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TECHNICAL CHALLENGES AND GAPS IN DIGITAL-TWIN-ENABLING TECHNOLOGIES FOR NUCLEAR REACTOR APPLICATIONS

December 2021

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ACRONYMS

AC	alternating current
AI	artificial intelligence
ASI	advanced sensors and instrumentation
DC	direct current
DIM	Data and Information Management
DT	digital twin
GUI	graphical user interface
LER	licensee event reports
ML	machine learning
NPP	nuclear power plant
NRC	Nuclear Regulatory Commission
O&M	operating and maintenance
PRA	probabilistic risk assessment
SSC	systems, structures, and components

EXECUTIVE SUMMARY

The Office of Nuclear Regulatory Research at the U.S. Nuclear Regulatory Commission (NRC) has initiated a future-focused research project to assess the regulatory viability of digital twins (DTs) for nuclear power plants. The objectives of this project are to:

- **Understand the current state of the digital twin technology and potential applications for the nuclear industry**
- **Identify and evaluate technical issues that could benefit from regulatory guidance**
- **Develop infrastructure to support regulatory decisions associated with DTs**

This report was prepared to explore digital twin technologies with nuclear applications to further enable collaboration among nuclear stakeholders. Digital twins and DT-enabling technologies are expected to be integrated with future nuclear reactor designs while also having the potential to improve the operations of currently operating nuclear power plants. Greater digital integration, improved instrumentation and control systems, and advanced operations and maintenance practices are all associated with DT-enabling technologies. This report presents a description of a DT system for a nuclear power plant followed by details of challenges and gaps in implementing DT-enabling technologies in current and advanced reactor applications.

The following are key challenges for their respective enabling technologies:

- Advanced sensors and instrumentation
    - Use of new types of sensors or multimodal sensors
    - Installation of a greater number of sensors and more varied sensors
    - Continuous, real-time collection of sensor data
    - Evaluation of uncertainty for new sensors
    - Integration of legacy sensors
- Modeling and simulation
    - Uncertainty quantification and propagation in model development and integration
    - Verification and validation of integrated, heterogeneous models
    - Development of real-time models adequate for nuclear DT application

- Data analytics
  - Integration of heterogeneous data
  - Treatment of noisy or erroneous data
  - Scaling data analytics
  - Capture of heterogenous and dynamic uncertainty
  - Decomposition of multimodal, real-time sensor data
- Machine learning (ML) and artificial intelligence (AI)
  - AI/ML training data requirements
  - ML algorithm selection
  - Ability to understand and explain AI algorithm behavior
- Physics-based models
  - Real-time simulation of high-fidelity physics-based models
- Data-informed modeling
  - Implementation of real-time, dynamic data-informed models
- Data and information management
  - Standards and guidance for cybersecurity, cloud storage, encryption, and geographic redundancy
  - Establishment and scaling of storage capacity, data-sharing bandwidth, and computational capability
  - Transition from document-centric to data-centric approach

Additional effort is needed from interested stakeholders to meet the challenges and bridge the gaps in implementing DT-enabling technologies in nuclear reactors. Due to stakeholder interest and industry trends, the NRC is continuing to explore the regulatory viability of digital twins for nuclear power plants by pursuing additional research in the application of advanced sensors for monitoring system performance, integration of security and safeguards within digital twins, and regulatory considerations for use of DTs. These activities aim to increase knowledge, enhance communication, and build mutual understanding of DT applications in nuclear power plants.

Digital twins (DTs) in complex industrial and engineering applications have proven benefits that include increased operational efficiencies, enhanced safety and reliability, reduced errors, faster information sharing, and better predictions. The interest in DT technologies continues to grow, and the technology is expected to experience rapid and wide industry adoption in the next decade. Some of the potential application areas of applying DTs in the nuclear industry are design and licensing, plant construction, training simulators, predictive operations and maintenance, autonomous operation and control, failure and degradation prediction, obtaining insights from historical plant data, and safety and reliability analyses. Current efforts in the nuclear industry are focused on specific enabling technologies needed to implement DTs, such as advanced sensors, digital computing and communication infrastructure, high-fidelity models, data analytics, machine learning (ML), artificial intelligence (AI), and multiphysics modeling and simulation [1]. In the future, these enabling technologies will coalesce to form a unified system or plant DT.

The Office of Nuclear Regulatory Research of the U.S. Nuclear Regulatory Commission (NRC) has initiated an effort to assess the regulatory viability of DTs for nuclear power plants (NPPs). This effort is led by Idaho National Laboratory in collaboration with Oak Ridge National Laboratory. The objective of the NRC's DT project is the identification and evaluation of technical challenges associated with the application of DTs in reactors that would impact the regulatory outcomes, with the goal of developing a regulatory infrastructure for the use of DTs as part of the regulatory programs. As part of this effort, the NRC sponsored the Virtual Workshop on Digital Twin Application for Advanced Nuclear Technologies in December 2020 and the second Virtual Workshop on Enabling Technologies for Digital Twin Applications for Advanced Reactors and Plant Modernization, in September 2021 [3]. The purpose of the workshops was to assess the current understanding of DTs and identify their potential benefits, opportunities, and challenges for nuclear reactors. The workshop provided a forum for the nuclear industry and DT stakeholders to discuss the state of knowledge and research activities related to DTs and their application in the nuclear industry and to understand challenges and gaps specific to DT-enabling technologies. The main topics related to DT applications in the nuclear industry that need to be addressed in the near term are the:

- Development of a common understanding, including an agreeable definition, of the structure and functions of a DT
- Identification of technical challenges and potential solutions related to implementing the DT-enabling technologies in nuclear
- Identification of regulatory readiness levels and gaps in applying DTs for nuclear reactor applications
- Engagement with stakeholders to identify the DT implementations in the current fleet and their potential regulatory impact.

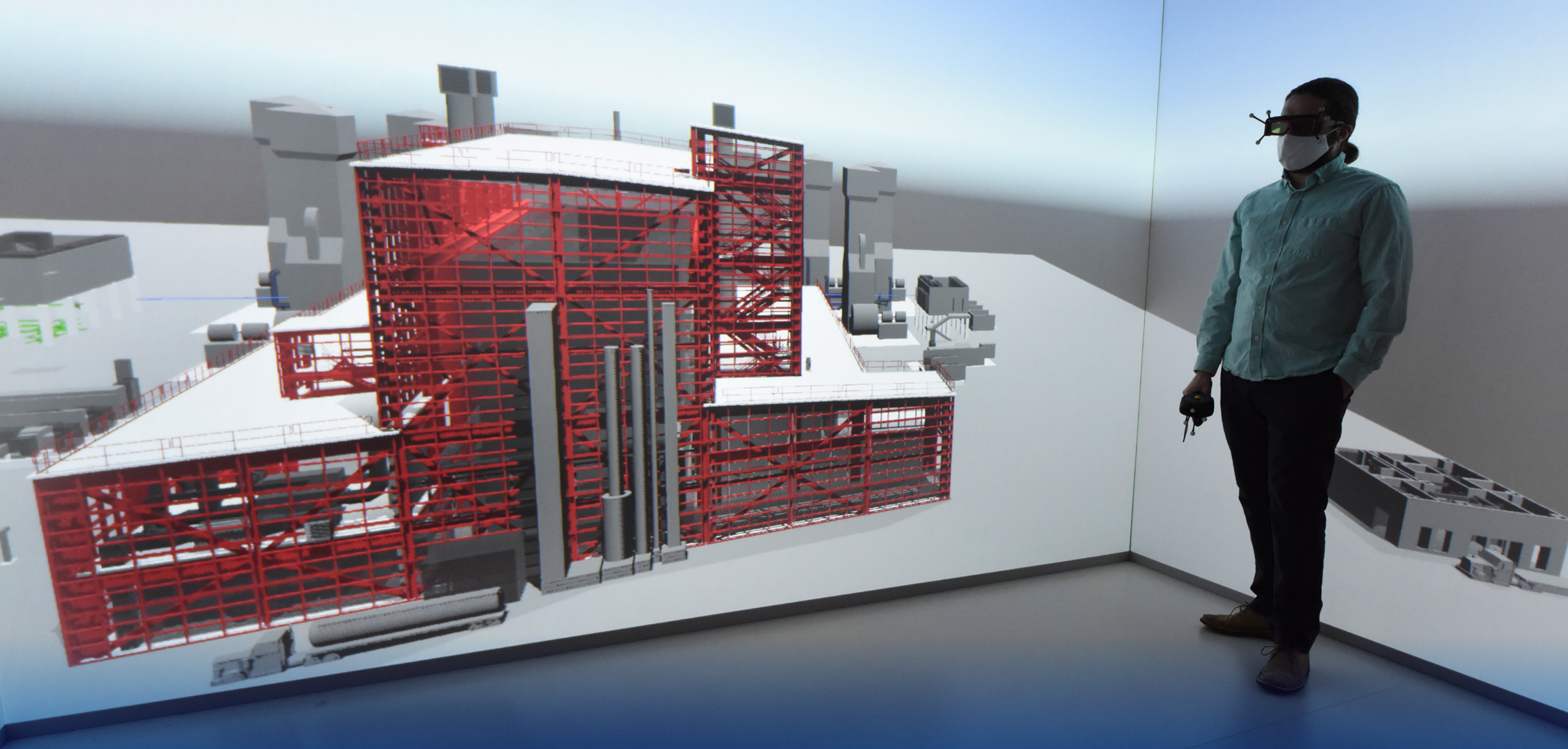
The purpose of this project is to better understand the potential applications of reactor DTs and explore the regulatory viability. This will be accomplished in two phases:

- ***Phase I:*** Identification and evaluation of technical issues that would impact regulatory outcome.
- ***Phase II:*** Development of a regulatory infrastructure for use of DTs as part of the regulatory programs.

As part of the Phase I efforts, one report has already been issued for the project that disseminates the findings of a state-of-the-art review of digital twin technologies and their applications in non-nuclear and nuclear industries [1]. Additionally for Phase I, this present report documents the technical challenges and gaps associated with the following DT-enabling technologies:

- Advanced sensors and instrumentation
- Modeling and simulation
    - Common challenges with modeling and simulation
    - Data analytics
    - Machine learning and artificial intelligence
    - Physics-based modeling
    - Data-informed modeling
- Data and information management.

