Towards cognitive interoperability in cyber-physical enterprises

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Abstract: This paper is about Cognitive Interoperability of Cyber-Physical Systems and Humans in an enterprise context where both are expected to have the capabilities to work collaboratively. We review the relevant state of the art, highlighting related concepts, propose a definition for Cognitive Interoperability in Cyber-Physical Enterprise context and list characteristics of Cognitive Systems, towards a Cognitive System-of-Systems.

Keywords: systems interoperability, cognitive interoperability, cyber-physical enterprise, cyber-physical-social system

1 INTRODUCTION

In an enterprise, dynamics in business are increased by new technical possibilities stemming from, e.g., the IoT, CPS, Digital Twin, Sˆ3 Enterprise (Sensing, Smart, and Sustainable Enterprise). Much effort is currently put into technologies to sense the environment, digitalise observed systems and maintain a link between the physical and the digital/cyber components. The introduction of Cyber-Physical Systems (CPS), together with advances in Information and Communication Technologies (ICT), has been the major driving force for the 4th industrial revolution (Arnold et al., 2016). The term CPS refers to a generation of systems with integrated computational and physical capabilities (Lezoche and Panetto, 2020) that possesses three basic capabilities (Cardin, 2019): Intelligence (computation), Connectedness (communication), and Responsiveness (control). Applying the CPS concept to the Enterprise domain, a Cyber-Physical Enterprise (CPE) (Panetto et al., 2019) consists of autonomous and cooperative technical elements, humans and sub-organisations that are connected based on the context within and across all levels of the global organisation, from processes, through machines and up to enterprises and supply-chains networks. Operating a CPE increases the complexity that must be handled by organisations, and consequently of the interoperability between all its components.

Interoperability is recognised as an essential requirement for Systems-of-Systems (Panetto et al, 2016) and CPE (Panetto et al, 2019) in particular. The understanding of information exchanged between two entities is the concern of *conceptual*, or *semantic interoperability*. Recognised as the most problematic among the seven types of interoperability issues faced by any collaboration (Panetto, 2007), semantic interoperability is about attaching meaning (semantics) to data, thus transforming it into knowledge that can be shared with a common understanding between entities or agents, be they technical (machines) or humans.

This is however the theory. Semantic interoperability is usually implemented using ontologies, which provide a formal representation of knowledge that machines can process, theoretically, in the same way. Today ontology-based solutions ensure that technological components (CPS) of a CPE share a common vocabulary and can reason on exchanged knowledge. Machine-readable ontologies are however not readable the same way by humans, who may have interpretations that are different from machines, simply because they do not necessarily understand all the formalism and have specific ways to reason and interpret, that can moreover be different from an individual to another. Consequently, relying on ontologies is not always enough to ensure CPS and human agents understand each other enough to cooperate or collaborate efficiently in a CPE context.

In 2018, the IoT European Research Cluster was highlighting that the next generation IoT should take a more human-centred perspective, where intelligent objects have social capabilities allowing seamless interaction between autonomous systems and humans (Vermesan et al., 2018). Similarly, on the Cyber-Physical Systems side, it has been argued recently that a CPS misses a “Social” component to become a Cyber-Physical-Social System (CPSS), able to collaborate with humans at the same level humans would do (Yilma et al., 2021) (Figure 1).

Semantic interoperability creates a common vocabulary that components of a system exploit to understand each other, but when humans are part of the system, this is not enough. *We argue here that going a step further is needed to ensure collaboration between entities (CPS and humans).* This step is about associating semantics with the reasoning process and would result in what we call *Cognitive Interoperability*. When entities can reason on exchanged knowledge, they are involved in a cognitive process. Reaching a mutual understanding allowing collaboration implies not only interpreting the semantics (meaning) but understanding the way it is processed (reasoning) and leads to actions, thus sharing the cognitive process. The boundary between semantic and cognitive interoperability starts here, and CPS implementing it would become CPSS, thus allowing seamless Human-CPS interaction and collaboration.

