An Overview of Research on Digital Replication Technology Implementation

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Abstract. Digital Twin is a technology that uses digital modeling to reflect physical entity changes based on physical and data driving, connect real space with virtual models, and simulate real models in virtual space [1]. This article summarizes the step-by-step implementation process and discusses physical modeling, virtual modeling, data acquisition and processing, connection between physical and virtual environment, development trend, and difficult problems. The focus is on the technical realization of digital twin technology.

Keywords: Industry 4.0, Digital Twin, Finite Element Model, Deep Learning

1. The current status of digital twin technology

Industry 4.0, which uses advanced technologies such as AI, IoT, robotics, drones, autonomous vehicles, and virtual reality, enhances efficiency and reduces cost. Digital twin technology is a vital component of Industry 4.0, enabling manufacturers to create virtual replicas by collecting data from IoT sensors and other connected devices. Siemens successfully integrated real and virtual worlds using digital twins in the automotive industry, facilitating faster on-site debugging, creating sustainable feedback for improvement, and reducing design optimization cycles. Digital twin technology plays a critical role in future production [2].

1.1 Implementation process of digital twin technology

Tao et al. [3] defined a complete digital twin as consisting of five parts: physical entity, virtual entity, data, service, and connection, shown in Figure 1. Deloitte Digital Twin Model classifies data, service, and connection as important components into four levels from simple to complex: L1 involves data flow from physical space to network space, L2 involves the opposite, L3 represents the impact on cyberspace, and L4 represents the impact on physical space [29]. Implementing these four levels enables bidirectional interaction to optimize and transform the physical world

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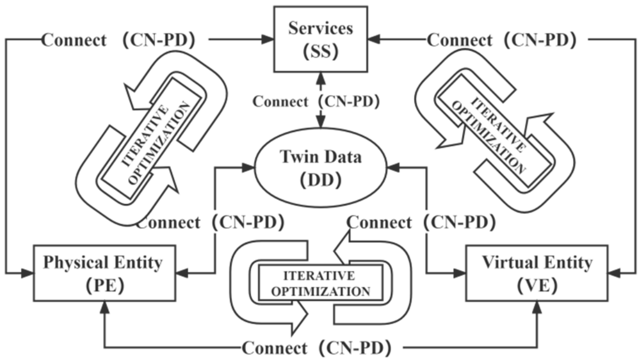

Fig. 1. Schematic diagram of a five dimensional digital twin model

2. Physical entity

Digital twin technology combines virtual and real elements to improve digital precision by specifying physical space structure. Careful modeling of virtual objects based on physical scenarios can complicate physical structure. Designing and modeling physical room components ensures accuracy of virtual model. Classifying physical room components into modular categories and matching modules in virtual model achieves functional specification. Different physical structures of digital objects lead to more accurate results closer to reality.

2.1 Definition of physical entity

Physical entity refers to the research object ontology and its auxiliary resources. Bevillaqua et al[30]. proposed a digital twin reference model, and the physical entity consists of physical industrial resources such as products, personnel, equipment, materials, processes, environment, facilities, etc.

2.2 Processing of physical entity

Jia [29] et al. proposed a two-step approach for decomposing physical entities based on MBES, involving function and use-based decomposition using spatial scale division, application scenario division, and functional component division. Jia [29] et al. also suggested a 4C architecture for hierarchical partitioning of complex digital twins. However, this method has scalability issues, and to address them, Jia [29] et al. proposes an optimization of the complex digital twin model by integrating all attributes and data into a container that can fuse information in different scales and backgrounds. Figure 2 illustrates the multi scenario application of MBES from a simple digital twin to a complex digital twin workshop.

