Exploitation of Digital Twins in Smart Manufacturing

Giacomo Cabri, Alireza Rahimi
Department of Physics, Informatics and Mathematics (FIM)
University of Modena and Reggio Emilia
Modena, Italia
giacomo.cabri@unimore.it, alireza.rahimi@unimore.it

***Abstract*—In this paper, we provide a structured summary of initiatives and a survey on the work done in exploitation of DT in Smart Manufacturing (SM) and its very close domains, and offer our points of view in the field.**

***Index Terms*—Digital twin, Smart Manufacturing, Industry 4.0, Cyber-physical spaces, Industrial internet of things, Human-Robot Collaboration (HRC), assembly, Quality control**

I. Introduction

Within the principal requirements of the Fourth Industrial Revolution or Industry 4.0 lies the interconnectivity and the integration of the virtual and physical environments. This capability is provided by the Digital Twin technology. The concept of Digital Twin was first introduced by Michael Grieves in 2002 at the University of Michigan [1] and has been evolving since then with the emergence of Internet of Things (IoT), bringing new evolutionary advancements, capacities and horizons to a wide spectrum of industries such as , manufacturing, construction, healthcare, agriculture, architecture, defence, oil and gas, etc. In this paper, we provide a summary of initiative information on the integration of DT in SM and related domains, Human-robot Collaboration (HRC), assembly and Quality Control (QC), and then a survey on some practical work done within the context.

II. An introduction to Digital Twin

A. Digital twin definition

As the name implies, a Digital Twin is the dynamically evolving virtual instance of a physical object, therefore there can exist Digital Twins of a product, factory, process or a business service. Considering the plethora of literature on the topic, a more appropriate definition of a Digital Twin has developed to outline the 'Different virtual representations at different stages of a products life-cycle' [2].

III. Influential aspects of DT in manufacturing

Digital Twin can influence the future vision of Smart Manufacturing shown in Fig. 1, in the following aspects [7].

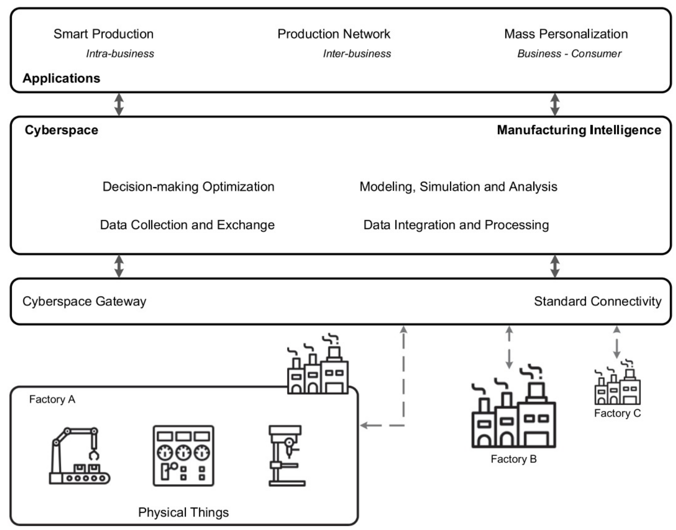

Fig. 1: Smart manufacturing vision [7]

A. Digital Twin for Manufacturing Assets

A manufacturing asset can be connected and abstracted to the cyberspace via its Digital Twin. Manufacturers can gain a clearer picture of real-world performance and operating conditions of a manufacturing asset via near real-time data captured from the asset and make proactive optimal operation decisions. With truthful information flowing from a manufacturing asset, manufacturers can improve their situational awareness and enhance operation resilience and flexibility, especially in the context of mass personalization [7].

B. Digital Twin for People

Digital Twins can also connect workers at the shop floor. The representation of a person, including personal data like weight, health data, activity data, and emotional status can help to establish models to understand personal well-being and working conditions of humans in a factory. The understanding of human state at workforce can help design human-centered human-machine collaboration strategies to increase the physical and psychological health of workers, as well as achieving best production performance. Workers can also upskill themselves via ultra-realistic training programs which blend physical factory setups with virtual what-if scenarios. The ability to set up personalized virtual training programs based on Digital Twins of workers and factories can lead to tremendous resource optimization and operational efficiency [7].

