Semantics for Cyber-Physical Systems: A Cross-Domain Perspective

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Abstract. Modern life is increasingly made more comfortable, efficient, and sustainable by the smart systems that surround us: smart buildings monitor and adjust temperature levels to achieve occupant comfort while optimizing energy consumption; smart energy grids reconfigure dynamically to make the best use of ad-hoc energy produced by a host of distributed energy producers; smart factories can be reconfigured on the shop-floor to efficiently produce a diverse range of products. These complex systems can only be realized by tightly integrating components in the physical space (sensors, actuators) with advanced software algorithms in the cyber-space, thus creating so-called *Cyber-Physical Systems* (CPS). *Semantic Web technologies (SWT)* have seen a natural uptake in several areas based on CPS, given that CPS are data and knowledge intensive while providing advanced functionalities typical of semantics-based intelligent systems. Yet, so far, this uptake has primarily happened *within* the boundaries of application domains resulting in somewhat disconnected research communities. In this paper, we take a *cross-domain* perspective by synthesizing our experiences of using SWTs during the engineering and operation of CPS in smart manufacturing, smart buildings and smart grids. We discuss use cases that are amenable to the use of SWTs, benefits and challenges of using these technologies in the CPS lifecycle as well as emerging future trends. While non-exhaustive, our paper aims at opening up a dialog between these fields and at putting the foundation for a research area on semantics in CPS.

Keywords: cyber-physical systems, Industrie4.0, smart energy networks, smart buildings

1. Introduction

Recent years have brought about accelerated developments in embedded networked systems such as the Internet of Things, communication technologies and information processing, as well as, as a side effect of these advances, their convergence to novel, complex systems generically referred to as *Cyber-Physical Systems (CPS)* [1]. CPS span the physical and cyber-world by linking objects and processes from these spaces. In a typical CPS, data are collected from the physical world via sensors while computation resources from the cyber-space are used to integrate and analyze the information in order to decide on optimal feedback processes which can be put in place by physical actuators. CPS have diffused and play an increasingly important role in a variety of (mission critical) domains and their infrastructures, including public transportation, energy services, and industrial production. Therefore, CPS are at the forefront of several national and regional research agendas [2, 3] and funding bodies[1,2].

In terms of the information processing aspect, an emerging concept in CPS research, and beyond, is that of a *Digital Twin (DT)*: the digital representation of a physical system, which dynamically reflects the sta-

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[1] EUs Digital Single Market Policy on CPS, https://ec.europa.eu/digital-single-market/en/cyber-physical-systems

[2] NSF Division on CPS, https://www.nsf.gov/funding/pgm_summ.jsp?pims_id=503286&org=NSF&sel_org=NSF&from=fund

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tus of this object thanks to data collected in real-time through sensors across the entire life-cycle of the system. The Digital Twin relies on the combination of several, heterogeneous, often dynamic data sources and should pave the way to analytics that support advanced functionalities – thus providing an excellent context for the use of Semantic Web Technologies (SWT).

Not surprisingly, the use of SWTs in settings that bridge into the physical space, have already been in the attention of our community ten years ago, for combining sensor networks with the Web [4] or augmenting products with a semantic description [5]. Since then, the application of SWTs has been steadily increasing focusing on entire systems (e.g., CPS), even in mission-critical domains. To this point, however, research naturally focused within the boundaries of concrete domains and research communities, for example, that of manufacturing [6, 7], electric grids [8] or buildings [9]. As a result, there is a lack of understanding of the commonalities and differences of applying SWTs in the CSP life-cycle, thus hampering the exchange of ideas between communities, the comparison of solutions and exchange of data e.g., by benchmarking.

With the amplified interest in CPS, this is therefore a good time to go beyond the boundaries of domain focused research communities, and to reflect on commonalities across them, such as:

- What are domain-overarching CPS *use cases* amenable for the use of SWTs?
- Which SWT *capabilities* can support CPS use cases best?
- What *challenges* were observed when applying SWTs in CPS life-cycle so far?
- What are *future trends* that will inform semantic research in CPS in the next decade(s)?

