

Digital Twin Perspective of Fourth Industrial and Healthcare Revolution

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ABSTRACT Digital Twin (DT) is bringing revolution to our lives by a digital representation of the physical system. DT is the creation of the joint usage of various technologies like Cyber-Physical System (CPS), Internet of Things (IoT), Big Data, Edge Computing (EC), Artificial Intelligence (AI), and Machine Learning (ML), etc. DTs are established to optimize a wide range of applications of industry, healthcare, smart cities, smart homes, etc. It is still in its early development stages. This paper fills the gaps by combining the extensive information on technologies utilized in the creation of DT in industry and healthcare. The paper focuses on studying the characteristics of DT, communication technologies and tools utilized in the creation of DT models, reference models, standards, and the researcher's recent work in smart manufacturing and healthcare. Challenges and open issues that need attention are also discussed.

INDEX TERMS Artificial intelligence, big data analytics, communication technologies, digital twin, edge computing, fog, cloud, health care 4.0, industry 4.0, RAMI 4.0.

I. INTRODUCTION

The fourth industrial revolution has changed the world completely as it directed the world into an age of automation and digitization. It was an era of digital transformation that took the industries, healthcare, communication, homes, and offices by storm. Various technologies help in achieving our daily tasks. The industrial revolution took decades as the First Industrial Revolution was started in 1850 and the Fourth Industrial Revolution term was coined by Klaus Schwab in 2015. First utilized the power of water and steam to mechanize production. The Second look toward electrical power for mass production. Third, made use of electronics and information technologies for automated production. The fourth revolution is the fusion of different technologies that are blurring the lines between the physical, digital, and biological spheres.

Industry 4.0 (I4.0), is also known as Fourth Industrial Revolution, is a hit rather than hype. At heart, Industry 4.0 is the trend towards automation and data exchange. It is the combination of the IoT [1], [2], big data [3], [4], CPS [5], and Artificial Intelligence (AI) [6]. These technologies have changed

our life's and with advancement in technology, they will keep on changing it. Multiple authors have discussed the origin, impact, examples, and future trends of Industry 4.0 in different publications [7]–[10]. The term, Industry 4.0, emerged in Germany and proposed a complete digital transformation of the product and its manufacturing [11]. It was labeled as *smart manufacturing* in the United States [12]–[16]. The smart factories represent the future of fully automated and connected systems, mainly operating without the human presence by data acquisition, processing, and performing necessary actions on it [8]. In [17], a smart factory research model is presented with various technologies and attributes. It is an illustration created from the work of authors [18]–[24]. Here, Fig. 1. represents a more compact and simpler version of the smart factory research model. It is a combination of various technologies like IoT, CPS, DT, big data, edge, fog, and cloud computation to create a smart factory environment.

Smart machines communicate with one another through the interconnectivity provided by information and communication technology called of Internet of Things (IoT). IoT has a key role in the scope of Industry 4.0. However, it is not only the IoT but also other technologies that have a considerable share to create Fourth Industrial Revolution. Industry 4.0 is an amalgamation of different technologies that provide

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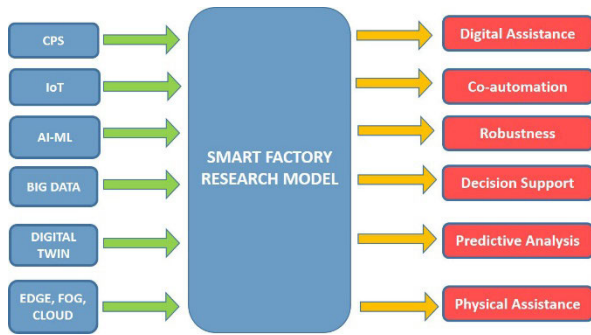


FIGURE 1. Smart Factory Research Model.

automation, operation efficiency, product quality, productivity, inventory management, security, better communication, asset utilization, agility, time to market, workplace safety and environmental sustainability, etc. These are only a few of the advantages of Industry 4.0 [17], [25]. The author of [26] provides an insight into different aspects that impact industry 4.0 strategic goals. Following are some of the aspects that need to be considered to create Industry 4.0:

1. Bandwidth has a direct impact on the numbers of users supported, and the ability to exchange a large amount of data (i.e. for predictive maintenance) [27].
2. Scalability provides smooth movement of devices/users in and out of a network without negative effects on the Quality of Service (QoS) [28] and functionality. The focus will be to provide a flexible network [29].
3. Cyber security is compulsory for industry 4.0 scenarios. It is important to protect people, industries, data, and assets from attackers [30].
4. Reliability will allow the systems in an IoT scenario to work properly in any condition [31]. It will help a long way in increasing productivity.

In the 21st century, Information Technology (IT) technologies such as IoT, cloud computing, big data, and AI, make it realistic to covert physical and virtual worlds. The cyber-physical integration [32] toward the digitalization of industries. Digital Twin (DT) is the crown jewel of Industry 4.0. This technology represents the physical system in the digital world with all its features and properties. The DT of any system is possible when multiple technologies like IoT, AI, ML, CPS, and big data work together. With the help of these technologies and real-time sensor data from the system, the DT of the system can perform numerous simulations, predictions, analyses in a safe environment. Despite the increasing research on Industry 4.0, the research remains scattered. The authors in [13], [33] gave importance to the structure and condense the vast knowledge of multiple fields of Industry 4.0. There is a difference between this work and previous literature reviews. The authors of [34], inspected the current state of the literature on Industry 4.0 whereas, [35] looked into the managerial literature only. The industry 4.0 technologies and their effects are discussed in [36]–[39]. Character or design principles were focused on by [40], [41]; human

resource management and organization implication was discussed in [42], [43]. Industry 4.0 in terms of operation and supply chain management was investigated by [44]. Literature on implementation of Industry 4.0 by [45]–[47] included the mixture of old technologies with new like Enterprise Resource Planning (ERP), Computer-Aided Design (CAD), Computer-Aided Manufacturing (CAM), and Electronic Data Interchange (EDI). Industry 4.0 is a combination of different technologies, so it is not possible to focus research on a single stream. Many of the researchers work on different aspects of Industry 4.0 such as technologies, current state, future trends, application scenarios, and open research areas [37], [48], [49]. Research surveys like [50] provide a detailed insight into DT literature, lifecycle, tools of various aspects of simulating digital models along with comparison. The authors of [51] provide a detailed overview of DT definition, characteristics, open challenges, and application cases of smart manufacturing and healthcare. In [52], a systematic overview of multiple industry 4.0 technologies and tools, and their utilization in numerous applications is elaborated but with no comparisons on numerous communication technologies and standards. The mentioned papers are in no aspect weak in terms of a literature review or knowledge, but they are missing insight into standards such as Reference Architecture Model Industrie 4.0 (RAMI 4.0), and edge-fog-cloud computing. There is a need to have literature in terms of IoT technologies comparison, DT simulation and modeling tools, big data analytics, edge-fog-cloud computing, open challenges, and standards for the creation of DT models along with an overview of research performed in applications of manufacturing and healthcare. This is the motivation for writing this literature review.

The paper is organized as follows, Section II explains the reference model of Industry 4.0, Section III discusses suitable communication technologies and their comparison based on various characteristics like range, data rates, power consumption, and the number of users supported. Section IV presents data analysis, management, and AI-ML. Section V details edge-fog-cloud computation in industry 4.0 while Section VI explores the latest concept of DT in terms of benefits, application areas, tools for the creation of digital models, data acquisition, and open research issues. Section VII shares the existing research performed in smart manufacturing and healthcare. Section VIII delineates some of the open research issues in Industry 4.0.

II. REFERENCE ARCHITECTURE MODEL OF INDUSTRY 4.0

The reference model for Industry 4.0 was the result of joint efforts of multiple German associations and institutions in 2015. Fig. 2 represents the RAMI 4.0. Industry 4.0 applications are implemented with assistance from such a model [53]. RAMI 4.0 was created to have a model that speaks the language of all levels of an enterprise and to connect them through a structured framework [54], [55]. This model allows researchers to implement existing and new technologies, techniques, and standards to identify gaps, overlaps,

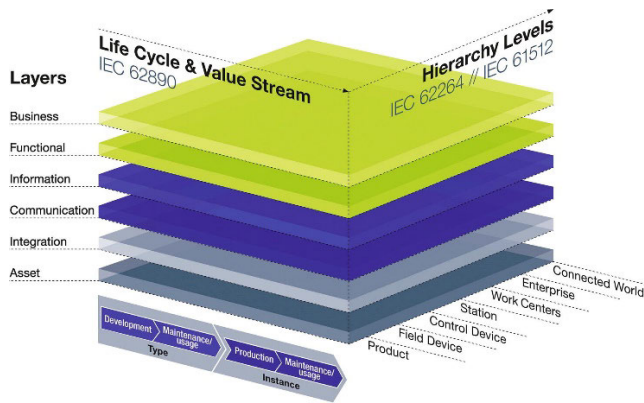


FIGURE 2. Reference Model RAMI 4.0 [62].

and loopholes in an Industry 4.0 environment. The crucial technological elements of I4.0 are compiled into RAMI 4.0. In Germany, it is registered as DIN SPEC 91345 standard [56]. The unique property of this model is to encapsulate assets in an IT “administrative shell” [57]. The administrative shell is a collection of interconnecting standards, for data security, data collection, data safety, and structuring. OPC Unified Architecture (OPC-UA) and Automation Markup Language (AutomationML) engineering plant information representation is an example of interconnecting ‘collaborative’ standards [58]. Another example is OPC-UA and IEC 61131-3 PLC data modeling for global control and monitoring [59]. Additionally, industrial providers are addressing smart industries communication requirements by providing unique data and connectivity services in form of PLCs/PACs. Examples are WAGO Cloud-enabled MQTT communication with “sparkplug” specifications [60], SIEMENS integrated OPC-UA servers [61].

