International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V73I2P112

Volume 73 Issue 2, 141-154, February 2025

Review Article

An Investigation and Design of Conceptual Framework of Digital Twin with Industry 4.0 Enabling Technologies

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Received: 20 August 2024 Revised: 13 January 2025 Accepted: 28 January 2025 Published: 21 February 2025

Abstract *- With the invention of Industry 4.0, a very revolutionary and smart manufacturing paradigm called Digital Twin (DT) was introduced. This system ensures deep penetration to the application of the massive data collected through the generation of information and digital technologies. Research and academia consider it a cutting-edge technology, as it has also successfully claimed its position in the industry. Due to the complex nature of handling and merging varied data types, the potential has been partially realized, and there is much more to be explored. It is essential for researchers and engineers to clearly identify the tools and technologies that suit the DT system. This review article provides a state-of-the-art review of key enabling technologies and the viability of DT with an industry approach. A generic framework consisting of tools, enabling technologies and their correlation with the digital twin is also explained. A generalized data flow and corresponding tools required for the DT system are explained. Finally, a brief discussion on challenges and future research outlook is provided.*

Keywords *- Digital Twin, Industry 4.0, Enabling technologies, DT framework, Interaction.*

1. Introduction

The continuous demand for rapid growth in every sector resulted in an industrial revolution known as Industry 4.0 in the current scenario. Industry 4.0 is exemplified by digital transformation and interconnectedness of products, machinery, and business models. Small and Medium Enterprises (SMEs), which form the support of Indian manufacturing, can influence Industry 4.0 technologies to become more responsive, augment production, optimize costs, remote handling, and lower risks, etc. Digital Twin technology is a developing notion that has gathered noteworthy attention from industry and, recently, from academia as well. Technology is a very common term, and it has been upgrading itself every day.

The development and upgradation in manufacturing started way back in the 18th century. Figure 1 depicts the journey of the Industrial Revolution and technology, which has updated itself to match ever-changing demand, increased flexibility, and customization with quality preferences by the end users. The first industrial revolution, called mechanization, happened in the late 18th century; this industrial machine was powered by water and steam. The laborious work by human beings was made easier by introducing mechanization and improved the value of life. The second revolution, known as Electrification, started in the late 19th century. In this revolution, mass production machines and assembly lines were powered by electricity. Better, simpler, and compact machines were introduced to cater to demand, which was the key feature of this revolution. The third revolution, called automation, started in the late 20th century; in this, the use of electronics and computers was made to enhance production in many ways. Extensive use of embedded technology to support automation and robotic technology was successfully implemented.

The fourth revolution, which started in the early 21st century and is said to be a Digitalization and Communication world, also refers to a seamless integration of industry with information technology. In this, extensive use of connected devices, sensors, cyber-physical systems, data analytics, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), and cloud computing is done. This advanced technology gathers real-time data for future analytics and decisioning. It facilitates a full set of industrial applications like adaptable automation, predictive maintenance, and supply chain management optimizations. These significant advantages have been realized by the manufacturing sector, which has resulted in the transformation and upgrade of existing technology to a globally competent standard. The paper presents Section 2, which describes the literature survey. Section 3 introduces the key enabling technologies of DT.

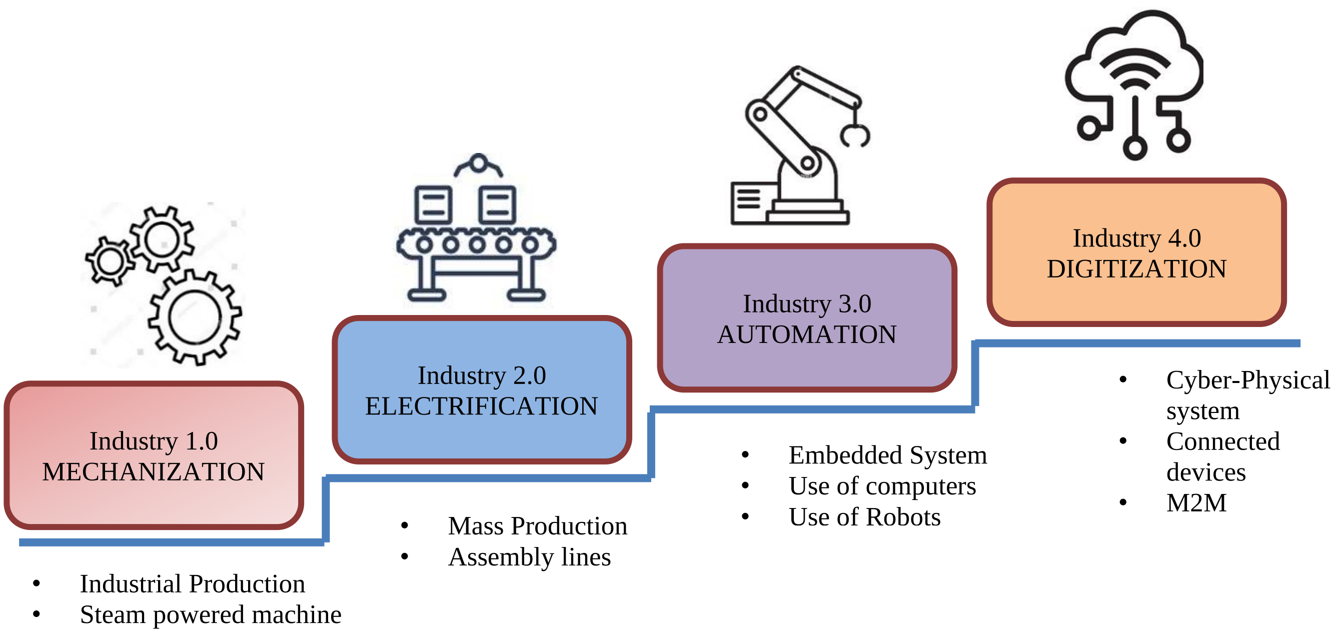

Fig. 1 Journey of the industrial revolution

Section 4 explains a generalized conceptual framework showing the interlinking of DT and enabling technology at various steps. Section 5 discusses the conclusion and future work.

2. Literature Survey

Digital Twin is an upcoming and promising technology in Industry 4.0 aiming at increased productivity and efficiency in manufacturing. A decent volume of literature surveys has been conducted in various industries and applications. A very important driver of smart manufacturing is Digital Twin technology. A digital twin is a digital imitation of a physical entity that provides necessary and meaningful output based on the true data. DT provides a mirror of the asset and environment for analyzing and making accurate decisions based on analytics [1, 2]. Many researchers and scientists have defined DT as their functionalities and applications. The National Aeronautics and Space Administration (NASA) defines Digital Twin (DT) as an integrated Multiphysics, multiscale, and probabilistic simulation of a system or vehicle in its actual built form. It uses the finest accessible real models, sensor data, and past information to duplicate the life cycle of its equivalent operational complement [3]. The authors in [4, 5] focus on expanding specific components of Digital Twin (DT) and their implementation, custom-made to encounter the necessities of the respective application field using various tools. Qinglin Qi et al. have proposed a 5-dimension digital twin model by adding two more dimensions, providing a greater understanding and ease of implementation of DT [6]. The dimensions include physical assets, virtual models, data, service, and connection. Weifei Hu et al. added one more dimension called Environmental coupling, which aids in delivering an accurate representation of virtual components compared to the current digital twin model [1]. A DT environment coupled with data analytics and some means to make decisions is a perfect combination for fault detection and predictive maintenance. Hence, a DT with Artificial intelligence makes the system smart and enables decision-making. This is the biggest benefit realized in manufacturing, as monitoring machines and assets saves time and money, thereby increasing productivity and profit margins. Authors in [7] thoroughly review the key components of DTs and industrial applications of DT and summarize the supporting technologies for DT demonstration, simulation, data synthesis, interaction, and collaboration.