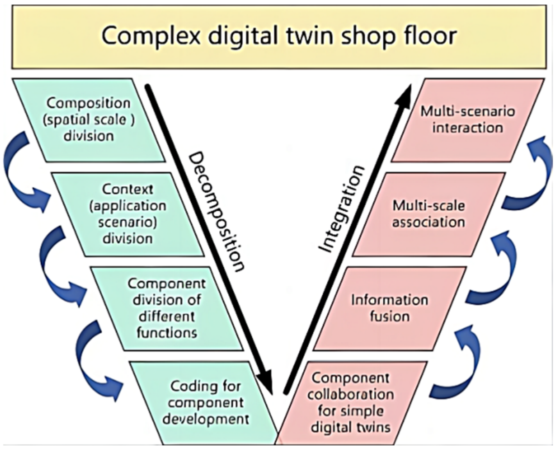

Fig. 2. excerpted from simple digital twin to complex digital twin part II Multi scenario applications of digital twin shop floor

3. Virtual Entity

Virtual entities are the twins of physical entities in various aspects. They possess corresponding characteristics of the physical entity studied and monitored in virtual space, including geometric shape, assignment of physical attributes, and simulation of behaviors such as change, evolution, response, and degradation. Personalized modeling can be performed based on the twin entity's characteristics to improve modeling logic and accuracy. We have summarized the methods and corresponding tools used for modeling various parts of virtual entities in Table 1.

3.1 Geometric modeling

Geometric modeling visually represents the physical entity through its geometric shape, which is the foundation of virtual entity. It is not only used for shaping but also provides the structural integrity and data accuracy necessary for motion analysis, optimal design, virtual interaction, and more [4].

3.1.1 Geometric modeling technology.

3D modeling of physical objects is now mature, and many software can meet most requirements for geometric modeling. Notable methods include point cloud modeling, which constructs a 3D structure of an object from laser-scanned dense points. Figure 3 is an example of a model built using point cloud modeling technology. Specialized industrial machinery software like Pro/E, CATIA, SolidWorks, and UG are also advantageous for 3D part construction and surface processing. BIM technology and digital twins can provide a digital and integrated environment for road projects to efficiently carry out the entire process [5]. To realize a digital twin of a complex physical entity, the physical model is split into parts, and modeling technology is used separately for geometric modeling before being assembled.

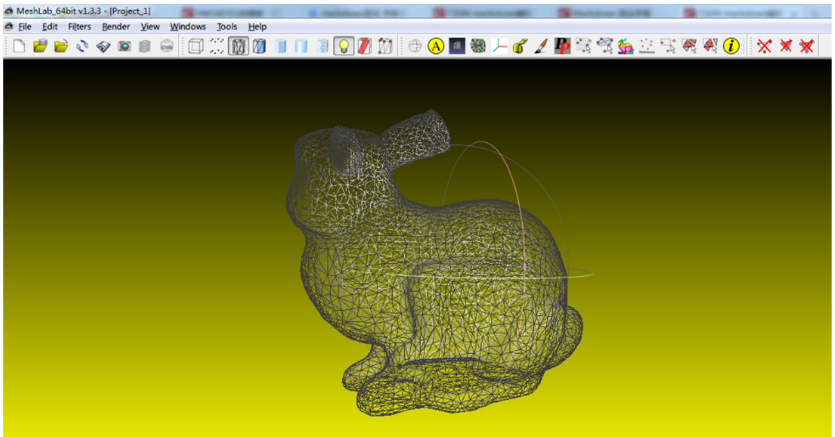

Fig. 3. Example of point cloud modeling ， excerpted from https://blog.csdn.net/HW140701/article/details/78876507

3.2 Physical Model

Physical models describe physical properties of objects, analyze their properties, and support predicting entity changes [4]. Static physical models quantitatively model physical properties, states, and behaviors. For example, Spreitzer et al. established a digital twin model using close range aerial photogrammetry (SfM) to simulate parameters like density, volume, and moisture content of a wooden riverbed. Dynamic physical systems, such as heat conduction in mechanical parts, require calculating nodes in the spatiotemporal solution domain. Cao [6] et al.established a reduced-order hydrodynamic model based on POD and dynamically analyzed hydrodynamic data of a blade under wake excitation.

3.2.1 Technical methods for constructing physical models.

Cao [6] et al. established a finite element model using FEM, which divides structures into unit grids for easy modeling. ANSYS, OpenFOAM, and SimScale are examples of finite element modeling tools.Figure 4 shows the finite element model established using ANSYS Cao et al. used OpenFOAM's SnappyHexMesh to generate a mesh based on the established finite element model. Bhogal[7] et al. used Ansys to establish a Finite Element Model and analyze cutting force and heat transfer during turning. They imported a tool model from Solid Works and determined stress, deformation, and thermal dispersion on the tool surface at different cutting depths.

