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Muhammad Intizar Ali
Dublin City University, ali.intizar@dcu.ie

Pankesh Patel
University of South Carolina - Columbia, ppankesh@mailbox.sc.edu

John G. Breslin
NUI Galway, john.breslin@nuigalway.ie

Ramy Harik
University of South Carolina - Columbia, HARIK@mailbox.sc.edu

Amit Sheth
University of South Carolina - Columbia, amit@sc.edu

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Muhammad Intizar Ali, *Dublin City University Glasnevin, Dublin 9, Ireland*
Pankesh Patel, *University of South Carolina, Columbia, SC, 29208, USA*
John G. Breslin, *NUI Galway, Galway, Ireland*
Ramy Harik and Amit Sheth, *University of South Carolina, Columbia, SC, 29208, USA*

Smart manufacturing or Industry 4.0, a trend initiated a decade ago, aims to revolutionize traditional manufacturing using technology-driven approaches. Modern digital technologies such as the Industrial Internet of Things (IIoT), Big Data analytics, augmented/virtual reality, and artificial intelligence (AI) are the key enablers of new smart manufacturing approaches.

The digital twin is an emerging concept whereby a digital replica can be built of any physical object. Digital twins are becoming mainstream; many organizations have started to rely on digital twins to monitor, analyze, and simulate physical assets and processes.[1] The current use of digital twins for smart manufacturing is largely limited to i) *status monitoring*, ii) *simulation*, and iii) *visualization*. For status monitoring, digital replicas of physical assets (e.g., machines) are created, machines are continuously monitored using IIoTs, and the latest status of a machine can be assessed by querying its digital twin. For simulation, digital twins of machines, processes, and products are created to mimic real settings. Simulation allows the design, development, and testing of new products and processes using their digital twins before applying them to actual physical assets, this is presented in.[5] For visualization, digital twins can include real-time dashboards and alert systems to monitor and debug an operational environment.[2] However, in contemporary cases, digital twins are simply considered to be an exact replica of the physical assets, without any value-added services built on top of them which could convert physical assets into autonomous intelligent agents. A major advantage of this enhanced design of digital twins is that they can offer much more than just an exact replica to support value-added services on top of digital twins, which are not possible on the physical assets.

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COGNITIVE DIGITAL TWINS

Cognitive digital twins are an extension of existing digital twins with additional capabilities of communication, analytics, and intelligence in three layers: i) *access*, ii) *analytics*, and iii) *cognition*.

The *access layer* is responsible for communication with the machine and gets access to data regarding the status of a physical asset to update the status of the digital twin. The *analytics layer* provides edge analytics capabilities at the device level. Similar to the edge analytics at the edge, this layer of the digital twin can perform additional analytical tasks on top of real-time collected data to help with the process of decision making by converting the raw sensory input into actionable knowledge.[3] The *cognitive layer* enables cognition by the digital twins. It is capable of performing complex decision making using edge analytics, domain expertise, and global knowledge bases. It is also responsible for communication among digital twins, allowing them to build their own networks and perform autonomous decision making. Cognitive digital twins will convert traditional digital twins into smart and intelligent agents that can access, analyze, understand, and react to their current status. In case of anomalies, rather than resorting to a simple alert system, the cognitive digital twin can interact with the operational environment and digital twins of products, running processes to further analyze and intelligently understand the anomalies. The cognitive digital twin can draw conclusions of situations locally and then