The in-depth discussion of the appropriate definition, characterization, and implementation process of Digital Twin is carried out in [8]. The details of its components and the desired benefits should be driven by the detailed framework of DT. This, in turn, helps to set the needs for the essential data, prototypes, and procedures to update the prototypes based on the data.

Also, a variety of enabling technologies required for DT implementations are explored. Barbara Rita Barricelli et al. in [9] present the results of the prime characteristics a DT should acquire and the various domains of DT applications presently being established. Further, the design propositions focused on the DT lifecycle and its impact on social and technical aspects. A framework for safety management using IoT and digital twin-enabled tracking solutions is proposed in [10]. A case study that demonstrated the implementation of the physical and cyber world with appropriate technologies is discussed.

The work carried out by authors in [11] comprised presenting a joint concurrent exploration of "Digital Twin" and "Maintenance" terms to examine the association between them and deliver a deeper understanding of the interactions between both theories. The impacts of flexibility on the favorable predictive maintenance scheme are discussed in [12]. With digital twins, the important components required for flexible production structures and different interfaces are also presented in detail. Panagiotis Aivalioti et al. [13] primarily reviews and describes the use of digital twin concepts for manufacturing applications like condition monitoring and predictive maintenance. The gaps in the previous studies are recognized and examined. In a brief scheme of the approach, the previously prevailing technologies can go further than is described. A greater understanding of the constraints and assets, challenges and opportunities of the current Predictive Maintenance issues is proposed in [14].

The design summarizes some major research problems to be referred to for the successful expansion and deployment of IoT-enabled Prognostic Maintenance in manufacturing. The design of a digital twin and quality production check are discussed in [15]. The designed and tested digital twin architecture with digitalization of data supports a comprehensive digital prototype that can be used as a prototype for the actual manufacturing of SMEs. Authors in [16] review the sustainability of smart manufacturing using Digital Twin. The related matter of smart manufacturing, involving industrial apparatus, approaches, and facilities, is examined. An extensive literature survey on DT and subsequently on digital manufacturing, smart systems, enabling skills and challenges of Digital twin, and its implication on the manufacturing industry is carried out. Based on the gathered information and study, the research methodology is explained in the flow diagram shown in Figure 2.

