Cognitive Digital Twin for Manufacturing Systems

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***Abstract*—A digital twin is the virtual replica of a physical system. Digital twins are useful because they provide models and data for design, production, operation, diagnostics, and autonomy of machines and products. Hence, the digital twin has been projected as the key enabler of the Visions of Industry 4.0. The digital twin concept has become increasingly sophisticated and capable over time, enabled by many technologies. In this paper, we propose the cognitive digital twin as the next stage of advancement of a digital twin that will help realize the vision of Industry 4.0. Cognition, which is inspired by advancements in cognitive science, machine learning, and artificial intelligence, will enable a digital twin to achieve some critical elements of cognition, e.g., attention (selective focusing), perception (forming useful representations of data), memory (encoding and retrieval of information and knowledge), etc. Our main thesis is that cognitive digital twins will allow enterprises to creatively, effectively, and efficiently exploit implicit knowledge drawn from the experience of existing manufacturing systems and enable the transfer of higher performance decisions and control and improve the performance across the enterprise (at scale). Finally, we present open questions and challenges to realize these capabilities in a digital twin.**

***Index Terms*—Digital Twin, Manufacturing Systems, Cyber-Physical Manufacturing Systems, Cognitive Systems, Industry 4.0.**

I. Future of Manufacturing

Manufacturing has gone through three major transformations in the past: the industrial revolution in the 18th and 19th centuries, mass production in the first half of the 20th century, and information technology-based automation of production in the second half of the 20th century. We are now at the early stages of the fourth major transformation. As such, visions of the future of manufacturing are being developed across the world under different labels: Industry 4.0, Smart Manufacturing, connected industries (as part of Society 5.0 in Japan), Made in China 2025, etc. Most of these visions aspire to bring together wireless (and wired) communications, smart sensors, cyber-physical systems, internet-of-things [1]–[3], advanced robotics [4], [5], additive manufacturing, simulation and high-performance computing, advanced data analytics, machine learning and artificial intelligence, cloud computing, and cybersecurity [6]. The goal is to achieve personalized, affordable, efficient, resilient, adaptive, and sustainable products and production across distributed factories and supply chains.

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The digital twin technology is a crucial enabler of this vision [7], [8]. Digital twins of products, processes, and systems of a manufacturing system have applications in design, maintenance, planning, and optimization at various scales and stages. Although the concept of the digital twin is not new, sophisticated modeling and simulation capabilities, pervasive deployment of IoT sensors, standards and interoperability among digital technologies, tools and computing infrastructure, and availability of large volumes of data from different stages of the product lifecycle are being leveraged by the digital twin technologies. These enabling technologies that constitute increasingly sophisticated and powerful digital twins are illustrated in Figure 1.

It is projected that the digital twin concept will impact all the stages in the product life cycle of a manufacturing system: product design and optimization, testing, production system design and operation, supply chain management and control, prognostics, maintenance, aftermarket services, cybersecurity, etc. The applications and usages of digital twins are rapidly evolving and shaping the future of manufacturing. Gartner has listed the digital twin as one of the top ten technology trends for 2019 and the years to come [9]. According to recent research, the digital twins' market size is projected to grow from US$3.1 billion in 2020 to reach US$48.2 billion in value by 2026 [10]. The aerospace and automotive industries are leading in the use of digital twin technologies. Probably, other manufacturing sectors will also leverage digital twins [10], [11].

In this paper, we present a new digital twin concept that can pave the way for realizing the visions mentioned above. In this spirit, we propose a novel conceptual framework called *cognitive digital twin* inspired by the advances in cognitive science, machine learning, and artificial intelligence in digital twins and manufacturing. Cognitive digital twins' development is a major challenge that will require novel conceptual frameworks and algorithmic breakthroughs. We highlight a cognitive digital twin's impact on the product design stage among different product life cycle stages. Moreover, while presenting several properties of the cognitive digital twin, we leverage the idea of cyber-physical production systems (CPPS), which integrate physical production devices and systems with sensors, communications, and control systems.

