Digital Twin in IoT/ Artificial Intelligence

Keywords: **Digital Twin (DT), Artificial Intelligence, Internet of things**

I. INTRODUCTION

Innovative concepts to smart industries and manufacturing have opened in cyber world with the enhancement in IT technologies, IoT and AI, having wide range of applications in smart engineering and development [1]. This digitization of industries has unbolted several opportunities. It was anticipated in 2016 that it is possible that in near future, more than 20 billion gadgets would be associated and linked to each other generating 40 zettabytes of unstructured or semi-structured raw data [2,3]. Therefore, it is the need of time to bring together, analyze and gain valuable information using this raw data with the help of progressive computing algorithms and mechanism [4,5].

Earlier, computer aided tools were used for designing the structure, and evaluating the life span of the simulated model by measuring the performance analysis for physical testing algorithms. Though these conventional approaches were better to optimize the model for maximizing the performance and cutting down the cost but it had limitations regarding tolerances, configuration and planning strategies etc. [6]. Nevertheless, with the advancement of AI/ ML, IoT industry and computational power, "digital twin" has enabled the skill of digitization and real time control [7]. Physical scenarios including processing and systemization are epitomized using "digital twin". DT builds an interface by observing past and present functions and forecasts the predictions by intelligently combining the data structure, environmental framework and performance of the physical system [8]. Hence, DT with the integration of software analytics and AI, designs the simulation based digital model that continuously updates and changes on changing the physical equivalence by delivering real time observations using several sources at a time. In this way, DT builds the virtual prototype based on physical model, where the prototype behavior is predicted through simulations in digital way [9]. These prototypes can then comprehend the behavior of physical object by sensing the data for approximation and analyzing the dynamic variations. DT is able to gain the optimization of the complete industrial and manufacturing process [10].

II. DIGITAL TWIN- A CONCEPT

The progress of digital technologies is making its way for building smart cities comprised of the physical objects having in built computing abilities to sense the environment and link with one another for providing the amenities. This intelligent linkage and interoperability is known as IoT ("Internet of Things") [11]. Important sub domains of smart cities include, smart home, smart manufacturing, smart industry and smart transport system. Fig. 1 represents the concept of DT in regards to simulation of real word based on physical model (an example of a robotic arm). Data acquisition has become much easier as compared to previous time because of the accessibility and convenience of sensors and actuators. Analyzing and identifying the manufacturing machines via internet is strenuous task to implement. In addition to that, merging of physical and virtual systems is one of the major challenge of "cyber physical system (CPS)" where computer system controls and monitors the mechanism using computer based algorithms. This field of mechanical analysis in DT requires more research. In order to overcome these tasks, a concept of industry 4.0 was idealized [12]. Keeping in view the intelligent and smart production system for efficient work, "digital twin" was considered to be one major development that could tackle this.

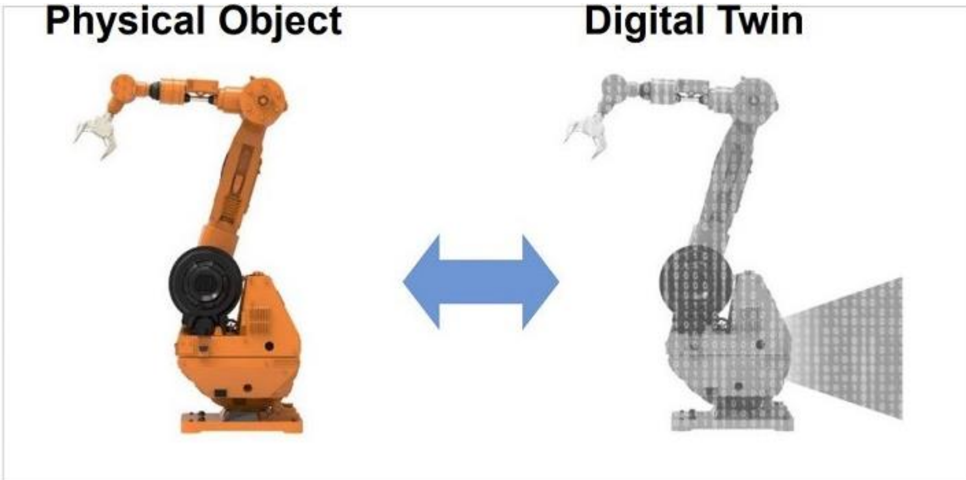

Fig. 1. CONCEPT OF DT [17]