According to the model, IEC 62890 standard, product lifecycle, and facilities with corresponding stream values are labeled on the horizontal left axis [63]. The model provides a difference between the type and instance. When a system design and prototype is completed, it converts from type to instance and is ready for production [56]. IEC 62264 is on the right axis of the model. It represents all hierarchical levels of any enterprise from the “Product” (for example, a work-piece) to the “Connected World”. The “Connected World” makes use of IoT and Internet of Service (IoS) to connect enterprises, customers, and suppliers [53, 56]. It is important to discuss the vertical layers of the model. The model is a systematic migration to future industrial environments. The layers provide a guideline to digitize and integrate all aspects of an enterprise.

The communication layer in RAMI 4.0 handles the connectivity or intercommunication between devices in industry 4.0. Numerous communication technologies can provide communication between large numbers of entities or systems in industry 4.0. The question that needs to be answered is which communication technology or protocol to choose for any specific scenario to meet its requirements. Section III will

provide details on IoT, multiple communication technologies, protocols, features, and comparisons.

III. INTERNET OF THINGS (IoT)

Advancements in technology have allowed researchers to create new and better communication technologies with long coverage rates, multiple operating frequency ranges, and exceptional data rates. However, the implementation of any communication technology depends on the needs of the application or scenario. It is critical to understand multiple existing wireless and wired technologies for communication in smart industries, smart homes, and healthcare.

The term IoT is mentioned in literature by many researchers. The purpose of IoT is to provide a connection between the internet and things. “Things” refers to anything like an object or a person [64]. The “Internet” refers to the network of the networks. Standard Internet Protocol (TCP/IP) is utilized worldwide to provide users with interconnected computer networks. But TCP/IP is not sufficient for most distributed applications due to the constraints of limited number of available addresses, overhead, and energy consumption. IoT has a wide range of applications within the areas such as transportation, healthcare, or utilities [65]. IoT networks can be in various forms such as Thing-to-Human, Human-to-Human, and Thing-to-Thing connected to the internet. Individually identified objects also exchange information inside this network [66], [67]. IoT is described by Sezer *et al.* [65] as: “*IoT allows people and things to be connected anytime, anyplace, with anything and anyone, ideally using any path/network and any service*”. In the words of Bortolini *et al.* [68], IoT is a global presence to provide connectivity between various objects and things networking and cooperating. IoT enables digitization of any physical system. Digital information is useful in various ways. In terms of industry, entire production lines such as machinery and related resources can be the “things” managed and virtualized by Industry 4.0 [69], [70]. In general, digital data can be utilized to modify system design, optimize production lines, increase efficiency, and be cost-effective. Through the use of sensor data and a virtual replica of the physical world [69]. IoT can work both in heterogeneous and decentralized environments [71]. In other words, we can make use of IoT in industries, smart homes, construction, education, and healthcare sectors. Research in mobile devices has increased the scope of implementation of IoT. IoT is realized with connected Wireless Sensor Networks (WSN), RFID, Cloud Computing (CC), Wi-Fi, middleware, and Software-Defined Networking (SDN) [67], etc. These are some of the enabling technologies. Fig. 3 presents the multiple technologies used in IoT.

IoT provides a connection between different entities over the network. It is an important technology in terms of integrating heterogeneous devices or systems. Service-Oriented Architecture (SOA) is utilized to support IoT. It is successfully utilized in research areas of WSNs, vehicular networks, and cloud computing [72]–[78]. Authors of [79] provided

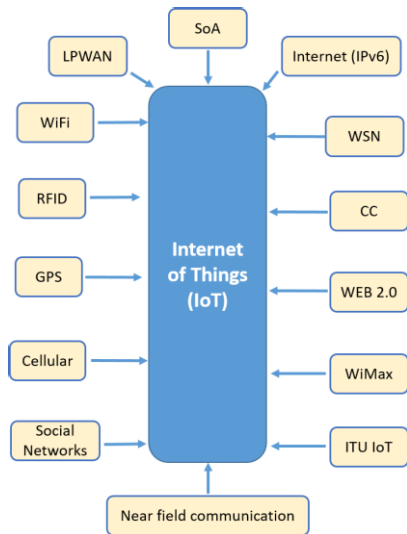


FIGURE 3. Various technologies in IoT.

a four-layer architecture for IoT i.e., sensing, networking, service, and interface.

Communication technologies depend strongly on communication mediums i.e., wired, and wireless. In this fast-track world of technological advancements, the focus of organization or society lies on how quickly a communication technology can send and receive any information. Both wired and wireless communication technologies have been used in IoT scenarios depending upon their constraints. A detailed list of differences between wired and wireless technologies is provided in [80]. In contrast to IoT users, industries require real-time data with high reliability [81]. With regards to industrial applications, literature provides the term “Industrial Internet of Things (IIoT)”. IIoT provides a connection of industrial products such as systems/machines or components to the internet. IIoT systems design generally display capabilities such as:

- 1- Scalability: The ability of the system to connect to more devices without facing any degradation in QoS [82].
- 2- Interoperability: The ability of the system to communicate with various devices to achieve the same goal [83].
- 3- Extensibility: The ability to easily add something to the system. To enable a software to handle more functionalities or interface without increasing the size of the system.
- 4- Modularity: The components of a system that can be separated and replaced or recombined to provide flexibility and variety in use.

For example, IoT application in manufacturing industrial automation application [84]. Another example can be connecting the collected sensor data in a factory with IoT platforms to increase the efficiency of production with big data analysis [66]. An overview of the wireless technologies for IoT is provided in Fig. 4. Various wireless technologies can

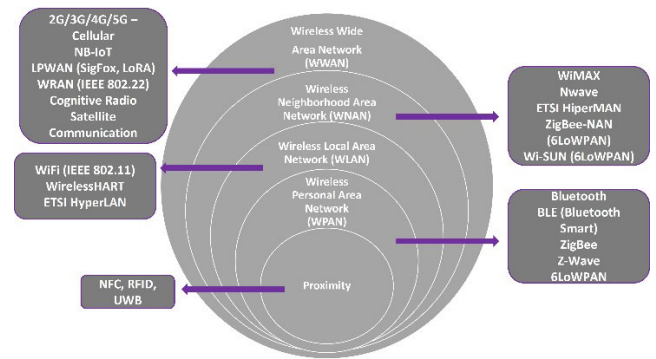


FIGURE 4. Wireless communication technologies for IoT.

fulfill IoT requirements in an environment, few of which are labeled in this figure.

Table 1 provides a comparison of multiple communication technologies based on frequency, data rate, coverage range, power consumption, and the number of devices supported. Some of the wireless communication technologies or protocols are not included in this table, such as IEEE 802.11af. The reason why 802.11af cannot be utilized in a dense urban environment is due to the unavailability of “white space”. White spaces are the unused television spectrum frequencies in UHF and VHF which can be utilized to transmit information. Frequency ranges from 470–790 MHz in Europe and non-continuous 54–698 MHz in the United States. IEEE 802.11af would work best in rural settings with other Wi-Fi protocols being better suited to utilized in urban environments.

A detailed comparison, on Open Systems Interconnection (OSI) model layers, of multiple wired and wireless communication technologies utilized in or possibly used in industries is given in Table 2. The OSI layer 1 and OSI layer 2 i.e., Physical and Medium Access Control (MAC) layers, define the wireless technology.

IV. BIG DATA AND AI-ML

Increasing growth in data from IoT sources and information services is driving the industries, hospitals, smart homes, and smart cities to create more tools and models to handle big data. Big data is characterized by volume, variety, value, veracity, and velocity. These characteristics are named “The 5Vs” [89], [90]. This data needs to be analyzed, stored, and secured to improve system efficiency, scalability, and security. Implementing big data platforms requires significant knowledge and expertise in data science and IT domain due to its complex infrastructure and programming models. Numerous tools are available in the market for organizations, but they are less popular due to their complexities. A trend in this domain is to create a level of abstraction to utilize popular data processing platforms. Apache Beam allows its data flow programming model to be utilized for multiple runners like Apache Spark and Apache Flink, Machine learning algorithms are applied on data streams in Apache SAMOA, whereas applications created on SAMOA can be executed

TABLE 1. Comparison of multiple wireless technologies: adapted from [85], [86].

Features	IEEE 802.11 (n/ac)	IEEE 802.11ah	ZigBee/802.15.4e	BLE	3GPP MTC	LPWAN		Cellular	
						LoRaWAN	SigFox	5G	6G
Frequency	Unlicensed 2.4, 5 GHz	Unlicensed 900 MHz	Unlicensed 868/915 MHz, 2.4 GHz	Unlicensed 2.4 GHz	licensed < 5 GHz	Unlicensed 867 – 928 MHz	Unlicensed 868 – 902 MHz	Sub-6 GHz and above 24.25 GHz	95 GHz to 3 (THz)
Data Rate	6.5-6933 Mbps	150 kbps to 346 Mbps	<250 kbps	<1 Mbps	<1 Mbps	<25 kbps	<1 kbps	20 Gbps	100 Gbps
Coverage Range	<200 m	<1.5 km	<100 m	<50 m	<100 km	<20 km	<40 km	1,500 feet without obstructions	10 meters
Power Consumptions	Medium	Low	Low	Low	Low	Low	Low	Low	Low
Devices Supported	2007	8000	65,000	Unlimited*	>100,000	>100,000	>1,000,000	1,000,000	10 times to 5G

*Unlimited based on the configured address space

TABLE 2. Communication technologies mapped to the OSI model: adapted from [87], [88].