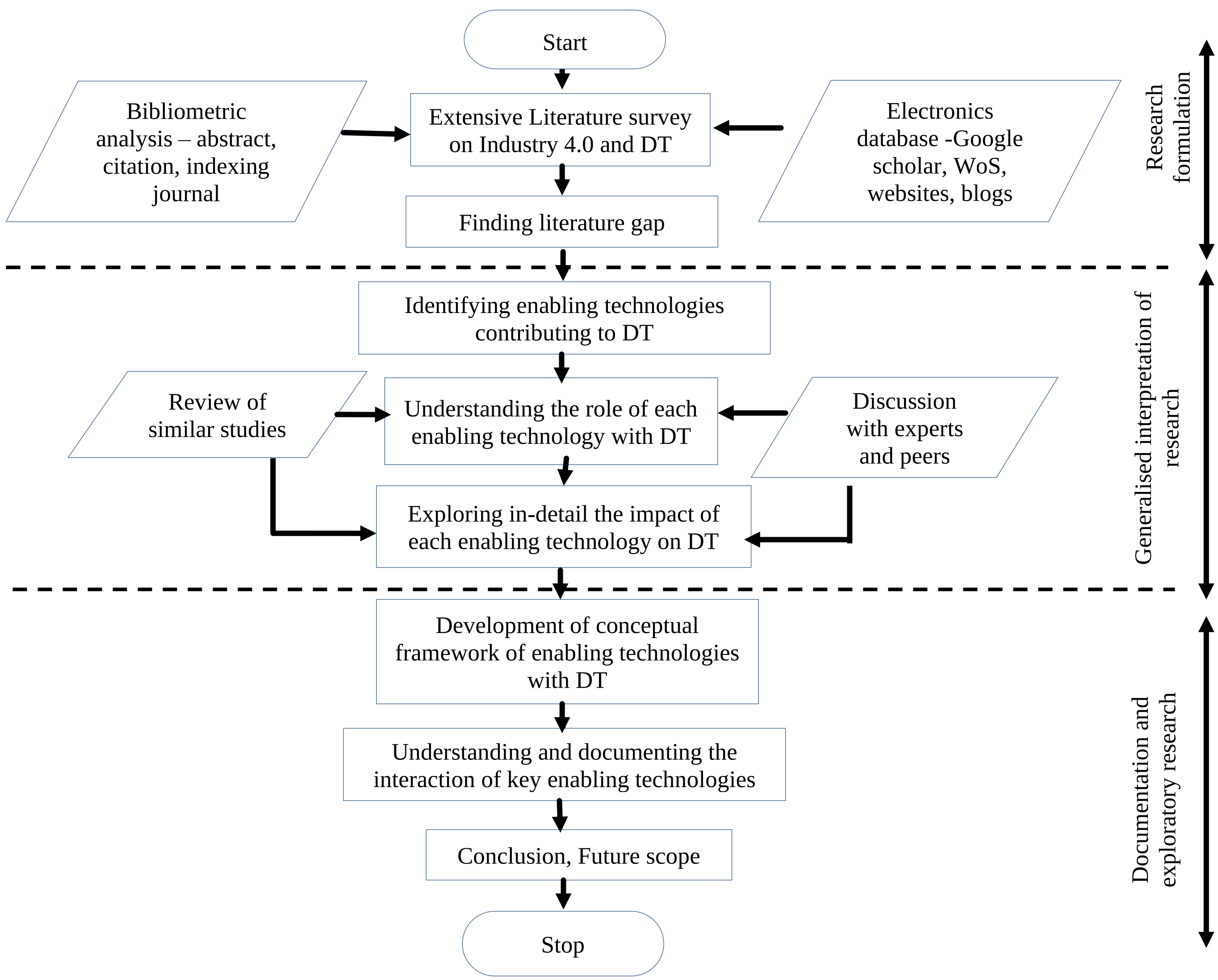

Fig. 2 Research methodology flow chart

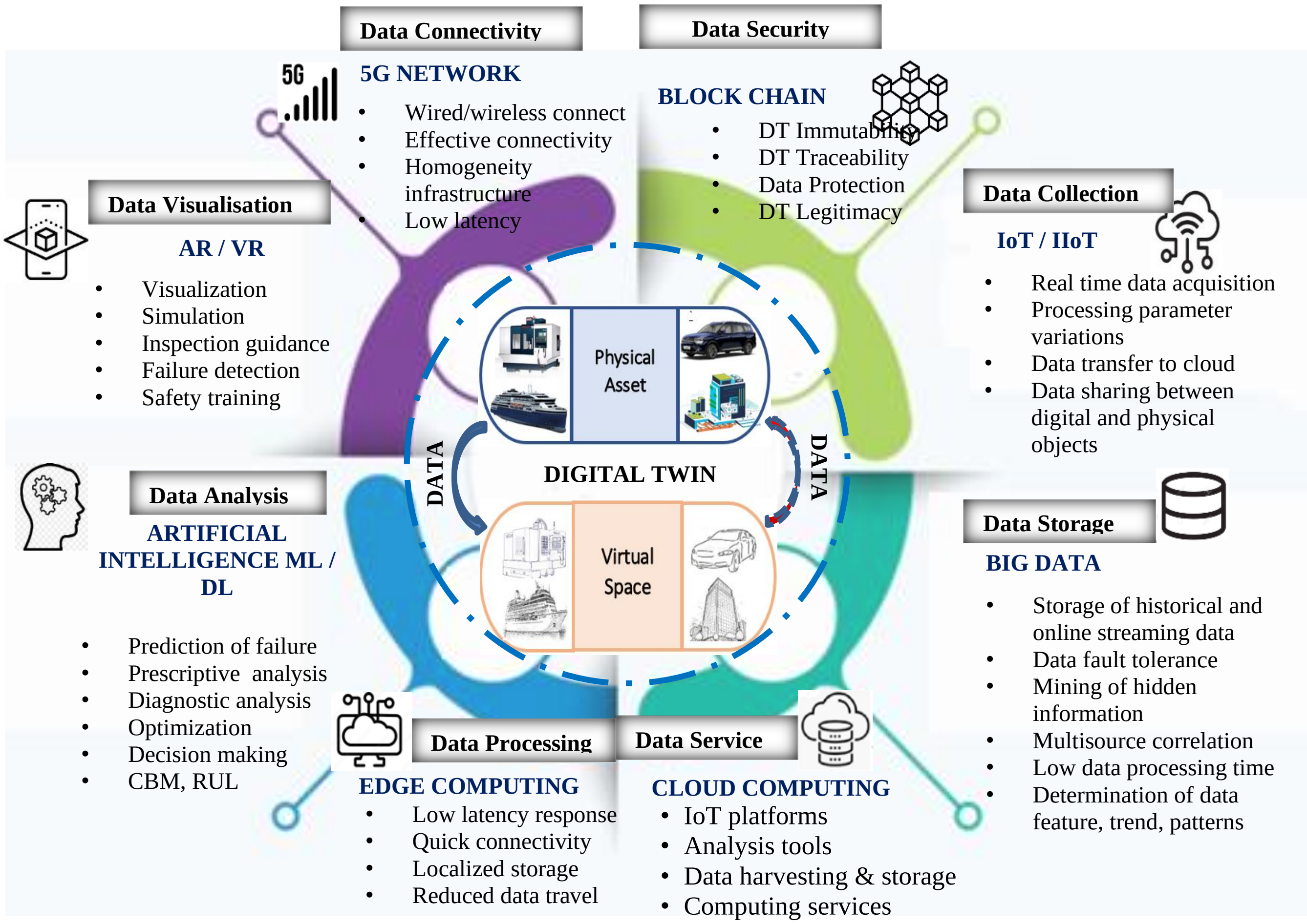

Fig. 3 Conceptual framework for digital twin

2.1. Introduction to Enabling Technologies for Digital Twin

With the invention of Industry 4.0, various enabling technologies gained importance when implemented in areas like construction, manufacturing, healthcare and many more. This section deals with introducing key enabling technologies and the proliferation in the functioning of the DT system. The Internet of Things (IoT) is described as the system of physical entities linked with sensors and devices to exchange data wired or wirelessly with other systems over the internet with the help of advanced communication technology. When used for industrial applications, the system is recognized as the Industrial Internet of Things (IIoT). Sensors are deployed to monitor the modifications in parameters and environment in real-time. [17, 18] Cloud Computing can make the business process simple, effective, efficient, economical, and more powerful. Cloud helps in both storage and processing of data. DT can be considered a computational service representing models for integrating products, processes, and various life cycle stages of real-world entities [19]. A popular enabling technology called Machine learning is a subset of Artificial Intelligence; it is the set of instruction procedures given to the computer. Based on algorithms, the computer learns the data's pattern, behavior, and characteristics. Machine learning uses sophisticated algorithms by which it can take up the data and analyze it autonomously [20, 21]. Deep learning is an autonomous learning by use of neural network method. It learns from unlabeled, unstructured data, as in the case of unsupervised learning. This learning takes comparatively longer time to train from the error it has committed as many layers of the neural network are involved. But, it offers much better accuracy and is commonly used [23]. Augmented Reality (AR) is an enhanced version of reality in which digitally generated information is superimposed on a physical world, thereby adding more value to the real environment. Thus, an amplified environment is available to the user, enabling an improved perception of reality [25]. Virtual Reality (VR) technology is a computer replication system for virtual space by creating three-dimensional artificial images with the help of interactive hardware and software. Mixed Reality (MR) technology is sometimes called hybrid reality [26, 27]. In MR, a new environment is obtained by fusing the real world and virtual space, giving a rich experience to the user. It is an upgrade of AR, wherein a new virtual world is formed with the same kind of physical conditions for simulated things. Blockchain collects the information in groups like a block. When multiple information blocks are connected to the parent or genesis block, the chain formed is called a Blockchain [28].

3. Conceptual Frameworks of Enabling Technologies with Digital Twin

With a clear understanding of the conceptual framework, specific goals of implementing enabling technologies in developing the DT system can be achieved. A common framework illustrated in Figure 3 indicates the impact of enabling technologies with DT. This framework clearly highlights the associativity of all the key technologies in assisting the design and functionality of the DT system and enhancing the industry 4.0 standards practically in every application area.

3.1. Interaction of Internet of Things with Digital Twin

Before Industrial Revolution 4.0, data acquisition from physical assets was a tedious task. Conventional devices were used to measure the physical properties of machines and structures, but there were several limitations. Inherent problems like low accuracy and sensitivity, high latency, low repeatability, size, portability, etc. IoT is a promising data generation and management method, irrespective of indoor or outdoor positioning, industrial safety, hazardous machines, and zones [29]. DT, combined with IoT concepts, have proven exceptionally well in extracting actual information from physical entities through sensors for safety, process, tracking, monitoring, scheduling, etc. [30].

Figure 4 shows IoT devices and their connectedness with the DT.Sensors generate data by simultaneously sensing minute changes or variations from different sources for further usage. This eliminates the manual process of feeding unrealistic and irrelevant data. The data generated is communicated wired or wirelessly to the edge device, router, proxy server, and finally, the cloud. IoT plays a fundamental role in the functioning of DT by gathering online data from different sources without any losses and transmitting it to the storage device. Data sharing between the physical object and the digital twin and vice versa enables the smooth functioning of DT. This IoT service supports the massive data and contributes to the analytics of the gathered information. On the other hand, the edge IoT gateways implemented at specific locations communicate the information to the virtual world for decision-making; hence, IoT-enabling technology is very important in the entire DT system [31].

3.2. Interaction of Big Data Analytics with Digital twin

Big data analytics is done on the cloud using its tools, models, and algorithms, as the cloud offers more effective storage and processing power [32, 33]. Most of the actual information gathered from sources like design, planning, manufacturing, inspection, maintenance, etc., is massive in size. Big data generation is because of the current scenario shift to rely on inspiration and experience based on real-time and analysis-based data [34, 36]. The large and complex dataset must be harvested and stored for further actions like configuration, monitoring, diagnostic and prognostic analysis. This collection, maintenance, and further processing of data is termed big data analytics. An analysis done on the cloud helps to identify the critical process, cause, and impact of the problem and subsequently helps find appropriate solutions [36]. From Figure 5, Big data and digital twins complement each other and contribute to the smart system [34]. An important function of Big data towards DT includes storage of historical as well as live stream of online data. The storage of actual data in sliced data nodes safeguards the loss of data in case of failure of the data node. This is termed fault tolerance, achieved by replicating data in various data nodes depending upon the replication factor.

