Towards Cognitive Intelligence-Enabled Manufacturing

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Abstract. Cognitive intelligence-enabled manufacturing (CoIM) uses machines to utilize technologies that mimic human cognitive abilities to solve complex problems in manufacturing. With the support of a cognitive intelligence-enabled manufacturing system (CoIMS) architecture, information flow is organized and coordinated appropriately, starting from the machine sensory system, central system to the motor system. Machine perceptive abilities monitor, sense and capture equipment performance, aggregate data, and help gain valuable insights into the production process. It uses the industrial internet of things, data analytics, artificial intelligence and related techniques and cognitive computing and related technologies to address production issues in an autonomous manner. As such, CoIMS solves complex production problems. It also transforms manufacturing by improving product quality, productivity, and safety, reducing costs and downtimes, identifying knowledge gaps, and enhancing customer experience. Even so, a CoIMS is not responsible for making the final decision. Instead, it supplements information on the fly for engineers to take necessary actions.

Keywords: Cognitive intelligence · Manufacturing · Self-X cognition · Smart decision making · Artificial intelligence

1 Introduction

Smart factories are automated production facilities that use sensors, cyber-physical systems (CPS), industrial internet of things (IIoTs), artificial intelligence (AI), robotics, and other modern technologies to improve efficiency and reduce costs [1]. These technologies also aid in monitoring, diagnostics, and prognostics. However, cognitive intelligence can strengthen the learning mechanism in manufacturing systems. For instance, the 5C architecture for implementing CPS inherently supports the reasoning in making manufacturing cognitive intelligent [2]. The CPS manages the interconnected systems between the physical assets and computational capabilities while leveraging the interconnectivity of machines to become cognitive intelligent [3]. Besides, the CPS coupled with IIoTs

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adds a layer of knowledgeability to any system through data collection and monitoring. This is established through the Data-Information-Knowledge-Wisdom (DIKW) hierarchy, which facilitates the functional relationship between data, information, knowledge, and wisdom to better understand a subject [26], a trait of human cognition. Strube (2001) defines *cognition* as "*a class of advanced control mechanisms that allow for sophisticated adaption to changing needs (e.g., learning and planning) through computations operating on mental representations*" [4]. These mental actions form the foundation for cognitive science. Cognitive science studies human thought processes, including perception, memory, language, reasoning, problem-solving, decision making, planning, and learning [5]. It has been used across many fields. For instance, Tesla electric vehicles utilize cognitive intelligence features in their vehicle maintenance program to monitor their health condition continuously, and users are signalled in case of any aberrations while proactively and independently ordering the replacement ahead of servicing schedules [6].

The human mind is a complex system otherwise described as an information processing machine that receives, stores, retrieves, transforms, and transmits information through computational processes [5, 7]. With the help of the sensory receptors, humans extract meaning from a sensation due to contact with external stimuli through perception [8]. Figure 1 illustrates the stages of information processing in humans. Humans use their senses to gather information acquired through environmental stimulation. It is then followed by perception, cognition, or recognition within the information processing region. For example, humans recognize objects by their shape, colour, size, or speech. Consequently, the human cognitive system makes decisions by identifying and comprehending these patterns. In this paper, the authors use the information processing mechanism in Fig. 1 and the general view of human cognitive architecture in Fig. 2 as the foundation and inspiration for proposing a CoIMS, where Fig. 2 details the stages of information transfer.

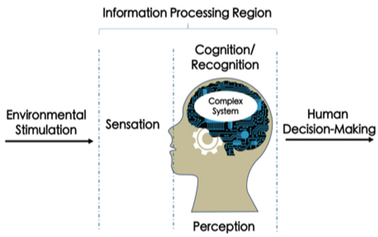

Fig. 1. Cognition, perception, and information processing

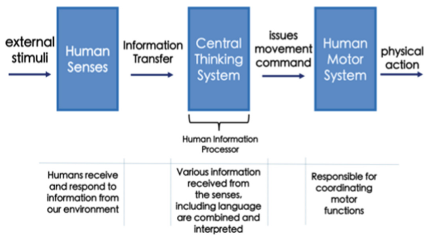

Fig. 2. A general view of human cognitive architecture

Manufacturing is evolutional, and CoIM is a phase in this advancement. This progression toward human-machine collaboration and Self-X cognitive systems is the inspiration behind CoIM and the proposed architecture of CoIMS. In addition, this paper highlights the enabling technologies of CoIMS and ongoing applications across selected industries using cognitive intelligence-enabled technologies.