This report also presents a description of a DT for a typical NPP application, including the description of its various elements and technologies. Section 1 presents a detailed description of DTs for nuclear power plant applications. This section provides the necessary conditions for a DT, defines key technical terminologies used in the report, and describes each technical element that will contribute to forming a nuclear DT. Section 2 presents a comprehensive discussion of challenges associated with DT-enabling technologies listed above. Section 3 provides a summary and conclusions from this task.



1 DESCRIPTION OF DIGITAL TWIN IN NUCLEAR

In recent years, DT technologies have started to be applied in the nuclear industry both in the current light-water reactor fleet and in the advanced reactors. The state-of-the-art survey report provides an extensive account of the DT application in the nuclear industry [1]. These efforts include collaborative efforts across advanced reactor designers, nuclear utilities, DT vendors, university researchers, and national laboratories and are focused on a variety of applications throughout a plant's lifecycle, such as design, licensing, regulatory compliance, emergency response, modification, engineering analysis, construction, operation and maintenance (O&M) efficiency, and testing.

The following section lays the foundation for the rest of the report by describing various possible attributes and features of an NPP DT.

The term "digital twin" evolved from the concept of product lifecycle management and can be attributed to the work of Michael Grieves and John Vickers [4-7] over the last two decades. The first instance of the term, coined by John Vickers, is found in their presentation [8]. In [8], the DT model is composed of the physical product, its representation as a digital twin, data flowing from the physical to the DT, and information flowing from the digital to the physical twin. Figure 1 illustrates the digital twin concept for the nuclear power industry that broadly comprises four elements: 1. Nuclear Power Plant, 2. Digital Twin, 3. Data and Response from Nuclear Power Plant to Digital Twin and 4. Actions and Recommendations from Digital Twin to Nuclear Power Plant. These elements are described in detail in this section, and the challenges associated with creating and using DTs of these elements are discussed separately.

Various interpretations of a DT may exist based on different technologies, applications, or other criteria. The description of a nuclear power plant DT system or simply nuclear DT system in this report is for illustrative purposes only and should not be considered definitive. The term nuclear DT in this report is described with regard to a typical commercial NPP to provide a framework for discussion of nuclear applications of DT technologies.

Several DT technologies discussed in this section have already been in use prior to the advent of the term "digital twin." For instance, 3D CAD models have been used by parts designers and manufacturers for over two decades, and multiphysics modeling and simulation have long been used by stakeholders in the nuclear industry for representing neutronics and thermal hydraulics. It can

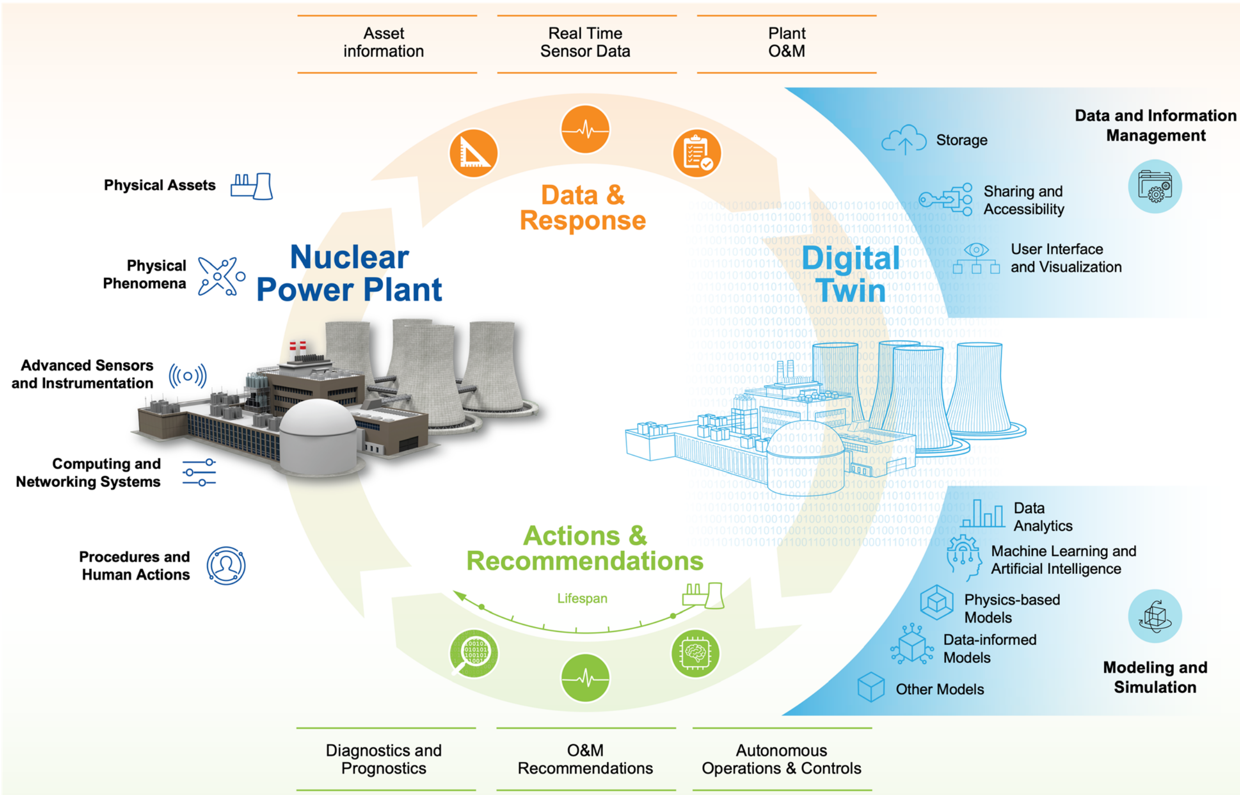


Figure 1. *Overview of DT system in an NPP application.*

be asked then, why should these existing and proven technologies now be referred to as components of a DT? This report identifies the following three conditions for any existing or new technology to be referred to as or be a part of a nuclear DT:

1. **Digital Form:** The technology must exist in a digital form that can be managed, processed, and executed on a digital device. This condition seems obvious but needs to be explicitly defined for the nuclear industry because some nuclear plant data and information have traditionally been handled in a non-digital form. For instance, historical information at an NPP, such as maintenance records, may exist in a non-digital forms such as paper or microfiche. Information of this type must first be transformed into a digital format, e.g., via machine-readable scans and context aware processing, before it can be used within a DT.
2. **State Concurrency:** The technology must be capable of updating dynamically and in real time to represent the state of a physical entity or physical phenomenon and must maintain that state concurrency. For example, a multiphysics model of a reactor core can be referred to as a DT only if it represents, in real time, the current conditions of the reactor, such as fuel temperature, reactor fluid temperature, neutronics, etc. The update frequency needed to maintain the real-time state concurrence is of course dependent upon the underlying rate of change of the represented physical system. For instance, real-time sensor data may require an update frequency of seconds or minutes, but real-time maintenance work order data could only require an update frequency of weeks.
3. **Purpose:** The technology must have an underlying purpose related to an NPP lifecycle activity. That is, a nuclear DT must be part of a DT system and be coupled in terms of both state and purpose with the physical NPP. For instance, performance data from a pump might be used to train an ML model, but to be called a DT, the model must both be updated frequently enough to reflect the current pump state and also serve a plant-related purpose, such as informing pump maintenance.

Additionally, for the purpose of clarity, we will use the following terminology throughout this report:

Digital Twin Technology or simply digital twin: when generally referencing the approaches and technologies used to implement a DT.

[Specific instance name] digital twin: when referencing a particular instance or implementation of a DT (e.g., a pump digital twin, a sensor digital twin, a ship digital twin, a design digital twin, an operational digital twin). Note that an instance DT can exist in the absence of one of the above elements of Figure 1.

Digital twin system: when referencing the overall system that is comprised of, in general, the physical system, the digital twin of that system, and the relationships between physical system and digital twin e.g., information and data flows. Figure 1 presents a DT system for an NPP.

While the nuclear industry has years of experience with technologies that may be used as elements of a future nuclear DT system (e.g., models and simulations of physical plant systems, highly instrumented plant systems, and high-density collections of plant performance data), these elements by themselves do not constitute a DT system. As illustrated in Figure 1, generally, a nuclear DT system must have a physical system, a digital twin of that system, and a set of relationships, as well as a means of maintaining the relationships, between the two. However, one or more of the system elements of Figure 1 may exist on its own. For instance, advanced reactors, such as microreactors, are currently in the concept or design stage, and therefore, the physical elements of such reactors do not exist. However, the DT of these reactors may exist for certain purposes, such as design and licensing.

Digital-twin-enabling technologies: or simply enabling technologies, when referring to a set of technologies that are needed to successfully implement a nuclear DT. Referencing Figure 1, all the technologies within the DT are essentially DT-enabling technologies. Additionally, the Advanced Sensors and Instrumentation and Computing and Networking Systems are DT-enabling technologies within an NPP. The description of challenges and gaps in the following section of this report will therefore focus on three broad DT-enabling technologies: 1. Advanced Sensors and Instrumentation, 2. Modeling and Simulation, and 3. Data and Information Management.

1.1 NUCLEAR POWER PLANT

An NPP is a complex entity that can be divided in numerous ways depending on objective and purpose. For the purpose of being part of a DT system, the physical entities of an NPP are divided into five broad technical areas. Two criteria are used for this division, 1. Entities that can be represented with a DT and 2. Entities that enable the creation, operation, and maintenance of DT. Physical assets, physical phenomena, and procedures and human actions are three broad areas that are based on criterion 1, whereas advanced sensors and instrumentations and computing and networking systems are two broad areas that are based on criterion 2. Note that it is possible for sensors and instrumentation or computing and networking systems to also be criterion 1 entities, i.e., represented within a DT. While referring to NPP in this report, the terms "NPP" and "plant" will both be used interchangeably.

Physical Assets

A typical NPP comprises a wide range of physical assets that are generally termed as systems, structures, and components (SSCs). These SSCs include structures such as the reactor and plant buildings, systems such as cooling systems, feedwater systems, power generating systems, electrical systems, and others that are made up of thousands of mechanical, electrical, and other components such as pumps, motors, valves, chillers, circuit breakers, compressors, fans, and batteries. The SSCs work together toward the safe, reliable, efficient, and continuous operation of the plant to generate electricity. The scale and function of SSCs range from a small mechanical component, such as a valve, to the reactor itself.