C. *Digital Twin for Factories*

Digital Twins can also work for factories, making a replica of a live factory environment. Digital Twin and data-driven production operations can allow the establishment of a self-organizing factory environment with complete operational visibility and flexibility. Connectivity and data tracking throughout the complete manufacturing process enable factory operations to be transformed into data-driven evidence-based practices, offering the capabilities of tracing product fault sources, analyzing production efficient bottlenecks and predicting future resource requirements [7].

D. *Digital Twin for Production Networks*

By connecting manufacturing assets, people and service via Digital Twin, every aspect of business can be virtually represented. Connecting distributed Digital Twins between companies will allow companies to build virtually connected production networks. Leveraging Big Data capabilities, this strategy provides unprecedented visibility into operation performance and creates the possibility of predicting future needs in a network of Digital Twins [7].

IV. Principles of the Integration of DT in Smart Manufacturing

In this section we review the principal aspects and architecture of the integration of DT in smart manufacturing and the related sub-domains of Human-Robot Collaboration systems, assembly and quality control.

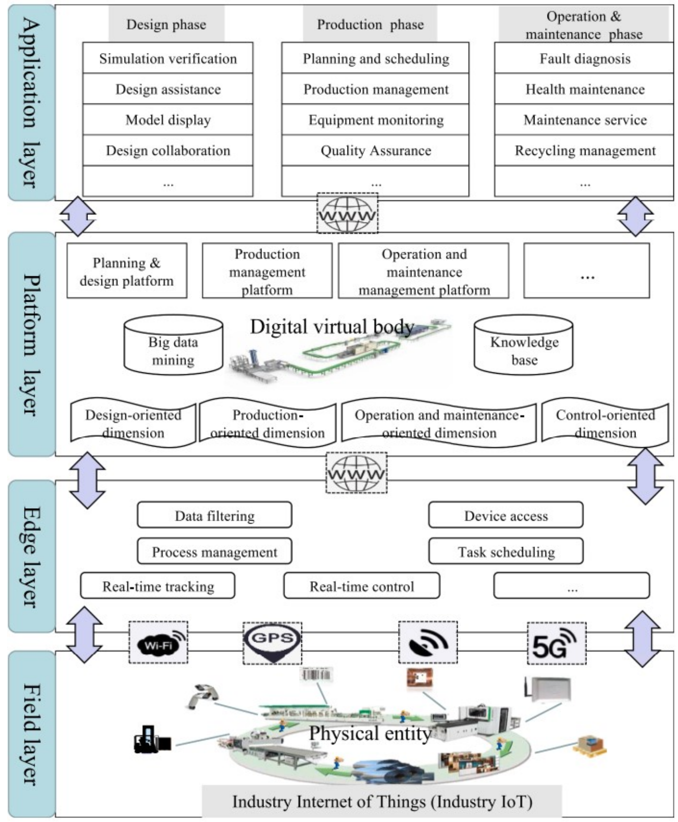

Fig. 2: The architecture of typical digital twin-based industrial information integration system in smart manufacturing supported by industry IoT [11]

A. *DT in Smart Manufacturing*

With the development and evolution of digital technology, the use of digital technology to describe the essential factors in product manufacturing began with the use of simple coding and identification technology, and has developed to the digital twin technology of virtual reality interaction [8]–[10]. In the smart manufacturing system with industrial internet as the framework and platform, digital twin plays a key role throughout the whole process [8], [9]. Fig. **??** shows the architecture of typical digital twin-based industrial information integration system in smart manufacturing supported by industry IoT. As shown in Fig. 2, digital virtual body mainly exists in cloud platform layer, and its control-oriented dimension model is arranged in edge layer to participate in real-time control. Industrial internet is composed of field layer, edge layer, platform layer and application layer. The application of digital twin is analyzed from these layers and the time dimension of design, production and operation and maintenance phases [11].