The rest of the paper is organized as follows: Section II introduces digital twin and its role in Industry 4.0; Section III introduces the concept of a cognitive digital twin; Section IV highlights some of the impacts of cognitive digital twin at the design stage of the product lifecycle and the need for

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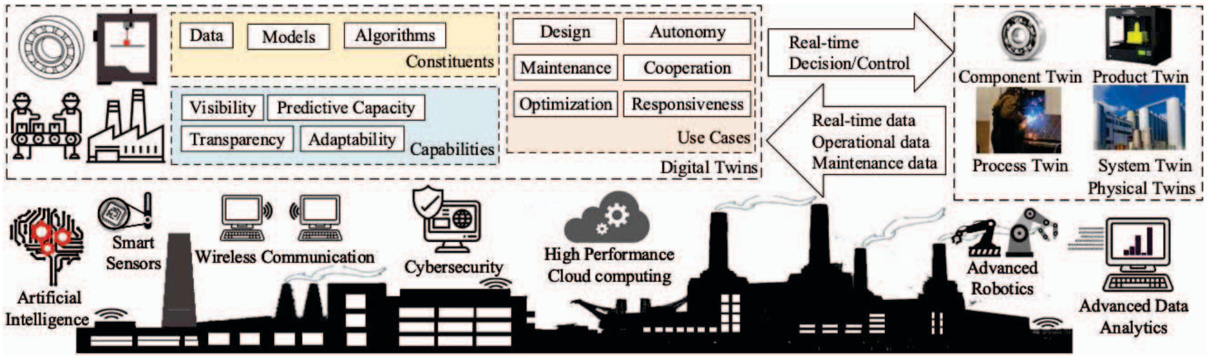

Fig. 1. Digital Twin in the context of cyber-physical production systems

algorithms and methodologies; Section V highlights several research challenges to accomplish the vision of cognitive digital twin; finally, the paper is concluded in Section VI.

II. Digital Twins and Manufacturing

The term *Digital Twin* was first used by John Vickers of the National Aeronautics and Space Administration (NASA) in 2002. It also gave the first formal definition of the digital twin in 2010 for air vehicles as "*an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin*" [12]. The most basic and simplest definition of a digital twin can be stated as in [13]: "*A digital twin has a digital or a virtual part, a physical part and a connection between them.*"

Since its inception, the digital twin concept has evolved and expanded to various products, processes, and domains. The digital twins have been proposed for many applications or use cases such as predicting real-time behavior, monitoring, decision support, planning, production optimization, and control [14]–[16].

Figure 1 illustrates the digital twin in the context of a CPPS and the overarching use cases (or functions). The top part of the figure illustrates the digital twin ecosystem: (i) major building blocks and constituents of digital twins, namely, data, models, and algorithms; (ii) capabilities digital twins can enable, namely, visibility, transparency, predictive capacity and adaptability; and (iii) the various use cases ranging from design to autonomy and cooperation and the bottom part of the figure shows the key enabling technologies. The top-right side of the figure shows the physical manufacturing system. CPPS related data (e.g., operational data and maintenance data) are collected in real-time and provided to the digital twins. Digital twins send real-time feedback (e.g., decision and control) to the physical manufacturing system. Therefore, real-time two-way seamless communication is established between the physical manufacturing system and the corresponding digital twin.

The use cases of digital twins span the entire life cycle of a product: product design and optimization, testing, production system design and operation, supply chain management and control, prognostics, maintenance, aftermarket services, cybersecurity (Fig. 1). For example, the digital twin of a component or a product can be used to simplify and streamline the design process by enabling virtual testing of the specifications to ensure that the product meets the standards (verify) and the performance requirements (validate) [15]. The digital twin of a product can be used to detect the early onset of faults (predictive maintenance), help diagnose the fault, and provide customized solutions for performance optimization, maintenance, and compliance [15]. A manufacturing company can offer new services based on digital twins for optimizing the performance of the product during operation. Thus, digital twins provide organizations with opportunities for offering new products and services. The digital twin of a production system can be used to optimize the system for throughput (performance), reduce waste (efficiency), improve quality [15]. Digital twins can also enable processes involved in CPPS to be adaptable and responsive to disruptive events [17].

