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Multi-Domain Ubiquitous Digital Twin Model for Information Management of Complex Infrastructure System

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Abstract

Digital twin reflects multi-physics and multi-scale attributes and functions of facilities composed by multiple components with various usages, technologies, and forms. Transdisciplinary stakeholders are always involved in the long-term and cross-scene management of IoT and digital twin-enabled smart infrastructures and facilities. The intensive interactions among stakeholders often cause conflicts due to the variations in experience, knowledge, and interests. Moreover, with the change propagation of digital twins, cyber-physical resources can't be efficiently and consistently established, connected, and utilized with multi-domain information through selective simplification and structured methods. This paper proposes a Ubiquitous Digital Twin (UDT) model for the information management of complex infrastructure systems based on Domain-Driven Design (DDD). To achieve the unified and structured description, six domains are deployed in UDT model with sequential or parallel tuples for shared understanding of overall system framework or specific functional modules. Three cases of one smart nuclear plant management scenario are hierarchically instantiated to evaluate the UDT model.

Keywords: Digital Twin; Ubiquitous Model; Information Management; Complex Infrastructure System; Transdisciplinary Management; Domain-Driven Design (DDD)

1. Introduction

Information management of huge, complex, and composite infrastructure system with a series processing stages, such as design, construction, operation, and maintenance, is more and more required in current construction industry [6,20,42]. The increasing complexity dealing with the information management for complex infrastructure system is caused by the number of items interconnected through the intricate dependencies and constraints, always filled with heterogeneous data, transdisciplinary functional demands, and composite structures [9,18]. A functional infrastructure such as a nuclear plant is composed of multiple components with differentiated functions, technologies, and forms, which requires transdisciplinary stakeholders to process cross-domain knowledge in a multi-subproject condition [8,28,35].

Cutting-edge Information Technology (IT), such as Internet of Thing (IoT), Artificial Intelligence (AI), Virtual Reality (VR), and cloud computing, are widely applied for the digital transformation of complex infrastructures, generating massive digital twins for the corresponding information management [21,25,32,45,46]. Digital twin can reflect both semantic and geometric attributes and functions of the infrastructures through virtual models and data on a real-time basis [15,36,43], which can realize the cyber-physical convergence and interoperation [29,37]. It provides an approach to monitor all the activities in the infrastructures and automatically optimize the performance based on simulation or prediction results through digital twins [14,19,40]. Multiple business domains involved in information management of complex infrastructures with digital twins need seamless collaborations with each other, such as design, construction, operation, and maintenance. For some technical domains, structure design, model drawing, computer hardware and software development, are also necessary to be integrated into complex infrastructure management, some of which are complicated due to the large number of activities, stakeholders, teams, and organizations with interwoven relationships [41].

Selective simplification and structuring of domain information can be achieved through a digital twin reference model for the information management of complex infrastructure systems, which is composited with multiple components of transdisciplinary functions, technologies, and forms involving trans-disciplinary stakeholders [2,12]. A ubiquitous model enables transdisciplinary stakeholders to understand the meaning and relationship of various domains involved in the information management process, and focus on the core issues in each domain [1,2,24]. However, several challenges still exist in digital twin-supported complex infrastructure management. Firstly, there is a lack of domain-driven models to describe and couple the multiple domains of digital twins during smart infrastructure management [23,24]. Digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of an object or an activity to mirror the corresponding physical twin. Thus, cross-domain collaboration is necessary and important, while transdisciplinary stakeholders and teams must provide their own expertise, knowledge, and resources for the cross-domain collaborative works [43]. However, such intensive interactions often cause conflicts due to the variations in transdisciplinary experience, knowledge, organizational or personal interest, professional loyalty, and interpretation of the project purpose [8]. For example, under the treatment of emergency events, the multi-source heterogeneous sensing data and business operation data based on digital twins cannot be seamlessly connected and coordinated, resulting in the inability to support the closed-loop data flow in the same business domain or scenario [10]. The IoT-based warning metadata, key resource positioning data, spatial model data, and processing operation data cannot be connected and cooperated with each other, so it is difficult to support the closed-loop prediction before the event, comprehensive decision-making in the process, and post reanalysis after the emergency. In addition, long-term-cycle management of digital twins is also a dynamic process with the change propagation, where an alteration of one digital twin always causes the changes in other twins and even the whole system, forming a complex change network. Thus, it's also a potential risk of ambiguity or error caused by compounded domains in the transdisciplinary information management due to the lack of a shared understanding of the overall system framework or specific functional modules.

Furthermore, multiple scenes with transdisciplinary functionalities, spatial-temporal characteristics, and internal attributes are digitalized in long-term-cycle infrastructure management using different platforms to generate cross-scene digital twins [33]. From the perspective of compatibility, the semantics and syntax of digital twins on different scenes and models are not unified, and most of the relevant platforms form their own closed-loop software ecosystems, resulting in poor reusability of digital twin tools, models, and platforms. From the interactivity level, different digital twin application scenarios are composed of different mechanisms and decision-making models, and there is a lack of attention for the integration tools and models in the interaction and cooperation of multi-domain and cross-scene digital twins. Currently, different digitalization models and methods are applied to establish digital twins in different scenes with low reuse rate and high cost. Multi-domain and cross-scene cyber-physical resources involved in the infrastructure management cannot be efficiently and consistently established, connected, and utilized through a unified description method. Thus, a ubiquitous digital twin model with enhanced utilization rate is needed for the selective simplified and structured description of different scenes with different spatial scales, progress stages, and functional emphases in the information management of complex infrastructure systems.

To address the above challenges, the objectives of this paper are as follows: (1) to propose a ubiquitous digital twin model containing transdisciplinary domains to achieve the unified description for the information management of complex infrastructure systems; (2) to develop a roadmap for the design and development of interoperability among digital twins in cross-scene situations; and (3) to conduct the proposed ubiquitous digital twin model in a hierarchical scenario of smart infrastructure to determine the varied emphases on differentiated stages with differentiated scopes. To achieve the mentioned objectives, this paper proposes a Ubiquitous Digital Twin Model (UDT) for the information management of complex infrastructure systems based on Domain-Driven Design (DDD). DDD is the approach to match the structure and language of software design, development, deployment, and implementation with the business domain for the creative collaboration between technical and business experts [4]. Combined with digital twin, DDD relies on trans-disciplinary, multi-variable, multi-scale, and multi-probability concepts to express knowledge about the business domain and transfers the project to focus on the key domain [47]. UDT model can provide a unified reference specification and description approach for the information management of complex infrastructure systems with cross-domain knowledge requirements among trans-disciplinary stakeholders in a multi-subproject situation. Firstly, this paper introduces a ubiquitous digital twin model with six domains (e.g. geometry, structure, data, interaction, application, and timespan) for the digitalized complex infrastructures. Each domain has sequential or parallel tuples for the description of differentiated digital twins. Secondly, a roadmap with Unified Modelling Language (UML) is proposed for the collaborative design, development, deployment, and implementation of complex infrastructure management among trans-disciplinary stakeholders with cross-domain knowledge. Thirdly, three cases (e.g. water pump for design and deployment, smart prefabrication construction for production and construction, and integrated nuclear plant for operation and maintenance) for the transdisciplinary management of a smart nuclear plant with IoT-enabled self-detection and AI-enabled self-optimization services are hierarchically instantiated based on the proposed UDT model.

The rest of this paper is organized as follows. Section 2 is the literature review of digital twin model used in design, development, and operation management. Section 3 presents the UDT model for the information management of complex infrastructure systems. Section 4 instantiates three cases in a IoT/AI-enabled smart nuclear plant scenario based on UDT model. Section 5 discusses the conclusion and future research.

2. Related Works

Infrastructure system involves transdisciplinary business and technical domains aiming to improve the functionality and stability of the buildings and infrastructures [10]. The information management of complex infrastructure systems aims to provide efficient and accurate object-oriented information and a collaborative mechanism for creation, organization, and dissemination of knowledge across multiple domains for smart facilities [3,26]. Data, information, and knowledge are integrated in a timely manner during the infrastructure lifecycle from the project planning, design, construction, and maintenance for decision support [17,33]. Emerging technologies, such as Internet of Thing (IoT), Artificial Intelligence (AI), Augmented Reality (AR), cloud computing, and machine learning, are combined with Building Information Modeling (BIM), paving the way for the digital twins of multi-domain components in smart infrastructure management [5,17,30,44]. Digital twin can shift current paradigm towards the digital transformation in Construction 4.0 era with real-time monitoring, dynamic control, and intelligent decision-making services during the information management of complex infrastructure systems [11,16,34].

Reference model of digital twin provides the method to establish the elements and cyber-physical interoperation in information management system [1]. Five-dimension digital twin model has been proposed for the dynamic mapping of geometry, physics, behavior, and rule of objects in Prognostics and Health Management (PHM), which consists of physical entity model, virtual equipment model, service model, and DT data model [39]. This DT model has provided the generic and strategic basis for the further development of digital twin-enabled management and cyber-physical system [38]. For digital twin modelling method, there are some inspired papers for the management of complex digital twins. For example, a digital twin architecture reference model analyzes the key CPS properties about computing, control, and communication with hybrid interaction for Cloud-based Cyber-Physical Systems [2]. Hybrid cyber-physical model is described using finite state machine, Bayesian network-based context model and fuzzy logic-based controller model are analyzed for dynamic control module. However, this reference model mainly focuses on the 3C concept of CPS without more insights for the whole picture of digital twin system. Moreover, an architecture reference model Digital Twin as a Service (DTaaS) integrates and hierarchies four layers (e.g. Digital Model, Digital Shadow, Digital Twin, and Digital Predictive) inspired by the DIKW (e.g. Data, Information, Knowledge, and Wisdom) model to support different integration levels though an agile process [1]. Biomimicry principles also inspires some researchers to develop digital twin modelling method. A multi-physics digital twin model is constructed with three sub-models (e.g. geometry model, behavior model, and process model), which can interact with each other and integrates to match different physical processes [24]. Three key characteristics from this model are valuable for further digital twin model development, including multi-physics, dynamics, and integration. Skin Model Shapes concept have been utilized for digital twin representation and abstraction models with several properties, including scalability, interoperability, expansibility, and fidelity [31]. These properties extents the geometry and physics dimensions from previously proposed digital twin model and also points out the importance of interaction of different twins.