Physical Phenomena

Natural processes, such as reactor thermal hydraulics and corrosion, influence both plant performance and changes to plant states. In order to represent an NPP with a DT, important physical phenomena must be defined and characterized in relation to their effects on the plant and other physical phenomena. Examples of important physical phenomena include reactor thermal hydraulics, corrosion, concrete degradation, etc. Some physical phenomena have been well studied historically and can be represented in the form of physics-based modeling and simulation. Unlike reactor thermal hydraulics, physics-based models of several physical phenomena at a plant either currently do not exist or cannot be defined. For example, reliable physics-based concrete degradation models are not well developed. However, such processes play a critical role in plant operation and in integrating physical phenomena models with other types of models in a DT. Valid representation of all important physical phenomena will provide immense value in understanding the current plant processes, predicting future plant states, and making decisions for future plant operation and safety.

Advanced Sensors and Instrumentation

One way in which the NPP gathers data needed for O&M, as well as interactions with the DT, is through a combination of legacy and advanced sensors and instrumentation (ASI). The sensors and instrumentation provide the eyes, ears, and other senses required for the DT to track what is happening in the NPP. While some of the sensors are already in place as part of the existing NPP control and monitoring system, advanced systems of sensors are under development to enable more complete knowledge of the NPP and to add new capabilities, such as the detection of incipient sensor failures without requiring the introduction of vast amounts of redundancy. As a DT-enabling technology, ASI include not only sensors but also powering requirements and communication or data transfer infrastructure, such as cable or wireless technologies. A connection to the control systems within the NPP may provide the means by which a DT is able to autonomously influence the operational state of the NPP. Of course, the controls available to the DT might be limited to certain particularly well-suited subsystems or applications, such that the consequences of mis-operation are within an acceptable range for the qualification of the DT system.

Computing and Networking Systems

The computing and communication hardware utilized to enable a DT system can span a wide range from complex computing clusters to simple handheld devices, each playing a separate role to fulfill a system need. Complex, recurring analyses may require the use of either dedicated onsite or cloud-leased high-performance computing systems. Tasks requiring interaction with users in operational environments can be best handled by handheld robust units which wirelessly transmit data back to a central storage and processing system. It is important to note that the computing and networking systems referred to here include the computing infrastructure required to create, operate, and maintain DTs of parts of the plant.

Procedures and Human Actions

At any given time, a large number of procedures performed by humans are required to control and support an NPP. Some of the procedures involve normal reactor operations, refueling, engineering, maintenance, safe shutdown, and chemical control, etc. The procedures can be continuous, such as procedural operator actions to control power, or periodic, such as scheduled testing, maintenance, and upgrades. Regardless of the type, intent, or periodicity of the procedures, it is important for a DT to represent these complex processes. How the plant staff interact with SSCs in the plant can impact plant physical processes, plant procedures, power-generation, plant safety, and response to critical events. It is critical to understand and represent human actions in DTs for an accurate depiction of plant operations. In addition to plant operations, the human-machine interface is an important consideration in how humans interact with computer hardware and software in the control room, remote monitoring, and diagnostic centers and with handheld devices in the field.

1.2 DATA AND PERFORMANCE

Information about the plant, its SSCs, physical phenomena, procedures, actions, and data from sensors and instrumentation is vital for the creation and for the sustained, accurate, reliable, and efficient operation of a DT. An NPP is such a complex entity that the data, information, and response to recommendations from DT can be quite heterogenous. Following are some examples of heterogeneity in plant data and response:

- Digital and non-digital form
- Historical and real time
- Different time resolutions ranging from milliseconds to a yearly update
- Different sensor modalities
- Manually collected or automated acquisition
- Numerical, text, categorical, or other format

Categorizing such complex data and response is not trivial; however, for the purpose of this report it is categorized as follows.

Asset Information

Various plant asset information, such as dimensions, geometry, topology, material, chemistry etc., could be needed for creating and maintaining a corresponding DT (e.g., pump DT or motor DT). The plant asset information required will be dependent on a variety of factors, including SSC type, SSC function, and the requirements of the digital representation. For example, a digital representation of a turbine building sump pump may require little more than pump capacity and periodic pump run state data, while the representation of the reactor core may require real-time, high-fidelity, high-bandwidth data.

Real-Time Sensor Data

Traditionally real-time sensor data have been the mainstay of NPP control room operations where the reactor is controlled based on real-time data, such as reactor power level, pressurizer level and pressure, control rods, and steam generator, etc. Outside of the control room, real-time data acquisition has historically been limited. Data acquisition in the rest of the plant has been aimed at ensuring the safe and reliable operation of SSCs and has been mostly performed manually and periodically. In order to develop and operate a real-time DT, it is important to enable an automatic, continuous and real-time data acquisition from plant SSCs. Advanced digital sensors with a wireless capability, high bandwidths, and quick installation will enable real-time data acquisition and a large number of sensor modalities, such as vibration, temperature, pressure, flowrate, voltage and current on a much larger and more diverse subset of plant SSCs.

Plant O&M

Plant O&M activities range from day-to-day engineering and controls to planned and unexpected repairs and maintenance, and to extensive undertakings, such as refueling outages and asset replacement. U.S. commercial plants traditionally keep paper or computer records of past and planned O&M activities that can prove valuable in informing the past, current, and future state of a DT. Corrective and preventive work order logs, functional equipment groups, outage logs, and licensee event reports are some examples of non-numerical data providing comprehensive details about O&M activities that can be valuable for DT applications. With the use of DT-enabling technologies, such as ML, these records can provide deeper insights, such as failure trends, maintenance effectiveness, and efficiency, and classification of activities.

1.3 DIGITAL TWIN

For a DT to exist, especially for an NPP, we identify two broad categories of technology: 1. Modeling and Simulation (M&S) and 2. Data and Information Management (DIM). M&S is the technology that is the primary engine behind a DT, while DIM technology supports the creation, operation, and maintenance of a DT.

Modeling and Simulation

For the purpose of this report, we consider the following definitions: "A model is a representation of a system" and "A simulation is the act of executing the model". Models can take different shape and form depending on the system they represent, and the information used for creating the model. As part of nuclear DT described in this report, we describe modeling and simulation to consist of one or more of the following: data analytics, ML/AI, physics-based models, data-informed models, and other models.

Data Analytics

NPPs generate a wealth of data as part of their routine operation and from installed sensors and instrumentation. The process of using this data to make decisions related to the plant can be termed data analytics for NPPs. Data analytics can be as simple as using fluid flow rate data from a process to make a fluid rate control decision, or data analytics can be as complex as using multiple streams of historical and real-time data in a statistical toolkit, such as R, to provide insights on operation, maintenance, economics, safety, power-generation, etc. In this report a difference between data analytics and other data-based models is that data analytics does not include predictive models.

ML/AI

AI is a broad term used for the science and engineering of making intelligent machines that can think and act like humans [9]. ML, a type of AI, is the term used for computer algorithms that learns from a set of training data to classify or make predictions [10]. ML has been widely used in solving problems, such as classification, clustering, dimensionality reduction, and anomaly detection, etc., and has been successfully applied in real-world applications, such as image processing, image recognition, product recommendation, email filtering, internet search, etc. As part of a nuclear DT, ML/AI algorithms can be built from past and current "Data and Performance" (Figure 1) of the plant to provide insights, predictions, and recommended actions on O&M, economics, safety, power-generation, etc.

Physics-Based Models

Physics-based modeling involves the modeling and simulation of a plant's physical assets and phenomena according to the laws of physics. In a nuclear reactor application, physics-based models can include a variety of phenomena, such as neutronics, heat transfer, fluid flow, electromagnetics, and mass transport and their effects on plant physical assets such as the reactor vessel and containment. The coupling of multiple physics-based models is essential for applications where traditional single-physics analyses are inadequate to account for the simultaneity of real events. Several multiphysics models are currently in use by nuclear stakeholders, such as reactor designers, researchers, operators, and regulators, for applications such as full core nuclear reactor simulation, nuclear fuel analysis, thermal hydraulic for reactor transient analysis and more [11-18]. Physics-based models will be implemented holistically within a nuclear DT to represent a plant's physical assets, their integrated performance, and the physical processes by which they change.

Data-Informed Models

Data analytics and ML/AI models are fundamentally based on past and current data; however, other models, such as physics-based models or probabilistic risk assessment (PRA) models, are typically structured using knowledge of the modeled domain and its governing equations, not data. However, because models are only representations and approximations of physical reality, even the most accurate model's state will eventually diverge from the state of the system represented. Thus, to maintain continuous state concurrency (e.g., to ensure that the DT is always an accurate representation of the NPP) DT models must be integrated or informed with real-time plant data. In this report, models that can be updated and/or corrected with live plant data are referred to as data-informed models. Data-informed models can enable real-time model updates and adjustments to DT performance to match that of the NPP. For instance, digital twin data-informed physics-based models of thermal hydraulics, neutronics and reactor components can be integrated with real-time plant data such as reactor temperatures, pressures, fluxes, and flow rates to ensure the models accurately represent actual reactor performance and can provide real-time insights into and valid predictions of reactor states.

Other Models

For an accurate and effective nuclear DT, it is critical that the variety of SSCs, processes, ASI and computing infrastructure, and human actions be accurately modeled and simulated in the digital twin system. To that end, a corresponding variety of model types and formalisms beyond those already discussed may be required for a nuclear DT. Examples of these other types of models include models of workflows, 3D system geometries and configurations, control and logic, PRA, online risk, physical security, cybersecurity, and human procedures and actions.

Data and Information Management

The ability of a DT to gather, process, and disseminate data depends entirely upon its ability to both store and retrieve information in a logical and organized manner that complies with all applicable requirements and presents the information to users and computer interfaces in a manner that can be clearly visualized, absorbed, and verified for integrity and correctness. Three of the aspects to be considered are the rate at which data can be processed, the provability of data integrity, and the maintenance of concurrency across multiple interconnected data streams. This data can be displayed through use of a graphical user interface (GUI) and supporting visualizations.

Storage

Currently operating plants have traditionally generated a large amount of data in non-digital format. To support DT implementation, the existing and newly generated plant data must be stored in a digital, structured, scalable, and centralized environment. Data storage systems needed to support DTs may include local plant servers, fleetwide data infrastructure, or cloud-based storage systems.

Sharing and Accessibility

Software solutions for handling structured and unstructured plant data can comprise data handling tools and associated user interface, accessibility protocols and cybersecurity solutions. Data handling solutions must ensure the seamless integration of the heterogenous plant data, uninterrupted data availability, and real-time interaction across DT models and data storage.