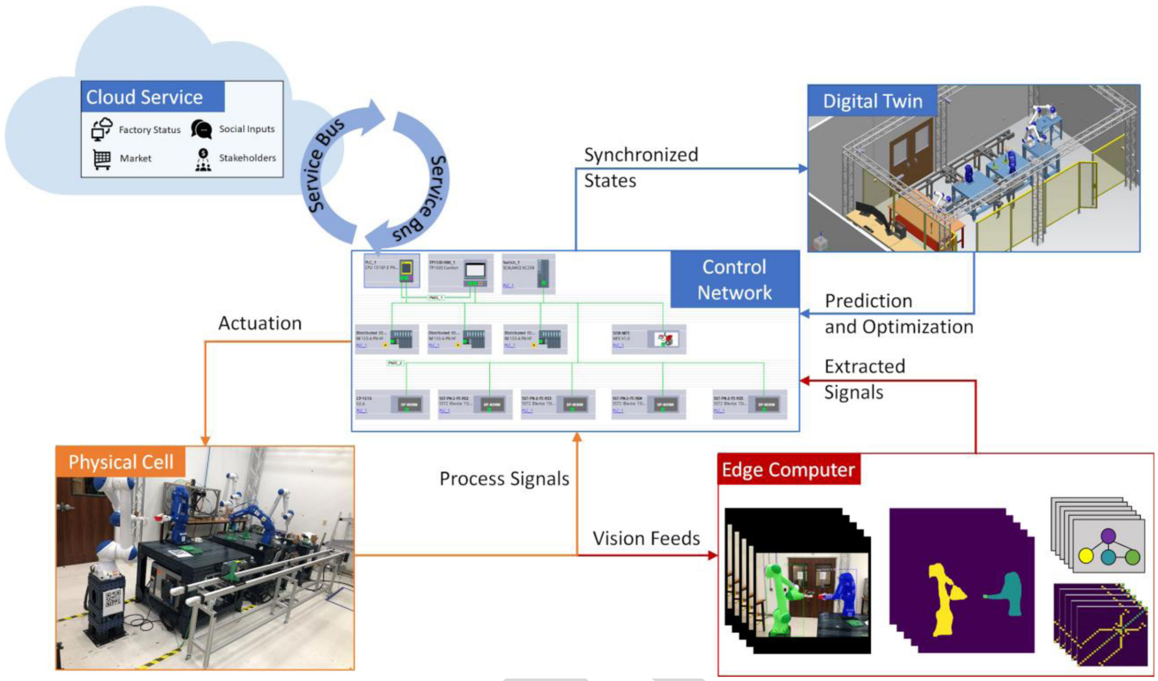

FIGURE 1. Proposed CPS-enabled control for future factories: control network administers physical cell and digital twin to synchronize process signals and intelligently actuate field devices by system smart layers. System smart layers consist of business intelligence from cloud services and semantic integration of visual signals from the edge ends.

also interact with other digital twins of physical assets operating in similar operational conditions to better understand shared local anomalies. Once identified, cognitive digital twins can interact socially with other peers and share knowledge and generate alerts in advance of any future potential unexpected situations. Insights from the analytics performed by cognitive digital twins will eventually help to build enterprise-level knowledge graph extraction, capture, and storage of domain knowledge.

Cognitive digital twins will disrupt existing technologies and applications used for digital twins by making them intelligent as well as social. The emerging concept of self-healing, self-configuring, and self-orchestrating systems is made possible using this approach. The team at the Confirm SFI Research Centre for Smart Manufacturing has implemented an initial prototype of cognitive digital twins using a benchmark dataset for production line performance monitoring[6] and intend to fully test the implemented prototype on the actual production lines of a smart factory in collaboration with an industry partner. An initial factory of the future to assess and implement this emerging concept is also being constructed at the University of South Carolina (Figure 1, see Xia *et al.*[7] for details). Having a social and interactive network of digital twins and a shared knowledge space will allow analytics and intelligence to go beyond the physical walls of a factory where digital twins can share their experience and lessons learned across the board.