However, several research gaps are identified for the cross-scene and multi-domain digital twin modeling in information management of complex infrastructure systems. Firstly, studies are lacked about the domain-driven model for complex infrastructure management among trans-disciplinary stakeholders with cross-domain knowledge. Secondly, a ubiquitous model with improved utilization rate is needed for the design, development, and operation of digital twins in different scenes with different spatial scales, progress stages, and functional emphases during smart infrastructure management. Thirdly, an industrial scenario or case study is missing for the practical studies of multi-domain and cross-scene digital twins for the management IoT/AI-enabled smart infrastructure, such as a smart nuclear plant. Therefore, this paper conducts the related works from the perspective of selective simplification and structural description methods for cross-scene and multi-domain digital twins in the digitalized complex infrastructure.

3. Multi-Domain Ubiquitous Digital Twin (UDT) Model

Ubiquitous Digital Twin (UDT) model is proposed for collaborative design, development, and deployment for in the information management of complex infrastructure systems among transdisciplinary stakeholders with cross-domain knowledge. As shown in Fig. 1, UDT model consists of tuples of six domains, including three sequential domains (e.g. geometry, structure, and data) and three parallel domains (e.g. interaction, application, and timespan), described as follows:

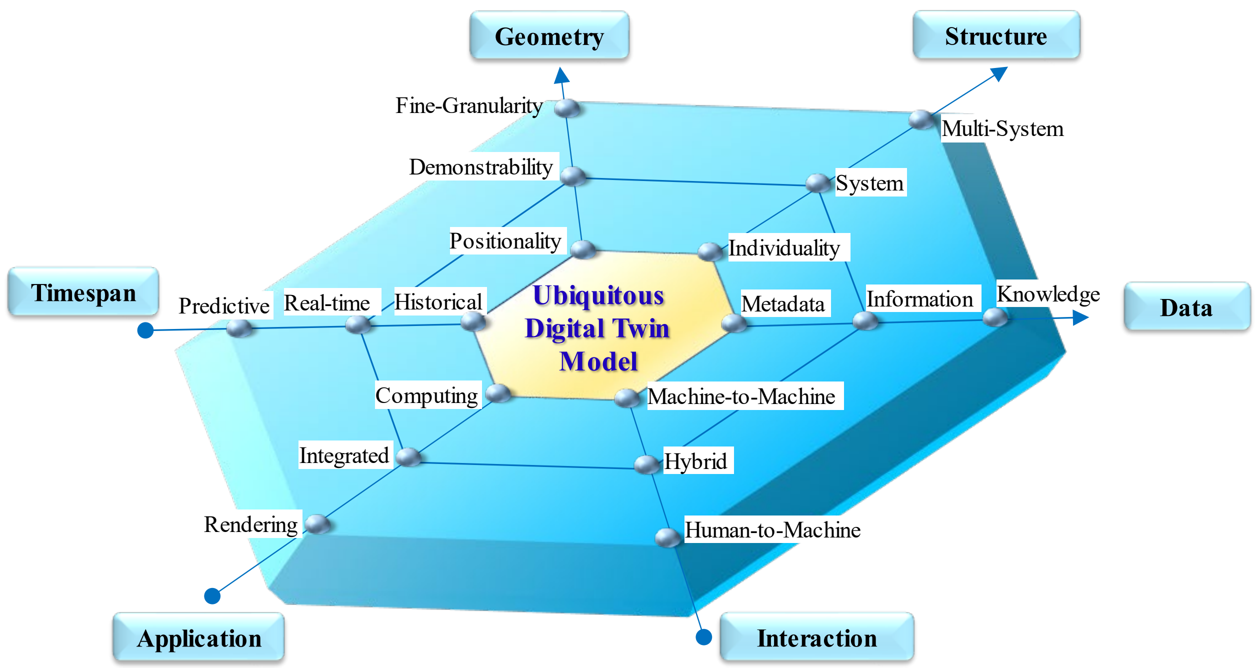

Fig. 1. Multi-domain Ubiquitous Digital Twin (UDT) model

Definition 1: *The formalized definition of UDT model is a six-tuple* $UDT = \{G, S, D, I, A, T\}$, *where:*

- G is the tuple of *geometry* domain, which represents the visualization attributes (e.g. positions, sizes, and shapes) of digital twins in complex infrastructure systems;
- S is the tuple of *structure* domain, which represents the spatial and functional relationships among different components in complex infrastructure systems;
- D is the tuple of *data* domain, which contains qualitative or quantitative variables to semantically describe the properties or behaviors of digital twins;

- I is the tuple of *interaction* domain, which involves active actions with responses where two or more components effect upon one another, aiming to achieve a unified functional objective;
- A is the tuple of *application* domain, which contains specific activities conducted through the digital twin system to fulfill the requirements of stakeholders;
- T is the tuple of *timespan* domain, which contains accumulated time points processed by digital twin system.

Definition 2: *The geometry domain is described as a five-tuple* $G = \{G_P, G_D, G_F, \varphi_G, \delta_G\}$*, where:*

- G_P is *positionality* set, which means that digital twins only have three-dimensional spatial coordinates without specific shapes and sizes;
- G_D is *demonstrability* set, which means that digital twins are processed with specific sizes, shapes, and positions that can be virtually identified, but the precise item-level characteristics are limited;
- G_F is *fine-granularity* set, which means that digital twins contain multiple fine elements for elaborate item-level mapping and characterizing under the requirements of high-precision monitoring and dynamic control;
- φ_G is morphological function to transfer *positionality* into *demonstrability*, $\varphi_G: G_P \rightarrow G_D$;
- δ_G is fine-graining function to transfer *demonstrability* into *fine-granularity*, $\delta_G: G_D \rightarrow G_F$.

Definition 3: *The structure domain is described as a six-tuple* $S = \{S_I, S_S, S_{MS}, R, H_S, NH_S\}$*, where:*

- S_I is *individuality* set, which means that digital twins only have signal or limited components without complex spatial and functional correlations;
- S_S is *system* set, which is a closed-loop set of interacted and interrelated components that work together under specific rules;
- S_{MS} is *multi-system* set, which means that multiple subsystems with interdependent functional responsibilities collaborate together through multi-directional interoperations;
- R is the set of relationships r_{ij} between components or subsystems consisting in information management, $r_{ij} \in R$;

- H_S is the matrix of hierarchical relationship between the parent class and subclass, such as components with their control system ($H_S \subseteq S_I \times S_S$), subsystems with their central system ($H_S \subseteq S_S \times S_M$), $H_S = \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix}$;
- NH_S is the matrix of relationship without hierarchical connections among subsystems and components, such as components with components, subsystems with subsystems, $NH_S = \begin{bmatrix} r_{11} & \cdots & r_{1v} \\ \vdots & \ddots & \vdots \\ r_{u1} & \cdots & r_{uv} \end{bmatrix}$.

Definition 4: *The data domain is described as a five-tuple* $D = \{D_M, D_I, D_K, \mu_D, \nu_D\}$*, where:*

- D_M is *metadata* set, which is the raw fact with incomprehensible meaning and redundant symbols;
- D_I is *information* set, which is the filtered, integrated, and arranged metadata without uncertainty and redundancy;
- D_K is *knowledge* set, which is the systematic understanding of the complex infrastructure systems after concise and global summary of historical data and information;
- μ_D is the transfer function to refine the information from integrated metadata, $\mu_D: \sum_{i=1}^{n} D_M(i) \to D_I(j)$;
- ν_D is the transfer function to refine the knowledge from integrated information, $\nu_D: \sum_{j=1}^{m} D_I(j) \to D_K(r)$.

Definition 5: *The interaction domain is described as a three-tuple* $I = \{I_{M2M}, I_{H2M}, I_{HI}\}$*, where:*

- I_{M2M} is *Machine-to-Machine (M2M)* set, which means that manufacturing and maintenance are mainly executed by smart machines with automatic interaction based on AI algorithm;
- I_{H2M} is *Human-to-Machine (H2M)* set, which means that human and machines collaborate to execute tasks;
- I_{HI} is *Hybrid Interaction (HI)* set, which means that M2M and H2M couple together during information management of complex infrastructure systems to establish the interoperation network among various resources.

Definition 6: *The application domain is described as a three-tuple* $A = \{a_C, a_R, a_{IA}\}$*, where:*

- a_C is *computing* set, which means that the infrastructure system is mainly applied for the numerical analysis of parameters such as status, event, and progress with input and output of continuous or discrete data;
- a_R is *rendering* set, which means that the infrastructure system is mainly used for the visualization of basic status and progress of specific object, resource, and system;
- a_{IA} is *integrated application* set, which means that the infrastructure system applies both computing and rendering for the analysis and monitoring in infrastructure management.

