Cognitive Digital Twins for the Process Industry

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***Abstract*—The concept of a Cognitive Digital Twin (abbreviated CT or CDT) is presented in this paper as an extension of Digital Twins (DTs) with cognitive capabilities in the context of the process industry. With cognitive capabilities, we foresee possibilities for the next level of automation in process control systems. This article proposes an architecture associated with a CT control system, exemplified in a process industry use case. The CT is therefore seen as a more comprehensive approach in comparison to a traditional DT.**

Keywords- Digital Twin; Cognitive Digital Twin; Cognitive Architecture; Cognitive Services; Process Industry, COGNITWIN.

I. INTRODUCTION

DTs are emerging nowadays as a popular technology approach in many industries. A DT is generally considered a digital replica of a physical system that captures attributes and behaviours of that system. The purpose of a DT is to enable measurements, simulations, and experimentations with the digital replica in order to gain understanding about its physical counterpart. A DT is typically materialized as a set of multiple isolated models that are either empirical or first-principles based.

In the context of the process industry (including sectors such as chemicals, ferrous and non-ferrous, ceramics, etc.), the existing automated systems, while performing well in predictable environments, require substantial human intervention when faced with unanticipated situations for which they weren't designed to handle. Such situations require perception, reasoning, decision making, learning – aspects usually associated with cognition and addressed in the area of cognitive computing.

Cognitive computing is the ability of machines to mimic human ability to sense, think, and make optimal decisions in a given situation. Although the journey to reaching fully cognitive systems is still in its infancy, there are several application areas where the technology has already been implemented (e.g., the use of chatbots by the service industry to provide optimal answers to customer feedback). The genesis of such cognitive systems in the process industry would be DTs where physical systems are represented by mathematical models. CTs can be seen as extensions of DTs where the semantic and cognitive aspects are also featured in the DTs.

For realizing CTs in the process industry, an essential aspect is to devise the architectural building blocks that can serve as a foundation for cognitive systems in this domain. In this paper, we present an architectural framework for CTs in the context of process industry. This work contributes to one of the fundamental challenges for building intelligent systems, where cognition plays an important role in the underlying infrastructure of such a system. A cognitive architecture should provide a blueprint, supporting a wide range of abilities similarly to human capabilities [9]. Indeed, the architecture proposed in this paper can be seen as a cognitive architecture for building CTs.

The rest of the paper is organized as follows. In Section II, we review the various definitions of the emerging concept of CTs. In Section III, we present our proposal for an architecture for CTs, including cognitive services and challenges for implementing the identified cognition services. In Section IV, we discuss a concrete use case from the process industry and the role of cognitive services in that particular use case. Section V summarizes the paper and outlines possible future work.

II. DEFINITIONS OF COGNITIVE DIGITAL TWIN

The concept of "Cognitive Digital Twin", often used in its shorter form "Cognitive Twin", has recently emerged in the context of DTs as a mean to expand their scope by encompassing cognitive capabilities.

The concept appears to be first introduced in the industry context. For example, El Adl [5] defined CT in 2016 as a "digital representation, augmentation, and intelligent companion of its physical twin as a whole, including its subsystems and across all of its life cycles and evolution phases" [5]. The "Cognitive Digital Twins" LinkedIn group, established in 2016, and administered by the same person, defined CTs as "highly interconnected distributed cognitive systems and in specific cases very large complex systems. They live in the digital space, span physical and virtual

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systems and will evolve over time as the Things they represent evolve. They should represent all the life cycle phases of Things. CTs should be able to interact and collaborate across domains, physical and virtual worlds, as well as evolve to be able to autonomously take smarter contextual decisions and execute complex tasks on behalf of the physical things or humans. In many cases, they will replace physical components with intelligent software components" [10]. Furthermore, the group identifies aspects needed in the definition and realization of CTs, such as categories of CTs, reference architectures, actions and interactions of CTs, artificial intelligence (AI) & machine learning (ML)/deep learning (DL) in the context of CTs, real world applications, CTs interaction to its physical body (machines), and cyber and physical security of CTs.