Protocol	Physical	Data Link	Network	Transport	Session	Presentation	Application	Data Rate	Devices
ControlNet	RG-6 coaxial cables, 5 Mbps	ControlNet CTDMA	ControlNet, 99 nodes	ControlNet	CIP protocol family			<5 Mbps	99
DeviceNet	CANbus with twisted pair cables, 1 Mbps	CAN bus CSMA/NBA	DeviceNet, 64 nodes	DeviceNet	CIP protocol family			<0.5 Mbps	64
Modbus-RTU or ASCII	Serial cable, ex: RS-232, RS-485	Modbus	Modbus, Map, 247 nodes	Modbus			Modbus client or server + interface	19.2 kbps (default)	<247
PROFIBUS	RS-485 cables, fiber optical cable or MBP	PROFIBUS Fieldbus data link	32 nodes, 126 with fiber optical cable	Not used	Not used	Not used	PROFIBUS DP	<12 Mbps	<126
PROFINET	Ethernet 10/100/1000 MBPS	Ethernet CSMA/CD	IP	TCP/UDP	Not used	Not used	PROFINE	<1000 Mbps	>1000
Modbus – TCP/IP	Ethernet 10/100/1000 Mbps	EtherNet	IP, 254 nodes/module	TCP port 502	Modbus TCP		Modbus client or server + interface	<1000 Mbps	>1000
EtherNet / IP	Ethernet 10/100/1000 Mbps	Ethernet CSMA/CD	IP	TCP/UDP	CIP protocol family			<1000 Mbps	>1000
EtherCAT	Ethernet 10/100/1000 Mbps	EtherNet w/EtherCAT slave & controller chip	IP with timing layer, up to 65535 nodes	TCP/UDP	EtherCAT			<100 Mbps	>1000
HART (Wired)	Simultaneous hybrid analog & digital signaling, 4-20mA copper wiring	Mechanical/electrical connection transmits raw bitstream		Auto segmented transfer of large data sets, reliable stream transport, negotiated segment sizes	Not used	Not used	Command oriented, predefined data types and application procedures	1.2 kbps	62
HART (Wireless)	2.4 GHz wireless IEEE 802.15.4 based radios, 10dBm transmission power	Secure and reliable, time synched TDMA/CSMA, frequency-agile with ARQ	self-healing wireless mesh network		Not used	Not used		<250 kbps	<3000
802.15.4/ZigBee	On the air operating at 868/915/2400 MHz	802.11 LLC with 802.15.4 MAC	ZigBee routing (AODV)	ZigBee App Object + ZigBee Security Services				<250 kbps	65000

on Apache Samza, Apache Strom, and Apache S4. The 5Vs of big data have provided a doorway to a new realm of solutions. Multiple frameworks [91]–[94] have been designed

to utilize big data for effective analytics in various fields and applications. To overcome the challenges of big data in industry 4.0 or any other application, AI-ML can be utilized in

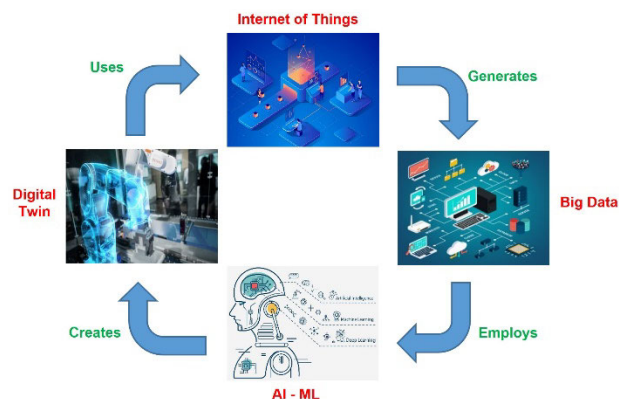


FIGURE 5. DT relationship with IoT, Big Data, and AI-ML.

combination with big data. The AI tries to digitally replicate three human cognitive skills: learning, self-correction, and reasoning. Digital learning is a process of converting previous data into actionable information. Digital reasoning is to select the best option to reach the desired goal, whereas self-correction is a repetitive process of reasoning and learning. All models follow such a build for a smart system, which performs a task that will normally require human intelligence. Various AI methods are utilized such as machine learning, data mining, deep learning, rule-based algorithms, logic-based algorithms, and knowledge-based algorithms. There is a general focus on ML and deep learning in AI approaches. This conjunction of technologies like IoT, AI-ML, and big data helps visualize the concept of DT. A representation of the overall relationship between multiple technologies with DT is shown in Fig. 5.

The amalgamation of technologies leads to very interesting applications, especially in industries, such as indoor asset tracking [95], real-time monitoring of physical systems [96], manufacturing [97], and outdoor asset tracking [98]. The IoT devices allow for real-time data acquisition, which is critical for the creation of DT models of the physical assets [99], achieve maintenance [100] and optimization [101] by linking the physical system with the digital replica. There is a deep connection between data and IoT devices, thus big data analytics has a major role in developing a successful DT model.

However, managing such an enormous amount of data in the industrial and DT domain requires advanced architecture, techniques, tools, frameworks, and algorithms. Authors of [102], [103] have presented a big data processing framework for industries and maintenance in a DT situation. Cloud computation is one of the platforms that can be used to process and analyze big data [104], [105]. It is important to implement applicable AI-ML techniques or algorithms to make the DT models more intelligent. In the end, DT will be able to perform tasks such as:

- 1- Prediction (e.g. maintenance in industry systems and health care status) [100].

- 2- Optimization by process control, planning, assembly line, and scheduler [106], [107].
- 3- Detecting best resource allocation, safety detection, best process strategy, and fault detection [108].
- 4- Dynamic decision-making based on digital twin data/physical sensor data.

Big data, AI, ML, and IoT have significant importance in industry 4.0. Industries utilize the concept in the same way as in other fields, by processing a large amount of data collected from smart sensors through the cloud or IIoT platforms to improve the overall efficiency of the operations. Finding correlations is one of the major tasks but it is not the only job. More than discovering patterns and correlations, the use of computational intelligence tools (AI, ML, and Big Data) will bring real results when it helps to find the causal nexus throughout analyzed processes. Smart healthcare applications use these concepts in applications of healthcare monitoring, drug discovery, intensive care, diagnosis of diseases, and training of healthcare professionals [109].

V. EDGE COMPUTING

With fast-growing IoT devices and increased data size, it is necessary to reduce the load of computation at the operating station or on the cloud. Edge Computing (EC) allows the network to perform computation or data processing at the edge. The integration of IoT, mobile services, and applications in complex scenarios like smart cities and industry 4.0 has created new challenges for Cloud Computation (CC) [110], [111]. A typical CC performs storage and computation of data in a centralized system. EC, however, performs data processing at the extreme (edges) rather than centralized or distributed nodes (core). The term EC can be defined as computation performed at the ends of the network. EC can meet the requirements of battery life, latency, response time, data protection, and privacy [112], [113]. With the various network operations that EC can perform, the edge must be designed efficiently to ensure reliability, privacy, and security. EC can provide significant support not only in industries but also in other areas such as smart homes [114], smart cities [115], smart logistics, and environment monitoring. In healthcare domain, EC can improve the efficiency by reducing data circulation and providing faster data processing [116]. Sensors and wearable devices are a way to actively monitor patients, at home or in care homes, who are suffering diseases or have a high risk of heart attack [117].

More efficient methods are required to process data at the edge of the network due to a large amount of data being produced. Previous methods of cloudlet [118], data center [119], and fog computing [120] can reduce the load of computing on the cloud but data processing at the cloud is not efficient when data can be produced at the edge of the network. The authors of [112] stated some of the reasons for utilizing edge computing. The authors mention that more services are diverted from cloud to edge of the network because data processing at the edge can guarantee shorter response time

and better reliability. Edge computing will save bandwidth if a large amount of data is processed at the edge rather than at the cloud. The burgeoning growth of IoT and mobile devices has changed the purpose of edge devices from data consumer to data producer. Fig. 6. represents the infrastructure of edge, fog, and cloud.

IoT has an important role in EC [110]. The authors of [121] provide details on Mobile Edge Computing (MEC), communication technologies, and comparison with Mobile Cloud Computation (MCC). Communication is necessary to provide interconnectivity between edge devices and transfer data from the edge to the cloud if extensive computation is required. The IoT technologies, discussed in Section III, can be implemented based on the application requirement. At the present, several research directions are aimed at establishing standards for the development of architectures, concepts, or processes implemented in EC solutions. Various independent organizations and entities have proposed different specifications, i.e., security, communication protocols, data protection, and reference architectures specifically for industrial environments. The authors of [122] presented a tiered architecture with a modular approach that helps to manage the complex solution for industries as well as smart cities, healthcare, and smart energy. The major contribution of the architecture exists in security and privacy provided by blockchain technologies.