Definition 7: *The timespan domain is described as a four-tuple* $T = \{T_H, T_R, T_P, \omega_T\}$*, where:*

- T_H is *historical* set, which means that imitation of the various parameters (e.g. status, event, and progress) of construction or maintenance using historical data combined with AI algorithm;
- T_R is *real-time* set, which means that the response times of interaction can be guaranteed within a short time window. A real-time digital twin-enabled infrastructure system can output responses from digital space in defined time stamps and fast enough to affect the physical space where events occur;
- T_P is *predictive* set, which means that key parameters can be inferred in advance through AI algorithm based on big data (real-time & historical) for dynamic adjustment of planning, scheduling, and execution or disturbance event during information management;
- ω_T is AI algorithm to predict infrastructure management parameters or disturbance events based on big data, ω_T: $[T_R + \sum_{i=1}^{n} T_H(i)] \rightarrow T_P$.

4. UDT-based Instantiations for Information Management of Complex Infrastructure System

In this section, UDT model is applied for digital twin-enabled information management of smart prefabricated nuclear plant *HUALONG One* in *Fuqing*, *Fuzhou Province*, as shown in Fig. 2. Three digital twin cases including two sub-scenes (water pump, prefabricated construction) and one integrated huge smart infrastructure (nuclear plant) are instantiated with differentiated scales and emphasis. Hexagon radar chart is used to present the configuration in each domain, and class diagram is used to explain the interoperations among different domains.

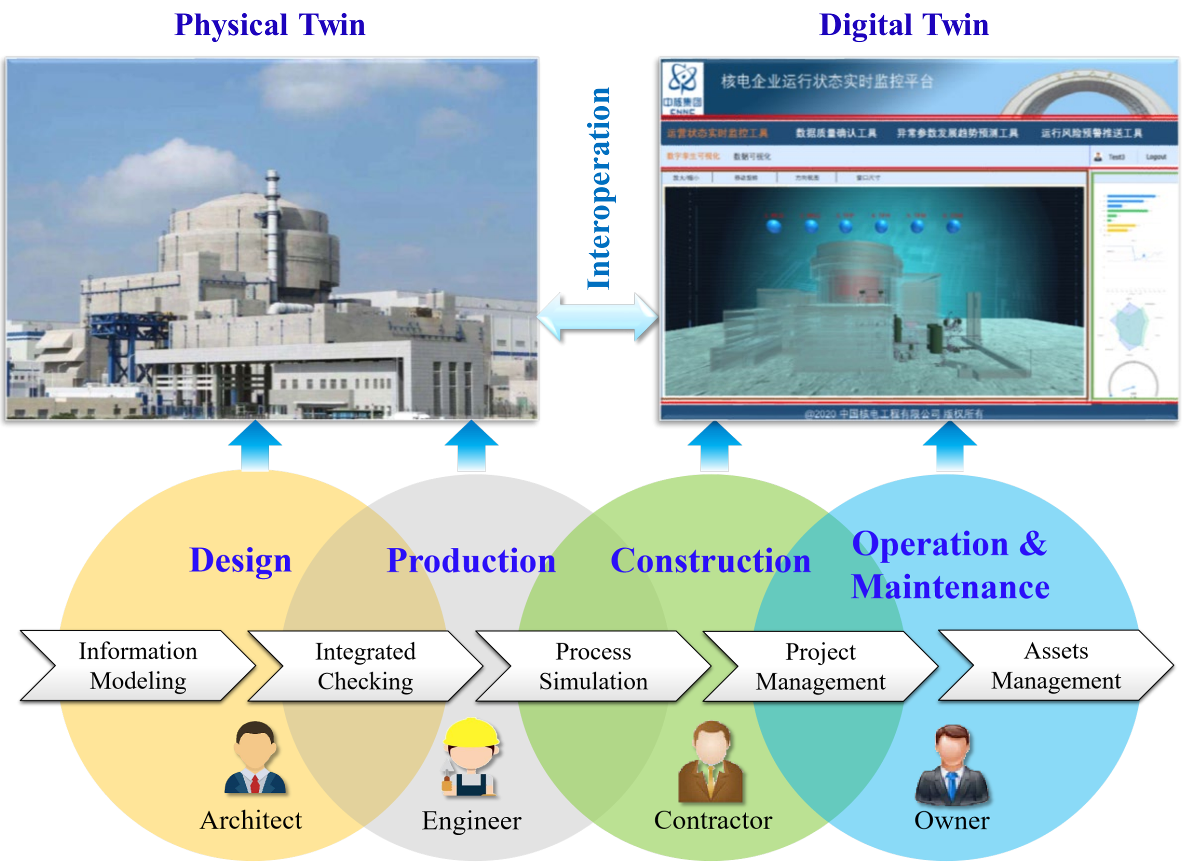

Fig. 2. Digital twin-enabled information management of smart prefabricated nuclear plant *HUALONG One*

4.1 Instantiation 1 (Design and Deployment Phase): Water Pump

Water pump *Fuqing-5.6 units (Series A)* is a typical equipment in the cooling system of *HUALONG* nuclear plant. This Instantiation 1 concerns the design and deployment phases of a subcomponent in smart infrastructure management. The tuple of UDT model for water pump is described in formula (1), the interactive relationship is shown in the class diagram in Fig. 3.

Instantiation 1: $UDT_{WaterPump} = \{G_F, S_I, D_I, I_{M2M}, T_R, A_R\}$ (1)

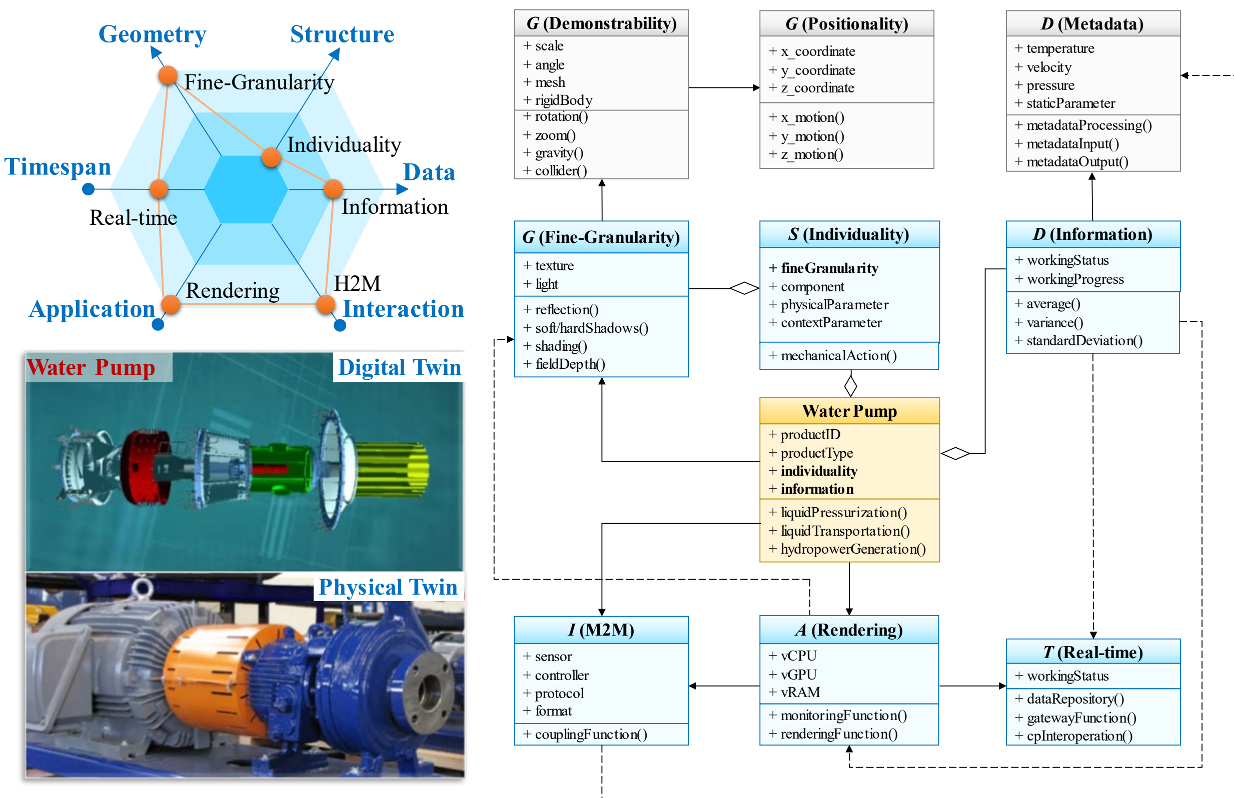

Fig. 3. UDT-based instantiation for water pump in smart nuclear plant

(1-1) *Fine-granularity* G_F is a high-polymerization set in the sequential domain *geometry* for water pump digital twin, which is progressively inherited from *demonstrability* and *positionality*. Water pump is a key product in cooling system with highly concretized virtual model and multi-measurement points reflection. The main attributes of *positionality* are *(x, y, z)* coordinates, while the key method is the spatial mobility of digital twins. *Demonstrability* inherits spatial coordinates from *positionality*, with the newly assigned figuration attributes (e.g. scale and angle) and physicalization attributes (e.g. mesh and rigidbody). Figuration means that digital twins only have geometric appearance without physical properties. Physicalization means that digital twins occupy specific density and mass which is the basis for physical behaviors, such as elastic collision and free fall. Methods of rotation and zoom are also applied to support the real-time monitoring with flexibility. *Fine-granularity* inherits the basic attributes of *demonstrability* with more assigned refined attributes (e.g. texture and light) and rendering methods (e.g. reflection, soft/hard shadows, shading, and depth of field) to generate high-fidelity digital twin models for detail checking and scene rendering, as shown in Fig. 4 (a). *Fine-granularity* as a basic characteristic for high-fidelity model rendering is relied by *application* and also associated with the core datatable *waterPump* for full-lifecycle visualization of digital twins.