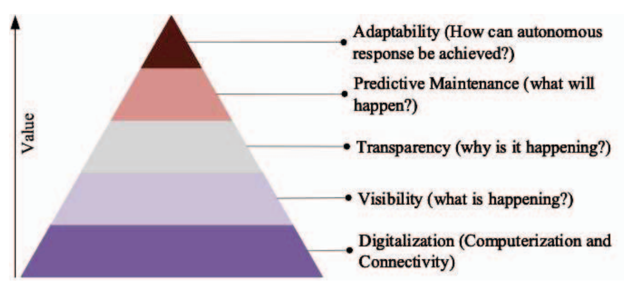

Fig. 2. Pathway to Industry 4.0

Let us consider the stages in the Industry 4.0 development path as proposed in [18]: visibility (what is happening), transparency (why is it happening), predictive capacity (what will happen), and adaptability (how can an autonomous response be achieved) (see Fig. 2 which is an adaptation of Fig. 3 in [18]). These stages are key for realizing the visions of Industry 4.0. For example, visibility is key for assessing the shop floor changes and operating conditions and so adaptability and responsiveness. This will impact every decision in the production pipeline. With this ability, the overall system can adapt quickly and effectively, reducing downtime and costs. Transparency

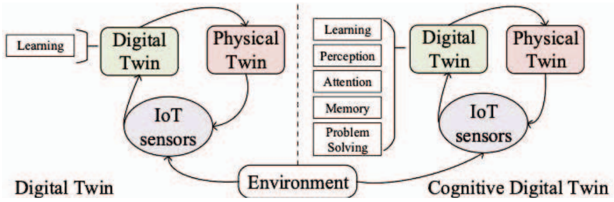

Fig. 3. Standard digital twin and cognitive digital twin

and predictive capacity are essential for understanding and inferring how to respond and directly affect the performance under changing circumstances. Finally, adaptability enables the system to respond to a changing situation by itself instead of a human-in-the-loop making the decisions and self-correcting its decisions based on feedback. When this happens across interacting physical processes, the system can achieve seamless cooperation in how it responds. Digital twins can and will play a huge role in each of these successive stages in progress in Industry 4.0.

III. Cognitive Digital Twin

The definition of *cognitive digital twin* is inspired by major advances in cognitive science and machine learning and artificial intelligence. Neisser's classic definition of cognition [19] includes "... ... *all the processes by which the sensory input is transformed, reduced, elaborated, stored, recovered and used* ... ...". Fundamental aspects of cognition include attention (selective focus), perception (forming useful precepts from raw sensory data), memory (encoding and retrieval of knowledge), reasoning (drawing inferences from observations, beliefs, and models), learning (from experiences, observations, and teachers), problem-solving (achieving goals), knowledge representation, etc.

The standard view of the digital twin and the conceptual framework of the cognitive digital twin we propose are depicted in Fig. 3. The digital twin showed on the left of Fig. 3 is the standard digital twin, which has a digital part, a corresponding physical part, and a connection between them. This version of the digital twin has the ability to learn. The digital twin we propose is shown on the right of Fig. 3, which in addition to having the ability to learn, is endowed with the other elements of cognition such as perception, attention, memory, reasoning, problem-solving, etc. In the following, we describe these capabilities in the context of a digital twin.

A. Cognitive Capabilities

1) Perception: in cognitive psychology could be defined as *the organization, identification, and interpretation of sensation to form a mental representation* [20]. We extend this definition to define perception in cognitive digital twin as *the process of forming useful representations of data related to the physical twin and its physical environment for further processing*. It is well established that machine learning techniques are less effective in learning representations of high dimensional and large data volume [21]. Since CPPS (and IoT) generate multi-modal, high-dimensional, large volumes of data, we posit that perception is a key cognitive capability to form useful *precepts* upon which further cognitive processing can occur in a digital twin. Perception in a digital twin will enable visibility in manufacturing systems.

