A Distributed Digital Twin Architecture for Shop Floor Monitoring Based on Edge-Cloud Collaboration

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Abstract— **Throughout recent years, many "Smart Factory" concepts have been emerged to escort the current technological progress. Among these concepts, we found the Digital Twin which is a burgeoning technology that attracts great interests from academics and industry. Akin to other technologies, the power of Digital Twin can be strengthened by leveraging other technologies' benefits such as those of cloud computing and edge computing. First, to support the implementation of the Digital Twin for the shop floor monitoring, a conceptual architecture of the Digital Twin based on edge-cloud collaboration is proposed. This architecture is believed to enhance the real-time capabilities of the Digital Twin while dealing with the abundant amounts of manufacturing data. Moreover, the paper discusses how the microservices architecture can benefit the proposed Digital Twin architecture. On the other hand, in order to provide an underpinning to researchers on the Digital Twin topic, the paper sums up the description and an up-to-date output of the Digital Twin, highlighting four manufacturing application scenarios.**

Keywords- Smart Manufacturing, Shop Floor Monitoring, Digital Twin, Edge-Cloud Computing, Microservices

I. INTRODUCTION

With the fast market expansion and facing the demand increasing, the companies are obliged to enhance their productivity to survive the fierce concurrence. In this regard, many strategies have been proposed to upgrade traditional manufacturing systems with some degree of intelligence, such as Made in China 2025, American Industrial Internet, and German industry 4.0. These strategies have effectively altered the facade of many manufacturers. As a matter of fact, the transition to smart manufacturing renders companies to continuously understand, learn and extract knowledge from the generated data which is of importance to promote production processes. Among the technologies that assist the company in this transition, we find Digital Twin. Since the introduction of this concept in 2003 by Michael Grieves, the Digital Twin has been embraced by many sectors, to name but a few, manufacturing, smart city, construction, healthcare, agriculture, automobile, aerospace, and aviation industry. Today and besides its classification as one of the top ten strategic technology trends for four successive years (2017-2020) ([1]-[4]), it is believed that the market of Digital Twin is projected to reach 48.2 billion USD by 2026 [5].

Broadly speaking, Digital Twin in manufacturing can be considered as a virtual copy of manufacturing systems (e.g., machines, products, processes, and factories) that strives to represent its physical counterpart as accurately as possible [6], in order to provide different information in a consistent format enabling decision-making, such as predicting future performance, state, behavior, and maintenance needs of a manufacturing system as well as its real-time monitoring through online optimization, real-time feedback control, and dynamic production scheduling.

It is noteworthy that based on the magnitude of integration and connectivity in the physical world, [7] categorizes the manufacturing digitalization into three levels, namely, Digital Model (DM), Digital Shadow (DS), and Digital Twin (DT). As depicted in Fig. 1, DM represents the low level of system digitalization which does not use any form of automated data exchange with the physical system. DS is a digital representation that has an automated one-way data flow from the physical system to the digital system, and a manual data flow conversely. At the top level, DT has a bidirectional data flow between the physical system and the digital system, which involves a reciprocal impact between digital and physical systems state. Otherwise, Digital Twin can be considered as an evolution of complex simulation models thanks to real-time data from the physical system [8]. Indeed, while simulation partakes typically in product design and what-if scenarios analysis, Digital Twin covers the entire product life cycle starting from prototype optimization.

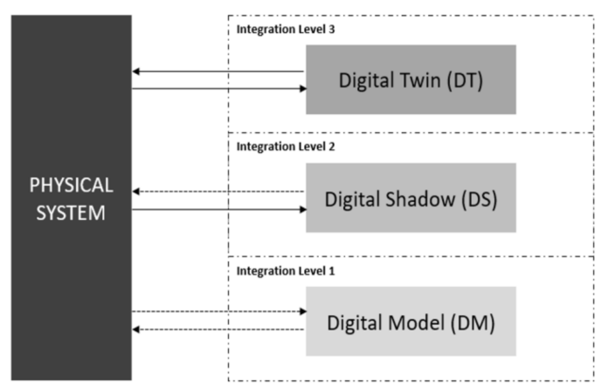

Figure 1. Manufacturing digitalization levels.