Also, huge volumes of data can be handled in very little time as the input data is mapped at multiple points. Thus, when operating digital twins, data management becomes lean, more efficient, and more comparative. In brief, with the help of models and algorithms, big data analytics help in optimization, rapid and accurate planning, detection of the root cause of malfunctioning, increase in quality output and proactive decision making.

3.3. Interaction of Cloud Computing with Digital Twin

Information analytics is an incredibly important phase in the process of setting up a digital twin. As mentioned earlier, clouds can make the business process simple, effective, efficient, economical, and more powerful. The continuous stream of data generated from the electronic device is extremely unstructured and unorganized, with undesirable characteristics and quality. This data needs to be gathered on the cloud through some communication devices and protocols. Hence, the cloud helps store huge amounts of data produced by sensing methods. In brief, data analytics is the extraction of significant evidence from the huge data generated through the field devices, sensors, actuators, etc., of the DT system.

Cloud computing forms the service provider to DT by offering independent services for computing infrastructure over the internet whenever required. It offers high flexibility and scalability for simulation and excellent computing performance required for the functioning of DT. Working teams can collaborate to share common data and platforms from widespread locations over the internet. It provides high scalability, fidelity, and high synchronization, as well as execution to get information from real-world entities [37, 38]. Figure 6 shows the cloud interaction in the entire DT system.

The cloud helps to assist the generated information of the real-world assets like condition and parameter changes, thereby providing a seamless interface between real entities and virtual models. It also offers a common platform and computing services for teams to work on the data from various remote locations [37]. Some of the cloud platforms and their capabilities are mentioned. Platforms like Predix help in creating DT. It provides a very simple ecosystem to analyze and monitor the targeted factory assets with the help of actual data. This platform is safe and scalable and provides optimization of operations and condition assets. Thing-Worx is a very simple, powerful, and successful leading platform created by Parametric Technology Corporation (PTC) for various industrial uses. It is a fast and easy platform capable of deploying and extending industrial projects and applications. It provides excellent simplicity when connecting with electronic devices and can be operated remotely. It offers integration with machine learning for smart decision-making. Large-scale machine integration can be very well managed by IBM's developed platform called Watson.

It is simple and offers PaaS (Platform as a Service). It gives secure communication of real-time data exchange, also capable of handling bulk volumes of data. Cisco IoT Cloud Connect offers mobile connectivity. It has flexible and useful options in the deployment of various heterogeneous devices. Microsoft Azure provides profitability and productivity by offering multiple services through IoT solutions. It offers real-time streaming and data registry. It is flexible, secure, and has a scalable platform for analyzing and visualization.

3.4. Interaction of AI / ML with Digital Twin

One of the significant impacts of artificial intelligence on the digital twin is simulation. Digital twin simulation can be greatly improved with the aid of machine learning models and procedures. A simulation explains the behavior of a product or process in a given environment. Considering historical and current data, ML helps predict the condition of physical entities and ultimately helps in decision-making.

It reduces or sometimes eliminates prototyping, hence saving in cost, time, material, and energy resources. As the experimental data is very high, means each simulation is an experimental run. Machine learning algorithms help in faster solutions. Hence, it becomes practically easy to simulate the process for DT with the help of machine learning.

The computerized model helps to decide and test the implemented strategies without actual visits to the asset, machine, process, or plant [39, 40]. Figure 7 shows a hybrid algorithm, i.e., with the help of a supervised and unsupervised algorithm, the pattern or path identification is done and further updated to decide the finalized pattern.

Due to this enabling technology, DT can perform predictive, prescriptive analysis based on real-time online data. Condition-based monitoring and alerts by bottleneck processes and events can be obtained through machine learning algorithms, hence understanding current and future conditions for prognostic analysis and estimating remaining useful life [41, 42]. Hence, optimization in a product or process helps in adopting a better and more cost-effective way of operation.

3.5. Interaction of 3R with Digital Twin

A very innovative visualization technology of Industry 4.0 is termed 3R, which involves augmented reality, virtual reality, and mixed reality. This technology finds its important place in a DT system. Figure 8 shows the interaction of 3R in the DT environment. In VR, only a single directional interaction occurs between the digital twin, 3R system, and user. There is no backward flow of information towards the DT from the user, as shown. The high-fidelity digital information from the virtual space is transferred to the user. The characteristics of a physical world are depicted digitally using the simulated entity technique. Whereas AR works on two-way interaction between virtual space and user. The AR system works in association with DT by taking information through the deployed sensors and feedback from virtual space.

The AR system proves to be more interactive as compared to VR as the interaction is two-way, thereby improving the overall perception of the physical environment. MR system is more compressive in terms of interactive and immersive experience. This is because the MR system works on bi-directional interaction between virtual space and the natural scenario. In addition, collaborative interaction exists between the AR approach and the user.

Hence, the information is more reasonably overlapped to build the MR environment. Hence, the integration of DT and 3R technology enhances the visualization of the virtual and physical world. It also provides comprehensive simulation assistance and flawless decision-making for equipment or assets. Technology can be extended, especially in industrial applications like visualization of inspection processes, failure detection on machine elements and products, planning processes and assemblies, equipment, safety training, etc.

3.6. Interaction of Blockchain with Digital Twin

Due to huge development in high-performance computing software, it help enable the creation of digital models conveniently and affordably. On the other hand, besides the significant expansion in sensor technology, microprocessors and controllers, and wireless sensor networks, the IoT has spread to every corner of the world [43, 44].

As shown in Figure 9, the process layer suggests the physical asset, product, process, equipment, etc. IoT devices generating the data serve as a foundation for connecting physical entities and digital replicas [45]. The connection layer generates a unique code called a cryptographic hash for every detailed information.

Thus, the unique code representing the information describes the integration of digital twins with blockchain [46]. Through DT, a product or assemblies can be tested for their design, performance, and durability for their intended purpose to ensure authentic quality and safety. In this complete process, data exchange throughout various stages becomes essential.

