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Impact of AI and Digital Twins on IIoT

Bin Han[1], Björn Richerzhagen[2], Hans Schotten[1], Davide Calandra[3], and Fabrizio Lamberti[3]

[1]Technische Universität Kaiserslautern, Germany
[2]Siemens Technology, Germany
[3]Politecnico di Torino, Italy

Abstract

We discuss the role and impact of AI on the Industrial Internet of Things (IIoT) as envisioned by the European flagship project on 6G, Hexa-X. The envisioned ecosystem of trustworthy collaborative digital twins (DTs) lays the foundation for emergent intelligence (EI) and utilization of AI for industrial scenarios. One important building block for utilization of AI in IIoT is the inclusion of the human: we therefore provide insights on AI at the intersection between DTs and human-machine interfaces (HMIs).

Keywords: Hexa-X, industrial internet of things, digital twin, artificial intelligence, emergent intelligence, human-machine interfaces, immersive technologies.

7.1 Introduction to the Hexa-X Project

Hexa-X[1] is the European flagship project on 6G. It defines the vision, use cases, as well as key performance and value indicators for upcoming 6G systems. The project studies technical enablers for novel 6G capabilities and provides an initial end-to-end architecture for 6G systems. The key

[1]hexa-x.eu

societal values of sustainability, trustworthiness, and inclusiveness drive the contributions in the project [1].

Use cases considered in Hexa-X span seven families, as detailed in [1]. The use case families *from robots to cobots* and *massive twinning* capture key characteristics of IIoT for which technical enablers and concepts are being developed in the project. In the following, we focus on DTs and the use of AI and novel HMIs as technical enablers and their impact on IIoT. First, we outline an ecosystem concept for DT that highlights the relations between twinned aspects of the IIoT and the underlying information flow enabled by a 6G system with its novel sensing and processing capabilities. We discuss the concept of EI being enabled by (collaborating) DTs and its impact on IIoT and elaborate on the potential of collaboration among local and global management entities and their respective DTs to benefit from additional local insights in AI-based decision making and optimization. Before concluding the discussion, we analyse the role of AI at the intersection between DTs and novel HMIs.

7.2 An Ecosystem Concept for Digital Twins in IIoT

With the massive deployment of DTs, in the era of 6G, conventional cyber-physical systems (CPSs) that have been widely used in industrial scenarios is envisaged to evolve into a human-centric industrial ecosystem, which is illustrated in Figure 7.1. With a generic framework to support constructing and maintaining a digital replica for an arbitrary physical entity, it allows every machine, every person, and every component of the data infrastructure that is involved in the industrial process to offload its context information to the digital intelligence (which is commonly deployed in the cloud or at the network edge), analyse it online, and exchange such information with other involved entities or DTs in an agile, efficient, and secured fashion.

To support such an ecosystem, future IIoT must leverage the numerous advantages and conveniences provided by 6G DTs, which are including, among others: the ubiquitous and ultra-dense connectivity to support massive twinning; the timely status synchronization between the physical entities and their DTs; the data-driven intelligence that generates empirical insights on the physical environment and processes. Empowered by these technical enablers, various novel use cases can be envisioned, which we have clustered into eight categories upon the flow of information between the cyber and physical/human worlds, as shown in Figure 0-1. In the following sections of this chapter, we will focus on three selected technical aspects to demonstrate

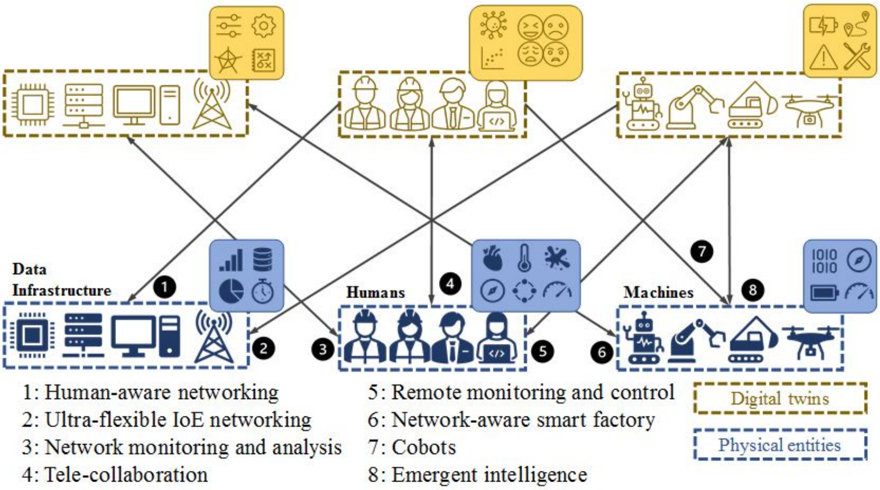

Figure 7.1 The ecosystem of 6G human-centric industrial DTs, with the arrows indicating the direction of the information flow.