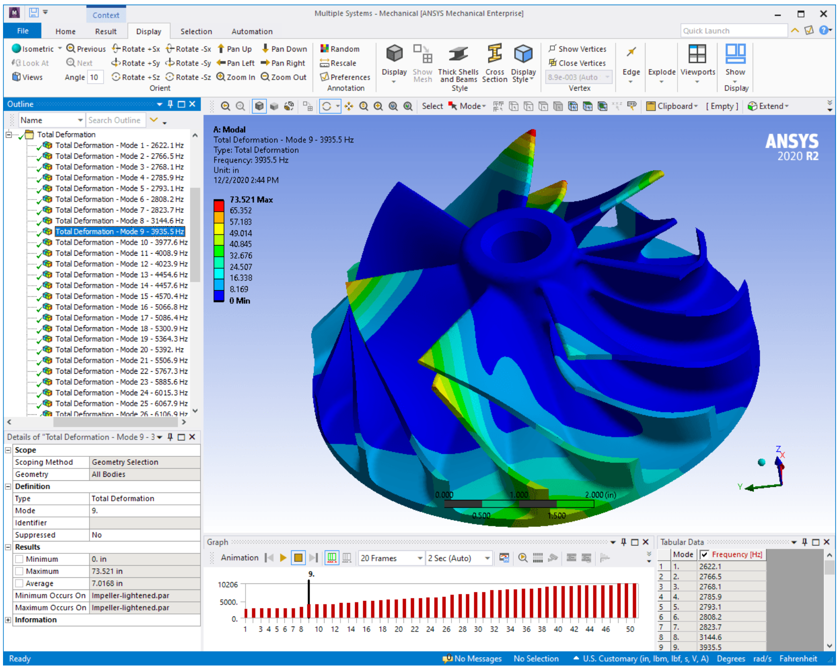

Fig. 4. Example of using ANSYS software， excerpted from https://www.padtinc.com/2021/01/06/ansys-mechanical-outputting-results-1-high-resolution/

3.3 Behavior Model

Behavior models describe physical entity behaviors, and their accuracy impacts digital twin predictive results. Processing abnormal data is crucial for accurate behavior modeling. Dallel [8] et al. proposed a new method for coupling DT and VR to obtain a digital human body model with processed abnormal data. Gao [9] et al. developed a method for monitoring abnormal motion status of AUVs using dynamic models, complex network theory, and support vector machines. This method accurately identifies normal and abnormal conditions and classifies abnormal situations, implementing AUV motion status monitoring.

3.3.1 Tools and Methods for Building Behavior Models.

Simcenter Amesim, Ansys, Flexsim, and CarSim can implement digital twin behavior in virtual environments. Li et al. [10] simulated the energy accumulation and migration behavior of a petrochemical network model using the Gaussian KELM algorithm in MATLAB. Quin et al. [11] proposed a digital twin framework for robust control of robotic biological systems created in OpenSim based on SimBody. White [12] et al. developed a digital twin model with citizen feedback and traffic simulation using SUMO, connecting to Unity3D models via the Traffic Control Interface to enhance traffic patterns with different behavioral styles.

3.4 Rule Model

Rule models can empower complex experiences and knowledge through data mining, information processing, knowledge measurement, and graphical mapping [4] Et al. The rule model can deduce changes to the physical entity at the knowledge level, enabling the final digital twin model to have intelligence and extract data according to historical experience and professional knowledge to contribute to further optimization and decision-making. Beke [13] Et al. used artificial neural networks for simulation and cost-effective development by processing time series input datasets.

3.4.1 Method of Building Rule Models.

Rule modeling technology extracts rules from historical data, operational logic, and professional knowledge for digital twinfunctions such as decision-making and optimization. Beke et al. [13] developed a digital twin for continuous pharmaceutical powder mixing processes using PAT and QbD guidelines. Hu [14] et al. have proposed a new GGS-CNN, which was trained and implemented in DTIRG for intelligent robot grabbing.Liu et al. [15] proposed a method to transfer DRL algorithms from digital twins to physical robots effectively. Tools such as Ansys, Simcenter Amesim, Demo 3D, and Simulink can construct rule models.

