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The state of framework development for implementing reasoning mechanisms in smart cyber-physical systems: A literature review ☆

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ABSTRACT

Smart CPSs (S-CPSs) have been evolving beyond what was identified by the traditional definitions of CPSs. The objective of our research is to investigate the concepts and implementations of reasoning processes for S-CPSs, and more specifically, the frameworks proposed for the fuzzy front end of their reasoning mechanisms. The objectives of the paper are: (i) to analyze the framework concepts and implementations of CPS, (ii) to review the literature concerning system-level reasoning and its enablers from the points of view of the processed knowledge, building awareness, reasoning mechanisms, decision making, and adaptation. Our findings are: (i) awareness and adaptation behaviors are considered as system-level smartness of S-CPSs that are not achieved by traditional design approaches; (ii) model-based and composability approaches insufficiently support the development of reasoning mechanisms for S-CPSs; (iii) frameworks for development of reasoning in S-CPS should support compositional design. Based on the conclusions above, we argue that coping with the challenges of compositionality requires both software-level integration and holistic fusion of knowledge by means of semantic transformations. This entails the need for a multi aspect framework that is able to capture at least conceptual, functional, architectural, informational, interoperation, and behavioral aspects. It needs further investigation if a compositionality enabling framework should appear in the form of a meta-framework (abstract) or in the form of a semantically integrated (concrete) framework.

Contents

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1. Introduction

Cyber-physical systems (CPSs) are understood as systems that closely integrate constituents from the cyber and physical domains. The computational parts of CPSs monitor and control the physical processes through a network of sensors and actuators. They are typically designed using model-based approaches and are pre-programmed for given situations based on a set of rules and regulated with traditional feedback control loop (Derler, Lee, & Vincentelli, 2012). CPSs may be implemented on various scales, ranging from the nano-world to large-scale systems of systems. Their complex interaction with the environment and interoperation with other systems may lead to the unpredictable phenomena and behaviors (Tanik & Begley, 2014). To cope with emerging behavior, CPS should be equipped with system level smartness that goes beyond what was typically achievable with adaptive systems.

Model based design is the most widely used approach in system design and engineering for developing complex systems. It provides tools and methods for modelling systems on different levels of abstraction and for studying component and system behaviors under different application conditions. Model based design is a conceptual framework that supports system design by abstraction of physical phenomena, data driven modeling, representation of logical, and physical and interconnection structures (Putten, Der, Voeten, Geilen, & Stevens, 1998). The frameworks currently used for the development of traditional CPSs support model-based development and operation (Liu, Mashayekh, Kundur, Zourntos, & Butler-Purry, 2013; Liu, Zhang, & Chen, 2017). Consequently, they are facilitating a composability orientated approach in system development. The major assumption of this system design principle is that systems can be composed in a bottom-up manner by interfacing non-adaptable components. This kind of frameworks, however, poses many constraints for the development of compositional systems. A compositional approach operationalizes a top-down perspective and considers the systems in a holistic manner. It intends to create a synergy among the functional elements of the systems in order to realize system-level properties that cannot be achieved by integrating the local properties of the system components (Horváth & Gerritsen, 2013).

Our preliminary studies concluded that there is knowledge gap related to framework development supporting a compositional design of reasoning mechanism for S-CPS. The major issue is how a framework should facilitate the development of reasoning in smart cyber-physical systems. The specific objectives of our literature study are: (i) to analyze the framework concepts and implementation of CPSs based on the various design aspects (ii) to review the literature concerning system-level reasoning, computational implementation, and its enablers from the points of view of the processed knowledge, building awareness, reasoning mechanisms, decision making, and adaptation. Our ultimate goal

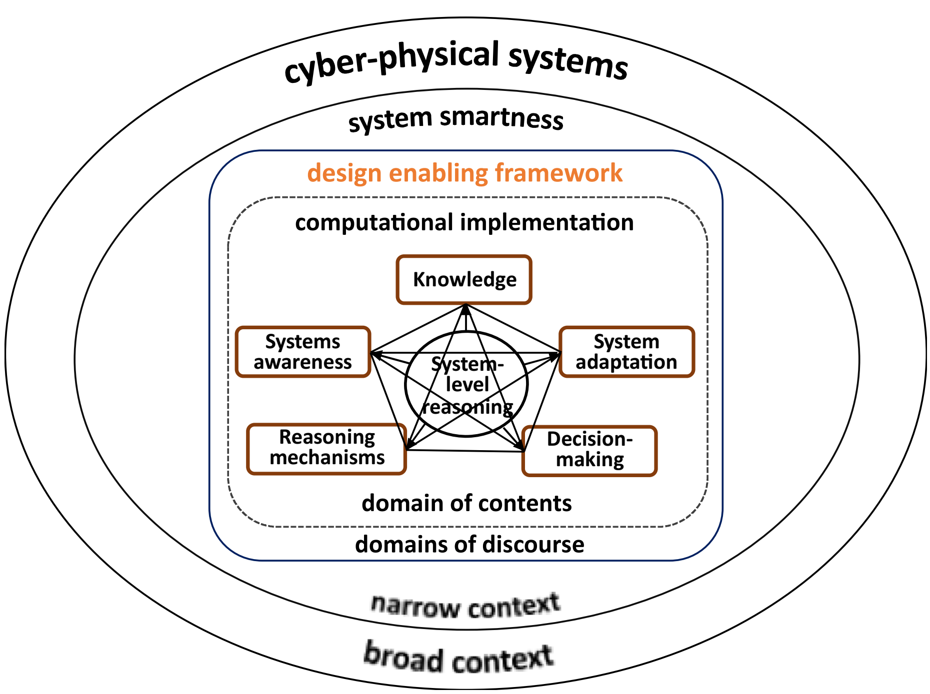

Fig. 1. Reasoning model for conducting the literature study.

is to create a novel framework that supports the development system-level reasoning.

2. Preparation of the literature study

2.1. The reasoning model for conducting the study

This paper reports on the results of the research we completed collecting publications from web repositories to get insight in the current status of frameworks for designing reasoning platforms for smart cyber-physical systems. More specifically, we focus on the frameworks that support design of reasoning mechanisms, which create system-level smartness by implementing various reasoning processes needed in the context of CPSs (Seshia, Hu, Li, & Zhu, 2017).

We completed our study according to the reasoning model shown in Fig. 1. There are three main constituents of this reasoning model: (i) the domains that provide the context information for the research, namely: cyber-physical systems and system smartness, (ii) the domain of discourse of the research, design-enabling framework, and (iii) the domains that provide content information for studying frameworks, namely: system-level reasoning, computational implementation, and generic enablers of reasoning. The latter includes concepts such as system knowledge, self-awareness, self-adaptation, reasoning mechanisms, and decision making. These are seen as necessities to implement smartness in S-CPSs (Horváth, Rusák, & Li, 2017). It made our study complicated that there are many epistemological and methodological relationships among the domains and their elements. We will use this reasoning model in structuring the rest of the paper.

2.2. Method of data collection

The term *framework* was used as the primary keyword in our literature research. A wide range of relevant keywords are formulated concerning research related to reasoning models, for example: *system-level reasoning, self-awareness, self-adaptation, smartness, smart cyber-physical systems, knowledge, context and situation awareness, reasoning mechanisms, and system adaptation*. To validate our reasoning model, we have explored the relationships among these keywords within the publications found by our literature search.