In this paper, for the first time to our knowledge, we aim to answer these questions by taking a cross-domain view on the applications of Semantic Web research for CPS. To do so, we build on an extensive study of the use of SWTs in smart manufacturing [6] and extend it with experiences in the areas of smart grids and buildings gathered in Austria's largest Smart City Living Lab, the Aspern Smart City Initiative[3]. Admittedly, we aim at focusing on a few key aspects of the topic and do not have the ambition to be exhaustive, but rather to establish a first dialog across researchers applying SWTs in different CPS domains.

[3]Aspern Smart City Research: https://www.ascr.at/en/

We start with a brief introduction of the three CPS-based application domains that informed this paper in Section 2, then discuss topics regarding semantics-amenable use cases, benefits and challenges of SWTs as well as emerging future trends in Sections 3 to 5.

2. CPS in mission-critical domains

We briefly introduce the three mission-critical domains on which we focus in this paper, we discuss the notion of CPS in these fields, and why SWTs are promising in these fields.

2.1. Production Systems (Industry4.0)

The manufacturing sector is currently facing a number of challenges including shorter time to market, increased product diversification and customization, highly flexible (mass-)production while ensuring high product quality and improved production efficiency. Several initiatives around the world aim to address these challenges by modernizing industrial production: *Industrie 4.0* [10] in Germany, the *Factory of the Future* initiative in France and the UK [11] or the *Industrial Internet Consortium* in the USA.

Core to these initiatives is the focus on increased digitization of production systems in factories and of production processes. These digitization efforts lead in the first phase to the upgrade of traditional factories to **cyber-physical *production* systems (CPPS)** as well as a digital representations of the CPPS through their corresponding digital twin.

Industrial production has several characteristics that make it an attractive application area of *Semantic Web* research. First, it is a *knowledge and data intensive* domain: the engineering of products as well as of the factories that produce them rely on complex engineering knowledge; large data sets are handled both during the *engineering* (e.g, a factory may be described by tens of thousands of signals) and *operation* of CPPS (e.g., logs of the production process). Second, the engineering of complex mechatronic objects, especially production systems, is increasingly driven by information models that enable representing different aspects of the produced system [12]. To that end, a range of IEC/ISA standard information models are adopted during the engineering of factories. However, these standard *information models lack a formal semantics* that would make them amenable to automated processing. Third, data exchange standards, such as SysML and

AutomationML [13], provide standardized schemas to represent engineering information and as such address syntactic heterogeneity across engineering disciplines, but again they *do not address semantic heterogeneity* of the data encoded with them. Therefore, challenging tasks according to [12] include: model representation, model transformation, model integration, model consistency management and flexible comparison of components, as detailed in Section 3.

2.2. Energy Systems (Smart Grids)

Smart Grids, also referred to as **cyber-physical *energy* systems (CPES)** [14], are intended to be the next evolution step of the traditional power grid and are characterized by a bidirectional flow of information and energy [15]. One of the main drivers for this trend is a paradigm change towards a more sustainable energy supply by using renewable energy resources (also known as *'Energiewende'* - i.e., energy system transition). This fundamental change influences the whole value creation chain in electric power systems as well as the operation of the underlying energy infrastructure. In order to manage the volatile nature of renewables, smart grid solutions are highly depending on advanced automation and control concepts as well as elaborate information and communication technologies. The complexity of applications offering new services, such as demand response, load shedding and shifting [8] is steadily increasing. Various controllers, actuators, sensors and measurement units connected to devices from different stakeholders have to work together with supervisory control and management (SCADA) systems, often in heterogeneous environments [16]. Furthermore, due to the coupling to ICT networks, the energy markets are switching from a consumption-oriented towards a production-oriented paradigm with the ability for dynamic pricing as well as offering flexibility as a service [17] to improve the economics and reliability of the power grid.