IBM has been active in the CT domain. In this context, Saračević [17] presented the CT concept in 2017 as a "virtual representation of a physical object or system across its lifecycle (design, build, operate) using real time data from IoT sensors and other sources to enable learning, reasoning and automatically adjusting for improved decision making" [14]. A similar definition is presented by Eran Gery who also presented a CDT architecture based on IBM technologies in the area of Cognitive Computing and Cognitive Sensing: "The Cognitive Digital Twin is the virtual, state-full representation of a physical object or system across its life-cycle (design, build, operate) using operational real-time data and other sources to enable understanding, learning, reasoning, and dynamically recalibrating for improved decision making" [7]. Mikell and Clark [12] discussed about the use of cognitive computing techniques such as natural language processing (NLP), ML, object/visual recognition, acoustic analytics, and signal processing in the context of DT: "using cognitive to improve testing a digital twin can determine which product tests should be run more frequently and which should be retired. Or cognitive sensing can improve what/when data from sensors is relevant for deeper analysis. Cognitive digital twins can take us beyond human intuition to design and refine future machines" [12].

Furthermore, in 2018, Miskinis [13] discussed about the possibility to manufacture DTs that have cognitive functions (together with the hidden dangers of CTs). CTs are introduced as DTs that execute conscious actions, for example, "by having the ability to execute cognitive tasks, a digital twin of a service fulfillment or product manufacturing process will be able to examine the current structure of a system or a process and give recommendations regarding what can be improved at the current moment" [13].

The CT concept also appeared in specific sectors. For example in the telemetry sector CT is introduced as an "artificially intelligent Digital Twin that has the potential to serve as an 'autonomous maintenance engineer'" [1].

More recently, the CT concept got traction in the scientific literature. For example, Fernández et al. [6] consider CT as a "digital expert or copilot, which can learn and evolve, and that integrates different sources of information for the considered purpose. The structure of a CT partially emulates the structure of the corresponding human mental models" and define an architecture for "Associative Cognitive Digital Twin". Lu et al. [11] consider CTs as "Digital Twins (DT) with augmented semantic capabilities for identifying the dynamics of virtual model evolution, promoting the understanding of interrelationships between virtual models and enhancing the decision-making based on DT". In our recent work [2], we introduced a layered framework of twins, consisting of three layers: DTs, Hybrid Twins (HTs), CTs, in which each higher layer is defined in terms of extensions to the lower levels. We thus defined a CT as "an extension of HT incorporating cognitive features that enable sensing complex and unpredicted behaviour and reason about dynamic strategies for process optimization, leading to a system that continuously evolve its own digital structure as well as its behaviour". Furthermore, Eirinakis et al. [4] proposed the concept of "Enhanced Cognitive Twin" (ECT) in the context of process industries, as a way to "introduce advanced cognitive capabilities to the DT artefact that enable supporting decisions, with the end goal to enable DTs to react to inner or outer stimuli. The ECT can be deployed at different hierarchical levels of the production process, i.e., at sensor-, machine-, process-, employee- or even factory-level, aggregated to allow both horizontal and vertical interplay" [4].

Finally, it is worth mentioning the CT concept appears also in non-engineering contexts. For example, Somers et al. discuss CT as a "digital reflection of the user, intended to make decisions and carry out tasks on the user's behalf", to "highlight the key role that cognitive mechanisms play in modeling human decision making in the IoT digital space" [16]. CT was applied to professional education, where a CT is "used by applications owned by an individual to identify knowledge obsolescence and gaps" [15]. Du et al. [3] introduces a personal DT model of information-driven cognition (Cog-DT). Cog-DT is a "digital replica of a person's cognitive process in relation to information processing", including a VR platform that collects information preference data during training, contains the modelling and optimization algorithm of DT modelling of human cognitions, and an adaptive UI design based on real-time cognitive load measures and Cog-DT models.

As can be seen from the above review of existing CT definitions, a common agreement appears to be that a CT is a DT extended with some forms of cognitive capabilities, however there is no widespread consensus on what kind of cognitive capabilities a CT should encompass. This is probably partly because the CT concept is still an emerging concept, and that various sectors may require various types of cognitive capabilities.

