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# An Ontological View of Components and Interactions in Behaviorally Adaptive Systems

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**Abstract** Cyber-Physical Systems (CPS) and Socio-Technical Systems (STS) are two popular paradigms for the analysis and modeling of engineering and social systems. These paradigms are complementary and particularly apt to model complex adaptive behaviors from both the component and system points of view. Notwithstanding historical and methodological differences, nowadays research in CPS and in STS converge to study similar system characteristics. The integration of expertise from both these domains can help to develop new approaches to study information- and human-centered systems like factories in Industry 4.0 and urban environments. To foster their integration, an overarching framework and a coherent conceptualization of adaptive systems must be put forward. This paper faces the challenge by the introduction of core distinctions, the characterization of the class of *Agent-based Cyber-Physical Social System* (ACPSS), and the development of an ontology-based framework. The paper builds on the traditional notions of component and interaction here re-elaborated from a domain-neutral viewpoint. The outcome of this analysis is proposed as a foundational basis to model behaviorally adaptive engineering systems.

**Keywords**: Cyber-physical system, Socio-technical system, Ontology, Interactivity, Agent.

## 1. Introduction

The term 'system' is used in all disciplines and research topics but the mere understanding of what a system is, has always been a challenge. Generally speaking, one starts from an informal use of the term taking for granted that its meaning is already shared and agreed upon. The term is indeed cognitively rich but hard to characterize, and essentially grounded in the idea of unity. However, the notion goes well beyond unity: a system is a unity composed of parts which are (inter-)connected by a variety of different relationships. Due to these relationships, a system may evolve in a variety of ways for internal and external reasons like the interaction across internal parts or the interaction with the environment. One can reverse the order of this analysis and say that a system is an ongoing process (a continuous change) whose characteristics

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evolve maintaining a sense of unity. It is easy to list examples since any discipline is rifle with systems: from biology (a human body) to natural sciences (a tornado), from engineering (an airplane) to geography (a valley), from astronomy (a galaxy) to mathematics (the number system as understood in constructive mathematics). One can further specify common intuitions at the theoretical level, like in cybernetics (Ashby, 1961), or at the practical level, like in urban planning (Hall and Tewdwr-Jones, 2010). In talking about systems, adaptability is a property of the chain of changes that the system undergoes over time. Not a single change but the history of changes manifests adaptability. This turns adaptability into an emergent property (emergent from the observer's viewpoint) grounded on the components' behaviors, from which the interest on behaviorally adaptive engineering systems. Note that the term 'engineering' in this paper is used quite broadly. It is not limited to designed systems as it comprises social and more generally evolutionary systems where, nonetheless, technology has a relevant role.

When one qualifies the notion of system with the idea of complexity, understood as the amount of information needed to describe it (Bar-Yam, 2002), the focus moves from the study of the system to the study of the class to which the system belongs. The notion of complexity can be interpreted also with a contextual twist when measured against the capacity to build a model of the system via available techniques: with the introduction of more powerful modeling techniques, the types of system that fall out of existing modeling capacities, and are thus complex to model and manage, reduces. No matter how one understands complexity in talking about systems (Van Dam et al., 2012), it is a fact that the modeling of complex systems remains a challenge.

To put some order in the variety of systems studied in science, distinct classes have been proposed. Here are a few of them characterized by high-level features. These classes are fairly common in the literature and do not form a coherent (ontological) classification because they concentrate on orthogonal features. For example, how a system comes to exist vs. what is its purpose. In particular, these classes are not mutually exclusive and a system may belong to several of them.

- *Natural system* (e.g. a valley). These are systems that exist essentially because of natural evolution. These systems do not need to be uncontaminated by the intentional activity of agents, yet they must have evolved beyond the purposes of those activities. For instant, a woodland which by natural evolution overspreads, to the point of incorporating, a disbanded railroad.

- *Organized system* (e.g. a painting, a Japanese garden). Systems whose structure is in large part the result of an intentional act to realize a design. The focus is on the overall structure, not on the realization of special or selected interactions among the parts of the system.

- *Artifactual system* (e.g. a candle carousel, a designed neuronal network). These are systems with components organized so to realize designed interactions. The difference with respect to the previous case is that here the intentionality focuses also on the interactions among the components of the system. If the component is an agent, then the agent is seen as a predictable entity, that is, its behavior in the system is constrained by the system's design.

- *Functional system* (e.g. a forest, the shop floor of a traditional factory). These are systems organized to perform some functions and whose design constrains the agentive components (if any) to behave according to (possibly tacit or implicit) guidelines and procedures. For example, the design of a traditional assembly line or transportation system establishes that a worker (e.g. a line worker or a conductor) has to behave in a given manner for the system to perform its function, e.g., deliver a service. Similarly, a nuclear power plant is organized to produce electricity and constrains the behaviour of technicians (among other components) in both standard and exceptional situations.

- *Agentive system* (e.g. an industrial robot, an office) These are systems that can perceive the environment, plan to achieve proper or given goals, and act according to these plans. They are the simplest systems that can be said to have intentionality.
- *Autonomous system* (e.g. a company, a city) These are systems that can decide how to behave on the basis of their internal status, goals and reasoning capabilities without direct external supervision or control. They can regulate the process of the interactions they initiate.

These are large classes often further specialized. For instance, functional systems can be refined by distinguishing degrees of autonomy. Generally speaking, by varying the degree of artifactuality and autonomy one spans the variety of functional systems. A fully artifactual functional system has the aim to implement just the desired interactions for as long as they are possible. A functional system which is fully autonomous, instead, is a system whose primary function is to realize its own goals (in other words, its identifying criterion is that it behaves to achieve all and only its own goals). Once the notions of component (Section 5) and of interaction (Section 6) have been clarified, it will be easier to see the limitations and usage of classifications like these. For the time being terms like component and interaction will be used informally.