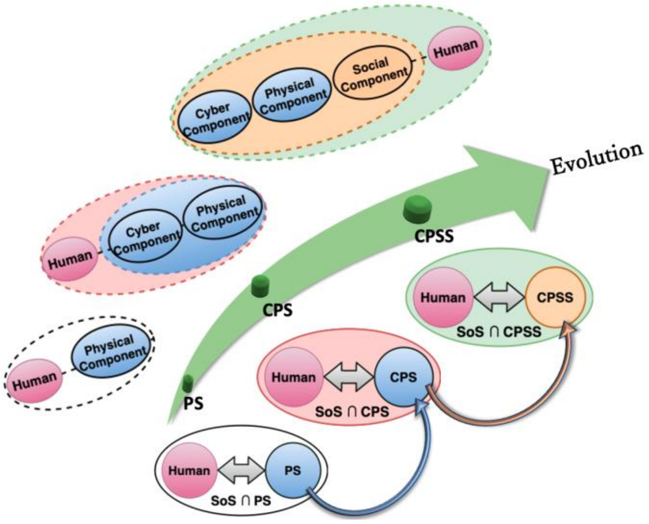

Figure 1: CPSS as a Cognitive SoS (Yilma et al., 2021)

This paper introduces cognitive interoperability as a prerequisite for human-CPS collaboration, defining the concept from related state of the art. We first recall what cognition means. Then, we summarize existing references to cognitive interoperability in the literature and give a definition in the CPE context. In the following, we review the different forms that takes machine cognition in Industry 4.0/5.0 systems, focusing especially on human-machine/AI collaboration and justifying the need for cognitive interoperability.

2 ABOUT COGNITION

Cognition is mainly about knowledge and understanding. Although it is a research subject by itself, we can refer to a well admitted definition used in human experimental psychology since years (Neisser, 1967): "*Cognition is all the processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used*". Those processes include in particular: attention, language, learning, memory, perception and thought[1]. As essential aspects of cognition, memorisation and the capability of learning allow to manage knowledge, reason on it, and take decisions.

Social cognition (Bradford et al., 2015), (Rusch et al., 2020) is required when entities want to interact together. Defined as an element of the Theory of Mind (Premack & Woodruff, 1978), it refers to the capabilities needed to interact with others. Social cognition involves complex brain processes, where an agent behaviour is driven by interactions with other agents. Understanding and recognizing others' actions is a key mechanism of social cognition. It is supported by low-level brain processes linked to the observer's own representation of the observed actions. This leads to the *motor resonance* mechanism in the observer's brain, where an observed action either interfere with the execution of a different action or leads to execute the same action. This in turn leads to the *perceptual resonance* phenomenon, which is the effect of an action on the perception of others' actions. These two mechanisms are key to reach attuned interactions, not only between humans, but also between humans and artificial agents as shown in (Wykowska et al., 2016). The high-level brain processes involved in social cognition are linked to perception: the perception of others' intention, and joint attention. The first relates to predict and explain other's behaviour, by inferring their mental states, e.g., beliefs, desires, and finally intentions. It is completed by recognizing patterns of action sequences, allowing to anticipate upcoming events or actions. Joint attention is "*the triadic coordination between at least two individuals and their focus of attention, wherein the individuals attend to each other and also to the content of their attentional focus, thus sharing attention*" (Wykowska et al., 2016); it is seen as an essential component to establish a common social context.

3 ABOUT COGNITIVE INTEROPERABILITY

There is not a lot about Cognitive Interoperability in the literature, but it appears under different forms since 2003. The first reference is probably in the military domain, related to human collaboration only. Referring to the C4ISR model, cognitive interoperability concerns the minds of participants and the sensemaking process resulting in decision-making, which involves perception, awareness, understanding, beliefs and values (Blad and Potts, 2003). It refers to a unity of mindsets, confidence/trust and mutual understanding based on shared education and values. It is understood as a human function and "*a state of mind that sets the foundation for cooperative and effective action.*"[2]. In the nearby domain of crisis management, (Kwon et al., 2011) studies the socio-cognitive aspects of interoperability to support communication and joint decision-making among multiple safety

[1] https://www.verywellmind.com/ what-is-cognition-2794982

[2] Brian, O. Cognitive interoperability – creating a joint state of mind. Technical report. https://www.academia.edu/28803917/Cognitive_Interoperability_creating_a_joint_state_of_mind

organisations. Those aspects concern the impact of human factors on all interoperability dimensions with issues faced by humans in this particular context, which have to be taken into account to improve communication and decision-making.

Referring to information systems technical interoperability in e-government, Cognitive Interoperability in (Goldkuhl, 2008) is a part of organisational interoperability related to the "*congruence in thought and perceptions*" or "*the human actors' way of thinking*".