III. COGNITIVE DIGITAL TWIN ARCHITECTURE

In this section, we provide the conceptualization of the cognition services, which are the main concept used for realizing human-like cognition on the top of DTs. As illustrated in Fig. 1, to cope with challenging industrial cases, we designed a hierarchy of twins (DT/HT/CT), whereas each layer provides a set of services required for realizing various operations on data and models, resulting in a cognition-based replica of a physical system. As presented in the figure, the architecture enables a control loop that supports a continuous

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adaptation of the real industry system (e.g. settings, reconfiguration). In this paper, we focus on the CT layer. Further details on the components of the DT and HT layers can be found in [2].

more connected view on the data and models. The key advantage is the introduction of new knowledge that should provide missing insights for resolving original cases, as illustrated in Fig. 2.

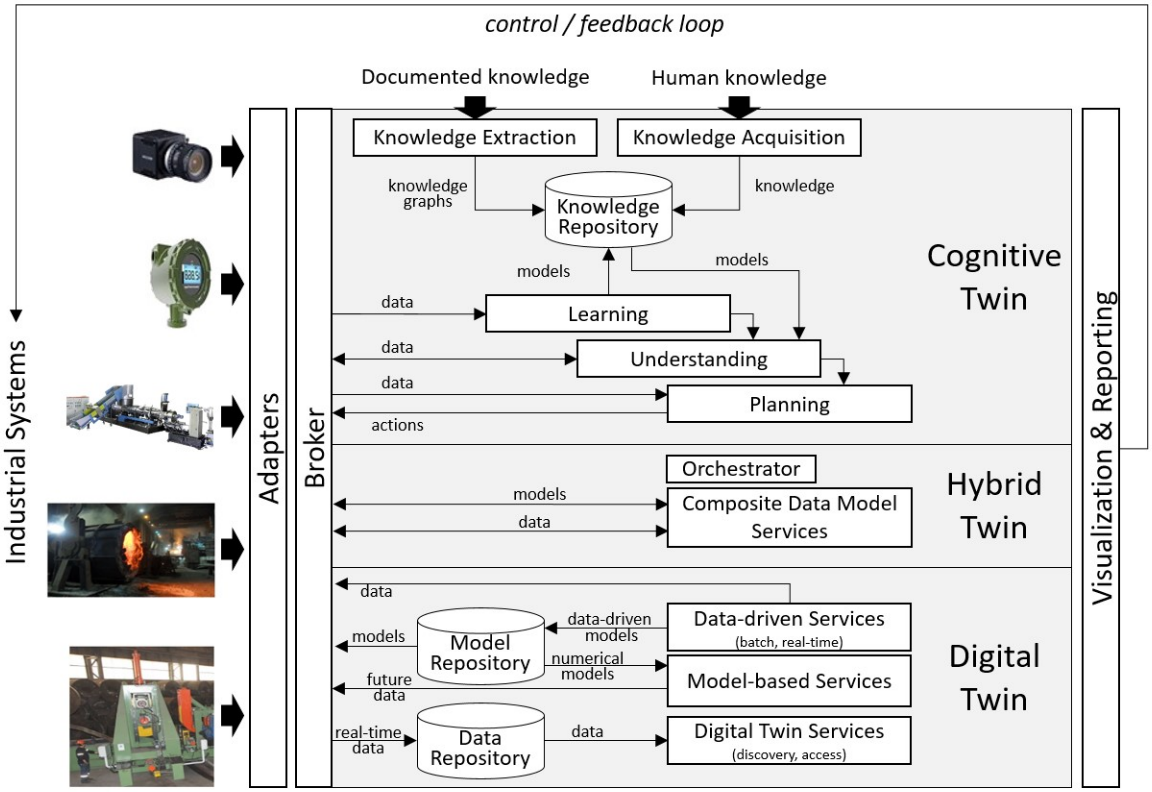

Figure 1. Conceptual architecture for CTs (based on [2]).

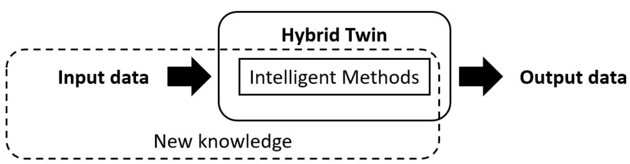

Figure 2. Cognition extending HT solution.