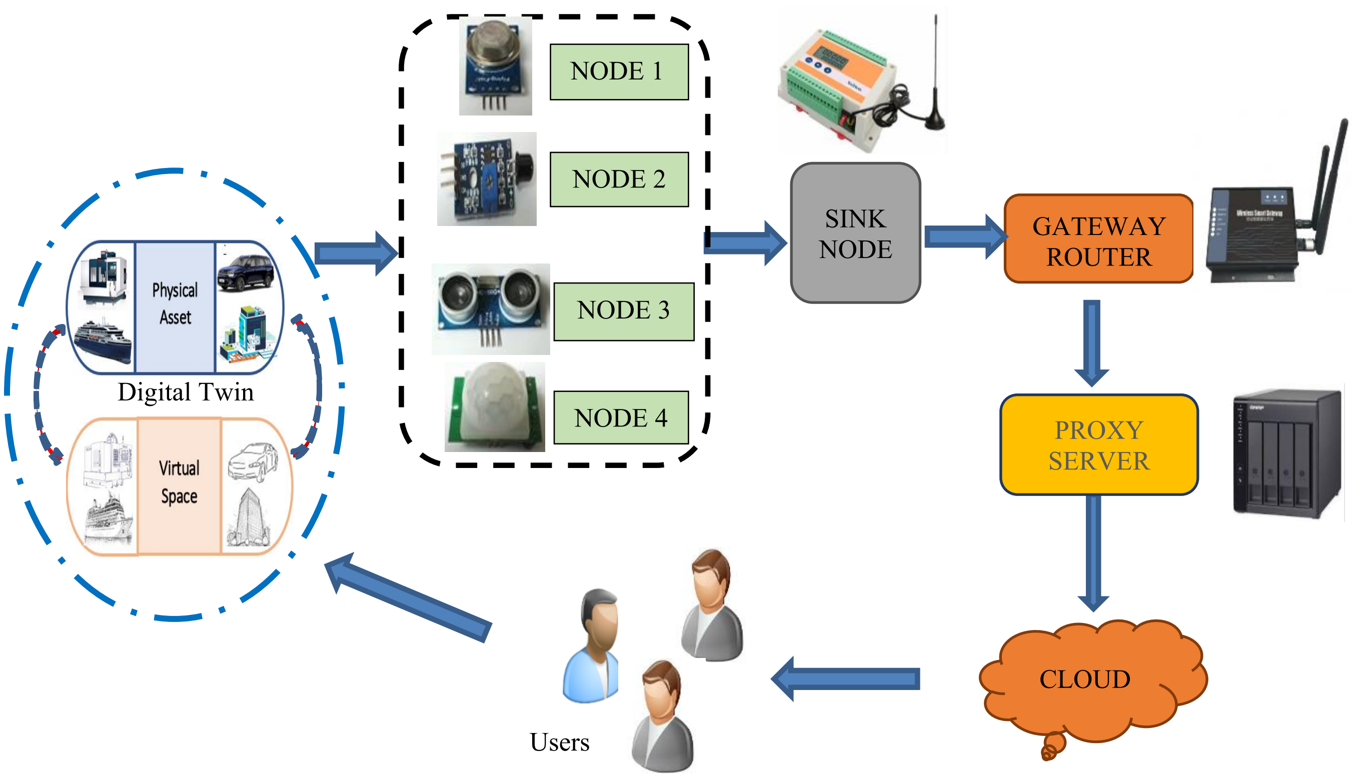

Fig. 4 Interaction of IoT with DT

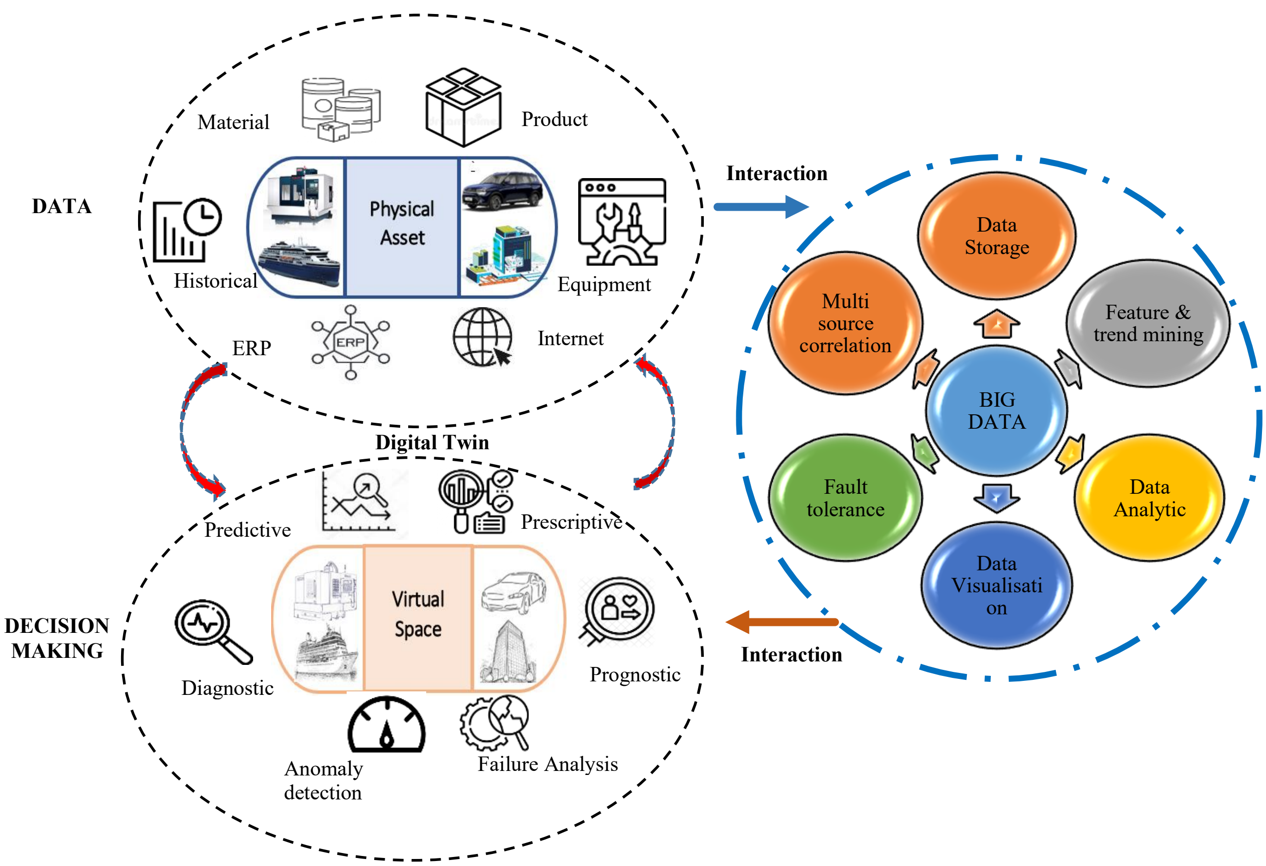

Fig. 5 Interaction of bigdata with DT

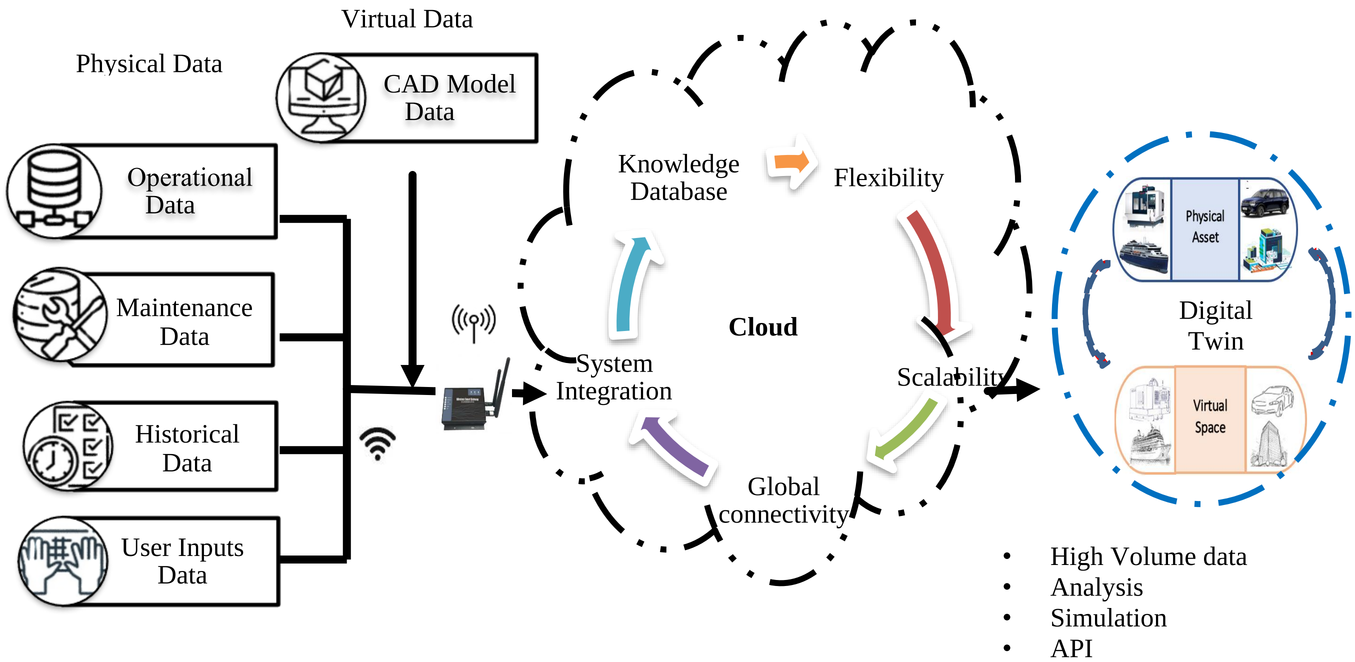

Fig. 6 Interaction of cloud computing with DT

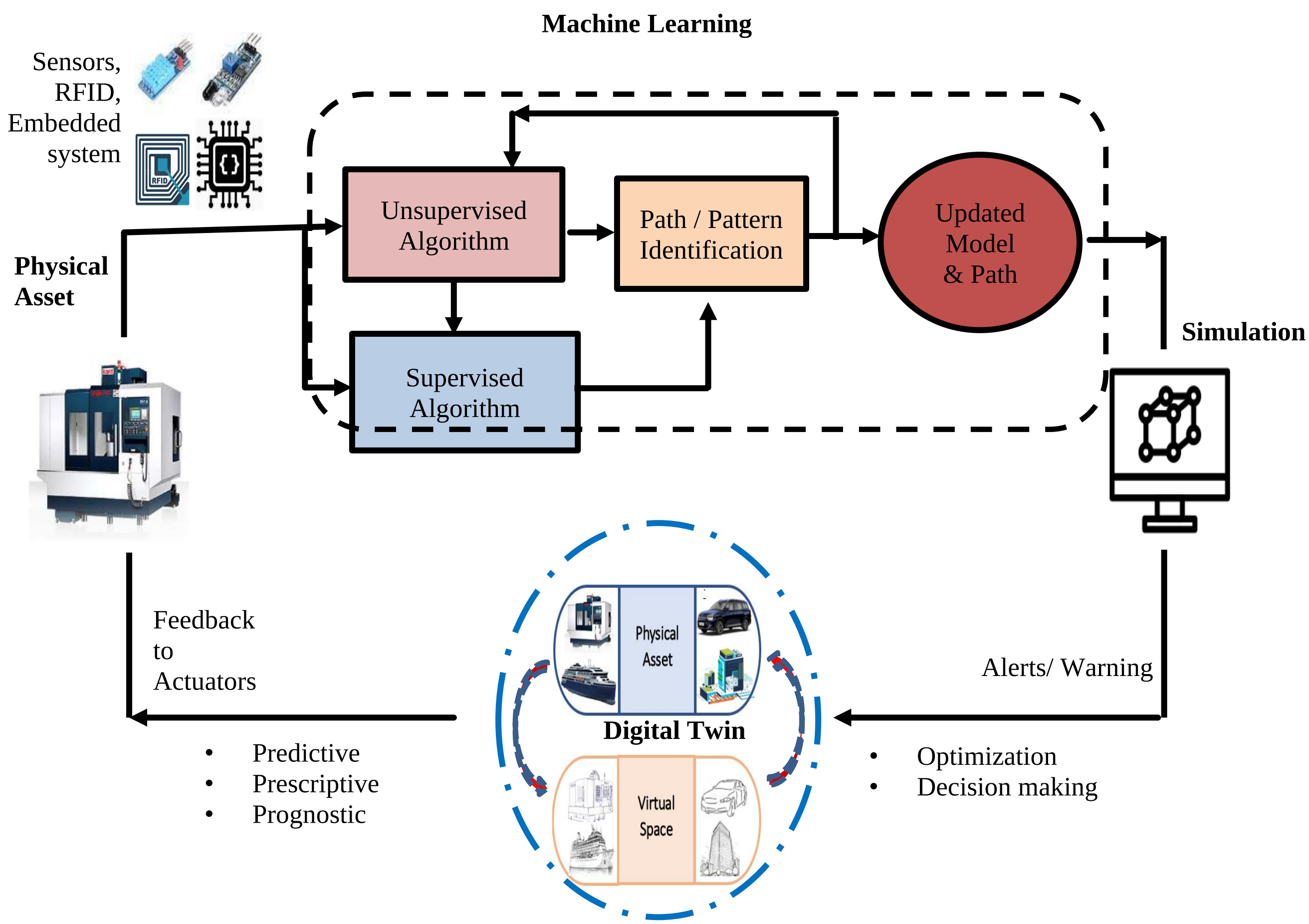

Fig. 7 Interaction of AI/ML algorithms for data solution with DT

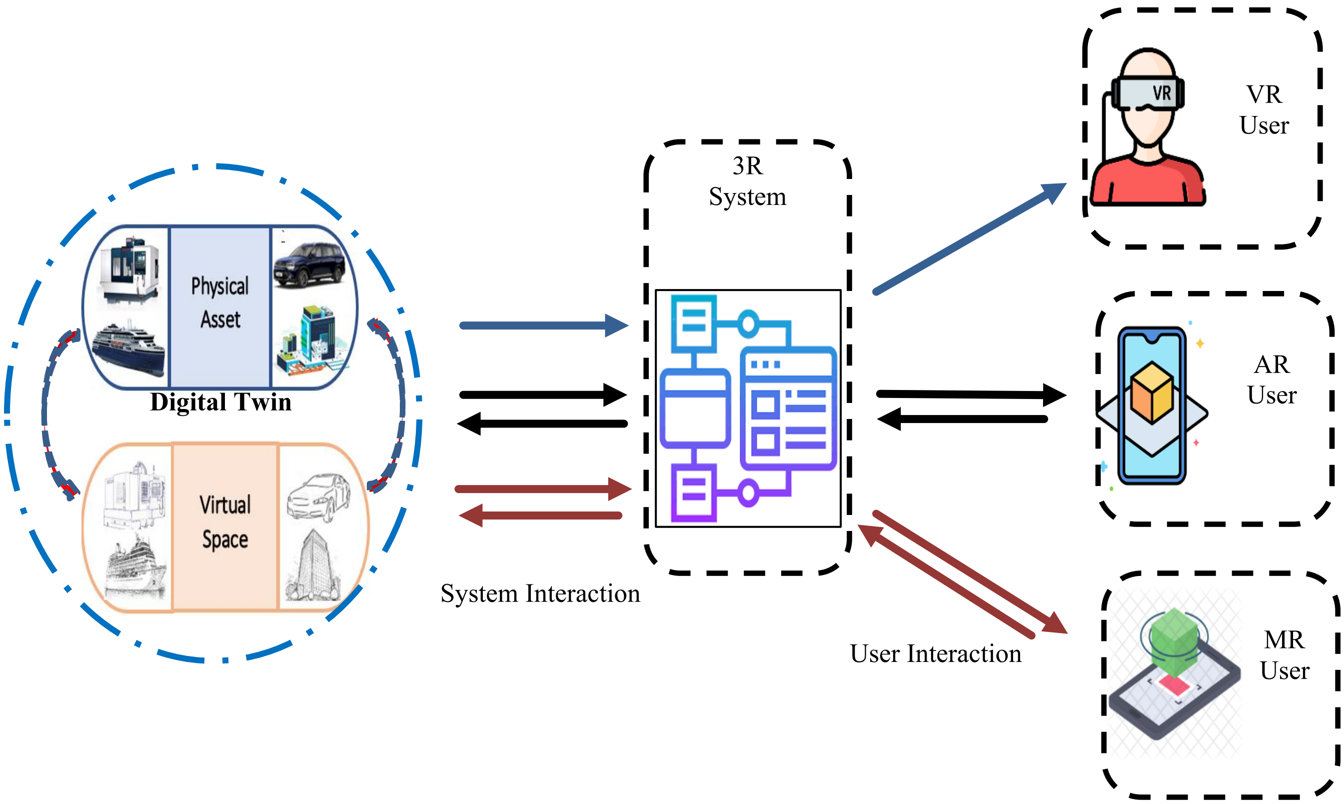

Fig. 8 Interaction of 3R system with DT

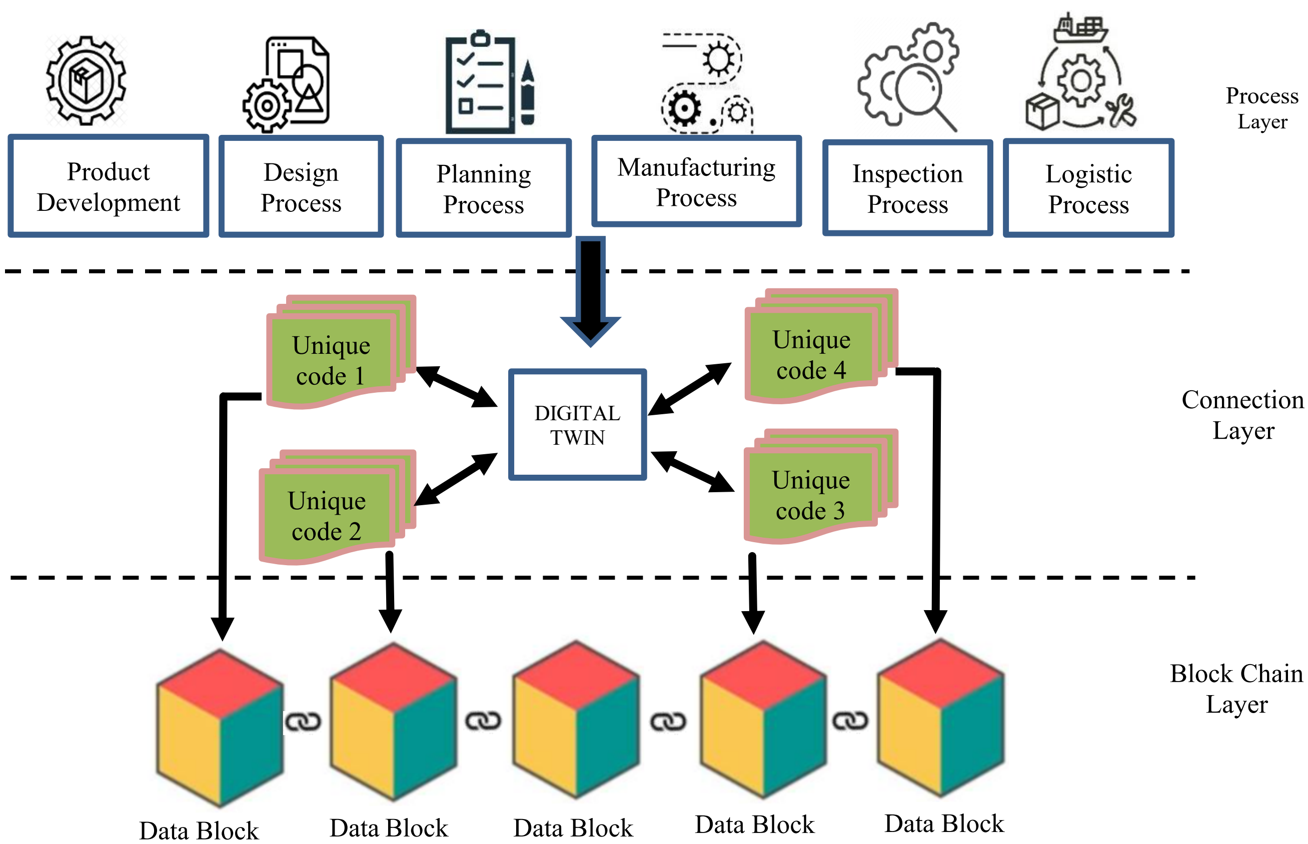

Fig. 9 Role of blockchain with DT

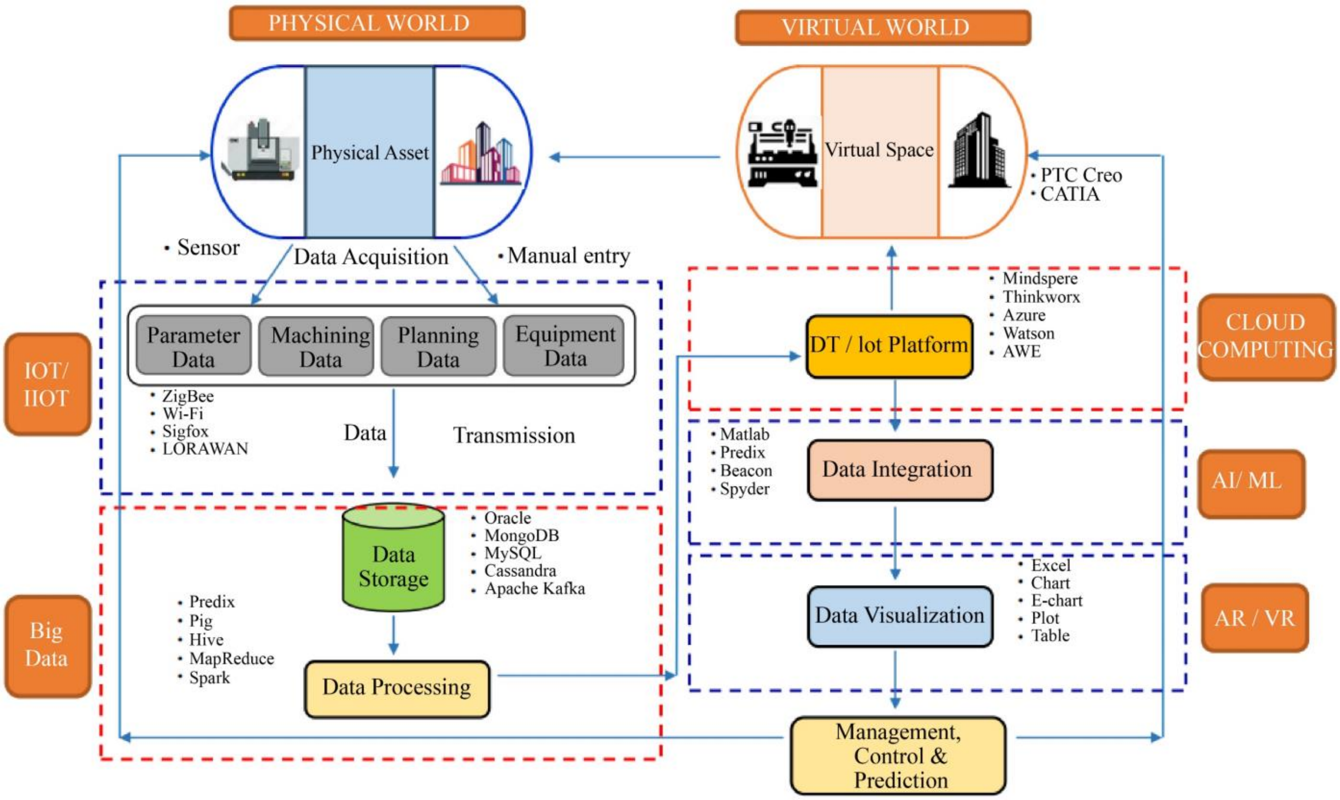

Fig. 10 Generalized data flow and tools for digital twin system

This data needs to be circulated in a very systematic, transparent, and trustable manner. Hence, in the blockchain layer, unique blocks are created for every code and are interconnected with each other, forming a blockchain that helps DT to provide trust, security, and protection to highly sensitive data. This feature of blockchain ensures originality and secure data transmission across various stages of DT. A blockchain strengthens security and offers many more benefits when associated with DTs. Immutability is one such feature that ensures indelibility while keeping its history unaltered. This helps to trace any unnecessary changes or data tampering at any process stage of DT. The originality of twins is also an essential attribute that needs to be protected. Blockchain takes care of the legitimacy and identity of DT so that any copy, modification, or fake replica of DT is avoided. With blockchain, the DT can be easily located or traced accurately, and the history associated with the DT can be easily assessed from any corner of the world. Table 1 highlights eight enabling technologies - IoT/IIoT, Big Data, Cloud Computing, AI/ML, AR/VR/MR, Blockchain, Edge Computing, and 5G Networks - along with their key features and recent real-world examples. These technologies drive advancements such as actual examination, predictive maintenance, data-driven insights, and enhanced connectivity. Companies like Siemens, Netflix, and Tesla are leveraging these innovations to enhance operations, amend management, and enable smarter systems through industries like manufacturing, entertainment, automotive, and more.

4. Data Flow and Tools of Digital Twin System