In Geographic Information Systems, (Raubal, 2005) introduces Cognitive Semantic interoperability, arguing that semantic interoperability should build on the theories of *cognitive semantics* and *human spatial cognition*. This highlights that when sharing knowledge, because the meaning of terms is in people's heads, the mental models of both the sender and the receiver have to be mapped for a complete understanding.

In the human-machine interaction research field, semiotico-cognitive interoperability is presented in (Berthier, 2006) as the link AI seeks to establish between human and machine. Cognitive interoperability is limited here to virtual agent-to-agent communication using standardised languages and normalised means to translate between different knowledge representations, including ontologies. The term semiotico-cognitive interoperability is used especially for man-machine communication, where an artificial agent "*appears to behave in the same way as a human agent would in the same situation and, in particular, that (to a predefined extent) some meanings seem to be shared between the user and the agent*".

Globally, cognitive interoperability can be seen as a mean to align the minds of entities interacting together and a prerequisite for efficient cooperation. With this alignment comes a shared, mutual understanding and perception of situations, which is also a prerequisite for collaboration. In this sense, cognitive interoperability is implemented through social cognition (see previous section). When entities comprise artificial agents, this implies they have a human-like way of thinking and behaving, allowing them to act as pairs. In a CPE context, cognitive interoperability can be established when CPS entities are capable of social cognition, in a way that is as close as possible to the human way.

4 COGNITIVE INTEROPERABILITY AND HUMAN-ARTIFICIAL INTELLIGENCE

To implement social cognition, a CPS should embed some artificial intelligence. Cognitive Interoperability between humans and CPSs is thus closely related to human-AI collaboration.

In 2017, the concept of Cogniculture was introduced by IBM's researchers (Pimplikar et al., 2017), referring to the study of a system where humans and machines are considered as cognitive agents collaborating in symbiosis. Collaborative AI in this context considers the collaboration of such cognitive agents, including cooperation, competition, or coordination[3]. The resulting combination of human and artificial intelligence is referred as Hybrid Intelligence (HI) (Akata et al., 2020). This concept can be refined in Collaborative HI and Adaptive HI, referring respectively to the challenges of making AI systems capable of working in synergy with humans, and learn from and adapt to humans and their environment. HI thus shares research challenges with cognitive interoperability.

With HI aiming at reciprocity between humans and computer agents, authors identify a set of key challenges for Collaborative HI: understanding of humans by the AI system, a theory of mind for H-AI groups, understanding of joint actions and the implementation of social norms (e.g. reciprocity) by both Humans and AI systems, but also the need for multimodal interaction means for AI systems and machine perception of social and affective human behaviour. Taking a different perspective, (Zheng et al., 2017) introduces *Hybrid-Augmented Intelligence* (HAI), as the mixing of human cognitive capabilities with AI. Two approaches are distinguished to qualify existing works: human-AI collaboration ("*Human-In-The-Loop hybrid-augmented intelligence*") and Cognitive Computing systems, where a cognitive model mimicking the functions of the human brain is embedded in the AI (Cognitive Computing -based HAI). Authors highlight the complementarity of human and artificial intelligence: normalisation, repeatability and logicality of AI needs the creativity, complexity and dynamism of human intelligence to deal with difficult problems. While with HAI, human-AI collaboration is about complementarity, HI goes a step further calling for reciprocity. The second category of HAI, i.e., cognitive computing -based, could be an enabler for this.

5 COGNITIVE SYSTEMS, COMPUTING AND ARCHITECTURE

Cognitive interoperability relates to cognitive systems interacting together. Humans can already be qualified as such, but machines or CPS not yet. Embedding specific functions related to cognition into a CPS is a way to make it a cognitive system. In the following we review the related concepts and theories and highlight the expected characteristics of such systems, which CPS should acquire to support cognitive interoperability in CPE.

5.1 Cognitive Systems

Cognitive systems in their truly, human-like version, implement the Man-Computer Symbiosis paradigm, where the machine is not working for or in replacement of the human being, but in a collaborative or symbiotic way (Vermesan et

[3] https://researcher.watson.ibm.com/researcher/ view group.php?id=7806

al., 2018)). Particularly, they would be "*capable of human-like motivation, emotion, and personality, highly skilled and knowledgeable, and performing human-like reasoning and learning*". More generally, human-like characteristics in machines are expected to facilitate human-machine communication and mutual understanding, where humans can more easily interpret and predict machine behaviour. The similarities would allow humans and machines to socialize and establish a trust relation, thus allowing collaboration and partnership. Once again, this refers to social cognition, which we defined as an essential element of cognitive interoperability.

