, and networking capabilities.	[19,22–24,28–30]
Big data analytics	Big data is characterised by volume, variety and velocity (the 3Vs), and it requires new techniques of data processing and analysis.	[22–24,29,30]
Cloud technologies	Cloud computing is related to the ICT-infrastructure that allows ubiquitous access to data from different devices.	[22–24,28–30]
Cybersecurity	Cybersecurity is the set of technologies, tools and processes to guarantee the security of networks, devices and the large amount of data collected, stored and communicated via IoT.	[22,29]
Virtual reality	Virtual reality is a computer interface that allows the user to be fully immersed in an experimental situation, i.e. a virtual	[22,25,31]

	environment, enabling the looking, moving and interaction of users in a world that is like the real one.	
Augmented reality	Augmented reality (AR) allows the creation of a virtual environment in which humans can interact with machines using devices able to recreate the workspace.	[22,29]
Smart sensors	Smart sensors are traditional sensors embedded with intelligence capabilities, i.e. on-board microprocessors, which can be used for processing, conversions, calculations, and interfacing functions.	[22,23]
Simulation	Simulation provides a digital representation of products and processes, in order to identify in advance potential issues, avoiding cost and resource wastes in production.	[22,29,31]
Additive manufacturing / 3D printing	Additive Manufacturing (AM) consists in a cluster of technologies that enable to produce small batches of products with a high degree of customisation by adding rather than removing material from a solid block.	[22,23,29,31]
Advanced robotics	The evolution of traditional robots opened the way to new collaborative solutions of robots (i.e. Co-Bots) that are able to work together with humans in a safe and efficient way. Moreover, embedded intelligence in robots can allow them to learn from human activities, improving their autonomy and flexibility.	[29,31]
Energy saving technologies	Energy saving technologies include the monitoring and optimisation systems that allow reducing the energy consumption in manufacturing.	[22,23,31]
Horizontal and vertical integration	Horizontal integration refers to the creation of a global value network through the integration and the optimisation of the flow of information and goods between company, suppliers and customers. The vertical integration, instead, is the integration of functions and departments of different hierarchical levels of the single company creating a consistent flow of information and data.	[28,29,31]
Multi-agent technologies	Multi-agent systems (MAS) are an organised set of agents that represent the behaviour of objects of a system, capable of interacting and negotiate among them to achieve individual goals.	[24,27,30,32]

Table 1. List of the most cited Industry 4.0 Enabling Technologies with the main reference sources

Nevertheless, to analyse the impacts of these technologies in the manufacturing sector, it is crucial to understand their current implementation. In the Italian landscape, the statistics published by the Italian Ministry of Economic Development [33] report that Internet of Things is the technology in which most of the investments have been addressed. High relevance is given also to all the technologies that allow data exchange, integration and analysis, while the adoption of simulation and augmented reality is still rather limited (Figure 1).

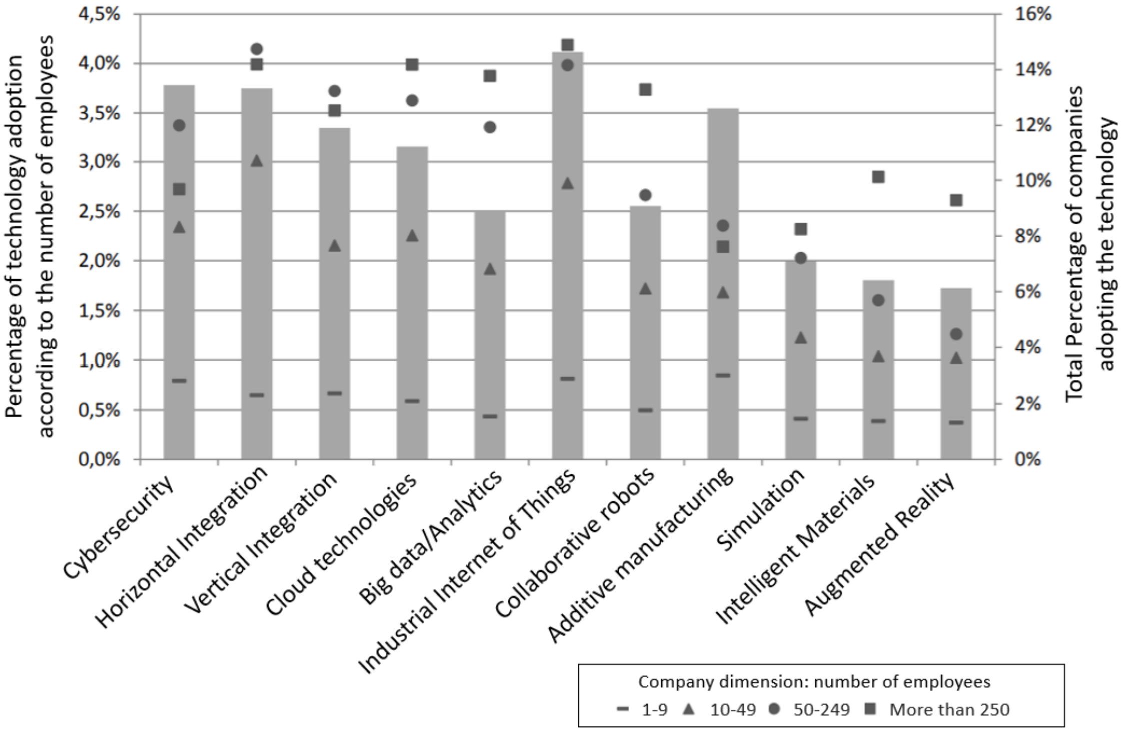

Figure 1. Level of adoption of Industry 4.0 technologies in the Italian industrial context (adapted from Ministero dello sviluppo economico, 2018)

Similar results have been shown by the European Commission (Figure 2), according to a survey conducted in European manufacturing companies with the aim at exploring the smart technology adoption in industry [34]. Also in this case, technologies related to data integration are the most relevant in the industrial implementation, and conspicuous investments have been performed in the last years to introduce big data

& analytics, IoT, and cloud technologies. Indeed, it is worth noticing that introducing new technologies requires companies to perform a careful analysis of the investment, since estimating the return on investment of such implementations represents one of the main challenges for manufacturers [10]. In order to perceive the advantages of introducing Industry 4.0 technologies in the production systems and reach suitable performances, proper integration and new operating models are required. Therefore, companies need to support new technology adoption within their strategic business transformation agenda.