In order to facilitate the creation of such solutions for the industry, in the context of the H2020 COGNITWIN project we are currently developing the COGNITWIN Toolbox (CTT), which represents a set of technological components that can be used to build DTs, HTs, and CTs. Fig. 1 represents the conceptual architecture of a solution created by the application of the CTT.

A. *Cognitive Twin Layer*

There are many definitions of the cognition, but for this paper, we focus on that derived from the cognitive computing domain, which is related to reasoning and understanding at a higher level, in a manner that is analogous to human cognition [8]. We specialize this view for the complex cases where there are many uncertainties inherent in the available data and models. We expect that a human-cognition-like approach will enable a broader, as well as a more connected view on the data and models.

As presented in the figure, we assume that "intelligent methods", which can be a part of Hybrid Twin (see [9]), supports the development of a solution that "maps" inputs into outputs. However, the solution might be missing a high accuracy, due to not having enough data in the training set. As illustrated, cognition supports augmenting the input data, as well as intelligent methods with new knowledge (gathered directly from experts or other sources), with the goal to generate new outputs (with a higher accuracy). Therefore, we argue that the uncertainty inherited in the problem (e.g., missing data or models) can be resolved by augmenting data and intelligent methods to compensate missing information. Notice that this process is not about getting new data, but rather new insights about existing data (through cognition).

Therefore, the main role of cognition services is to enable understanding of the behaviour of the monitored system under various types of uncertainties/unknowns, to support reliable decision making (by human experts) or control (in autonomous systems). Uncertainties can be of different types, but we focus on two most important types from the DT point of view: lack of data and unavailability of models regarding the current system behavior. Other types of uncertainty can be related to the uncertainty in the data values and the precision of available models. For our

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approach, it means that the current system behaviour cannot be understood neither by analysing past data, since the relevant data is missing, nor by simulations of numerical models, since these do not exist (or are not accurate enough). In such cases, it is important to compensate these unknowns by introducing new processing steps that will gradually improve the understanding of the system behaviour, until this understanding is enough for the desired action. This process we consider as cognition, where the processing steps are part of cognition services.

The main challenge is that real-time data is not enough for understanding the current situation (regarding the underlying problem). The main goal of the cognition service is to enable resolution of the original problem by introducing new knowledge that provides new insights for the model learning/creation processes, e.g., introduction of some constraints in the interpretation of originally collected data. Therefore, cognition is working on the top of existing models, which can be derived using AI methods, extending the intelligence with deep understanding and reasoning strategies.

We can materialize this general process through following four steps:

1. Inserting new knowledge (relevant for the problem).
2. Learning models that are more accurate by applying new knowledge.
3. Better situational understanding (e.g., lower interpretation uncertainty), by applying new models.
4. Planning actions for resolving the problem, based on improved situational understanding. We describe these steps as follows:
   a. Knowledge extraction and knowledge acquisition, for gathering knowledge from the existing data sources (e.g., unstructured and semi-structured content) and from experts, respectively. The goal is to collect knowledge, which is related to the uncertainties in data and models. Since the process is related to supporting human-like understanding, it is important that the process is driven by well-defined knowledge structures (like knowledge graphs) which provide a general description of the domain. Indeed, one of the main characteristics of the human cognition is a very fast discovery of hidden connections between arbitrary information items, which is based on large memory maps.
   b. Learning, which encompasses applying new knowledge on the existing data, models, and methods, with the goal of learning more accurate models (from existing datasets). There are three main activities:
      - Transforming existing datasets into anomaly free ones, which can be used for learning models that are more accurate.
      - Improving used learning methods by introducing some knowledge-driven constraints in the learning process.
      - Adding new methods that can complement existing ones in the context of the above-mentioned uncertainties.
   c. Understanding, which is related to applying new models on real-time data for getting a better interpretation of the situations of interests (e.g., problem/anomaly detection). We assume that, as in the human-like cognition, this process can be iterative, i.e., understanding a process can generate data, which can be used for improving the learning process (like in reinforcement learning).
   d. Planning, for defining optimal actions based on system behaviour understanding.