In the existing literature, notwithstanding that abundant research studies have been conducted on this topic, it still has a good way to maturity since there are many challenges that ought to be addressed. In fact, Digital Twin challenges can be mainly summarized in (i) information management

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including data collection, interoperability, synchronization, and security, (ii) Digital Twin modeling including interpretability, self-learning capability, flexibility, and reconfigurability, (iii) Digital Twin's uncertainty management including accuracy, fault tolerance, and physical system safety, (iv) and Digital Twin architecture improvement. Dealing with these challenges will pave the way for manufacturers towards a smooth implementation of the Digital Twin concept and enable them to harness the maximum benefits of it.

Considering the deficiency of Digital Twin architectures, this paper proposes a conceptual architecture of distributed Digital Twin that takes advantage of the storage and computing power characteristic of the cloud computing and the low-latency and real-time response of the edge computing. In fact, as the manufacturing system evolves with time, data management becomes an arduous task for manufacturers. To manage the substantial manufacturing data, cloud computing and edge computing techniques are considered as underpinning for data analytics, storage, and networking. Unlike cloud computing architectures that centralize processing and storage in a single data center, edge computing allows computing and storage resources to be distributed near data sources via decentralized computing infrastructures. Edge computing provides low-latency responses, better data security and privacy, and lower network congestion ([9]-[11]). With large data volume and considering the strong computing and storage power of cloud computing, a synergistic architecture that combines both edge and cloud computing should be leveraged in the Shop Floor Digital Twin so as to espouse the current manufacturing data evolution.

The rest of this paper is rolled out as follows. Section 2 discusses some existing architectures of Digital Twin. Then, the proposed architecture is explained in Section 3. The advantages of microservices architectural style are discussed in Section 4. Some of the manufacturing scenarios of Digital Twin are discussed in Section 5. Finally, the paper is concluded in Section 6, where we will point out some perspectives.

II. RELATED WORKS

In terms of the architecture of a typical Digital Twin, there are already several works available. First, [12] stated that the Digital Twin needs three main components, the physical system, the virtual system, and the bidirectional communication which is a prerequisite to enliven the virtual system. Then, [13] extended the previous framework to a five-dimensional one by adding two more elements, DT data and services. Although this architecture provides a reference for the Digital Twin, it is deficient in details when dealing with real scenarios.

In actuality, the Industrial Internet of Thing (IIoT) is deemed as a foremost infrastructure of Digital Twin that partakes in the convergence of the physical world and the digital world. However, the more IIoT data are generated, the more the data collection, storage, and processing become cumbersome, and the more the Digital Twin becomes overloaded. Based on Big Data ecosystems, [14] proposes an architecture which contains six layers, Physical layer, Ingestion layer, Persistence layer, Inference layer, Service layer, and Consumption layer. Succinctly, once the data signal is generated by the physical layer, it will be preprocessed by the ingestion layer, where it is transformed into certain appropriate formats for storage purpose in the persistence layer, then it will be processed in the inference layer, provided by the service layer as data services and consumed in the consumption layer.

In the same direction, in order to exempt companies from mundane IT tasks and expedite the DT implementation, the proposed architecture in [15] combines the edge and cloud computing power, where edge computing collates and pre-processes the data from the physical system before feeding it back to the cloud.