User Interface and Visualization

The main control room at current nuclear power plants have been the mainstay of user interface and visualization of reactor and plant operations. When integrated with DT, the panels, control boards, alarms, and plant computer inside a control room would experience significant digital upgrade and modernization. In addition to the control room, DT integration would introduce additional user interfaces, such as a plant monitoring and diagnostic center, interface for modeling and simulation, and also handheld digital devices.

1.4 ACTIONS AND RECOMMENDATIONS

The objective of implementing a DT system lies in providing actions and recommendations for safe, reliable, and efficient operation. To this end, the actions and recommendations from a DT can be classified into the following areas:

Diagnostics and Prognostics

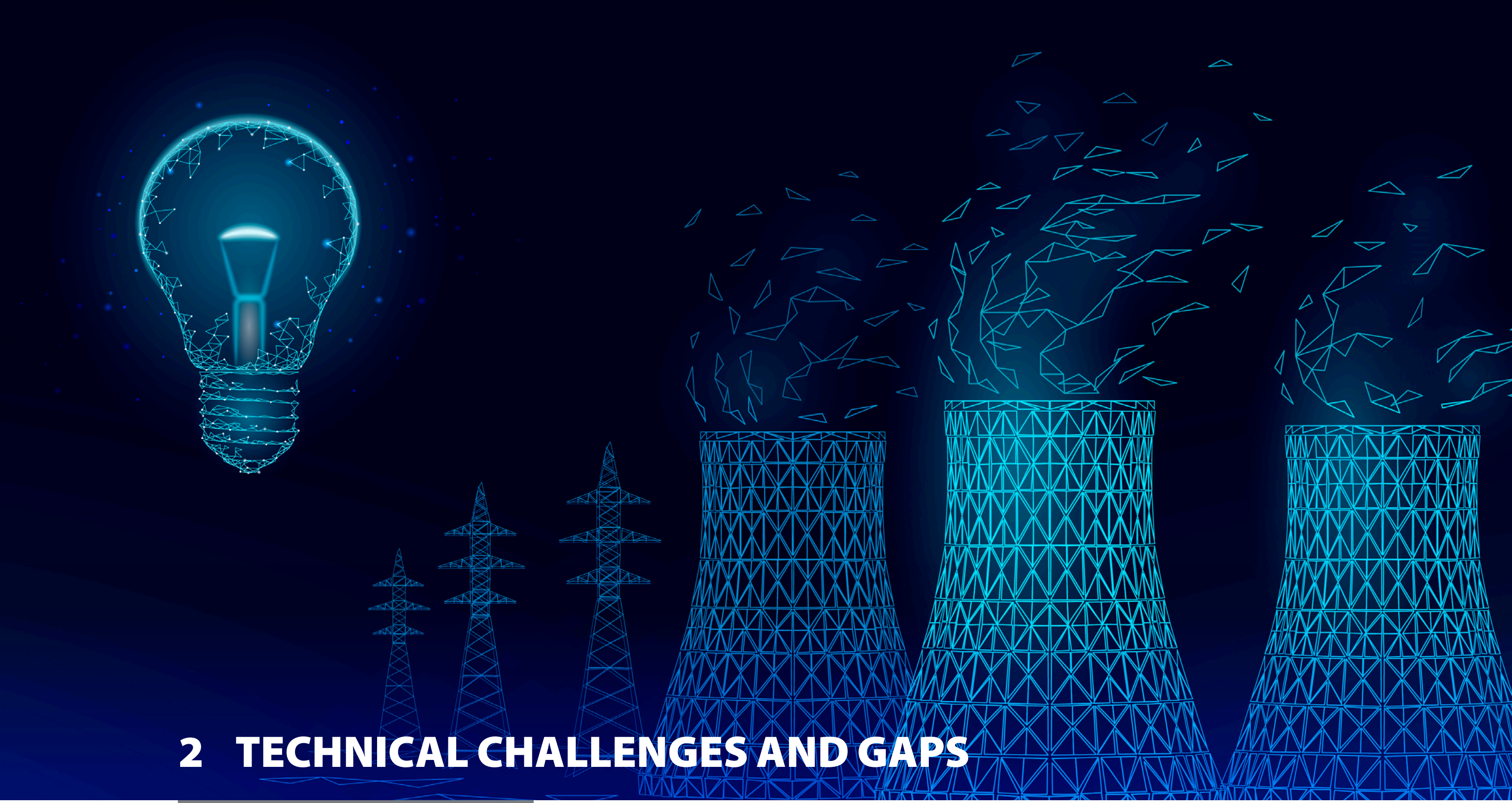
The health and condition monitoring data primarily acquired by installed sensors can provide direct information to perform diagnostics and prognostics. Historically in NPPs, human operators observe data and rely on manual diagnostics and prognostics to characterize current and predicted health and condition of plant SSCs. With the use of DTs, a large volume of heterogenous data and information can be processed at a much faster speed to perform diagnostics such as anomaly detection, identification of sensor malfunction, differentiation between true anomalies and sensor malfunction, failure prediction, critical event prediction, and more. A DT capable of modeling and simulating integrated plant operations and activities will feature high levels of awareness of plant state and can detect and predict anomalies in advance of the identification of such issues by plant staff. This capability can be leveraged to provide real-time notification and recommendations to plant staff of emergent or future conditions requiring action as well as visualization tools to help plant staff understand ongoing events. Since a DT can be used to understand and analyze plant states more broadly and more rapidly than human plant staff, it can supplement staff mental models of the plant and be a powerful operator aid.

O&M Recommendations

O&M practices in NPPs have traditionally aimed at ensuring safety and reliability and over time have resulted in added conservatism in O&M practices. DT technologies hold promises to transition the commercial nuclear industry from the current scheduled and preventive maintenance practice to a more efficient predictive maintenance posture. Predictive algorithms in DTs can use component health and condition monitoring data and, in combination with historical and current maintenance records, can provide recommendations for efficient O&M practices. Some examples of benefits of using DTs for O&M are eliminating certain maintenance, transitioning from manual to robotic maintenance, reducing the frequency of scheduled maintenance, optimizing maintenance scheduling such as combining more than one maintenance effort to reduce downtime, selecting which specific action to perform, reducing maintenance labor hours, and maximizing generation.

Autonomous Operations and Controls

Almost all operations and controls in existing NPPs are manual; however, this paradigm is potentially shifting, as many of the advanced reactor designs have substantial passive safety features that can make the plant “walk-away safe” thus increasing the acceptability of autonomous vice human operations. Autonomous operations and controls technology have matured and become popular in several applications, such as aviation, autonomous vehicles, etc. DT technology offers the possibility of ML/AI not only recommending but also performing certain operations and control actions in an NPP. In the early stages, such technology might be applied to non-safety systems for small and clearly defined tasks, and then as acceptance is gained, gradually move toward application to more complicated or safety-related tasks.



2 TECHNICAL CHALLENGES AND GAPS

This section is structured based on the following enabling technologies that form a DT, as discussed in Section 2 (Figure 1):

1. **Advanced sensors and instrumentation**
2. **Modeling and simulation**
    i. **Data analytics**
    ii. **ML and AI**
    iii. **Physics-based modeling**
    iv. **Data-informed modeling**
3. **Data and information management**

This section provides a description of major technical challenges and gaps associated with the implementing enabling technologies as part of a nuclear power plant digital twin. Challenges are identified as new or difficult tasks and problems associated with DT implementation, while gaps describe what is needed beyond available resources to meet those challenges.

Each section presents discussions on major challenges and gaps associated with use of the respective enabling technology within DTs. The challenges and gaps presented in this section are identified based on complexities and roadblocks related to different aspects of an enabling technology's lifecycle, such as research, development, design, manufacturing, licensing, qualification, deployment, and O&M. Exploring such a wide range for each enabling technology results in an extensive set of challenges and gaps, discussion of some of which are beyond the scope of this work. Therefore, each subsection dedicated to an enabling technology provides a detailed discussion of only those challenges and gaps that have a significant or novel impact on the use of the enabling technology within a DT. This section concludes with a summary of all the challenges and gaps for each enabling technology identified in this work.

Before discussing challenges associated with DT-enabling technologies, it is important to note the major challenges associated with existing plant SSCs in supporting a DT. The wide-ranging scale, heterogeneous functions, and interrelationships among the SSCs pose a unique challenge to the digital twinning SSCs of an NPP. Such challenges include defining component DTs, system and structure DTs or plant DTs with the SSC-specific resolutions, fidelities, accuracies, objectives and applications as well as the relationships and interfaces among the SSCs needed to adequately represent the physical space (Figure 1). Combining DTs to form a larger, integrated DT (e.g., pump, motor, and valve DTs combined to form a coolant system DT) poses a significant challenge to integrating DTs with different fidelities and resolutions.

2.1 ADVANCED SENSORS AND INSTRUMENTATION

The collection of operating condition data is integral to the implementation and execution of an NPP DT. A system of sensors must be installed into an NPP and sampled to meet the following primary goals:

- Provide real-time and uninterrupted information on the true condition of an SSC or a process
- Maintain state concurrency between DT and NPP
- Provide input and updates to models and simulations within the DT

ASI featuring new designs and capabilities are under consideration for the current fleet of light-water reactors and for many new and advanced reactor designs, with one goal being the development of a more fully instrumented plant. A DT system will leverage the existing and novel data streams available in a fully instrumented plant to inform its digital representations, and thus, ASI will be a key enabling technology for DT.

2.1 | KEY CHALLENGES

Use of new types of sensors or multimodal sensors

Installation of a greater number of sensors and more varied sensors

Continuous, real-time collection of sensor data

Evaluation of uncertainty for new sensors

Integration of legacy sensors

A more fully instrumented plant, including a greater number of more varied sensors, is an important component of developing a high-fidelity NPP DT. Not only are there challenges with data collection and integration, but there are challenges with respect to the design of sensor placement, sensor installation, and sensor maintenance. For example, the design of microreactors poses challenges with physical space constraints where enough space may not exist to install all desired sensors. The optimization of sensor choice and placement is beneficial for all design considerations and integral for some reactor applications. Virtual sensors may be used in the design process using a DT to optimize instrumentation. For the current light-water reactor (LWR) fleet, analog-to-digital conversion could be installed on existing equipment and would enable the use of pre-existing instrumentation for DT. However, this would require installation and calibration of additional equipment. Although not specific to DT, maintenance plans must be considered for the additional instrumentation.

