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Review

# Current status of digital twin architecture and application in nuclear energy field

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ABSTRACT

Digital Twin (DT) technology has gained significant attention in various areas, including nuclear energy. Technologies such as machine learning, artificial intelligence, and high-fidelity modeling and simulation have been studied to further the digitalization of the nuclear industry. In this paper, an overview of the DT initiatives and developments for the design optimization and intelligent transformation of nuclear energy systems is described to provide a development trend of DT technology for nuclear reactors. For the design of DT for complex systems such as nuclear reactors, Model Based Systems Engineering (MBSE) technology offers requirements models, design processes, and system verification that are clearer, more precise, and more comprehensive. Four properties of Digital Twin for Nuclear Reactor System (DTNRS) are summarized, which are given by the block definition diagram of MBSE philosophy. Then, to bridge the gap between numerical models and theoretical research of DT, a systematic and hierarchical "V" architecture is proposed, which reflects the digital-related technologies of the DTNRS throughout the whole life cycle. Furthermore, a four-layered decomposition construction model is developed and a prospective application scenario of DTNRS is pictured. Finally, the five-step instructive demonstration of the DTNRS is given based on a Generation III (GEN-III) reactor with its visualized condition map.

## 1. Introduction

Over the last few decades, the concept of the digital twin (DT) has gained significant recognition across various industries and has greatly transformed the industrial sector (Tao and Qi, 2019). The evolution of the DT notion for almost two decades has been summarized (Wang et al., 2022a). DT technology is currently being implemented in many industries such as computer science (Jbair et al., 2022; Siqueira and Davis, 2021), intelligent manufacturing (Li et al., 2022a; Sun et al., 2022a), aerospace (Giannaros et al., 2022; Candon et al., 2022), military (Lee et al., 2021; Mendi et al., 2021), communication (Liu et al., 2021a; Lu et al., 2020; Wang et al., 2021), healthcare (Ferdousi et al., 2021; He et al., 2021), and energy (Spinti et al., 2022; Gong et al., 2021; Hu et al., 2021). Fig. 1 shows the state of research in 15 domains based on the over 200 scientific publications found in the SCOPUS database as of July 2023.

Among many different meanings of DT in varied contexts, three of them are frequently used: the first, **the entire DT system**, i.e., the whole five-dimension (Physical entity, Virtual equipment model, Services model, DT data model, and Connection model) DT system (Tao et al., 2019; Tao et al., 2018), the second, **the virtual component of the entire DT system**, i.e., Virtual equipment model in the five-dimension model (Tao and Qi, 2019; Tao et al., 2022; Rasheed et al., 2020; Zhang, 2020), and the last, **the general DT technologies**, i.e., the tools or methods to realize DT (Li et al., 2022a; Wang et al., 2021; Zhang et al., 2022a). The definitions of DT found in literature, especially in nuclear field, are shown in Table 1. To avoid confusion, the current paper uses DT for Nuclear Reactor System (DTNRS) to refer to the whole system and uses digital reactor to represent the virtual component.

When DT is deployed for a complex industrial system such as the DTNRS, generosity data generated by different components needs to be analyzed and shared. To avoid misunderstandings and improve the accuracy of numerical models, the International Council on Systems Engineering (INCOSE) proposed Model-Based System Engineering (MBSE) as a replacement for text-based system engineering. MBSE supports system requirements, design, analysis, verification, and validation, to supersede text-based system engineering (Friedenthal et al., 2007). More crucially, for the realization of DTs in complex systems, MBSE offers a strong philosophy of verification and management.

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**Nomenclature**

*Acronym*

| | |
|---|---|
| ANL | Argonne National Laboratory |
| CAD | Computer Aided Design |
| CAINI | Computer Application Institute of Nuclear Industry |
| CASL | Consortium for Advanced Simulation of LWRs |
| CEA | French Alternative Energies and Atomic Energy Commission |
| CIAE | China Institute of Atomic Energy |
| CGN | China General Nuclear Power Group |
| CNNC | China National Nuclear Corporation |
| CNPE | China Nuclear Power Engineering Co., Ltd. |
| CNRS | French National Centre for Scientific Research |
| DOE | Department of Energy |
| DOE-NE | DOE Office of Nuclear Energy |
| DSA | Deterministic Safety Analysis |
| DT | Digital Twin |
| DTNRS | Digital Twin technology for Nuclear Reactor System |
| DW | Drywell |
| EDF | Electricite De France |
| EPRI | Electric Power Research Institute |
| ESI | Engineering System International |
| GDCS | Gravity Driven Cooling System |
| GE | General Electric |
| GEMINA | Generating Electricity Managed by Intelligent Nuclear Assets |
| GEN-III | Generation III |
| I&C | Instrument and Control |
| ICS | Isolation Cooling System |
| INCOSE | International Council on Systems Engineering |
| INL | Idaho National Laboratory |
| IPSO | Improved Particle Swarm Optimization |
| ISU | Idaho State University |
| LANL | Los Alamos National Laboratory |
| LBNR | Lawrence Berkeley National Laboratory |
| LLNL | Lawrence Livermore National Laboratory |
| LOCA | Loss of Coolant Accident |
| MAGNET | Microreactor Agile Non-nuclear Experimental Testbed |
| MBSE | Model-Based System Engineering |
| MEPI | Moscow Engineering Physics Institute |
| MIT | Massachusetts Institute of Technology |
| ML | Machine Learning |
| NCSU | North Carolina State University |
| NNSA | National Nuclear Security Administration |
| NPIC | Nuclear Power Institute of China |
| NPP | Nuclear Power Plant |
| NRC | Nuclear Regulatory Commission |
| NUMAP | Nuclear reactor Unified Modeling and Analysis Platform |
| O&M | Operation and Maintenance |
| PARCS | Purdue Advanced Reactor Core Simulator |
| PCCS | Passive Containment Cooling System |
| PIMA | Post-Industrial Midwest and Appalachia |
| PNNL | Pacific Northwest National Laboratory |
| PSA | Probabilistic Safety Analysis |
| PSPC | le Projet Structurant Pour la Compétitivité |
| PU | Purdue University |
| PWR | Pressurized Water Reactor |
| QR | Quick Response |
| RELAP | Reactor Excursion and Leak Analysis Program |
| RINPO | Research Institute of Nuclear Power Operation |
| RPV | Reactor Pressure Vessel |
| SNL | Sandia National Laboratories |
| SPIC | State Power Investment Corporation |
| TRACE | TRAC/RELAP Advanced Computational Engine |
| TSE | Text-based Systems Engineering |
| UL | University of Lorraine |
| UM | University of Michigan |
| UTK | University of Tennessee Knoxville |
| VDNPP | Virtual Digital Nuclear Power Plant |
| VERA | Virtual Environment for Reactor Applications |
| VERCORS | Vérification Réaliste du Confinement des Réacteurs |
| V&V | Verification and Validation |

Younes et al. employed MBSE to design a robotic space system architecture and showed its efficacy in handling system complexity (Younse et al., 2021). Zhu et al. developed the reactor safety injection system's requirement architecture (Zhu et al., 2020). It appears that MBSE is a useful method for handling variations and finishing requirement analysis for complex systems. In 2019, the first study (Madni et al., 2019) demonstrating a connection between DT and MBSE was published. The proposal suggested integrating DT technology into MBSE methodology and experimentation testbeds. Bickford et al. proposed a construction process along the system lifecycle and the method benefits to promote the development of DT in the MBSE framework (Bickford et al., 2020). To create a DT that can choose the best route, Lee et al. offer an MBSE technique (Lee et al., 2021). Subsequently, Liu et al. introduced a shop-floor DT "V model" based on MBSE (Liu et al., 2021b), which is implemented in four dimensions (requirements, structure, behavior, and parameters) and three stages (problem domain, solution domain, and implementation domain). Zhang et al presented a hierarchical, modular, and generic architecture based on MBSE to illustrate comprehensive and variable industrial robot DT (Zhang et al., 2023).