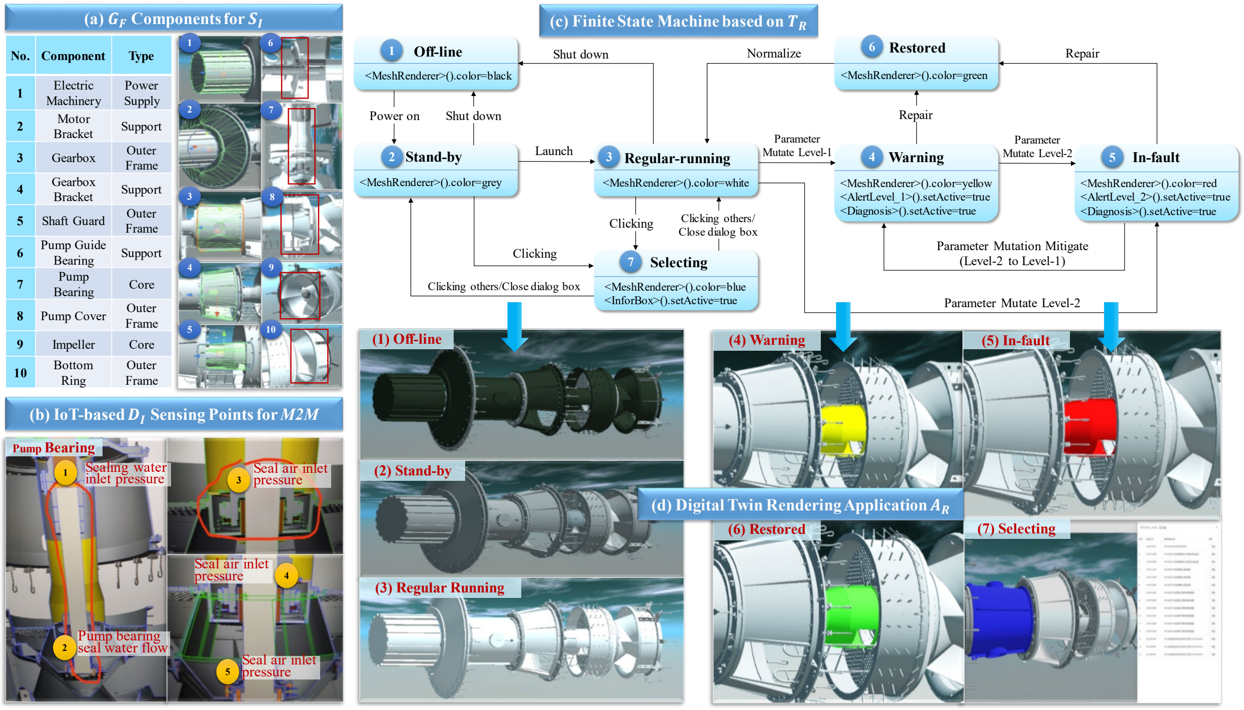

Fig. 4. (a) Fine-granularity structural components. (b) IoT-based measurement points. (c) Finite State Machine (FSM) for real-time status.

(1-2) *Individuality* S_I is a high-atomicity monomeric set in the sequential domain *structure* of water pump. Water pump is composed by several atomic components, such as electric machinery, gear box, and pump bearing, as shown in Fig. 4 (a). Physical parameters and context parameters are assigned to the structural components to support semantic digital twins. Constraint rule is also applied to standard the operation mode of water pump based on both self-state and context-state limitations. Mechanical action is the key method for *individuality* of water pump such as the rotation of impeller. *Geometry* is aggregated into *structure* to concretize the structural component organically, while *structure* is aggregated into the core datatable *waterPump* to assign visibility and interactivity to digital twins.

(1-3) *Information* D_I works to realize the semantic digital twin for water pump. *Metadata* contains real-time dynamic data and static data. Dynamic data are collected by sensors on a real-time basis, including four measured parameters: temperature, humidity, velocity, and pressure, as shown in

Fig. 4 (b). Static data are the initial input values, such as inlet/outlet section areas and routine power. *Information* is associated from *metadata* with more intuitive attributes (e.g. working status and working progress) after integration and processing of metadata. Pump flow Q_τ and water head H_τ are two KPIs modeled as $Q_\tau = \frac{1}{2}(v_I^\tau \cdot A_I + v_O^\tau \cdot A_O)$ and $H_\tau = z_O + \frac{p_O^\tau}{\gamma} + \frac{{v_O^\tau}^2}{2g} - (z_I + \frac{p_I^\tau}{\gamma} + \frac{{v_I^\tau}^2}{2g})$, which are instantiated from the data processing function $\mu_D: \sum_{i=1}^{n} D_M(i) \to D_I(j)$ in Definition 4 to refine specific information from metadata. Information $D_I(j)$ (e.g. Q_τ and H_τ) are calculated by the collected metadata $D_M(i)$ at real time point τ, which are consisting of dynamic data (e.g. inlet velocity v_I^τ, outlet velocity v_O^τ, inlet pressure p_I^τ, and outlet pressure p_O^τ) and static data (e.g. inlet section area A_I, outlet section area A_O, inlet altitude z_I, and outlet altitude z_O). *Information* is aggregated into core datatable *waterPump* as the key tool to generate semantic digital twins, which is relied by *timespan* and *application* domains due to the reflection from physical space to digital space (P2D) and also the control feedback from digital space to physical space (D2P).

(1-4) *Machine-to-Machine (M2M)* I_{M2M} is mainly applied for the parallel domain *interaction* of water pump. Several kinds of sensors are deployed on the core structural points (e.g. electric machinery, bearing, and impeller) to collect the measurement parameters (e.g. temperature, humidity, velocity, and pressure) on a real-time basis. One instance of the sensor deployment in core component pump bearing is shown in Fig. 4 (b). Controller is applied to adjust the operating parameters such as impeller velocity based on the real-time sensing data. Mobile Gateway Operation System (MGOS), as a simple-to-use and easy-to-deploy lightweight middleware for real-time interoperation, is used to manage digital twins in a uniform protocol standard through wireless network [22]. All the smart components are organically coupled together to support the *rendering application*, also serve as the physical fundamentals for *waterPump*.

(1-5) *Real-time* T_R is the set in parallel domain *timespan* in water pump. The working status and progress can be visualized in digital twin model cooperated with updating information in digital Kanban with a limited time latency. T_R is relied on the real-time cyber-physical interoperation through sensing data (P2D) and control data (D2P). Real-time statuses of components in water pump digital twin are driven by real-time metadata, described as {*off-line*, *stand-by*, *regular-running*, *warning*, *in-fault*, *restored*, *selecting*}. Finite State Machine (FSM) is applied to show the state transition relationship of real-time statuses, as shown in Fig. 3 (c). The FSM of real-time status of water pump is modeled as formula (2):

$$T_R = \{S, \Gamma, \xi, s_O, s_F\} \tag{2}$$

where S is a finite and non-empty set of states $S = \{s_1, s_2, \ldots, s_n\}$, Γ is the set of potential events in water pump digital twin $\Gamma = \{e_1, e_2, \ldots, e_n\}$, ξ is the state-transition function, $\xi: S \times \Gamma \rightarrow S$, s_O is the initial state and s_F is the final state of one component. Differentiated colors are assigned for components to indicate differentiated real-time statuses. High level parameter mutation will trigger the in-fault status for urgent diagnosis, and lower level parameter mutation will lead to warning status to remind mangers for checking. Each component can be selected to monitor the real-time status and check the basic attributes.

(1-6) *Rendering* A_R is the key *application* associated with the core data table *waterPump* to provide digital twin-enabled smart services for various users. Rendering also named image synthesis is the function to generate a photorealistic or non-photorealistic images from 3D models to provide real-time monitoring services with high-fidelity visualization. A_R is mainly influenced by GPU of digital twin system. Virtual models are established through CAD software (e.g. UG, Solidworks, and Creo) and imported into game engines (e.g. Unity 3D and Unreal Engine) to develop digital twin functions, such as camera moving, response events, and simulated activities. Stand-alone digital twin is transferred into JavaScript through Web Graphics Library (WebGL) and be uploaded to the web-based information management system [16]. The working status and progress of water pump are visualized based on the processed information. Real-time data collected by IoT devices is uploaded and stored in the central database. The corresponding data is visualized in digital twins, and control orders are sent to corresponding physical objects for real-time interoperation.

4.2 Instantiation 2 (Construction Phase): Prefabricated Construction

This Instantiation 2 focuses on the construction stages during information management of complex infrastructure systems. The construction of smart prefabricated nuclear plant has three phases: component production, component logistics, and on-site assembly. The UDT model for prefabrication construction are described in formula (3), and the relationship of several domains is shown in the class diagram in Fig. 5.