AI and ML algorithms in combination with EC will play an important role in the advancements of many applications i.e., healthcare and industries. Edge Machine Learning (Edge ML) is a new concept in which smart devices can process locally with the help of a machine and deep learning algorithms. Edge devices can still send data to the cloud, but the ability to process the data locally provides screening of the data before sending it to the cloud while also allowing for real-time data processing and response. In-memory computing and ML processors are inventions for the embedded chips to be utilized in the future. In-memory chips provide high performance by storing data in RAM and performing parallel processing. ML processors are utilized for edge learning tasks. Floating-point Operations Per Seconds (FLOPS) is considered for measuring computing performance. It is the number of floating-point calculations a computing resource could perform per second, the higher the FLOPS, the better computing performance.

Authors of [123] have provided a comparison of multiple ML processors such as Field Programmable Gate Array (FPGA), Graphical Processing Unit (GPU), Microcontroller Unit (MCU), and microcomputer, etc. A detailed literature review of EC in Smart Grid (SG) has also been provided. Merging deep learning and EC is predicted to bring new possibilities to both interdisciplinary research and industrial applications. Deep learning can provide greater data processing capability and innovation in novel applications such as autonomous driving and video surveillance [124] etc. EC alone and in combination with various technologies is quite effective in industries as well. Merging blockchain and

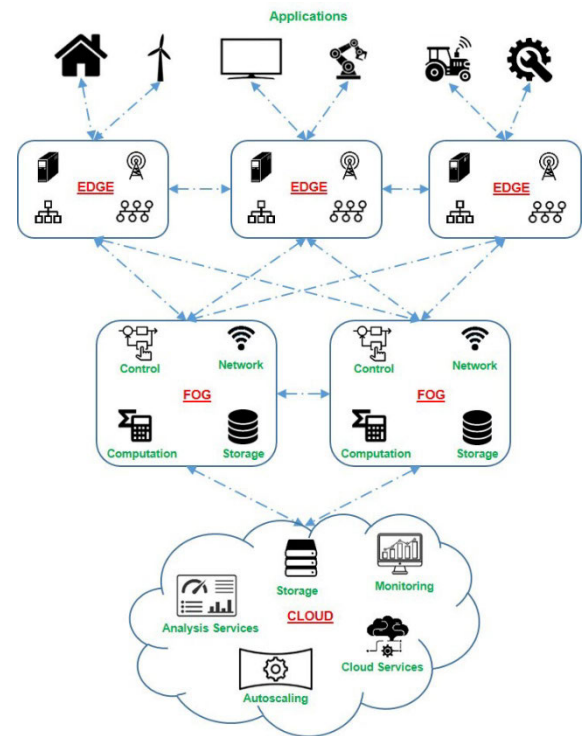


FIGURE 6. Edge-fog cloud infrastructure.

EC paradigms can be effective in overcoming security and scalability issues. In [125], authors implemented blockchain and EC paradigms in IIoT/IoT critical infrastructure to overcome security and scalability issues. They also provided a survey and discussed open research areas for security and scalability. The authors of [126] had given a very informative insight into the industrial internet revolution, where industrial edge computing is implemented to facilitate fast connectivity, data optimization, and real-time control. This also has the benefits of empowering smart applications, ensuring better security and protecting user privacy. Edge Computing Nodes (ECNs) are utilized by industrial edge computing. It allows for bridging the gap between the physical and digital worlds by substituting as smart gateways for assets, systems, and services. IEEE P2805 standards, are also discussed, which aim to solve problems of self-management, data acquisition, and ML through cloud-edge collaboration on ECNs.

The relationship between EC and industry 4.0 is considered in the form of on-site data centers. We can summarize the relationship by the benefits EC provides in industry 4.0 e.g., faster data processing, quicker decision making, increase productivity at all levels of management, and reliable big data infrastructure to name a few. EC can itself be a pillar in industry or a replacement for cloud computing in Industry 4.0 if the two function in tandem with each other.

VI. DIGITAL TWIN

Digital Twin, which incorporates Big Data, AI, Machine Learning (ML), and IoT, is a key technology in Industry 4.0.

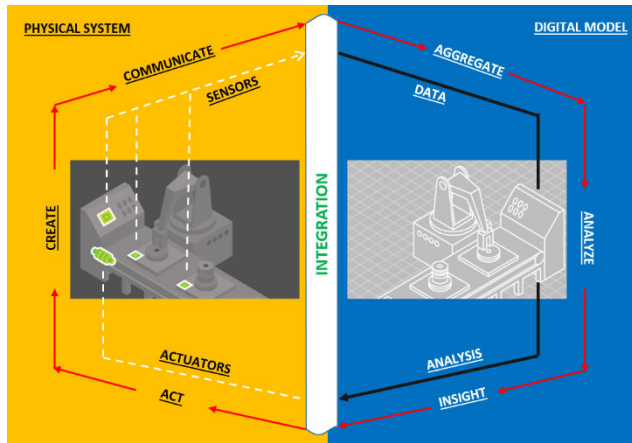


FIGURE 7. DT model of manufacturing application.

Authors of [127] and [128] have reviewed different definitions of DT. At present, Grieves and NASA gave the two definitions that are globally accepted. NASA define DT for a space vehicle as: “A Digital Twin is an integrated multi-physics, multiscale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin” [129]. Multiple companies utilize the concept of DT. A company like Chevron saves millions of dollars in maintenance costs by implementing DT for its oil refineries and fields [130]. Siemens utilizes the concept of DT to minimize failures, reduce time to market and create new business directions [131]–[133]. Fig. 7. represents the relationship between physical and digital twins in manufacturing applications.

DT was looked to as the next generation of simulation tool [134] but Tao and Zhang, worked towards creating a way to achieve a point of convergence of digital and physical systems [135]. The DT is a way to provide a better human-machine connection. It is bi-directional communication between the digital model and the physical world. The simulation model utilizes real-time sensor data of the selected parameters to replicate the performance and working of the system under consideration [136]. Any digital representation of physical systems helps in predictive analysis, monitoring health, business models, avoiding downtime/delays, and improving product design with lower cost. In [137], the importance and challenges of DT in personal healthcare are discussed. Bagaria *et al.* [138] summarized the technologies and application requirements to implement DT for personal healthcare. The author of [139] mentioned that DT provides a novel direction to represent a physical system in the digital model concerning its position, shape, status, gesture, and motion. By utilizing real-time sensor data along with AI, machine learning, and big data analytics, DT can be used for diagnostics, monitoring, prognostics, and optimization [140], [141]. This way, DT can make a wide range of operations in decision-making possible. Once the DT

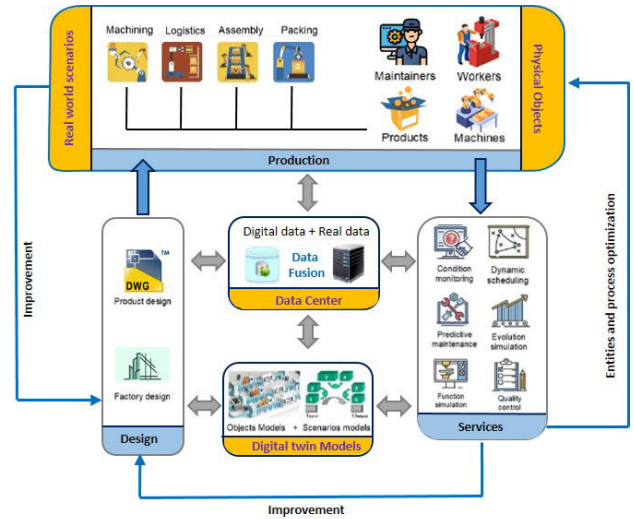


FIGURE 8. Configuration and application of digital twin.

model of the facilities, environment, and people is prepared, it can be used to train users, operators, maintenance workers, and service providers. DT is a fruitful method to improve industries or companies productivity, and efficiency [142].

The applications of DT, according to the product lifecycle, can be linked to the design, production, and use phases as shown in Fig. 8. DT, at the product design stage, enables designers to visualize, digitize, and materialize the elusive concepts of systems (ship, aircraft, and factory) that have multiple components and implicit coupling [143], [144]. The quality of the designs can be compared, evaluated, and validated with DT rather than building expensive physical prototypes [144].

The digital representation of the production and the usage scenarios can help explore all the possibilities and variations of the manufacturability and functionality of the entities to create an optimal design. This way the department of design and production can work together to identify the faults, quality defects, and provide better solutions [145]. Authors of [143] and [146] demonstrated that DT could simulate the whole factory design process ranging from the layout and, material handling to equipment configuration. Zhang *et al.* [147] worked on a simulation-based method for plant design and production planning. This approach can be implemented to create DT models of the plant. At the production stage, a DT can help optimize production management through the simulation, verification, and confirmation of the process planning and production scheduling. DT can help with optimal placement of workers, equipment, on-site resources, and work-in-process [148]. In terms of control and execution, DT keeps track of all the activities occurring in the physical world to forecast, and enhance the control approach [149], [150], and align the process with planning [151]. A DT model of a construction site can help detect and predict potential issues before they occur in the real world. The DT can also help to optimize planning,

processing, and resource allocation. [135], [152]. Further, the authors of [153] proposed architecture for utilizing cloud-based ubiquitous robotic systems for smart manufacturing of the customized product. They also provided implementation procedures for the creation of cloud-based ubiquitous robotic systems. Wang *et al.* utilized Holon, which consists of a logical part and a physical part, to mimic the cyber and physical entities of CPS [154].

