

THE STATE OF TECHNOLOGY OF APPLICATION OF DIGITAL TWINS

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Vaibhav Yadav, Hongbin Zhang, Christopher P. Chwasz, Andrei V. Gribok, Christopher Ritter, Nancy J. Lybeck, Ross D. Hays, Timothy C. Trask
Idaho National Laboratory

Prashant K. Jain, Vittorio Badalassi, Pradeep RamuhalliOak Ridge National Laboratory

Doug Eskins, Ramón L. Gascot, Daniel Ju, Raj Iyengar U.S. Nuclear Regulatory Commission

Division of Engineering
Office of Nuclear Regulatory Research
U.S. Nuclear Regulatory Commission
Washington, DC 20555–0001

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Vaibhav Yadav, Hongbin Zhang, Christopher P. Chwasz, Andrei V. Gribok, Christopher Ritter, Nancy J. Lybeck, Ross D. Hays, Timothy C. Trask Idaho National Laboratory

Prashant K. Jain, Vittorio Badalassi, Pradeep Ramuhalli Oak Ridge National Laboratory

Doug Eskins, Ramón L. Gascot, Daniel Ju, Raj Iyengar U.S. Nuclear Regulatory Commission

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Idaho National Laboratory Idaho Falls, Idaho 83415

http://www.inl.gov



EXECUTIVE SUMMARY

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

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

This report presents the details of an assessment of the state-of-technology for digital twin applications for nuclear reactors and facilities. Five global digital twin technology companies were reviewed for their current digital twin capabilities and future vision. This report includes a discussion on their notable digital twin applications in nonnuclear industries. The assessment of digital twin applications in the nuclear industry presents the effort undertaken by U.S. commercial utilities to implement various elements of technologies that can potentially form digital twins. This discussion highlights the efforts of commercial nuclear power plants (NPPs), in collaboration with digital twin vendors and researchers from university and national laboratories and academic institutions to implement digital twins aimed at achieving operation efficiency, enhanced safety, and reliability.

Following are the key observations from the assessment across the spectrum of digital twin technology in general and its nuclear reactor applications in particular:

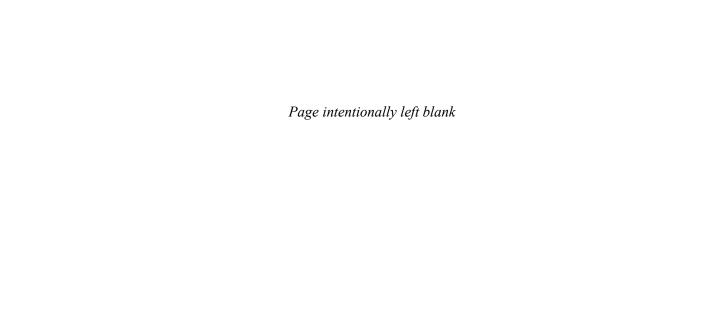
- Digital twins in complex industrial and engineering applications have proven benefits that include increased operational efficiencies, enhanced safety and reliability, reduced errors, faster information sharing, better predictions and many more.
- ❖ The interest in digital twin technologies continues to grow and the technology is expected to experience rapid and wide industry adoption within the next 10 years.
- Current efforts in the nuclear industry are focused on specific enabling technologies that form a digital twin, such as advanced sensors, digital computing and communication infrastructure, hi-fidelity models, data analytics, machine learning and artificial intelligence, and multi-physics modeling and simulation.
- ❖ In the future the above enabling technologies will coalesce to form a unified system or plant digital twin. To pave the way for a smooth and successful application of digital twin technology in nuclear, it is imperative to understand and address the challenges and gaps associated with specific enabling technologies.

- Some of the focus areas of applying digital twins in 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 analysis.
- The main topics related to digital twin application in nuclear that need to be addressed in near term are:
 - Development of a common understanding, including an agreeable definition, of the structure and functions of a digital twin,
 - Identification of technical challenges and potential solutions related to implementing the digital twin enabling technologies in nuclear,
 - Identification of regulatory readiness levels and gaps in applying digital twins for nuclear reactor applications, and
 - Engagement with stakeholders to identify the digital twin implementations in the current fleet and their potential regulatory impact.