This increased complexity, heterogeneity and automation of the energy grid brought about by the *Energiewende* requires adequate digitization, i.e., thorough digital twins. Electric digital twins could enable planning, operation, and maintenance of grids based on a set of information models. For instance, it will be possible to plan how to integrate new components and controls in the daily network operation business considering different steps of operation, e.g. the planning process or the daily field work. In addition, digital twins could offer a solution to dealing with sensor data - created as a side effect of decentralization and renewables - which is complex to manage and exchange.

In the context of *'Energiewende'*, Distribution System Operators (DSOs) are faced with the challenge to optimize costs through advanced monitoring and prediction capabilities [18]. There is only one physical power grid, but a typical DSO maintains a variety of network related information models - each associated with a different enterprise domain. Each of these information models exists in silos - with its own data format and team of experts to manually maintain the data [19]. SWTs are candidates for representing and managing these heterogeneous models.

Electric digital twins enabled by semantic technologies are already available for high voltage grids because these grids contain a relatively small and static number of devices. It is therefore feasible to semantically describe these devices and manage this static digital twin [4]. There is also an abundance of domain vocabularies for modeling power grid information. For example, the Common Information Model (CIM) is a UML model for describing power system resources such as energy management systems, SCADA systems and power system topology. It can therefore act as a domain ontology for digital twins in the energy sector. While CIM ensures interoperability in power networks, IEC 61850 aims to improve interoperability between so-called intelligent electronic devices.

In low-voltage grids, however, both the number and diversity of devices is much higher than in high-voltage grids thus making the application of SWTs more desirable, but at the same time also more challenging. Therefore, medium-sized DSOs which are in charge of low-voltage grids, are still at the beginning of the journey of mapping their infrastructure to a coherent electrical digital twin, and providing a promising application area for SWTs.

2.3. Building Management (Smart Buildings)

Residential and commercial buildings are the third main sector of final energy consumption besides industry and transportation. Key to sustainability in this area are *cyber-physical systems* in the form of networked automation systems, also known as *building automation systems* (BAS). While BAS provide technological means to increase energy efficiency and preserving comfort, a recent trend is the evolution of build-

[4] https://new.siemens.com/global/en/products/energy/energy-automation-and-smart-grid/electrical-digital-twin.html

ings towards so-called *smart spaces*, in which humans and technology-enabled systems interact in open, connected, coordinated and intelligent ecosystems [20].

The need for information modelling and integration of heterogeneous data is present in several aspects of smart buildings and has evolved with the domain itself. The development of BAS over the years lead to a heterogeneous landscape of networking standards, technologies and proprietary BAS solutions. Deployed BAS solutions are often specialized for a distinct field of application (i.e., trade) in a building which makes it necessary to deploy more than one technology within an installation of a single building. Today, these subsystems cannot be considered functionally isolated and efforts must be made to allow information exchange across them. These efforts include the creation of data models and interfaces (i.e., digital twins). A recent survey shows that SWTs, and in particular ontologies, are extensively used for information modeling for building automation to describe automation devices and their functions, and how these models are structured [9].

Another active area of research is ensuring interoperability between different BAS standards. Within this context, *OPC Unified Architecture* (OPC UA, IEC 62541) is one of the most important standards supporting the modelling of engineering and runtime data through an object-oriented approach, where information is modelled in form of nodes carrying attributes and references linking the nodes. For technical equipment in buildings, also more specific models and taxonomies are used, for example *brick schema* [21] or the *project haystack* [22], some of which already rely on SWTs such as RDF, to facilitate some level of integration across standards.