Another intriguing DT architecture is the one proposed in [16] which fosters collaboration between similar manufacturing resources and integrates the Multi-Agent System (MAS) concept to create digital twins. The architecture is constituted by four layers, physical assets, virtual assets, Digital Twins, and Social Platform. First, Virtual Asset ensures that the data from the physical asset is pushed regularly to the digital twin in a standardized format. Then, Digital Twin analyses these data to perform tasks such as health management and performance optimization. Collaboration is enabled through the social platform that clusters similar assets and orchestrates communication between Digital Twins as well as interactions with the external world. Collaboration might be useful in many applications of Digital Twin. For instance, in prognosis, the trajectories corresponding to new events can be shared among similar assets to enhance their awareness of such circumstances in the future. Moreover, sharing data between similar assets enables the improvement of the performance of underlying algorithms by making a richer dataset available for training and prediction purposes. [17] investigates the application of Digital Twin to improve quality control, which draws less attention in the literature compared to other applications. The authors propose a DT modeling method that combines simultaneously MAS, ontologies, and the five-dimensional DT architecture. Herein, the different manufacturing elements of the production line are presented as agents to facilitate the interactions among them, while ontologies are adopted to improve interoperability during the interactions between agents.

Recently, there is a new tendency that integrates cognition capabilities with the Digital Twin, which results to what is called Cognitive Digital Twin or Cognitive Twin for short. Cognitive Twin is considered as the next generation of the Digital Twin where cognition capabilities are provided by knowledge base and Artificial Intelligence. This makes the Digital Twin learns from experiences; Thus, they can autonomously take smarter decisions. In [18], the proposed architecture includes five layers, Physical Space, Digital Space, Data Space, Knowledge Space, and Social Space. Herein, the Knowledge space acts as the brain of the Digital Twin, where dynamic knowledge bases and knowledge-based intelligent skills are implemented to render the Digital Twin cognitive.

Although the above-mentioned papers provide intriguing Digital Twin architectures, this area of Digital Twin is still in its infancy, especially with the arrival of new technologies such as edge and cloud computing and the growing tendency to adopt them. Thus, more endeavors should be done to adapt Digital Twin with such technologies. As an effort in this direction, this paper investigates how the Digital Twin, edge computing, and cloud computing can be coupled together.

III. Digital Twin Architecture

The overall architecture is shown in Fig. 2 As depicted, the architecture presents a two-level Digital Twin which encapsulates three layers: physical layer, edge layer, and cloud layer, along with connection of these layers and data security management. Each layer will be detailed in its respective subsections.

A. Physical Layer

Before the data start their journey in the Digital Twin framework, they must be collected first from physical assets on the shop floor. Data are distributed on the shop floor in various forms such as sensor readings, RFID tags, videos/images, and so on. The collected data must contain any information that pertains to the purpose of the Digital Twin such as equipment operating data, scheduling data, and manufacturing environment data. Quintessentially, shop floor data include data from human, machine, material, and environment. Human refers to workers, supervisors, and managers. Machine includes machine tools, industrial robots, transporting equipment such as automatic guided vehicles (AGVs) and conveyors, etc. Material includes raw materials, sub-systems, semi-finished products, finished products, etc. Environment includes operating conditions such as temperature, pressure, noise, humidity, etc.

B. Edge Layer

The edge layer presents the first level of the Digital Twin. Here, the data journey in this layer goes from two steps. First, raw data are filtered in the Data Preprocessing sublayer. Then some equipment-specific analytics will be performed in the Local Digital Twin (DT) Tasks sublayer. Finally, the clean data and the processed data will be regularly transferred to the cloud for backup and long-term storage as well as releasing edge storage resources. To promote the cognitive capabilities of the Digital Twin system, these transferred data are utilized not only as historical data but also could form a knowledge base in the cloud so that the different Digital Twin algorithms can provide better predictions and decisions.

1) Edge Data Preprocessing: The above functionalities of the edge layer can be implemented on various computing systems such as Raspberry PI 4, BeagleBone AI, industrial PCs, small workstations, and any computing system that guarantees sufficient computing power for manufacturing data processing.