B. *Challenges for Cognition*

There are several challenges to be addressed in order to realize the vision of CTs, with the most important ones discussed in the following.

1) *Knowledge representation challenge*

The first question to be clarified is how knowledge can be formally represented to enable the fact that a DT learns from experience and behaves intelligently, like a human. All cognitive services mentioned above heavily depend on this decision.

The more complex the representation of knowledge, the more difficult it is to acquire this knowledge automatically. However, more advanced reasoning services can be offered. Our goal is not only to support the decision-making process, but also to increase its accuracy and human-acceptance. Thus, both declarative and procedural knowledge is needed, as questions such as ‘what?’, ‘how?’, ‘when?’, ‘in what context?’, ‘what-if?’, etc., should be answered.

Several knowledge representation formalisms seem to be suitable for CTs. To clearly separate general knowledge from specific knowledge, it makes sense to structure the knowledge into two parts: ontologies for representing the domain knowledge and rules for representing the problem-solving knowledge.

To better understand a current situation (i.e., the asset itself, the context in which it is used, its environment, etc.), we consider using ontologies. They are a knowledge representation method that is on one hand expressive enough and on the other hand extensible. They could be used to:

- Represent the domain knowledge which includes the vocabulary domain-experts apply (e.g., brick wall, types of bricks like red shale or clay bricks, the features of bricks like thermal shock resistance or mechanical strength, etc.) as well as the constraints (e.g., temperature threshold at which the stone is unusable).
- Take into account existing standards for the domain (e.g., standards from the steel process industry for the use case described in Section IV).
- Support collaboration between DTs, e.g., for cooperative execution of complex tasks.

Although simple constraints (e.g., temperature of a ladle must not exceed a certain threshold) can be modelled by using ontologies, there are many scenarios where complex (functional or behavioural) constraints should be considered (e.g., calculations that include results of different physics-based/AI/statistic-based models).

To mimic the reasoning of human expert in solving knowledge intensive problems, there is a need to use rules (e.g., event condition action rules). Rules should be used even in the present of incomplete and/or uncertain information to (i) focus the attention to the most important aspects and (ii) collect additional, goal-oriented information relevant for a given context. This can be done by mapping of raw sensor data and/or outputs of different DT models to actions (such as control decisions or recommendations for human operators).

2) Knowledge acquisition challenge

The second challenge is collecting knowledge which is not only spread in different documents (e.g., excel tables) and software systems (e.g., error reports in MES systems), but could be also implicit as it is based on personal experience that is even more difficult to express. To make the tacit knowledge explicit and machine-understandable and machine-processable, different cognitive technologies could be used such as NLP, speech recognition, etc. For example, one possibility is to apply a speech-to-knowledge approach, as speech is relevant for the shop floor workers for short information interchange allowing hands-free conversations. Since in recent years the multilingual speech functionality has become a commodity available on smart speakers, mobile phones, and computers, the pre-existing solutions could be reused and added to the CT to enable speech communication channels with human operators. Ontologies can help achieving higher accuracy of resulting rules, as synonyms, multilingual aspects, context, etc., can be taken into account. In this way, the domain and problem-solving knowledge will be connected.

3) Knowledge update challenge

In addition to collecting knowledge, the ability to learn, to unlearn and continuously update knowledge is crucial for CTs to create competitive advantage. Knowledge update is however a complex process, which includes knowledge extension (e.g., adding a new entity in the ontology for new types of bricks), knowledge forgetting (removing an ontology entity representing material not used anymore for bricks) and knowledge evolution (e.g., changing a max temperature of a ladle). The similar strategies can be applied on the problem-solving rules. The challenge lies not only in ensuring the consistency after applying a change, but also more importantly in discovering the need for a change. This can be done by applying usage-driven strategies (e.g., by monitoring whether the proposed decisions were accepted by domain experts) or by using structure-driven methods (e.g., by using ontology-based reasoning to discover conflicting rules or generalized/specialized rules).

IV. Cognitive Digital Twin Use Case From the Process Industry

To illustrate the concept and role of CTs in process industry, a discussion on an application of such an approach to a real-world problem from steel production process industry is presented in this section. The use case shows how various hurdles concerning asset maintenance and predictive controls from the process industry can be further improved from its current state.