The architecture of DT is a complex phenomenon and depends on the area of application and its practical approach. The three main fragments of DT include the real world, virtual systems, and interconnection between each other. This connection is maintained with the help of the data, which flows through various devices, keeping the system connected.

As shown in Figure 10, the process involves data procurement, data communication, data processing, data amalgamation and data visualization. The physical world could be anything, such as a human being, machine, material, equipment, etc. A complete understanding of the physical world is the utmost important element of successful DT. In-depth knowledge of multidisciplinary engineering aspects may involve understanding material properties, machine dynamics, mechanics, acoustics, vibrations, thermodynamics and many more. Combining all these required parameters makes it impossible to develop a virtual system that best resembles the real domain. To accomplish this, the model needs to be verified, validated, and accredited in the real world. Hence, to develop a high-fidelity virtual system, one needs to be fully aware of the physical world.

Table 1. Overview of key enabling technologies and their real-world applications

Sr. No.	Enabling Technologies	Features	Recent Example
1	IoT/IIoT	Real-time monitoring, process optimization, predictive maintenance	Siemens: Smart factories using IoT for optimization and predictive maintenance.
2	Big Data	Advanced analytics, predict product performance, data-driven insights	Netflix: Uses big data to personalize content and optimize streaming.
3	Cloud Computing	Scalable data storage, on-demand access, remote collaboration	AWS: Cloud solutions for scalable data processing and storage.
4	AI/ML	Predictive analysis, automation, real-time decision-making	Tesla: AI-driven self-driving cars with continuous algorithm improvements.
5	AR, VR, MR	Visualization, virtual training, remote troubleshooting	Microsoft HoloLens: Mixed reality solutions for training and remote support.
6	Blockchain	Data security, decentralized storage, fraud prevention	IBM Food Trust: Blockchain for supply chain transparency and safety.
7	Edge Computing	Reduced latency, data optimization, resilience	NVIDIA: Edge AI solutions for real-time processing in autonomous systems.
8	5G Networks	High-speed connectivity, real-time data, IoT support	Verizon 5G: 5G networks supporting smart cities and IoT devices.