Virtual entity			
Geometric models	Physical model	Behavioral models	Rule models
3D modeling technology： Finite element method： ContextCapture Other 3D modeling tools:： Pro/E CATIA SolidWorks UG Combination of BIM and Digital Life	Finite element method: Physical model building tools: ANSYS[7] OpenFOAM[6] SimScale	Behavior modeling tools: SimScale ANSYS Amesim Flexsim Carsim Unity3D[12]	Artificial Neural Networks[13] Convolutional Neural Networks [14] Deep Learning Rule model building tool: ANSYS Amesim Simulink Demo 3D Simcenter

Table 1. Summary Table of Virtual Entity Modeling Technologies and Tools mentioned earlier

4. Data

Data plays a crucial role in digital twin technology, directly affecting prediction and monitoring accuracy as well as enabling optimization and control of physical entities. High-quality and accurate data is essential for reliable and stable digital twin results. This article explores data collection and processing technologies in digital twin technology. Figure 6 briefly shows the process of data interaction during the digital twin process

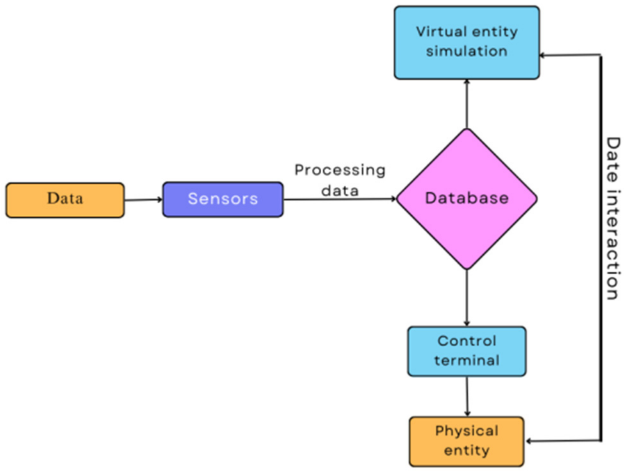

Fig. 5. The process of data interaction

4.1 Data Collection

Sensors are crucial for data acquisition in digital twin technology, monitoring physical entity states and enabling the simulation of research variables. Zhao [16] et al. trained an artificial neural network model based on collected data to establish a fishing net digital twin model, while Yang [17] et al. constructed a virtual digital space of the ocean using sensors to detect seasons, climate, and ocean currents. Data visualization methods include charts, maps, and dashboards, allowing for intuitive observation and analysis by users.

4.2 Data processing

Data collected by sensors must be processed to extract useful information, including data cleaning, analysis, and mining. Data cleaning removes duplicates, noise, and fills in missing values, while data analysis is used to identify hidden patterns and trends. Data mining utilizes machine learning and statistical methods to gain insight from data. Zhang [18]] et al. implemented an intelligent production line for automotive MEMS pressure sensors utilizing data mining, machine learning, and statistical analysis to achieve process monitoring and traceability management. Feng [19] et al. developed a gear health management method incorporating a high-fidelity digital twin model, using MMD loss in the advanced feature layer to reduce domain offset and improve deep learning model performance.

5. Communication transmission

Sensors collect raw data in a digital twin system, which requires processing to filter and store effective data. The digital twin model can simulate physical systems and provide prediction and optimization functions, while the controller enables remote monitoring and control. Digital twins enable precise management and optimization of physical systems, improving efficiency and quality. Data transmission can be categorized into two types: communication between twin objects for system stability, and between twin and external systems such as CMS, MES, and EPR.

5.1 Communication through data bus

A data bus connects various devices and components in a computer network or system to enable data transmission, often using shared transmission. Digital twins rely on data buses like LANs, WANs, and the internet for data exchange between twin models. Wang [20] et al utilized a LAN to control a robot's joints for human welding operations while transmitting welding information from the welding space to the digital twin via the same LAN. In the DT, the workpiece model is preloaded and the robot model's joint rotation reconstructed from sensing data to reconstruct motion in physical space.