2 Fundamentals of CoIMS

The CoIMS imitates ordinary brain-related skills and acts as the information processing region, including memory, attention, concentration, problem-solving, creativity, and critical thinking. A CoIMS applies these imitated skills to execute regular manufacturing tasks. The information processing capacity of humans, plus the system's mechanism, is described as cognitive architecture (see Fig. 4) [5]. Like brain-based skills, the CoIMS has different compartments with specific skills for performing categorical functions, as shown in Fig. 3.

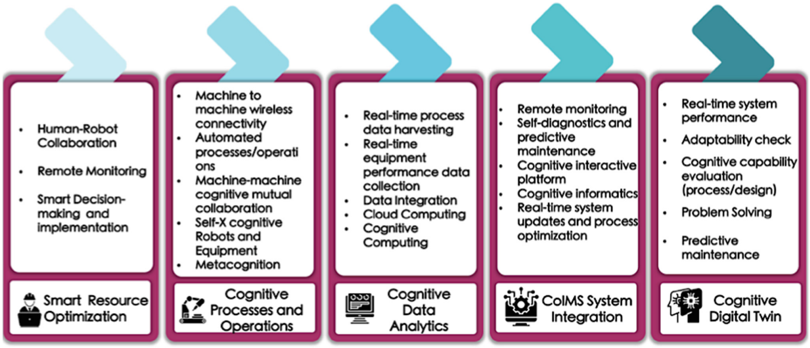

Fig. 3. CoIMS composition

Engineers have, over the years, made tremendous progress in automating the replication of human senses. These human-like sensory systems are used in smart manufacturing for system diagnostics and prognostics. For instance, machine vision [9] technologies are used in visual inspection, fault diagnostics, and product defect detection. Other machine perceptions include machine audition [10], machine olfaction [11], machine touch or tactile perception [12], and machine gustatory (the process of mimicking the perception of taste and feel experiences food at a machine level), a term coined purposely for illustration, has seen very little progress. Machine perceptions mimic human senses to gather data on the manufacturing operations and their surroundings. Data collected is forwarded for analysis and interpretation. Then, the machine motor systems coordinate certain machine motor functions as per the directives of the CoIMS to solve production issues. Based on this logic of mimicking human cognition, perception, and information processing to solve problems as described in this paper, we define *cognitive intelligence-enabled manufacturing (CoIM) as using machines to utilize technologies that mimic human cognitive abilities to solve complex problems in manufacturing.*

Generally, human cognition and learning are based on three thematic theories: "the nature of knowledge, learning and transfer, and the nature of motivation and engagement" [13]. A CoIMS is structured on the same pattern of cognition and learning. Unlike humans, machines acquire knowledge through data supply (historical and real-time). Subsequently, they learn new information from the acquired data using knowledge graphs [14] to map data points using relationships. Identical to human knowledge transfer and learning is the machine learning technique called transfer learning [17]. Transfer learning is used in transferring knowledge in different but related source domains to improve the performance of target learners on a target domain [15, 16]. As humans learn and transfer knowledge, they are motivated extrinsically or intrinsically to become better at their tasks. Likewise, machines use reinforcement learning (RL) [21]. Applications of RL are seen in robotic control, end-to-end control, recommendation systems, and natural language dialogue systems [18, 19]. However, a critical cognitive skill, Metacognition, is barely used in smart systems. Metacognitive processes refer to the ability to reflect on one's thinking processes and evaluate them for improvements [20]. Metacognitive skills such as self-monitoring and evaluation, help the system to reflect on its performance, thus enabling it to be self-motivating, engaging, and enthusiastic about finding problems. Such abilities enable machines to identify problems early and take corrective action.

3 CoIMS Characteristics and Enabling Technologies

CoIMS simulates human cognition to perform production tasks and solve problems. It learns from experience and adapts its behaviour based on system feedback. However, the CoIMS needs the support of enabling technologies, to learn from data and perform tasks efficiently without explicit programming.