As said earlier, this paper focuses on behaviorally adaptive engineering systems. It does so by driving attention to the interplay between two factors: technology and agentivity. These factors can be better understood comparing two well studied classes of systems, namely, Cyber-Physical Systems (CPS) (Derler et al., 2012; Lee, 2008) and Social-Technical Systems (STS) (Trist, 1981; Van Dam et al., 2012). CPS and STS cut across the previous classification of systems and have been investigated for more than 50 years providing a consolidated literature to rely upon. Research in CPS developed from engineering and cybernetics (the term CPS was introduced much later (Lee, 2015)) and research in STS from social sciences. These communities were interested in similar kinds of phenomena but put attention on different aspects. If one were to compare a traditional CPS model and a traditional STS model of the same factory, she would fail to recognize that these are models of the same factory. Today things have changed. The CPS and STS communities have understood that they need to be more inclusive in their analysis, their models now take into account features that where previously left out. This is evident even in the terminology they now use, the expression "social CPS" in the the CPS community, the term "materiality" (as a way to refer to enduring devices' features and capabilities) in STS. The research questions they aim to address remain different but this convergence suggests that both may gain from developing a stronger connection.

Today work on behaviorally adaptive engineering systems, and in particular among the CPS and STS communities, is hampered by the lack of a shared view (a conceptual framework) and a shared language (a way to identify entities and consistently refer to them). The presence of a shared view and language is a necessary condition for cross-fertilization and for the integration of techniques. To move forward one needs to rethink the topic perhaps via techniques devoted to foster interoperability. Ontological analysis, the technique adopted here, is one of them (Guarino and Welty, 2000).

The work in this paper differs from functional, structural and behavioral studies as its aim is a domain-neutral classification of the elements we use to talk about systems, namely, components (like natural objects, devices, agents, knowledge) and interaction types (like connecting, stabilizing, acquiring and exchanging). Ideally, once a common view and terminology is in place, a system model and its behavior analysis would be accessible to both the CPS and STS perspectives, finally leading to a better understanding of important features, e.g., adaptability and resilience in heterogeneous multi-agent multi-purpose systems like today's factories and cities.

Structure of the paper: Section 2 discusses three novelties that in the last 20 years changed the techniques to model behaviorally adaptive engineering systems. Section 3 isolates a class of systems, called ACPSS, that is central to the analysis in this paper and to the CPS and the STS communities. The next section, Section 4, shows that the increasing similarity in some CPS and STS works is not an occasional overlap of interests; the research aims of these communities push them to focus on an overarching systemic view and to identify same component and interaction types. This section justifies the need for a common view of behaviorally adaptive engineering systems. The study of a common view is initiated in Section 5 with the ontological analysis of the notion of component. The analysis of interaction is presented in Section 6, and an overall discussion of the results with indications of future steps in this research program is in the last section, Section 7.

## 2. Changes in System Modeling Frameworks

Complex systems comprise many features. Some are directly inherited from their components and others are ‘emergent’, the result of regularities from combined interactions. Partial reviews of these features and related modeling approaches can be found in (Bar-Yam, 2002; Horvath and Gerritsen, 2012; Newman, 2011; Trist, 1981). The modeling of these features has changed in the last few decades due to the introduction of new modeling techniques.

Roughly speaking, out of the three major approaches for system modeling in the late 1980’s, namely dynamical, logical and qualitative/statistical approaches, the last two were quite limited. Also, the models they could generate were too different to be interoperable, let alone integrated.[1] The modeler, given a goal and a suitable approach, was driven to model the specific views handled by that approach: behavioral patterns in dynamical models, structural and procedural rules in logical models, organization and actual interactions in qualitative/statistical models.

The application of the logical approach relies on a conceptual and cognitive analysis of the system aimed to decompose it into objects, properties, relations and possible states of the system. This is a demanding endeavour for the need to identify and combine general as well as contextual rules. Moreover, logical systems are brittle, and at the time automated tools for formal verification were not available. Where they fell short of the needs, as in urban planning (Friedmann, 1987), the practitioner took over (Schön, 1983) shifting from the problem-solving perspective to the integrated study of social, cognitive and action views. This allowed to collect qualitative and tacit knowledge about the system (Goffin and Koners, 2011; Zhang et al., 2016) at the cost of abandoning logical precision and automatic reasoning. The development of participatory design and the collection of new types of knowledge (social practices and narratives) led to separate organization and role modeling from individual agents’ perspectives, needs and expectations (Al-Kodmany, 1999; Calafiore et al., 2017).

In the 1990’s there have been three innovative changes in formal modeling: the exploitation of game-theoretic semantics (Hintikka, 1996), the development of multi-agent systems (Goranko, 2001; Osborne and Rubinstein, 1994) and the introduction of applied ontology (Guarino, 1998). Briefly, game-theoretic semantics introduced a new ‘dynamic’ interpretation of logical quantifiers, the core elements of first-order logic, which could now be understood as agents’ choices and more easily connected to ‘applied’ logics like knowledge, action and temporal logics. At the same time, specific formalism for multi-agent systems were growing (Goranko and Jamroga, 2004) including the possibility to explicitly model the perspectival knowledge of agents (van Ditmarsch et al., 2007) and the relationships between the capacities of agents and those of the coalitions they form (Borgo, 2007). Applied ontology brought a profound change in system analysis by providing reliable guidelines on how to identify and decompose entities (Guarino, 2009; Guarino and Welty, 2009) including general ontological frameworks for conceptual consistency (Borgo and Masolo, 2010; Herre, 2010; Mizoguchi, 2010). In short, applied ontology showed how to define, distinguish and classify entities in a domain-neutral approach. By adopting an ontological framework, one is driven to

[1] Attempts to take advantage of both qualitative and quantitative research approaches can be traced back to the 1980s under the name of Mixed Methods Research (Johnson and Onwuegbuzie, 2004).

consistently separate objects from the role they play in the system, and to identify components only on the basis of their essential features and capacities. The classification of regularities and changes across the components and their relationships is thus facilitated and, to some extent, built-in while model refinements and extensions are possible without disrupting previous modeling decisions. Even when one decomposes a system following different criteria, say by concentrating on structural features vs behavioral aspects, the resulting models are largely interoperable, if not integrable, provided both decompositions follow the same ontological framework. This makes possible to compare behavioral, logical, multi-agent and qualitative analyses of adaptive systems.