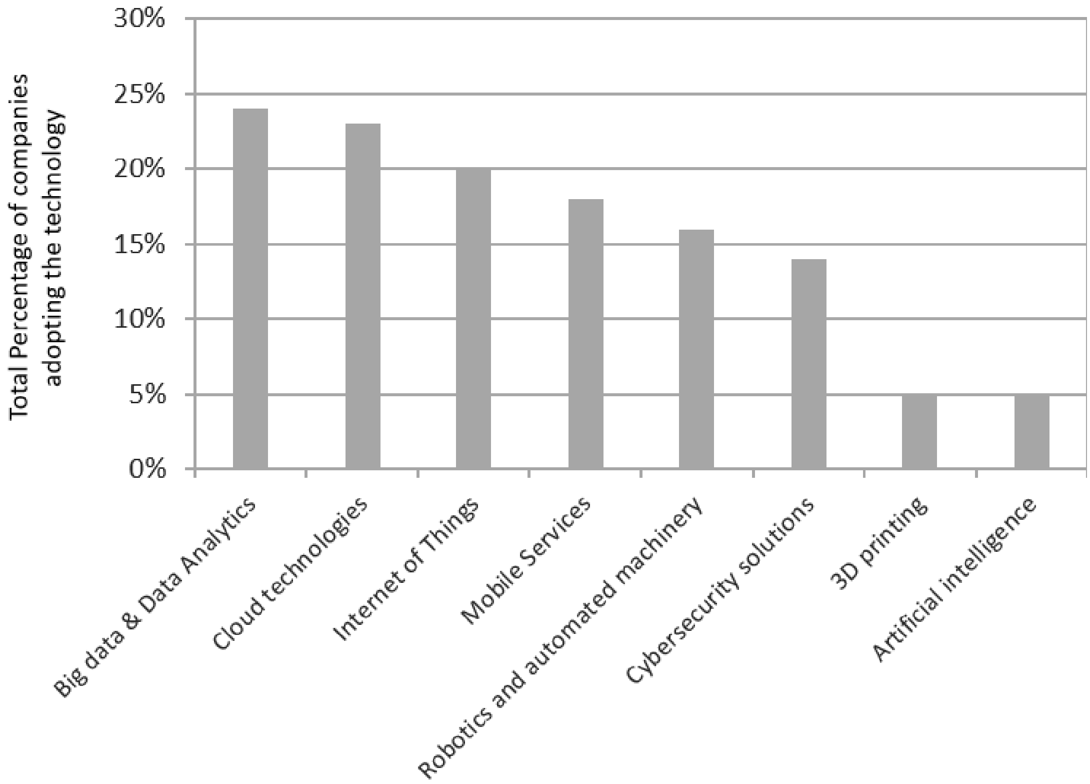

Figure 2. Smart technologies adoption in Europe (adapted from European Commission, 2018)

The above-mentioned technologies have different fields of implementation. Consequently, they can impact the human work in the manufacturing system in several ways. In particular, technologies can support humans enhancing their capabilities both at the physical and cognitive level [5]. In the former case, the introduction of technologies, such as collaborative robots or exoskeletons, aims at combining the efficiency of automation systems with intrinsic flexibility of manual operations [35]. In the latter case, technology enables better performance in cognitive capabilities, which are defined as the capacities of undertaking mental tasks (e.g., perception, memory, decision, etc.) [36]. Referring to the technologies listed in Table 1, it is useful to view them in relation to the physical/cognitive support they may provide to the operators in manufacturing. To this end, Table 2 provides, with no claim of exhaustiveness, a summary of some exemplary contributions found in the extant literature. Indeed, due to the relative recency of some of the topics under analysis, extant literature can be considered a solid ground upon which new concepts and interpretations can be built.

Physical support			**Cognitive support**		
Technology	**Capability**	**Source**	**Technology**	**Capability**	**Source**
Augmented reality	Sensing	[37]	Cyber-Physical Systems	Decision making	[38]
Virtual reality	Manual operations	[39]	Internet of Things	Data collection and communication	[40]
Advanced robotics	Manual operations	[41]	Big data analytics	Data analysis	[42]
Additive manufacturing/ 3D printing	Manual operations	[43]	Cloud technologies	Planning and control	[44]
			Smart sensors	Data retrieval	[41]
			Simulation	Optimisation	[45]
			Additive manufacturing/ 3D printing	Design	[46]
			Energy saving	Decision making	[47]

	Horizontal and vertical integration	Planning, diagnostics	[30]
	Multi-agent technologies	Decision making, scheduling	[48]

Table 2 – Industry 4.0 technologies in relation to physical or cognitive support

To this purpose, we first analysed literature contributions that directly reported the application of a specific technology in a defined context, allowing the evaluation of the role that technology has in supporting the activities performed by humans. For instance, some articles provide a description of pilot cases in selected enterprises or depict the implementation of technological applications developed by the authors. In parallel, other contributions, including literature reviews about Industry 4.0 technologies and conceptual models and architectures for the implementation of technologies, were analysed. Some of these contributions, in particular, described from a theoretical perspective the interaction of humans with several technologies. For this reason, even though not all of them report specific technological applications, they have been taken into account to abstract the impact that technologies have on human activities and build Table 2.

From the literature analysis, we tried to extract which human capabilities are augmented and assisted by these technologies. For instance, smart sensors are able to perform a pre-processing in order to provide already aggregated data to the human decision-makers. Hence, despite sensors are physical devices, they support cognitively the operators. On the contrary, virtual reality, which is able to reproduce a digital representation of the reality, can support the manual activities that operators usually carry out when dealing with the evaluation of different prototypes and assembly instructions alternatives. The virtual reality is able to replace the need for manual operations to explore, for instance, collisions during assembly activities.

As it emerges from Table 2, the majority of technologies supports the cognitive tasks usually performed by the workforce. Therefore, according to the previous discussion about technology adoption in manufacturing companies, the main expected benefits of Industry 4.0 implementation concern the opportunity of improving typical human intelligence processes and operations, providing large amounts of data, information, and additional computational capacity. In fact, the limitations of human work often depend on a restricted capacity in dealing with complex and multiple systems [49]. For this purpose, cognitive technologies provide efficient assistance to raise awareness in operators and improve manufacturing processes management by workers. IoT, big data analytics, cloud technologies, as well as horizontal and vertical integration, contribute to the development of new smart manufacturing processes in which humans and technology complement each other to achieve the main goals of productivity, flexibility and responsiveness, which are current market requirements and demands for an enterprise [50].

4. The human role in the smart factory

4.1. The smart factory as a socio-technical system

The coexistence of technology and humans in manufacturing makes it possible to characterise the smart factory environment as a Socio-Technical System (STS), that is an environment where “social and technical elements must work together to accomplish tasks” and where the “work systems produce both physical products and social/psychological outcomes” [51]. The STS concept could be properly associated with the smart factory context, in which the interaction between humans and technology turns out to be essential as well as critical [52]. Actually, in a socio-technical production system, several interrelated elements can be recognised (e.g., people, technology, processes, infrastructure, etc.) and conceptual models have been provided in literature to describe the relationships among them [53]. To fit the Industry 4.0 socio-technical scenario, some authors proposed the Human-Technology-Organisation (HTO) model [11,54,55], aiming at describing the functioning of the Smart Manufacturing System through the interaction of the three subsystems, as defined by Karltun et al. (2014) [54], and reported in Table 3.

Subsystem	**Description**
Human	1) A biological energy processing system; 2) an information processing system; 3) a psychic subject with a unique history and 4) a member of social groups and cultures
Technology	Means for transforming input to output using artefacts, procedures, and methods including know-how
Organisation	Consciously coordinated social entity, with a relatively identifiable border, which is relatively continually working for reaching common goals

Table 3. HTO subsystems definition [56]

Such a scenario suggests that a proper integration among the three subsystems must be achieved to reach a suitable performance of the whole system. This is, even more, the case of a smart factory, in which data are canalised and filtered, information overflow is managed, and correct updated information must be accessed by the right person at the right time. As described in literature [2,57,58], a smart manufacturing system should provide human workers with real-time information/fact-based decision support in production activities, resulting in an optimisation of the manufacturing process. For these reasons, technology and humans must be integrated and proper organisational strategies must be adopted to coordinate and arrange all the strategic, decisional and operational processes in the factory.

