Machine-Learning-Based Digital Twin in Manufacturing

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Contributor: Sharmin Sultana Sheuly, Mobyen Uddin Ahmed, Shahina Begum

The Digital Twin (DT) concept in the manufacturing industry has received considerable attention from researchers because of its versatile application potential. Machine Learning (ML) adds a new dimension to DT by enhancing its functionality.

Keywords: advanced manufacturing ; digital twin ; machine learning

1. Introduction

Digital twin is a multi-disciplinary, multi-physical, multi-scale, multi-probability simulation process that makes full use of physical model, sensor update, operation history and other data to complete the mapping in virtual space, thereby reflecting the full life cycle of the corresponding physical equipment process. A digital twin is a concept beyond reality that can be viewed as a digital mapping system of one or more important, interdependent equipment systems.

Digital twin is a universally adaptable theoretical technology system that can be applied in many fields, especially in product design, product manufacturing, medical analysis, engineering construction and other fields.

At first, the idea of digital twin was named "Information Mirroring Model" by Michael Grieves of the University of Michigan, and then it evolved into the term "digital twin". Digital twins are also known as digital twins and digital mappings. The digital twin is developed on the basis of MBD. In the process of implementing model-based systems engineering (MBSE), enterprises generate a large number of physical and mathematical models, which lay the foundation for the development of digital twins. In 2012, NASA gave a conceptual description of digital twins: digital twins refer to the full use of physical models, sensors, operation history and other data to integrate multi-disciplinary and multi-scale simulation processes. The whole life cycle process of the corresponding physical entity product. A digital twin refers to an information model that exists in a computer virtual space that is completely equivalent to a physical entity, and can simulate, analyze and optimize the physical entity based on the digital twin. Digital twins are technologies, processes, and methods, and digital twins are objects, models, and data.

In the 21st century, both the United States and Germany proposed the Cyber-Physical System (CPS), which is the "information-physical system", as the core supporting technology of advanced manufacturing. The goal of CPS is to realize the interactive fusion of the physical world and the information world. Through the simulation analysis and prediction of the new generation of information technology such as big data analysis and artificial intelligence in the virtual world, the operation of the physical world is driven by the optimal results. The essence of digital twin is the equivalent mapping of the information world to the physical world. Therefore, digital twin better interprets CPS and becomes the best technology to realize CPS.

2. Machine-Learning-Based Digital Twin in Manufacturing

Digital Twin (DT) technology is being applied in different areas. The first application was in the aerospace industry. However, it is now being used in healthcare, manufacturing, networking, communication, etc. [1]. In the manufacturing industry, the DT is used for machine health monitoring [2], predicting failure [3], product design [4], and human–machine collaboration [5].

Conversely, data produced in manufacturing have been used to schedule maintenance or create product logs [6]. These data have fostered machine learning (ML) and artificial intelligence (AI) applications in DT for manufacturing systems. AI algorithms such as genetic algorithms, particle swarm optimisation (PSO) [7][8], and fuzzy logic [9] have been widely used in various applications. A primary screening of manufacturing-domain publications showed that most AI-based studies focused on ML. There has been a sharp rise in the scientific study of DT in the manufacturing industry from the ML perspective. The reviews that have already been published on DT in the manufacturing domain focus on broad areas such as the current research state, role of AI, ML, and applications.

There has been no review narrowing down bibliometric and evolutionary analysis of ML-based DT in the manufacturing industry. Evolutionary analysis captures changes in the characteristics and structure of a system, product, or algorithm over the trajectory of time.

In NASA's Apollo program, a DT of a space vehicle was created for the first time. The target of this creation was to check the physical space vehicle's condition during missions [10]. Michael Grieves from Michigan University has been widely acknowledged as the person who first coined the term DT in 2002 [11]. Grieves described DT as "The Digital Twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level". The DT concept has received popularity since then, and other definitions have been published. Tao and Zhang [12] described DT as a means of converging physical and virtual spaces. Yuqian and Chao [13] described DT as a representation of a physical object which merges cyberspace and physical space through near-real-time synchronisation. According to Glaessegen and Stargel [14], DT is a simulation of physical space. Reifsnider and Majumdar [15] described DT as an ultra-high-fidelity simulation of its physical counterpart.

An ML-based DT can be defined as "an application-specific DT which is comprised of components such as physical entity, ML model, ML data, real time synchronisation, IoT and used for tasks such as process control, scheduling and prediction" The differences between ML-enabled DT and AI-enabled DT are

- ML-enabled DT is a subset of AI-enabled DT.
- ML-enabled DT involves algorithms such as ANN, RF, kNN, whereas AI-enabled DT involves algorithms such as genetic algorithm, ant colony optimization, and particle swarm optimization, in addition to ML algorithms.
- ML-enabled DT is primarily used for process control, scheduling and prediction, whereas AI-enabled DT is primarily used for optimization, scheduling, and resource allocation.
- ML-enabled DT is more abundant than AI-enabled DT

Grieves defined a three-dimensional DT architecture with a set of tests called the test of virtuality (GTV) to examine the fidelity of a DT. These three dimensions are (a) physical entity (PE), (b) virtual entity, and (c) the connection between physical and virtual worlds. However, Grieves did not define any auxiliary technology needed to build DT. With the advancement of sensor technology, IoT, and the introduction of big data and ML, DT architecture has evolved into a five-dimensional architecture. These five dimensions are (a) PE, (b) virtual entity, (c) services, (d) Digital Twin data, and (e) connection [2]. These five dimensions have evolved over time to eight dimensions: (a) integration breadth, (b) connectivity mode, (c) update frequency, (d) CPS intelligence, (d) simulation capabilities, (e) digital model richness, (f) human interaction, and (g) product lifecycle according to CIRP Encyclopaedia [16]. An analysis of these architectures shows that DT has been evolving over time with the incorporation of data, CPS, simulation, and humans. The CIRP Encyclopaedia dimensions have been considered in the proposed review because of their versatile dimensions.

The specific characteristics/dimensions of DT in manufacturing are:

- DT in the manufacturing life cycle.

  - Manufacturing design.

  - Manufacturing service.

  - Manufacturing process management.

- Simulation of manufacturing process.
- Big data associated with manufacturing.
- Cyberphysical system.
- Human-integrated manufacturing.

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