Cognitive computing and *Cognitive architectures* are enabling technologies for building cognitive systems. The latter are detailed in section 5.3. Cognitive Computing was presented as the next generation AI by IBM, as "*a computing paradigm where computing systems are no more deterministic, following their programming rules, but rather probabilistic, by learning, reasoning and adapting to a changing environment*". It materialises the concept of embodied cognition[4], which refers to embedding cognition capabilities in some (physical or virtual) entity with which humans can interact naturally. The focus is given on the ability of agents to become cognitive systems, i.e., able to *"observe, recognize and identify"* and able to *learn* and *improve themselves, to negotiate* in their interactions, and even *capable of empathy* (Sathi, 2016).

5.2 Cognitive Things

The Cognitive thing concept originates from the Internet of Things (IoT) research domain. It is a cognitive system implementing the cognitive computing principle, which is designed to augment human intelligence: with cognition capabilities and with which humans can collaborate and interact naturally (derived from (Vermesan et al., 2018)). As cognitive systems, cognitive things are objects *"empowered to learn, think, and understand physical and social worlds by themselves"* (Wu et al., 2014), in collaboration with humans. They are autonomous agents gathering data from their environment, making sense out of it to take decisions or helping their users to take decisions. They can learn complex tasks, interact with humans via natural interfaces (Sathi, 2016). For Cognitive Things to sense, observe, analyse and take decisions, they need different capabilities like speech (voice), hearing and listening, vision (visual recognition), motion (response and detection), text analysis (structured or not), data sources crawling, situation detection and identity resolution, up to emotion recognition and empathy (Sathi, 2016). Those capabilities allow in particular the integration of immersive technologies like Virtual, Augmented or Mixed Reality (resp. VR, AR and MR) (Vermesan et al., 2018).

Cognitive things are very similar to smart objects, which is a concept around for two decades originating from the ubiquitous computing domain (Kortuem et al., 2010). More recently, (Kaisler et al., 2018) define a smart object as an "*object representation that is computationally aware – meaning self-defining and self-reflecting, and, possibly, self-modifying/self-adapting*". A framework for designing smart physical objects is proposed in (Cena et al., 2017), and although it is defined for physical objects, it can be extended to virtual cognitive objects. Indeed, in human-object interaction especially, we can expect the same behaviour from virtual objects than from physical ones. Generally, cognitive things, as smart objects, would have the following properties. From intelligent agents, they inherit reactivity, proactivity, social ability and the ability to learn. Following ubiquitous computing, they are smart agents, able to perform intelligent task, because they *"perceive the quality of being effective in a given situation"*. They are autonomous physical/digital objects, having sensing, processing and networking capabilities, that can share information, collaborate and interact with their environment in a useful manner. According to the framework of (Cena et al., 2017), this can be summarized in five abilities attached to cognition or to interaction:

- Cognitive abilities: knowledge management, reasoning, learning
- Interaction abilities: thing-to-thing (object object) interaction, human-to-thing (human object) interaction

The ability to learn is an essential feature of smartness, but the importance of the interaction abilities is also highlighted. Indeed, smart objects adapt their behaviour (interaction modalities) in human-object and object-object interaction, to the humans, the objects and the context. Moreover, they have a social consciousness, giving them the capability to interpret social relationships and act in a social community, generating new relationships (Cena et al., 2017).

5.3 Cognitive Architectures

Cognition refers also to cognitive models or cognitive architectures grounded in psychology, cognitive and neuroscience theories. Such approaches exist since some time now, like the SOAR architecture and some others reported in (Vernon et al., 2007), or the LIDA model (Franklin et al., 2016). LIDA aims at providing a control structure for an autonomous agent, attempting to model minds and their cognitive processes: perception, attention, memory, emotion, decision making, action selection, etc. It conforms to different models of cognition, including embodied, situated and enactive cognition and builds on the action-perception cycle. LIDA-based agents implement the LIDA model, which defines different modules and processes, modelling a complete cognitive cycle, with: perception of sensory inputs, leading subsequently to attention, learning and action, generating an effect on the environment. In short, it relies on different kinds