As described in the previous section, many technologies can be implemented in a factory to move towards the Industry 4.0 concept. Their orchestration contributes to the development of manufacturing processes that are defined as “smart”. According to Kusiak (2018), a smart manufacturing enterprise is structured in two layers, the physical one and the cyber one, which are linked by an interface. The same vision is represented in [59] under the label of Cyber-Physical Production System.

In this sense, smart manufacturing grounds on the CPS theory [60], which postulates the connection of physical entities with digital counterparts that represent them in the cyberspace [61]. Moreover, the terms “Smart Manufacturing Systems” (SMS) and “Cyber-Physical Production Systems” (CPPS) are often used interchangeably to refer to manufacturing processes characterised by real-time data access capability, reconfigurability, decentralised decision-making and intelligence [59]. For these reasons, in this work, the terms Smart Manufacturing Systems and CPPS are considered interchangeable as well. Enlarging the vision from a single CPPS to a smart factory, it appears that several smart manufacturing processes coexist and require proper communication interfaces and infrastructure, in order to create a real-time integrated network. Integrating humans in smart manufacturing requires the definition of the human role in the context of a cyber-physical production environment, addressing RQ1. In this system, data from the physical equipment is sent to the cyberspace to be elaborated. Conversely, decisions are pushed down from the cyber to the physical layer. Nevertheless, in SMS, intelligence is present both at central and distributed levels, enabling responsiveness through decentralisation and, at the same time, wide-awareness at system level [7].

According to the HTO theory, two aspects are relevant: i) the interaction between humans and intelligent manufacturing equipment (e.g., smart machines) and ii) the involvement of humans in the intelligent orchestration of the manufacturing environment.

To address these aspects, it is crucial to understand the possible ways of interaction of SMS elements envisioning appropriate organisational and control models. It is also essential to understand what roles humans can play in such a scenario.

4.2. Modelling Smart Manufacturing Systems with agents

To deal with the complexity of a smart manufacturing environment, new organisational forms and production control architectures are required to manage the emerging hybrid scenario where humans and CPS cooperate to deliver outputs. The concept of multi-agent systems is a well-suitable approach to model and control smart manufacturing systems [62]. Since an agent is "an autonomous component that represents physical or logical objects in the system, capable to act in order to achieve its goals, and being able to interact with other agents, when it does not possess knowledge and skills to reach alone its objectives" [63], a smart factory can be compared to a multi-agent system (MAS), that is an organised set of agents. In [30], smart shop-floor objects are modelled as agents, which cooperate through intelligent mechanisms to reconfigure dynamically a production system. These objects are machines, conveyors, and products. The main features of agents are autonomy, reactivity, pro-activity, social ability, cooperation, organisation, rationality, learning and mobility [64]. The same characteristics are associated with *holons*, which are autonomous and cooperating conceptual entities that can represent a physical or logical object/activity [63]. In the past, agent-based and holonic manufacturing systems (HMS) have been conceived to model decentralised and distributed intelligence in manufacturing control. Both MAS and HMS are considered roots of CPPS [65] and are still suitable concepts to model the control architectures of Smart Manufacturing Systems [5]. Despite few differences, the agents and holonic paradigms share similar concepts and basically have the same properties [64]. Therefore, the terms agent and holon will be used as synonyms in this research. These architectures enable a dynamic adaptation and reactivity against production uncertainties [66], which are necessary requirements of SMS. Reactive control systems, in fact, highly support the productivity and flexibility of a manufacturing system [67]. A detailed description of relevant agent characteristics supporting specific CPS aspects is reported in [68].

A framework for agents technology applied to Industry 4.0 is proposed in [69] and reported in Figure 3. In this framework, the information flow among agents is enabled by wireless technologies to realise a reconfigurable manufacturing system. Nevertheless, the human factor is not identified by a specific agent, and the interaction between human and technology is not depicted.

As distributed intelligence solutions usually implemented in MAS and HMS architectures enable to complement the human skills in the management and control of production processes, the integration of humans in such systems, also referred as human-in-the-loop (HITL), is an important issue in the development of CPSs [68]. Different opportunities for designing the role of human-in-the-loop are recognised and discussed in the following section.

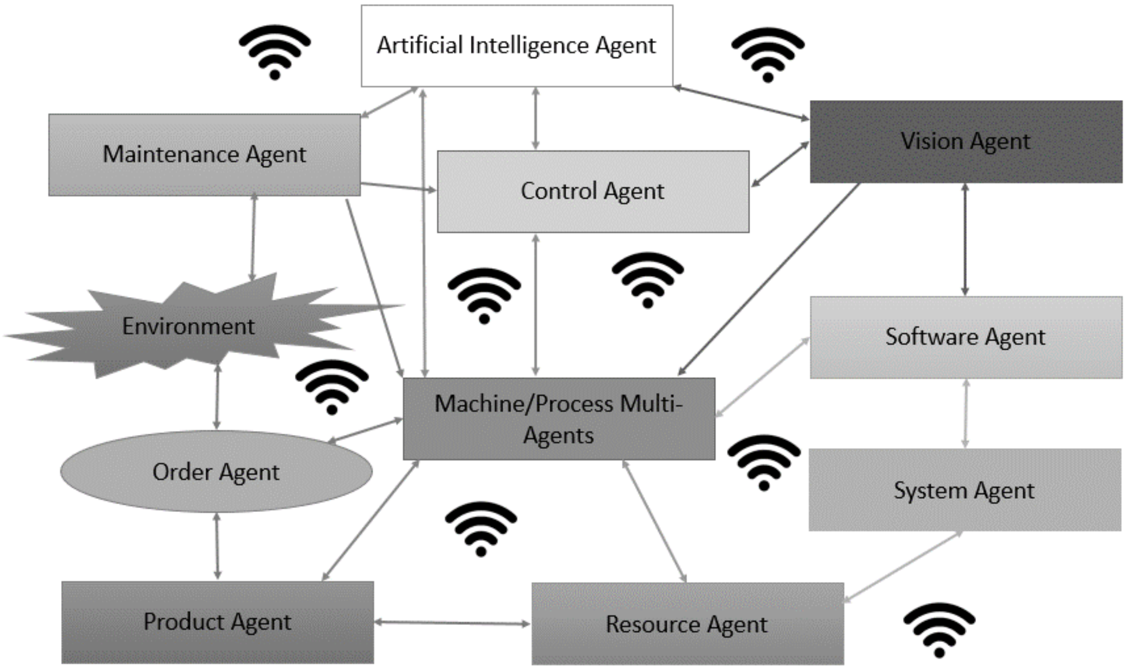

Figure 3. A Framework of agent technology for Industry 4.0 [65]

4.3. Human agents in CPPS

For many years, manufacturing systems based on multi-agent and holonic technologies have been designed with a “techno-centric” approach, considering the human operator as an external supervisor devoted to manage unforeseen situations and issues and support the intelligent control of the manufacturing system [70]. Control algorithms and systems that include actions performed by humans, represented by transfer functions in block diagrams, are commonly named as Human-in-the-loop control problems [71]. A related concept, called Man-on-the-Loop (MOTL), has been proposed in [72] to support a paradigm shift from a direct human intervention (the HITL approach), to indirect human supervision, which employs psychological and social influence to control complex systems' behaviour. As a matter of fact, the role of humans in the supervisory control of complex, near-automated system (such as multi-agent systems and cyber-physical production systems) has always been a critical issue [73]. The MOTL theory suggests that there is an optimal level of human intervention, which enables the best performances of the system. This approach is based on continuous interaction between agents and humans that are in charge of monitoring and intervening only when required.