## 3. Adaptive Systems as A Subclass of ACPSS Systems

The first difficulty in modeling a complex system lays in the variety of components and of interactions it presents. Traditionally studies of CPS and of STS made different choices on what to concentrate upon. However, recently CPS studies have started to address explicitly human and social aspects (Frazzon et al., 2013; Horvath, 2012; Jiang et al., 2016; Liu et al., 2011; Pirvu et al., 2016; Wang, 2010) practically broadening the scope of their research. In a similar fashion, STS studies have enriched the analysis of work conditions and organizational environments by including the modeling of technical components and infrastructures. After all, the evolution of these impacts work practices and conditions (Baxter and Sommerville, 2011; Mumford, 2006; Van Dam et al., 2012). These changes, introduced as extensions of the traditional viewpoints, have not triggered a rethinking of the foundations of these research lines. Remaining within their historical views, the two communities do not yet see the benefits to start talking to each other.

Consider for a moment the area of Human-Computer Interaction (HCI) (Dix, 2009). In comparison, HCI is a relatively simple domain that focuses on the study of interactions between technological devices and humans. Like CPS and STS, this research has been influenced by the evolution of technology in the last few decades. Differently from CPS and STS researchers, people in HCI have recognized these changes and investigated how to understand interaction beyond or independently of technological changes (Dey, 2001; Dix, 2009; Goodman et al., 2011; Schmidt, 2000). The social turn in CPS and the increasing focus on technology in STS should spark an equivalent attention on reassessing systems and on classifying interactions. As a matter of facts, some attempts were made in the STS community (Clegg, 2000; Norman and Stappers, 2015) but these efforts are addressing the understanding of cognitive, social and economic aspects (the soft sciences) without questioning what is a system's component. The general goal of this paper is to drive attention to foundational aspects and to take steps towards the development of a new ontology-based approach.

One can take the ongoing convergence of CPS and STS modeling efforts as evidence that to model complex systems one needs to develop a framework for all *forms of interactions* across heterogeneous components and that, to build such framework, one has to *understand what components are*. When one starts concentrating on the study of components and interactions, she is led to identify a class of complex systems that is characterized by the presence of heterogeneous components and relationships. In (Borgo and Sanfilippo, 2018) these systems are called *Agent-based Cyber-Physical Social Systems* or ACPSS.

An ACPSS is an ontological object (that is, something existing according to the adopted conceptualization of reality) that endures over time in a process-like fashion and satisfies the following conditions:

(a) it can be ontologically decomposed in more than one way,

(b) it has parts of different ontological types like natural objects, software, robots, humans or non-human animals; and

(c) it can manifest relationships that vary in non-codified patterns. By this I mean that the ACPSS components instantiate interactions of different types (physical, biological, cognitive, functional etc.), and that the characteristics of the interactions themselves can evolve over time without necessarily forming a predetermined pattern (e.g. from independent to master-slave, from collaborative to conflictual, from individualistic to social).

Point (a), the existence of multiple decompositions, highlights that an ACPSS cannot be reduced to a single perspective, e.g. as the mere result of an assembly operation. Note also that by saying 'ontologically decomposed' one rules out decompositions that merely differ at the granularity level (as when comparing the model of an assembly that uses only elements in the bill of materials vs the model of the same assembly that refers also to sub-assemblies). This characteristic shows that to understand an ACPSS system one must embrace multiple paradigms like the structural, the functional and the behavioral views.

Point (b), the presence of a variety of component types, shows that ACPSS cannot be reduced to traditional assembly or multi-agent systems where the components can be taken to be all of the same type. Indeed, the variety of components (typically ranging from mere natural objects to human agents and organizations) is an important factor for the complexity as well as for the wide-ranging behaviorally adaptive capability of the system.

Point (c), the variety of and changes in the system's interactions, is crucial since complex adaptive systems tend to evolve beyond foreseen scenarios (e.g. agents' preferences, goals and actions cannot be fully predicted), and this forces to break the view of interaction as a fixed pattern. While the possible changes can be classified ontologically, the actual evolution of an interaction is contingent, influenced by the participants, the local organization, the feedback loops etc.

The distinctive characteristics of ACPSS modeling are:

(1) the recognition of the cyber-physical and agentive/social levels;

(2) the ontological distinction across natural, artefactual and agentive components;

(3) the correspondence, for each system decomposition, between the capabilities of the components (including subsystems), and the types of interaction to which these components may participate.

Given the ACPSS class of systems, one can put the basis for a general modeling perspective within which to develop methodologies and techniques for both the CPS and STS research lines. Ideally, by sharing the terminology and the ontological analyses of an ACPSS system, it becomes possible to integrate the models developed in CPS and STS studies. The first step in this direction is the classification of the core elements. Looking at the commonalities across CPS and STS and at their individual contributions, one should start from *component* and *interaction*, the general notions at the core of requirements (b), (c) and (3). Indeed, points (a) and (2) are part of the ontological foundation, and (1) is the distinguishing point that qualifies ACPSS as a specific subclass of the class of systems.

From the previous characterization, an ACPSS system is characterized by its components and their interactions. Yet, one could still raise two questions: why should these two notions (component and interaction) be central? and; why should these be the most central? I give two answers to these questions, one theoretical and one practical.

After twenty years of ontological analysis, a consensus has emerged on four classes: objects, events, qualities (or properties) and abstracts, see e.g. (Borgo and Masolo, 2010). These classes are at the core of most top-level ontologies in the literature today. Within a system it is preferable to talk of components instead of objects since the focus is on qualified parts (in some structural or functional sense) of the system. Similarly, interaction is more precise than event because one is concerned not with generic happenings, but with changes that occur to the system's components. Finally, the class quality in this context is used to further qualify components (e.g. in terms of features) and interactions (e.g. in terms of possibilities), thus it is strictly related to these. Finally, the abstract class is not included in our discussion as it collects things like numbers and sets. To sum up, while modeling in general may require to investigate all these classes at once, in the context of systems, and ACPSS in particular, the modelling activity starts from the identification of components and interactions. Recall that, ontologically speaking, information is a (non-material) object, thus a type of component in this view.