[4] Grady Booch, presentation given to IBM 's Academy of Technology, March 23, 2016.

of memories, where knowledge extracted from observation of the internal and external environment can be stored, situational models that are built from those observations, learning mechanisms, and mechanisms for selecting actions and behaviours (see full description in (Franklin et al., 2016)). In addition to the development of software agents, the Java LIDA framework has also been successfully used for simulations in neuroscience studies. Today, cognitive architectures constitute a class of models that are probably the closest to human cognition. However, they are by themselves complex systems, like the phenomena they model, with related research still in progress after more than twenty-five years. But LIDA or others are certainly interesting candidates to give a "brain" to cognitive things, making a step towards cognitive interoperability.

6 THE PLACE OF COGNITION IN INDUSTRY 5.0

The 2020 report of the World Manufacturing Foundation on Manufacturing and AI (2020 World Manufacturing Report) highlights Collaborative Intelligence where humans and AIs collaborate. AI cognition is considered through six components: machine learning, knowledge representation and reasoning, automated planning, natural language processing, machine perception, and intelligent robots. From the human perspective, it is highlighted that AI can expand human cognition capabilities or taking it into account for tailored training and (re)skilling of workers. However, handling cognition from the generic perspective to enhance human-AI interactions is not done. Nevertheless, there are different approaches or technologies qualified with the "cognitive" adjective and that implement partially cognitive functions in industry 4/5.0 systems: *Cognitive Automation, Cognitive CPS (CCPS) and Cognitive Digital Twin (CDT)*.

6.1 Cognitive Automation

The automation (by machines) of tasks related to information processing or cognitive activities like, e.g., situation evaluation or decision-making, is referred as *Cognitive Automation* in the Control community (Thurman et al., 1997). More largely, referring to the automation of business processes, (Engel et al., 2022) gives a definition grounded in AI: "*Cognitive Automation refers to seizing ML for automating knowledge and service work to realize value offered by AI, which is based on implementing artificial cognition that mimics and approximates human cognition in machines.*" In the same paper, authors refer to a definition of cognition related to the process of developing knowledge and understanding.

6.2 Cognitive CPS

The Cognitive CPS (CCPS) concept is relatively new. (Khargonekar, 2019) presents a vision for it, where it is defined as a CPS that has cognitive functions and capabilities. Those can be programmed by design or be learned from interactions with other CCPS and humans. It is also referred in (Rahman, 2019), where the focus is given on establishing mutual trust in human-robot collaboration. More recently, (Oliveira et al., 2021) presents it as an autonomous cooperative system of CPS with a cognitive architecture enabled by AI, which can interact deeply with a physical system. Cognition here is a tool to move from controlled to autonomous systems that do not necessitate human intervention. The authors refer to the coupling with Digital Twins, who can play an important role in CCPS, allowing emulation and simulation to explore new operating modes and planning, and to diagnose and predict, without the need for the real system. This leads us also to the concept of Cognitive Digital Twin, which is also a recent research trend.

6.3 Cognitive Digital Twin

A Digital Twin (DT) is a holistic digital and virtual engineering model of a product or more generally a system. Different tools and technologies are available for developing high-fidelity virtual models (Schleich et al. 2017). They use different techniques, such as simulation and emulation, including distinct functionalities (McGregor 2002). Simulation capability of a DT is provided by a design of its environment allowing to approximate off-line the behaviour of the real systems to represent how the system reacts (Law, Kelton, and Kelton 2000). It can be thought as a "static feature" of the DT. On the other hand, the emulation refers to the capability of a DT to be synchronous with the real system, so as it behaves almost similarly to the actual behaviour of the physical system (Ayani, Ganebäck, and Ng 2018). Accordingly, this feature of DT can be thought as a "dynamic feature". An emulation model operates in a hardware-in-the-loop configuration to perform the same work of the physical system (Semeraro et al., 2021). It provides a closer replication with respect to the simulation model (Lee and Park 2014). The concept of Cognitive Digital Twin (CDT) was introduced to designate Digital Twins that are extended with AI processes and functions giving them reasoning, decision-making and autonomous acting capabilities. So far, in all works on CDT, these additional capabilities make CDT an *autonomous intelligent agent* as defined in AI (Russell and Norvig, 2010) (Maes, 1995) and Agent-Based Computing (ABC) (Luck et al., 2004) fields.