Similarly, the complexity of advanced digital nuclear energy

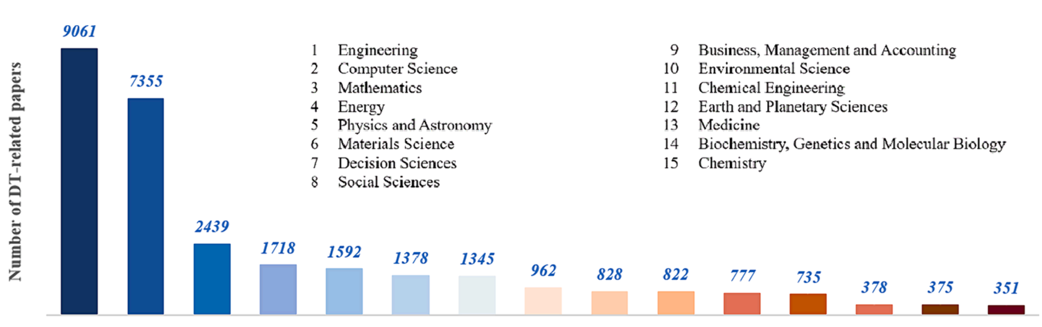


**Fig. 1.** Number (over 200) of papers about DT in different disciplines in the SCOPUS database.

**Table 1**
Definition of DT in literature.

| Categories | Definition | Reference |
|---|---|---|
| Entire DT system | The DT is modeled in three dimensions, i.e. the physical entity, virtual model, and connection, and is characterized by the physical–virtual interaction | (Tao et al., 2018) (Tao et al., 2019) |
| | The DT for nuclear power plant includes physical reactor, virtual reactor, control system, data processing platform, simulation system, and data interaction | (Hu et al., 2021) |
| Virtual component of the entire DT system | DT is a data-enabled physics-informed model for online monitoring purposes, aiming to predict the operational parameters | (Gong et al., 2022) |
| | A DT serves as a digital model of a real system that can be updated in real-time by using data from sensors, and it also integrates the system's aging and performance history | (Sandhu et al., 2023) |
| | A DT for nuclear reactor monitoring can be implemented using either a physics-based model or a data-driven model | (Prantikos et al., 2022a) |
| | A DT is a virtual representation of a physical system, incorporating both physical and digital data to model the system's behavior in real time | (Minetti et al., 2023a) |
| | A DT is a digital replica of an operating asset that can display data, update a physics model, compute predictive results, and apply asset control accordingly | (Browning et al., 2022) |
| DT technologies | DT is the method or tool developed for handle high multi-physics problem | (Soleilhet et al., 2023) |
| | Implementing structural calculations and capitalizing computations along with post-processing in what may be referred to as a DT of the mock-up | (Charpin et al., 2022) |
| | The real-time DT is the dynamic set of digitized data and accumulated in the format of time series | (Zhabitskii et al., 2021) |

technology keeps rising. Thus, this study attempts to construct a systematic and hierarchical DTNRS in an effort to bridge the gap between numerical models and theoretical research. An overview of the initiatives and state of research in several nations was provided first to show a trend of DTNRS in Section 2. Then, in Section 3, a review of technology and properties that can be implemented into a DTNRS is presented. In Section 4, a system "V" architecture based on MBSE that represents the entire life of a DT system in nuclear energy is put forth. To bridge the gap between the theory and numerical simulation, the four-layered decomposition construction model is proposed and its prospective application scenario is imaged. Moreover, a detailed five-step instructive demonstration is given based on a Generation III (GEN-III) reactor. Finally, conclusions are given in Section 5.

## 2. Status of DT technology research in nuclear energy

According to Yang et al., safety assurance is now a crucial requirement for the advancement of nuclear energy (Yang et al., 2022a). DTNRS has potential to provide financial stability and satisfy requirements for multi-accident scenario verification. The nuclear industry is using this digital transformation to accelerate the development of DT applications. This section will introduce the nuclear energy DT organizations and related projects that are being done in different countries. To the authors' best knowledge, the organizations, institutions, and enterprises in major nuclear energy countries—the United States, France, China, Russia, the United Kingdom, Germany, and Japan—that have been found involved in the digitalization of nuclear energy systems are reflected in Fig. 2.

### 2.1. The U.S.

The majority of entities working on DT nuclear energy are found in the United States. The main players contain universities, including Massachusetts Institute of Technology (MIT), University of Michigan (UM), North Carolina State University (NCSU), Purdue University (PU), Idaho State University (ISU), and University of Tennessee Knoxville (UTK), national laboratories, including Idaho National Laboratory (INL), Los Alamos National Laboratory (LANL), Argonne National Laboratory (ANL), Lawrence Berkeley National Laboratory (LBNR), Pacific Northwest National Laboratory (PNNL), Sandia National Laboratories (SNL), and Lawrence Livermore National Laboratory (LLNL), as well as corporations, including Electric Power Research Institute (EPRI), Westinghouse, Moltex, GE (General Electric), energy, Exelon, Karios Power, Curtiss Wright, and TVA, as shown in Fig. 2.

As a pioneer project to advance the digital reactor technology, the Consortium for Advanced Simulation of LWRs (CASL) (DOE, 2010) project was initialized by the U.S. Department of Energy (DOE) in 2010 to develop the Virtual Environment for Reactor Applications (VERA) that can analyze and simulate reactor operating conditions (Turner et al., 2016). The report "The Future of Nuclear Energy in a Carbon-Constrained World" was published by MIT in 2018 (Petti et al., 2018). It suggests a new paradigm for the development and deployment of nuclear reactor technologies, including DT. The first fully digital nuclear reactor instrument and control (I&C) system for PUR-1 was launched in PU and certified by the U.S. Nuclear Regulatory Commission (USNRC) in 2019. The effective method paves the path for the use of DT technology. The Generating Electricity Managed by Intelligent Nuclear Assets (GEMINA) program, which aims to halve the operation and maintenance (O&M) expenses for the next generation nuclear power plants (NPPs), is supported by the DOE with $27 million for nine projects (DOE, 2020; ARPA-E, 2020). Additionally, the DOE Office of Nuclear Energy (DOE-NE) and the National Nuclear Security Administration (NNSA) have provided funding for advanced nuclear DTs. The GE-Hitachi-led project team received $5.8 million from the U.S. DOE in July 2021 to develop three construction technologies (Office of Nuclear Energy, 2021). Advanced monitoring, coupled with DT technology, allows the creation of 3D replicas. In 2022, a DT was first used to test the virtual version of the Microreactor Agile Non-nuclear Experimental Testbed (MAGNET) built by the INL. The DT successfully predicted the heat pipe's temperature through integrated machine learning (ML) and identified trends toward an unfavorable threshold temperature.