From the practical viewpoint, one can look at different characterizations of CPS and STS to verify whether component, interaction and (their) quality are the core ontological classes.

- A CPS in embedded systems is "an integration of computation with physical processes whose behaviour is defined by both cyber and physical parts of the system." and "a system composed of physical subsystems together with computing and networking." (Lee and Seshia, 2016)

  The definition identifies two types of things: computation and physical processes on the one hand, cyber and physical parts (and subsystems) on the other. In this view, cyber and physical parts and sybsystems are called components, thus in the embedded system view the notion of component is essential to CPS. A computation can be seen as a rule-based change of an information input or as a physical process on a physical input. In either case it is a functional interaction (possibly distributed) that typically includes also the receiver(s) of the result. Since processes are a type of interactions, the necessity to include interactions is also implied by this view. Finally, the other elements in this definition do not point at different notions: integration is either the state of being joint or the achievement of that state, thus a type of interaction; behavior is the interaction between an entity and other components (perhaps including the environment); networking is either the set of relational qualities holding across the components of the system, or the interaction with which those qualities are manifested.

- A CPS in Service-Oriented architecture "brings computation and communication capabilities to physical components to create intelligence on traditionally isolated and passive devices." (Lin and Panahi, 2010)

  This definition is actually focusing on devices and their properties since it refers to computation and communication capabilities (a quality of components), physical and passive components (types of components) and isolated devices (a relational quality of components). Regarding intelligence, it is here understood as a the capability to instantiate suitable (possibly coordinated) behaviors. This capability is a quality of components and subsystems, and falls within the functional reading of interactions (Mizoguchi et al., 2016).

- In the internet of things CPS are "embedded ICT systems where computation and networking are integrated with physical processes and they control and manage their dynamics and make them more efficient, reliable, adaptable and secure." (Borgia, 2014)

  This view is interaction-oriented. It focuses on computation and networking, here both forms of information interaction, on physical processes as well as on control and management, these latter two seen as combinations of computation and interaction. This definition includes also qualities of interactions like efficiency, reliability and so on.

The characterization of STS in the literature moves along the same lines:

- STS are "systems that involve a complex interaction between humans, machines and the environmental aspects of the work system" (Baxter and Sommerville, 2011) and have five key characteristics (Badham et al., 2000; Baxter and Sommerville, 2011):

(i) have interdependent parts;

(ii) adapt to and pursue goals in external environments;

(iii) have an internal environment comprising separate but interdependent technical and social subsystems;

(iv) their goals can be achieved by more than one means;

(v) their performance relies on the joint optimisation of the technical and social subsystems.

The first part of the description ("interaction between humans, machines and environmental aspects") is explicitly focusing on interactions and components, and the latter is the aim of the characterizations (i) and (iii). Points (ii) and (v) are about interactions and the goals (a qualified state) of the interaction or of the system. Having multiple ways to achieve a goal, as stated in (iv), implies that different interaction patterns may achieve the sought state.

◦ Discussing human performance and safety in STS, the authors of (Kyriakidis et al., 2018) state that "[l]arge sociotechnical systems are complex and interaction-dominated. They have multiple interacting parts in terms of variegated spatial and temporal scales and interaction between the parts hold primacy."

As discussed earlier, the notions of interaction, part (more precisely, component) and scale are central to the approach here proposed. A temporal and spatial scale gives a means to identify or select components and interaction frameworks, thus justifying the core role of component and interaction in system modeling.

Finally, due to the foundational focus of this work, I do not take into account all characteristics of CPS as discussed in, e.g., (Horvath and Gerritsen, 2012), which to some degree are also present in STS systems. In particular, I will leave aside local and global features like real-time information processing capabilities and the ability of learning from history and situations in an unsupervised manner, which are additional features to specialize the underlying notion of system. Instead, features like the hybrid structure of components, in particular due to the presence of heterogeneous agents, and the presence of different (e.g. built-in, sensors-based, and reasoning-based) knowledge sources, since especially important to capture interactions, have an important role in the discussion of adaptive multi-component and multi-agent systems.

## 4. CPS and STS as Converging Paradigms

In modeling one continuously struggles to cover new features or increase expressiveness, flexibility, and reliability of the models. Much attention in these years has been given to extend CPS to include human agents or even to cover some form of social level following recent interests in the so-called human-in-the-loop paradigm that has already influenced domains like industrial production (Jiang et al., 2016; Liu et al., 2011; Wang, 2010) and robotics (H2020Roadmap, 2016).

At the moment the introduction of human and social aspects into standard CPS models addresses limited goals and avoids disruptive modeling choices. The anthropocentric cyber-physical system model presented in (Pirvu et al., 2016) proposes a strong integration between physical, cyber and human components within the manufacturing domain giving an example of a domain-driven application of ACPSS systems. In (Frazzon et al., 2013) the socio-cyber-physical systems (socio-CPS) are introduced to exploit the full potentiality of CPS in production networks. Among the aims is the recognition of "the creativity, flexibility and problem solving competence of human stakeholders." In short, these socio-CPS are traditional CPS integrated with behavioural aspects of human agents. Features usually studied in (human) decision making, organization and knowledge management contexts (e.g., procedure and learning models, implicit and explicit knowledge) find now a place into CPS models. These extensions are conservative with respect to the standard view of CPS, and make no attempt to classify interaction types occurring in these social extensions of CPS.

A broader perspective is proposed in (Horvath, 2012) with the introduction of social-cyber-physical systems. The intuition is that social-CPS "should work, on the one hand, according to the expectations of humans, communities and society, and on the other hand, under the constraints and conditions imposed by the embedding environment." (Horvath, 2012, p.8). The ACPSS systems that I discuss in this paper differ from and generalize socio-CPS and social-CPS in important aspects: from the overt recognition of the co-presence of artificial and non-artificial (human) components, to the systematic analysis of components types and the interactions associated to them.