2) Attention: can be viewed as the allocation of limited resources or a selection mechanism [22]–[24]. We adopt the latter view and define attention in a cognitive digital twin as *the process of focusing selectively on a task or a goal or certain sensory information either by intent or driven by environmental signals and circumstances*. Attention can be perceptual or non-perceptual and controlled or otherwise (see [22] for a detailed taxonomy of attention). Attention enables focus on the essential information from the raw sensor data and memory. So it can simplify and improve the process of perception and decision making in a cognitive digital twin. Attention will help monitor or select a task to focus on, paving the way for autonomy in manufacturing systems.

3) Memory: we define memory in a cognitive digital twin adopting the view of memory provided in [25]: *is a single process that reflects a number of different abilities: holding information briefly while working with it (working memory), remembering episodes of the physical twin's life (episodic memory), and knowledge of facts of the environment and its interaction with the physical twin (semantic memory), where remembering includes the steps: encoding information (learning it, by perceiving it and relating it to past knowledge), storing it (maintaining it over time), and then retrieving it (accessing the information when needed)*. Thus, memory, both working memory, and the remembered episodes and knowledge are an essential ingredient for the algorithms complementing the digital twin to autonomously control the physical processes related to the various stages of a physical twin because memory allows the algorithm to remember the context and additionally allows the digital twin to leverage past knowledge.

4) Reasoning: in cognitive psychology can be broadly defined as the 'process of drawing meaningful conclusions for informing problem-solving or decision making' [26]. Reasoning can be broadly classified under deduction, induction, and probabilistic reasoning [27]. *Thinking* and *reasoning* are cornerstones of human intelligence and so have been extensively studied in cognitive psychology [26], [28]–[30]. We define reasoning in cognitive digital twins adopting the definition proposed in [31]: *drawing conclusions consistent with a starting point — a perception of the physical twin and its environment, a set of assertions, a memory, or some mixture of them*. Thus, reasoning directly impacts understanding (transparency) and is central to decision making (autonomy).

5) Problem-solving: we define problem-solving in cognitive digital twin as *the process of finding a solution for a given problem or achieving a given goal from a starting point*. Thus, problem-solving is central to decision making and autonomy.

6) Learning: we define learning in cognitive digital twin as *the process of transforming experience of the physical twin into reusable knowledge for a new experience*. Hence, learning is essential for adaptability (or autonomy) and responsiveness of the physical system that the digital twin represents and becomes a key ingredient for intelligence in digital twins.

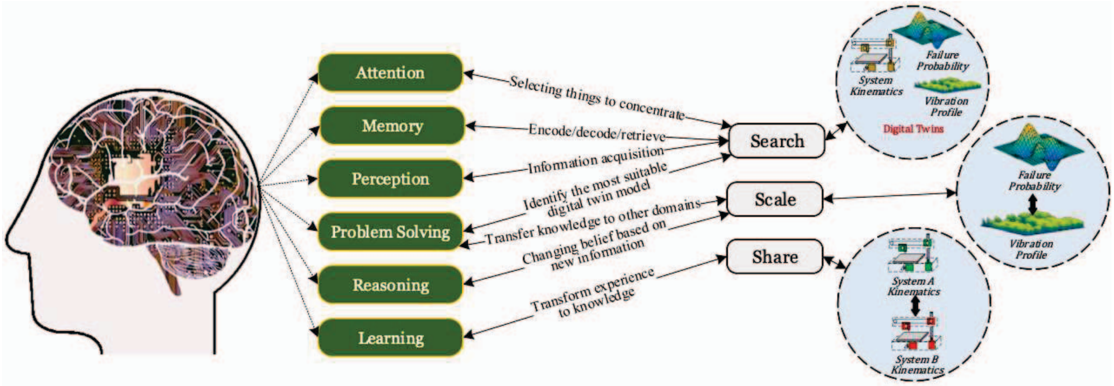

Fig. 4. Aspects of human cognition and its exemplary realization to the proposed enabling components in Digital Twins

IV. Impact of Cognitive Digital Twin in the Product Design Stage

Cognition in digital twins will have a major impact and help advance the visions of Industry 4.0 [32]–[34]. Due to space constraints and for ensuring a concrete and sharp focus, we will now describe how the cognitive digital twin concept can impact the product design stage. Specifically, we discuss three critical operations in the design stage which cognition will enable and enhance: (i) *search*; (ii) *share*; and (iii) *scale*.