Led by the Pennsylvania State University, the Post-Industrial Midwest and Appalachia (PIMA) Nuclear Alliance has been formed to innovate enabling technologies (e.g. DT, advanced manufacturing, etc.) (Allain and Allain, 2023).

Recently, ISU and INL developed a virtual replica of AGN-201 research reactor, claiming to be the first nuclear reactor digital twin (WNN, 2024).

### 2.2. France

The organizations participating in research on DT nuclear energy technology include the French National Centre for Scientific Research (CNRS), University of Lorraine (UL), Electricite De France (EDF), Cran, Boost, Framatome, Axone, Corys, Engie, Engineering System International (ESI), Dassault Systems, the French Alternative Energies and Atomic Energy Commission (CEA), and Aneo. The EDF R&D Center's first DT reactor is called VERCORS (Vérification Réaliste du Confinement des Réacteurs). It was initially used to predict the containment leakage rate and the location of the concrete cracking path. The system, whose construction started in 2014, functions as a virtual, 1:3 scale double-wall reactor containment that communicates with the real reactor through more than 700 sensors and 2 km of optical fiber. In-

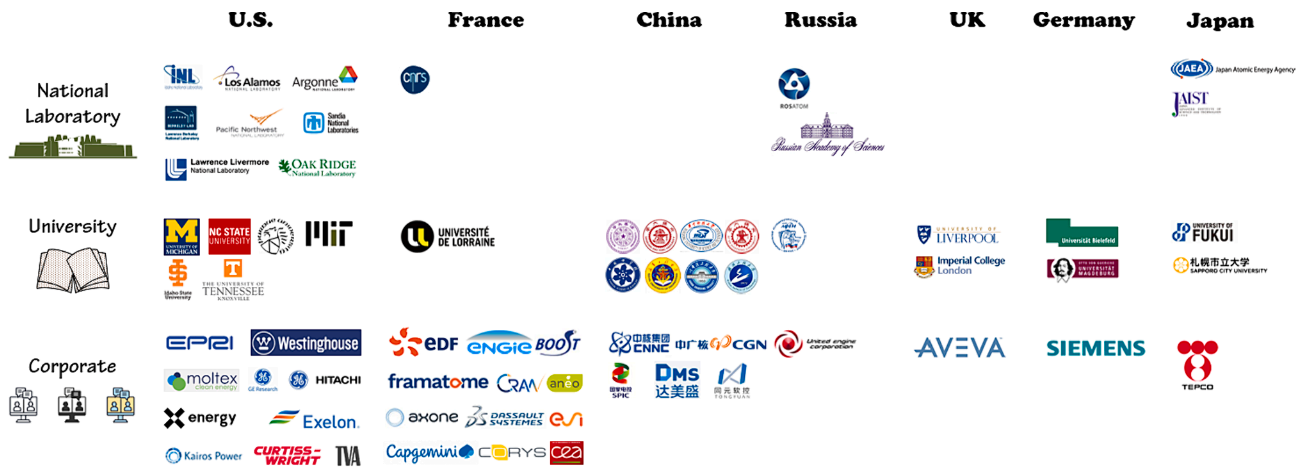


**Fig. 2.** Entities involved with DT of nuclear energy in different countries.

service DTs can also be used to optimize O&M. EDF is developing a DT of the steam generator to forecast shell-side deposition and fracture size, and monitor operation history and behavior because replacing crucial PWR components is expensive (Deri et al., 2021).

EDF has also partnered with Framatome, CEA, Corys, ESI, Aneo, Axone, Boost, and Cran to propel PSPC (le Projet Structurant Pour la Compétitivité) (Koren, 2021), a DT project for PWRs during 2020–2023, to digitally clone all nuclear reactor units in France. This is in addition to digitizing local components of NPPs. A long-term cooperation agreement was also signed by EDF, Dassault Systems, and Capgemini to jointly promote the digital transformation of nuclear engineering systems and implement cutting-edge DT solutions during the design, construction, and operation phases of nuclear energy system projects.

### *2.3. China*

A Nuclear Power Software and Digital Reactor Engineering Technology Research Center has been established by China National Nuclear Corporation (CNNC). The subordinate organizations involved in the center include the Nuclear Power Institute of China (NPIC), the China Institute of Atomic Energy (CIAE), China Nuclear Power Engineering Co., Ltd. (CNPE), the Research Institute of Nuclear Power Operation (RINPO), and the Computer Application Institute of Nuclear Industry (CAINI). To promote the research and development of digital reactor technology, a research and development team with more than 200 professional and technical members has been established.

According to CNNC's digital transformation strategy, the intelligent symbiosis between the nuclear industry and its DT in the real world is anticipated to be fully realized by 2035–2040. The NPIC also carried out related investigations into the DT design framework and its application to nuclear I&C systems (Wang et al., 2019). The use of DT technology in NPPs was also the subject of a preliminary analysis and discussion by the RINPO (Pan et al., 2020).

Additionally, research on nuclear energy DT is also being done at Tsinghua University, Shanghai Jiao Tong University, Xi'an Jiaotong University, University of Chinese Academy of Sciences, Harbin Engineering University, Huazhong University of Science and Technology, Naval University of Engineering, Wuhan Institute of Technology, Chinese Academy of Sciences, CNNC, China General Nuclear Power Group (CGN), State Power Investment Corporation (SPIC), Suzhou Tongyuan Software and Control Technology Co., Ltd., DMS corporation, etc.

### *2.4. Russia*

The All-Russian Research Institute on Operation of Nuclear Power Stations and the Nuclear Safety Institute of the Russian Academy of Sciences jointly developed the Virtual Digital NPP (VDNPP), which could be used in the sectoral project "PROVY" implementation. The use of a software package with various levels of models to verify the design of a power unit is one of VDNPP's capabilities. The software package combines the capabilities of detailed full-scale models of the automated process control system, detailed models of the main process components of the power unit, and precision models that can calculate the whole range of operating modes for the power unit. Rosatom, Moscow Engineering Physics Institute (MEPI), and United Engine Corporation are also making progress in DT application in nuclear field.

### *2.5. Other countries*

A collaborative UK-Japanese effort called LongOps has been creating new NPP decommissioning technology, for over four years since 2021. The project's goal is to create and use innovative DT techniques—-physical system models that enable in-depth data analysis. DT can be used to spot prospective issues and take the best possible care of them. DTs are used in this instance to show how an operator controls a distant live machine in real-time.

The white paper "The virtual nuclear reactor", published by Siemens of Germany, provides two examples of how DT technology might be used to improve nuclear reactor performance. Examples include innovative coolants and thermal striping (SIEMENS, 2021). Tecnatom of Spain and AFRY of Europe are developing DT technology to implement plant decommission.

The University of Waterloo suggested a paradigm that may intelligently allocate scarce resources for the development of DTs of legacy NPP assets and subsystems in the setting of a typical Canadian legacy NPP (Edwards et al., 2023).

Additionally, there are probably more DT in nuclear energy activities worldwide, which are not disclosed or have not been found by the current research.

## 3. Technology and performance of DTNRS

Although the use of DT technology in nuclear energy systems is still in its infancy, many academics have looked into the problems associated with it. Papers researched using the "TITLE-ABS-KEY" with digital-twin and "TITLE-ABS-KEY" with nuclear-energy in the SCOPUS database are summarized in Table 2. Several features that DTNRS should have are real-time synchronization, state prediction and fault diagnosis, decision-making support, and multi-terminal collaboration. The benefits and challenges of the four properties are analyzed in Fig. 3.