In the end, at the service stage, the physical systems behave differently in various usage scenarios for different purposes, DT is utilized to simulate the usage scenarios. In these circumstances, DT can provide new methods of diagnosis and prognosis of damage location [155], remaining life [156], and wear [157], reducing costs and downtime [158]. Iterative experimentation can be carried out with the help of the DT model to generate the best maintenance solution [136]. For example, the performance of aircraft engines in terms of pressure tolerance [140] and wear coefficient, DT driven Prognostics and Health Management (PHM) for wind turbines [159]. With the help of simulation tools and virtual reality tools, DT can allow operators to understand complex physical systems and processes. The creation of DT is a long-term process to orientate, operate and optimize and for the multiple software tools can be used in synchronization. Some of the research issues in the simulation community are (1) the need for big data analytics along with better sensor technology for data collection, data processing, and data analytics, (2) real-time synchronization between the physical system and the digital model to reflect the current status, (3) suitable methods for model generations, verification, validation, and uncertainty quantification.

The author of [50] provided practitioners and researchers with a detailed overview of key technologies and tools for the implementation of DT. The extensive details provided in this paper are very beneficial for all the researchers who are looking to understand different tools and platforms for modeling, connectivity, data management, diagnosis, optimization, cognizing and control of the physical world. Tools for DT services applications, modeling, and connectivity are represented in Table 3 to Table 5. A single tool can be utilized for multiple tasks based on its capabilities, functionality, and performance.

In Table 3, different tools for various DT service applications, such as optimization service tools, platform service tools, simulation tools, and diagnostics and prognosis service tools are shown. The diagnostic and prognosis service tools are very useful for predictive maintenance tactics for the system and reduce system downtime. This is achieved through analyzing the historic and real-time data of the twin. ANSYS simulation platform allows customers to design their systems to analyze their performance. This provides them with the opportunity for design changes and troubleshooting. MATLAB can be used to implement data-driven techniques (such as deep learning, neural networks, machine learning, and system identification) for predictive analysis, comparisons, and determining remaining useful life to inform operators to

TABLE 3. Tools for digital twin services applications.

Tools	Platform	Diagnosis and Prognosis	Simulation	Optimization
Beacon	√	√		√
ProMaCE	√			√
Proudthink	√			
Gizwits	√			
Sysware	√			
HiaCloud	√			
Predix	√	√		√
ABB Ability	√			
EcoStruxure	√			√
PTC ThingWorx	√	√		
3DExperience	√	√		
MingSphere	√			
MATLAB		√	√	
ANSYS		√	√	
Simplorer		√		
Suersence		√		
ANSYS Twin Builder		√		
Azure IoT		√		
Proteus			√	
Simulink			√	√
Labview			√	
COMSOL			√	
Fluent			√	
FEPG			√	
Mworks			√	
3DMAX			√	
MSC. Nastran			√	
SimulationX			√	
Abaqus			√	
Algor			√	
ADAMS			√	
Flexsim				√
EnergyPlus				√
Plant Simulation				√
PKPM- CHEC				√
IBM Bluemix				√
Tmsys				√

replace or service equipment. Similar tools for diagnostic and prognosis are presented in Table 3.

Optimization service tools provide extensive what-if simulations to evaluate the performance and need for adjustments

to the current system set-points. This allows the operators to optimize the system or control it during operations to lessen the risk, reduce energy consumption and cost, and increase system efficiency. Siemens provides Plant Simulation software to optimize the factory layout and production line scheduling [147]. Simulink is an add-on product to MATLAB. Simulink is more interactive and graphical to the user as compared to the code-based approach of MATLAB. Similar tools of optimization service are presented in Table 3.

Simulation tools not only provide diagnostics, predictive analysis, and determine the best approach of maintenance, but also provide next-generation system design based on historic and sensor data. Designing a CNC machine tool can be taken as an example. Without accurate Finite Element Analysis (FEA) simulation analysis of the design, the CNC machine tool will fail in vibration. Extra material can be added to strengthen the machine to reduce vibrations. However, this will increase the cost due to over-designing of the tool. FEA in ANSYS software provides the best solutions taking into account the performance requirements and, cost limitations, and can fulfil the lean design requirements of the CNC machine tool [160]. Siemens NX software is a commanding and flexible tool that can enable companies to understand and implement DT to its fullest. NS software provides futuristic design, implementation, and solutions along with handling all aspects of the system from design engineering to manufacturing. Similar simulation tools are presented in Table 3.

Service platform tools provide the ability to integrate technologies such as IoT, big data, and AI. The PTC ThingWorx platform allows the operator to connect the DT model with the system in operation, to represent and analyze sensor data. PTC ThingWorx platform allows multiple actions of data acquisition, industrial protocol conversion, big data analysis, device management, and other services. PTC ThingWorx allowed HIROTEC, a premier automation manufacturing equipment, and part supplier, to recognize the connection between CNC machine operation data and ERP data. Other service platform tools are presented in Table 3.

Digital models replicate the physical systems based on their physical geometries, behavior, properties, and rules. The tools for DT modeling include geometry modeling, physical modeling, behavior modeling, and rule modeling. These are presented in Table 4.

The geometric modeling tools provide details of the shape, size, position, and assembly association of systems. Based on this, geometric modeling tools perform structural analysis and production planning. An example of such a tool is 3D Max. It allows animation, 3D modeling, visualization, and rendering. It is used to describe a detailed environment and is widely used in games, multimedia production and architectural design. More examples of such tools are presented in Table 4.

Rule modeling improves the service performance by modeling the rules, logic, and laws of physical behavior. HPE EL20 edge computing system, with ML ability by PTC's

TABLE 4. Tools for Digital Twin Modeling.

Modeling Tools	Geometric	Physical	Rule	Behavioral
AutoCAD	√			
UG	√			
3D Max	√			√
CATIA	√			
SolidWorks	√			
Maya	√			
MeshLab	√			
ANSYS Twin Builder	√	√		√
inkerCAD	√			
FreeCAD	√			
ANSYS		√		√
Abaqus		√		
FEPG		√		
Simulink		√		
Stella		√		
Tecnomatix				√
Mworks				√
SimulationX				√
SimuWorks				√
ADAMS				√
MATLAB			√	
MindSphere			√	
Spyder			√	
Tensorflow			√	
Hyperdesign			√	

ThingWorx, can monitor the normal state of a pump when it is running. With the help of learning rules, DT can detect abnormal operations, predict future trends, and detect abnormal patterns. Similar tools are presented in Table 4.

The behavior modeling tools are utilized to develop a model which responds to external drivers and disturbance factors, to improve its simulation service performance. An example of the motion control system of CNC machine tool design is the soft PLC platform CoDeSys. The motion control system utilizes socket communication to transfer information with the multi-domain model of the 3-axis CNC machine tool developed in MWorks. In this manner, the motion control of the 1-axis and 3-axis interpolation of the CNC machine tool can be realized. The multi-domain model can respond to the external drive. More examples of such tools are presented in Table 4.

The physical modeling tools are used to build a physical model to analyze the physical states of physical entities. The physical model is developed by endowing the physical characteristics of the physical entities into geometric models. An example of such a tool is the FEA software by ANSYS. It utilizes the sensor data to represent the real-time boundary conditions for the integrated wear coefficient and geometric models or performance degradation in the digital

TABLE 5. Tools for Connections in Digital Twin.

Tool	Connection between physical and digital spaces	Connection between digital space of digital twin
HADA	√	√
Predix	√	√
Lumada	√	√
ABB Ability	√	√
Foxconn's Beacon	√	√
IBM Bluemix	√	√
PTC's ThingWorx	√	
Jasper Control Center	√	√
Siemen's MindSphere	√	√

model [161]. Also, Simulink has been used as physics-based modeling. Simulink contains a range of models of electrical components and mechanical. Similar tools are mentioned in Table 4.

The concept of DT is to connect the physical and digital world and break the shackles between physical and virtual realities. Table 5 presents various tools for connection between the physical and digital worlds as well as with digital models.

A wide variety of tools is required for connectivity between the physical and virtual worlds, as well as to connect different parts within a DT model. The connection within the DT model is the interaction, communication, and exchange of information between the system, service, data center, and digital model. PTC ThingWorx can act as a gateway between sensors and their respect digital model part to connect multiple smart devices to the IoT network. MindSphere is an example of a cloud-based tool from Siemens. It allows connection between products, plants, systems, and machines. MindSphere has the capability of advanced data analytics to allow the wealth of data use. Another example is of Jasper Control Center from Cisco Jasper, which can manage connected devices much better using NB-IoT technology. Jasper control center can continuously monitor the network conditions, IoT service status, and device behavior to ensure high service reliability through real-time diagnostics and proactive monitoring of the connection. Azure IoT Hub by Microsoft allowed Rolls Royce to create a DT of the engine and perform data analysis based on machine learning to detect multiple anomalies of the engine and prescribe timely solutions [162]. The connection is necessary for transfer of information to help develop problem diagnostics and troubleshooting, thereby, optimizing the performance of physical entities. It can also assist in developing optimized maintenance strategies based on every system's unique characteristics. Numerous tools are utilized in various ways in DT applications, e.g., PTC's ThingWorx can be utilized for platform services as

well as diagnosis and prognosis services but cannot be used for simulation and optimization. Tools, such as PTC's ThingWorx, Foxconn's Beacon, ANSYS, Siemens' MindSphere, and Dassault's 3D Experience, etc. are presented in Table 6. The addition of a single tool, MATLAB/Simulink, is made in Table 6 based on the information provided by authors of [50].

VII. APPLICATION AREAS

This section discusses the applications of multiple industry 4.0 technologies such as IoT, CPS, Big data, AI-ML, and robotics. They are grouped into two domains: smart manufacturing and healthcare.