The steel production process typically has three stages. First, the scrap steel is collected and melted in an electric arc furnace. In the second stage, the molten melt is transferred to the ladles for secondary metallurgy. In the third and final step, the casting process, the molten steel is moulded to a desired shape. In the secondary metallurgy process, the molten metal is mixed with several substances (or impurities are removed) to produce the specific grades of steel depending upon the customer requirements. This process is carried out in specially developed ladles that are designed to withstand such extreme temperatures and condition for a sustained period. The inner walls of the ladles are lined with magnesium oxide bricks and carbon, which is worn out little by little with every heat. After a certain number of heats, typically ranging anywhere from 50 to 100 heats, these brick walls are so thinned down that the brick lining needs to be completely demolished, and a fresh batch of bricks are placed along the inner walls. The challenge here is that the decision about when/whether or not the bricks need to replaced is taken by a technician or an engineer by visually inspecting the brick conditions and also taking a look at the process parameters. If the brick linings are not sufficiently thick enough, molten steel in the ladle can leak from the ladle and flow into the factory floor potentially causing accidents. Due to the enormous risk to the health and safety of the workers in the production plant, the technician usually makes the decision about whether or not to re-line with fresh batch of bricks based on the "better safe than sorry" philosophy. The drawback of this approach is that if the bricks are replaced even if they really do not need to be replaced, it results in increased production overheads and costs for the company.

If one were to address this problem using DTs, a mathematical model that simulates the behaviour and degradation mechanism of the bricks in the ladle would be an obvious starting point. By developing advanced ML algorithms, it may be possible to develop programs that can predict when the bricks need to be replaced. In addition, it is possible to develop physics-based models that simulate the brick wall conditions when subjected to severe mechanical and thermal stresses, which can further improve the ML-based models to create a HT of the process. The CTs on the other hand will include the human intelligence factor in the models to deal with the uncertainty inherent in the process. One of the main challenges for resolving this problem is the lack of sufficient data, given that the process is rather complex. Ideally, it would help to detect false negatives; meaning decisions to replace the brick lining were taken even if it was not required. This however is not always available due to practical reasons. The models in the CTs would include instances that were exceptional and rare scenarios and decisions taken by the manual intervention to best suggest whether the bricks in the ladle will need be replaced or repaired.

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V. CONCLUSION AND FUTURE WORK

In this paper, we introduced the concept of CTs in the context of the process industry and proposed a CT architecture a baseline for building CTs. Despite recent attempts in defining CTs, the concept is still emerging; with various aspects and perspectives presented in the literature and no shared agreement on the scope of CT, other than extension of DTs with cognition elements. We reviewed the relevant definitions in the literature and provided our architectural perspective on the type of cognitive services needed for CTs in the context of process industry, identified the challenges for realizing the proposed cognitive services, and discussed their role in the context of a concrete use case in the process industry. Progress on cognitive architectures is seen through the development of hybrid representations that combine symbolic and numeric content, mechanisms for learning procedural and control knowledge, incorporation of large-scale knowledge structures, construction of embodied and interactive agents, and support for both declarative and episodic memories [9].

Less progress has been made in areas such as abductive understanding, dynamic memories that acquire new conceptual structures, creative aspects of problem solving, emotional processing, agent personality, along with plausibly related topics of metacognition and goal reasoning [9].

We plan to apply the CT approach in a set of use cases as follows:

- Operational optimization of gas treatment centre (GTC) in aluminium production, where CT of the GTC recommends optimal operating parameters for adsorption based on real-time data gathered about conditions such as the pressure, temperature, humidity, etc., from sensors.
- Minimize health & safety risks and maximize the metallic yield in Silicon (Si) production to provide best estimates of when the furnace can be emptied to the ladle for further operations.
- Real-time monitoring of finished steel products for operational efficiency with an ability to react on its own to situations requiring an intervention, thus stabilizing the production process further.
- Improving heat exchanger efficiency by predicting the deposition of unburnt fuel mixtures, ash and other particles on the heat-exchanger tubes based on both historical practices and real-time process.

As part of future work, we plan to validate the proposed cognitive services architecture in all these use cases.

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