Instantiation 2: $UDT_{SMT-SF} = \{G_D, S_S, D_I, I_{H2M}, A_C, T_H\}$ (3)

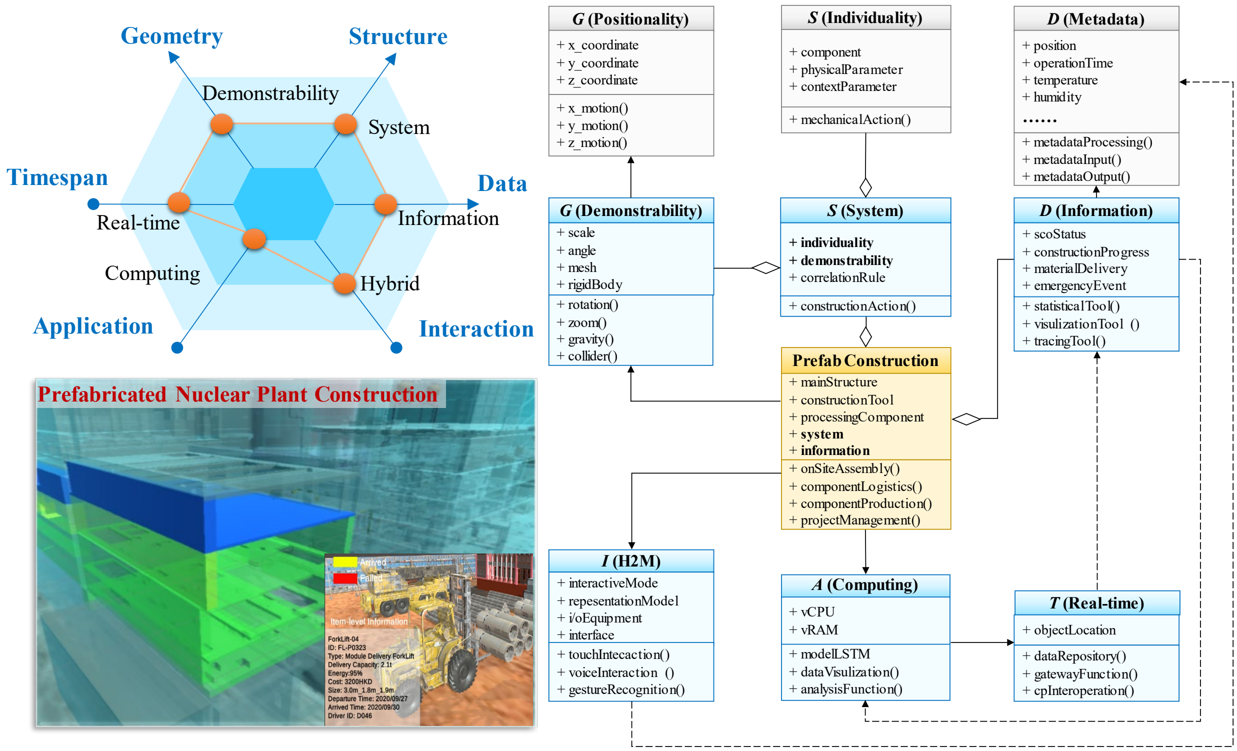

Fig. 5. UDT-based instantiation for smart prefabrication construction of nuclear plant

(2-1) *Demonstrability* G_D is a middle-polymerization set in *geometry* for digital twins of smart prefabricated construction. *Positionality* with spatial properties and mobility methods in *(x,y,z)* coordinates is associated with *demonstrability*. Figuration attributes (e.g. scale and angle) and physicalization attributes (e.g. mesh and rigidbody) are assigned to *demonstrability* to provide physical properties. Demonstrative methods (e.g. rotation, zoom, gravity, and collider) are assigned to the Smart Construction Objects (SCOs) to achieve the operability for real-time monitoring. *Demonstrability* as a key enabler for rendering is aggregated into *system* and associated with the core datatable *prefabConstruction* for visualization.

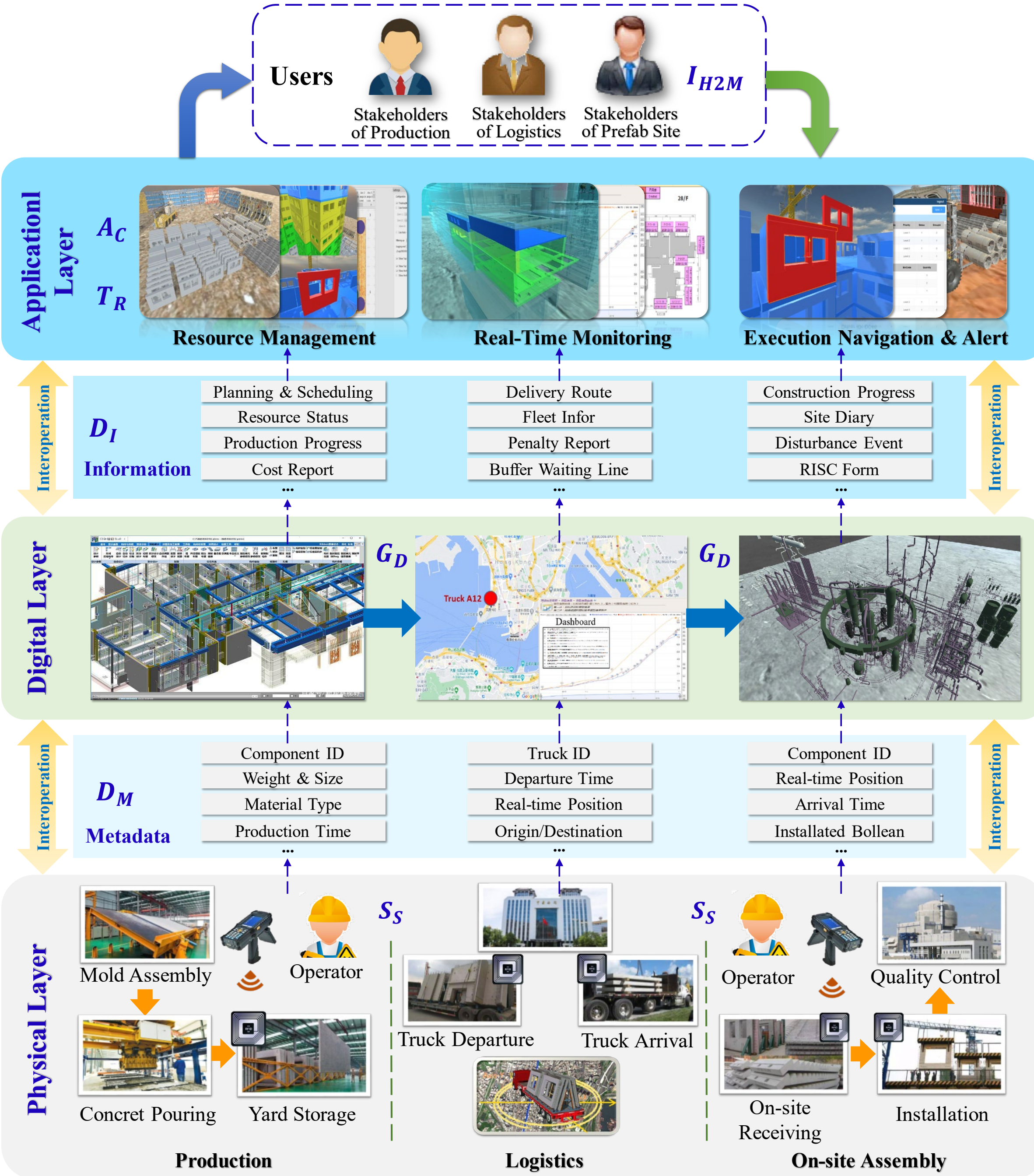

Fig. 6. Framework of information management system for prefabrication construction of smart nuclear plant

(2-2) *System* S_S is a middle-polymerization set in *system* domain. The framework of digital twin-enabled information management system for prefabrication construction of nuclear plant is shown in Fig. 6. Prefabricated construction of smart nuclear plant has three main phases: component production, component logistics, and on-site assembly. Each phase also has several sub stages about fixed and sequenced operations. Prefabricated construction can be simulated as a queuing system with one channel and multiple servers and phases in series to process a set of prefabricated components. Prefabricated component C_i delivery is represented through spatial-temporal trajectory $Tra(C_i)$ consisting of *n* phases P_j in smart prefabrication supplychain, which is modeled as formula (4):

$$Tra(C_i) = P_1 \xRightarrow{\langle M_1, W_1, T_{out}^1, T_{in}^2 \rangle} \dots \xRightarrow{\langle M_{j-1}, W_w, T_{out}^{j-1}, T_{in}^j \rangle} P_j \xRightarrow{\langle M_j, W_w, T_{out}^j, T_{in}^{j+1} \rangle} \dots \xRightarrow{\langle M_n, W_w, T_{out}^{n-1}, T_{in}^n \rangle} P_n \tag{4}$$

where M_j is the machine *j* in the corresponding phase, W_w is the related operator, T_{out}^j and T_{in}^{j+1} represent the time stamps when prefabricated components are delivered from phase *j* and enter into phase *j+1*. In this construction system, non-hierarchical relationship about construction resources is common. For instance, during component logistics phase, several trucks are assigned to delivery specific components to the construction site. The delivery sequence is predefined to cooperate with the installation operation sequence during on-site assembly. The non-hierarchical relationship among truck M_j and prefabricated component C_i can be described as formula (5), where $r_{ij} = -1$ means that C_i is not assigned to truck M_j, $r_{ij} = 0$ means that the assignment relationship hasn't been determined at the current time point, and $r_{ij} = 1$ means that C_i is assigned to truck M_j for delivery.