3.1 Characteristics of CoIMS

A CoIMS is knowledgeable, flexible, and attentive to be adaptive. It imitates human cognitive architecture using flexible programmable systems and technology for reasoning, planning, and solving problems. A CoIMS independently performs diagnostics and prognostics. It utilizes metacognitive abilities, cognitive reasoning, learning, knowledge transfer, mapping, and graphing.

3.2 Enabling Technologies in CoIMS

CoIM is dependent on enabling technologies which are integrated and work as collaborative systems. They include cognitive computing and informatics, machine learning, deep learning, big data and analytics, robotics, CPS, IIoTs, machine vision, cloud computing, knowledge graphs, natural language processing (NLP), and reinforcement learning. These techniques and technologies are tools for mimicking human cognitive abilities and are applied to manufacturing processes. As a result, the system performs diagnostics and suggests preventive and corrective actions. For example, to take proactive measures in CoIM, the machine learning (ML) and deep learning (DL) models are trained on the data harvested within the machine sensory system. The trained models acquire knowledge to identify patterns within a defined data group and present detailed information on the right approach to solve a production issue. The CoIMS supplements relevant information to engineers for analysis and implementation, thereby enhancing an interactive change and innovation drive.

4 The Proposed System Architecture of CoIM

A CoIMS functions effectively and efficiently with a defined architecture, named CoIMS architecture in this paper (see Fig. 4). The compositions of the CoIMS architecture in Fig. 4 are depicted in Fig. 3, which are modelled using Figs. 1 and 2. Inspired by the functionalities of Figs. 1 and 2, machine sensory systems perform the role of machine perceptions in a CoIMS. The machine central systems and motor systems in a CoIMS mimic human central thinking systems and motor systems shown in Fig. 2. The machine central system is the engine of the CoIMS, where it analyzes data from the machine sensory system (to identify inefficiencies and potential production issues). The machine motor system is also responsible for coordinating real-time and historical data in the machine central system for decision making. As a result, the CoIMS interacts with cognitive machines, processors, devices, and cloud platforms to identify issues and communicate them to engineers.

The CoIMS architecture is the underlying principle behind a cognitive intelligence-enabled factory. As depicted in Fig. 5, a cognitive intelligence-enabled factory comprises enabling technologies, a Self-X cognitive manufacturing network [21], machine-to-machine cognitive-mutual collaboration, a real-time data centre, a CoIMS system, and CoIM digital twin. Robots and other manufacturing equipment in this factory adopt self-X cognitive abilities in their operations. In this factory, machines can self-learn and unlearn. Enabling technologies and techniques enhance machine-to-machine interaction while optimizing operations and making the system adaptive and flexible to understand changes in the information process flow. It identifies problems by pulling historical data if the data in the problem is incomplete by using cloud computing methodologies. Thereafter, predictive actions are forwarded to engineers for decision-making and implementation based on data analytics. Simply, the CoIMS can be described as a consultant (an expert using key enabling technologies to function), and the human is the overseer. For instance, cognitive chatbots mimic human thinking processes using NLP to engage in causal analysis and advisory interactions with engineers on ways to improve total system performance. Besides, this factory adopts a cognitive digital twin (CDT) technology, a real-time virtual cognitive system [25]. The CDT aids in analyzing real-time performance, adaptability, and cognitive capabilities. Thence, results in real-world system optimization, problem-solving, and taking proactive measures.

Solving previously unknown issues birth new information to effectively leverage manufacturing operations. For instance, if a new issue of material quality defect arises during the production process, CoIMS will refer to historical data, draw inferences, and make diagnostics or prognostics where necessary. Solving this new problem adds to the existing knowledge database. As such, the CoIMS can be described as a system equipped with the ability to gather new information in the manufacturing plant and use the acquired information to improve product quality, productivity, and safety. The same approach applies to cost and downtime reduction, identifying knowledge gaps, and enhancing customer experience.

Besides Tesla, which comprehensively applies cognitive intelligence to their systems at a product level, IBM Watson IoT perfectly illustrated how cognitive intelligence-enabled systems could dramatically enhance efficiency and maximize performance on the shop floor within the manufacturing plant.