how the combination of AI and DT will impact these emerging use cases. More specifically, we will introduce 1) what is Emergent Intelligence (EI) and why it benefits from massive twinning; 2) how network-aware DTs can be used to generate local insights to support smart factory applications; and 3) how AI-empowered DTs can be exploited in human-machine interface to realize collaborative robots (cobots) and Extended Reality (XR).

7.3 Digital Twins for Emergent Intelligence

Future IIoT is envisaged to connect everything and everybody, not only the physical entities but also their DTs. Rich physical and context information can be therewith efficiently collected, shared, and exploited. Such ubiquitous interconnection and universal information sharing among equipment, products, infrastructure, and human participants will help to deliver an immersive AI capable of accomplishing future industrial tasks, which are not only complex, but also polymorphic and flexible (e.g., the manufacturing process may vary significantly from one product to another, and an occasional update of the AI solution is demanded in the future flexible manufacturing scenario).

Nevertheless, while promising numerous new use cases, the immersive AI in 6G IIoT is also raising concerns in safety, security, and data privacy. Most conventional AI solutions require the aggregation of user data at a central unit that makes decisions for all users as the AI engine, which leads not only to a concern of privacy leakage, but also a security risk of model manipulation through malicious data injection. Over the recent years, technologies like Federated Learning (FL) have been intensively studied and well developed to address the privacy concern in AI by distributing the responsibilities of data aggregation and model training to agents. Nevertheless, they cannot yet eliminate the risk of manipulation due to their central-model-based nature. As a model-less mechanism to implement complex system behaviour, EI may play an important role in future AI applications as a secured, privacy-intolerant alternative and complement to conventional solutions such as FL.

The concept of EI was first proposed in the late 1980s as a biological term, which describes the intelligence of animals originating spontaneously and emergently from many simple units that are interconnected and interacting with each other in a complex manner [3]. Thereafter, this phenomenon was rapidly noticed in the engineering field and has inspired to develop bionic intelligent approaches. The most typical and significant instance of artificial EI is the family of approaches known as particle swarm optimization [2]. Distinguished from classical AI approaches that require the task-specific global knowledge to be explicitly integrated into a problem solver, EI approaches exploit the numerous agents involved in the task to opportunistically operate upon their representation-specific local knowledge, whereas the task-specific knowledge can be separated from the distributed problem solver, i.e., the agents. A comparison is briefly illustrated in Figure 7.2. In the framework of classical centralized ML, data are aggregated from users to a central node, where a task-specific global model is trained and shared by all users.

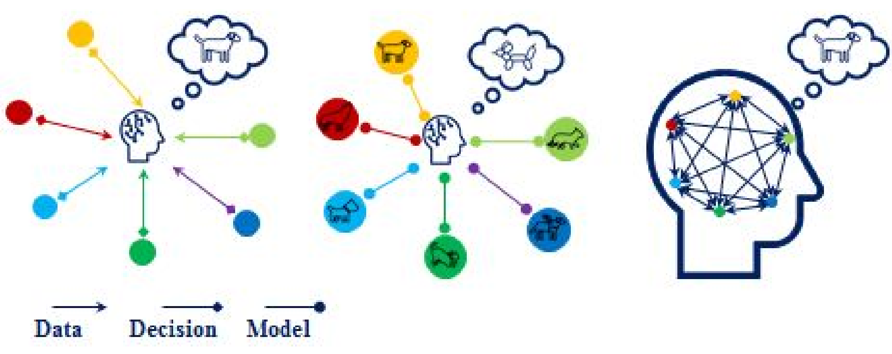

Figure 7.2 Comparing the conventional AI solutions based on centralized AI (left) and FL (middle) to EI (right).

Decisions are also usually made at the central node and sent back to the users, respectively. In the FL framework, instead of having one global model that applies for all users, the central node keeps only a so-called central model.

This model is shared with the users, so that every user locally trains it with own data and make decisions regarding the local model. The local model parameters of different users (instead of the raw user data) are aggregated and exploited at the central node to update the central model, which is then distributed to the users again to assist improving their local models. The framework of EI, in contrast, does not contain a central node, nor does it set up any explicit task-specific model. Instead, it relies on the decentralized information exchange among the users, which are architecturally equal and have no knowledge of the global task. From the reaction of each user to the information it collects from the others, some advanced behaviour pattern of the "colony" of all users can spontaneously emerge.