The advent of the *digital building* and *Building Information Modeling* (BIM) further increased the importance of modelling engineering and runtime (operational) data as well as the relation between them in the form of a digital twin. To that end, several industry standard data models were developed, such as Industry Foundation Class (IFC) or BIM. A recent trend is that this models evolve towards being increasingly compatible with each other, making it easier to integrate across systems that use these diverse standards for describing engineering data. SWTs can play a pivotal role for facilitating this integrated use of the models by relying on techniques such as ontology-based data integration or ontology matching.

3. Where can Semantic Technologies help?

In this section we provide a (non-exhaustive) list of use cases, valid across the three domains discussed above, where the application of SWTs is promising. We derive these use cases based on experiences of the authors team in these domains and illustrate them with concrete efforts that apply SWTs in each use case.

Fig. 1 captures a simplified view of the CPS life-cycle across two main stages, namely (1) engineering and (2) operation and maintenance. In each phase, we distinguish between the physical and the digital space. The physical space covers the concrete, material system both while it is constructed (engineered) and then, after commissioning, where the CPS is operated and maintained. The digital space depicts the main information models at each life-cycle stage and the use cases related to these data models, as described next.

3.1. Engineering

The engineering of a complex CPS (a smart factory, smart building, or smart grid), is typically performed in multi-disciplinary settings, where (engineering) experts with different expertise collaborate towards creating an *Digital Model* of the CPS according to which the real-world CPS is then built as part of the *deployment* process. Such multi-disciplinary settings are characterized by the need to support this collaborative effort towards (1) integrating heterogeneous engineering data models into a single, complete and consistent digital model; (2) ensuring the consistency of this model; (3) supporting meaningful modifications of this model through artefact reuse. Accordingly, there is an opportunity to use *Semantic Web technologies* to support these tasks, as follows:

Engineering model integration aims to bridge semantic gaps in engineering environments between project participants (and their tools), who use heterogeneous local terminologies. Therefore, a key challenge here is addressing this heterogeneity by aligning, and subsequently integrating engineering models (e.g., ontologies), at conceptual and/or instance level. This integration is a prerequisite for supporting the analysis, automation, and improvement of multi-disciplinary engineering processes that rely on this data. Model integration is also necessary for creating discipline-crossing *Engineering Tool Networks* that enable interacting appropriately within an engineering network covering different engineering disciplines, engineers, and engineering tools.