The substantial data generated by the physical assets acts as fuel for the overall functioning of the digital twin system. The actual data could be the data on machining inputs, machining parameters, data related to production planning, equipment health data and many more. The data generated should be acquired completely without any data loss, which needs to be further filtered, corrected, and modulated to extract the maximum benefits of the data.

The data generated is heterogeneous and comes from various sensors and electronic devices; secondly, the massive amount of information needs proper storage. The data should be systematically placed so that data retrieval becomes easier. Hence, data management becomes an important link in the overall digital twin system, whether the data is labeled, unlabeled, structured, unstructured, or in any other form. The acquired data is through the deployment of sensors capable of generating signals proportionally with the given parameters.

The data could be transmitted through wires or without wire, i.e., wirelessly; wireless technology has helped deploy sensors and data transmission in the areas where the approach becomes difficult. For a shorter range, the generated data is transmitted to the storage space by means of advanced communication protocols like Wi-Fi, Zigbee, Sigfox, LORAWAN, 5G, etc. In contrast, the GPRS communication protocol is used for a longer range, the use of satellite communication.

This overall activity of collection, filtering, and transmitting of the data could be mapped to IoT/IIoT enabling technology. Handling huge amounts of data and extracting meaningful information for subsequent use is challenging. As mentioned earlier, the data is available in huge volume, with variable content and high velocity. Effectively handling and simultaneously extracting meaning is not at all possible with the help of traditional means. To overcome this difficulty of big data storage with the help of SQL, New SQL, H Base, Cloud, MongoDB, etc. NewSQL is scalable and flexible, with high performance to handle all data types. The meaningful extraction of information is of utmost significance because the succeeding activity of data processing is largely dependent on it. It consists of noise cleaning, redundancy, raw data, smoothing and transformation. The tools used for data processing are Predix, Pig, Hive, MapReduce, etc. After processing, the data can be used for further analysis via the IoT platform.

5. Conclusion