$$NH_S(LogisM\_C) = \begin{array}{cc} & \begin{matrix} M_1 & \cdots & M_m \end{matrix} \\ \begin{matrix} C_1 \\ \vdots \\ C_n \end{matrix} & \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix} \end{array} \tag{5}$$

(2-3) *Information* D_I is processed from *metadata* D_M with statistical, visualization, and traceability tools. Conventional construction resources are equipped with IoT devices, such as RFID, UWB, iBeacon, micro-processors, and communication modules, to be augmented with cyber-physical visibility and traceability, and converted into SCOs [27]. SCOs could update the metadata about the related real-time positions, basic attributes, and environmental data to their corresponding digital twins. Statistical, visualization, and traceability tools can convert these metadata into information such as SCO status, construction progress, material delivery, and disturbance event, as well as trace the historical state to find root cause with specific time stamp. Real-time status of SCO is modeled through Finite State Machine $T_R = \{S, \Gamma, \xi, s_O, s_F\}$, described in Instantiation 1 *waterPump*; Disturbance Event (DisE) is identified by state transition of object, modeled as formula (6):

$$DisE = \phi_{id}\{\langle s_0, s_1\rangle, S_I, G_D, D_I, \langle t_0, t_1\rangle\} \quad (6)$$

where ϕ_{id} represents the event type & level identifier; $\langle s_0, s_1\rangle$ is the state transition of initial s_i to real-time or predicted state s_j; S_I is the SCO from *structure* domain, where the Disturbance Event occurs; G_D is the demonstration of event from *geometry* domain, which renders the event occurrence in virtual model; D_I is the *information* from *data* domain, which indicates the event attributes; $\langle t_0, t_1\rangle$ is the timespan of emergent event, while $t_0 = t_1$ if the event is instant.

(2-4, 2-5, 2-6) *Computing* A_C is the key application, while *Real-time* T_R is the temporal set and *Human-to-Machine (H2M)* I_{H2M} is the interactional set in smart prefabrication construction to provide cyber-physical visibility and traceability. Sensors collect the real-time data to the corresponding digital twins. AI model is applied to automatically detect the spatial-temporal trajectory $Tra(C_i)$ of SCOs in previous formula (4). A positioning algorithm A_C based on fingerprinting using Bluetooth Low Energy (BLE) in a real-time manner T_R is designed to locate SCOs on smart construction site. The information flow of I_{H2M} is based on Finite Element Method (FEM), where smart construction site is divided into a set of square subzones, with each covering 5m×5m as the minimal positioning unit. Each SCO is attached with a BLE tag that broadcasts message to the surrounding periodically. Gateways are mounted at the pivot of subzones in the four corners for every nine subzones as a cluster to detect signals from tags. Once the gateway receives the BLE signal, a value of Received Signal Strength Indicator (RSSI) will be obtained, which is the key parameter for real-time positioning. Then, the signal fingerprint of all locations can be established based on the vectors of RSSI in time series in line with the nearest four gateways. Subsequently, a Long Short-Term Memory (LSTM) network is used to learn the mapping relation between the signal fingerprints and actual locations at the offline stage. Amid, an LSTM cell state includes three gates to control the involvement of inputs and precedent states, namely Forget Gate (FG), Input Gate (IG), and Output Gate (OG). Three gates are featured by a sigmoid neural layer and a pointwise operation like addition and multiplication. Given the current input, the FG is concerned with the reservation of the former output, while IG and OG relate to the current state and output, respectively. These three gates satisfy the same structure of formula (7):

$$\overrightarrow{G_t} = \sigma\left(\overrightarrow{W_G} \cdot \left[\overrightarrow{PS_{t-1}}, \overrightarrow{I_t}\right] + \overrightarrow{b_G}\right), \quad G = FG, IG, OG \tag{7}$$

where $\overrightarrow{I_t}$ is the t$^{\text{th}}$ state in the input, $\overrightarrow{PS_{t-1}}$ represents the previous state, $\overrightarrow{W_G}$ and $\overrightarrow{b_G}$ are the weights and bias matrices for gates. Moreover, the current state $\overrightarrow{CS_t}$ is associated with the FG, IG and a candidate state value. The following formula (8) illustrates the relation:

$$\overrightarrow{CS_t} = \overrightarrow{CS_{t-1}} \cdot \overrightarrow{FG_t} + tanh\left(\overrightarrow{W_{CS}} \cdot \left[\overrightarrow{PS_{t-1}}, \overrightarrow{I_t}\right] + \overrightarrow{b_{CS}}\right) \cdot \overrightarrow{IG_t} \tag{8}$$

where $\overrightarrow{W_{CS}}$ and $\overrightarrow{b_{CS}}$ are corresponding weights and bias. Next, the current output can be computed by multiplying the OG and a modified current state as formula (9):

$$\overrightarrow{CO_t} = tanh\left(\overrightarrow{CS_t}\right) \cdot \overrightarrow{OG_t} \tag{9}$$

Then, an activation function, Rectified Linear Units (ReLU), and a Batch Normalization (BN) layer are linked to the current output vector in order. Finally, a three-layer Feedforward Neural Network (FNN) is connected to fulfill classification. The network trained offline is used for the online spatial-temporal and cyber-physical visibility and traceability of SCOs.

A robotic testbed experiment is used to examine the performance of UDT-enabled construction for this smart prefabricated nuclear plant, focusing on a smart construction site. The nuclear plant is divided into 28 components with a spatial scale ratio λ_l of 1.5%. The temporal scale ratio is based on the scale conversion equation $\lambda_t = \sqrt{\lambda_l}$ according to *Gravity Similarity Criterion*, which is added with an additional 10% reduced scale to facilitate the experiment. Virtual models are established in *Navisworks*, and physical components are produced by 3D-printing attached with smart tags. On-site assembly is simulated on a robotic testbed, and the corresponding digital twin is established through a real-time development platform *Unity 3D*. A 6-axis UR10e robot works as the smart crane to operate the SCO for on-site assembly. Digital twin is also applied to approximately locate the real-time positions of materials being transported and estimate the corresponding arrival times. Supported by the cyber-physical visibility and traceability of digital twins, the real-time statuses of resources and operations can be shared among buffer workers, superstructure workers, and crane operators for seamless collaboration to install components. An original planning, scheduling, and execution approach (OPSE) is adopted as a reference [7,13]. OPSE allows operators to strictly follow predetermined schedules of component arrival times and task start times without a primary focus on the real-time data. Different parameter combinations generate stochastic scenarios with different uncertainty levels {*Low Uncertainty (LU)*, *Medium Uncertainty (MU)*, *High Uncertainty (HU)*}, as shown in Table 1. To effectively compare the performances of UDT mode and OPSE mode, random data generated considering uncertainty are used in conjunction with the memory path algorithm for UR10e robot. The decision cycle to estimate the remaining transportation/assembly time and make dynamic adjustments based on real-time data is defined as 15s.

Table 1. Uncertainty generation for robotic testbed experiment

Class	Parameter	Value
Transportation	Standard Transportation Speed V_T	1.2m/s
	Standard Customs Duration D_c	11s
	Long Delay Rate P_d	6.3%
	Long Delay Duration D_d	[400s, 700s]
Operation	Standard Crane Moving Speed V_C	75% maxSpeed
	Standard Installation Duration D_I	214s
	Standard Rework Rate P_r	1.4%
Uncertainty Scenario	Low Uncertainty & Long Delay (LU)	{0.1, 0.1, 3%, 0, 0.1, 0.8%}
$\{cv(V_T), cv(D_c), P_d,$	Medium Uncertainty & Long Delay (MU)	{0.25, 0.25, 6.1%, 0.2, 0.3, 1.4%}
$cv(V_C),\ cv(D_I), P_r\}$	High Uncertainty & Long Delay (HU)	{0.4, 0.4, 15%, 0.3, 0.5, 3%}

The results of performance evaluation are given in Fig. 7. Two key indicators of prefabricated construction of this nuclear plant is used for evaluation, including holding time and construction duration. For the holding times of construction materials on buffer, UDT mode outperforms OPSE mode in all the scenarios and the decrease of holding time is significant. The boxplot ranges of UDT mode are generally smaller than OPSE's, which indicates that the material buffering capacity of UDT mode is more stable, especially in scenarios with higher uncertainty. For construction progress, UDT mode has higher resilience than OPSE due to the flexible dynamic adjustment scheme using real-time data. Original progress lags are smoothly eliminated by UDT mode under low uncertainty scenario and medium uncertainty scenario. In addition, holding times are also stable under UDT mode regardless of the uncertainty level, which implies that the real-time cyber-physical visibility and traceability can provide sufficient resilience for the on-site material supply.