The advanced sensor technologies may be broadly categorized by their application, such as reactor vessel instrumentation system, reactor protection system, SSC health monitoring, tritium control, chemistry monitoring, off-gas control, real-time dose monitoring, or by their sensor modalities, such as neutron flux, temperature, pressure, flow rate, vibration, coolant level sensors, chemistry, or even based on sensor environment in an NPP, such as in-pile, in-vessel, ex-vessel. For a presently operating NPP to implement a DT, there would be a need to digitize existing instrumentation outputs, such as installing gauge readers or valve position indicators, or to add new digital instrumentation to gather the same data. These ASI result in additional challenges to the design, implementation, and regulation of a DT in an NPP. The advanced reactor application of sensors can have unique challenges specific to reactor technology and other salient features of an advanced reactor, such as limited space for sensor installation, an under-water reactor, remote deployment. The instrumentation requirements are expected to vary based on the category and class of sensors under consideration. Table 1 summarizes some of the relevant characteristics of in-core sensors under consideration.

Table 1. Summary of some relevant characteristics of in-vessel sensors.

Sensor	Measured Parameter	Active/ Passive	Input Signal	Output Signal
Thermocouple (various types)	Temperature	Passive	NA	DC Voltage
Self-powered neutron detectors (various types)	Neutron Flux	Passive	NA	Current
Micro pocket fission detector	Neutron Flux	Active	DC Biasing Voltage	Current/ Charge Pulses
Ultrasonic Thermometer	Temperature	Active	RF Current	RF Voltage
Linear Variable Differential Transformer	Displacement/Pressure	Active	AC Voltage	Voltage
Thermal Conductivity Probe (transient dc method)	Thermal Conductivity	Active	DC Current	DC Voltage
Thermal Conductivity Probe (frequency method)	Thermal Conductivity	Active	AC Current	Phase Change in Resistance
Acoustic Emission Sensor	Fuel/Cladding Failure	Passive	NA	Voltage

The in-core or in-vessel sensors (active or passive) have varied output signal types, including direct current (dc) voltage (thermocouples), alternating current (ac) voltage, radio-frequency waveform, impedance, and resistance change. Traditionally, a dedicated one-by-one cabling is used to transmit measured parameters to the electronics (part of the instrumentation and placed outside the high-radiation area). Similarly, Table 2 summarizes some of the relevant characteristics of ex-vessel sensors that are under consideration. These ex-vessel sensors are connected to an electronic system (wired or wirelessly) for data conversion and transmission.

Table 2. Summary of some relevant characteristics of ex-vessel sensors.

Sensor	Measured Parameter	Active/ Passive	Input Signal	Output Signal
Resistance Temperature Detector	Temperature	Passive	Temperature	DC Voltage or Current
Proximity Probe	Vibration	Passive	NA	Acceleration, Velocity, or Displacement
Wireless Vibration Sensors	Vibration	Passive	NA	Acceleration, Velocity, or Displacement
Acoustic Transducer	Acoustic	Passive	NA	Voltage
Differential Pressure Meter	Pressure	NA	NA	Differential Pressure

The data from each category and representative class of sensors, discussed in Tables 1 and 2, are collected at different temporal and spatial resolutions and provide salient information to physics-informed mathematical models, enabling the development of an accurate nuclear DT by simulating the performance of the physical system it was developed to emulate.

As ASI and the associated infrastructure are key enabling technologies of any DT in an NPP, the challenges associated with them are explored more extensively in a dedicated task within this effort. The findings of that task will be discussed and published in a separate report focusing on the challenges and gaps in advanced sensor and instrumentation as part of a nuclear DT. This section presents the major challenges and gaps for use of ASI as part of a DT in currently operating or advanced reactors.

Real-time data collection and integration: In order to support the requirement of a DT to maintain state concurrency and provide timely predictions and recommendations for SSCs and processes at an NPP, it is critical for the ASI infrastructure to provide uninterrupted and continuous data from the SSCs or processes. Continuous data acquisition may not be considered an extraordinary requirement for sensors; the reactor vessel instrumentation system, for instance, sends real time and continuous controlling input to the feedwater control system and provides initiation or protection signals to the reactor protection system and core cooling system. However, data acquisition, the integration of data streams, integration with DT models, and handling, all performed in real time, poses novel challenges for ASI infrastructure. The process of data acquisition, transfer, and handling in other applications have been notoriously slow in keeping up with scaled performance demands. The ASI infrastructure, including sensors, instrumentation, and communication technologies (cables or wireless), can introduce bottlenecks in real-time data acquisition and transfer, which can adversely impact the performance of a DT. The ASI in an NPP must be designed and deployed to support the DT system in real time from plant SSCs and processes through the DIM system, modeling and simulation, and recommendations and controls (Figure 1).

Challenges with novel sensors: New sensor and instrumentation technology are under design and development across the technology readiness levels [19]. Multimodal sensors, those designed to report more than one type of data, are also being developed. The overarching challenge with new sensor technologies is the lack of operational experience of these technologies in a reactor or plant environment. The research and development efforts in novel sensors must not only focus on performance and testing but also on developing methodology and requirements for evaluation and qualification. Current research, development and demonstration efforts across national laboratories, universities, and private entities are actively addressing these challenges associated with novel sensor technologies. These efforts are addressing the gaps by developing innovative measurement technologies, exploring novel sensor modalities, demonstrating and studying novel sensor performance in a research reactor environments, and gathering sensor performance and evaluation data for enabling commercial deployment of novel sensors in the near to medium time frame.

Challenges with Operating Environment: Reliability of sensors and instrumentation (i.e., electronic and other systems) is one of the challenges as they are exposed to different harsh operating environments. High-temperature and high-radiation levels pose a significant challenge for in-core and in-vessel sensors and instrumentation. On the other hand, electromagnetic interference/radio-frequency interference and cybersecurity present additional challenges for ex-vessel sensors and instrumentation.

For in-core and in-vessel sensors and instrumentation, some of the challenges are:

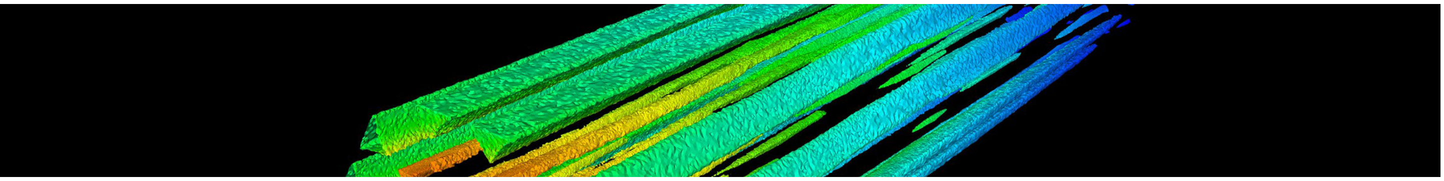
1. Radiation-hardened electronic system and electronically tunable antennas
2. Real-time measurement system to understand sensor drift or out-of-calibration issues due to high temperatures and extended radiation exposure
3. Miniaturization of sensor design to meet existing in-core requirements
4. Power harvesting technology to ensure sustained power source for sensors
5. Reliance on one-by-one cabling to transmit the data and power the sensors, creating long-term cable degradation issues due to high temperatures and radiation
6. Lack of deployable wireless communication infrastructure for in-core and in-vessel applications

For ex-vessel sensors and instrumentation, some of the challenges are:

1. Electromagnetic and radio-frequency interferences of digital signals during wireless communication and of digital sensors and electronic systems
2. Cybersecurity concerns related to digital sensor and electronic systems and of wireless infrastructures
3. Reliance on battery-power and limitation on life expectancy
4. Transmission of data from OSIsoft process information system to the state-of-the-art cloud-based platform
5. Lack of multiband heterogeneous wireless network architecture that can support different applications in NPPs

Table 3. *Summary of challenges and gaps in Advanced Sensors and Instrumentation*

Advanced Sensors and Instrumentation	
Challenges	**Gaps**
Characterization and quantification of the uncertainty associated with new types of sensors, especially dynamic changes in uncertainty due to sensor conditions	Insufficient operational experience with new sensor types to characterize and quantify output uncertainty especially with respect to changes due to age or environmental conditions Evaluation of sensor qualification requirements and methodology
Continuous collection of sensor data and ingestion/integration into databases and models	Infrastructure for real-time sensor data collection to support a digital twin
Installation of a greater number of sensors and more varied sensors. Determining optimum number, placement, and selection of sensors, especially new sensors.	Consideration of availability of physical space for sensors new smaller reactors Means of signal transmission by wired or wireless communication to support DT requirements Regulatory requirements for inspection and maintenance cycles of new sensors Development of virtual sensor technology to inform sensor optimization within DT
Use of new types of sensors or multimodal sensors, especially to adequately meet the needs of DT	Development of adequate sensors for advanced reactor domains, applications, or environment to inform DT models Adaptation, approval, and implementation of existing sensor technology for nuclear DT applications Using DT to evaluate new types of sensors, such as real-time virtual sensors Understanding the impact of failure of one or more modality on overall sensor performance in multimodal sensors
Integration of legacy sensors into DT infrastructure	Replacement of analog sensors with digital sensors, or digitization of hard to replace analog sensors Exploring use of legacy sensors to validate new digital sensors



2.2 MODELING AND SIMULATION

Modeling and simulation technologies are key to the implementation of a nuclear DT and present both common and unique challenges related to DT application. This section will first discuss some challenges common among all DT applications of M&S technologies and then discuss some of the specific challenges presented by the application of the following subsets of M&S technologies to DT: data analytics, data-based models created with machine learning and artificial intelligence, physics-based models, and data-informed models.

2.2.1 COMMON M&S CHALLENGES

Uncertainty Quantification and Propagation: Uncertainties within M&S, epistemic and aleatory, originate from lack of information about the system modeled, e.g., incomplete knowledge of underlying nuclear system processes or relationships, limitations of the modeling technology used to construct the representation, e.g., lack of model forms, methods of model construction, and numerical approximations utilized, or the random nature of the modeled system itself, e.g., neutron propagation. DT M&S is subject to these uncertainties, among others [20] and for a DT to be useful, e.g., trusted, accepted, verified, or validated, the associated M&S uncertainties must be acknowledged, and their effect described quantitatively, both initially and as the uncertainties propagate among the various coupled DT models. The assessment and quantification of uncertainty is a significant challenge for DT for several reasons. First, not all nuclear power plant modeled systems are understood to the extent needed to develop models with high levels of certainty. For example, the uncertainties associated with concrete failure modes may not be sufficiently understood to build a highly accurate model of the phenomenon.