"Digital Twin" is a concept that virtually builds the copy of the physical system to measure and forecast the performance of the system beforehand that continuously gets accustomed to environmental changes and functions by means of "real time sensory" data. DT is able to analyze and observe the possible issues occurring in its actual physical counterpart. Other than that, it permits the forecast of "remaining useful life (RUL)" of physical twin system by combining the physics based system and data analytics. DT is comprised of three shares: (1) Real physical product, (2) imaginary/ virtual product, (3) linkage among data and information that connects the real and virtual product. Hence, gathering and examining the bulk of manufacturing statistics to gain information and linkage is now the key to smart industrialization and manufacturing.

III. DT REFERENCE MODEL

In cyber computing, DT replicates the two-way dynamic mapping among physical system and its virtual model [13]. DT acts as a middleware structural design that summarizes the physical system using high level management to take real time decisions. Fig. 2 represents the reference modal of the Digital Twin. Here, at technical part, the formation of DT requires three elements including: (1) Information model (IM) that provides the features of the physical model, (2) communication system that communicates bi-directionally among DT and physical counterpart, and (3) data processing system that retrieves the information from diverse data to build the live virtual representation of the physical unit.

All of these three components combine together to create DT. It is meaningless to transmit data to the cyberspace without information model and extracting the characteristics of the physical entity in DT. This information model turns out to be one off snapshot of its counterpart without data synchronization system among physical unit and information link. High performance data synchronization is the important parameter to fulfil the gap among data stream and DT information system.

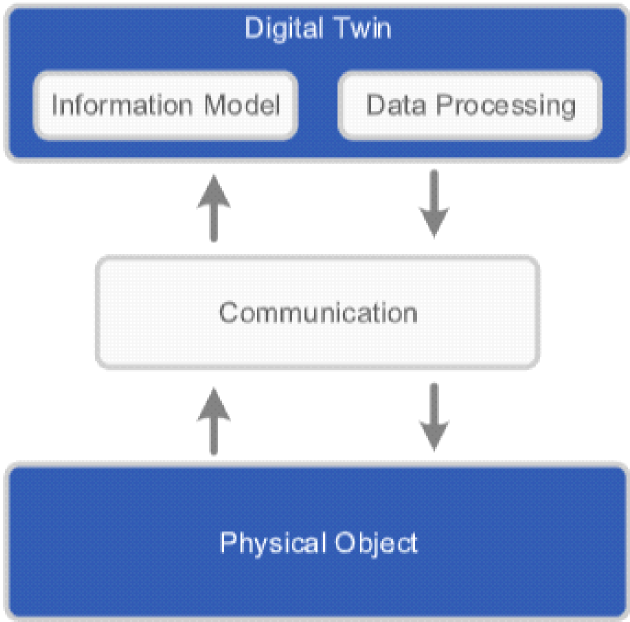

Fig. 2. DT REFERENCE MODEL [14]

A. Information Model (IM) of DT

Physical unit is occupied with the already defined Information model depicting concerned characteristics. Standard plays significantly giving the "information model" (IM) for elaborating several physical units in industrial and manufacturing domain. These IMs are comprised of two subtypes i.e., IM for *product* DT and IM for *production* DT.

B. Communication Network

A communication network enables the formation of DT system. A state of synchronization among DT and its physical counterpart is counted on real time and bi-directional communication. State variation to physical domain is detected by IoT sensors that are transmitted to it DT within cyber space. Considering this, "industrial communication protocols (ICPs)" help in gathering data from the physical units [14].