We utilized Web of Science core collection as the primary data source. Other sources, for example, databases in specific disciplines related CPSs and web repositories were used to complement the basis of our literature study. Though our primary focus was on publications form past ten years (2008–2017), in order to cover recent trends of S-CPS development, some publications were also considered from earlier years. 697 publications fulfilled the criteria of our search, and served as knowledge base for our literature study.

2.3. Results of the preliminary quantitative analysis

The objective of this section is to give an overview of the publications in particular reasoning for S-CPSs based on quantitative analysis. We aim at providing a broad view of the current status of development frameworks and finding a preliminary result. Browsing through the total of 697 collected documents, we found 209 publications in which the word '*framework*' was included either in the title or in the keywords. In this subset, we found 33 documents, which discussed some sort of framework related to the development of CPSs. Further investigation explored that 134 frameworks in total were related to one or another aspect of reasoning. There were 59 frameworks concerning the knowledge aspect of reasoning, 58 frameworks related to system awareness, 91 frameworks concerning the reasoning mechanisms, 11 frameworks related to decision-making, and 13 frameworks were targeted to system adaption. While there were frameworks related to two or more aspects of reasoning, we found no description of frameworks that would have addressed each of the five aspects simultaneously (see Fig. 2). Based on this finding we assumed that recent research has not dealt with this combined research and development challenge and that, therefore, there are no proposals for frameworks, which would cover all aspects of reasoning by S-CPSs.

3. Cyber-physical systems

3.1. Manifestation and evolution of CPSs

The term *cyber-physical system* was coined around 2006. CPSs are regarded as a kind of model for next generation engineered systems that have their roots in a tight integration of hardware devices, embedded software and massive data streams (Broy,

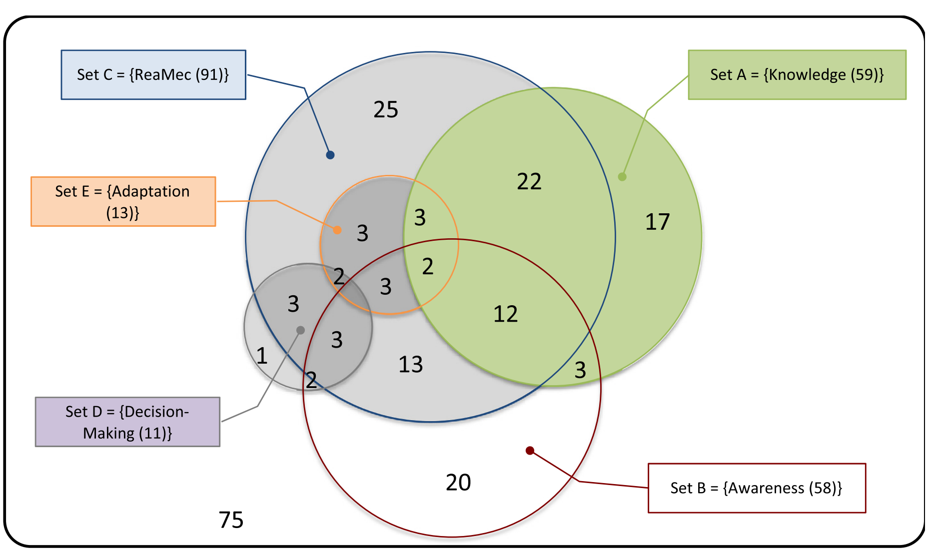

Fig. 2. Venn-diagram showing the number of frameworks addressing the five aspects of system-level reasoning.

Cengarle, & Geisberger, 2012). Conventional CPSs are typically designed using model-based approach. They are pre-programed with a set of rules concerning the given situations and regulated within the tasks close the Sensing-Processing-Actuation loop (Nawaz, Petrov, & Buchmann, 2014). Most of the CPSs manifest as systems of systems. They belong to larger systems that are interconnected through communication networks as an open system. The complex interaction and interoperation among systems may lead to the emergence of phenomena and behaviors. CPSs are supposed to be able to deal with uncertainty and unpredictable situations in operation, and to adapt rapidly to anomalies in the environment. This requires some level of intelligence from CPSs. However, not all traditional CPSs are able to satisfy this requirement (Dumitrache, 2011).

Engell et al. indicated a shift towards cognitive aspects of developing CPSs, and accounted on new research challenges associated with it (Engell, Paulen, Reniers, Sonntag, & Thompson, 2015): (i) handling large amounts of data in real life; (ii) situation awareness (iii) learning and adaptation; (iv) analysis of user behavior and detection of needs and anomalies. They also claimed that cognitive CPSs could step forward to the upcoming generation CPSs. Concerning the evolution of CPSs, scientists and practitioners have different views. There is no agreement on the next generations of CPSs yet. Due to the increasing need to clarify the theoretical, methodological and computational issues of system smartness, these topics have been identified as objectives of one of the branches of CPSs research. '*Smart Cyber-physical systems*' is a new term that has appeared in scientific publications since 2014 for example in (Daun, Brings, Bandyszak, Bohn, & Weyer, 2015; Håkansson, Hartung, & Moradian, 2015). The term smart cyber-physical systems (S-CPS) could be used to describe the upcoming generation CPSs, which are equipped with some level of computational intelligence that makes them capable to building awareness, reasoning about the objectives and states of operations, and adapt.

S-CPSs need different functional and structural frameworks than the conventional CPSs due to the necessity of supporting the implementation of system level compositional characteristics such as smartness, dependability, security, or openness. Ollesch, Hesenius, and Gruhn (2017) claimed that event-based control paradigms are vital enablers for adaptive analytical control mechanisms needed in S-CPS (Ollesch et al., 2017). However, to date, very few accounts exists how to engineer smart systems with intelligence based on real-time event processing. In our view, CPSs are networked knowledge-intensive multi-actor systems and smartness is becoming a paradigmatic feature of their next generations. They have been sorted based on the level of intelligence (self-awareness) and the level of organization (self-adaptation) (Horváth et al., 2017). Self-regulation and self-tuning are paradigmatic features of the first generation CPSs and they will be replaced by self-awareness and self-adaptation to become the second generation CPSs. These capabilities are not produced by a single component, but by a synergic operation of the entire system.

3.2. System smartness as a holistic capability

Smartness is an intermittent quality of human thinking, feeling, doing and making. Modern engineered systems are designed to be able to operate and provide services smartly. Nevertheless, the concept of system smartness has not been consolidated yet, especially not in the context of emerging products. For some, the term *smart* is used as a synonym of 'sophisticated' or 'crafty'. For others, it means 'intelligent', 'automated', and 'knowledgeable' (Metzler & Shea, 2010). Accordingly, it is hard to identify the real contents of, and to come a common understanding of system smartness. Based on system theory, smartness is a system-level characteristic that enables the systems to operate beyond that they have been specifically programmed for, but without fundamentally changing their domain, objective and resources of operation (Mele, Pels, & Polese, 2010). Smartness is interpreted as a paradigmatic feature of a class of systems. In line with the reasoning of Gottfredson (1997), it is a first level manifestation of a broader and deeper capability for comprehending our surroundings - 'catching on', 'making sense' of things, or 'figuring out' what to do (Gottfredson, 1997).