As seen in the previous section, the literature on STS talks about interactions between components (like humans and devices) or about collections of interrelated elements perhaps with a particular objective. These views are somehow more general than those in the CPS literature. Finally, I insist that one should be careful about imposing the existence of a specific goal on STS as these systems are only partially engineered and their goals, if present, depend on how we look at them and change with the evolution of the system itself. An adaptive system may change components and interactions as time passes so that to properly model the system and understand its behavior(s) one needs to know what kinds of component are present as time goes and what kinds of interaction the system can instantiate. For all these reasons, it is essential to first develop a framework of (actual and possible) components and interactions.

## 5. Systems' Components: An Ontological Classification

Foundational ontologies like DOLCE (Borgo and Masolo, 2010) provide guidelines and principles to distinguish and identify entities in a domain. These principles can be used to build a framework covering the ACPSS component types. The first distinction to introduce is between objects, events and qualities: objects are things that exist primarily in space (a machine, a tree, some oil), events are things that exist primarily in time (a computation process, a sport race, the signing of a contract), qualities are qualifiers of objects (e.g. color and shape) or of events (e.g. duration). Among the objects, ACPSS need to separate natural entities (e.g. mountains), artifacts (e.g. lathe machines) and agents (e.g. human agents, organizations) (Borgo et al., 2014).

These elements are constituents of ACPSS in two senses: they can be components of such systems (the structural view) and they can participate in what happens within these systems (the dynamical and functional views). Participation is better understood in terms of interaction: a given quantity of oil participates in an interaction (e.g. in a combustion engine) with its physical capabilities but a more complex object, say a lathe, may participate in different ways depending on the interaction type: a lathe is a production device when used to manufacture a product, it is a mere physical object when transported. (The two ways are not mutually exclusive.) A production device participates in an interaction with its physical and functional qualities. Instead, when it is transported the properties that count are only the physical ones like weight, size and resistance to impact. Technically, to make sense of this variety one introduces the role approach. In the examples, the lathe machine plays distinct roles: the active role of device and the passive role of transported object. Each role requires to satisfy some constraints: to be transported the object needs to be movable, to be used in manufacturing the object needs to have some engineering functionality. At each point in time a constituent of a ACPSS may play several roles depending on the interactions in which it participates. The distinction between the nature of a component and its role is essential for coherently developing structural, dynamical and functional models of ACPSS. Here the term functional indicates that the behavior of the component in the relevant interactions contributes to the realization of the focused behaviour of the system. For instance, the performing of a grooving operation by the lathe (a lathe's behavior) in a factory (a manufacturing system) contributes to realize the expected performance of the factory (a system's behavior). Thus, such lathe's behavior is functional to the factory system's behavior (Mizoguchi et al., 2016).

Since the analysis of ACPSS can be carried out at different levels of granularity, one can take some of these components as *atomic*[2] with the understanding that, changing perspective, these very elements may be further analyzed as themselves having components. A (production) factory, for example, is a complex artifact made out of smaller artifacts that are designed and arranged to interact in a certain manner. For modelling purposes, e.g. when focusing on consumption, one can ignore (in toto or in part) the internal structure of the factory assuming that only some machines or whole areas are relevant from this perspective. This is an example of filtering which is typical of *role-based modeling*.

Each technical artifact is the result of a design and is an object with boundaries, interfaces and capabilities. An example is the lathe machine. A regulation, namely an information object which is the content of some written text with a precise social status, is another example. Artifacts enjoy some kind of unity and their components and qualities are structurally arranged to satisfy design properties, allowing the manifestation of predetermined behaviours. For example, the components of a lathe form a topological whole that allows only some rotational and transverse movements, whereas the components of a factory form a whole from a different perspective (being located within a specific region and suitable for functional interactions).[3] Differently from artifacts, natural elements are not intentionally generated. The interested reader can find more information on the distinction between artifactual and natural objects in (Borgo et al., 2014).

The notion of agency, which is part and parcel of the view adopted in STS, is largely debated across disciplines like cognitive sciences, artificial intelligence and philosophy, where different characterizations have been proposed. In this paper I take an agent to be "a system doing something by itself according to certain goals or norms within a specific environment" (Barandiaran et al., 2009). In this sense, the agent is an individual (it has boundaries and an environment), is an active source of interaction, and its way to interact follows some regulations (which can be self-imposed). I specialize this view taking from (Russell and Norvig, 1995) the idea that interactions happen via specialized sensors and actuators, and that the capability to decide how and when to act is regulated by a decision module.[4] According to the definition, a lathe machine is an agent if it has sensors with which it acquires data (e.g., about the objects to be manufactured) and acts after elaborating such data, e.g., implementing feedback loops. (This gives the basis to qualify self-regulating and self-adaptive components.) People and higher-level animals form special types of agents to whom intentionality is ascribed.

When dealing with agents, in particular with humans, it is important to discuss how they make sense of a certain situation as this influences, and often determines, their behaviors. Here the notion of role helps to model social powers and properties that an agent may have in certain contexts. For example consider the CEO role: the CEO of a company has some rights (e.g., to have the keys of a specific office) and powers (e.g., to decide about a reorganization of the company). In social and production systems objects can play sophisticated roles as well. A car can be a taxi during operating hours and the driver (the person in charge of operating the car) can charge passengers (persons in the role of passengers) during those hours. The passenger cannot be charged for a ride in the same car when the car is not operating as a taxi. Roles are temporary and dynamic properties: one and the same individual can play several roles at the same time and a role can be simultaneously played by several individuals (e.g., the role of employee) (Masolo et al., 2004).

Finally, following (Bottazzi and Ferrario, 2009; Porello et al., 2014) I take organisations to be complex artifactual agents whose internal structure and behaviour are regulated by means of social norms, seen as

[2] Generally speaking, a component is considered atomic because of a modeling choice. That is, a component is atomic relatively to a perspective, namely, when from that perspective it does not have internal structure. This role-based view is ontologically consistent: given a system's behavior and a granularity, only some of the system's components are functional to that behavior (Mizoguchi et al., 2016).

[3] It should be clear from the example that factories, and ACPSS in general, may have only a partial artifactual nature: their actual state may be due to evolution and thus may not comply with a specific or explicit design.