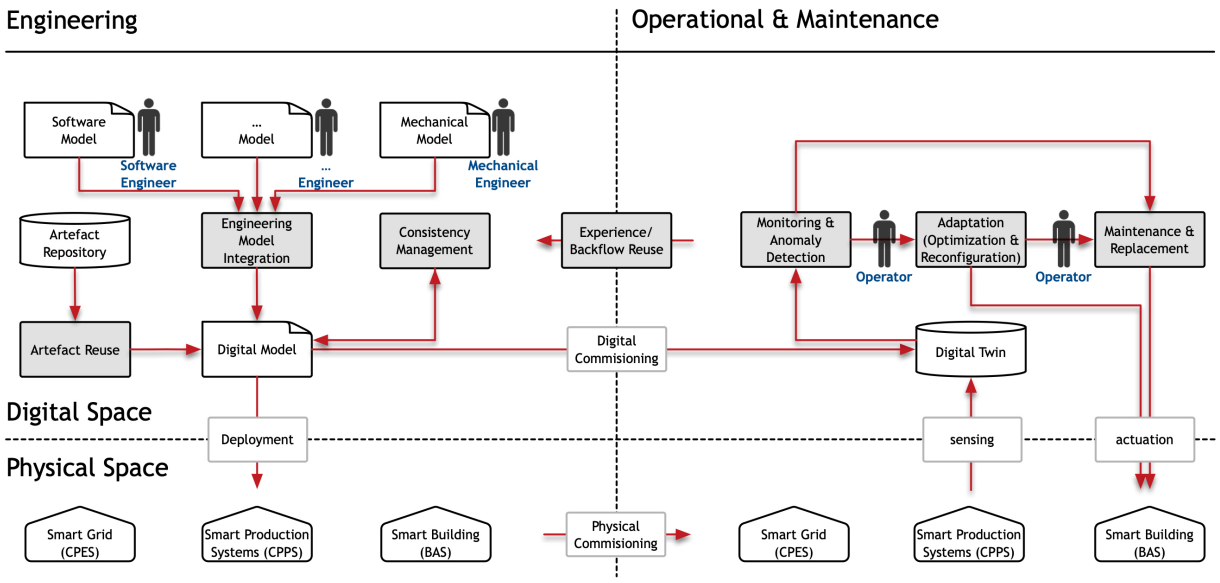

Fig. 1. Use cases amenable to the use of Semantic Web Technologies in the lifecycle of a Cyber-physical System.

In the area of production systems, ontology-based data integration methods are widely used to integrate engineering models [23] and, more recently, Knowledge Graphs in combination with probabilistic soft logic were proposed for addressing this task [24].

In the area of smart buildings, there are ontologies available for different engineering domains. However, [25] states that interoperability and improved interaction processes among different domains are crucial for building engineering. [26] introduces an approach for aligning these ontologies. In [27], an ontology is introduced that is compliant to the commonly used ones in the context of building engineering. In [28], a tool chain for a systematic engineering of BASs based on the *BASont* (cf. [29]) ontology is presented. A knowledge-based engineering approach for automation systems combining OWL and AutomationML is further introduced in [30].

To support the engineering of smart grids, an ontology matching process is proposed to align data models of the broadly accepted smart grid standards CIM and IEC 61850 [31].

Model consistency management refers to the task of detecting defects and inconsistencies in the digital model, including models of individual engineering disciplines as well as across interrelated models from diverse engineering disciplines. In smart manufacturing, SPARQL queries are used to check for inconsistencies across engineering models integrated by using RDF [32] or OWL [33, 34]. The *AutomationML Analyzer* tool relies on *Linked Data* principles to provide an interface for browsing and query-based consistency checking of integrated engineering models [35]. A recent trend is using the Shape Constraint Language (SHACL) for consistency checking of engineering models as demonstrated by [36].

In the smart building domain, different types of models are used, e.g., architectural models, models for technical equipment and functional models. Currently, several projects are conducted that focus on the consistency checks among different models, to guarantee a well-working building automation system. In the context of building construction, an environment for semantic rule checking of building models is introduced in [37], while [38, 39] present an ontology-based approach for conformance checking in construction.

Flexible comparison for artifact reuse has a focus on knowledge reuse within engineering organizations. The main tasks are the identification and preparation of reusable system components within or at the end of an engineering project, and the selection of such components within engineering activities. Here, the focus is on the required evaluation of component models to decide about the potential usability of the component within a CPS. To support the problem of parts exchange in an evolving manufacturing system, in particular, checking the compatibility of the old part and the new part, Feldmann *et al.* [32] propose translating SysML models into OWL ontologies and exploring the formality of OWL for checking compatibil-

ity constraints expressed in terms of SPARQL queries. SWTs were also used to enable flexible comparison among products and production processes during product ramp-up in order to identify a suitable production process at a target site which enables producing a product with the same quality as at a source site [40].

The design phase of the building automation systems is supported by the comparison of devices and the automatic evaluation of their interoperability. This is enabled by ontology-based device descriptions which enable detailed and semantic modelling of both hardware and software device characteristics [41]. [42] introduces a semantic framework to foster interoperability during design and construction work of buildings.

3.2. Operation and Maintenance

The transition from engineering to the stage of operation and maintenance is marked by the commissioning of the CPS: at the physical level this includes activities related to putting the system in operation (e.g, transporting and installing a previously engineered production system); at the digital level, the digital model is, ideally, also passed to the operation phase (note: in reality, the digital model is often not shared with the stakeholders in the operation phase).