Indeed, the commonality of both HITL and MOTL approaches is that in most of these systems, human intervention is invoked only to solve problematic situations that arise, contributing to the idea of a "magic human" able to always perform the right decision [70]. Conversely, in cyber-physical production processes, it is essential to consider the human presence and behaviour as a key inclusive part of the system, instead of an external factor [12].

To explore this changing paradigm, it is necessary at first to explore the different contributions that humans can give to a smart factory. For this purpose, in Nunes et al. (2017) [74] a taxonomy of the human roles in Human-In-The-Loop Cyber-Physical Production Systems (HITLCPPS) is presented. Starting from this taxonomy, the following revised proposal has been elaborated by the authors (Figure 4):

(1) *Data acquisition.* The capacity of humans to capture data and information makes it possible to assume them as sensors, able to feed the system with additional sources. For instance, the operators in the shop floor can provide the information systems with complex information about failures, which are difficult to detect with sensors. Indirect sensing can be achieved also using

wearable devices that gather data from the environment where the human is immersed, such as the temperature, humidity and light intensity of the production plant.

(2) *State inference*. Humans can directly provide additional data processing and computational capability to a system thanks to their cognition and mobile devices they are equipped with. The cognitive capabilities of humans (e.g. memory, calculation, and reasoning) directly allow data elaboration that supports, for instance, decisions about maintenance strategies, production control, logistics activities and so on.

(3) *State/system "influencing".* Given the possibilities to retrieve data from humans about their physical and psychological state, CPPS can adapt and modulate their functioning according to human needs, for instance in order to ensure health and safety against possible dangers.

(4) *Actuation*. Human actions still have extreme importance in the management of CPPS. In particular, human and machine actuation need to co-exist and be properly integrated, complementary or even collaborative. Humans actuate decisions through both manual operations and direct control of the production devices using Human-Machine Interfaces.

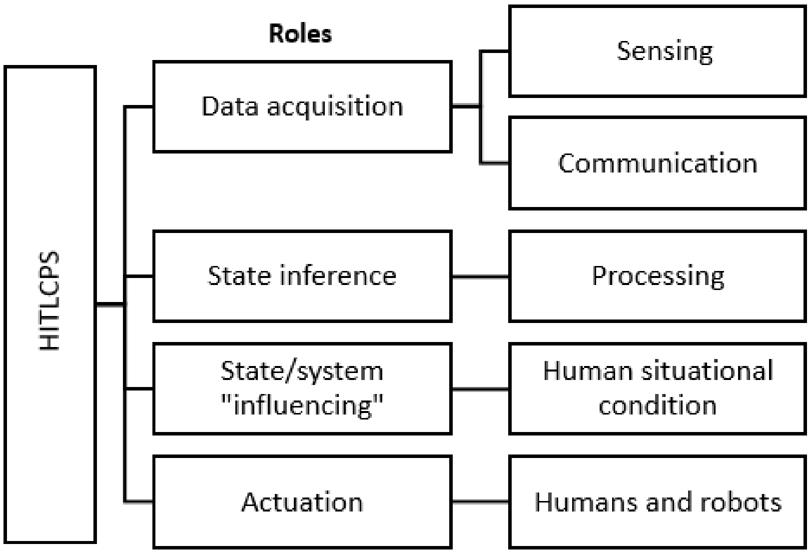

Figure 4. Taxonomy of human roles in HITLCPPS (adapted from [74])

The potential of HITLCPPS is not related only to the contribution that humans provide to the system, but also to the augmentation of human capabilities thanks to the introduction of the key enabling technologies characterising a smart factory, as previously discussed in Section 3. To match these two concepts, a matrix linking the enabling technologies with the role of humans in a HITLCPPS is provided in Table 4, thereby answering RQ1.

With respect to the technology overview presented in Table 1, Cybersecurity has been excluded from Table 4: in fact, being the body of knowledge that encompasses technologies, processes and practices designed to protect cyberspace from attacks and damages [75], cybersecurity provides information security in all the smart factory network. Therefore, for the purpose of our research, it has not been considered as a support to the integration of humans in CPPS.

HUMAN ROLES	Data acquisition		State inference	State influencing	Actuation
	Sensing	Communication	Processing	Human situational condition	Humans and robots
Physical	• Augmented reality • Virtual reality			• Advanced robotics	• Advanced robotics • Additive manufacturing / 3D printing
Cognitive		• IoT • Cloud technologies	• Cyber-physical system • Simulation • Big data analytics • Horizontal and vertical integration • Multi-agent technologies • Energy saving technologies	• Smart sensors • Cyber-physical system	

Table 4. Enabling technologies for human support in HITLCPPS

From Table 4, it emerges that technologies supporting the physical capabilities of humans are particularly useful to enhance the sensing and actuation role of human operators. For instance, augmented reality improves the visual sensing capability of the maintenance operators enabling to add virtual objects and information to the real space to perform better repair operations. On the other hand, communication skills and inference capacity are upgraded by many cognitive technologies, which augment human capabilities in processing and sharing information in a HITLCPPS. For example, big data analytics supports the elaboration of technical data collected by the machines to enable predictive maintenance while simulation allows the evaluation of different production plans to guide the choice of the better production planning strategy. Finally, state influencing interaction can take advantage of both physical and cognitive technologies. For instance, advanced and collaborative robots, which cooperate with the operator in production activities, are able to detect human position and movement and arrange their behaviour accordingly [76]. In this way, the human situational affects the state of the production system. In addition, cognitive technologies, such as smart sensors, are able to monitor human health condition through data collection from wearable (e.g., smartwatches) and fixed systems (e.g., cameras). For instance, when the operator health status is downgrading due to fatigue, smart sensors can provide information to the system that can change its state (e.g., production rhythm) to avoid possible accidents and damages for the operator.

5. Social Human-In-The-Loop Cyber-Physical Production Systems

5.1. Human-machine interaction in HITLCPPS

The previous section provides an answer to RQ1 highlighting how Industry 4.0 technologies affect human roles in a smart factory. In this section, the focus shifts to understanding how next generation production systems should be shaped to benefit from these new roles (RQ2).

Analysing a single human-machine interaction, it is possible to recognise different approaches. In typical HITL scenarios, human operators usually monitor and control machines through interfaces designed to display data and information, and to enable direct human control on the machine [77]. To accomplish this task, Human-Machine Interfaces (HMI) often refer to physical devices or control panels mounted on production equipment. The proper design of HMI is a deep-investigated research topic both at the theoretical and practical level. However, the attractive design of HMI for enhancing human performances in CPPS through better adaptable and intuitive interfaces is still recognised as one of the main fields of research and action [52]. It is possible to model such a human-machine system with holonic architectures as well. In this case, the HMI is represented by an interface holon (or an interface agent), which interacts both with a human worker and the machine system, controlling the information exchange between them [78].