**Table 2**
"TITLE-ABS-KEY" (digital-twin) and "TITLE-ABS-KEY" (nuclear-energy) related papers in SCOPUS database.

| Phase of Lifecycle | DT-related capability | Reference |
|---|---|---|
| Design | A functionality and cybersecurity analysis based on the DT of a Control System | (Lou et al., 2019) (Frepoli et al., 2022) |
| | Evaluate target effects and actual problems in the whole lifecycle of DT technology implementation | (Zhabitskii et al., 2021) |
| | Establish multi-dimension models to realize a collaborative design | (Guo et al., 2022) |
| | Realize the interaction between the DT model and the control system | (Li et al., 2022b) |
| | DT of hazardous production equipment such as NPPs | (Kirilov et al., 2022) (Zhao and Guan, 2022) |
| O&M | Predict the parameters of equipment | (Deri et al., 2021) (Jharko, 2021a) (Laouar et al., 2020) (Volodin and Tolokonskii, 2019) (Jharko et al., 2020) (Chistyakov et al., 2022) (Gong et al., 2023) (Ritter et al., 2022) (Lyalyuev, 2022) (Li et al., 2022c) |
| | Construction of DT virtual model | (Ping et al., 2021) (Varé and Morilhat, 2020) |
| | Prognostics and Health Management | (Oluwasegun and Jung, 2020) (Zhang et al., 2022b) (Yang et al., 2022b) |
| | Support and diagnostic systems | (Hu et al., 2021) (Nguyen et al., 2022) (Ayo-Imoru et al., 2021) (Jharko, 2020) |
| | A heterogeneous DT's implementation for a real control system of an NPP | (Semenkov et al., 2021) |
| | Cyber security protection of physical protection systems | (Guo et al., 2021) (Vaddi et al., 2022) |
| | Discuss the approach conformity with which the flexible software package is the kernel of the DTNPP unit | (Jharko, 2021b) |
| | Integrate forward and inverse uncertainty between physical sensor data to digital reactor data | (Kochunas and Huan, 2021) |
| | Performance monitoring system and visualization technology solutions | (Liu et al., 2022) (Moussallam et al., 2022) |
| | Propose a DT system of robots for auxiliary installation of out-of-core detectors | (Wang et al., 2022b) |
| | Operator decision support for the DT system | (Jharko et al., 2022) (Sun et al., 2022b) |
| | Data optimization and calibration | (Sun et al., 2022c) (Jansky and Langenstein, 2022) (Song et al., 2022) |
| | To develop a DT of the Central Solenoid Converter Power Supply grid used in the International Thermonuclear Experimental Reactor (ITER) | (Minetti et al., 2023b) |
| | A deep neural network for three-dimensional fluid dynamics that shortens the calculation time for real-time simulation | (Yang et al., 2023) |
| | A hybrid approach using differential equations-based physics model and data-driven ML method for DT nuclear reactor monitoring | (Prantikos et al., 2022b) |
| Decom-mission | Apply technologies such as VR, AR, and MR to decommission | (Taruta et al., 2020) |
| | Visualize the dose equivalent rate of radioactive substances and ion | (Sato, 2022) |
| | For efficient decommissioning of NPPs, maintain a knowledge base, ensure cyber security, and design DTs | (Jharko et al., 2021) |
| | A DT framework for intelligent allocating resources for legacy assets | (Edwards et al., 2023) |

### 3.1. Real-time synchronization

The digital reactor maintains synchronization with the physical reactor using real-time data, while the sensor data is either insufficient (due to the low acquisition frequency leading the system unable to capture transient behavior and data not spanning all of the accident scenarios), or inaccurate (due to interference from high temperature and intense radiation in-core on data transmission), making it necessary to supplement and correct the data. To optimize the flow parameters, Sun et al. proposed an improved particle swarm optimization (IPSO) algorithm (Sun et al., 2022c). This was done to improve the match between the single point pressure offline data and the real data, which may be utilized for the real-time computation of DT systems. To solve the problem of real-time data interfacing in the DT system, a comprehensive plan for data monitoring and visualization technology is put out, based on the thorium molten salt reactor-solid fuel (Liu et al., 2022). To establish the two-way interaction between the twin model and the control system, Li et al. (Li et al., 2022b) based on the OPC Unified Architecture communication protocol and Wang et al. (Wang et al., 2022b) employ the automation device specification communication protocol.

### 3.2. State prediction and fault diagnosis

Because of the complicated working conditions and strict safety regulations of the NPP, the digital reactor must be able to precisely track the physical reactor operation and forecast the likelihood of an accident based on available data. Hu et al. proposed a multi-dimensional assessment digital model of DTNRS for fault diagnosis (Hu et al., 2021). For thermal-hydraulic systems in NPPs, Nguyen et al. presented a physics-based diagnostics approach that is distinguished by generating interpretable diagnostic data (Nguyen et al., 2022). Two examples were given by Deri et al. to show how the DT predicts important performance metrics (Deri et al., 2021). Jharko created a flexible modeling system for predicting and simulating the NPP status, which is comparable to the DTNRS (Jharko, 2021a). After the principal component analysis was used to minimize the data dimension, Ayo-Imoru et al. trained artificial neural networks and adaptive neuro-fuzzy inference systems to detect defects (Ayo-Imoru et al., 2021). Jung et al. also used ML for anomaly identification (Oluwasegun and Jung, 2020). Ping et al. developed a DT for the PWR control system that could assess and identify a variety of issues using a sophisticated third-generation engineering simulator platform (Ping et al., 2021). The thermal-hydraulic parameters of an NPP indicate if it is running at peak efficiency. Using neural network methods, Bowman et al. forecast changes in the thermal-hydraulic characteristics of the flow loop in response to external impacts (Laouar et al., 2020). According to Yang et al. (Yang et al., 2023), if the accuracy requirements are met, a deep neural network model that predicts the local complex three-dimensional fluid dynamics can significantly reduce calculation time.

### 3.3. Decision-making support

Unexpected outcomes occur when operational decisions are made using non-quality-assured sensor data. The certified process data

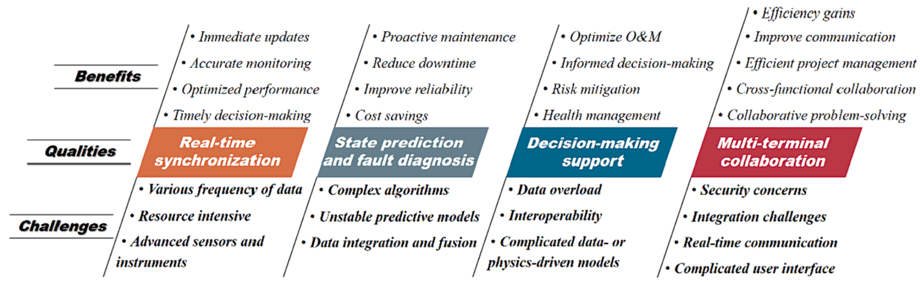


**Fig. 3.** The benefits and challenges of the four properties.

reconciliation method proposed by Jansky et al. eliminates 95 % of the data that was gathered and generates all pertinent process values with little to no uncertainty, which can steadily increase computational accuracy and decision-making speed (Jansky and Langenstein, 2022). Jharko et al. evaluated an approach in which the operator support information system kernel is a flexible modeling complex that can be utilized as a DT (Jharko et al., 2022). There are numerous sources of uncertainty in the simulation process, and it is crucial for economics to reduce and quantify the uncertainty. It facilitates decision support and offers theoretical support for the dependability and stability of DT systems by combining forward and backward uncertainties (Kochunas and Huan, 2021).