System smartness has been addressed from various perspectives in the literature. Dominant ones are (i) smart ubiquitous systems (Datta, Dey, Paul, & Mukherjee, 2014), (ii) smart software systems, (iii) sensor data driven systems (Scheidl, 2016), (iv) artificial intelligence enabled systems (Arel, Rose, & Karnowski, 2010), and (v) context-aware adaptive systems (Villegas, Tamura, Müller, Duchien, & Casallas, 2013). Characteristics for these systems that the relationships among the component properties create distinctive patterns of operation on system level, that cannot be assigned to any of the individual components, only to the whole (Saarinen & Hämäläinen, 2010). Smart operation assumes a high-level functional and architectural synergy among the parts of a system. It goes beyond an analysis and conventional system design based solely on reductionism and traditional model-based approach (Bogdan & Marculescu, 2011). In this sense, the holism should be concerned that smartness towards S-CPSs is a holistic capability. It is an example for compositional nature like other system-level behaviors (e.g. verification, dependability, and security) (Zhou, Zuo, Hou, & Zhang, 2017).

4. Design enabling framework

4.1. Foundational concepts of frameworks

The term *framework* has different connotations to different people and in various professions. There had been no consensus on the definition of the term framework in the field of system engineering (Stamer, Zimmermann, & Sandkuhl, 2016) As referred to the definition in Oxford dictionary, a framework is a structure of *somethings* serving a particular purpose. In scientific interpretation, the term *something* can be identified as an abstraction entity. Therefore, a framework is deduced to an arrangement of entities, which heavily depends on the context. Possible entity in a framework is e.g. theory, concept, variable, definition, function, system component, and method. A structure of and relations among entities can be arranged by various methods, e.g. causal relationships, hierarchical diagram, formal logical expression, topology, and mathematical model. A framework can be utilized for various purposes, e.g., for providing a prescriptive guidance, an explanatory account, a generative construct, analytical problem-solving enabler, and a predictive model. These purposes can be combined to develop a framework (in thousand ways based on a developer's mental model). It can be taken from a conceptual idea to a detailed description, which can guide how a system should be designed. It is probably constructed from an outline of structure (Alippi & Roveri, 2017) to a sophisticated structure as seen in component-based framework (Feng, Quivira, & Schirner, 2016). This shows no standard model for building a framework, especially in the context of compositionality-enabling system development frameworks.

4.2. Various types of frameworks used in system development

Various adjectives are used to identify specific kinds of framework such as: general framework, conceptual framework, and model-based framework. There are many other specific names used to highlight the purpose, context, and/or methods associated with different framework types. To grasp all of them we would need a rigorous taxonomy or classification. In the areas of system design, the following frameworks are used most frequently: (i) *Conceptual frameworks*, which are arrangements of concepts with several variations and contexts. It is a network of interlinked concepts such as a set of concepts, definitions of concepts and relevant variables, and building blocks of a theoretical model that together provides a comprehensive understanding of a phenomenon (Alippi & Roveri, 2017); (ii) *Logical frameworks,* which define the logical skeleton of systems with a specific purpose. Typically, the relationships of system functions are represented by factors and their definitions, and logical expression language (Choi, McCarthy, Kim, & Stehr, 2014); (iii) *Architectural frameworks,* which involve a common practice for creating, analyzing and representing system architectures during design and re-design processes (Díaz, Pérez, Pérez, & Garbajosa, 2016). They can be constructed on different levels of abstraction ranging from high-level of system behaviors to specific models that represent explicit context, tasks, or functions; (iv) *Component-based frameworks,* which are skeletons of component-based system implementation that can be specialized by a component developer to produce custom components (Cicirelli, Fortino, Guerrieri, Spezzano, & Vinci, 2016). They are constructed based on system components and their relationships, which are usually composed by reusable, replaceable, and extensible modules; and (v) *Model-based frameworks,* which capture information in abstract concrete representations, applying simplification to understand the essence and details of a system, and to provide answers related to the performance of a system based on models (Zhang & He, 2011). A set of models is an enabler of constructing a model-based framework.

4.3. An analysis the components of frameworks

The frameworks for developing CPSs are combination of various components. The analyzed frameworks cover a large variety of applications purposes including security, trustworthiness, reliability, data analysis and management, resource management, system verification, and adaptation issues. To impose an order and to create a comprehensive structure for future studies, we classified the frameworks into seven groups according to the application purposes: (i) control; (ii) dependability; (iii) network and communication aspect; (iv) resource management; (v) data-driven; (vi) reasoning for smartness; and (vii) compositionality. The frameworks reported in the literature were classified according to their types. They were analyzed from the aspects of: (i) the set of included concepts and relationships, (ii) formal logical expressions, (iii) architectural arrangements, (iv) information flows, (v) associated computational methods, and (vi) implementation guidelines. The architectural arrangements were further analyzed from the perspective of (a) abstraction level, (b) generic structure, (c) functional structure, (d) component-based structure, and (d) behavioral structure. We have analyzed 33 frameworks that were specifically developed for supporting the design and implementation of CPSs. The result of the analysis is shown in Table 1. The X cells represent the components of the particular frameworks.

As shown in Table 1: the analysis showed that the contents of framework are diversity. It depends on a developer's point of view even in the similar designing aspects. The utilization of framework is completely different as same as their architecture structures. The underlying concept of a framework is essential for defining guiding principles how a framework should be used. We can distinguish explorative, explanatory, analytical, predictive and decision-making frameworks based on their objectives and utilization. Our analysis showed that most of the proposed frameworks are supporting analytical problem solving. Frameworks play multiple roles in the design process of CPSs, including: (i) supporting observation and understanding of a phenomenon, (ii) addressing problems and proposing problem-solving methods; (iii) offering means to combine cross-domain knowledge to create new concepts, (iv) providing a logical structure to verify conceptual ideas, and (v) providing multi-level architectural structure that can be seen as a blueprint for designing a system.

The analysis implies that constructing a framework may happen in an infinite number of ways due to a range of possible components that may include a set of abstract entities ranging from high-level system abstraction i.e. concepts, generic components, and system behaviors to low-level of component operation i.e. functionality, component specification, and implementation guideline. This indicates that there is no standard method or *de facto* rules for guiding the construction process of a framework. This issue also makes a dilemma with regards to utilization of high-level abstraction frameworks that aim at explaining system-level behaviors as seen in Rajhans et al. (2014) and Kappé, Arbab, and Talcott (2016). These publications could not offer guidelines how systems should be implemented driven by frameworks. Opposing most of the frameworks that capture low-level of operations, they propose implementation guidelines, but they do not provide information on the concerned system-level characteristic. Thus, it is probable that implementation of system-level properties like smartness could not be guaranteed. Consequently, the exemplified frameworks do not address the compositionality issue explicitly.