C. Data Processing Through Physical Object

Data collected from several sources in physical space creates DT via Big data making it a third most important pillar of constructing a DT. Data processing methods, that make use of statistical analysis and prediction models disregarding noise and single data, are not applicable for constructing DT models [14].

IV. APPLICATION CASES OF DIGITAL TWIN

Digital Twin (DT) has various use cases that are classified into three main groups including manufacturing, aviation and healthcare. Some of the important application cases of DT are described below.

A. Manufacturing

Numerous works in this field make use of DT to adjust all the features of product manufacturing processes and its lifecycle. Practicing DT allows to construct a hi-tech electronic system that supervises every processing step of manufacturing using modular approach. "Smart Manufacturing Approach" automatically implements the complex tasks without human interference, analyzing between group of varying actions and reacting to the unforeseen and unanticipated events without disturbing the working of other modules by avoiding variations and reconfigurations. At processing end, the implemented algorithm should have the right to access real information that elaborates the ongoing state of the process and products as well that is possible by attaining real virtual realization of the physical unit i.e., DT.

B. Healthcare

Application of DT is also used for analyzing and visualizing the hospital system so as to build a safe and secure environment and examine the effect of possible variation on the system performance. Bedsides operational functions, DT also assists in enhancing the quality of health service that is provided to the patients. For instance, a heart surgeon can make use of IoT based DT to determine the working of patient's heart through digital visualization even before starting the operation and opening and heart. Fig. 3 below presents DT concept of human body for different organs.

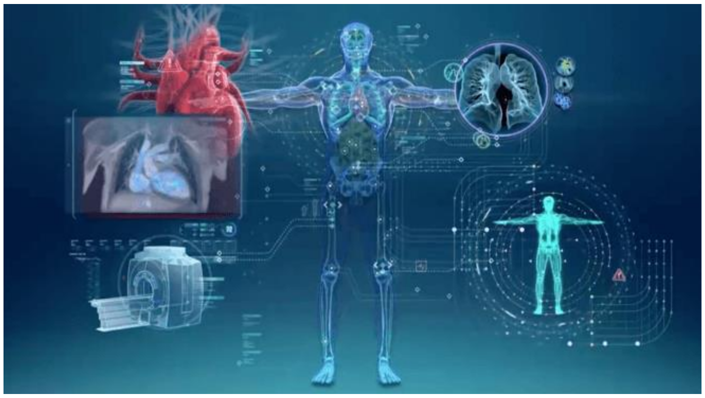

FIG. 2. DT CONCEPT FOR HUMAN BODY [18]

C. Machine Building and Maintenance

DT in IoT is used for creating digital replica of real machine that is developed and established at the same time. Statistical information obtained from real machinery is weighted into the digital replicated structure enabling simulation and examining the ideas that can be used for execution before building actual manufacturing product. DT can investigate the performance analysis of the gathered data with respect to time under various circumstances. For instance, a bus or car engine can be envisioned to classify and recognize necessary maintenance like a component that is near to burn or face a fault.

D. Performance Optimization

DT helps in finding out the optimum set of actions and constraints that assist in maximizing significant performance metrices and deliver predictions about long lasting planning. For instance, NASA suggested and embraced for observation on secure, safe and reliable optimization of space shuttle.

E. Smart Cities

The application of DT to be implemented in smart cities is growing on yearly basis in lieu of fast development in connection through IoT. With the more developed and established smart cities, more communities have connected to each other, resulting in more usage of DT. Besides collecting data from IoT sensors entrenched into the services within smart cities, DT also makes its way for research regarding progressive AI algorithms. The facility of implemented sensors within the infrastructure of smart cities while being observed with IoT devices proves to be of great value in upcoming near future. It not only benefits in providing planning and developing structure of current smart cities but also assists in under process developments of smart cities. In addition to the planning, it also helps the world in saving the energy. Progression for smart city is the prospective to utilize DT technology.

V. CONSTRUCTION OF DT USING AI & IoT

DT is comprised of sensors and measurement technologies, AI/ ML, IoT simulations and modelling. IoT sensors generates a huge amount of informative data that can be used anywhere. Generated IoT cloud models and big data consequently increases potential and incremental data of cloud services and upstream the data using IoT services.