### 3.4. Multi-terminal collaboration

Industrial engineering is driving increased demand for digital technologies. The development of DT technology has made it possible to perform multi-stakeholder collaborative design and optimization, digital delivery, parameter traceability, and online design changeability. Conventional text-based systems engineering (TSE) is gradually losing ground to more complicated and large-scale industrial systems. INCOSE proposed MBSE in 2007 to manage complex system design and accurately express comprehensive needs (Friedenthal et al., 2007). MBSE uses formal, unified, standard modeling languages to address complex system design requirements. As a result, in recent years, it has emerged as a viable path to actualize DT. MBSE is used in the U.S. Department of Defense Digital Engineering Strategy for both the Digital Thread and DT technologies.

## 4. Systematic and hierarchical architecture and demonstration of DTNRS

Reactor design, construction, O&M, life extension, decommissioning, and upgrading can all benefit from the application of DT for safety and efficiency. Furthermore, by using technologies like big data and ML, the working conditions that are difficult to measure or predict can be inferred, allowing for a more thorough diagnosis, prognosis, and evaluation. However, each of these components necessitates a significant amount of reusable system blocks, extensive V&V, and high-fidelity simulation of coupling systems. Therefore, for the whole lifecycle activity, a hierarchical and methodical DTNRS design needs to be presented. Ramos et al. pertinently offer MBSE as a solution to the growing complexity of systems (Ramos et al., 2011). It facilitates system-level verification, expedites the product development lifecycle, and specifies the properties of sub-system blocks, as illustrated in Fig. 4.

For the creation of DTNRS employing the MBSE philosophy (Jiang et al., 2019), Fig. 5 presents a system and hierarchical "V" architecture for the whole life cycle, including design phase, construction phase (little related papers), O&M phase, and decommission or life extension. To bridge the gap between theory and practice, the four-layered decomposition construction model is proposed and a detailed five-step conceptual illustration is given based on a GEN-III reactor in the

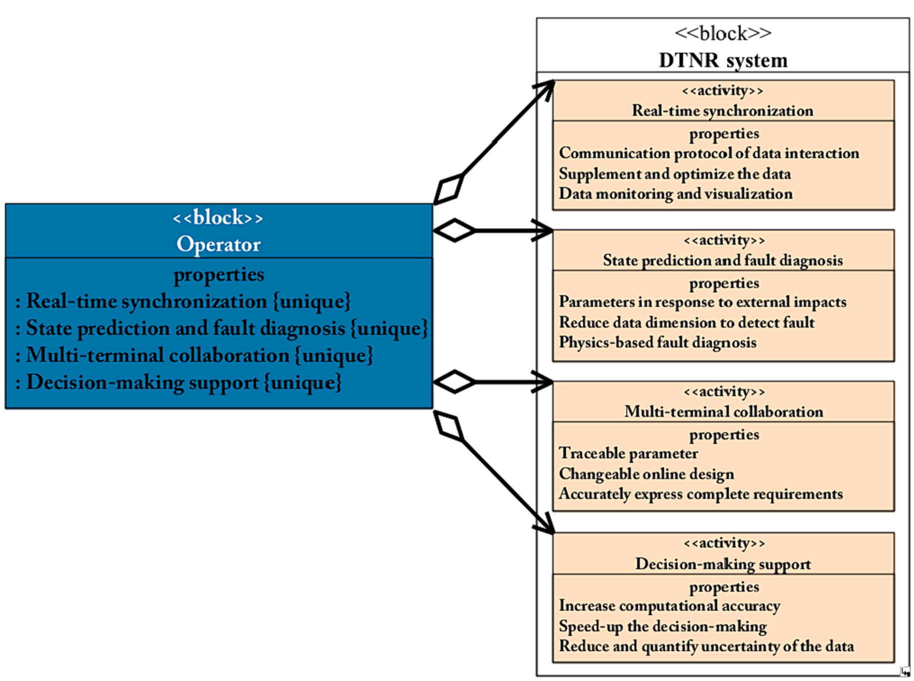


**Fig. 4.** Block definition diagram of four properties of DTNRS.

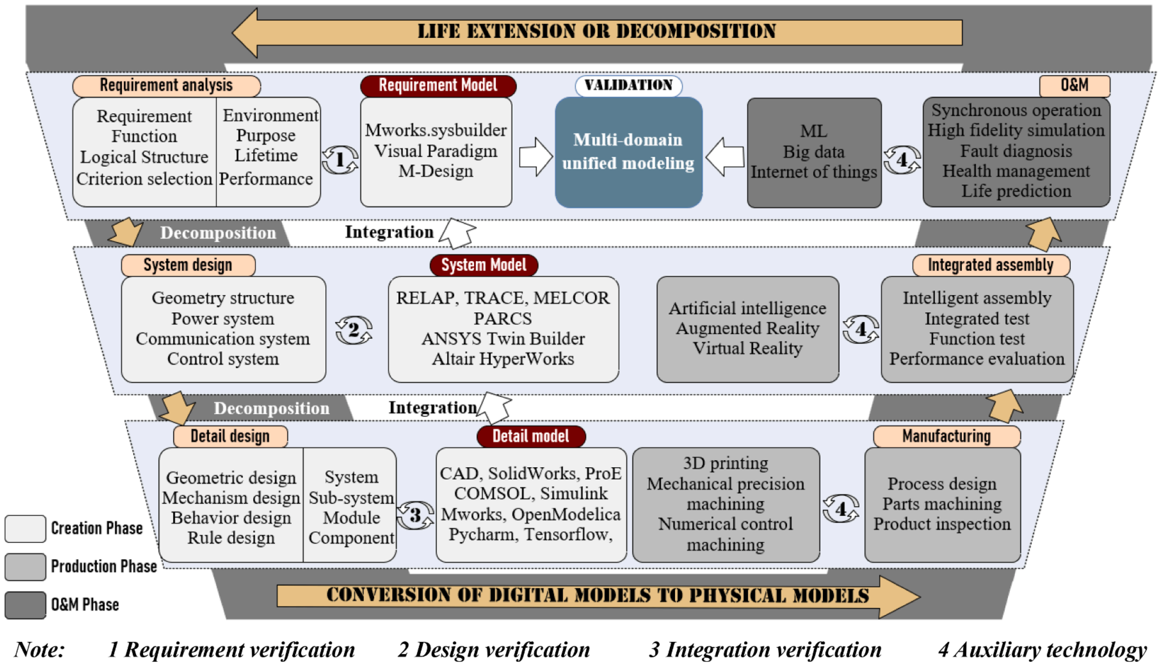


**Fig. 5.** The systematic and hierarchical "V" structure of a DTNRS.

following.

*4.1. The systematic and hierarchical "V" architecture of DTNRS*

Every stage of the life cycle is represented in the architecture (Grieves, 2005; Grieves and Vickers, 2017), with design taking place virtually, building, operations and maintenance, and decommissioning or life extension taking place in real space. Fig. 5 displays an overview of its realization pathways and particular functionality.