During the operation (run time) of a CPS, information is collected through *sensing* about the functioning of the system through various sensor streams. For example, in a production system, information about the materials used, the current process, the position of the industrial robots can be recorded. Similarly in smart grids, active and reactive power in the distribution grid is typically recorded. This dynamic information complements the "static" digital model created during engineering and results into the *Digital Twin* of the CPS, which enables a variety of use cases that could be supported by semantics, as follows:

Monitoring and anomaly detection focuses on the acquisition and interpretation of dynamic system data with the goal of the early detection of anomalies or faults in the system operation. For example, in smart factories a constraint- and reasoning-based approach has been proposed to identify those production processes where too much material is used (in comparison to quotas defined at engineering time) for creating a product [43]. In smart grids, reasoning on streams collected from distribution network field devices (e.g., battery energy storage systems) helps identify voltage levels that are defined as dangerous by operators through a rule management interface [44] in a realistic settlement at the *Aspern Smart City Research*. Temperature readings are monitored at gas turbines during their operation in [43].

Reasoning about fault propagation in building automation systems is achieved by means of a BAS knowledge base and building information models [45]. Therefore, the BAS knowledge is enriched with causal relations between building components and data points in such a system. These causalities can be automatically derived from a set of defined rules. In the context of building operation and facility management (FM), semantic models play an important role. [46] presents an approach for BIM-based facility management by semantically linking BIM information with FM information. In [47] the efficiency of buildings and comfort parameters for occupants is monitored.

Maintenance and Replacement Engineering focuses on finding and replacing faulty components, potentially after an anomaly detection phase. This use case requires the combined use of *dynamic* run-time data (for detecting anomalies) and *static* engineering data about the structure of the system (the Digital Model) and the characteristics of the faulty component that needs to be replaced. Device exchange in the context of power plants was considered in [48] with a solution based on the AutomationML language.

Adaptation through optimization and reconfiguration is the "*ability of the CPS to achieve an intended purpose in the face of changing external conditions such as the need to upgrade or otherwise reconfigure a CPS to meet new conditions, needs, or objectives*" [3]. We distinguish different levels of adaptation. *Optimization* changes the system behaviour through control if operation conditions change: if some condition is not fulfilled, then there is an actuation action (e.g., reduce temperature) of operations in a factory, or of the building. *Reconfiguration* is a more advanced notion of adaptation, where the system set-up changes to respond to new goals or external factors. For example, the run-time flexibility of production systems in order to produce new products, requires the integration of advanced knowledge about the production system and the product within the production system control at production system run time to enable the use of advanced techniques such as configurators [49].

In building automation, the *smart control ontology* (Colibri) follows a service-centric approach for modeling data and functionality [50] and is used as basis for the generation of optimization problems. By enabling the modeling of context information including building structure, devices, and appliances as well as

energy-related information and smart grid interaction, situations like the influence of actuating devices and their control services on certain building zones can be described. [51] introduces an ontology of an information system for energy-related use cases in buildings. An ontology for smart grid interactions with Building Energy Management Systems (BEMS) to optimize end-user consumption is built in [52] where models for communication technologies, interaction between stakeholders and grid structure are addressed.

A use case that spans both the operation and engineering phases of CPS, concerns enabling **backflow from operation experience to improve the engineering of similar CPSs**. The goal is to bring back operation data and analysis results from operational systems into the engineering environment in order to improve the engineering of new systems based on experiences with the performance of already built systems (e.g., frequent defects and affected devices). This knowledge intensive use-case has been only addressed to a limited extent with approaches from model-driven engineering in the area of production systems [53] and it could be very interesting for the application of SWTs.