ECOSYSTEM OF COGNITIVE DIGITAL TWINS

We envision that once the cognitive digital twins are in place, they can build a network among themselves, having fully automated machine-to-machine interaction and decision making resulting in an ecosystem of cognitive digital twins. The knowledge gained by edge analytics, communication among digital twins, and domain knowledge including user experiences will be captured as a unified knowledge graph. This knowledge graph will gradually evolve and will become a major source of information within the ecosystem of cognitive digital twins. Figure 2 presents a generic overview of cognitive digital twins ecosystems. We further elaborate our vision with an example use case of a manufacturing plant producing orthopedic implants,

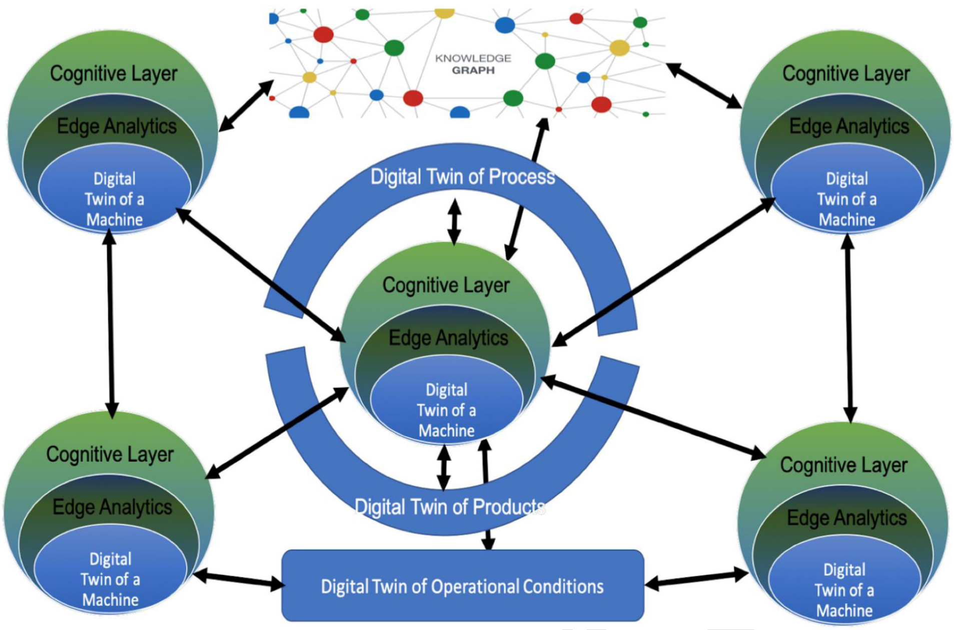

FIGURE 2. Cognitive ecosystem of digital twins.

e.g., knee, hip, and elbow joint replacements. On the shop floor, various machines are placed in an assembly line performing different operations, e.g., cutting, grinding, and polishing, etc. Each machine is equipped with different sensors to monitor its functional state, e.g., temperature, voltage, vibration, and rotation. A cognitive digital twin is created for all machines, products, and processes. Collaboration and communication among the digital twins during decision making is conducted in four stages as follows.

At the *first* stage, the cognitive digital twin of an industrial machine (e.g., a grinding machine) equipped with edge analytics is continuously monitoring values against predefined thresholds. An alert is created whenever a threshold is breached (e.g., the temperature of a motor inside the grinding machine goes beyond an acceptable threshold).[4] At the *second* stage, the cognitive digital twin starts the sensemaking process by collecting contextual information including product characteristics (e.g., to check the rigidity of a metal alloy being used for a product), configurations of the processes being applied by the machine (e.g., pressure and speed of a grinding process), and operational conditions on the factory shop floor such as temperature, humidity, etc. The cognitive digital twins are capable of correlating all acquired information and initiating a sensemaking process to understand whether the current spike in temperature is due to a fault in the machine, characteristics of the product being manufactured, the manufacturing process being applied, or conditions on the shop floor. A factory level knowledge base is gradually created for all previous anomalies detected and their remedial actions. If a preexisting similar cause is identified, and its remedial action is available in the knowledge base, the cognitive digital twin will adjust its configuration, request a process adjustment, and/or adjust operational conditions accordingly. In the *third* stage, if a cognitive digital twin is unable to make sense of local information, it seeks further assistance from the social network of its peers and requests information from similar machines with similar operational conditions, e.g., a grinding machine of the same make and brand being used in a different plant. If an anomaly in temperature is only being observed locally, the digital twin of the machine adjusts itself to the configuration of machines running optimally without any issues. If the anomaly is observed across the board, a network-wide alert is broadcasted to request remedial actions. In the *fourth* stage, a record of captured events, interactions, the outcome of analytics, and the sensemaking process together with domain expertise is stored in a shared knowledge base in the shape of an enterprise-level knowledge graph. This knowledge graph will act as a central information portal for any future occurrences of similar events. We see that in the future, this knowledge graph will act as a central hub for all operational machines to post questions and get immediate answers. When necessary, a human expert may also be consulted.