The use of domain-specific languages, the incorporation of intricate predictions and models, realistic simulations, system life-cycle modeling, and support for V&V are features of MBSE. It is one of several systems engineering solutions (Friedenthal et al., 2007). The system architecture contains the whole lifecycle of the DTNRS, including the design phase, construction phase, O&M phase, and life extension or decommission phase. The creation phase is executed in virtual space with top-down and bottom-up verification, while the other phases are completed in physical space. The validation between the digital model and physical asset is done based on the multi-discipline unified modeling technology, such as Modelica (Fritzson and Engelson, 1998).

(1) Virtual space.

Within the virtual space, there are three phases, requirement analysis, system design, and detail design, respectively, each with a unique verification procedure. With iterative cycles and continuous verification in the corresponding phases, the creation phase is divided into a top-down requirements refinement process, such as requirements analysis, system design, and detail design, and a bottom-up requirements integration process, such as detail model, system model, and requirement model. Through the use of modeling tools like Sysbuilder, the requirement analysis process, encompassing requirement decomposition, function analysis, logical architecture, and criterion selection, is executed while considering variables like the usage environment, purpose, lifetime, and performance. System design includes the geometric structure, power supply, communication, control, and other systems. After system modeling is completed, ongoing verification is performed utilizing neutron physical programs such as PARCS and thermal-hydraulic codes such as RELAP (ISL, 2006) and TRACE (Wang et al., 2009), in accordance with the system specifications. Using CAD and SolidWorks, the detailed design process models and verifies geometric, mechanism, behavioral, and rule design at the system, subsystem, module, and component levels. Following the completion of construction, the numerical model that was intended is used to build and function the physical entities.

(2) Physical space.

The real physical space is divided into three phases as well. The mechanical manufacturing stage finishes the process design, parts machining, and product inspection using 3D printing, mechanical precision machining, and numerical control machining. During product integration assembly, technologies like as artificial intelligence, augmented reality, and virtual reality can be employed to enable intelligent assembly, integration tests, function tests, and performance evaluation. Some of the main objectives of the O&M phase include high-fidelity simulation, defect prediction and diagnosis, health management, and life prediction. Additional technologies include ML, big data, and the Internet of Things. After the model is created, the fully functional physical entity can be validated with it to accomplish multi-domain unified modeling of the DT. Ultimately, based on pertinent guidelines, the choice of whether to prolong the life of the DT system or let it decompose can be made.

*4.2. The four-layered decomposition construction model*

To facilitate the systematic and hierarchical structure of a DTNRS and the construction process of a digital reactor, a four-layered decomposition construction model is proposed. The construction model also includes a construction circle, which is intended to bridge the gap between theoretical investigation and numerical simulation. A brief demonstration of the process of achieving DTNRS by numerical simulation and other methods is then given. As seen in Fig. 6, the construction of a DTNRS can be broken down into four layers: the data layer, the model layer, the simulation layer, and the Verification and Validation (V&V) layer.

***L1: Data Layer***.

The data layer includes three elements, namely data collection, data

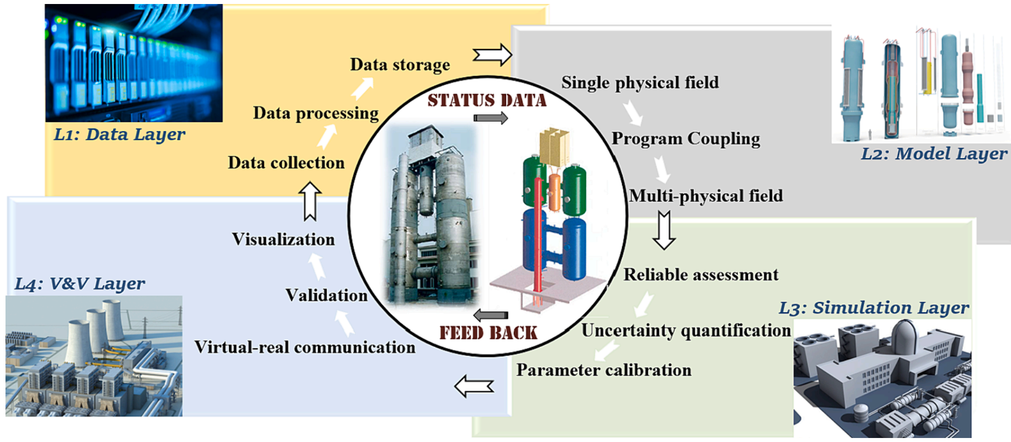


**Fig. 6.** The four-layered decomposition construction model of DTNRS *(In the figure: Schematic of PANDA facility (PSI, 1997)*.

processing, and data storage. For instance, take the DTNRS data flow depicted in Fig. 7 during an incident. 1) Data Collection: The sensor data is transmitted by the physical reactor. 2) Data processing: The simulation platform then processes the data using ML and constitutive equations. The operating analysis for determining the best accident mitigation strategies will be sent to the digital reactor. For later usage, the returned results are saved on the simulation platform. The I&C system sends the failure settlement to the physical reactor to lessen or eliminate the occurrence after obtaining the simulation platform's recommended changes. 3) Data storage: The data center will house all of these improved data sets.

***L2: Model Layer***.

The three elements of the model layer are single-physical field models establishment, program coupling, and multi-physical field model establishment, respectively. Using related single-physical field programs like RELAP and PARCS or coupled multi-physical field programs like NUMAP, we can create the numerical model based on the stored data. The different single-physics models, however, need to be coupled via coupling technologies in order to provide high-fidelity simulation.

***L3: Simulation Layer***.

At the simulation layer, the established model must be qualified by means of reliable assessment, uncertainty quantification, and parameter calibration. The uncertainty quantification guarantees that the predicted value can encompass the experimental data. Calibration of the parameters is required otherwise.

***L4: V&V Layer***.

The model enters the V&V layer if it is sufficiently precise and dependable. Establishing virtual-real connections, performing V&V, and achieving visualization are the next steps in the process. Once again, data collection is the first step towards next-generation design or experience reuse.

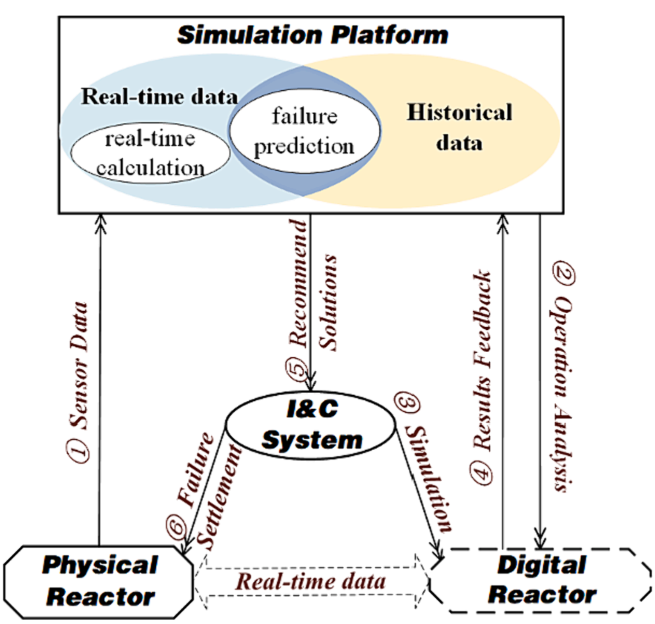


**Fig. 7.** Data flow diagram in data layer.

### 4.3. Conceptual illustration of the DTNRS

Fig. 8 illustrates the DTNRS in an intuitive manner using the four-layered decomposition construction model and the systematic and hierarchical "V" architecture. The real reactor system exists in physical space. A number of activities and different technologies, including kernel numerical simulation, multi-physical field global simulation, artificial intelligence, and real-time detection communication, are involved in the establishment of twin systems.