A second approach to describe the human interaction with machines has been researched under the term of Joint Cognitive Systems (JCS). In this case, humans and machines are no longer separated entities collaborating through an interface; instead, they execute tasks as a team. Main features of Joint Cognitive Systems are goal-orientation, control, and co-agency, defined as the working together of humans and machines [5,79]. Using the holonic architecture view, the human worker is now modelled as a holon embedding the interface needed to communicate with machines [78]. Within this approach, the holonic manufacturing system can have direct joint control over human and machines resources, with consequent enhanced flexibility and responsiveness. Joint Cognitive Systems aim at overcoming the need of awaiting direct actions on the system from a human agent in charge of decision-making but implies a collaborative scenario, in which continuous interaction and data exchange between humans and machines occurs. Moreover, all material and immaterial holons (such as machines, products, but also production orders) become parts of an assistance system that help humans enhance performance [70].

Although these two approaches are useful to describe a single human-machine interaction, a smart factory can be viewed as a network of agents that cooperate to perform a various combination of physical and cognitive tasks [5]. This suggests that further investigations have to be conducted to attain a wider perspective. In fact, in a smart factory many human agents can interact with a plethora of other agents, such as machines, products, software, artificial intelligence tools (see Figure 3). The objective of these interactions is to provide the system with the right decisions to control the manufacturing process, both through direct and supervisory control [80], ensuring high performance and productivity. Therefore, a Human-in-the-Loop control system, as described so far, is only a component of a more complex system: beyond the human-machine interaction, social interaction among smart factory agents needs to be modelled.

As suggested by the socio-technical scenario discussed in Section 4.1, besides the interaction between human and technology, the human-organisation and the technology-organisation relationships are of utmost importance. In a SMS, the organisation subsystem is in charge of the coordination of both human work and technological capabilities of the system, and includes all the social interactions and control mechanisms of a factory. In this field, it is possible to formalise different ways of organising the manufacturing processes and recognise an evolution of their control towards the smart factory paradigm. The steps of this evolution have been identified by the authors and are represented as scenarios in Figure 5. In each scenario, according to the previous discussion about the different possibilities in designing human-machine interaction, the human-machine cell is the single unit of analysis, and the interactions among these units are discussed. For the sake of simplicity, three units are depicted to represent a factory, being aware that in a real manufacturing process they might be more.

Scenario #1 represents a simple case in which humans collaborate and share information through direct communication among them. This kind of interaction is not supported by digital systems, as it usually occurs verbally or through paper-based documents. In this scenario, each operator can only have a partial view of the production system, which is strictly related to the machine that he is controlling. Machines do not have any capability in terms of direct communication with other systems. For these reasons, the control of this system can be particularly complex and suboptimal, because a limited view on the process means limited awareness about the whole system and does not allow humans to make optimal decisions. Traditionally, in the past, simple production systems, such as mechanical workshops, adopted this scenario to control the production.

In Scenario#2, a first evolution is represented by the introduction of digital support (e.g., ICT tools) for human-to-human communication. Also in this case, machines cannot communicate with each other, and humans have a partial view of the system; however, the introduction of stand-alone information systems allows the development of more complete Decision Information Packages (DIP) [81], that are the sets of information relevant for the operators for making decisions. Nevertheless, the control of the manufacturing process is decentralised, and data that compose the DIP reside in many systems that are not integrated, making it difficult to perform optimal process control actions. In real factories, this scenario is represented by production systems that adopt some departmental information systems which support independently different areas, such as internal logistics and warehouses, production plans, products information.

In both scenarios #1 and #2, manufacturing control is organized according to a heterarchical architecture, in which independent agents have local intelligence and cooperate through negotiation mechanisms to achieve their goals [82]. In the represented scenarios, human-machine cells represent single agents, that can arrange their work locally, and humans have direct control on the machines they are working with. The drawback of this approach is that it is not possible to use global information for managing all the human-machine systems present in a factory. Only single interactions between two human-machine systems are allowed, while multiple interactions are not possible. On the other hand, Scenario #3 represents a common control architecture for manufacturing processes in the era of ICT and automation. A central information system manages data sharing and communications among humans.

For instance, this is the case of Enterprise Resource Planning (ERP) and Manufacturing Execution System (MES), which collect and organise the information of the whole enterprise, to control the production and other related activities (e.g., materials flows, human resources, cash flows, etc.). In this scenario, centralised and hierarchical control structures can provide a good capability of optimisation and productivity [63]. However, also in this case, several issues arise: centralised systems have slower speed of response with respect to decentralised systems, due to the high quantity of work in charge of the central system in managing huge numbers of agents. In hierarchical architectures, problems in responding to real-time events can be caused by limited local intelligence combined with a short-sighted view of the high levels towards detailed information from the shop floor; these issues become more evident if the communication links between levels are not reliable [83]. For these reasons, agility and flexibility of such systems cannot be guaranteed.

Aiming at overcoming all the issues of both centralised and decentralised control problems, hybrid control solutions have been conceived and proposed, such as PROSA, ADACOR and, more recently, ARTI holonic architectures [82,84,85]. Scenario #4 represents a hybrid solution between hierarchical/centralised architecture and a heterarchical one, enabling at the same time local and central interactions among human-machine cells. In this scenario, both human-to-human and machine-to-machine communications are depicted. In fact, in the above-mentioned control architectures, both machines and humans are assumed as *resource* (PROSA and ARTI) or *operational* (ADACOR) holons, that is they are physical resources available in the shop floor and able to perform tasks and communicate with each other. Therefore, machines provided with communication capabilities enable new ways of interactions among the human-machine cells that have been considered as single units so far. In addition to the previously considered interactions (i.e., human-to-machine and human-to-human) a new kind of interaction – machine-to-machine – is represented by empty arrows in Figure 5.