5. Overview of the state of the art in system-level reasoning

5.1. Introducing compositionality in system-level reasoning

System-level reasoning is a capability of making cognitive inference created by an arrangement of reasoning constituents in an orchestrated manner. Several frameworks for reasoning have been proposed in the recent literature. For example, system-level reasoning in AI is usually summarized through the expression '*Sense-Think-Act*' (Raducanu & Vitrià, 2008) that mimics human thinking by using deductive reasoning (Bench-Capon & Dunne, 2007). Belief-Desire-Intention (BDI) paradigm is one of the operational architecture commonly suitable used for building complex agent-systems. A classical framework embedded this architecture is the Procedural Reasoning System (PRS) (Caillou, Gaudou, Grignard, Truong, & Taillandier, 2017). It includes three main processes: perception, interpretation, and execution. Another example is the FUSION framework, which implements a *Detect, Plan,* and *Effect* procedure. It can be used for designing and implementing the underlying adaptation logic of adaptive software systems. For instance, it support rule development for adaptation, such as *if the system works (*e.g. *satisfies the user, obtains the goal), do not change it; when it breaks, find the best fix for only the broken part* (Elkhodary, Esfahani, & Malek, 2010). The *Sense-Plan-Act* loop is also used as a reasoning concept for self-adaptive systems (Steinbauer & Wotawa, 2013). These cycles are basically executed by using rule-based reasoning which is implemented based on the principle of deduction (Berka, 2011).

Enhanced by the advancement of sensor and actuator technologies, systems can combine real-world data from their environments with the knowledge of the respective processes together with the knowledge of how systems work internally (Brusa & Calà, 2014). On the basis of these characteristics, system-level reasoning can be constructed through multiple feedback loops of various processes of sensing, recognizing an event, inferring a situation, learning from dynamic situations, strategy planning, decision-making, and adaptation. Designing of these processes conceptually differs. Compositionality is introduced as a new sys-

Table 1
Analysis of the components of the frameworks.

FW types	Designing aspect	Issues	Reasoning aspect	References	c[a]	log	Architectural structure					info	comp	imp	Outcome
							abs	gen	fun	com	beh				
conceptual	controlling	dynamic scheduling and control		Gaham, Bouzouia, and Achour (2015)	X			X	X			X		X	explanatory
	dependability	trustworthy		David, Du, Larsen, Mikučionis, and Skou (2012)	X								X		analytical
		reliability		Wu and Kaiser (2013)	X	X	X		X				X		analytical
	networking & communication	network management & operation	knowledge modelling, decision support	Siryani, Mazzuchi, and Sarkani (2015)	X	X									predictive
	resource management	self-organization based resource reconfiguration		Wang, Zhang, and Li (2016)	X		X								analytical
	data-driven	data analysis	decision-making	Crowley, Breslin, and Curry (2015)	X			X							decision-making
		prediction improvement		Siryani, Tanju, and Eveleigh (2017)	X	X								X	decision-making
	reasoning	***comprehensive***	***self-awareness***	Alippi and Roveri (2017)	X		X								explanatory
		knowledge transformation	***information fusion***	Li, Song, Horváth, Opiyo, Zhang, and Xiong (2014)	X			X						X	analytical
		knowledge modeling, decision support	***knowledge modeling, decision support***	Petnga and Austin (2016)	X			X	X				X	X	decision-making
logical	resource management	data storage and processing	knowledge sharing, reasoning rules	Kim, Stehr, and Talcott (2012)	X	X									explanatory
	reasoning	***adaptation***	***knowledge sharing; adapt to changes***	Choi et al. (2014)	X	X									decision-making
architecture	dependability	security		Kang, Lee, Jeong, and Park (2015)	X			X					X	X	analytical
		reliability& timeliness		Shih, Hsiu, Chang, and Kuo (2016)	X			X	X					X	analytical
	networking & communication	communication		Eliasson, Delsing, Derhamy, Salcic, and Wang (2015)	X				X	X					analytical
				Pace, Aloi, Caliciuri, and Fortino (2016)	X		X	X	X	X				X	decision-making
		communication &control		Youssef, Elsayed, and Mohammed (2016)	X			X	X					X	analytical
		interoperability	context information	Dillon, Zhuge, Wu, Singh, and Chang (2011)	X			X	X					X	explanatory
		adaptation	knowledge repository, adaptation	Tanik and Begley (2014)	X			X						X	explanatory
	resource management	resource management		Datta et al. (2014)	X			X							analytical
		data management		Zhang, Yan, Xu, and Su (2014)	X			X	X				X		analytical
		scalability, flexibility, adaptation, agility, & self-management	self-adaptation	Díaz et al. (2016)	X			X	X						analytical
		reassure management	Context awareness	Hossain, Rahman, and Muhammad (2017)	X			X	X					X	analytical
	data-driven	service-oriented (Big data analytics)		Sakr and Elgammal (2016)	X			X							analytical
component-based	***reasoning***	***context reasoning***	***context modelling***	Cicirelli et al. (2016)	X	X			X	X		X			explanatory
	controlling	design- Computational method		Feng et al. (2016)	X		X		X	X			X	X	analytical
model-based	controlling	efficiency (cost, accuracy)	self-monitor, decision-making	Liu et al. (2017)	X				X				X	X	analytical
		interoperability		Zhang and He (2011)	X										explanatory
	dependability	security	local knowledge	Liu et al. (2013)	X								X	X	predictive
		resilience/effectiveness		Chiaradonna, Di Giandomenico, and Masetti (2016)	X	X		X	X						analytical
	resource management	resource management		Nayak, Reyes Levalle, Lee, and Nof (2016)	X			X					X		analytical
	reasoning	***preferences aware component***	***awareness***	Kappé et al. (2016)	X	X					X			X	explanatory
	compositionality	system-level verification		Rajhans et al. (2014)	X	X	X	X			X				analytical

[a] Abbreviations: c =: concept; log =: logical expression; abs =: abstraction; gen =: generic; fun =: function-based; com =: component-based; beh =: behavioral; info =: information construct; comp =: computation methods; imp =: implementation guidelines.

tem manifestation principle for a development of system-level reasoning. This goes beyond the traditional component-based design approach that systems components (Seceleanu & Crnkovic, 2013).

The term *compositionality* was first introduced in the fields of linguistics, mathematics, and semantics. In linguistics it is defined as the principle to realize the meaning of a complex expression that is determined by the meanings of its constituents (Hoeksema, 2000). In computer science, compositionality is the principle of adapting system operation by composing and connecting system components together, and reasoning about the whole system (Ghani, Hedges, Winschel, & Zahn, 2016). In the field of system design, compositionality frameworks are used for system-level verification (Rajhans et al., 2014), system awareness (Kappé et al., 2016), and schedulability (Tripakis, 2016), but not yet for implementing system-level reasoning as well as reasoning mechanisms for S-CPSs.

5.2. Computational implementation for system-level reasoning

An implementation of system-level reasoning can be constructed on multiple behavioral levels using analytic and synthetic computational approaches. The former is based on a combination of hardware devices and software application, whose computational function is to generate conclusions from available knowledge using logical reasoning. The latter is based either on a single logical theory or on a composite logical theory, and/or a computational approach that tries to achieve a relatively high fidelity in comparison with human reasoning. According to the literature, these two approaches are normally used in different levels of abstraction.