In the *design* phase, the product design work is performed and the digital twin model of product design is created through collaborative design. After a series of simulation and optimization of kinematics, dynamics and other physical aspects, or technical services provided by a third party, the preliminary design and processing scheme are determined. Then, the virtual factory of manufacturing factory in cloud platform layer is used for virtual manufacturing to attain the simulation of the manufacturability. Now, the production phase can be triggered. At this point, the digital twin contains the physical characteristics of the product entity and all the information needed for manufacturing. The status quo key technologies supporting this phase are Model Based Design (MBD), multi-physical property and multi-scale simulation, high fidelity modeling and model lightweight technology [11].

In the *production* phase, the production tasks are managed by the production management platform in the cloud platform, and the scheduling and control tasks with real-time requirements are handed over to the edge layer for management and control. Product manufacturing is an integration process of virtual and real. The digital twin of physical factory runs in the virtual space of cloud platform. The devices in the physical factory and IoT composed of sensors are located in the field layer, which exchange data with the edge layer through low delay networks such as time-sensitive network (TSN), 5G, etc. These multi-source data need different processing. On the one hand, some data directly interact with the model of the control dimension of digital twin, and get the predicted data. The optimal control of the manufacturing process is completed in the control cycle to realize the controlling of the real entity by the virtual model; On the other hand, the edge layer filters these data, transmits them to the platform layer, drives the virtual factory in the cloud platform to run synchronously (i.e. the interaction of virtual and real), and stores it in the big database, which provides data source for knowledge mining and carries out non real-time prediction and optimization of the manufacturing process. The key technologies in this phase are the real-time virtual and real fusion of multi-source sensor data, model-based control, etc [11].

In the *operation and maintenance* phase, the digital twin of the product is also provided when the product is provided by the manufacturer. The user can create and activate the virtual body of the product according to the digital twin template provided by the manufacturer in the virtual space of the industry internet. If it is a component, the simulation and optimization research of assembly process and assembly process can be started in virtual space; if it is a complete product, the simulation and optimization of the use environment and working process can be carried out, and the interaction of virtual and real can be achieved in the use process. Suppliers, technical service providers and users can obtain the status information of products on this cloud platform, so as to provide targeted technical services. In the operation and maintenance phases of the product, it is necessary to monitor the spatial position, external environment, use status and health status in real time, and establish a resume information database, which users can access and use through the application layer. The health status, function and performance of the product are analyzed and predicted by virtual body on the cloud platform, the problems are warned in advance, and the vivid visual means are provided to assist the rapid fault location and troubleshooting. In addition, in terms of operation training and guidance, digital twin can also provide more realistic effects with the help of the fusion technology of virtual and real. The key technologies in this phase are: the interaction and fusion of virtual and real, simulation, prediction, etc [11].

B. DT in Human-Robot Collaboration (HRC) systems

In an industrial production environment a notable proportion of work is attributed towards assembly operations [12]. Since the assembly tasks are often credited with handling difficult product geometries and require higher production flexibility they have traditionally been hard to automate [13]. With Lean automation, the concept of hybrid automation has emerged with balanced introduction of human flexibility and machine efficiency. However, the desired flexibility and human co-existence lead to higher total complexity of the production system. The design, development, as well as operation - due to the frequent changes make it necessary to quickly validate the behavior of the system before it is put in the real world. DT is an emerging modelling and simulation technology that has been widely used in Human-Robot Collaboration (HRC), and aims to provide support for HRC in design, construction, and control. The operational hierarchy of a digital twin framework of an HRC system is shown in Fig. 3. All the objects of the physical system are synced with their digital shadows in virtual environment or, in other words, each element in virtual simulation is displaying the operating conditions of a connected physical object in the production system [14].