A. DT IN SMART MANUFACTURING

CPS acquires data from the environment, processes it, and makes an accurate decision. These systems are referred to as 'smart machines'. The physical and cyber layers combine to form CPS. These CPS are characterized by availability, performance, and reliability. They have a remarkable impact not only on industrial systems but also in our day to day lives.

Smart factories, which are centered on Cyber-Physical Production Systems (CPPSs), rely on these smart machines. At present, these smart machines are not far from the final solution to modern factories conditioned such that they can perform bidirectional communication, data management, storage, and analysis along with fault tolerance [163]. Numerous technologies are already present in factories to remove problems and provide a fully automated self-sufficient production line. The concepts of CPS and DT provide a new direction for smart manufacturing and healthcare by creating a closed loop between the physical world and digital model based on data acquisition, real-time data analysis, decision-making, and accurate execution. However, the DT model provides an effective and intuitive way of improvement in engineering. With the real-time data integration, DT model's ability to provide solutions can be improved. Fig. 9. depicts how digital models can be utilized to enhance the composition and functionality of CPS by providing capabilities of CC, predictive analysis, decision making, and big data analytics. The DT technology can be fundamental toward building CPS. With the combination of CPS and DT, manufacturers can achieve better efficiency, management, and precision. The concept of DT in smart manufacturing is very promising but some of the open research problems are [87]:

- 1- Incomplete knowledge of challenges and research questions regarding DT modeling, simulation, data management, and interconnection.
- 2- Limited reference models for DT.
- 3- Lack of adequate understanding of the architectures of implementing DT-driven smart manufacturing.

From a technical point of view, there are three components that must work together for the construction of DT. Visual representation of a DT reference model is given in Fig. 10. The components are as follows:

TABLE 6. Comparison of tools and their roles in various aspects of DT (✓ denotes it can be used in this part): adopted from [50].

Comprehensive Tools		Predix	PTC's ThingWorx	Siemen's MindSphere	ANSYS	Dassault' 3D Experience	Foxconn's Beacon	MATLAB/Simulink
Various Parts								
DT Evolution	Knowing the physical World				✓	✓		✓
	Changing the physical world	✓		✓				
Modeling	Geometrical					✓		✓
	Physical				✓	✓		✓
	Behavioral				✓			
	Rule		✓					✓
DT Data Management	Data collection	✓	✓	✓			✓	
	Data transmission		✓	✓				
	Data storage		✓			✓	✓	
	Data processing	✓				✓	✓	✓
	Data fusion	✓				✓	✓	✓
	Data visualization					✓	✓	
Services	Simulation services	✓		✓	✓	✓	✓	✓
	Optimization services	✓		✓			✓	✓
	Diagnosis and prognosis services	✓	✓	✓	✓		✓	✓
	Platform services	✓	✓	✓		✓	✓	
Connection	Connection in digital world	✓		✓		✓		
	Connection between digital and physical world	✓	✓	✓		✓	✓	✓

- 1- An information model to extract the physical characteristics of a system.
- 2- A communication mechanism to transfer data bidirectionally between digital and physical systems.
- 3- A data processing algorithm or module to extract information from multi-source diverse data sets to create a real-time digital representation of the physical system.

Information models are necessary to extract meaning from the large amount of data a system has received. The presence of data synchronization mechanisms is necessary between a digital model and a physical system. Otherwise, the connection between them will not be established. The Digital model will be a one-off snapshot of the physical counterpart. Standardization is key to reducing the heterogeneity of the data stream being sent to the DT information model. Fig. 11. enlists multiple standards that give details on information

models for describing physical objects in the manufacturing domain. International Standard Organization (ISO) is playing an active role in the development of a dedicated standard for DT manufacturing [164]. According to [87], information models for product DT and information models for production DT are two subtypes of information models.

For the information models for product DT, ISO 14649 [165] and ISO 10303 [166] are two outstanding standards. ISO 10303 provides a neutral data structure for exchanging product data between CAD systems. The AP242 [167] was created by combining AP203 and AP204 for Managed Model-Based 3D Engineering. With these information models, PMI information and geometric tolerance can be inserted into the system directly from product design files in the STEP AP242 model without the requirement of interpreting 3D drawings. These changes provide the communication necessary at various stages of product lifecycle

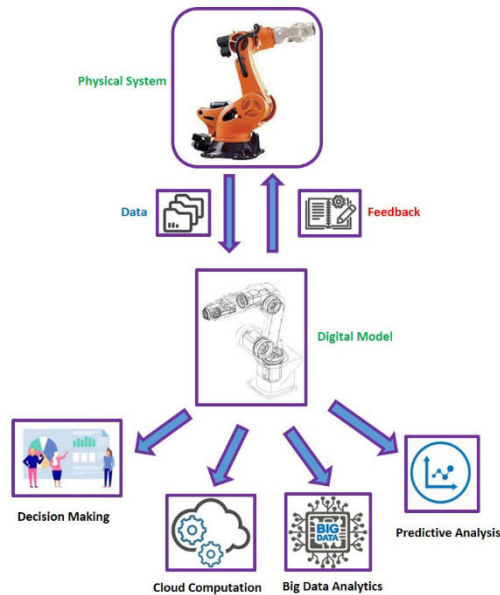


FIGURE 9. DT model of CPS.

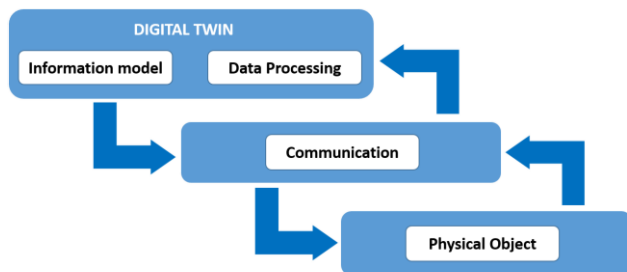


FIGURE 10. DT reference model.

along with autonomous process planning, manufacturing, inspection, and so forth. In the future, ISO 14649 [168] and ISO 10303-238 [169] (also known as STEP-NC) are planned to replace the ISO 6983 (RS274D) M and G code with an up-to-date associated language that can connect directly the CAD design data.

For the information models for production DT, ISO 13399 [170] is utilized for computer-interpretable representation and exchange of industrial product data regarding tool holders and cutting tools. It provides an explanation of product data regarding cutting tools. The model has been used for CAM/CAD/CNC integration, product data management, tool management, and manufacturing resource planning. ISO 14649-201 [171] is a similar model utilized for specifying machine tool data required for cutting processes. MTConnect standard offers a semantic vocabulary for manufacturing hardware to provide contextualized, structured data with no proprietary format. OPC-UA provides communication within machines, from machines to systems, and between machines in the industry. The combination of MTConnect and OPC-UA helps ensure consistency and interoperability between MTConnect specifications and the OPC-UA specifications.

A single information model cannot meet the heterogeneous requirements and wide range of DT applications. Previous studies suggest that a systematic information model development process guarantees maximum standard usability and conformance [172]. A bottom-up approach is suggested by OPC-UA and MTConnect community to allow the information models to be implemented in various new applications.

The authors of [173] introduced a tri-model-based approach (i.e. digital representation, computational model, and graph-based model) for the development of product-level DT. The three models work alongside each other to simulate the characteristics and behavior of the physical system (i.e., ANET A8 3D printer). The digital representation of the 3D printer was made on Neo 4 J. Raspberry Pi 3B was utilized for data extraction and consolidation module.

DT was utilized for dynamic scheduling in the job-shop, where the application of milling machine is making hydraulic valves [106]. Dynamic scheduling is day-to-day decision-making. The incorporation of DT allows the physical and digital world data to perform more predictive analysis toward machine availability and to detect any abnormality for timely rescheduling.

In [174], implementation of DT in Computer Numerical Control Machine Tool (CNCMT) is theoretically very fruitful but there are numerous difficulties in its implementation. The example of a rolling guide rail was taken to validate the effectiveness and operability of the proposed consistency retention method by the authors for the CNCMT DT model. The rolling guide rail is a part of CNCMT and hence the future direction is the DT model of all components and parameters. The authors utilized a 5 axis laser drilling machine as a case study for the DT model [175]. Linear actuators and direct drive rotary improve the performance of multi-axis machine tools but without the mechanical gearing, it increases the nonlinear dynamic coupling between axes. Making it difficult for digital models to identify accurately. A new approach of estimating nonlinear multivariable dynamic models non-intrusively using in-process CNC information was proposed. Features like actuator force/torque ripples, nonlinear friction, multi-rigid body motion, and vibration etc. were recorded.

High Precision Products (HPPs), with multidisciplinary coupling, are utilized in the application of marine, aerospace, and chemical. HPPs have compact and complex internal structures and the assembly process is dependent on manual experience. It can lead to poor consistency and low efficiency. A DT-driven assembly approach for HPPs is proposed in this paper by the authors [176]. A comparison between traditional and DT-driven assembly is also presented.

The authors in [177] created a DT model of a small-scale knuckle boom crane for condition monitoring. Nonlinear Finite Element (FE) analysis was performed with input as payload weight. Characteristics such as strains, stresses, and the load were determined in real-time. Condition monitoring increases safety and reliability. The authors state that this approach can be applied to various robotic manipulators used in the industry.

Faults in CNCMT may lead to less precision and affect production. Reliability is of paramount importance. Predictive maintenance is an effective way to avoid such failures. A hybrid DT-driven approach (i.e. DT model-based and DT data-driven) is studied by authors [178] on cutting tool life expectancy. Results indicated that the hybrid approach is more accurate and feasible than a single approach.