On the one hand, this model-less and emergent nature grants EI approaches several outstanding features that can benefit 6G IIoT, including low computational complexity, minimized computation and communication latencies, high robustness against local malfunction at arbitrary agent, data privacy, security, and scalability. On the other hand, 6G will also be able to enhance the performance of EI: it promises to deliver a ubiquitous, massive, and reliable connectivity in the IIoT environment, which will support to build a gigantic system with numerous agents networked with each other. Enhancements will be therewith introduced regarding the dimension and complexity of the networked system, as well as the efficiency of interaction between different system components. All these aspects have been proven to have critical impacts on the performance of EI solutions. In short words, 6G and EI are match made in heaven.

Nevertheless, it shall be remarked that the requirements of system scale and communication efficiency can be usually opposite each other. For example, when the number of agents increases within a limited coverage, the therewith increased access density may cause traffic congestion, resulting in either a higher latency or a lower link reliability. In another case where the access density remains consistent but the spatial dimension of the network increases, the coverage of a single radio access point becomes an issue. Message relaying will allow agents to interact over a long distance, but significantly increases the latency. Alternatively, it can be an effective low-latency solution to limit the communication range of agents but leads to a degradation in convergence performance. Furthermore, in addition to the user plane data exploited by the agents to make decisions, a significant signalling overhead must be generated to setup and accomplish the communication sessions between agents, which significantly reduces the energy efficiency and sustainability of the IIoT system.

To address these issues and support the deployment of EI in 6G IIoT, DTs will play an important role. In a massive twinning scenario, every EI agent can have not only its real-time status, context information and semantic model stored, analysed, and maintained at its DT, but also its decision engine migrated thereto as well. Thus, the information exchange between different agents can be shifted from the physical radio environment to the cyber world, and the radio link between every pair of agents can be replaced by an agent-cloud link for each individual agent, which will not only dramatically reduce the traffic load, but also mitigate the massive radio signalling overhead. Therewith, DTs will improve the radio resource efficiency and reduce the communication latency for EI applications.

7.4 Network-aware Digital Twins for Local Insight Generation

Industrial DTs of machines, processes, or whole factories might contain sensitive and business-critical information that needs to be retained within a local management domain (e.g., a private network or locally managed IT/OT systems). Traditionally, industrial DTs did not focus on the network, but on the industrial application and machinery. With an increasing share of wireless communication enabling novel Industry 4.0 scenarios and the vision of 6G as a network of networks, supporting local, independently managed network *islands* or *sub-networks*, this is changing significantly. One way to allow industrial DTs to benefit from network-awareness and utilize additional sources of data offered by novel capabilities of a 6G system (e.g., localization, sensing, computation, or AI as a Service) is the collaboration of DTs as illustrated in Figure 7.3.

The local DT on the left-hand side of the figure captures relevant aspects of the Industry 4.0 application or process being executed by several collaborating machines and humans. Local network infrastructure (wireless and wired) enabling this collaboration is also represented in the local DT to aid in network management and optimization tasks. This local loop of configuration and optimization based on the local DT is augmented with information from the 6G DT and its capabilities. Relevant aspects include the joint optimization of compute resources by utilizing the respective 6G services, or the joint optimization of network resources across management domains. Both

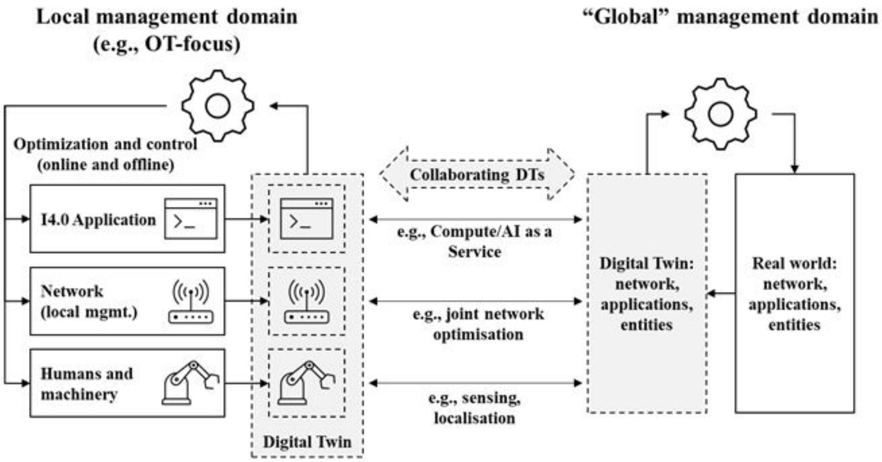

Figure 7.3 Illustration of collaborating DTs in IIoT.

domains could further benefit from a privacy-preserving exchange of sensing information to increase, e.g., location accuracy or confidence in measurement data for specific use cases. One example of such an exchange with mutual benefit is the joint optimization of trajectories of automated guided vehicles to increase process productivity while at the same time making better use of available communication resources. Instead of sense-and-react, both sides can benefit from the proactive exchange of information as foundation for AI-based decision making in the respective processes.