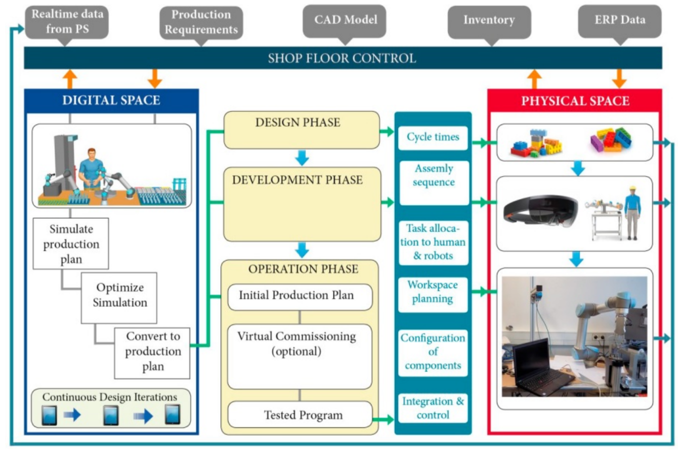

Fig. 3: Digital twin framework of a human-robot work-cell [14]

C. DT in Assembly and Quality Control

Typical complex product such as missiles, satellites and others, have characteristics of small batch production, long assembly cycle, complicated assembly data and interdisciplinary application [15], [16].

A digital twin approach for assembly process optimization is a useful mechanism to improve the quality of complex product assembly, because of its ability to provide a precise simulation result and avoid a lot of trial and error [17]. The deployment and implementation procedures for a data-driven and hardware-in-loop digital twin system can be divided into following steps [17]:

1) Build the Digital Entity of the Assembly Line: The digital entity of the assembly line is the one to one corresponding virtual mapping in the digital world of the assembly line from the physical world. Building the digital entity of the assembly line is usually based on the history data and process knowledge provided by the knowledge base. It is worth noting that for an equipment or a product, its digital entity is a digital representation considering over its entire life cycle.

2) Real-time Online Sensing in Multi-Source Heterogeneous Environment: To guarantee the real-time consistency between the physical assembly line and its digital entity, the multi-source heterogeneous environment data sensing technology is very important by transferring the real-time data from the physical world to the digital word. Typically, the data sensing technology in the multi-source heterogeneous environment should solve the problems of hardware equipment deployment and management, data collection and multi-source heterogeneous data processing.

3) Real-time Simulation of Equipment and Assembly Process: With the help of the multi-source heterogeneous environment data sensing technology, the real-time data from the physical world can be analyzed and utilized to realize the real-time simulation of equipment and the assembly process. It should be noted that, the history data and process knowledge stored at the knowledge base should be accessible to train a more precise simulation mode and provide reference benchmarks to the real-time simulation process.

4) Realizing the Intelligent Production Scheduling under Uncertainty Conditions: Based on the analysis from the realtime simulation of equipment and assembly process in the digital world, the intelligent production scheduling under uncertainty conditions can be realized. The intelligent production scheduling technology should include functions such as the generation and simulation of the work plan, predictions and analysis based on data and models, decision-making and optimization of assembly process.

5) Dynamically Adjusting the Assembly Process: The ultimate aim of the digital twin system is to dynamically adjust the assembly process, although the analyses on the real-time simulations have provided many insights to the factory workers. In reality, this step is usually added manual actions considering the production safety.

V. Literature Review

Hung et. al in [18] propose a novel implementation framework of digital twins for intelligent manufacturing (IF-DTiM), whose information and communication platform (ICP) is built on a cloud platform, an edge platform, and many IoT devices. They illustrate and construct an example of a DTiM system for CNC machining based on IF-DTiM.

Zheng and Tian in [19] analyzed the characteristics of mechanical product digital twin, and proposed a knowledge-based digital twin model evolution and version management method, which takes the advantage of mechanical hierarchy and continuously optimizes the model structure while meeting the traceability requirements. They verified the feasibility and effectiveness of the proposed method by taking the digital twin model of a helicopter and its transmission system main reducer clutch as an example.