[4] The notion of 'decision module' is here broadly understood: a piece of software in the case of software and robotic agents, a cognitive module in the case of animal and human agents.

constraints agreed across agent communities. Amongst the relationships presented in (Bottazzi and Ferrario, 2009), the most relevant for this work is that of *affiliation* linking an agent to an organisation via the role(s) it plays in it. For instance, John is affiliated to a company through his role of CEO. According to (Bottazzi and Ferrario, 2009), a fundamental distinction that characterizes organisations in opposition to general groups are the memberships conditions. More precisely, "[t]he agent who decides to become member of [...] an organization agrees to undertake all the rights and duties connected to the role that (s)he will play within the organization" (ibid.). Note that the work in (Bottazzi and Ferrario, 2009) focuses on intentional agents. Due to the larger focus of ACPSS and the broad characterization of agents in this paper, I apply part of that view to non-intentional agents as well. Part of the ontological analysis presented in this section is depicted in Fig. 1.

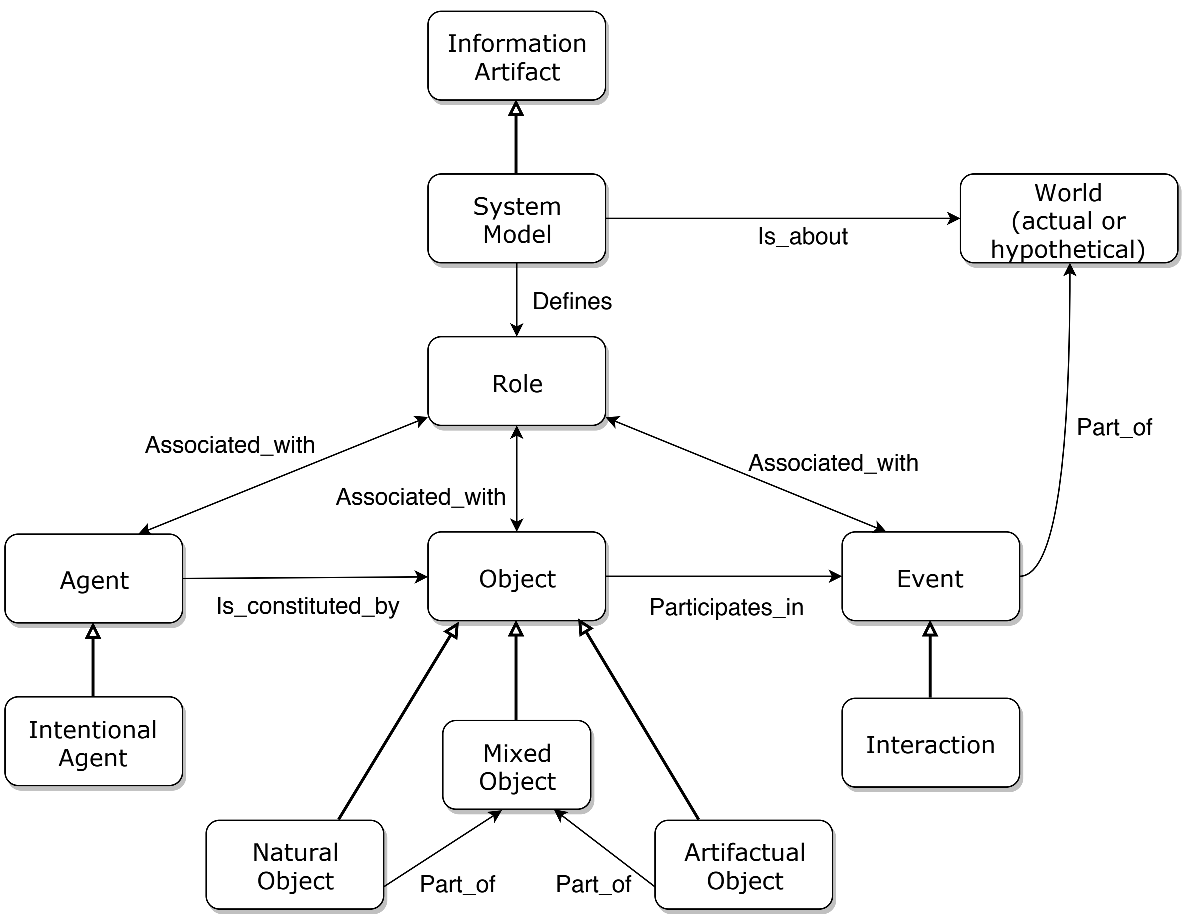


**Fig. 1. Section of the ontological categories and relationships holding between a system model and the fragment of the world it represents. Arrows without label stand for the subclass relationship (ISA).**

## 6. Interaction, Interactivity and Interactability

This section concentrates on the notion of interaction. In particular, I focus on how the components of a system contribute to the behavior and adaptability of the system determining its existence and persistence in time. This is an essential step to grasp and integrate the structural and dynamical views of systems especially when composed of heterogeneous sets of entities.

In the previous sections the term interaction has been used informally to refer to the case of entities that affect each other's behavior. It is time to fix the terminology to deepen the discussion. I define *interactivity* to be an event, something that happens between two or more entities when the behavior of one affects the behavior of the others (and possibly vice versa). Note that the behaviour of a component does not need to affect the others at each instant of the interactivity period. The intuition is that these components affect each other at least at some time during that period but that one has to consider the whole period to observe the interactivity. This notion is very close to the one proposed in (Janlert and Stolterman, 2017) with an important distinction. In (Janlert and Stolterman, 2017) interactivity is presented as an ongoing process. In (Galton and Mizoguchi, 2009) the distinction between events and processes is put forward as follows: an event is the God's view of the (possibly complex) series of changes that an object undergoes during a period of time, a process is the instantaneous change that the very same object undergoes as time passes. The process aims at the view of what happens instant after instant, the event at the global view of these changes. The process is best suited to focus on how a change determines the next one; to analyze the impact of the series of changes over a period of time, one has to look at the event. Note also that interactivity has no teleological nor agentive reading: interactivity does not require a goal or a purpose, nor agent's intentionality or a sense of use. In other terms, an interactivity is an event in which the behaviors of the entities participating to it are the results of the mutual influence among these entities. When there is interactivity among some entities, there exists a relationship among them that the interactivity makes manifest. Following (Janlert and Stolterman, 2017) I call this kind of relationship *interactability* and generalize it beyond the HCI domain. Thus the interactability, or better the network of interactabilities, of a system is one of the core notions this paper focuses upon. After all, interactability determines the extent to which a system can manifest behavioral adaptability. In the following I will use the generic term interaction to refer to interactivity and/or interactability when no confusion arises.