Creating a digital model of the entire reactor system is the first and most important work. This usually involves accurate specification and attributes of real object, multi-physical modeling, and system integration. This task alone can be quite challenging since the reactor system consists of many physical fields such as neutron physics, thermal-hydraulics, materials, structure mechanics, and chemistry. The coupled calculation is typically performed because there isn't yet a computational tool or algorithm that can handle this multi-physical simulation directly.

Once the digital model is finished, the physical reactor and the digital model should be able to communicate via commands and data. This communication includes normal state information, abnormal parameters, instructions, and so on.

The digital model should be more than just a mirror image of the actual reactor system; it should be a virtual organism with all the data from the analogous reactor as well as all the algorithms, databases, physical mechanisms, correlations, and intelligence required for the operation. The digital model can continue to run forward, self-sustaining, with its current state even in the event that communication is disconnected.

The DT system can be implemented in a way that allows the real reactor and its twin to operate simultaneously once the digital model and communication have been created. The condition of real reactor is being monitored by its DT, who can maneuver the operation of real reactor by providing feedback commands when necessary. For instance, when signs of an accident appear, early warning and precautionary measures are triggered in accordance with intelligence arithmetic based on current parameters and conditions. Building a full digital reactor is

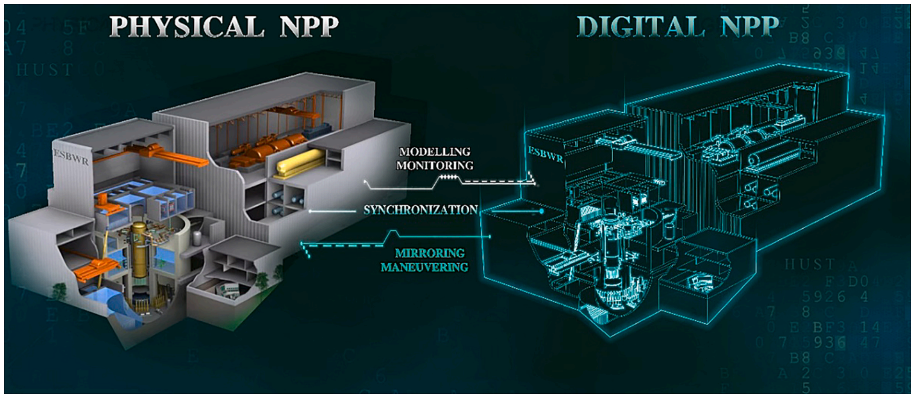


**Fig. 8.** The prospective application scenarios of DTNRS (In the figure: ESBWR schematic, GE-Hitachi (GE-Hitachi, 2011)).

not easy, but we can demonstrate how to set up the DT system by concentrating on a single component of the reactor system, such as the thermal-hydraulics system seen in Fig. 9.

There are five indispensable elements, physical entity, virtual model, database, services, and high-precision simulation platform, which are connected through data transformation. The process will then be broken down into five steps to explain how to connect the five components and create a DTNRS. Actually, the deployment of DTNRS faces challenges in time, cost, and model validation. Creating a high-fidelity DT requires expensive, time-consuming modeling procedures. Verification, validation, and uncertainty quantification of physics-based models add to the time and cost, demanding extensive testing and validation against real-world data. Data-driven models bring validity concerns, requiring assurance of accurate representation and comprehensive training data coverage. These challenges extend deployment timelines, pose financial constraints, and necessitate rigorous risk mitigation in the safety-critical nuclear industry. The effective integration of DT in nuclear reactor systems requires striking a balance between cost, efficiency, and accuracy. Technical challenges and potential technical solutions in the construction of DTNRS are also given in Fig. 10.

***The first step:*** to establish a reliable and robust database about nuclear reactor operation, which has undergone dimensionality reduction, fusion, screening, and calibration, using ML or sensitivity analysis, before being saved.

***The second step:*** to develop numerical simulation platform including thermal-hydraulic, neutron physics, materials, mechanics, and control fields, which can give precise prediction.

***The third step:*** to create a virtual model, obtained after requirement design, system design, and detailed design. The numerical model can be established through coupling each single-physical-field model, such as