Search operation in a cognitive digital twin may be defined as the process of identifying the appropriate digital twin models of a manufacturing system by searching over the Internet, just like the way Google's search engine works. *Share* operation may be defined as passing relevant information gained during the life cycle of the digital twin of a manufacturing system to a new digital twin in its early design, development stage, and usage. Finally, *scale* operation may be defined as sharing knowledge across non-overlapping domains. Thus, these operations can greatly enhance the design stage.

We briefly discuss how cognition will impact these operations. The search operation cannot function without memory because memory is the process by which information is encoded, stored, and retrieved. Perception and attention will allow the *search* operation to selectively focus on a set of appropriate models, which depends on the design requirements. Problem-solving can further improve the *search* operation by enabling it to identify the most suitable digital twin model. Learning directly influences the *share* operation of a cognitive digital twin because it enables transforming the experience into knowledge reusable by a new digital twin. Reasoning allows digital twins to conclude existing and new contexts enabling knowledge sharing at *scale* (across domain not seen before). Therefore, reasoning will enhance the *scale* operation. Moreover, successful problem-solving in one domain can be transferred to solve problems in another domain. Figure 4 presents a conceptual mapping of cognitive capabilities presented in Section III-A to the proposed operations of a cognitive digital twin.

While humans are naturally capable at *searching, sharing, and scaling*, enabling these operations in a cognitive digital twin is far from trivial. In this paper, we highlight the need for algorithms and methodologies to convert these abstract concepts of operations within a cognitive digital twin into mathematical representations and frameworks that are suitable for computational processing without giving any particular solution.

We discuss the state-of-the-art research related to our presented concept and underlying research challenges to realize these cognitive operations in a digital twin (search, share, scale) in the following subsections.

A. Search Operation in a Cognitive Digital Twin

There is a vast amount of information related to manufacturing products, processes, and the system available on the internet. Without search engines like Google, which ranks the pages (based on more than 200 metrics), it would be impossible to find the internet's relevant information. Just like the web pages, in the future, there may also be a large number of products digital twins (such as open-source CAD models in the maker space), and system digital twins (such as aging model) available on the internet or in the enterprise intranet within a company or across companies.

Currently, researchers and engineers spend a large amount of time building a new product, process, or system without leveraging the knowledge that already exists for a similar or somewhat closer product, process, or system [35], [36]. For example, there are resources such as GrabCad [37], which contains CAD models of many engineering systems, that can be used as a base design for creating new models. These CAD models are part of the digital twin of the product that goes through the manufacturing process to be converted into the physical twin. Various methods have been proposed for exploring 3D models (a partial digital twin model defining the physical twin geometry and manufacturing information). For example, authors in [38] created a 3D search engine that utilizes the spherical harmonics descriptor for acquiring the signature vector and use the Euclidean distance among these vectors to find a similar polygon model. Authors in [39] utilized the shape similarity metric on 3D PDF to enable the discovery of parts and assemblies existing in the company's database. Authors in [40] utilized a similarity measure based on various attributes (such as name, description, etc.) to calculate a score for discovering CAD models in repositories. Google has a search engine [41] dedicated to finding the 3D models for augmented and virtual reality applications. Although all these research efforts have been focused on searching and discovering 3D models, the digital twin models comprise more than geometry information of the physical twins. We anticipate new methodologies to search and discover digital twins of systems, processes, and parts in the future.

B. Share Operation in a Cognitive Digital Twin

Current research in modeling the digital twin is focused on utilizing the large velocity and resolution of data in creating a model of the physical system that can perform advanced analytics and represent the physical twin throughout its lifecycle. However, most manufacturing systems operate with the human in the loop and require human inputs constantly for various purposes (such as quality control, machine maintenance, etc.). Therefore, human knowledge and experience as input are potentially valuable to the digital twin model.