Chen et. al in [20] propose a bionic digital brain (BDB) as the intelligent core of a digital twin-cutting process (DTCP) framework. Their BDB was built with digital neurons (DN) as the basic functional unit, and the reaction mechanism between the DN stimulated the BDB to compute intelligently in real time (RT). The left brain obtains the prophetic theoretical processing information through the DN.

Zhang et. al in [21] propose a visual-tactile fusion method to predict the results of grasping cluttered objects, which is the most common scenario for grasping applications.Their multimodal fusion network (MMFN) uses the local point cloud within the gripper as the visual signal input, while the tactile signal input is the images provided by two high-resolution tactile sensors. They propose a digital twin-enabled robotic grasping system to collect large-scale multi-modal data-sets and investigates how to apply domain randomization and domain adaptation to bridge the sim-to-real transfer gap.

Yao et. al in [22] propose a DT-based framework of task rescheduling for robotic assembly line (RAL) and its key methodologies, having used PLC and RFID sensing technology to realize the perception and access of multi-source data, a virtual-reality interaction mechanism promoting the evolution of the DT, and a mathematical model established by taking the total working time and the load balancing as the objectives, which all leads to analysis of the adaptive target thresholds from the perspectives of event trigger and user demand trigger, that yields a DT-driven multi-level rescheduling strategy.

Wei et. al in [23] studied the digital twin (DT)-driven manufacturing equipment (ME) development method, based on axiomatic design (AD). Their DT model is constructed of two core components which are the DT model of the manufacturing equipment (ME), and the DT model of the smart manufacturing system (SMS) associated with the ME.

Xiao et. al in [24] have conducted the geometric modeling of the digital twin shop floor (DTS) based on their model reuse-based geometric modelling method DTS, performed the behavior modeling of equipment production in DTS and DTS production process, and derived the DTS service of the abnormality handling is derived. They verified their proposed procedures and methods on an aerospace product assembly shop floor.

Perno et. al in [25] present a framework for developing ML-based DTs to predict critical process parameters in real time. Their choice of focusing merely on machine-learning and not extending the scope of the study to other potentially relevant methods such as first-principle or hybrid approaches, is claimed to be due to machine learning being a more advanced and powerful technology expected to yield accurate results using the data available from the process plant. Their proposed framework is tested through a case study at an international process manufacturing company in which it was used to collect and process plant data . They extracted initial data collection from company's enterprise resource planning (ERP) system and used them as a dataset to train and test the models for the ML-based DT, built accurate predictive models for two critical process parameters, and developed a DT application to visualize the models' predictions.

Lugaresi et. al in [26] define the problem of checking the validity of digital twins for production planning and control while the physical system is operating. They proposed A methodology describing the data and the types of validation including a set of techniques to be used at different levels of detail. They measured congruence between the physical system and the corresponding digital model by treating data as sequences and measuring their similarity level with digitally-produced data by exploiting a proper comparison technique. They show the potential of the proposed approach and its applicability in realistic settings through numerical experiments dealing with input validation and logic validation, by carrying out performance-level validation with two different reference KPIs which are system time and inter-departure time. Their system and the digital model used to conduct the experiments are discrete-event simulation (DES) models realized on Rockwell Arena Simulation Software, and their online validation methodology has been implemented in python.

Also Lugaresi and Matta in [27] describe the problem of discovering manufacturing systems with complex material flows, such as assembly lines. They proposed an algorithm for the proper digital model generation, aided by the new concept of object-centric process mining. This algorithm identifies stations in which components are assembled into final or work-in-progress products, and the corresponding material flows. With the addition of their Grapg Completion Problem (GCP) and the corresponding solution procedure, the blocking condition related to the availability of component parts can be added to a simulation model, allowing for the proper estimation of the system performance. They successfully applied their proposed approach to two test cases and a real manufacturing system and attained results that show the applicability of the proposed technique to realistic settings.