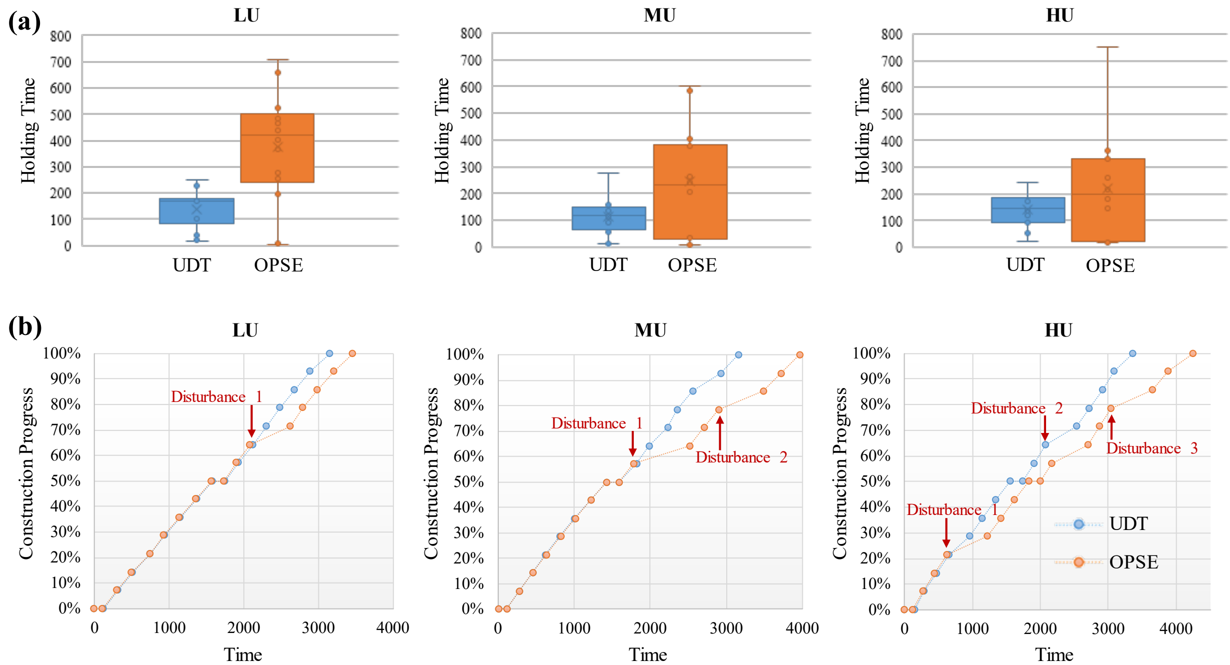

Fig. 7. Performance results of robotic testbed experiment between UDT and OPSE: (a) Holding time; (b) Construction progress

4.3 Instantiation 3 (Operation and Maintenance Phase): Smart Nuclear Plant

Smart nuclear plant *HUALONG One* is an integrated system with multiple subsystems as a complex infrastructure. Nuclear plant uses the heat energy generated by power reactors to provide electricity. Digital twin-enabled information management system can support the real-time monitoring of equipment status and AI-enabled prediction of disturbance events. This Instantiation 3 focuses on the smart operation and maintenance during information management process. The sets of UDT model for nuclear plant are described in formula (10), the interactive relationship is shown in the class diagram in Fig. 8.

$$\textbf{Instantiation 3: } UDT_{NP} = \{G_p, S_{MS}, D_K, I_H, A_{IA}, T_P\} \tag{10}$$

(3-1) *Positionality* G_p is the high-atomicity set in *Geometry* domain of the nuclear plant digital twin. Nuclear plant has a large spatial scale with multiple resources (e.g. pipelines, tanks, pressure regulators, pumps, reactants, and workers). Thus, high granularity is not required for the digital twin visualization. The static structures of nuclear island and conventional island are established with low graphics properties, which are qualified for the real-time monitoring and dynamic control of reaction activities. Dynamic positions of key objects (e.g. Nuclear Fuel-Uranium and operators) are sensed through iBeacon devices and visualized as points with (x, y, z) coordinates in virtual models.

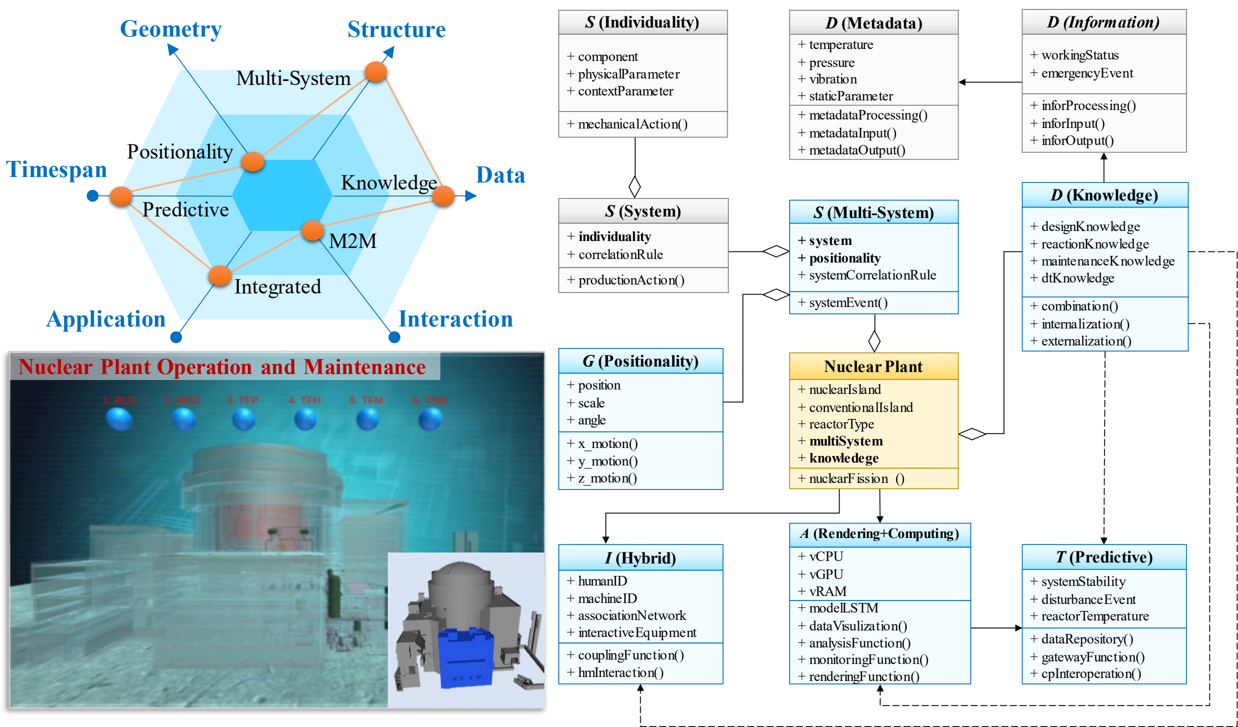

Fig. 8. UDT-based instantiation for operation and maintenance of smart nuclear plant

(3-2) *Multi-System* S_{MS} is the set in *structure* domain to reflect the complexity of nuclear plant. The nuclear plant can be roughly divided into two parts: nuclear island and conventional island. Several subsystems are composed together to form the whole picture based on specific correlation rules, which is presented through structure model in Fig. 9. The set of *structure* in Definition 3 is instantiated as $S_{NP} = \{S_S, S_{MS}, R, H_S, NH_S\}$. Core subsystems such as reactor cooling system are hierarchically coordinated by specific relationships. Digital twin system is applied for the interoperation of core systems, which are deployed with sensors and actuators for the key components. Subsystems with physical and digital resources are aggregated into the ontology of nuclear plant. Ontology editor Protégé is used to establish the domain ontology of nuclear plant digital twin in the form of JSON/RDF syntax. Entities S_S and S_{MS} are firstly defined and then assigned with value objects D_I. Hierarchical relationship H_S and non-hierarchical relationship NH_S are determined to couple the subsystems of nuclear plant through incidence matrix. Finally, ontology representation of this *multi-system* structure is established, while managers can edit and upload the JSON/RDF files to the web server for the digital twin virtualization and parameter configuration.

Fig. 9. Structure domain of nuclear plant digital twin based on UDT model

(3-3, 3-4) *Knowledge* D_K is the set from *data* domain of UDT model in nuclear plant digital twin. *Metadata* (e.g. temperature, pressure, and vibration) in the core systems (e.g. reactor system and cooling system) are processed to generate related *information* (e.g. working status and disturbance event). Real-time working status of subsystem is modeled through Finite State Machine $T_R = \{S, \Gamma, \xi, s_O, s_F\}$ as mentioned in Instantiation 1; Disturbance Event (DisE) of subsystem is identified by state transition and modeled as $DisE = \phi_{id}\{\langle s_0, s_1\rangle, S_S, G_P, D_I, \langle t_0, t_1\rangle\}$, which is similar as Instantiation 2, where S_S is newly applied to represent the subsystem in *structure* domain and G_P is newly applied to reveal the event occurrence position (spatial point or spatial area) in *geometry* domain. *Hybrid* interaction I_H with both H2M and M2M is the set from *interaction* domain in Instantiation 3. The horizontal interoperation among subsystems (M2M) is automatically coordinated together, which is driven by dynamic parameters. The vertical interoperation between the main system and operator (H2M) is established by real-time status monitoring service and dynamic control service. Knowledge supports the continuous optimization and prediction of key indicators of manufacturing enterprises, and realizes the transformation from experience-based decision to data-based decision. Knowledge can be extracted from the quantitative decision making system of *information* for design, reaction, maintenance, and digital twin.