The awareness of Digital twins is growing in every field, especially in manufacturing, and the potential seems to be much higher. It is obvious that the success of DT lies in vital supporting technologies like IoT, Artificial intelligence, Cloud computing, Bigdata, etc. However, some limitations still need to be tackled to penetrate this technology further. Challenges like lack of IT infrastructure, lack of standardization of implementation, security and safety of data, trust in performance, lack of skilled human resources, etc., are important barriers that must be worked upon.

Also, the overall DT system is complex in nature and requires close integration of multidiscipline engineering, and complete awareness is not common. Using proper platforms, applications, tools, and enabling technologies is a crucial aspect of operational DT.

However, the selection of proper communication protocol and their service restrictions also contribute to the delay in implementation. The main aim of this review is to attempt to put forward a common conceptual framework that will help understand the implementation, implication and interaction of each key enabling technology for Digital twin. This framework is a common reference for accessing the impact and implementation of enabling technologies with DT on any physical assets. But still, it is a long journey of implementation of DT for every physical entity and in manufacturing industries, such as product life cycle management, predictive maintenance, condition-based monitoring, fault diagnosis, etc., so that potential benefits can be availed.

However, creating a generalized methodology is a complex aspect, as the area of concern and purpose have a huge variability from case to case. Hence, it is very important to further work upon the stated challenges and try to fine-tune them. Besides, the contribution is still awaited in developing a common data format for real-time data, which should include all parameters essential for DT with ease of handling and storage of heterogeneous data, which is still a very important concern that needs further investigation.

Also, the implementation of backward integration, i.e., the changes made in the virtual space, should be successfully reflected on the real asset, which could be the areas for future interest and investigation.

Availability of Data and Materials

The data supporting the findings of the article is available within the article.

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