2.2.1 | KEY CHALLENGES

Uncertainty quantification and propagation in model development and integration

Verification and validation of integrated, heterogeneous models

Development of real-time models adequate for nuclear DT application

Second, state of the practice modeling technology may neither be capable of fully quantifying uncertainty within singular models nor capable of adequately quantifying that uncertainty as it propagates to other model types. For example, if a data-based model of pump performance is constructed using machine learning and is coupled to a physics-based model of fluid flow, a challenge may exist in both identifying and quantifying the uncertainty associated with the data-based model as well as in understanding how that uncertainty will affect the results produced by the physics-based model.

Finally, some of the underlying systems within a NPP present aspects of random processes. Examples of random processes include component failures, electromagnetic interference, or various radiation effects. While the uncertainty due to randomness within certain individual systems or components has been modeled, quantifying the uncertainty associated with overall plant processes within a model, especially the highly integrated models needed by DT, is a challenge.

Verification and Validation: As mentioned previously, for DT M&S to be useful, it must be verified, e.g., ensure the model has been built properly, and validated, e.g., ensure the model accurately represents the system of interest. The nuclear DT application of various M&S technologies presents challenges in at least two areas. The first area is the lack of high-quality and high-fidelity data with which to validate the model, especially the model's performance during rare events. For example, advanced reactors do not yet have years of operational data on which to benchmark a model's performance, and the rare set of existing NPP events limits the data available for validating integrated DT plant models. The lack of data to support the validation of DT M&S remains a challenge and new experiments from integral test facilities may be required to provide high-quality and high-fidelity data to validate DT models.

The second challenge is the lack of integrated testing methodologies for complex model interactions. A nuclear DT features highly coupled, heterogeneous models for which verification includes testing the functionality of the coupled calculations, the data exchange between different models, and the interaction of models to simulate the combined effects. While approaches such as those described in NRC's Evaluation Model Development and Assessment Process (EMDAP) [21] may provide future frameworks needed for verification, the development of tools and methodologies capable of verifying complex integrated models remains a challenge to DT M&S technology.

Model Integration: A nuclear DT will utilize a variety of models featuring heterogenous domains, interfaces, granularity, and time scales. All these model types must be integrated to form an accurate representation of the NPP. For example, models of maintenance activities, security response, and reactor operations must be capable of interacting in real time just as their representative elements do within the NPP. Developing methods to efficiently integrate such a diverse set of modeling formalisms poses several challenges such as determining sufficient fidelity and accuracy, maintaining scalability from individual parts to components to system level models, handling and exchange of data between component models, managing integrated model performance while updating and changing component models, and verification and validation of the models. While these challenges are common to model integration generally, the scale and scope of integration featured within a nuclear DT presents a novel challenge to DT implementation.

Development of Adequate Models: Because a nuclear DT can model an entire NPP, it may require models of systems and processes that have not been previously developed or are inadequate for application to a nuclear DT. For example, models of high-temperature molten salts, digital instrumentation and controls, or cyber security posture may need to be developed or improved to fully implement a nuclear DT. As DT M&S technology advances, it will be an ongoing challenge to determine what and how systems should be modeled, requirements for modeling these systems, and whether existing models are adequate for nuclear DT application.

Table 4. Summary of challenges and gaps in Modeling and Simulation

Modeling and Simulation	
Challenges	**Gaps**
Quantification and propagation of epistemic and aleatory uncertainty especially with respect to heterogeneous input data and its propagation throughout the model	Applying appropriate methods for uncertainty quantification and propagation, especially when using multiple, integrated models
Verification and validation of integrated (ML + Physics-based + Data-informed) models	High-quality and high-fidelity integrated test data for integrated models especially for advanced reactors Integrated testing methodologies for complex model interactions Techniques to leverage existing or new codes and solutions for validation and verification methodologies of integrated models Verification validation and uncertainty quantification approaches to reduced-order models, especially with respect to delivering necessary fidelity
Development of computationally efficient interfaces among multiple heterogeneous models sufficient for integrated information exchange in real time	General approach for modeling heterogeneous domain interactions New code designs to improve data transfer efficiencies among models (e.g., data sharing, efficient data transformations) Dynamic measures of cross-model coupling strength to adaptively focus computational efforts efficiently Modeling formalism that allows real-time integration with live data

2.2.2 DATA ANALYTICS

NPPs generate a considerable amount of data, and it is imperative to have sufficient technologies and protocols to obtain insights and aid informed decision-making based on an analysis of plant data. Basic data analysis in the form of signal processing and trending has been traditionally applied in NPPs to support reactor operation and safety [22]. More recently, several commercial NPPs have come up with plant monitoring and diagnostics centers that use data analytics techniques, such as anomaly detection and trending, to support routine operation, plant monitoring, diagnostics, and maintenance. There are several popular data analysis methods, techniques, and a statistical toolbox that support applications such as data cleaning and preprocessing, exploratory data analysis, statistical inference, regression, etc., which is a discussion beyond the scope of this work. When integrated within a DT, advanced data analytics techniques can support real-time recommendations leveraging a variety of data not limited to sensor signals but also integrating other data streams, such as plant process data and historical data. DT promises to go beyond the traditional O&M applications of data analytics to almost every aspect of reactor lifecycle ranging from design and licensing through fuel storage or decommissioning. Following are the major challenges that will be encountered in implementing data analytics within DT.

2.2.2 | KEY CHALLENGES

- **Integration of heterogeneous data**
- **Treatment of noisy or erroneous data**
- **Scaling data analytics**
- **Capture of heterogenous and dynamic uncertainty**
- **Decomposition of multimodal, real-time sensor data**

Integration of heterogeneous data within a common database such that the structure, fidelity, granularity, and density is sufficient for DT requirements. Data and information obtained in an NPP can be highly heterogenous (i.e., it can be in various shapes and forms). A recent report divides nuclear data into the following three categories [23]:

1. **Operator experience data** is observed and harvested as NPPs operate and is the data collected over the course of plant operation. An example of operating experience data is data acquired from sensors and instrumentation, such as neutron flux, reactor pressure, coolant temperature, steam generator water level, radiation dose, etc.; plant logs that record important events in the plant, such as control room logs, operator round notes, etc.; internal plant failure reports; maintenance data, such as work orders for preventive and corrective maintenance; regulatory data, such as licensee event reports (LER) to comply with regulatory requirements; and both miscellaneous data, such as plant operating guidance, and plant business data, such as inventory management, procurement and finance, etc.
2. **Experimental data** is produced by a laboratory or field experiment conducted offsite on plant SSCs. Experimental data and operator experience data can overlap if an experiment is conducted as part of plant operations, such as surveillance testing [23]. An example of experimental data is data collected during testing of a pump or motor at manufacturer's site prior to installation in the plant.
3. **Synthetic or simulated data** is artificially generated from running computational models to simulate processes or systems using computers programs or DTs. Examples of synthetic data include imputed data to address missing data, ML/AI generated data to address a lack of sensor signals, or outcomes of physical phenomena obtained from physics-based models.

The wide variety of data generated in an NPP has further heterogeneity in data formats, such as numerical, text, categorical, image, symbol, audio, video, etc.; storage formats, such as in digital or physical forms; data structure, such as tabular numerical data or an unstructured handwritten log; and data speed and resolution, such as real-time data acquired continuously by sensors or periodic data obtained at certain intervals, such as monthly. Handling such wide heterogeneity in data from a single plant poses a major challenge for any data analytics approach.

Processing noisy data or data containing erroneous observations and outliers so that it meets DT requirements: All real-world data contains noise, erroneous observations, and outliers. Erroneous observations are the observations that may, with good reason, be suspected as being an error in some manner or other and can be attributed to several underlying reasons, such as sensor degradation, sensor drift, sensor failure, interference in data transfer, or even human error. A reliable data analytics approach within DTs must be equipped to not only identify such errors but also point to the underlying cause of error. Outliers are extreme observations that may occur due to errors or indicate an actual deviation from normal operation and are therefore critical to be identified and addressed appropriately. Errors and outliers in data must be identified in the data sets and appropriately addressed when used as training or testing data for ML algorithms. The erroneous observations and outliers can adversely impact the prediction accuracy and trustworthiness of predictive algorithms. Appropriate filtering techniques must be applied to reduce noise in the data. The excessive amount of high-frequency noise in the data can not only pose challenges in training the predictive algorithms but also compromise the results and validity of the algorithms. Events of interest, such as adverse events or failures, are rare in NPPs. Using data analytics to predict rare events runs into a major challenge of false positives. Owing to a conservative approach to failures in NPPs, false positives could result in waste of resources on the inspection, mitigation, or repair of failures that did not even occur. Addressing false positives, therefore, is extremely crucial while applying data analytics in nuclear.

Lack of data, missing data, and inconsistencies in data are major challenges while working with a diverse set of data. Resolving missing data can be a simple and straightforward process using appropriate imputing techniques. However, the main challenge is identifying missing data in a dataset before the dataset is used in a predictive algorithm. Data can go missing for several reasons such as sensor failure or human error. It is important to identify and address missing data appropriately. For example, missing sensor data from a component might indicate sensor failure; however, it is critical to use the maintenance log to verify the cause of missing data as sensor failure, component out of service, or other. Currently operating NPPs have traditionally stored data in paper form or in an unstructured soft form. For example, LERs are created by NPPs to report certain events that meet NRC reportability criterion. The LER provides a detailed record of a significant event at the plant in an unstructured form. However, in order to utilize the wealth of data and information in LERs, it is important to convert the information in structured and machine usable form.

Scaling data analytics: Developing preliminary data analytics may focus on a specific component or application. Maximizing the value of standing up a DT infrastructure at an NPP lies in its ability to scale up the DT application beyond initial or pilot implementations. Several currently planned DT applications, for instance, are focused on non-safety components and applications, such as predictive maintenance of components on a secondary side [1]. Success of such preliminary efforts will invariably lead to DT applications in other systems such as using vibration data from a specific pump for predicting pump degradation. It is challenging to scale up such analytics to other components such as other pumps and motors, using different sensor modalities, such as temperature measurement, or for different applications, such as failure prediction. It is important to address the scalability challenge in order to ensure application of data analytics across several systems, units, plants, and fleet.