5.2 Through TCP/IP protocol

TCP/IP protocol is responsible for data transmission over a network, with TCP dividing and reassembling packets and IP processing addresses. The client sends a request and the server responds through TCP, while IP ensures that packets reach their destination [21]. Pires [22] et al. connected physical assets to a virtual model using customized Java applications and Modbus TCP/IP protocol, remotely accessing robots as long as they are in the same network. A JAVA application retrieves data from the Modicon M340 PLC using Modbus TCP/IP protocol and collects real-time conveyor system data. Communication between the application and the virtual model uses remote API functionality in V-REP simulation environment for data transmission and exchange.

5.3 Through CoAP protocol

CoAP is a RESTful web application transport protocol designed for constrained nodes and networks that enables device functionality and data to become URI resources. These resources are fully integrated into the web, with low-power and low-latency communication capabilities [23]. Campolo[24]et al. used CoAP to study mobility in edge digital twin tracking MaaS applications, conducting experiments that demonstrated the request/response method allows interaction between clients and servers (IoT devices hosting resources). CoAP can also perform publish/subscribe monitoring of IoT resources by observing extensions. Requests with observation header options can be sent to CoAP resources via a Uniform Resource Identifier (URI).

5.4 Through the MQTT protocol

MQTT is a lightweight messaging protocol that uses publish subscribe operations for exchanging information between clients and servers, providing reliable connections with limited network bandwidth [25]. Mittal [26] et al. proposed creating Java agents or software robots with custom libraries to interact with digital twins and NEST cloud. The agent communicates with the twin through RabbitMQ message broker using MQTT protocol, sending commands to the NEST cloud using authentication code, PIN, and device ID from the NEST developer's API to assign tasks to the device, such as obtaining a list of devices and sending thermostat commands (e.g., setting target temperature setpoints or operating mode of HVAC).

5.5 OPC UA

OPC UA is an industrial communication standard for safe and reliable data exchange between monitoring systems, PLCs, actuators, and sensors [27]. OPC UA servers share data with clients, allowing clients to retrieve and analyze it. Redelinghuys et al. [28] proposed using Tecnomatix PS client subscription connections to OPC UA servers for data change events. PS model updates continuously reflecting physical twins' changes based on sensor changes on OPC UA server. Digital Twins use cloud to check historical information stored from IoT gateways to cloud servers, displaying new information to users as each cycle progresses.

6. Summary

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References

[1] Somers R J, Douthwaite J A, Wagg D J, et al. Digital-twin-based testing for cyber–physical systems: A systematic literature review[J]. Information and Software Technology, 2022: 107145.

[2] SIEMENS, digital twins https: //www. plm. automation. siemens. com/global/zh/our-story/glossary/digital-twin/24465. SIEMENS, Digital twin of respiratory products. https: //new. siemens. com/global/en/company/stories/industry/digitaltwin-simulation-vyairemedical. html. SIEMENS, A wind of change through digitalization. https: //new. siemens. com/global/en/markets/wind/equipment/digitalization. html.

[3] Liu X, Jiang D, Tao B, et al. A systematic review of digital twin about physical entities, virtual models, twin data, and applications[J]. Advanced Engineering Informatics, 2023, 55: 101876.

[4] Tao F, Xiao B, Qi Q, et al. Digital twin modeling[J]. Journal of Manufacturing Systems, 2022, 64: 372-389.

[5] Jiang F, Ma L, Broyd T, et al. Building demolition estimation in urban road widening projects using as-is BIM models[J]. Automation in Construction, 2022, 144: 104601.

[6] Cao Y, Tang X, Gaidai O, et al. Digital twin real time monitoring method of turbine blade performance based on numerical simulation[J]. Ocean Engineering, 2022, 263: 112347.

[7] Digital twin real time monitoring method of turbine blade performance based on numerical simulation

[8] Digital twin of an industrial workstation: A novel method of an auto-labeled data generator using virtual reality for human action recognition in the context of human–robot collaboration

[9] Gao S, He B, Yu F, et al. An abnormal motion condition monitoring method based on the dynamic model and complex network for AUV[J]. Ocean Engineering, 2021, 237: 109472.

[10] Li H, Yang D, Cao H, et al. Data-driven hybrid petri-net based energy consumption behaviour modelling for digital twin of energy-efficient manufacturing system[J]. Energy, 2022, 239: 122178.