Since the Digital Twin results strongly hinge on data quality, the collected data must be preprocessed before being ingested by Digital Twin algorithms so as to make data truly reflect the production process. Indeed, the collected data are often corrupted with outliers, missing values, and variations, which may lead to spurious conclusions. Data preprocessing includes mainly four steps: redundancy checking, outlier elimination, missing value imputation, and standardization or normalization. In the end, the size of data to be circulated in the network is reduced which enables to improve bandwidth, efficiency, and economy. These data will be utilized to perform local DT tasks, global DT tasks, and to update virtual models. Moreover, to improve data security, data encryption can be performed before the data are sent to the intended destination.

2) Local DT Tasks: To incorporate the edge computing power in the Digital Twin such as improving real-time capabilities of the Digital Twin and reducing the computing load of the cloud, real-time monitoring tasks should be performed in the edge layer. This will significantly improve response time, awareness, and safety of the various shop floor elements. Local DT tasks include real-time control, real-time state optimization, equipment prognosis, and other equipment-specific tasks, especially, real-time tasks. For real-time control, a closed-loop Digital Twin module could be established to provide real-time actions once an anomaly occurs. For example, based on simulations of virtual models, the physical systems can be adjusted and controlled in a real-time manner. However, more endeavors should be allotted to ensure safe Digital Twin feedbacks. Finally, the real-time diagnosis, prognosis results, and executed control operations are shared with the intended destination, mainly, the cloud layer, where they will be stored and utilized as models' inputs, and edge user interfaces, where they can be provided as reports for example.

C. Cloud Layer

The cloud layer is the next level of Digital Twin, it is formed by two main components. The persistence database where data and knowledge are managed and Global DT Tasks sublayer.

1) Persistence Database: The data received from the edge layer and from the cloud analytics are stored in the cloud database according to data type. Structured data are stored and managed in the distributed database system (DDBS). XML describes the semi-structured data which are unified and stored in the relational database management system (RDBMS) or DDBS. The Hadoop distributed file system (HDFS) or the not only structured query language (NoSQL) are utilized to store and manage the unstructured data.