An analytical approach offers the computation methods for reasoning about the system-level behaviors. In Dragomir, Preoteasa, and Tripakis (2016), a compositional semantic and analysis framework is proposed for hierarchical block diagrams of a simulation model. The framework provides a series of predicates and property transformers as semantics of composition in a series, in parallel, and in feedback of individual blocks. The approach aims at reducing the complexity of the real system to an abstraction model. For example in (Schaefer & Poetzsch-Heffter, 2008), compositional reasoning is proposed in model-based verification for designing embedded systems. It applies a formal semantics to capture the features of system components at a high level of abstraction. On system-level models, the reasoning should confirm that a system and its model have the same behaviors with respect to the considered properties. A limitation of this approach is that it cannot provide computational models for reasoning about how smart systems are operated. However, in most of software engineering, computer science, and AI practices, the abstraction is constructed in formal or computational models through coding processes, but the designed system can only be separately executed or deployed (Saitta & Zucker, 2013; Subagdja & Tan, 2016).

In a synthetic computation approach, the term *synthetic* means that the reasoning architecture, process, and results are produced by computational synthesis. This approach is usually applied in the field of cognitive robots, context-aware system, and self-adaptive system by means of AI-based (Guo, Lu, Gao, & Cao, 2018), Machine learning (Majewski & Kacalak, 2017), and cognitive architecture (Ng, Du, & Ng, 2017). For example, Memory-Attention-Composition (MAC) framework (Hudson & Manning, 2018), it is an end-to-end differentiable architecture to perform multi-step reasoning process. To solve a problem, the model is decomposed into a series of inferred reasoning steps associated with computational units. In Sarathy and Scheutz (2018), the framework is proposed for computational cognitive affordances. The cognitive cycle consists of two parts, namely logical-based representation and a computational architecture that performs a synthetic reasoning, *Action-Planning-Reasoning, Sense-Making* tasks. These approaches do not address compositionality issue, explicitly. An attempt to improve compositionality in CPSs was found in Zhou et al. (2017). Several structures of component composition for reliability and duration are illustrated. The composition rules are formulated. These rules confirm compositionality at component level, but an achievement of system-level compositionality cannot be guaranteed. It assumes if the entire systems are manifested by the composition rules, system-level properties can be achieved.

5.3. Enablers for system-level reasoning

System smartness needs a particular synthesis of reasoning mechanisms associated with knowledge transformation such as context-based reasoning, situation awareness, goal driven strategy planning, functional adaptation and behavioral evolution that interplay in a synergistic manner to produce smartness. Enabled by the reasoning, the systems could make decision and adapt themselves during the run-time operations. In the following section, enablers of system-level reasoning from a point of views of system knowledge, system awareness, reasoning mechanism, decision-making, and system adaptation are reviewed.

5.3.1. System knowledge

Knowledge is awareness and familiarity of the semantic meaning of information in a given context. System knowledge is the symbolization process of knowledge that is deeply linked to learning and reasoning processes (Kunze, Hawes, Duckett, Hanheide, & Krajník, 2018). It is used for supporting the systems to perform cognitive processes based on common functions including sensing, perception, building situated awareness, reasoning and learning, planning and control, and actuating through a feedback-controlled loop (Metzler & Shea, 2010). Recently, knowledge is the main component of smart systems included CPSs (Lanting & Lionetto, 2015; Petnga & Austin, 2013). They also require the integration of various kinds of knowledge i.e. common sense knowledge to reason about things, encyclopaedic knowledge to define actions and objects, and spatial–temporal knowledge to describe the system states at different point of time (Tenorth & Beetz, 2013).

System knowledge is the symbolization process of knowledge that is deeply linked to learning and reasoning processes (Kunze et al., 2018). It can be obtained from different sources and captured by knowledge representation. The construction of new knowledge also demands the use of previous knowledge and different cognitive processes. This means knowledge could be captured and made available to systems. It can be obtained from different sources and represented in several forms, including distributed, symbolic, non-symbolic, declarative, probabilistic, and rule-based (Rajeswari & Prasad, 2012). The knowledge has been modelled that ranged from very informal as Object-Attribute-Value scheme to strictly formal as OWL DL.

Almeida and Lopez-de-Ipina (2012) claimed that ontology is regarded as one of the best approaches to transform context information into knowledge. Ontology often defined as an explicit specification of conceptualization. It describes concepts and relations that can be expressed as a hierarchy concept tree. In reality it is difficult to manually create ontology covering all permutations of the enormous number of entities, properties, and attributes. Technically, as the number of triples in the ontology increases the inference time for environment actions becomes unsustainable (Almeida & Lopez-de-Ipina, 2012). This is actually a well-known drawback of the knowledge engineering based approach to knowledge modeling.

5.3.2. System awareness

Awareness is a product of knowledge processing, and monitoring (X. Li, Martinez, & Rubio, 2015). It encompasses context, situation, and self-awareness. Systems operating in dynamically changing environment should be able to build up awareness about (i) their context of operation (i.e. need for dynamic adaptation of tasks and objectives as response to external factors), (ii) the situation they are operating in (i.e. understanding of the impact of the environment on the operation), and (iii) self-awareness (i.e. understanding of the system's abilities and the availability of its resources for performing operations).

Context can be considered as a kind of knowledge (Gomes, Marques, Costa, Novais, & Neves, 2010). It refers to any information that used to characterize a situation of an observed entity. A system probably not recognizes a situation from an isolated entity. It needs multiple entities i.e. person, place, physical or virtual object that combined to model the semantic context (Gouin-Vallerand, Abdulrazak, Giroux, & Dey, 2013). It is usually assumed that context modeling using knowledge engineering techniques will create complete accurate models. Different approaches have been used for reasoning on certain context information i.e. fuzzy logic, probabilistic logic, ontology-based, Bayes networks, Hidden Markov models, and the Dempster-Shafter theory of evidence (Bettini et al., 2010). Each technique has its own advantages and disadvantages as it can be seen in the review presented in Gilman (2015). In order to support knowledge-intensive context reasoning, ontology-based models proved to be the most promising technique to yield meaningful context information (Li, Martínez, & Rubio, 2017).

Situation awareness is a computing paradigm, which usually involves the use of the concept of the situation in real life. If a situation is specified as a set of relations with other objects, then both the objects and their relationships may change with both time and location. In a framework for cognitive situation modeling (Jakobson, Buford, & Lewis, 2006), situation awareness is a part of situation management, which is based upon the steps of sensing and perception, and is aimed at building an understanding of a current operational situation. Situation modelling and inferring can range from using simple conditional rules to application of more complex techniques. They are classified into specification-based techniques (e.g. formal logic, spatiotemporal logic, and evidence theory), and learning-based techniques (e.g. Bayesian deviations, Artificial Neural Network, and web mining) regarding their correlation to increasing complexity of problem descriptions (Ye, Dobson, & McKeever, 2012).

Self-awareness can be seen as a higher level of situation awareness (Lewis, Chandra, Parsons, Robinson, Glette, Bahsoon, & Yao, 2011) for instance, a system is continuously aware of its operational and servicing states and behaviors. In other words, self-awareness refers to the capability of a system to gather and process information from its environment and to autonomously understand the situation of those external and internal entities that can affect the system in the accomplishment of its operational goal (Schlatow, Moostl, Ernst, Nolte, Jatzkowski, Maurer, & Herkersdorf, 2017). This capability is based on self-monitoring, which is typically implemented by a network of hardware and software sensors. Based on an engineering perspective in computational self-awareness, it is not only the capability, but it can be considered as an emergent property of collective systems, even when no single component has global awareness of the entire system (Gurgen, Gunalp, Benazzouz, & Galissot, 2013). As a paradigmatic feature of S-CPSs, self-awareness plays a crucial role in realizing dependable operation under changing circumstances during run-time.