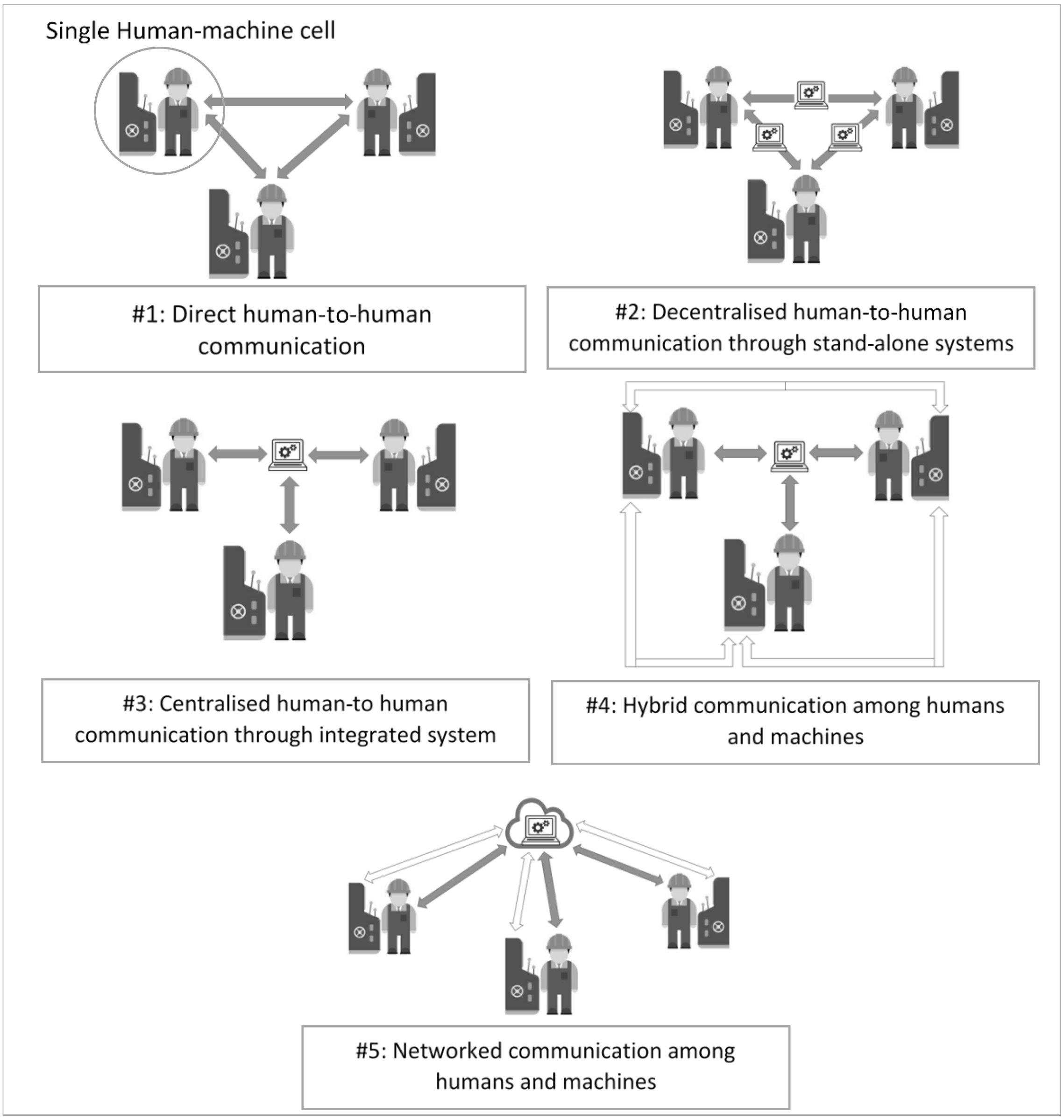

Figure 5. Social Human in the Loop Cyber-Physical Production Systems scenarios

This interaction can critically affect the human role in the manufacturing process control. In this hybrid scenario, the centralised and decentralised modes are both available as control strategies for the holons/agents; proper switching mechanisms from one mode to another are put in place to have a global optimal behaviour, still maintaining a reactive and responsiveness approach to disturbances [66,86]. Hence, in these systems, humans and machines can be considered independent agents, undertaking actions and making decisions based on the information shared with other agents. In this scenario, the human-in-the-loop approach can include direct or supervisory control over machines [74], because automated negotiations and decisions among machines are allowed even without human intervention. Although in literature this kind of scenario is widely discussed, real implementations in industry are limited and mainly concern the production planning and scheduling activities [68].

Furtherly enhancing this scenario, the paradigm of Industry 4.0 aims at overcoming all the issues emerging from the previously described architectures by enabling wider communication among all involved resources. In scenario #5, upgraded human-to-human and machine-to-machine interactions are depicted, supported by Industrial Internet and the Cloud [87]. In this case, machines and humans share real-time data and information with all the other agents through the cloud, which makes data and information available from everywhere. Therefore, the possibility to access data increases the awareness of all the agents about what is occurring in the production system, enabling the implementation of efficient real-time process control, in which effective decisions are allowed thanks to the high visibility about the system. Scenario #5 represents a Social Human-in-the-Loop Cyber-Physical Production System, in which vertical integration from shop floor equipment (e.g., machines) to managerial and strategic level can be achieved, and smart machines and equipment form a self-organised system [30], enabling responsive feedback actions for controlling production processes. Scenario #5 encompasses the advantages of all the previously discussed scenarios. As it occurs in Scenario #3, human operators can benefit of a central information system: in addition, more information from other human-machine systems can be consulted and examined in real-time thanks to a cloud-based architecture, in order to enhance their situational awareness. To avoid the risk of slowing down the speed of response of the centralised system, decentralised computational capabilities are embedded into machines, which are able to pre-process data. At the same time, similarly to Scenario #4, Social HITLCPPS can take advantage of a hybrid control structure, in which decisions can be taken at decentralised level or through central optimisation strategies that consider the real-time state of all the elements of the system [48].

Despite the strengths of Scenario #5, some socio-technical challenges need to be addressed. In the design of Cyber-Physical Systems, indeed, one of the main issues is the runtime system adaptation that is required to manage the external dynamic environment and find the optimal configuration in any occurrence [88]. Even if the designers attempt to include all the possible scenarios of CPS behaviours in relation to potential dynamic situations, there is a chance that unexpected occurrences generate unforeseen CPS behaviours. A critical implication of this in a human-in-the-loop system concerns the possibility that not only CPS could have a non-optimal behaviour in terms of system performance, but also can results in dangerous behaviours for humans [89]. For this reason, one of the key aspects to take in consideration when developing HITLCPPS concerns the need of envisioning and anticipating emerging behaviours, that are neither explicitly nor implicitly accounted for but result from the collaboration of the system elements [88]. Moreover, due to the complexity of CPS, these systems can be subjected to frequent faults, requiring specific attention to detect malfunctioning and, in addition, deploy preventive strategies to achieve proper resilience [90]. Ensuring system resilience, which concerns fault tolerance and stability against local variations, becomes increasingly relevant with the introduction of the human factors in the control loop of Scenario #5 because humans can be an additional source of uncertainty. At the same time, however, humans being ‘in the loop’ can provide resilience and agility to the system. This requires a certain degree of reliability in human actions, which must be properly assessed [91] and can be achieved through targeted training strategies to develop soft skills, such as problem-solving, useful to manage unexpected situations [92].

6. A Social Human-in-the-Loop Cyber-Physical System architecture

If the integration of humans is relevant in a single HITLCPPS, in a social environment it is of utmost importance. Above all, two main challenges concern i) the interpretation of human behaviour and ii) the coordination of human agents with other agents. Capturing and understanding the human behaviour requires system identification and modelling techniques difficult to implement, considering the wide physiological, physical and social variables of human being [93]. In addition, proper orchestration mechanisms are required to coordinate the human work in an environment in which all agents are provided with intelligence and autonomy. Holonic architectures and multi-agent technologies are again suitable solutions to model these mechanisms and support real implementation of Social HITLCPPS. Specifically, in these systems, HMS and MAS can support decision-making based on continuous information exchange at different levels, namely strategic, tactical and operational level [70].

Wang and Haghighi (2016) [94] propose a CPS architecture combined with HMS holarchy, defining the two layers of physical and cyber processes connected by a network layer (Figure 6). Nevertheless, in this architecture, human users are considered as a third party with respect to the system, which interact with physical and cyber elements, pushing decisions, similarly to the concept of "magic human" discussed in Section 4.3.