For instance, interactivity is manifested by two manufactured pieces that are securely joined to form an assembly: the movement of one of the pieces constrains the movements of the other via the existence of the joint, an interactability relationship. Similarly, interactivity is manifested at the cognitive level between a person and a chair when the chair is within the person's reach provided the person is aware of the affordance the chair provides (an interactability relationship at the cognitive level), and is thus influenced by it. The interactivity becomes physical when the person sits on the chair (realizing a different, since physical, interactability relationship). In this latter case the person adjusts herself on the chair which, in turn, reacts to the forces exerted. The latter example shows that interactivity itself can be specialized to *perspectival interactivity*. Perspectival interactivity is an interactivity seen from the point of view of one of the involved entities. The person perspectivally interacts with the chair (is affected by its presence) when she becomes aware of it. The chair perspectivally interacts with the person only when there is a physical contact with the person. This shows that different entity types may be associated with different perspectival interactivity types and that interactivity is not a symmetric relation.

The previous examples show that interactivities occur in different forms depending on the available interactabilities. Since ACPSS embed the multi-agent view, it is natural to classify interactability types by qualifying their participants and the capacities needed for the corresponding interactivity to happen. Here are some distinctions.

(I1) Natural interactability: this is the form of interaction that is manifested by objects because of their physical nature, e.g., the interaction between the river water and the river bed, and the interaction between a magnetic field and a positive particle. This interaction type is common to all physical systems.

(I2) Design interactability: this is the form of interaction that is manifested between non-agentive artifacts, e.g., the manufactured parts that compose an assembly like a table. The way in which the table legs and the table top interact depends on a variety of factors constrained by the design of the table components, e.g., their shapes, mass and other engineering feature. Similarly, a drilling machine gets electric power when plugged into a socket because both the machine and the socket have been designed to connect in certain ways and perform some functionalities while in that relationship. From this perspective, non-agentive artifacts interact on the basis of their designed characteristics.[5] This form of interaction is essential to CPS and to ACPSS as well.

(I3) Tool interactability: this is a form of interaction that is manifested between agentive and non-agentive artifacts. Here the notion of agent is quite general and includes artificial, human, animals as well as cyborg agents. The non-agentive components have the role of tools in this relationship. The interaction type is determined by the agent's capabilities and goals, as well as by the artifact's capabilities and functionalities: a person drives a van playing the role of driver with the goal of transporting goods by exploiting the car's functionality. Similarly, a software (agent) controls the house sensors and actuators (tools) to keep the house temperature and light levels within some range (goal).

(I4) Homogeneous agent interactability: this is a form of interaction that is manifested among fairly homogeneous agents (from both the physical and the knowledge viewpoints). These agents must have comparable perception systems with which to detect the actual situation, and similar (or shareable) interpretation of the situation, what I call the scenario. I emphasize that at the agent level there might be multiple concurrent interactions each determined by some roles the agents play. For example, two people in the roles of taxi driver and passenger, respectively, manifest an interactability type which is different from the one they manifest talking as supporters of a soccer team during the same period. These interactions are at the level of cognitive agents and the behaviours are determined by distinct social roles (if not by their agents' status). In the meanwhile the agents interact also at the physical level, that is, as physical objects. Analogously, there are different interaction types across non-human homogeneous agents.

(I5) Heterogeneous agent interactability: this is a form of interaction that is manifested between agents of distinct types, often across artificial, human, animals and cyborg agents. A largely studied scenario today is the interactability (and corresponding interactivities) between human and artificial agents, typically robots. This kind of interaction exemplifies in different manners and depends on the role of the agents. For instance, the interaction between a human agent and an industrial robot may occur at the cyber-physical level when they share the work space, or lack the physical level when they are kept in separate cells for, say, safety reasons.

What can one say of this classification of interactabilities? First, I distinguished natural vs design interactions making the basic distinction between interactions that are the bare result of physical laws and those that are intentionally planned. Note that every design interaction of physical non-agentive components is implemented via a physical interaction: using a welding machine to join two pieces one performs two interactions: the planned welding interaction and, as it happens following the natural laws, the welding physical interaction. The planned welding interaction answers the question 'why does the interaction happen?', the physical interaction answers the question 'how does it happen?' The third type (I3), that I called tool interaction, corresponds to interactions between agents and physical objects to intentionally modify reality in some way (in the non-human animal studies these are called 'tool use') and correspond to the notion of user function (Mizoguchi et al., 2016). Interaction types (I4) and (I5) introduce a different distinction that happens across agentive components. The distinction is raised to distinguish the agents' capability to understand a situation and thus to establish how to interact. Two agents with similar capabilities (homogeneous)

[5]These components may still interact in ways irrelevant to their specific design, e.g., they participate to natural interactions as defined earlier. Similar observations holds also for the other interaction types.

have a comparable understanding of the physical environment since they perceive it in a similar way. They have the capability to understand each other's standpoint even though they may decide to interpret the situation differently for, e.g., cultural reasons (Borgo and Blanzieri, 2018). Heterogeneous agents may lack this commonality, and one may identify and classify things that the other(s) does not even perceive, or not even recognize the other(s) as agent. The interactions that arise in (I5) cannot rely on a common understanding of the situation (and the agents might not be aware of this) and thus are quite different from those in (I4). Clearly, all these interaction types can be refined by considering other factors, e.g., the number of components participating in the interaction (Yanco and Drury, 2004). The complexity of the interaction can also be used to refine the interaction types. Similarly, one can introduce a distinction based on the agents' operational capabilities (e.g., communication, actuators, types of teams they can form, preassigned roles, e.g., master-slave, peer, bustander etc. (Goodrich and Schultz, 2007)). Note however that the number of components, the complexity of the interaction, and the operational capabilities are not ontological qualifications of the interaction itself and thus I do not investigate them here.