Table 5. *Summary of challenges and gaps in Data Analytics*

Data Analytics	
Challenges	**Gaps**
Integration of heterogeneous data within common database such that structure, fidelity, granularity, and density meets DT requirements	Homogeneous techniques to obtain data or to transform data in order to maintain fidelity that can be used for many different programs and algorithms Conversion of non-digital data in a digital form into a way that can be properly used by DT
Processing noisy data or data containing erroneous observations and outliers so that it meets DT requirements	Appropriate techniques to identify and address erroneous data within DT
Lack of data, missing data, and inconsistencies in data	Techniques to identify missing data in a dataset before the dataset is used in a predictive algorithm
Scaling of data analytics	Infrastructure to scale or transform data to use in different components, applications, systems, and across the fleet
Capture of appropriate heterogeneous and dynamic uncertainty information	Appropriate metadata/format to capture heterogeneous and dynamic uncertainty information Appropriate and computationally inexpensive data analytic technique for developing dynamic uncertainty information from live data streams
Real-time decomposition of signals from multimodal sensors	Data analysis techniques to meet unique requirements of multimodal sensors, e.g., preprocessing or filtering technique for one signal can impact other signals

2.2.3 MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

2.2.3 | KEY CHALLENGES

AI/ML training data requirements

ML algorithm selection

Ability to understand and explain AI algorithm behavior

ML/AI are key DT-enabling technologies that can be used to make or inform design, operations, or maintenance decisions with no or limited understanding of the underlying mechanisms involved. There are many situations and physical processes occurring in NPPs that do not lend themselves to first principles modeling (e.g., fuel performance, piping erosion/corrosion), because the process is too complex to run a first principles model or the underlying physical mechanism is not understood well enough. ML/AI technologies can use data-driven empirical models to conduct detailed analysis and generate predictions in such cases if sufficient process data is available. This allows ML/AI algorithms to accomplish tasks, such as calculating operational efficiencies, detecting performance anomalies, autonomously performing or recommending mitigative actions when problems occur, or ensuring that the O&M processes are optimized across the power plant. ML/AI algorithms could be helpful at any stage of the plant lifecycle, but they will be particularly important in the design and O&M phases.

The report [23] provides a compilation of current and near-term application of ML/AI in the nuclear industry as follows:

1. Reactor system design and analysis: ML algorithms are focused on an uncertainty analysis of models and codes to aid in the development and application of physics-based models [23].
2. Plant O&M: ML techniques are employed to support an operator's decision-making, load following operation, smart core controller, alarm processing system, monitoring and diagnostics, and anomaly detection [23].
3. Safety and risk analysis: Current efforts are focused on using natural language processing to extract causal relationship among failure-contributing factors from historical text reports of NPPs, estimating pressurized-water reactor coping time, extract relative importance of performance shaping factors for human reliability analysis, clustering to analyze simulation-based PRA data.

The above mentioned and other applications of ML in nuclear when implemented within DT will continue to have a major impact on design, licensing, operation, maintenance, safety, and other aspects of plant operation. Early identification and addressal of challenges associated with ML in nuclear is therefore vital for almost every aspect of lifecycle of an NPP. In this section, a subset of the ML/AI challenges will be discussed that are particularly germane to DT applications.

Optimum input data: One of the most challenging aspects of constructing ML/AI algorithms is to determine the optimum amount of quality data that is relevant, representative, and complete so that the algorithms can produce reliable results. Advanced reactors do not yet have any operational data, and due to the prevalence of analog sensors and instrumentation, the current fleet of commercial NPPs lack a repository of large volumes of sensor data in digital form. Within DT, input data for ML/AI algorithms can also be in form of simulated data from computational models. Implementing DTs will require determining the optimum amount of data needed for training, testing, and validating the ML/AI algorithms. Initial ML/AI implementations in nuclear applications can either experience too little data, such as no component failure events since installation of digital sensors, or too much data, such as work order logs covering four decades. It is not trivial to obtain answers to the following questions: What is the optimum size for training and testing data sets? What variables should constitute an input data set? Of the collected data, what variables should be excluded from input data set? What is the optimum sampling frequency? Following are some important characteristics that impact answers to these questions:

- Size of the available data set: not only in terms of the volume of data but also the heterogeneity in data, number of parameters, frequency and speed of data acquisition, etc.
- Uncertainty in input data: can be simple to estimate for the small size of quantitative data but can be challenging to determine for large or non-numerical data sets
- Uncertainty in algorithm output: critical to define the acceptable level of uncertainty in algorithm outcome and results

- Inherent complexity in the modeled phenomena: can be driven by inherent physics of the problem, non-linearity, dependency, or correlation among input parameters or lack of complete knowledge in defining the problem
- Complexity of the chosen algorithm: constructing or training different ML algorithms will have different requirements for minimum input data size
- Desired level of algorithm performance: can be defined by the desired level of performance characteristics, such as prediction accuracy, false positive rate v/s missed detection rate, or output confidence intervals etc.
- Computational infrastructure to support the data

Algorithm selection: Recent successes of ML algorithms in a wide variety of applications such as image recognition, medical diagnosis, and fully autonomous vehicles, have increased user confidence in ML methods that may lead to improper implementing of off-the-shelf ML solutions in other applications. It is critical for the nuclear industry to dedicate efforts toward ML algorithm selection and understand which techniques and methods are best suited to the specific application. While several ML algorithms currently exist that address problems such as anomaly detection, clustering, dimensionality reduction, supervised and unsupervised learning, and more, there is no platform or toolset that explores the range of ML algorithms for nuclear-specific applications. Discussion on the benefits and limitations of each of these methods is beyond the scope of this work. Selection of the appropriate algorithm to be implemented within a nuclear DT depends on the following major factors:

- Application: arguably the most important factor in algorithm selection. Defining the problem and the objective of the ML algorithm for a given application will result in a short-list of suitable algorithms. Dedicated algorithms exist specific to applications such as anomaly detection, clustering, dimensionality reduction, supervised and unsupervised learning, etc.
- Size of training data: can have an impact on algorithm selection, especially when limited data is available for training. Certain techniques employing bias and variance in input data can inform method selection.
- Complexity of training data: heterogeneity and large numbers of input variables can impact algorithm selection and also impact feature and hyperparameter selection and tuning within a given algorithm. Other complexities in training data can be in form of non-linearity, correlated or dependent inputs, etc.
- Desired performance of the algorithm: some algorithms can have an inherent limitation in achieving the desired level of performance that can be defined by parameters such as prediction accuracy, false positive rate v/s missed detection rate, or output confidence intervals, etc.
- Complexity in training the algorithm: certain ML algorithms can possess simple and robust structures, such as a support vector machine, which is a method well-known for its simplicity of structure and implementation. However, certain ML algorithms can be complex to construct and can have an impact on speed and efficiency of training and performance of the algorithm.
- Scalability of algorithm: the selected algorithm must be able to adapt to scaling up in the form of additional features or input variables, additional output variables, integrating novel dataset and feature set, integrating with other models, scaling up from pilot implementation through plant or fleet wide implementation, etc.
- Deployment and business case: in certain cases, final algorithm selection might boil down to the software implementation and deployment of the algorithm that can be impacted by factors such as legacy solutions, management decision, cost, return on investment, etc.

Explainability: Explainability in ML and AI is the extent to which the underlying phenomenon between the input and output of the algorithm can be understood by humans. In recent times, “Explainable AI” has been the popular term for AI that can be understood by human users in contrast to “black-box” algorithms for which the implementers themselves may not be able to explain the underlying phenomenon or output of the algorithm. The significance of explainability of an ML algorithms actions and recommendations in nuclear cannot be overemphasized because understanding the underlying semantic structure of a model is key to regulatory acceptance. Whether an ML algorithm can impact plant operation and safety directly or indirectly, a plant operator must understand how the models are generating the results, what the results mean, and how these results can affect the safety of the plant. Recent research efforts funded by the Defense Advanced Research Projects Agency are focusing on developing "glass-box" ML techniques that address the explainability of ML algorithms through transparency and interpretability [24]. Some techniques that address explainability of ML algorithms are as follows:

- Explainability in input data: prior to addressing explainability in ML algorithms, it is critical to address the explainability of input data to ensure that the data is consistent with the expected behavior of components, system, or phenomena under consideration. Modelers and users of the ML algorithm must ensure that the input data is explainable at the (a.) feature level, for example the sensor signals is consistent with expected performance, and (b.) data level, for example the statistical distribution and bounds of data are as expected.
- Generating textual and graphical explanation of model actions at each step: At each significant step of training the ML model, the model generates an explanation in human natural language or graphically of (a.) what it did and (b.) the rational for what it did. The textual and graphical explanation are aimed at being specific and unique to a model action and to be deeply grounded in human identifiable evidence [24].
- Measurable parameters for explainability: quantities such as "Explanation Goodness," "Understanding," "Performance," etc. can provide a numerical value (such as percentage) of the explainability of an algorithm. These quantities can be used for comparing the explainability of algorithms, determine good vs poor explainability, set explainability threshold, etc.
- User survey-based assessment of explainability: by asking users about their level of satisfaction with the explainability of a given algorithm. The hypothesis is that, if humans can predict whether the model succeeds or fails better than chance, they understand something about the model's decision process [24].
- Creating and optimizing the user's mental model toward ML algorithm: Human users are exposed to examples of algorithm behavior to develop a mental model of algorithm's behavior. These mental models are expected to improve the human's understanding of a black-box algorithm's objective functions and in which cases the algorithm can be trusted.
- Two-way dialog between user and algorithm at every step of action: this approach reinforces learning of the algorithm and also trains the algorithm to provide an optimal explanation at every step [24]. The user-algorithm dialog can be in textual form or in non-textual form, such as numerical, categorical, graphical, analytical, game-based, etc.

Table 6. *Summary of challenges and gaps in ML/AI*

Machine Learning and Artificial Intelligence	
Challenges	**Gaps**
ML/AI algorithms require significant amounts of DT training data to produce reliable results	Insufficient existing nuclear data in digital form Quality nuclear data that is relevant, representative, and complete
Identification of the appropriate ML algorithm	Platform or toolset that explores the range of ML algorithms for nuclear-specific applications Unbiased technical basis for model selection to address bias in current model selection based on data-scientist's experience and preference
Ability to understand and explain the inner workings and input-output relationship of AI algorithms	Qualitative and quantitative techniques toward explainable AI as part of DT

2.2.4 PHYSICS-BASED MODELS

2.2.4 | KEY CHALLENGE

Real-time simulation of high-fidelity physics-based models

A range of physics-based M&S has been applied in design, analysis, operation and performance of nuclear reactors for several decades. Challenges associated with physics-based M&S in general are beyond the scope of this work. This section presents some of the challenges associated with physics-based M&S specific to implementation within DT.