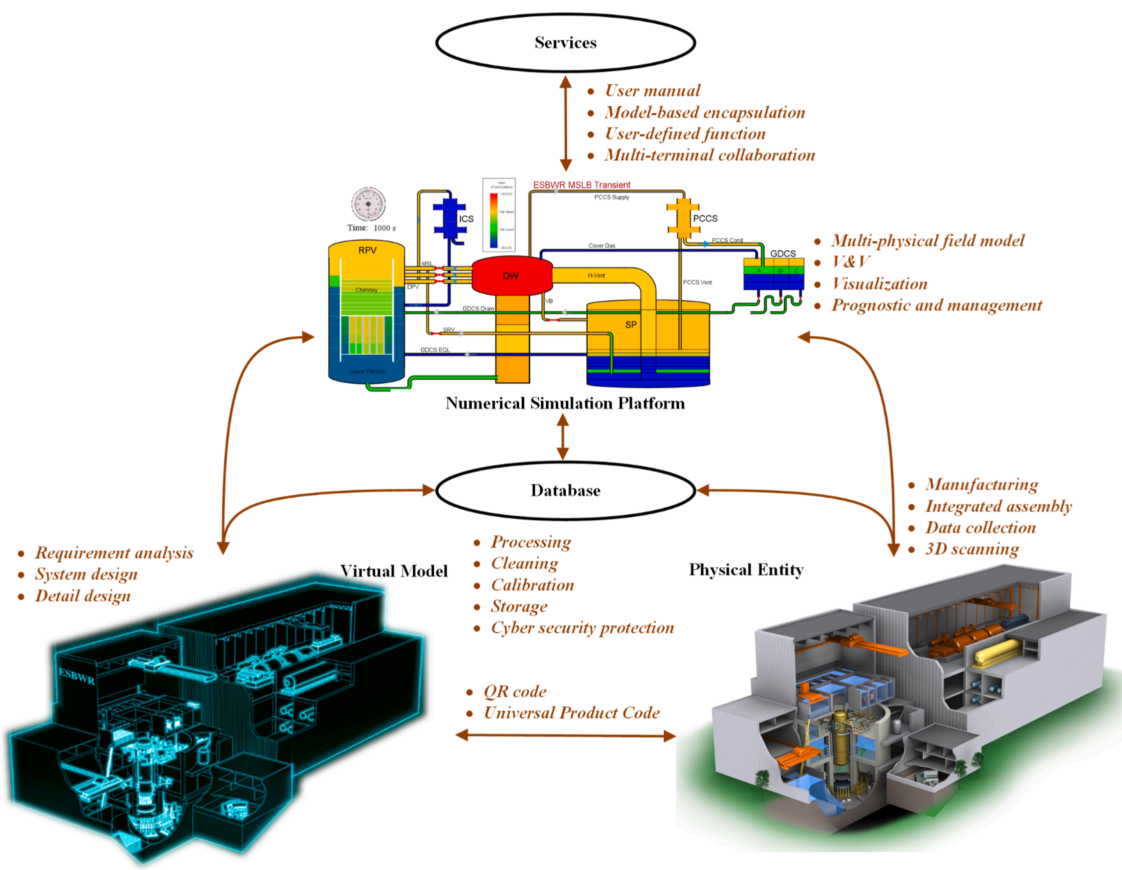


**Fig. 9.** The demonstration of DTNRS (In the figure: ESBWR schematic, GE-Hitachi (GE-Hitachi, 2011)).

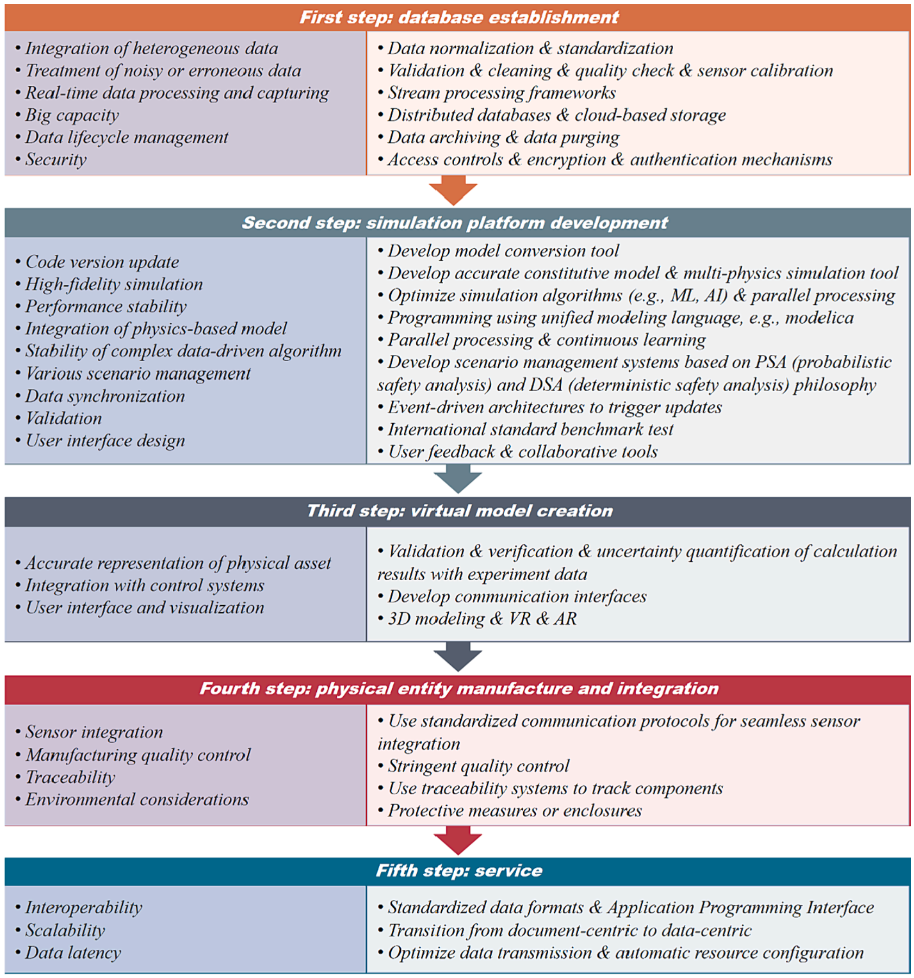


**Fig. 10.** Technical challenges (left) and potential technical solutions (right) in the construction of DTNRS.

RELAP and PARCS, or through multi-physical-field tools, like NUMAP. Then use the GEN-III BWR as a numerical simulation illustration. Taking thermal hydraulics as an example, the RELAP code is one of the widely used simulation tools, its representation is shown in Fig. 9 of the passive cooling system (GE-Hitachi, 2011; World-Nuclear-News, 2015). It consists of Reactor Pressure Vessel (RPV), Drywell (DW), Gravity Driven Cooling System (GDCS), Isolation Cooling System (ICS), and Passive Containment Cooling System (PCCS), respectively.

***The fourth step:*** While the physical entity is manufactured and integrated directed by the digital model in the fourth step. The objects in physical space and virtual space, corresponded by QR code or universal product code, must keep synchronous operation and results prediction in each time step with high-fidelity simulation after V&V. Information gathered from the physical asset is sent to the database for prognostication and simulation under normal conditions or accident occurrence through high-precision scanning and sensors. The user can be presented with prediction results for temperature, pressure, and void fraction under different conditions via a visual interface designed for management and prognosis.

***The fifth step:*** is carried out for services, principally user manual, model-based encapsulation, and user-defined function interface. Model-based packaging increases modeling efficiency by enabling scientists to employ models with the same function to construct alternative numerical models, such as RPVs in CAP1400 and AP1000. Additionally, the multi-terminal collaboration feature—which enables professionals in different areas to collaborate on modeling and validation—is essential.

DTNRS can be used after completing the aforementioned steps. Under typical circumstances, the sensors in the physical reactor communicate data and images to the database, the virtual model reads data to maintain synchronous operation, and the simulation platform reads data for state prediction. When interference and abnormal parameters occur, the simulation platform communicates the operators fault mitigation strategies based on the forecast results via the visual interface. The operator uses the remote control to make physical reactor modifications in an attempt to stop or mitigate the impact of the accident. In addition, automatic status monitoring, intelligent analysis and judgment, and autonomous command feedback will be applied when they reach a highly intelligent stage. In this way, they will become truly unmanned nuclear energy systems.

## 5. Conclusion

This paper summarized the digitization of nuclear energy systems and DT-related projects conducted by organizations, institutions, and enterprises in major nuclear energy countries. The current digital explorations can serve as a foundation and a reference for the future application of DT technology.

Second, we compiled a list of features that the DTNRS ought to have based on literature related to DT and nuclear energy using the MBSE philosophy. The physical and virtual components of DT must be in synchrony. With the help of the inherent numerical models and algorithm, the DT reactors could forecast the status parameters and potential errors, providing accident forewarning. Additionally, the redundant nature of the sensor data makes it difficult to increase the effectiveness of decision-making. As a result, data cleanup is also required.

Finally, this paper proposed a "V" architecture based on the MBSE philosophy to integrate all the aforementioned components into the ecology system of the DTNRS. The entire reactor lifecycle is discussed in the system architecture. Then, to fill the gap between the theoretical and numerical simulation, a four-layered decomposition construction model is also provided. Finally, taking a GEN-III reactor as an example, the five-step demonstration guidance of the DTNRS is given to show that the parameters are predicted and visible for fault detection. Meanwhile, the multi-physical field simulation, artificial intelligence, and real-time detection communication technologies are of primal importance for the establishment of DTNRS. Finally, the prospective application scenario of DTNRS is given.

It is believed that DT technology in the nuclear field will further develop with the recognition and efforts of the nuclear community.

## CRediT authorship contribution statement

**Hu Mengyan:** Conceptualization, Software, Methodology, Writing – original draft. **Zhang Xueyan:** Methodology, Writing – review & editing. **Peng Cuiting:** Conceptualization, Writing – review & editing. **Zhang Yixuan:** Conceptualization, Writing – review & editing. **Yang Jun:** Conceptualization, Methodology, Writing – review & editing, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

No data was used for the research described in the article.

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