RESEARCH CHALLENGES

To realize the vision of cognitive digital twins, we envision a design and implementation of a distributed cross-domain autonomous system for smart manufacturing. The goal of this system is to enhance autonomous manufacturing by empowering manufacturing resources to think, learn, and understand the dynamics of industrial environments by effectively integrating human cognition through AI and Semantic Web technologies into the design of autonomous manufacturing, respecting the Industry 4.0 system design principles. The approach can be cross-disciplinary, involving AI, semantic-empowered techniques, as well as semantic data integration in autonomous manufacturing scenarios. To achieve the above-mentioned vision, the following intertwined Research Questions (RQs) need to be addressed:

RQ1: HOW TO CREATE AN AUTONOMOUS DISTRIBUTED SYSTEM CONJOINING THE BOTTOM-LEVEL MANUFACTURING RESOURCES TO ENHANCE RESPONSIVENESS AND INTELLIGENCE? THIS RESEARCH QUESTION IS FURTHER DIVIDED INTO THE FOLLOWING RESEARCH AREAS:

- **A Collaborative Network of Intelligent Agents**: This research investigates the design of an autonomous system that can discover and detect faults and disturbances autonomously as well as collaboratively. In addition to this, it can attempt to go beyond the existing knowledge of known problems to mitigate new problems and anomalies, thus capable of operating in unknown environments. Furthermore, they can build a collaborative network of intelligent agents locally to improve the responsiveness of the system.
- **Automated Analytics for Resource-constrained Manufacturing Resources[8]:** This research requires the investigation of the suitability of existing interoperability standards (e.g., Web of Things, RAMI 4.0, Semantic Web) and the suitability of existing architecture patterns (e.g., fog, Intelligent edge,[3] and smart agent) for resource-constrained manufacturing resources as it demands quick response and automatic analytics with enhanced intelligent capabilities.
- **Autonomous Models on top of Knowledge Graph:** This research requires investigation of incorporating several autonomous models on top of semantic-empowered technologies as we do not want to limit our vision of cognitive digital twins only for a specific autonomous model. For instance, an integration of self-comparison models, where a single machine can be compared with a fleet of similar machines. This capability can be extended further by leveraging historical information to predict its suitability for autonomous resource allocation.

RQ2: HOW TO ENABLE AN AUTONOMOUS CROSS-DOMAIN REASONING OVER DISTRIBUTED INDUSTRY 4.0 APPLICATIONS?

Industry 4.0 applications are currently designed while keeping a single application domain in view. Most of these applications target a domain-specific problem. Cross-domain collaborations allow to deduce additional events from a silo and can be turned into useful actuation, e.g., before allocating manufacturing resources, a system considers external electricity rates and supply chain data (e.g., weather and traffic conditions) in order to achieve the goal of reducing the factory's energy consumption and carbon footprint.

To address this research question, we need to investigate an autonomous cross-domain system, which can leverage semantic reasoning to derive new knowledge and AI techniques to monitor and process events from totally independent applications. It can integrate the techniques of knowledge discovery and inference that is not possible from data generated by a single application. Moreover, it can use algorithms for autonomous decision-making with uncertain, dynamic, and incomplete information. Having a framework among industrial machines and shared collaborative intelligence identified in RQ1 can prepare the necessary ground to achieve RQ2, synthesizing analytics and intelligence of factories with other external knowledge and services for decision making.

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