Authors of [179] studied centrifugal pumps in ventilation, heating, and air-cooling (HVAC) system. DT models were created for continuous anomaly detection of pumps. The digital model helped in automated and efficient asset monitoring in Operation & Management (O&M).

Augmented Reality (AR) is utilized to realize the DT model of an EMCO milling machine in [180]. AR gives the operator control and ability to monitor the machine tool, while providing access to DT data at the same time. It allows for a consistent and intuitive human-machine interface to improve the efficiency of the manufacturing process.

DT model of a 3-axis CNC engraving machine controlled via Arduino is created with real-time data of the position of the axis in [181]. A CAD model represents the digital model of the testbed.

A data-driven DT model, in the combination of hybrid model prediction method based on deep learning technique Deep Stacked GRU (DSGRU), is created for predictive maintenance of the manufacturing machines. Testing is performed on vibration data of milling machine tool to show the performance of the DT model toward tool wear prediction [182].

Predictive maintenance of automotive brake system with ThingWorx IoT platform allowed braking pressure to be measured at various speeds. CAD model implemented in CREO simulation was used for prediction of brake wear [183].

Qualification is an important process that every product must pass. 3D tool printing has important applications in healthcare, automotive, and aerospace industries. The utilization of DT, with machine learning and big data, can reduce the number of trials and errors in order to create the desired product [184].

The utilization of cloud-based platforms to create DT is performed in [185]. The authors utilized a single edge micro-cutting machine tool in a collective cloud-based PLM platform (3D Experience from Dassault Systems). The DT model helped in estimating and simulating the behavior of the system under various cutting conditions.

MQTT broker is utilized for connectivity through a broker-client architecture between the physical system (a bending beam test bench) and its DT model [186]. FEA simulations are conducted to analyze the performance of the bending beam. The results are represented numerically and graphically in CAD.

DT also has applications in helicopter industry. In [187], authors have worked to create DT of helicopter dynamic systems (i.e. swashplate rotor assembly). Manufacturers are interested in developing DT models to have the ability to predict the lifetime of mechanical parts. Data recorded during flights is utilized to simulate the loads the mechanical parts

undergo. The simulation models will help in developing the new model of bearing and its validation based on bench tests.

The authors of [188] simulated the cutting process of a CNC machine through the DT model. The simulation can help in reducing costs, decreasing material waste, reduce collision by tools, increase system life, and help simulate the cutting process to ensure accuracy and precision.

There are numerous situations where an operator will work in collaboration with a robot or is present in the space of a robot. In [189], the authors worked towards creating a DT model to support the design, build, and control of human-machine cooperation. A case study of an industrial assembly is considered for a human-robot collaborative.

Any digital environment is prone to cyber-attack, and it is an open research direction. The authors of [190] analyzed cyber-attack modes in a collaborative robotic CPS. Details of severity and categorization of cyber-attacks and safety of the human worker during human-robot collaboration are provided. A two-pronged security strategy is devised and tested on teleoperation benchmark (NeCS-Car).

Controlling a group of robots working together without any conflicts is necessary for smooth operation of factories but it is problematic. A DT model for a multi-robot monitoring system is simulated to avoid collisions and detect robot movements in the real environment [191]. A six-degree-of-freedom robot arm manipulator with OPC-UA providing connectivity is the case study. The design system can simulate a real-world scenario and help in monitoring industrial robots to enhance the production efficiency of the factories.

The complexity of any system, product, or manufacturing process increases the chances of human-generated error. An overhead assembly operation from a vehicle assembly plant is considered by [192]. The DT of the human operator is created in the Siemens Technomatix suite. The DT helps in analyzing human anthropomorphic models to discover the boundaries in performing the assembly tasks based on weight, height, and gender. The DT of mobile robot design to assist the human operator in the assembly process will help evaluate process time, human-robot collaboration, and joint ergonomic impact to reveal limitations of DT in human-robot collaboration.

B. HEALTHCARE

The rapid population growth has placed a massive strain on existing healthcare resources. New technologies are necessary to help in fast, accurate, and economical solutions to medical emergencies, diagnoses, and procedures. Smart healthcare educates people about their health conditions and enables them to manage some of their conditions by themselves. IoT plays its role in healthcare through Healthcare-Internet of Things (H-IoT). It is a complex system of medicine, microelectronics, health systems, AI, and more [193]. This allows for remote monitoring of patients in hospitals and homes with a focus on enhancing healthcare quality, preventing and managing emergencies and

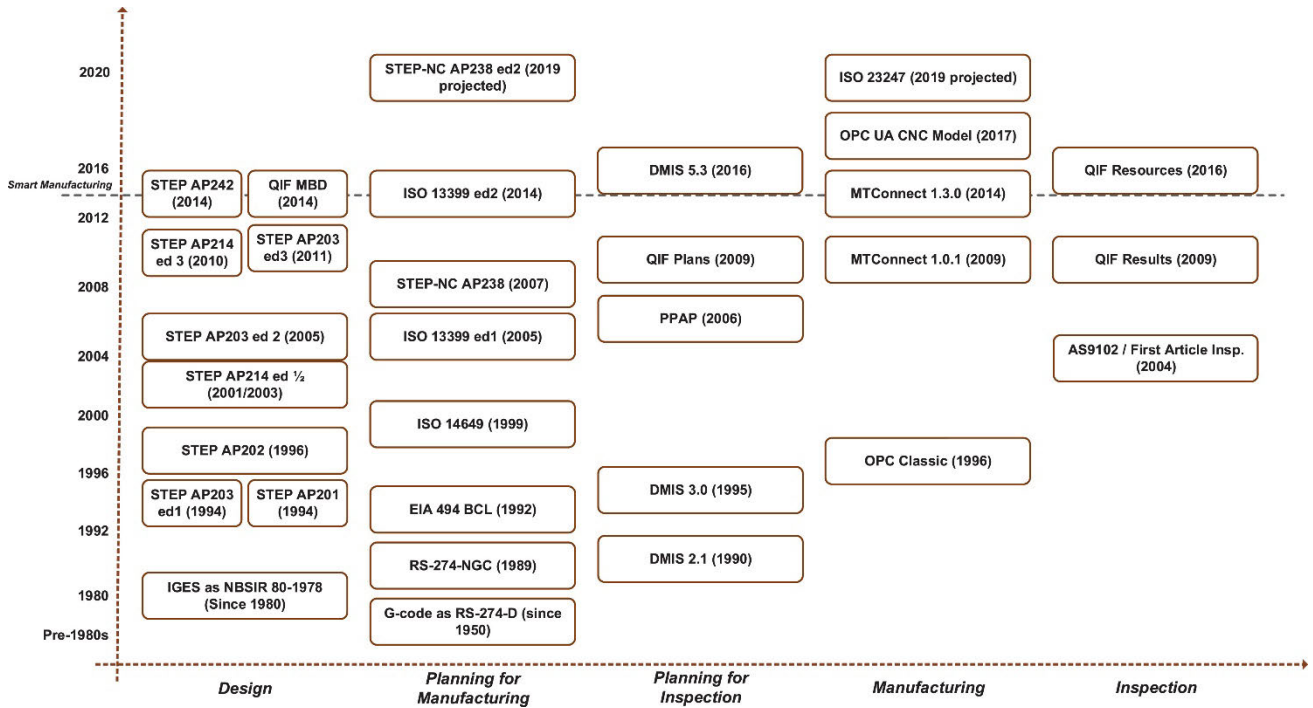


FIGURE 11. Timeline-based depiction of standards for Digital Twin in the manufacturing domain: copyright acquired from [87].

reducing healthcare costs [194], [195]. The vast implementation opportunities of DT in the area of healthcare and studies that will guide future research are emphasized in [196].

IoT also has a strong foothold in DT technology. DT in healthcare has numerous applications and open research problems. It can ideally replicate the human body, which employs a large data set and AI-powered models to replicate human physiology and provide possible answers to a range of clinical questions [197]. DT models can also be utilized to predict the outcome of various clinical procedures. Digital models will help young practitioners, doctors, and surgeons to work in a safe environment, conduct training procedures and perform testing on the digital human body. But many technical, privacy, and ethical issues need to be resolved before this can be practically happen. The implementation of ML and data mining algorithms will provide accurate outcomes of various medical procedures with real-time data and processing capability [198]. Another example of DT is optimizing hospital lifecycle. Edge, Fog, and Cloud computation are used in the creation of a network. Cloud-based IoT [199] can overcome problems caused by processing capabilities and storage limitations. A large amount of data is transmitted in this cloud based IoT paradigm. The transmission of a large amount of data can cause latency and requires high-bandwidth internet connection to name a few constraints. The application that operates in real-time cannot be utilized. Edge and fog computation are the solutions to the problem of latency. IoT networks developed in this aspect will have three parts of device, edge, and cloud. It will have several benefits but also give rise to various problems in design and devel-

opment [200]–[203]. A cloud-based DT system for geriatric healthcare was proposed by [204]. The authors introduced a reference framework of Cloud-DTH, which is the combination of cloud architecture and DT healthcare (DTH). The aim was to provide computational and management capabilities in healthcare systems. The author worked on two case studies, but they lacked performance and results in the evaluation. It is not clear in the prediction process whether AI or ML algorithms were used. A successful DT healthcare system relies on efficient and accurate machine learning algorithms to manage multiple processes. The healthcare requirements can be divided into functional and non-functional. Functional needs are completely distinctive and work according to pre-defined responsibilities. There are open areas in nonfunctional needs, attributes that can define system quality, in the healthcare system i.e. lower power connectivity, quality of service, system reliability, interoperability, higher efficiency, and real-time operations [205]. The authors of [206] provide an extensive literature review of IoT and associated technologies in healthcare. The correct cyber resilience technology and policy are important to maintain and preserve a healthcare digital twin. Authors of [207] pointed toward vulnerability detection as an essential technology for cyber resilience in healthcare DT. Deep Learning (DL) is implemented to overcome the limitation of machine learning in vulnerability detection. They implemented a novel deep neural model to capture bi-directional context relationships among the risky code keywords. It showed improved results as compared to the latest DL-based methods for vulnerability detection. Another example is the implementation of Artificial Neural

Network (ANN) on patient data for decision making and monitoring health as discussed by [208].