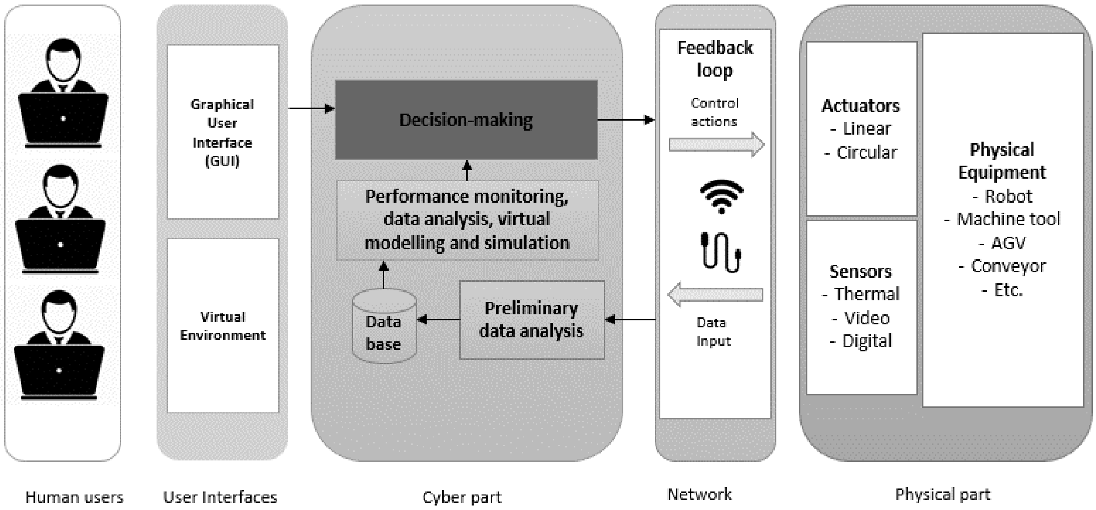

Figure 6. CPS architecture combined with HMS holarchy [94]

Based on this architecture, a Social Human-in-the-Loop Cyber-Physical Production Systems (Social HITLCPPS) architecture, based on three layers (physical, control and cyber), is proposed by the authors and represented in Figure 7. Differently from [94] where humans are considered external to the manufacturing system and interact with the cyber part through interfaces, in the proposed architecture the cyber and physical layers embed human operators that interact with equipment and information systems. In more detail, the three layers are the following:

- **Physical layer**: In the physical layer, humans directly interact with machines, transportation and robot systems, which are embedded with IoT technologies to communicate, and with local intelligence to make decisions at a decentralised level. According to the roles of humans in the HITLCPPS reported in Figure 4, operators in the physical layer can contribute to *Data acquisition*, *Communication* and *Actuation*, but also to *State influencing,* depending on their behaviour. In the physical layer, humans and smart equipment can make operational decisions jointly. In some situations, smart equipment can automatically put in place self-adjusting strategies; otherwise, they can communicate with humans to have direct intervention and control. The physical layer is the source of all the data collected from the shop floor that are then sent to the upper levels to be processed and contribute to the decision-making process.

- **Cyber layer**: From the physical layer, data can be sent to the cyberspace, to allow for more specific cognitive functions, such as data processing and visualisation as well as virtualisation of the production process. In this layer, human operators can interact with the cyber representation of reality. For instance, they can access raw data collected from sensors and consult central IT systems, such as the ERP. Moreover, they can use applications for data analytics and simulation tools to support the decision-making at strategic level. Indeed, big data and analytics can support companies to improve decisions as well as operational and financial performance [30]. The interaction of humans at this level fits with the human-in-the-mesh approach presented by [95]. In fact, the human intervention on the system is not direct to the physical equipment of the factory, but is mediated by software applications, which contribute to the interpretation of the behaviour of the factory elements through a cyber-representation, and allow the operator to take more aware decisions that are then sent to the physical layer. The roles of humans in cyberspace mainly concern *State inference.*

- **Control layer:** this middle layer (between cyber and physical layers) encompasses control agents, which mirror and reproduce the behaviour of the single physical objects. This control layer includes both the multi-agent system and shop floor control and execution systems. The holonic and multi-agent control approach is compatible with Shop Floor control systems (e.g., SCADA) and MESs [96], which, if properly integrated, can provide real-time information and control over the production system [97]. The main features of the control layer can be summarised as follows:

    a. Agents collect inputs from physical entities and use them to perform negotiations with other agents.
    b. Social interactions among physical objects are reproduced by the multi-agent system, thanks to sensors embedded in all the production processes and entities, including operators.
    c. The control layer provides a model of social interactions among objects to the upper cyber layer.
    d. Decisions from the cyber layer are transferred to physical objects through actuators.

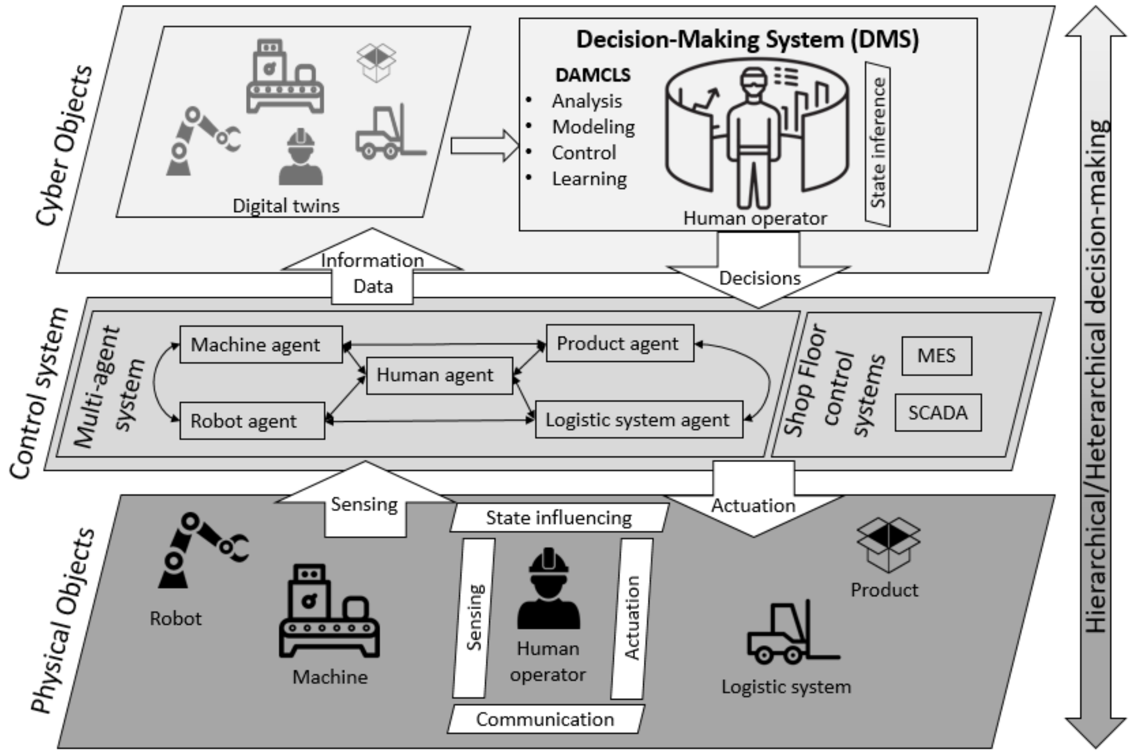

Figure 7. Social Human-in-the-loop Cyber-Physical Production System architecture (authors' elaboration)