(Kalaboukas et al., 2021) describes CDT as able to reason on information they exchange (data), understand it and perform actions accordingly, taking into account the physical twin state and behaviour (self-awareness). There, Cognition is understood as "*the ability to understand context, reason on top of existing information, predict and optimize behaviour*", and the CDT model integrates services supporting each of these. CDT is presented as a necessary enabler for agile supply chains, fulfilling the need for synchronization, knowledge sharing, responsiveness, and optimization across the potentially complex network of actors. Thanks to its cognitive features, the CDT is expected to be able to detect different types of behaviours of the physical twin, for any combination of predictable and desired status, and predict impacts. The

CDT model, or profile in (Kalaboukas et al., 2021), is implemented as an ontological knowledge graph associated to status, behaviour, specifications, processes the DT is part of as well as API and optimisation services supporting the cognition process.

(Abburu et al., 2020b) considers three progressive levels of cognition augmentation for DT: *Digital Twin*, corresponding to the classical digital replica where isolated models of the physical twinned are created; *Hybrid DT*, where the models are interrelated allowing some prediction; and finally *Cognitive DT*, which has knowledge manipulation and problem-solving capabilities allowing to deal with unknown situations. The cognitive capabilities of the CDT include sensing, reasoning and self-learning, leading to continuous adaptation of structure and behaviour, and thus proactivity. In (Abburu et al., 2020a), the authors highlight that cognition functions enable understanding: they make sense out of data under uncertainties, generating knowledge that supports reliable decision-making or control. They formalise the cognition process as: inserting new knowledge, learning new models, better situational understanding, and action planning. This leads to challenges related to knowledge representation, acquisition and update, which are in fact classical ones in knowledge engineering.

6.4 Human-CPS collaboration and the need for cognitive interoperability

From section 4, we have seen that cognitive interoperability was tightly linked to human-AI collaboration. Specially in the industry 4.0 domain, the concept of Operator 4.0 (Fast-Berglund et al., 2016) has appeared some years ago, defining categories of augmented workers, where humans are assisted by different so-called smart technologies to facilitate or improve their work: "*Operator 4.0 refers to smart and skilled operators of the future, who will be assisted by automated systems providing a sustainable relief of physical and mental stress and allowing the operators to utilise and develop their creative, innovative and improvisational skills, without compromising production objectives*" (Romero et al., 2016). Part of these categories refers to integration of technological tools with humans: the super-strength operator, e.g. using exoskeletons, the Augmented Operator using some AR/VR tools, the Healthy Operator augmented with wearable well-being sensors and the Social Operator sharing knowledge through social networks. Here the technologies are simply used, and even when they have their own embedded intelligence and potentially cognition mechanisms, there is no dialog and no collaboration. The operator types concerned by collaboration and cognitive interoperability are the following: the *Smarter and Analytical Operators*, where AI assists in activity planning or data analytics; the *Collaborative Operator*, e.g. interacting with Cobots; and finally the special *One-of-a-kind Operator*, which refers to adaptation and personalisation capabilities needed to be added in technologies to be tailored for humans.

We list here the most common kinds of human-CPS interactions where cooperative or collaborative work would require a high level of mutual understanding between the entities, justifying a need for cognitive interoperability.

- *Human-Robot*: This refers to collaborative operators of Operator 4.0. Cobots, as robots made for collaboration with humans, should have a certain degree of autonomy and cognition capabilities. Although currently they have the autonomy but rarely the cognition, they should be able to adapt their behaviour to humans and communicate and act in a way humans can understand. This means capabilities of learning, reasoning, and autonomous acting, human-like or human-understandable interaction means (HMI), human-like actions (which humans can anticipate or understand), capability to explain behaviour, social capabilities…, i.e., enough capabilities for social cognition. Globally, the integration of cognitive abilities with perception and interaction abilities in robots remains a challenge for a meaningful human-robot collaboration (Castro et al., 2021).
- *Human-AI*: This refers to smarter and analytical operators of Operator 4.0, when human and AI work together in cooperative / collaborative problem solving and decision-making frameworks. For the AI, this implies having the following capabilities: reasoning, learning, autonomous decision-making, social capabilities (for teamwork), explainability of reasoning or decisions, i.e., enough capabilities for implementing Hybrid AI (see section 4).