GE healthcare has been using DT for hospital management optimization. They have focused on predictive analytics platforms and AI capabilities to transfer huge patient data into actionable intelligence. GE healthcare designed the “Capacity Command Center” that is implemented in Johns Hopkins Hospital in Baltimore for simulations and better decision-making capabilities. Mater Private Hospital (MPH) in Dublin is optimized by DT technology with help of Siemens Healthineers. One of the tasks performed by Siemens Healthineers and MPH was to implement DT in the radiology department with the help of AI computer model for the department and its operations. MPH was able to overcome the challenges of increasing clinical complexity, aging infrastructure, delays, increased patient demands, and the large bulk of data with the help of DT.

In [209], the authors supported the implementation of DT technologies in medicine i.e. in medical cyber-physical systems [210], [211]. Kocabas *et al.* [212] worked in the direction of medical cyber-physical systems having multiple layers of data acquisition, data analysis, cloud systems, and actuators. Combining Wireless Body Area Network (WBAN) with IoT networks and cloud computation has been considered as an open research area in healthcare applications [213]. Wearable devices and AI were implemented for human data acquisition and analysis to simulate human processes such as user behavioral motivation understanding, emotion recognition, and recognition of user intent [214]–[216]. Furthermore, it has helped to create interactive games to help artists utilize their creativity. Lastly, it can be used to carry out health monitoring and provide instructions to help users improve their health. Psychologists have started to utilize physical activity levels using actigraphs in order to predict the onset of various episodes of bipolar disorder [217]. The authors of [218] have put forward the idea of creating collaboration of computational simulations with tissue engineering for higher reliability, predictable and accurate clinical outcomes. A framework of DT in remote surgery is provided in [219]. The authors of [220] presented a context-aware healthcare system using the DT framework. A rhythms classifier model, of ECG, was built utilizing ML to detect heart problems and diagnose heart disease. Cardio twin architecture is utilized for Ischemic Heart Disease detection on the edge [221]. With the help of a convolutional neural network, non-myocardial and myocardial conditions can be classified. By utilizing the database of 200 different people called the “PTB diagnostic ECG database” from Physio Bank. The author’s implemented model had an accuracy of 85.77% with 4.8 seconds taken on classification of each sample. DT of the human airway system was created by researchers at Oklahoma State University’s Computational Biofluidics and Biomechanics Laboratory (CBBL) [222]–[225]. Healthcare 4.0 is one of the research directions that can benefit deeply from the implementation of DT technology.

VIII. FUTURE RESEARCH

Multiple research areas need considerable work with respect to DT implementation in various fields.

The latency requirements, between a physical system and its DT, depend on the application at hand. The cost and complexity of the system increase significantly as the latency requirements become strict. A wide range of communication technologies, 4G, 5G, 6G, Wi-Fi, and ZigBee, are available that can be utilized to provide minimum latency, higher data rates, and increased coverage range. To replicate the physical system into the DT model, the latency needs to be minimum to receive the data in real-time. IEEE 802.11ah, created in 2016, is labeled as Wi-Fi brand IoT technology by researchers and companies. It has the capability of higher data rates, considerable range, and can connect around 8000 devices compared to worldwide used 802.11n. Research needs to be carried out on a large range of DT applications to specify the best suitable communication technology for that specific application. A practical example is a DT model of shop floor monitoring that can manage higher latency compared to cloud-based industrial control. BMWi, Germany [226] specified the nominal latency requirements for various manufacturing applications, which can be used as a standard for designing the system architecture of a DT application. Not only the IoT requirements, but appropriate data capturing techniques are also important. If a robot arm manipulator is performing a milling process, wired sensors or wireless sensors can be utilized to record the changes occurring during the process. Similarly, we can utilize a High Definition (HD) camera to take snapshots for monitoring the process. A comparison is necessary for all three data capturing methodologies to validate the optimal approach for various DT applications.

Furthermore, big data analysis is necessary before utilizing the data for monitoring, diagnosis, and prediction. Data analysis and management is an open research issue. Instead of relying on cloud computation, integration of edge, fog, and cloud infrastructure is necessary to distribute the responsibility of data processing. The challenge related to enormous data acquisition, analysis, limited awareness of methodology and modeling is still unresolved [227]. In terms of healthcare, edge, fog, cloud, AI-ML algorithms, and big data analytics holds importance in processing data for monitoring, diagnosis, selection of best surgical method, comparison with hundreds of previous patients, and predictive analysis. In this field, problems like scalability, energy, co-design approach, data privacy, data storage, and services available to heterogeneous sources are open to research [228].

There are two architectures available for the creation of DT models i.e., server-based, and edge-based. In server-based, the centralized server receives the complete data to perform data analysis and creates a DT model. This method is much more economical and easier to maintain. In edge-based models, the data is routed back to the centralized server, but some data analysis is carried out at the ‘edge’ of the system. It is the

pre-processing performed not the raw data at the edge. It has its benefits, if designed correctly, but it is more complex to maintain.

Existing DT applications utilize the concept for monitoring and prediction. But future research can be to provide DT models for decision-making support for human operators. The ultimate purpose of the industrial revolution is to provide autonomy to the systems. For example, human presence is essential in smart manufacturing but autonomous feedback control with minimum latency between the DT model and the physical system can provide the support for decision-making. Humans still have a role to play in DT-driven environments. Some of the autonomous operations do not require human operators but decision-making still requires the human intellect. A DT model, which is a completely synchronized real-time replica of the physical system, along with strong AI algorithms, can assist in decision-making without the need for human intervention. It can be further investigated by incorporating new technology such as Augmented Reality (AR) to improve human-machine interactions. Future research can focus on the topic of DT for people in smart manufacturing, smart surgeries, healthcare, and robot-assisted tasks. To have the level of autonomy and human presence, a digital twin model should be flexible to the changes in the physical world. Limited or rigid DT models will waste time and money if the complete model is to be recreated from scratch every time there are changes in the physical system. Therefore, different DT models should be made, stored, and synchronized with the real system over time. Different data capturing methods can be utilized to acquire accurate data with multiple data management and simulation tools for a different version of the DT model. Although anyone can create a DT of the physical system; standards will provide the permanency of a DT solution. DT models that are standard-compatible can inherit interoperability, flexibility, and scalability of the existing and future standards for communication, data management, and implementation. It is important for an open network of Digital Twins. Not only in the manufacturing industry but also in the field of healthcare, robotics, and oil & gas. Another important future research direction can be toward cyber security. A physical system controlled by a DT may have catastrophic consequences if it succumbs to a cyber-attack. DT has the potential to strengthen the integrity of the physical system by providing improved observation, testing, and verification process. But a corrupted DT can be used to mislead operators. Cyber-attacks can create inaccuracies in DT. Any analysis or prediction, performed by a cyber-attack affected DT, is likely to be unreliable. Not only that, data modification and damage by cyber-attacks, in transmission or storage, must also be avoided. DT can create new failure points, for cyber-attacks to take control of the system, damage the system, mislead operators, or listen to data being communicated between the DT and the physical system. In healthcare, around 7.7 million patient data from LabCorp Clinical Laboratory was compromised by cyber-attack in July 2019 [229]. In May 2019, data of 11.9 million patients from Quest Diagnostics was affected

by cyber-attack [230]. Manufacturers of various industries have concerns regarding high cost and data security on the applications of DT [231]. Research needs to be carried out to ensure data protection.

IX. CONCLUSION

This paper presents an overview of the integration of numerous enabling technologies for the creation of DT along with core concepts, standards, reference models, and research work on DT in smart manufacturing and healthcare.

Research has been conducted throughout the world on DT but there is a gap towards the implementation of flexible and real-time synchronized DT models, IoT limitations, and control of the physical system through the digital model. Communication technologies like 5G, 6G, or IEEE 802.11ah, etc. allow for various DT applications to be tested. However, selecting and implementing an appropriate technology to fulfill the application IoT requirements and successfully provide bi-directional data/information transfer for the creation of DT models is a challenge.

Cost limitations, complexity of implementation, integration between DT models and within DT model are other challenges researchers are facing. The common data collection and processing methods do not fulfill the needs of DT. Sole reliance on CC will not fulfill the requirement of processing a large amount of data quickly and providing useful data for DT models. Edge-fog-cloud computation and AI-ML can provide the necessary support for pre-processing data, diagnosis, and prognosis on data along with reducing the load on communication channels for data transfer and lessening the burden on CC.

These considerations are not only to be implemented in the domain of industries, but healthcare, robotics, smart city, oil & gas, and education sectors too. The potential of DT must be explored in various applications. We have also shed light on some of the future challenges and open research avenues of Industry 4.0, especially DT.

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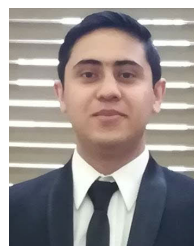
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