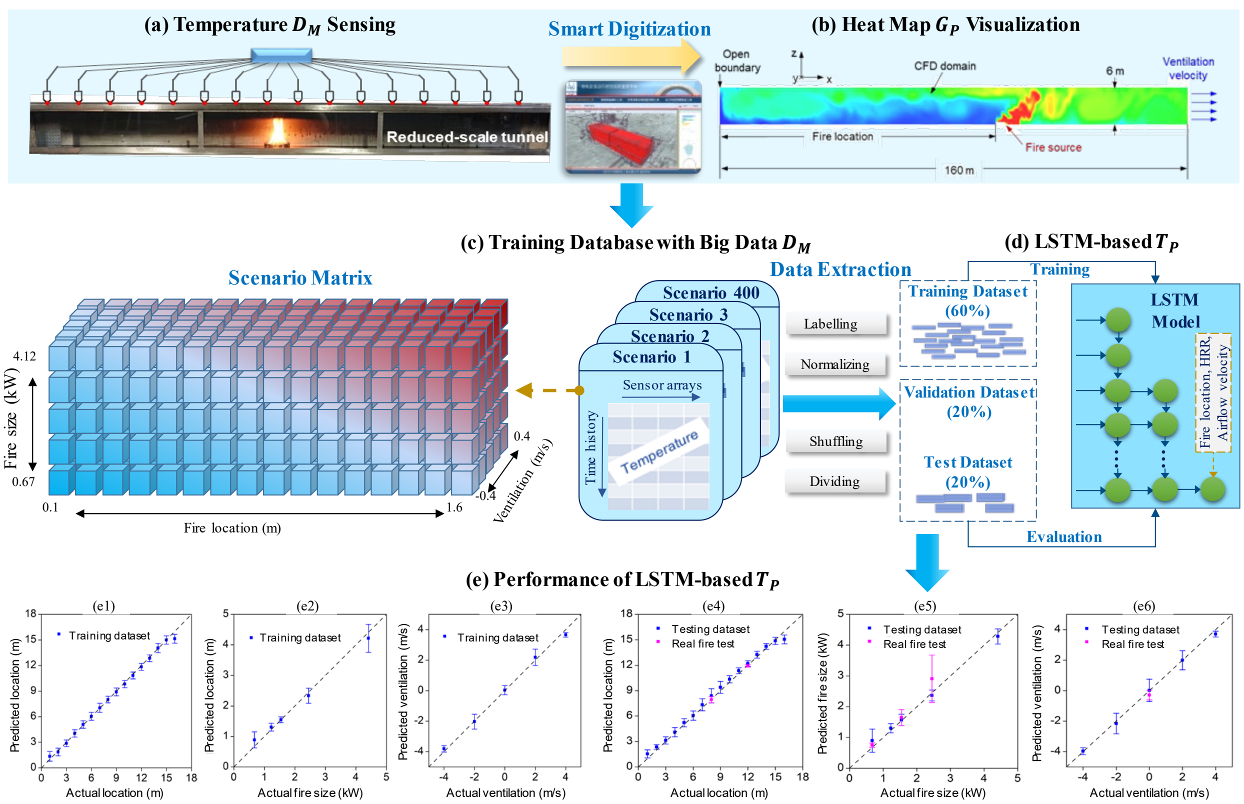

Fig. 10. LSTM model for predictive maintenance in digital twin-enabled information management of complex infrastructure system

(3-5, 3-6) *Predictive* T_P is the set from *timespan* domain, while *computing & rendering* A_{IA} is the set from *application* domain in nuclear plant system. Safety problem of nuclear plant is a huge concern in smart infrastructure, which has a high requirement for smart prediction of disturbance event. AI algorithm ω is applied for *predictive* set, which is tested in fire prediction service for smart nuclear plant. LSTM network is used to treat temporal series data to output key fire parameters (e.g. Heat Release Rate (HRR), fire position, and smoke ventilation capacity) when a fire situation happens in nuclear plant. As shown in Fig. 10 (a), a reduced-scale tunnel ($1.7m \times 0.17m \times 0.14m$) with a scale ratio of 1:50 is adopted for the actual case testing, which mimics a real facility in the smart nuclear plant. Temperature metadata D_M are collected and visualized in heat map G_P through smart digitization. According to the Froude-number scaling equation, the HRR and flow velocity in the reduced-scale model are $\frac{Q_m}{Q_f} = \left(\frac{l_m}{l_f}\right)^{5/2}$ and $\frac{u_m}{u_f} = \left(\frac{l_m}{l_f}\right)^{1/2}$, where l is the length scale, subscript "m" and "f" represent the model and full scales. Big data is necessary for the better performance of LSTM model, thus the training database is established using a large set of experimental and numerical data. 400 (16×5×5) fire scenarios are modeled with Fire Dynamics Simulator (FDS V6.7) with 16 fire locations, 5 HRRs, and 5 ventilation conditions, as shown in Fig. 10 (c). For all the models, the mesh size of 0.2m is adopted along x-, y-, and z-axes. All the available scenarios stored in the database constituted a scenario matrix with three domains, fire location from 0.1m to 1.6m along the tunnel, fire size from 0.67kW to 4.12kW and ventilation from -0.4m/s to 0.4m/s. The temperature of the recognized fire scenario and the temperature generated by its most similar scenarios in all three domains in the scenario matrix, are deployed adjacently and compared. Thus, as shown in Fig. 10 (d), real-time sensing data T_R and historical data T_H are cooperated together through LSTM model ω for the key parameters T_P prediction: $\omega_T: [T_R + \sum_{i=1}^{n} T_H(i)] \rightarrow T_P$. Considering the influence of radiation heat transferring, temperature is normalized with the "MinMaxScaler" function $T^* = \frac{T^4 - T_{min}^4}{T_{max}^4 - T_{min}^4}$ to facilitate the recognition of fire severity, where T_{max} [K] and T_{min} [K] are the maximum and minimum temperatures. The outputs will also be uploaded into the database using the Python through the MySQL Connector command lines. Because the sensing data may be invalid or noisy, a filter algorithm is applied to pre-process and interpolate the raw data. Fig. 10 (e) shows the prediction of numerical dataset tests (e1, e2, e3) and the prediction of fire scenarios on reduced-scale tunnel fire tests (e4, e5, e6). Compared with testing dataset of the numerical data, the trained AI model has a comparable performance in predicting fire location and ventilation with a lower deviations of the predictions on real test data.

4.4 Discussion

UDT model provides a unified description approach for the multiple-domain digital twins during information management of complex infrastructure systems among transdisciplinary stakeholders in a multi-subproject condition. Six domains in UDT can comprehensively reflect the attributes and behaviors of three cases in the information management of smart nuclear plant. The quality evaluation of UDT model is analyzed through three quality characteristics based on *Software Engineering (Product Quality) GB/T 16260*, including scalability, usability, and maintainability. (1) *Scalability*: The ability to move from one scene or business domain to another. UDT can be adopted to different scenes with different scales with different characteristics during information management. On the one hand, small-scale scene, such as Instantiation 1 *waterPump*, is descripted with high fidelity. Fine-granularity virtual models and real-time running status are provided for monitoring and dynamic control for these individual components. On the other hand, large-scale scene, such as Instantiation 3 *smartNuclearPlant*, describes the complete picture of the entire smart infrastructure for integration of different functionalities, applied technologies, and involved transdisciplinary stakeholders; (2) *Usability*: Usability refers to the ability of software product to be understood, learned, and used by stakeholders. The structure of UDT is based on class diagram and tuple, which is easy to understand. Whatever the knowledge domain of stakeholders, UDT is a simplified model for stakeholders to apply it in digital twin-enabled information management. Because UDT follows domain-driven design approach, stakeholders in each domain can grasp the related operation methods of the corresponding digital twin systems; and (3) *Maintainability*: Maintainability refers to the ability to be modified. Modifications may include correction, improvement, and software adaptation to fit the changes of project requirements and functional specifications. UDT can fit with different stages during information management of complex infrastructure systems. In this smart nuclear plant scenario, Instantiation 1 mainly focuses on design and deployment, Instantiation 2 focuses on the construction phase, and Instantiation 3 is used for operation and maintenance. Three instantiations are separately prepared for different infrastructure management stages, but UDT can reflect the key attributes and functional activities of each stage based on project's requirements.

5. Conclusion and Future Research

This paper proposes a Ubiquitous Digital Twin (UDT) model for selective simplification and structural description of cross-scene and multi-domain digital twins in the information management of complex infrastructure system. Firstly, based on Domain-Driven Design (DDD), six domains are deployed in UDT model, and each domain has sequential or parallel sets for the shared understanding of overall digital twin system or specific functional modules; Secondly, a roadmap is introduced for the collaborative design, development, deployment, and implementation in information management of complex infrastructure among transdisciplinary stakeholders with cross-domain knowledge; Thirdly, hierarchical cases (e.g. water pump, prefabricated construction, and integrated nuclear plant) with IoT-enabled self-detection and AI-enabled self-optimization services are instantiated based on UDT model for the information management of one smart nuclear plant.

Several contributions are concluded as follows: Firstly, UDT model provides a unified reference specification and description approach for information management of complex infrastructures in construction industry, which can be further extended into other research fields, such as manufacturing, medicine, and logistics. Secondly, UDT model efficiently supports the collaborative information management with cross-domain knowledge requirements among trans-disciplinary teams in a multi-subproject situation. Thirdly, scenario of developing digital twins for smart facilities, such as smart nuclear plant, is theoretically and practically discussed, which provides the basis for the information management of complex infrastructure systems in Construction 4.0 era. Some limitations arise from several facts. The automatic control and execution are still poor for current digital twin system, hindering the D2P bridge. Connections and communications between each stage in information management of complex infrastructrues are not comprehensively explored in this study. Moreover, massive heterogeneous data are collected by IoT during information process. How to fuse, integrate, and visualize these massive data in a near-real-time manner to provide real-time visibility and traceability services is also a challenge for digital twins.

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