Several domains contribute for executing DT that includes cloud computing, networking, ML and sensors etc. In AI domain, "Bayesian Network approach" was first AI algorithm that was used for modeling DT providing concept for tracing the progress of time dependent variables to observe the aircraft assembly [15].

In IoT domain, AI increases the operability of DT where software based dynamic model is created on a physical system that counts on sensor data to realize the object state, reacts to the variations and enhances functionality by adding value in it.

Currently, Industrial IoT make use of DT for execution in manufacturing industry. In [16], management and optimization of IoT based devices and their lifecycles with the help of DT mechanism is elaborated and discussed.

In manufacturing industry, IoT procedures collect the data from product specifications including design, and manufacturing etc. This data is usually collected considering the following features [14].

- From manufacturing system: “Product Data Management” (PDM), “Enterprise Resource planning” (ERP) and computer aided softwares including “Computer aided design” (CAD) or “Computer aided manufacturing” (CAM) etc.
- From internet websites including Facebook, twitter, Amazon etc.
- From industrial manufacturing apparatus in regards to real time processing, product material and environmental data.

For executing DT, the gathered data is processed through several steps to obtain the information. When the data is collected using sensors, “application programming Interface (API)”, and “software development kit (SDK)” etc., it passes through the cleaning procedure before being processed and analyzed [14]. The cleaned informative data is then integrated and stored for exchanging industrial data at all levels. Moreover, real time and virtual data analysis using AI/ ML techniques performs the cloud computing in DT systemization [15]. The important information that is obtained from the huge amount of dynamic and fuzzy set of data supports manufactures to enhance their considerations about several stages of manufactured product lifecycle. Therefore, DT assists manufactures to take more balanced and knowledgeable decisions.

VI. SECURITY CONCERNS REGARDING DIGITAL TWIN

Although DT brings many opportunities when internet is linked with manufacturing industries but with benefits, it also brings some challenges with it. As the data and information travel across many communication network, it raises the questions regarding data security that was not a problem at the time of constructing conventional machines generation to work without any programs and without being connected to any other infrastructure just power. So, in order to provide security to the current industrial system to the organizations have become a challenging task in lieu of cyber-attacks and intrusions within ongoing scenario. In order to counter such security inconsistencies, following possible solutions must be taken into consideration.

- *Public Key Infrastructure*: It is used to secure the communication layer, by making system that authenticates the configuration and integrity of the device that is connected to the system providing high level security without affecting the system performance.
- *Data encryption:* It is used to encrypt the data allowing only authorized users to access the data into the system by deploying antivirus softwares.
- *Intrusion Detection system:* It is also used to secure the two-way data communication.

For a system to be secured needs full understanding of the type of threat, evaluating susceptibilities and vulnerabilities, measuring the lost value if security breach occurs, and endowing security properly. This provides the self-driven model where products and machines participates actively in IoT performing as self-driven representative during the course of production line.

VI. CONCLUSION

DT has been documented and renowned by several organizations such as “International Business machines” (IBM), and “General Electric” (GE) as next generation significant infrastructure that focus more on artificial intelligence (AI) based technologies. IoT and AI in smart industrialization has been the pioneer procedure to revolutionize the IoT sensors as prerequisite in the machine part from where real time analysis takes the data. Combination of human intelligence and data driven smart algorithm has influential impact on manufacturing efficiency. Nevertheless, rigorous communication and large amount of statistical data carry out the challenging tasks. In this paper, digital Twin has been discussed with the fusion of IoT and AI data driven in smart industry. Linkage and synchronization between the physical data and virtual data to execute digital twin has been elaborated in this paper. It is considered to be significant that adapting IoT and AI for smart manufacturing embeds the security even before starting the virtual conceptualization of the physical product. Hence, it can be concluded that junction of IoT and AI with DT can enhance the productivity, improve quality and streamline manufacturing of the product.

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