The functions of the one-of-a-kind operator of Operator 4.0 should indeed be considered as inherent functions of the CPS entity as part of human-robot or human-AI collaboration. Finally, other kinds of human-CPS collaboration should end-up in one of the two categories above. For example, human-machine collaboration leads to transform a machine in a smart machine, embedding some AI, and depending on its functions, the requirements for efficient collaboration will be similar to those for human-AI or human-robot collaboration.

7 A PATH TO COGNITIVE INTEROPERABILITY

Implementing cognitive interoperability in a CPE is not trivial. The CCPS and CDT approaches (section 5) provide a basis, but which will need to be extended with concepts from cognitive systems (section 6). So far, implementations of CDT (Abburu et al., 2020b) focus on bringing capabilities for reasoning to twinned CPS, with enough self- and context-awareness to allow some autonomy in actions and decision-making. Current research coupling (C)CPS with (C)DT are still limited in that they focus on the twinned CPS only, without considering enough interactions with its environment. For Human-CPS collaboration, cognitive capabilities should include more as we have seen in the previous section. We can cite the following: (1) replicate human cognitive process, to facilitate understanding and anticipation by humans; (2) acting in a self-explainable way or provide explanations, to facilitate understanding; (3) using human-like interfaces to communicate (e.g. use talk, gestures, vision, touch...). Some works (Semeraro et al, 2021) make the hypothesis that a simulation environment that closely resembles the system and recreates its stochastic behaviour, is sufficient to generate the training data for an AI-based cognitive system. Such environment can be composed by a set of collaborative DTs representing the interoperating systems, where AI technology is used to enhance and train these CDs to correctly mimic the true physical realities as close as possible (including faults and rework situations). This approach can be extended to CDT if we assume the training set can also be representative of the cognitive functions. However, there will be a semantic gap (called reality gap) between the training dataset generated from the simulation/emulation of a CDT model and the actual knowledge that emerges from the different exchanged data in the real system. A possible solution to close this divergence of the simulation from the real behaviour of interoperable CPS could be to use adversarial deep learning methods, based on Generative Adversarial Networks (Goodfellow et al., 2014), able to generate new data from a given training set, with the same statistical characteristics. Such a trained CDT, able to generate cognition-induced behaviours, should be able to compensate or integrate the semantic gap of the knowledge emerging from the interoperation between Cognitive CPS (CCPS).

A Cyber-Physical Enterprise (CPE) may be considered as a System-of-Systems (SoS) (Weichhart, et al, 2020) including in particular CPSs, built on five basic capabilities (Boardman and Sauser, 2006): Autonomy, Belonging, Connectivity, Diversity and Emergence. Extending to a cognitive version, this would be a Cognitive SoS (CSoS), consisting of autonomous set of cognitive sub-systems. Sub-systems of a SoS may be considered as agents, capable of sensing their environment, plan actions and execute them in the environment. The environment typically reacts to these actions. Agents are independent and have their own goals they follow. Agents are evaluating their actions against these goals to see if a goal can still be reached. These agents might either be communicating directly to each other with messaging or might indirectly communicate with each other by placing signals in the environment. The loose coupling of agents in a CSoS should allow some unplanned cognitive behaviour to emerge, creating a collective intelligence. Might this be considered as a cognitive system-of-systems? This remains to be demonstrated. By establishing cognitive interoperability, the ultimate goal is the transition towards an overall cognitive system-of systems, optimized across all layers of a CPE.

From a systems engineering perspective, the notion of SoS was best described as an emergent system from at least two loosely coupled systems that are collaborating (Morel et al, 2013) (see Figure 2). The SoS principle dictates that the relationship between component systems is recursive as any system is produced by another higher system, answering specific requirements. For a dedicated project, the target system is the final produced system in this recursive loop.

Hence, (Yilma et al, 2021) postulate that a true CPSS should be the evolution of CPS devices as an independent system with the addition of a social component. As described in a part of the CPSS meta-model (Figure 2), this makes it possible for a new kind of CPSS to emerge as SoS from the interaction of these socially capable CPSS devices with humans as well as other non-human entities possessing a social component. By nature, the CPSS is indeed a CSoS, as the function of the social components is to implement cognitive functions allowing human-like behaviour of CPS. We thus propose the CPSS approach as a basis to establish cognitive interoperability in CPE.