5.3.3. Reasoning mechanism

Reasoning is the ability to manipulate previously acquired knowledge to draw novel inferences or answer new questions (Hudson & Manning, 2018). A reasoning mechanism executes a comprehensive inference process that usually involves multiple logical operations on logical expressions/statements to draw conclusions (Patokorpi, 2006). In the case of smart systems, the computational algorithms included in the reasoning mechanisms process the input data and derive new knowledge based on the preprogrammed in a particular context for a given purpose.

Consisting of a composition of computational algorithms, a reasoning mechanism is a means to operationalize smart systems. Several reasoning methods were applied in the context of smart systems, intelligent systems, and autonomous systems. Rule-based reasoning offers a natural way of handling and inferring knowledge. A rule-based knowledge system features modular structure, can easily be extended with additional rules, and provides a uniform representation of knowledge (Basu, Agrawal, Hazra, Kumar, Seetharam, Beland, & Lafond, 2014). However, it provides limited expressiveness to describe certain complex features. Therefore, it cannot fully exploit the potential offered by events. Case-based reasoning is frequently used in the decision-making process (Sene, Kamsu-Foguem, & Rumeau, 2015). It can define a course of actions based on a certain situation. Ontology based reasoning is used for conceptualizing the relationships between entities to create knowledge. It is typically combined with other reasoning methods such as rule-based reasoning in order to infer a situation from context information (Cimino, Lazzerini, Marcelloni, & Ciaramella, 2012), or case-based reasoning in order to automate the decision-making process.

Probabilistic reasoning, such as Bayesian Networks (BNs), and Hidden Markov Models (HMM), is appropriate for reasoning with uncertainty (Romdhane, Bremond, & Thonnat, 2010). BNs are used for the analysis of data and expert knowledge, especially in uncertainty. They can easily process probabilistic knowledge from different sources in a mathematically coherent manner (Uusitalo, 2007). HMM's have more flexibility to capture unobserved variables and thereby provide a basis for reasoning about emergent behavior of the system. Fuzzy logic is one of the very promising techniques with its ability to deal with uncertainty, imprecision, and model non-deterministic problems (Pan & Bester, 2018). Combined with other reasoning techniques such as ontologies, probabilistic modelling, and rule-based reasoning it can cope with qualitative interpretation of probability, treat probability with natural language expressions, and human like decision making (Yan, 2012) Hybrid reasoning approaches have been proposed in the recent publications. The degree of integration can be performed in several models (Prentzas & Ioannis, 2011) i.e. sequential processing, embedding processing, and co-processing.

In complex reasoning mechanisms for such smart systems, however, they require multimodal processing with more specific temporal, non-monotonic reasoning, and learning from data, for example to realize a situation, to be aware of the changes in the situation, and to make decisions based on a dynamic situation. A variety of reasoning methods leads to a typical question is how to select the reasoning mechanisms that can reason with data, information and knowledge over a dynamically changing situation? The answer to this question depends on many factors i.e. domains of applications, an objective of the developing systems, nature of obtained data, and required system performances (Hao, Bouzouane, Bouchard, & Gaboury, 2018). It is impossible to apply a single reasoning method through its entire processes. For dynamic processes, reasoning mechanisms should be composed during runtime with high level of interoperability. Although, some methods are able to work together in several degrees of integration, many of these methods are not yet interoperable. Their computational components are needed to be modified or require an interface to couple them seamlessly. This implies the need for different conceptual framing of reasoning mechanisms and different design principles, since they need holistic compositional approach in terms of the implemented reasoning process and synergy in terms of the generated knowledge.

5.3.4. Decision making

A decision is defined as a process of choosing the best alternative among multiple actions for the purposes of attaining a goal or a set of goals. Decision-making often involves the integration of data from multiple sources, and harnesses knowledge from multiple domains (Tsafnat & Coiera, 2009). The goal of decision-making process is to choose the best alternative from a set of possible alternatives that satisfies an objective or multiple objectives. An optimization is a common problem solving method in decision making (Yu & Luo, 2006). In real-world problems, there is more than one objective, which may possibly be in conflict with each other. It is impossible to obtain a complete and exact set of optimal solutions. As the number of *m*-objectives increased, the number of solutions increase exponentially (Li, Li, Tang, & Yao, 2015). That is why an optimization model with multiple objectives is not suitable in practice.

In a dynamic situation, when a decision making process is confronted with new situations, goals and kinds of data, the process must evolve and adapt. This requires reasoning methods, which is often based on more than logical conclusions (Ong, Khaddaj, & Bashroush, 2011). In human decision-making process, system-level reasoning can be made as a closed loop, for example *Observe-Orient-Decide-Act* (OODA) loop (Senne & Condon, 2007). A decision maker performs the cycle repeatedly: *Observe* the facts by capturing, fusing, and filtering data about the entities and environment; condense the information from the facts to *Orient* with the revealing situation by applying prior knowledge; formulate hypotheses to explain the observations and *Decide* based on the best scenario; and then *Act* following the internal guidance from the orient process and test the hypotheses. Corresponding to the OODA loop, Knowledge Intensive Data System (KIDS) framework is an example of self-adaptive decision making (Baclawski, Chan, Gawlick, Ghoneimy, Gross, & Liu, 2017). The framework proposed flexible data structure based on ontology. The reasoning processes as instance of *Classify-Asses-Resolve-Enact* represented by CARE loop. It transforms input data into facts, perception, hypotheses, and directives through the reasoning processes, respectively. The different instances are applied by different reasoning methods for example, reducing data into facts at the classification tasks generally would use statistical techniques, but in some case, both logical and probability reasoning was applied. This framework shows compositionality issue should be concerned for developing synthetic reasoning in human-like decision-making system.

5.3.5. System adaptation

System adaptation is the planning of adaptation based on the outcome of previous processes. In the context of engineered systems, system adaptation is inspired by biological and natural systems having the ability of a system to modify itself to a new condition when its environment or purpose changes (Brun, Di Marzo Serugendo, Gacek, Giese, Kienle, Litoiu, & Shaw, 2009). The modification is done by adjusting parameters of the system in response to change in the system itself or in their environments. It also adapts to similar setting without explicitly being ported to them and adapt to solve a new problem (Berka, 2002). However, there is no absolute optimization exists in complex systems (Levin, 2002). System operation always changes to a new stable state overtime. Frequently, there are multiple point attractors (Watson, Buckley, & Mills, 2011). Although, the systems can modify the parameters and somewhat reach the desired state but it might be shifted to another point as the consequences of the actions. Therefore, the self-adaptive capability should incorporate reasoning about the objective of the system operation, investigating possible strategies for performing adaptation, and planning and executing adaptation plans based on available cyber and hardware resources (Salehie & Tahvildari, 2009).