4. Lessons learned from the application of Semantic Web technologies

4.1. Benefits of Semantic Web technologies

The following SWT capabilities were perceived as beneficial during their application in the CPS life-cycle in the various application domains:

- **Formal and flexible semantic modeling with ontologies** refers to the capability of explicitly capturing a universe of discourse. Unlike other (semantic) modeling approaches (e.g., UML, SysML), Semantic Web knowledge representation languages offer unambiguous, *formal*, model-theoretic semantics that enable reasoning. Additionally, the ability to evolve an ontology on the schema and instance levels at run time, a characteristic called *agile schema development*, provides a high degree of *flexibility* [54]. This capability is at the basis of all semantic-enabled use cases. Indeed, ontologies have been used to represent a variety of engineering knowledge [7, 9].
- **Intelligent, web-scale knowledge integration** is enabled by ontology matching, Linked Data, and ontology-based data integration techniques. This capability addresses those use cases where the heterogeneity of engineering data requires model and data integration solutions. In particular, ontology-based data integration is a a widely-used approach to integrate engineering data [23].
- **Quality assurance of knowledge with querying and reasoning** support data validation and consistency checking both during CPS engineering (e.g., model consistency management) and operation (e.g., monitoring and fault detection). The formal semantics of ontologies and links between ontology concepts and instances (e.g., owl:sameAS) enable quality assurance tasks such as consistency checking (e.g., through reasoning, SPARQL constraints) or data validation (e.g., with the emerging SHACL constraint language).
- **Browsing and exploration of distributed data sets** is enabled by Linked Data technologies that offer user-friendly browsing and exploration of distributed data sets, some of which might have been already integrated previously, such as in [35]. In the context of engineering applications, this capability can be used to efficiently browse and explore both engineering models internal to an organization and external data sources, such as Web resources coming from third-party providers, supporting, for example, artefact reuse.

4.2. Challenges in using Semantic Web technologies

As discussed above, SWTs are a good match for addressing the aspects of heterogeneity in CPS life cycle due to their capability to integrate data intelligently and flexibly on a large scale. Yet, some requirements and assumptions of CPS are fundamentally different from typical Semantic Web application areas, which focus on the better integration of Web-scale data and knowledge. This leads to a number of challenges when using SWTs in CPS engineering and operation.

- **Lack of knowledge acquisition interfaces** that are easy to use by engineers is a major challenge for the adoption of SWTs and has only be mitigated with partial solutions. For example, widespread engineering tools or modeling languages (e.g., SysML, SysML4Mechatronics) are used as a “front-end" to acquire engineering models and these models are then translated into ontologies, on which reasoning is performed. Alternatively, Excel is often used in practice by engineers as knowledge acquisition tool, which is

handy as a flexible semantic prototyping tool, however, it misses the means for formal semantics definition. Therefore, the short-term benefit of using Excel can become a major liability as it is hard to check the semantic correctness of data exchanged using Excel [55]. Finally, domain specific knowledge acquisition tools are built, such as the SOMM tool in [43].

- **Weak support for modeling engineering-specific knowledge structures**. Modeling engineering knowledge in CPS is characterized by the need to model system components with their *roles*, as well *part-of* or other *connections* between these components [56]. While modeling these structures is not straightforward in ontology engineering languages (e.g., there is no OWL *part-of* relation with formal semantics), ontology design patterns [57] can offer a solution to translate engineering modeling needs into ready-to-reuse modeling solutions.
- **Lack of support for mathematical calculations**, which are frequently required in engineering-specific settings relying on processing of numeric data. For example, constraints can be represented as numeric equations or numeric measurements about the quality of a process are recorded. While SWTs focus mostly on logics-based knowledge representation and do not have a strength in advanced processing numeric data, hybrid solutions are often proposed that combine SWTs with techniques more suitable to mathematical data processing, such as data mining, statistical analysis or *Relational Constraint Solvers* (RCS) for solving cardinality problems.
- **The Open World Assumption(OWA) is not a natural fit to the engineering domain**, as traditional engineering approaches, e.g., databases, planning methods, and quality assurance methods, rely, in general, on a *Closed World Assumption* (CWA). This issue is partially addressed by mechanisms that combine open- and closed-world reasoning [58], including: expressing negations in SPARQL 1.1 queries; or modified reasoning mechanisms that rely on notions such as DBox [59] or NBox [60].
- **Difficulties for technical integration with existing enterprise systems** are two-fold. First, they stem from differences between the traditional object-oriented methods in the business environment that typically rely on task-specific models and ontologies that are conceptual domain models. Second, the lack of SWT skills among engineers hampers the adoption of these technologies. A solution for enabling software engineers to develop enterprise systems on the basis of an ontology in their familiar environment relies on an adjustable transformation from OWL to *Ecore*, which allows authoring of and programmatic access to a reference ontology, by his or her familiar development environment (e.g., Eclipse) [54].