The digital twin model built using the sensor system and architecture may be applicable in another digital twin model. For example, the digital twin, modeled for a manufacturing system to predict the built 3D objects' surface quality, may be applicable in predicting the geometry variation. A truly cognitive system should utilize the knowledge gained while performing one task (such as vibration mode prediction) in another task (for example, failure prediction). Knowledge transfer among the digital twins is limited to similar, or related domains [42]. There is a large research gap in flexibility and scalability of transferring knowledge from one digital twin model to another. In this context, transfer learning concepts may be utilized, which is not new and has been explored in the machine learning literature [43]. There have been various approaches explored (for instance, transfer, feature representation transfer, etc.) to perform inductively (labeled data available in target domain), transductive (labeled data available only in source domain), and unsupervised (labeled data not unavailable in either source or target domain) transfer learning [44]. These approaches have been heavily utilized in computer vision models [45] and reenforcement learning [46]. An effective transfer learning theory for cognitive digital twins in the manufacturing system will break new ground and enable much greater knowledge sharing and transfer.

C. Scale across Domains in a Cognitive Digital Twin

Recently, there has been a spike in research in the computer science community for transferring knowledge across domains [47], [48]. However, transfer learning's scalability while building the digital twin models for smart manufacturing systems is still in infancy. The digital twin research community is interested in knowing how knowledge transfer can be performed across multiple domains (such as manufacturing systems with different technology)? The development of effective knowledge transfer theory across domains in cognitive digital twins in the manufacturing system will enable very new and exciting capabilities, e.g., a digital twin model developed to predict failure may be utilized to model digital twins responsible for quality maintenance.

V. Open Research Challenges

We presented a few operations *searching, sharing, and scaling* in Section IV to concretize the abstract and generic concept of cognition in the digital twin for the design stage of the manufacturing system. However, these operations are far from a comprehensive approach to achieving the full potential of benefits from cognitive digital twins. The research community has immense opportunities in new contributions on mathematical representations, algorithms, tools, and methodologies for developing and using cognitive digital twins. In this context, we formulate and pose several research questions.

- What are the appropriate mathematical representations of digital twins that can enable the incorporation of cognitive capabilities? Examples here include differential equations, discrete-event dynamic systems, logic-based models, graph models, connectionist network models, etc. How can such models be used for simulations, state estimation, and control and decision making?

- How can high-performance computing and numerical simulation tools be leveraged to enable cognitive capabilities in digital twins? For example, can numerical simulations (along with experimental data) create large memory banks that can be used for interpreting and acting on real-time streaming data from IoT sensors? Can they be used for real-time response to changes in the manufacturing system environment?

- How to enable searchability of the digital twin models? More specifically, how to embed metadata in complex digital twin models (parts, processes, and systems) so that they can easily be searched over the internet during the design phase?

- How to enable knowledge sharing capability in digital twins? This question demands us to rethink the fundamental design principles for modeling the digital twins leading to a reformulation: "how do we model manufacturing domain digital twins (such as for systems, process, and products) so that we can enable knowledge transfer?" The knowledge transfer in digital twins will involve passing information gained while estimating and maintaining the digital twin over its lifetime to other digital twins in its early development or use stage.

- How do we make the knowledge sharing scalable in digital twin models? Scaling may fall under the scope of generalizing knowledge sharing across multiple domains. Scalability is non-trivial and is a challenge of its own due to the complexity of cross-domain knowledge sharing. However, the digital twin models may be capable of sharing knowledge across non-overlapping domains (for example, across manufacturing systems utilizing different technologies, between the aging model and quality prediction model, etc.).

VI. Conclusion

We present a novel conceptual framework of a cognitive digital twin, which is inspired by the advances in cognitive science, machine learning, and artificial intelligence in the context of digital twins and Industry 4.0. We envision cognitive digital twins will impact all the stages of the manufacturing systems. In the paper, we have particularly highlighted the impact of the cognitive digital twin in the product design stage. We presented three operations (search, share, and scale), where cognitive capabilities may be incorporated. We believe that multiple research communities need to collaborate on issues such as leveraging domain expertise, simulations, algorithms, methodologies, engineering automation tools, security and privacy, standards and practices, and business models for sharing across organizational boundaries and supply chains to fully realize the potential of cognitive digital twins.

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