In the self-adaptive software research community, self-*properties are organized into levels where self-adaptiveness is at the top, while self-awareness is a primary level like context awareness (Cámara, Bellman, Kephart, Autili, Bencomo, & Diaconescu, 2017). Self-adaptive system is typically implemented by control loop mechanisms (Brun et al., 2009). Self-adaptive control mechanisms typically include sequential iterative processes of: (i) sensing the context and reasoning, (ii) deciding what kind of adaptation is required, and (iii) implementing the adaptation by reconfiguration (Amara-Hachmi, 2006). An *Event-Condition-Action* (ECA) rule is usually implemented in the self-adaptation of service based processes (Daniel, Matera, & Pozzi, 2008; Wang, Feng, Huang, & Tan, 2017). It is also used to describe different responses to various runtime events. The semantics of the rule are: *when the event has been detected, evaluate the condition, and if the condition is satisfied, execute the action.* The general syntax is 'on *event*-if *conditions*-do *actions*' (Poulovassilis, Papamarkos, & Wood, 2006). In software adaptive system, *Monitoring-Analyzing-Planning-Executing with knowledge* (MAPE-K) loop is one of the most well-known adaptation mechanisms (Macías-Escrivá, Haber, del Toro, & Hernandez, 2013).

Although the terms and notions used for describing the self-adaptive methods above are different, the general process of self-adaptation is implemented on a rather common concept. This concept consists of (i) perceive the current state from input data, (ii) monitor and analyze changes, and (iii) plan and adapt the process/system to the optimal state. The concept of closed loop mechanism limits the possibilities of adaptation when open-loop interaction with the external environment is becoming a fundamental aspect of the system (Baclawski et al., 2017). Approaches to true self-adaptive behavior are still in their infancy.

5.4. An analysis of framework contents for computational reasoning

Frameworks for computational reasoning were analyzed from the same aspects as frameworks of CPSs. Reasoning frameworks are shown with bolded fonts in Table 1. We found no comprehensive framework that provides multi-aspect guidelines addressing all relevant aspects of designing reasoning mechanisms for smart CPS. Only the framework of knowledge modeling and decision making by Petnga and Austin (2016) provides support for designing computational methods for reasoning at the time of designing cyber physical systems. However, this framework lacks features that would facilitate the composition of reasoning methods and analysis of their interoperability. It is also notable that many frameworks lack support of designing architecture of computational reasoning mechanisms and information flows between components. The analysis is shown in Table 2.

No holistic framework covering all aspects of system-level reasoning has been developed so far (see Table 2). Existing reasoning frameworks for designing adaptive software systems facilitate only specific aspects such as context awareness or knowledge modeling and management to support the execution of self-adaptive process loop. Integration of these dedicated frameworks into a holistic solution should go beyond simple interconnection of these framework implementations. Their fundamental concept architecture and information flow should be based on the same principles and guidelines. Without a rigorous unifying framework, system integration and integration of the analysis results for various frameworks remains ad hoc. This requires a multi-aspect framework that can integrate reasoning mechanisms on various abstraction levels ranging from defining system objectives to concrete implementation of adaptation at run-time.

Table 2
Analysis of framework contents concerning system-level reasoning aspects.

types of FW	system-level reasoning aspects					domains of context	references
	knowledge	system awareness	reasoning mechanism	decision-making	system adaptation		
conceptual		learning in nonstationary environments	approximate computing			smart cyber-physical systems	Alippi and Roveri (2017)
	knowledge transformation		context reasoning			cyber-physical systems	Li et al. (2014)
	knowledge modelling		rule-based reasoning (RBR)			cyber-physical systems (a traffic light time-based reasoning system)	Petnga and Austin (2016)
		context information	case-based reasoning (CBR)model	evidence-based practice		healthcare management	Lapaige (2009)
	uncertainty knowledge		non-axiomatic logic			crisis response management	Slam, Wang, Xue, and Wang (2015)
		context awareness	combining fuzzy RBR with a case-based model			smart home healthcare	Yuan and Herbert (2014a)
		uncertainty situation	logic-based programming based on BDI paradigm			agent-based systems	Bauters, McAreavey, Hong, Chen, Liu, Godo, and Sierra (2016)
logical	knowledge sharing		integrating logic with quantitative algorithms		adapt to changes	networked cyber-physical systems	Choi et al. (2014)
architecture	ontology for describing the problems	data fusion	context reasoning			multi-sensor fusion applications	Mart (2015)
	ontology modeling& semantic similarity		CBR	medical decision-making		telemedicine	Sene et al. (2015)
		situation awareness	CBR/hierarchical clustering of contexts			inferring a situation using IoT sensor data	Park, Sohn, Jin, and Lee (2016)
		context awareness	fuzzy RBR; CBR			pervasive healthcare system	Yuan and Herbert (2014b)
		context awareness	RBR			wireless machine to machine networks	El Mougy, Kamoun, Ibnkahla, Tazi, and Drira (2014)
	semantic knowledge base	context awareness	context reasoning			ubiquitous service management	Tiberghien, Mokhtari, Aloulou, Biswas, Zhu, and Lee (2011)
			CBR		adaptive SW systems	multi-agent system	Campos, Lopez-Sanchez, Salamó, Avila, and Rodríguez-Aguilar (2013)
	knowledge based diagnosis		neural network based pattern recognition	decision-making		monitoring to machining	Caggiano, Segreto, and Teti (2016)
	knowledge discovery (data mining)		ontological reasoning	decision theory & multi-obj. prog.		agent-based decision support system	Sokolova and Fernández Caballero (2012)
component-based		context modelling	context reasoning			smart cyber-physical environments	Cicirelli et al. (2016)
			RBR; CBR; genetic algorithm		self-adaptive software system	web service	Neto, Costa, De Lucena, and Silva (2009)
		situation awareness	RBR			evaluation of energy consumption in data center	Ferreira and Pernici (2016)
	knowledge processing		classifier rule			autonomous robots	Tenorth and Beetz (2009)
model-based		spatial & temporal information	data fusion reasoning mechanisms			traffic systems	Pradhan and Akinci (2012)
	OWL-based on human activity	situation awareness	context-driven situation interpretation algorithm			human activity recognition	Meditskos and Kompatsiaris (2017)
	OWL-based representation of policies		reasoning about semantic formulas for policy analysis	policy conflicts		distributed agent-based systems	Sensoy, Norman, Vasconcelos, and Sycara (2012)
	descriptive knowledge	awareness	logical reasoning			cyber-physical systems	Kappé et al. (2016)

6. Findings and discussion

As discussed by many researchers, the paradigm of cyber-physical systems is rapidly evolving, and the domains of investigations, implementations and applications are proliferating fast. This is the reason why thinking in generations of CPSs was proposed in Horváth et al. (2017). It can be seen that while CPSs are showing more 'system intellect' in their operation, their control regime must be more sophisticated, and they should be equipped with many self-* characteristics. S-CPSs present many system level operational characteristics as opposed to the component operation driven aggregative manifestation of system characteristics. They go beyond what can be analyzed and designed based solely on reductionism and traditional model-based approach. These statements are becoming our research challenge how to develop smart CPSs with capabilities of self-awareness and self-adaptation. The study was completed by using mixed qualitative and quantitative methods. The publications related to CPSs and system smartness represented the broader and the narrower contexts of the study. The domain of discourse included the domain of system development frameworks in the contexts of designing system-level reasoning and its enablers. The major findings are summarized as follows.