5. Looking Forward: Future Research Trends

The challenges discussed above offer ideas for short/medium term research. To conclude this paper, we discuss selected emerging trends in CPS that will require substantial, long-term research.

Cross-domain applications. So far, heterogeneity and data integration is addressed within domains. Future applications, however, will exceed the boundaries of such traditional domains (a *Smart Factory* occupies a *Smart Building* supplied by the *Smart Grid*). Consider an *e-Car charging* scenario, where product information (of the e-Car), building energy management system, and smart grid information are equally important. Or a production system that can monitor the surrounding temperature and adjust it by relying on the *Building Energy Management System*. New challenges arise such as the discovery of suitable sensors and on-the-fly integration of data from these sensors to create cross-domain applications.

As an example use case, consider a building automation system that realizes predictive heating, cooling, and ventilation of the building, in case that comfort conditions can be provided without requiring notable amounts of energy. For this purpose, environmental conditions are exploited, for example, sunlight may be used to heat a room and cool night air to lower temperature in summer. The system uses weather information (favorable conditions, such as specific weather situations) to calculate an optimal schedule. The system favors the use of local energy or free cooling and free heating to keep or establish comfort values in the building. To reach optimized building operation several dimensions of information need to be available, related to buildings (e.g., architecture, structure), resources (e.g., facilities, appliances), energy (e.g., energy supply), building processes(e.g., control strategies), user (e.g., behavior, preferences) and exterior influences (e.g., weather and climate parameters). For such scenarios, it will be necessary to dynamically dis-

cover available sensors, to access, interpret and integrate their data by taking into account their semantics. FIWARE and *Web of Things* (WoT) are notable emerging efforts towards large-scale, semantic sensor discovery and integration.

Towards *Cyber-Physical Social Systems* (CPSS). In contrast to CPS, CPSS consist not only of software and raw sensing and actuating hardware, but are fundamentally grounded in the behaviour of human actors who can act as sensors, actuators or decision makers within the CPSS [61–63]. A fundamental change in these systems is that data is both received from (e.g., from mobiles, social networks, medical sensors) and distributed to (e.g., in terms of updates, alarms, constructions) human actors. In other cases, behavior patterns of the groups affected by the system have a direct influence on the system's behaviour. These characteristics open up new topics related to: (1) integrating data about the social component of the system from a variety of sources (e.g., social networks, mobile operators, mobile apps, wearables) both during the design and operation of the system; and, therefore, (2) data privacy, such as privacy-aware data integration and presentation. Explicit, semantically represented usage policies are a first step in this direction. An example application of semantic usage policies in a data processing workflow is reported in [64].

Explainable CPS. CPS increasingly underlie complex infrastructures, and, in many cases directly interfere with every-day activities of a large user base (e.g., as in the case of smart energy grids). It becomes therefore important that these systems can provide (on demand) comprehensible explanations of the reasons for their status/behavior to a range of stakeholders including end-customers as well as infrastructure operators (e.g., through a relevant chain of causation events). Among others, explainable CPS will require novel functionalities for detecting, representing and reasoning about events within and outside the boundaries of the system - a knowledge intensive task by excellence which can benefit from several capabilities of SWTs (knowledge representation, provenance tracking, data integration across heterogeneous data sources, to name just a few).

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