These latter observations help to extend the classification of agents of Section 5 by distinguishing agents' capabilities. There are different types of artificial agents with quite different capabilities to sense and model the world as well as to plan, execute and control what to do and how the world is being changed. Ontologically speaking, the focus here is on the capability type and not on operational constraints. The interaction between two artificial agents with different degrees of the same cognitive capability is a form of heterogeneity within the same homogeneous class. For instance, an agent may be able to form a model of the other agent while the latter may do only partially due to computational limitations. These subclasses are important to study interactivities in automated industrial scenarios as well as in traditional social systems, e.g., the social services devoted to people with different types of disabilities.

Finally, one may also distinguish between agents designed or performing in a way that is *transparent* to others vs. agents whose design or behaviour is opaque to others (in general or in the specific interactivity). An example of a transparent agent is a case-based thermostat, whose decisions are grounded on a set of explicit predefined rules (explicit because given in the instruction manual).[6] Examples of non-transparent agents, at least in interactions with human agents, are agents using artificial neural network (ANN) since "it is virtually impossible for a human to understand how they work and predict their computations and input-output behavior" (Strannegård et al., 2012).

Going back to interaction types, the environment is another factor that can further qualify them. From the ontological viewpoint there are two major dimensions to consider: location and resources. Here by location I mean the spatio-temporal region that hosts the interaction. For instance, in the case of physical interactions the location is a spatio-temporal location occupied by the physical agents during the interaction. In the case of information interaction (content exchange), the location includes a region in the information space of the agents which is affected by the interaction. In most cases the location is a complex combination of regions belonging to different spaces among which the physical, the information, the cognitive and the social spaces.

Regarding resources, I mention two cases: $(a)$ the interaction occurs because both agents want to use the same resource like in a production line where two agents are acting on the same working piece (the interaction is about the availability of the resource to the agent); $(b)$ the interaction occurs because the agents coordinate via an external object. The latter case can be exemplified by a device for remote meetings or for coordinating decision making. Here the focus of the interaction is not the device itself, which is more simply a means for the interaction, but the coordinated pattern of actions that the device allows to execute.

I have discussed interactabilities and interactivities looking at participants and intentionality. Another

[6] Some would not consider such a thermostat to be an agent. I use the thermostat to give a simple example but do not wish to take stock on this issue.

ontological dimension is the functional aspect of the interaction, that is, what the interaction is supposed to achieve when read from some perspective. In this case interactions are classified depending on the effect they have on the system (or subsystem) itself. The focus of this classification is the contribution of each interactivity to the system's behavior and thus, from this perspective, one analyzes basic interactivities as well as combinations of interactivities. For instance, pushing a switch in a control office is a simple interaction that has as effect the change of position of the switch. Combining the pushing of the switch with the interaction that the switch has with the cooling circuit system of a nuclear plant to which the switch is attached, is a complex combination of interactions that is associated to a broader behavior of the system. The pushing-of-the-switch interaction has a functionality and is part of a more complex interaction which has a different, yet related, functionality. Ontologically speaking, the engineering basic functionalities can be summed up as follows: collecting information (e.g. testing), exchanging information (e.g. communicating), changing the state of some objects (e.g. creating), modifying some quality of an object (e.g. trimming) and, finally, changing relative relationships among objects and/or their qualities (e.g. stabilizing). This classification is inherited from functional studies in engineering design (Borgo et al., 2018; Kitamura et al., 2007; Pahl et al., 2007).

## 7. Conclusions and Future Work

The convergence of research communities toward the study of behaviorally adaptive engineering systems is an important opportunity to join forces (theoretical understanding, languages, techniques, experiences, funding) and to set bolder research goals. This paper was motivated by the observation that the CPS and STS communities are developing common interests in modeling cyber-physical as well as human/social aspects. A discussion on how to foster interoperability across these research communities is needed. The isolation of the ACPSS class of systems (Agent-based Cyber-Physical Social Systems), introduced in this paper, marks a process that started more than 20 years ago with (*i*) the introduction of new modeling perspectives that benefited from logical, ontological and computational changes, and (*ii*) the transformation of the socio-technical systems with the pervasive introduction (in and out the work environment) of information devices.

I have proposed to ground the modeling of behaviorally adaptive systems on a new conceptual perspective built on top of an ontology-driven analysis. The core of the proposal is to start from the notions of component and interactivity. These are known concepts already exploited in modeling engineering systems but understood in different ways in different communities. I analyzed these notions afresh and proposed to interpret them from an ontological and domain-neutral viewpoint. In this way, a conceptual framework starts to appear based on the use of these terms with precise meanings which are: well-motivated, semantically clear, mutually consistent from the conceptual viewpoint, and independent from specific application concerns. Another result presented in this paper is a high-level classification of components and interactions (via more precise terminology like interactivity and interactability) as well as a discussion of interactions' participants, of the capabilities required for an interaction to occur, and of the teleological reading of interactions.

A series of issues need to be further investigated as the framework develops and becomes more inclusive. For instance, I have not provided a definition of system, even though the notion system for the class ACPSS is largely characterized in Section 3. I believe that to provide a definition of system one first needs an ontological notion of context, which I am currently studying. Also, it remains to be shown how to methodologically develop models from these bases and how to incorporate existing methodologies that are based on the multi-agent/multi-component paradigm. One should also verify the completeness and possible drawbacks of the proposed integration of engineering and social functions, including how these are connected to the interaction classes discussed in Section 6. Similarly, the paper has discussed just a minimal structural organization of ACPSS. To better tackle this issue, one needs to further develop the interaction framework and, in particular, to discuss how structure and interaction types affect each other at the ontological level. Many other points remain open. Nonetheless, the potentiality of the ontological approach can already be appreciated for the clearness and the generality of the framework and, hopefully, for the shown potentiality in applications.

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