Rachmawati et. al in [28] present a novel approach to sensor data-driven fault diagnosis, utilizing Artificial Intelligence (AI) technology to investigate the temperature imbalance in the extruder and printing surface. They proposed a Lightweight Convolutional Neural Network (LCNN) to detect faults from sensory data, and using the Unity Engine created a DT environment that mimics the conditions of a physical FDM 3D printer for fault detection. Their simulation results show that the proposed LCNN with a DT environment can effectively monitor, detect, and control the physical workplace.

Ashok et. al in [29] propose a digital twin virtual reality concept of robotics-based intelligent production systems with a novel model, having used augmented reality & VR technologies by the operators.

Wang et. al in [30] introduced the generalized sparse identification of nonlinear dynamics (GSINDy) algorithm to enlarge the SINDy's applicable range. SINDy algorithm, as an automatic system identification technique which is robust to measurement noise is critical for the development of high-fidelity digital twins and their applications, automatically determines the parsimonious governing equations for physical systems. They proposed the modified GSINDy (MGSINDy) algorithm, in which an objective function is constructed to simultaneously identify the digital twin input time-series dynamics model and output model while separating noise from the noisy input.

Abdoune et. al in [31] propose a data-driven methodology for integrating the energy consumption (EC) model for the production of industrial sector into Digital Twins, towards sustainable and energy-efficient manufacturing. They ran an investigation on an industrial robots Kuka KR6 and KR10 as a case study, paying attention to the variability of different operation parameters (such as velocity, payload) and dynamic behavior of the robot and their impact on the EC behavior of the robot by relying on a data-driven approach.

Yi et. al in [32] propose a novel approach to developing a human-robot collaborative assembly system and apply it to the field of digital twins. They explore a deep learning-based model is to develop a depth camera-based human recognition system for accurate prediction of key points for human skeletons model and high-precision human localisation in a human-robot collaborative setting. After the functional mapping of robot calibration, a collision warning module leverages coordinates of key human-robot points to facilitate efficient and safe human-robot collaborative assembly.

Liu et. al in [33] present the enablement the prototype of an MTConnect-based Cyber-Physical Machine tool (CPMT) with DT. Their prototype was developed based on a Sherline 3-axis milling machine. Various real-time machining data were collected from the CNC controller and different sensors such as radio frequency identification (RFID) tags, dynamometer, accelerometer and RPM sensor.

Zhu and Ji in [34] proposed a digital twin–driven (DTD) method for real-time monitoring, evaluation, and optimization of process parameters that are strongly related to product quality. Based on a process simulation model, production status information and quality related data, combined with an improved genetic algorithm (GA), they built a time sequential prediction model of bidirectional gated recurrent unit (bi-GRU) with attention mechanism (AM), to flexibly allocate parameter weights, accurately predict product quality, timely evaluate technical process, and rapidly generate optimized control plans.

Hashash et. al in propose a novel edge continual learning framework proposed to accurately model the evolving affinity between a physical twin (PT), an autonomous deriving vehicle and its corresponding cyber twin (CT) while maintaining their utmost synchronization.

VI. Conclusion

Towards optimization of DT in SM, considering the industry-based digital thread, we suggest that the inclusiveness and coherency of the DT framework may improve its efficiency. This coherency can be realized through physical proximity of the supply chain sites that share a common general DT framework which is comprised of hierarchically distributed DTs. The proximity also provides the possibility of more locally-efficient type of connectivity, which are low-range but fast within the DT LAN.

Another positive impact can be derived from the inclusion of the logistics systems in the DT ensemble, resulting in even further reduction of product life-cycle. We believe that the governance of Model-Based Systems Engineering (MBSE) over the complete industrial process and as a result its DT platform will optimize the complete product and DT life-cycle. In our perspective, the forthcoming extended inclusion of DT as an integral component of smart manufacturing, will expose the capabilities of DT even further, that will revolutionize the atmosphere of not only manufacturing but also other domains including healthcare, agriculture, etc. and also fields such as city planning and municipal operations, military operations, commerce and governance. We believe that DT's benefits will overcome the challenges of a short temporary period such as the lack of awareness and reluctance to admit cost of implementation. We expect and envision a Digital Twin boom comparable to the dot com boom.

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