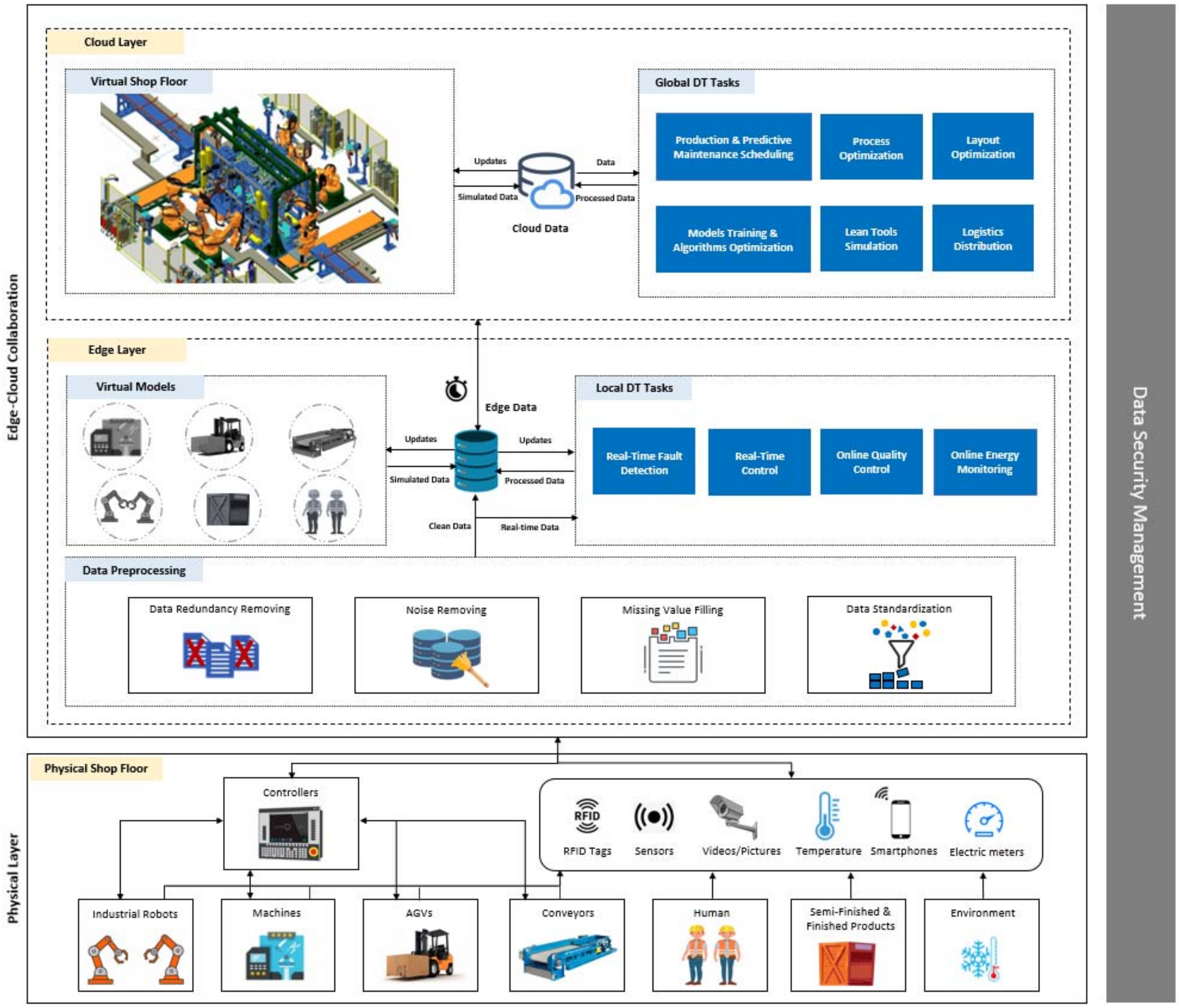

Figure 2. Digital Twin Shop-Floor Architecture Based on Edge-Cloud Collaboration.

2) Global DT Tasks: Here, the global DT tasks such as production and predictive maintenance scheduling, production optimization, and production performance prediction, will be performed by collaborating with the local DT tasks. For instance, the scheduling service in the cloud layer will communicate with prognosis services in the edge layer to elaborate a production and predictive maintenance scheduling. Moreover, some global DT tasks services must collaborate to perform a certain goal. For example, the scheduling service and simulation service (virtual shop floor) must collaborate to elaborate the optimal production and predictive maintenance planning. On the other hand, the cloud layer must contain replication of models performed in the edge layer so as if an edge node is dysfunctional, its models are not lost. Besides, the cloud layer is responsible for training and optimizing algorithms and models in both edge and cloud layers. The local Digital Twin algorithms will be regularly updated and optimized in the cloud and sent again to the edge, that is, the edge layer will contain the up-to-date versions of algorithms and models. Moreover, collaborative learning can be carried out in the cloud through data sharing between similar equipment which is believed to dramatically improve the accuracy of fault prediction, detection, and recovery. Further, collaborative learning can be performed in both cloud and edge layers, presenting another edge-cloud collaboration aspect. For example, a basic model can be formed and trained in the cloud based on historical data of all similar equipment, then this pretrained model is migrated to the edge nodes where the model will be fine-tuned based on each equipment's data.

D. Connection

Transmitting data from the physical shop floor to the edge or interconnecting the edge and the cloud, connection is imperative for the operation of Digital Twin. The Physical layer and Edge layer require real-time communication to realize real-time synchronization. Transmission protocols include DDS, MQTT, CoAP, OPC UA, Modbus, MTConnect, TCP/IP, RS232, ZigBee, and WIFI. On the other hand, edge and cloud layers do not require necessarily real-time communication, thus only a limited synchronization is achieved. Edge and Cloud layers can communicate using the public Internet such as MQTT, TCP/IP, HTTPS, Remote Procedure Call (RPC).