[11] Quinn A, Saxby D J, Yang F, et al. A digital twin framework for robust control of robotic-biological systems[J]. Journal of Biomechanics, 2023: 111557.
[12] White G, Zink A, CodecáL, et al. A digital twin smart city for citizen feedback[J]. Cities, 2021, 110: 103064.
[13] White G, Zink A, CodecáL, et al. A digital twin smart city for citizen feedback[J]. Cities, 2021, 110: 103064.
[14] Hu W, Wang C, Liu F, et al. A grasps-generation-and-selection convolutional neural network for a digital twin of intelligent robotic grasping [J]. Robotics and Computer-Integrated Manufacturing, 2022, 77: 102371.
[15] Liu Y, Xu H, Liu D, et al. A digital twin-based sim-to-real transfer for deep reinforcement learning-enabled industrial robot grasping[J]. Robotics and Computer-Integrated Manufacturing, 2022, 78: 102365.
[16] Zhao Y P, Lian L, Bi C W, et al. Digital twin for rapid damage detection of a fixed net panel in the sea [J]. Computers and Electronics in Agriculture, 2022, 200: 107247.
[17] Yang J, Xi M, Wen J, et al. A digital twins enabled underwater intelligent internet vehicle path planning system via reinforcement learning and edge computing [J]. Digital Communications and Networks, 2022.
[18] Zhang Q, Shen S, Li H, et al. Digital twin-driven intelligent production line for automotive MEMS pressure sensors [J]. Advanced Engineering Informatics, 2022, 54: 101779.
[19] Feng K, Ji J C, Zhang Y, et al. Digital twin-driven intelligent assessment of gear surface degradation [J]. Mechanical Systems and Signal Processing, 2023, 186: 109896.
[20] Wang Q, Jiao W, Wang P, et al. Digital twin for human-robot interactive welding and welder behavior analysis[J]. IEEE/CAA Journal of Automatica Sinica, 2020, 8(2): 334-343.
[21] Jain A, Bhullar S. Network performance evaluation of smart distribution systems using smart meters with TCP/IP communication protocol [J]. Energy Reports, 2022, 8: 19-34.
[22] Pires F, Melo V, Almeida J, et al. Digital twin experiments focusing virtualisation, connectivity and real-time monitoring[C]//2020 IEEE conference on industrial cyberphysical systems (ICPS). IEEE, 2020, 1: 309-314.
[23] Rodrigues L, Guerreiro J, Correia N. Resource design in federated sensor networks using RELOAD/CoAP overlay architectures [J]. Computer Communications, 2021, 179: 11-21.
[24] Campolo C, Genovese G, Molinaro A, et al. Digital twins at the edge to track mobility for MaaS applications[C]//2020 IEEE/ACM 24th International Symposium on Distributed Simulation and Real Time Applications (DS-RT). IEEE, 2020: 1-6.
[25] Shilpa V, Vidya A, Pattar S. MQTT based secure transport layer communication for mutual authentication in IoT network [J]. Global Transitions Proceedings, 2022, 3(1): 60-66.
[26] Mittal S, Tolk A, Pyles A, et al. Digital twin modeling, co-simulation and cyber use-case inclusion methodology for IoT systems[C]//2019 Winter Simulation Conference (WSC). IEEE, 2019: 2653-2664.
[27] Gilles O, Pérez D G, Brameret P A, et al. Securing IIoT communications using OPC UA PubSub and Trusted Platform Modules[J]. Journal of Systems Architecture, 2023, 134: 102797.
[28] Redelinghuys A J H, Basson A H, Kruger K. A six-layer architecture for the digital twin: a manufacturing case study implementation[J]. Journal of Intelligent Manufacturing, 2020, 31: 1383-1402.
[29] Jia W, Wang W, Zhang Z. From simple digital twin to complex digital twin part II: Multi-scenario applications of digital twin shop floor[J]. Advanced Engineering Informatics, 2023, 56: 101915.

[30] Bevilacqua M, Bottani E, Ciarapica F E, et al. Digital twin reference model development to prevent operators' risk in process plants[J]. Sustainability, 2020, 12(3): 1088.