6.1. The decision-making system in the HITLCPPS

The heart of the Social HITLCPPS architecture is the Decision-Making System (DMS), which is resident in the cyber layer and takes advantage of the profitable use of data. Only when data are analysed and transformed into knowledge, they can support decision-making processes within organisations [98]. Nevertheless, it is worth noticing that the usefulness of data and related analytics is strictly related and dependent on the data quality. In [99], four dimensions of data quality have been discussed (completeness, conformity, validity and accuracy) and a measurement of these dimensions is proposed to assess data quality. Indeed, ensuring data quality represents one the main steps in the development of analytics supporting decision-making [99]. The DMS is based on the virtual representation of physical objects, which includes all their features, namely their physical and material characteristics, their computational properties, their collected data and their control behaviour. Virtual representations of physical objects are often referred to as *digital twins*, and continuous synchronisation is ensured between the two counterparts [100,101]. Control systems, such as the ones represented in the middle layer, can interact with the digital twins influencing the functioning of the whole system [85]. The digital twins, reproducing continuously the behaviour of physical objects, contribute to making smart decisions. In Gölzer and Fritzsche (2017) [102], data-driven decision-making processes are discussed with the aim of highlighting the potentials of data usage for automatic feedback-control-loops. In the Social HITLCPPS architecture, we aim at furtherly explore the data proficiency for improving human decisions. In fact, human decision-making is supported by several technologies that enhance cognitive capabilities mainly exploiting data potentialities, which enable real-time monitoring, analytics, optimisation and simulation consequently. Panetto et al. (2019) [103] summarise decision-making tools for supply chain management under the acronym of DAMCLS (namely, Decision Analysis, Modelling, Control and Learning Systems).

Applying the same approach to manufacturing, DAMCLS represented in the proposed architecture encompasses these functionalities:

- *Analysis* - descriptive and diagnostics data analytics that allow performance evaluation and forecasting; such tools can support, for instance, maintenance and logistics.
- *Modelling* - mainly refers to simulation that can supports process optimisation, particularly useful when dealing with what-if analysis in the process design phase.

- *Control* - real-time monitoring to enhance visibility and awareness over the production processes; monitoring involves both technical and non-technical parameters of the system (i.e. machine parameters as well as production data).
- *Learning* - includes all the adaptive techniques and algorithms to interpret and acquire knowledge about the functioning mechanisms of the physical system; predictive maintenance and energy management are suitable areas in which learning mechanism can support human decisions.

As hinted before, it is relevant to consider that, despite the high potential of DAMCLS, in data-driven decision-making, the quality of decisions is influenced by the data reliability. In a complex system, such as the Social HITLCPPS, in which data are collected from many sources, ensuring a proper level of data quality becomes a very relevant issue and claims for governance mechanisms and specific data processing procedures in order to ensure that analytics could not provide incorrect or biased outcomes [104]. With respect to this, companies will have to rely on the knowledge and experience of human decision-makers for a long time to come.

Finally, the Social HITLCPPS architecture enables different configurations ranging from a hierarchical to a pure heterarchical based organisation. Beyond the social interaction that occurs horizontally among the objects within the single three layers (i.e. interactions in the physical, control and cyber layers), there is a further vertical interaction between humans in the cyber and physical layers.

On one hand, in a hierarchical structure, the human operator represented in the cyber level is the decision-maker, while the human operator represented in the physical level carries out a mere decision actuator role. On the other hand, thanks to the tools that can augment the cognitive capabilities of the shop floor operator (e.g., wearables, mobile devices), the DAMCLS functionalities can provide an on-field decision-making support for operational and short-term optimisation. This in turn enables a decentralised and heterarchical organisation and establish a better convergence between the human decision-maker supervising the cyber layer with the human operator controlling the physical layer. In any case, the final goal of introducing tools to support decisions is to improve the decision power of the operators. Increasing the irreplaceable human capacity to conduct a production system in compliance with the target performance objectives is also a mean to ensure higher resilience to the HITLCPPS.

7. Conclusion and future research

This paper reviewed the role of humans in smart factories, in order to envision a scenario for Social Human-in-the-Loop Cyber-Physical Production Systems. Given the socio-technical nature of the smart factory, modelling properly the interaction of humans with all the smart objects (e.g., products, machines, robots) is a priority. Indeed, the spread of Industry 4.0 requires investigating the impact of the implementation of its technologies on human roles (RQ1). To address this research question, Industry 4.0 technologies have been considered in relation to their physical or cognitive support to human operators. Further, the coexistence of technology and humans in manufacturing systems has been addressed as a socio-technical system, thereby discussing a taxonomy of human roles in smart factories. In conclusion, it is possible to state that technologies supporting physical capabilities of humans are particularly useful to enhance the sensing and actuation role of human operators, whereas communication skills and inference capacity are upgraded by many cognitive technologies, which augment human capabilities in processing and sharing information.

Keeping the human operator at the centre of the analysis, the integration of Industry 4.0 technologies and humans into next generation production system represents the following area of investigation (RQ2). First, five scenarios in the evolution of control organisations towards the smart factory paradigm have been identified. This led to the proposal of a Social Human-in-the-loop Cyber-Physical Production System architecture, which determines that the integration of humans operators and technology in a CPPS can be attained through a three-level perspective where a *physical layer* and a *cyber layer* embed human operators that interact with equipment and information systems in a *control layer*. In turn, the control layer makes use of an agent-based perspective to address social interactions and decision-making processes through different types of configurations (from hierarchical to pure heterarchical) of the organization.

This study extends the available literature, enabling an extensive and comprehensive understanding of the role of humans in the development of the next generation manufacturing systems, and depicting the data-driven decision-making processes of a smart factory. The in-depth analysis of human-technology interactions in a CPPS can guide practitioners in defining the most suitable technologies to support the human work, according to their own company strategy.

This research outlines the importance of properly integrating humans in cyber-physical production systems. Moreover, companies that are changing their operational processes towards the Industry 4.0 paradigm can benefit from the formalisation of the three-layer architecture, in which the relationships between humans, technologies, and data flows are represented.

However, it is possible to put forward the limitations and possible development directions of this research. The architecture of the Social HITLCPPS has been defined theoretically and could be applied in an industrial pilot to validate its potentialities. Modelling real objects in a factory can test if the architecture encompasses all the possible social interactions that occur. In addition, an empirical application of the architectures allows the development of refined mechanisms to regulate the hierarchical/heterarchical structure of decision-making, which are difficult to define at a general level. Indeed, a sharp distinction between operational, tactical and strategic decision levels cannot be defined universally and deep knowledge about the specific smart factory requirements is required to allocate decisions to each level ensuring both the flexibility and robustness of the manufacturing process. From a real implementation of the architecture, possible issues concerning communication and interoperability among agents can also arise and push additional researches to solve them.

Moreover, starting from the suggested architecture, instructions and rules to design a smart factory environment could be provided in further research. They concern technologies that support human work, cooperation aspects between humans and machine, social interactions in complex systems, as well as other specifications about the architectural structure of decision-making. These instructions could be also differentiated in relation to the production system typologies. In particular, different levels of intelligence and automation are related to decision capabilities in the equipment and define different control task allocation between humans and machines. For this purpose, it is worth mentioning that to achieve the best performance in a smart factory development, manufacturing process and human work design must be carried out simultaneously. Further developments in human work design in a Social HITLCPPS are required as well.

Finally, enlarging the smart factory vision towards the whole supply chain context, similar architectural models can be depicted for modelling the relationships between suppliers, manufacturers and final customers. Multi-agent approaches can be successfully used to simulate negotiations among the involved stakeholders, while other smart technologies can support humans providing horizontal integration of information, contributing to the development of a social supply chain in the Industry 4.0 context.

8. References

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