Being able to limit the exchange of data to trustworthy entities and act in a privacy-preserving fashion by sharing only the most relevant information among DTs allows cross-layer optimization for both, local and global management domains while still maintaining full control over own processes and data.

7.5 AI at the Intersection between DTs and HMI in Industrial IoT

The idea behind DTs is to create intangible replicas of physical assets or processes capable to capture key information that can be used to support design and planning activities, as well as to help operation and supervision tasks [4]. Initially developed in the context of, e.g., industrial plants and city infrastructure, today are progressively widening to encompass any real entity, including human beings [5].

There are several technological enablers that are easy to recognize as key to the implementation of DT solutions. One of them is indeed represented by mobile communications. In particular, there is a great expectation for the deployment of 6G networks, as their latencies and data rates are regarded as capable to make applications such as, e.g., autonomous driving and remote surgery, finally feasible [6].

The previous sections discussed the major role played in this context by AI. In fact, with AI, insights gathered through DTs can allow humans to make better operational decisions. AI can also make DTs more intelligent, to the point that they can even get able to make decisions and prescribe actions to the physical world on their own.

Using AI techniques, the DT of a city could, for instance, leverage information about road works and closures, pollution levels, or even citizens' habits to manage in real-time connected vehicles traffic [7]. Similarly, the DT of an industrial plant could constantly monitor machines' status and use collected data to instantaneously reconfigure processes to mitigate, e.g., downtimes and bottlenecks [8]. In logistics, the AI abilities could allow DTs to make fact-driven decisions regarding planning and scheduling based, e.g., on demand and distribution models, and support the implementation of optimization and control strategies aimed to improve efficiency and, ultimately, profitability [9].

Indeed, the traditional application domain for the DT paradigm is the industrial one, within the context of IIoT. A recent review of the role of AI in this context is reported in [10]. Within the commonly pictured scenarios for digital twinning, an area in which AI is expected to foster important developments is that of HMIs. Thanks also to forecasted advancement in mobile networks and edge computing capabilities, ever new ways in which the human and machine intelligences cooperate in CPSs can be envisaged. A typical use case is that of robotics, in which computer vision technology is essential for the navigation of mobile robots [11] or the interaction with collaborative robots (or cobots) [12]. Another typical application of AI techniques is that of human-action recognition from images and data collected by other sensors (like depth cameras) to perform, e.g., trajectory forecasting and path planning for safety assurance in scenarios involving the operation of co-located human and robotic agents [13], [14].

A final family of technological tools that shall be mentioned in relation to AI-powered DTs and HMI is that of XR, a term generally used to refer to a blend of tools like Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR). XR plays a primary role in the scenarios depicted above

[15]. As a matter of example, VR-based simulations are commonly used for visualization purposes in pre-production processes or in the planning of surgery interventions, whereas AR is typically exploited in customer service applications or in Head-up Displays typically mounted aboard autonomous vehicles.

It is worth observing that DTs coupled with AI and XR are expected to represent extremely powerful tools also towards sustainability. In fact, the possibility to rely on virtual, distant copies of real-world entities means avoiding unnecessary travels to the physical location of such entities. This can be the case, e.g., of remote healthcare or maintenance applications [16]. It also means less energy consumption and waste since, as said, machine failures can be predicted in advance, and designs validated and tested before being realized [17].

7.6 Conclusion

In this chapter, we discussed the impact of AI on IIoT from the perspective of the 6G European research project Hexa-X. We outlined an ecosystem of collaborating DTs as a potential enabler for emergent intelligence and local insight generation in a privacy-preserving and trustworthy way. We further elaborated on the role of AI when it comes to the intersection between the DT and the way humans interact with it by means of novel HMIs in an industrial context. In Hexa-X, we study additional enablers for trustworthy, collaborative DTs and the utilization of gathered data for flexible resource allocation and dependable operation of applications and services as important cornerstones for most IIoT use cases.

Acknowledgements

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