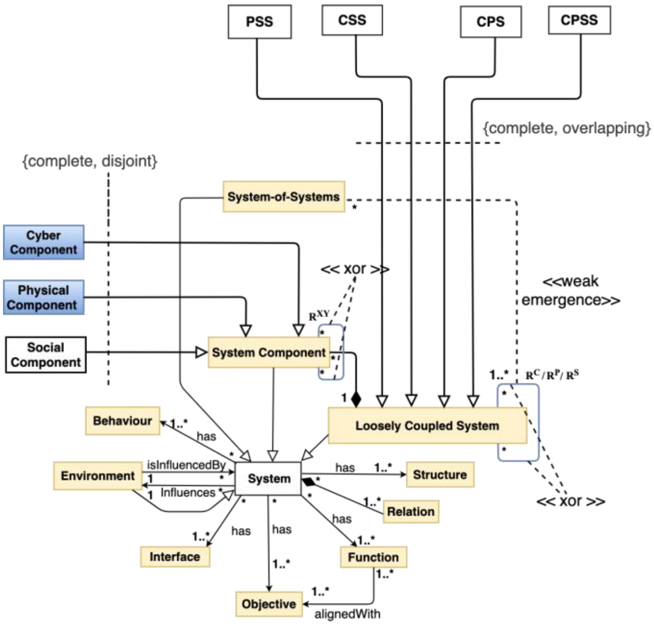

Figure 2: CPSS metamodel (Yilma et al., 2021)

9 CONCLUSIONS AND FUTURE DIRECTIONS

In this paper we have introduced cognitive interoperability in cyber-physical enterprises, giving background on cognition and different kinds of cognitive systems, focusing on industry4/5.0 approaches. We have made the link with human-cyber-physical systems collaboration and proposed a basis for the establishment of cognitive interoperability with cyber-physical-social systems.

Cognition and understanding are a first prerequisites allowing the machine to adapt its behaviour to the presence of humans (situation identification), and to individuals (personalisation). Then, having sentiments, compassion or empathy (i.e. emotional responses) leads to another level in the evolution of machines, which is related to anthropomorphism, a research topic in social robotics and Human Computer Interaction (HCI) (Duffy, 2003). Cognitive CPS and, by extension cognitive SoS (CSoS) are a big shift from CPS to CPSS as a mean to make interactions with CPS devices more anthropomorphic through the addition of cognitive functions (as social component of the CPSS). Hence, the "Social" part carries a broader meaning relating to complex emotional, cognitive and behavioural aspects. Although our focus is on human-CPS interoperability, it is worth noting that CPS interactions can also be with non-human entities. For instance CPS for animal care (Own, 2012), CPS for crop cultivation and gardening (Stepney et al., 2012), etc. Generally, capturing the full spectrum of the social cognition aspect in CPSS essentially means to amend the design of machines inspired by human-like cognitive functions which allow CPSS to detect, reason and adapt to the various needs of the interacting entities, supported by a mutual understanding and shared mindset.

In this era of digitisation, where virtual workplaces are becoming a common trend, the popular opinion, and fear is that machines will continue to take ever larger portions of human work activities eventually replacing us. Despite, the progressive changes especially in Industry 4.0 (and currently the so-called Industry 5.0), we are on track towards full automation, there are still a wide range of opportunities to reimagine digital workplaces in the context of human-machine collaboration. As opposed to a race against one another we can redesign these systems blending human-machine participation to perform far more efficiently than either could individually. The ultimate vision of the CPSS paradigm shares this notion of fostering a seamless human-machine collaboration by instrumenting the human and socialising the machine (Carrozza, 2019). Nowadays as more and more people are becoming users of wearables and sensory devices, the leap in the concept of "quantified self" opens opportunities to instrument humans by taking advantage of the humongous amount of collected data.

Although humans are still being instrumented for various purposes in the realm of CPSS, extrapolating true socio-cognitive dynamics for the socialisation of machines is yet to be explored. The future of CPSS will be the formalisation of its “social dimension” without necessarily trying to mimic the humans but conceptualising the relations that they can develop with a human in an interpretable and understandable way. At this point we can say that the lack of a common understanding and a comprehensive means of representing social aspects in CPSS are still issues.

Thus, opening opportunities for multidisciplinary efforts to gradually introduce socio-cognitive aspects in CPSS research is strategic for a multidisciplinary approach in the quest towards a true cognitive interoperability between CPSS and thus in the related Cognitive Systems-of-Systems.

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