Real-time simulation: Physics-based M&S requires extensive computational power especially with respect to hi-fidelity simulations. When integrated with DT, physics-based M&S must run in real time and provide results with minimum time lag. There are several challenges to providing this level of performance. One challenge is to provide sufficiently powerful computational resources to run DT models in real time. While cloud-based resources may make such resources available in the future, information security and other considerations challenge the provision of high-power computation at an NPP.

Another approach to enabling real-time performance is to develop modeling technologies that require fewer resources yet deliver sufficient fidelity for nuclear DT applications. Approaches such as efficient reduced-order modeling and variable model coupling can address this challenge. Reduced-order modeling attempts to replicate a complex physics-based model with a simpler and more computationally efficient model. Variable coupling models attempt to exploit the varying needs of model interactions based on the current model state. There are two types of "cross-physics coupling": strong and weak coupling. Efficient multiphysics algorithms will preferably allocate the extra work of enforcing tight coupling only where the interaction is strong and will default to loose coupling where the interaction is weak thus reducing the needed computational power. Much work remains in both developing, verifying, and validating reduced-order and variable coupling models adequate for DT applications.

2.2.5 DATA-INFORMED MODELING

2.2.5 | KEY CHALLENGE

Implementation of real-time, dynamic data-informed models

One of the major advantages of DT is the maintenance of state concurrence between the physical plant and the digital twin. State concurrence ensures that information gathered from the DT mirrors that of the NPP and is enabled by integrating streams of live plant data with concurrently running DT models. Models capable of updating their state based on real-time data are referred to as data-informed models. The major challenge in creating and running data-informed models is as follows.

Integrating real-time input data: traditional (usually physics-based) models created for nuclear application are not designed to update their internal states directly from dynamic data streams. These models were created for fixed input, static boundary and initial conditions, and the simulations of these models are run for a given static case. As a model runs over time, its state will eventually diverge from that of the system represented, and while current nuclear domain M&S can interact with other running models, e.g., via data exchange, they do not commonly feature the ability to self-correct or modify their internal states based on external information. A data-informed model within a DT must have this ability so it can synchronize its state with that of the NPP. It is an ongoing challenge to define model formalisms and protocols that enable traditional models to evolve into DT-driven dynamic models.

2.3 DATA AND INFORMATION MANAGEMENT

The methods and mechanisms for storing data used at an NPP must meet varying levels of requirements depending primarily upon their proximity to safety functions and baselines. Completed, approved documents (records) of safety systems, procedures, or other safety-adjacent calculations must be reviewed, approved, and archived according to regulatory requirements or guidance and implemented through mandatory guidelines, such as the American Society of Mechanical Engineers Quality Assurance Requirements for Nuclear Facility Applications (ASME NQA-1) [25]. While these documents are updated as technology progresses, there is necessarily a time lag between the introduction of breakthrough technologies and the point at which they are sufficiently well understood and proven that they can be accepted for uses where failure cannot be tolerated. As such, many of the new technologies underlying the uses of DTs in other industries may not be directly or readily transferrable at this time for safety-significant nuclear applications. This also applies for the verification and validation of software used to process stored data. One prominent example of this is the use of cloud storage systems; where many technical guides will contain discussions on such topics as proper magnetic tape tensioning, acceptable levels of damage prior to reconstruction, and fire ratings for single versus redundant storage locations, very few address issues surrounding management of encryption or geographic redundancy in cloud storage locations. Adapting these standards to evolving technology represents a key step in reducing the barriers to accessing these improvements.

2.3 | KEY CHALLENGES

Standards and guidance for cybersecurity, cloud storage, encryption, and geographic redundancy

Establishment and scaling of storage capacity, data-sharing bandwidth, and computational capability

Transition from document-centric to data-centric approach

While the safe retention of data is one key function of a data storage system, the other is to provide that information in a usable format and timely manner to those users or applications that are properly authorized to receive it. The ability to widely share data across organizations has improved greatly from the days when approved documents were archived in filing cabinets and copied by skilled draftsmen. The ubiquity of computer networks, both within facilities and between, has enabled updated documents to become available to all customers within seconds of their approval. The next advance beyond this is to extend beyond a document-centric approach, where the data, metadata, and supporting contextual information are contained in a static format, to a data-centric approach, where the data and metadata are able to be updated and cross-linked so that all of the consumers of the data are able to update automatically. This is a non-trivial endeavor, as the data and its context are often intricately linked. However, many aspects of data are amenable to such linking if the metadata is consistent with application and context. These provide a formal, yet flexible, method of defining both the data and the relationships that it may take to other data.

A GUI allows the user to view data, results, graphs, visualizations (both 2- and 3-dimensional), and system status as a collective dashboard in one unified space. The GUI shows a view of the project without directly interfacing with sensors and equipment. Contributors and subject-matter experts for a project define what is needed for a user of the GUI based on the parameters of a project, components, and data. The development team then designs and reliably implements this vision, following traditional user experience principles. The data in a GUI most often comes in the form of results from model simulations that have been run by the entirety of the DT itself. The GUI displays these in a few ways: 1) results as single entries such as temperatures, pressures, and statuses; 2) graphs best suited to show large amounts of data, especially in relation to time; and 3) visualizations that come in both 2- and 3-dimensions, allowing a visual representation of a particular system or component and its associated data. While GUIs are generally output oriented, they sometimes will need to allow input as well. In this case, a user will define the data through simple user components such as dialog boxes and drop-downs or 2- and 3-dimensional visualizations.

Table 7. *Summary of challenges and gaps in Data and Information Management*

Data and Information Management	
Challenges	**Gaps**
Standards and guidance for technologies such as cloud storage, cybersecurity, geographic redundancy, encryption management, etc.	Nuclear-specific standards and guidance for various DT-enabling technologies Methods to leverage existing standards and guidance are not well understood
Sufficient scaling of storage capacity, data-sharing bandwidth, and computational capability to support DT implementation	Hardware and software requirements for nuclear DT capabilities not defined or well understood
Transition from document-centric (data and information are static) to data-centric approach (data and information are cross-linked and dynamic)	A holistic approach for computer-based procedures in nuclear industry does not exist Supporting hardware and software requirements for data-centric approach not identified or developed

SUMMARY AND CONCLUSIONS

This report presents a detailed description of possible formative elements of a DT system for NPPs, identifies technologies needed to enable a nuclear DT system, and discusses some of the important challenges and gaps associated with the DT-enabling technologies.

The formative elements of such a DT system are:

1. Nuclear Power Plant
   - Physical Assets
   - Physical Phenomenon
   - Advanced Sensors and Instrumentation
   - Computing and Networking Systems
   - Procedures and Human Actions
2. Digital Twin
   - Modeling and Simulation
     - Data Analytics
     - Machine Learning and Artificial Intelligence
     - Physics-based Models
     - Data-informed Models
     - Other Models
   - Data and Information Management
     - Storage
     - Sharing and Accessibility
     - User Interface and Visualization
3. Data and Performance from Nuclear Power Plant to Digital Twin
   - Asset Information
   - Real Time Sensor Data
   - Plant O&M

4. Actions and Recommendations from Digital Twin to Nuclear Power Plant
   - Diagnostics and Prognostics
   - O&M Recommendations
   - Autonomous Operations and Controls

Each DT-enabling technology is briefly described followed by a discussion of significant challenges and gaps associated with each enabling technology. Challenges are selected based on their impact on DT implementation and examples specific to nuclear application are included where appropriate. The following are the key challenges identified for respective enabling technologies:

- Advanced sensors and instrumentation
  - Addressing lack of operational experience and performance data of novel sensors
  - Developing guidance for evaluation and qualification requirements for advanced sensors
  - Acquiring real-time data and integration with DTs
  - Ensuring sensors can survive the challenging environment in advanced reactors
- Modeling and simulation
  - Identifying, quantifying, and propagating uncertainty associated with DT models
  - Addressing lack of high-quality and high-fidelity data for model validation
  - Developing methods for efficient integration of diverse modeling formalisms
  - Developing new models adequate for nuclear DT application
- Data analytics
  - Identifying and integrating heterogeneous NPP data needed for DT application
  - Addressing lacking, missing, inconsistent, and noisy data
  - Developing scalable data analytic methods
- Machine learning and artificial intelligence
  - Determining optimum input data for training and testing DT ML/AI models
  - Selecting appropriate algorithms for development of DT ML/AI models
  - Providing explainability for ML/AI model structure, output, and decisions
- Defining model formalisms and protocols that enable Addressing computational resource requirements for real-time simulation of high-fidelity physics-based models
- Data-informed models
- Data and information management
  - Establishing protocols for data storage for nuclear DT application
  - Establishing methods for data sharing
  - Identifying and establishing DT user interfaces

The discussion in this report frames some potential elements of the nuclear DT system problem space and is aimed at enabling and encouraging collaborative efforts among nuclear stakeholders toward research, development, design, and demonstrations that address challenges within this problem space. Because the application of DT-enabling technology is likely for future nuclear reactors and is a potentially critical toolset for long-term viability of currently operating reactors, identifying and addressing the challenges and gaps associated with DT-enabling technologies is an important step toward preparing for advancements within nuclear power. Such advancements may feature integrated digital technology, more fully instrumented plants, improved plant information and control systems, and advanced operations and maintenance practices, all of which may be integrated within a DT system.

The gaps identified in this report suggest the need for additional efforts to be undertaken by research institutions, national laboratories, reactor systems designers, vendors, and licensees to address challenges in data, modeling, and real-time integration of data and models consequential to the implementation of a nuclear DT system. The NRC continues to assess the regulatory viability of DT for nuclear power plants by identifying and evaluating technical challenges associated with the application of DT in reactors with the goal of developing a regulatory infrastructure appropriate for the use of DT. In addition to past work exploring state-of-the-art applications of DT and continuing outreach to nuclear stakeholders, the NRC is pursuing research activities in the application of advanced sensors for monitoring system performance, integration of security and safeguards within digital twins, and regulatory considerations for use of DTs. These activities will help identify and explore additional areas of intersection between DT and nuclear stakeholders.

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