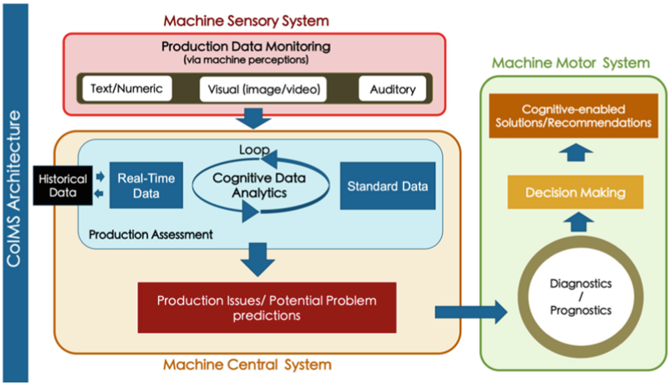

Fig. 4. A cognitive intelligence-enabled manufacturing system (CoIMS) architecture

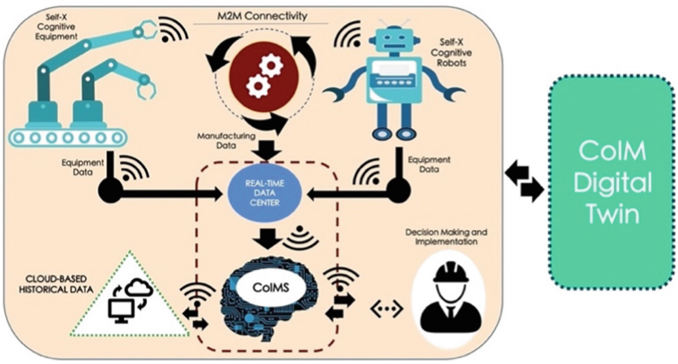

Fig. 5. A cognitive intelligence-enabled factory

For instance, in their illustrative video case study, an NLP-enabled cognitive chatbot relies on an enormous amount of manufacturing data, similar to the operation of the machine sensory systems in Fig. 3. The chatbot uses a visual inspection system to identify defective products and based on historical and production data, it recommends probable servicing actions to the maintenance team 24. After that, the engineers feed the new solution into the cognitive system for future proactive decision-making.

Furthermore, Zheng et al. (2021) highlighted the Self-X cognitive manufacturing network and focused on an industrial knowledge graph (IKG)-based multi-agent reinforcement learning approach in manufacturing networks with a higher level of automation. They used a simulated multi-robot based on their proposed IKG-based MARL-enabled approach, comprising the Self-X cognitive attributes [22]. The success of the Self-X cognitive manufacturing network lays a strong foundation for a cognitive intelligence-enabled factory in Fig. 5. Also, Zheng et al. (2022) introduced the visual reasoning-based mutual-cognitive human-robot collaborative (HRC) system. The proposed system will enable industry robots to develop visual cognitive reasoning and perception during task executions, which is relevant to activities on a manufacturing shop floor. With a holistic scene analysis, robots can logically and cognitively understand activities around them, and then predict and support human actions in that environment [23].

Lastly, works on cognitive digital twins (CDT) for manufacturing are explored for future implementations where it uses learning, reasoning, and automatic adjustment for better decision-making using real-time IoT data [25, 27]. A CDT is relevant as it requires semantic modelling, systems engineering, and product lifecycle to achieve higher levels of automation and intelligence [27]. Nevertheless, it is a critical technology for the establishment of a cognitive intelligence-enabled factory.

5 Conclusion and Future Work

This paper described the inspiration behind CoIM. Fundamentals and enabling technologies in CoIMS coupled with illustrative examples were also discussed. In addition, we echo the Self-X cognitive manufacturing network with multi-robot collaboration and envision a cognitive intelligence-enabled factory that generates a massive amount of data to enable manufacturers to gain deeper insight into the workings of CoIMS. After that, the cognitive system can gather new information in the manufacturing plant and use the acquired information to subsequently improve product quality, productivity, and safety. Others include cost and downtime reduction, identifying knowledge gaps, and enhancing customer experience. In the near future, the authors shall explore the fluidity in collaboration between varying robots (having distinct functions) with Self-X cognitive capabilities in a cognitive intelligence-enabled factory.

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