E. Security

Processing sensitive data locally in the edge layer greatly shields physical systems from malicious attacks. However, data security still must be addressed. Data security should be tackled in the two communication tunnels, between the physical devices and the edge layer on a side and between the edge layer and the cloud layer on the other side. For both, we should preserve data from not only external attacks but also internal attacks that could be achieved by users that have already authorization to some resources in the network, thus, they can tamper with sensitive data, damaging the physical system.

IV. Microservices for Digital Twin

It is noteworthy that the proposed Digital Twin architecture should be developed in a microservices architectural style which consists of dividing services into a set of small services. Microservices architecture is deemed to be promising for the modular development of flexible, evolving, and distributed systems such as the proposed architecture. Indeed, the microservices architecture provides elasticity, in terms of the ability to update frequently the Digital Twin framework at run-time, which also enables Digital Twin to start with one application and extend over other ones without affecting the Digital Twin operation. Moreover, microservices reduce the software delivery and probability of cascading failure of the whole Digital Twin framework. Besides, they provide elasticity which allows responding quickly and effectively to workload changes that edge and cloud resources may undergo, that is, microservices allow Digital Twin tasks to be orchestrated among multiple edge and cloud resources. Furthermore, to enable microservices to fully realize their potential, they can take advantage of containerization, which facilitates microservices deployment, reduces latency and infrastructure costs, and increases speed and performance.

V. Manufacturing Application Scenarios of Digital Twin

In order to make the reader aware of the possible applications of Digital Twin in industry, this section gives an insight into some of the important manufacturing scenarios, namely, Equipment Health Management, Production Scheduling, Production Control and Optimization, and Quality Control. Each of these applications is discussed in its respective subsection.

A. Equipment Health Management

Equipment Health Management is the first application of the Digital Twin; NASA's Apollo space program is the pioneer of this concept, which has adopted it to simulate and predict the state of a launched spacecraft [19]. In the manufacturing context, many studies have been conducted in this application of Digital Twin. Reference [20] presents a model-driven approach to estimate the Remaining Useful Life (RUL) of an equipment's component based on data from the real machine's controllers and simulation of virtual models. Considering the case of insufficient data, [21] proposes a two-phase Digital Twin framework to enhance fault diagnosis at the beginning of manufacturing. The first phase provides an intelligent design where potential design faults can be detected and solved. Then, data generated from the physics-based model's simulation will be utilized to train a fault diagnosis model. In the second phase, to enable real-time monitoring and predictive maintenance, the pre-trained diagnosis model is transferred from virtual space to real space and fine-tuned using the transfer learning technique. On the other hand, a two-part series ([22], [23]) proposes a multi-scale, probabilistic Digital Twin framework for fatigue life prediction. More specifically, the first part presents the pre-diagnosis phase which is distinguished by the significant lack of information available due to the absence of the damage. While the second part considers that fatigue damage is observable, thus, the prediction model is calibrated, and prediction uncertainty is dramatically reduced using in-situ observations. Assuming that damage is observable, [24] proposes a Digital Twin framework for intelligent mission planning that aims at maximizing the machine utilization before the complete failure. This is believed to be convenient when spare parts delivery is delayed, or a loaded production plan.

B. Production Scheduling

Production scheduling is one of the foremost activities that have a direct impact on profitability. Indeed, to meet increasing demands for diverse and personalized consumer products, the production schedule must be optimized by reducing non-value-added time. With the same objective and unlike the "target + model + algorithm" method that has been extensively employed in past studies, the Digital Twin presents a new approach that alters production scheduling. In [25], the authors introduce a Digital Twin-based scheduling framework that combines Genetic Algorithms and field-synchronized simulation, where an Equipment Health Index (EHI) module is integrated into the simulation module to continuously synchronize it with the physical system and predict the equipment health, so that the final production schedule is more realistic. Reference [26] proposes an intelligent workshop scheduling by combining both Digital Twin and supernetwork technologies, herein the supernetwork is adopted to deal with large, multi-relational heterogeneous data in the digital twin workshop. The final schedule is validated in virtual workshops and re-optimized if a production constraint is not met. In [27], the authors propose a Digital Twin framework for dynamic job-shop scheduling purpose. In this framework, the detection of disturbances based on comparison between physical and virtual models. Besides, based on simulation, this function enables the prediction of the impact of disturbances, thus, trigger the rescheduling to prevent hazardous and/or cascading effects. Finally, before the rescheduling execution, Digital Twin simulates machine indicators to assess its performance. Reference [28] presents a Digital Twin-based opti-state control system framework to be applied in a synchronized production operation system to keep the system performance in optimal condition after disruptions. Herein, a scheduling model that integrates many cooperative units such as production, transportation, and storage units is formulated and optimized dynamically.