Despite that some of the computational reasoning mechanisms are able to imitate some aspects of human like reasoning, most them remained data driven and operate according to statistical and/or rule-based methods. While computers are strong in processing of and making decisions based on large amount of data and predefined rules, they are currently weak in reasoning with analogies and intuitive inferencing. Efforts, on the other hand, are already visible in the state-of-the-art literature that aim to mimic human like reasoning and extending the existing approaches with human like capabilities such as intuitive belief network generation. The authors expect that more research efforts will be focused on development of reasoning mechanisms capable to (i) explore semantic relationships of data and information elements of emerging situations and unknown operation based on analogies, or ontologies, (ii) create belief networks for representing potential associations of knowledge elements in order to fill in incomplete knowledge and information over processes, and (iii) adapt reasoning strategies to ill-defined problems and heterogeneous knowledge and information representations. These trends, on the other hand, pose specific requirements on frameworks supporting the design of reasoning mechanisms. Frameworks should (i) accommodate and cope with the heterogeneity of newly developed and existing knowledge representations, (ii) be flexible to incorporate novel reasoning mechanisms and decision making processes, and (iii) provide means to explore the interoperability of the sub-solutions, (iv) capture functions and operating conditions of reasoning methods.

Our research has shown that it is difficult, if not impossible, to apply a single reasoning method to tackle complex reasoning problems that S-CPSs are typically facing. As S-CPSs operate under unpredictable, emerging conditions, their ability to run-time adapt to changing conditions in a safe and predictable way is essential for their robust operation. Reasoning about emerging conditions and their effect on system performance creates a complexity that cannot be tackled by predefined reasoning methods. This complexity is caused not only by demands for real time computational requirements or by the need to cope with incomplete information, but also by the problem of finding optimal reasoning and adaptation strategies matching the nature of the emerging situation. It requires run time composition of reasoning strategies and adaptive use of reasoning methods. The challenge for designers of reasoning mechanism is to narrow down the solution space of composition of reasoning mechanisms that provide synergetic operation of S-CPS. Frameworks supporting the design of reasoning mechanism should offer methods and tools for (i) exploring possible matches of reasoning mechanisms and the nature of emerging conditions, and (ii) verifying the interoperability of reasoning mechanisms synergetic reasoning operation.

We found that synthetic computational approaches have the ability to compose reasoning methods at run time. They, however, implement a low-level smartness by straightforward composition of methods that are only activated if given conditions are fulfilled. Smartness is, however, not only a collective property of a system, but it is also a holistic and synergistic behavioral characteristic. The orchestration of synergetic interoperation of reasoning methods goes beyond condition-based composition. It should utilize the complementary and strengthening effects of reasoning methods. Frameworks should have the ability to actively explore compositions that strengthen or weaken the quality and performance of compositional reasoning methods. With proliferation of AI technologies, massive amount of knowledge of the applicability and limitations of reasoning methods are generated that is not documented, and structured for design purposes. They should actively expand their knowledge base by recording applicability, limitations of compositional reasoning approaches and they should provide guidance for designers based on case-based reasoning.

Design of compositional reasoning requires comprehensive means for supporting the entire design process. Frameworks should support the design of knowledge representations, system awareness models, reasoning mechanisms, decision making scenarios, and system adaptation plans. Their support should facilitate modeling system knowledge with a wide range of formalisms (i.e., from generic domain knowledge to specific task knowledge). As far as knowledge representation by frameworks dedicated to designing reasoning mechanisms is concerned, they should be equipped with many knowledge representation means in order to be able to cope with the representational challenges. In the background of this is the expectation that S-CPSs should be able to select and handle knowledge synthesis mechanisms that operate with heterogeneous and/or incomplete knowledge. System awareness is a fundamental ability of S-CPS from the point of view of realization of the overall smart behavior of the system. This ability enables systems to control their performance and operation, and to interact with their embedding environment purposefully.

Awareness is built by syntactic and semantic processing of data obtained from a range of hardware and software sensors. Designing for system awareness also requires computational data fusion technologies and models, and various inference mechanisms for transforming data to information and knowledge. The design process of decision making mechanisms needs to consider: (i) when a decision can be made by the system based on acquired and inferred knowledge, (ii) what methods of decision making are the most suited for the problem and the knowledge at hand, (iii) how to verify the decisions with regards to the objectives of the system, and (iv) how to evaluate and learn from the consequences of the decisions. Another challenge is designing systems for run time adaptations. System adaptation goes together with the need to develop strategies for generating alternative operation modes for the system. It requires computational mechanisms (i) to transform the changing system objectives into feasible action plans, (ii) to decide on the operationalization and timing of the chosen action plan, and (iii) to execute the adaptation in a fully controlled manner. Design of reasoning mechanisms covers (i) the selection of the modality of reasoning (e.g. deductive, inductive, abductive) that is the most suited for building awareness, making decisions and adaptation of the system, (ii) composition of reasoning methods, (iii) design of compositional reasoning workflow, (iv) interfacing the elements of the reasoning mechanism for a seamless interoperability, and (v) verification of compositional framework of reasoning.

7. Conclusions and suggestions for the future works

7.1. Proposals based on the completed analysis

Compositionality regarding reasoning mechanisms manifests in different levels of abstraction that are: (i) on the system level, it achieves a synergy of knowledge through the entire reasoning processes that is needed for multi-task problem solving; and (ii) on the component level, system components should be interoperated in compositional manner. Without a rigorous unifying framework, synthesis reasoning and an integration of the analysis results based on analytical computational approaches remain *ad hoc*. This requires a multi-level framework that can integrate system-level reasoning on various abstraction levels ranging from defining system objectives to concrete implementation of adaptation at runtime. The framework should be taken into account throughout the entire design process, starting with a realization of system-level behaviors to run-time adaptation.

The range of functions for the framework for designing compositional reasoning creates a complexity that cannot be handled by single monolithic framework. The complexity of this problem requires composite framework that is able to capture all relevant aspects of system conceptualization and design that can be the basis of multi-aspect system models, e.g. system behaviors, including reasoning methods and their interoperability, knowledge transformation throughout the multiple reasoning processes, exploration of adaptation strategies, and self-adaptation. These aspects should be captured in the framework at least conceptual, functional, architectural, informational, interoperation, behavioral aspects. This also needs further investigation if a compositionality enabling framework should appear in the form of a meta-framework (abstract) or a semantically integrated (concrete) framework.

The essence of compositionality-enabling framework is the combination of system level architecture design with requirements capturing and functional specification of reasoning mechanisms. If we consider the reasoning methods and computational algorithms as resources for developing reasoning mechanisms, a development framework should facilitate a system designer with these tasks e.g. guiding how to select the right reasoning method with proper algorithms, providing an example of the best coupled reasoning methods in a particular case, comparing alternatives for the integration of multiple methods, and giving a recommend about the feasible solutions.

7.2. Future inquiry options

The challenge of the future research is how compositional enabling framework can support both software-enabled constituent integration and multi-aspect knowledge-synthesis for a development of reasoning mechanism. It seems to be necessary to import many relevant principles of compositional software development, but it will ultimately be sufficient. Holistically smart system operation needs integration of data, information and knowledge, which can be achieved only through number of semantic transformations. Future research should focus on data, information and knowledge fusing technologies that enable the implementation of compositionality.

Conflict of interest

None.

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