C. *Production Control and Optimization*

Production control and optimization are of importance in the smart manufacturing paradigm. Although Digital Twin is deemed as a compelling technology for online control and optimization in the manufacturing context, academic research on this application remains deficient. Reference [29] proposes a Machine Learning-driven Digital Twin framework that continuously selects the optimal set of controllable parameters' values to realize production control optimization. The proposed framework contains various machine learning algorithms whose results are compared through specific validation indicators and the best result is applied in the real world. Reference [30] leverages Reinforcement Learning in Digital Twin to autonomously control and select the optimal path towards manufacturing task completion, either in normal conditions or while abnormalities. Reference [31] presents a reactive Digital Twin through tying the Manufacturing Execution System (MES) software and a Digital Shadow model which endows the Digital Twin with the possibility to exchange information with its physical counterpart in a real-time fashion. In [32], a data-driven digital twin framework is presented combining virtual modeling, process monitoring, diagnosis, and optimized control configuration, this framework can automatically make decisions and optimizations to guarantee stable control and safe production in both normal and faulty cases. However, more efforts should be done to improve the real-time tracking of complex systems, reactivity, and recovery [33].

D. *Quality Control*

Digital Twin can support producing near-zero-defect products by analyzing incoming real-time data to evaluate whether the quality standards are met. In [34], a Digital Twin-driven approach for online quality control of machining process is proposed. The framework consists in tool life prediction, workpiece roughness and tool wear monitoring, and machining parameters analysis and optimization. In [35], the authors present a digital twin framework based on closed-loop in-process (CLIP) quality control approach which fuses in-process data (e.g., sensors data), data-analytics (e.g., Deep Learning, statistical methods), and physics-driven simulation to expand the application of Digital Twin to New Production Introduction (NPI) phases, where it is possible to prevent defect propagation from design phase to production phase, thus, enhance product quality. In [31], the authors propose a Digital Twin-driven reactive disassembly framework which can decrease assembly quality issues by automatically scheduling a customized disassembly order once quality standards of an assembled component are not met.

VI. CONCLUSION

This paper proposes a conceptual architecture that exploits the advantages of edge computing and cloud computing. Herein, cloud computing represents a key technology to tackle bulky manufacturing data. However, since cloud computing presents some limits when dealing with time-sensitive applications such as production control, the Digital Twin architecture for shop floor monitoring should integrate edge computing that consists in migrating some Digital Twin algorithms including real-time control near data sources. In the proposed architecture, edge computing encapsulates data preprocessing and local DT tasks, and cloud computing encapsulates global DT tasks and persistence storage. That is believed to not only enhance the real-time capabilities of the Digital Twin but also relieve the pressure on the cloud, thus improve the cloud performance. Moreover, we discussed some of the main advantages of Microservices architecture for the proposed architecture.

As perspectives, we would amend this architecture by focusing on a single Digital Twin task, where we would investigate the following research points: 1) Microservices architecture: we would expound on how the selected Digital Twin task can be presented as microservices. 2) Communication Protocols: Considering the heterogeneity of the collected data, communication protocols ought to be addressed 3) Data Security and Privacy: To handle this issue, we would incorporate the Blockchain technology into the proposed architecture which will enhance the distributed nature of the Digital Twin architecture.

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