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ACRONYMS

AI Artificial Intelligence

ANL Argonne National Laboratory

ANN Artificial Neural Network

APR Advanced Pattern Recognition

APS Arizona Public Service

ARMI Advanced Reactor Modeling Interface
ASI Advanced Sensors and Instrumentation

CASL Consortium for Advanced Simulation of Light Water Reactors

CDF Core Damage Frequency

CFD Computational Fluid Dynamics
CMFD Coarse Mesh Finite-Difference

CRAB Comprehensive Reactor Analysis Bundle

CRUD Chalk River Unidentified Deposits

CTF COBRA-TF

CWS Circulating Water System
DOE Department of Energy

EPRI Electric Power Research Institute

EDF Électricité de France

GE General Electric

GEMINA Generating Electricity Managed by Intelligent Nuclear Assets

HTGR High-temperature Gas-cooled Reactors

I&C Instrumentation and ControlINL Idaho National Laboratory

IoT Internet of Things
IS Intelligent Systems

KAERI Korean Atomic Energy Research Institute

LFR Lead-cooled Fast Reactors
LOCA Loss-of-Coolant Accidents

LOTUS LOCA analysis toolkit for the US

LWR Light Water Reactor

M&D Monitoring & Diagnostic

MAGNET Microreactor AGile Nonnuclear Experimental Testbed

MARS Maintenance of Advanced Reactor Sensors and Components

MBSE Model-Based Systems Engineering

ML Machine Learning

MOC Method of Characteristics

MOOSE Multi-physics Object-Oriented Simulation Environment
NAMAC Nearly Autonomous Management and Control System
NEAMS Nuclear Energy Advanced Modeling and Simulation

NLP Natural Language Processing NNS Newport News Shipbuilding

NPP Nuclear Power Plants

NRC Nuclear Regulatory Commission
NRIC National Reactor Innovation Center

O&M Operations and Maintenance

ORIGEN Oak Ridge Isotope GENeration code

ORNL Oak Ridge National Laboratory

PARCS Purdue Advanced Reactor Core Simulator
PGSFR Prototype Gen IV Sodium Fast Reactor

PLM Product Lifecycle Management
PSEG Public Service Enterprise Group
PRA Probabilistic Risk Assessment

ROM Reduced-Order Models

SAFARI Secure Automation for Advanced Reactor Innovation

SAM System Analysis Module

SFR Sodium-cooled Fast Reactors

SSC Systems, Structures, and Components

TRISO Tristructural Isotropic

VERA Virtual Environment for Reactor Analysis

VTR Versatile Test Reactor

WO Work Order

ZPPR Zero Power Physics Reactor

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The State of Technology of Application of Digital Twins

1 Background

In the last 15 years, the world has witnessed a revolutionary spread of digital and *smart* technologies that have resulted in faster, almost instant, information sharing, exponential growth in computational capabilities, small and intelligent devices, increased automation, and enhanced economics, safety and reliability of machines and operations. Digital technologies such as Internet of Things (IoT), advanced sensors, data analytics, advanced modeling and simulation, faster and more accurate predictions etc., are now part of our everyday life ranging from something as simple as traffic navigation to complex applications such as self-driving cars, aircraft controls, smart city operations, power distribution, advanced manufacturing, or managing global supply chains. In recent years, commercial nuclear power plants (NPPs) have been adopting digital and advanced technologies across a variety of applications such as advanced sensors and instrumentation [1], predictive maintenance, load following [2], advanced simulators for training and qualification, data analytics, and machine learning and artificial intelligence. New and advanced reactors, such as small modular reactors and microreactors, may begin operations as early as the mid-2020s and will likely accelerate the digital transformation of nuclear power by increasing the use of advanced digital technologies across sensors, data acquisition systems, design, licensing, operations, and controls [1]. Undoubtedly, the NPPs of the future, both currently operating and newly built, will use digital technologies for the monitoring and control of plant systems, structures, and components (SSCs) and for decision making supporting operations and maintenance. Digital technologies for nuclear reactor applications can take various shapes and forms, such as 1) digital data acquisition infrastructure utilizing wired or wireless sensors, 2) wired or wireless communication and data transfer hardware, 3) data processing software and hardware including support for big data sets and data analytics, 4) predictive computer models for the detection of abnormal events and decision making, 5) humancomputer interface of data and models, 6) computer-based 3D models of SSCs, and 7) computer-based modeling and simulation of physical phenomena, such as fuel performance, thermal-hydraulics, and many more. It is conceivable that the NPPs of the future will utilize the above digital technologies to operate either autonomously or with limited human interface, and/or be completely remotely operated.

Such futuristic plants might even be conceived, designed, simulated, and approved digitally before building the physical plant. These "digital twins" offer a powerful approach to designers, manufacturers, vendors, operators, regulators, applicant and licensees to perform life estimates, calculate operational efficiencies, detect performance anomalies, and render or recommend mitigative actions to ensure that the operations and maintenance (O&M) processes are optimized across the power plant. Further, this technology allows for effective and detailed sharing of information and data with vendors, regulators and other stakeholders. Digital twins of future operating NPPs could offer more complete informational transparency across the machine, plant, and fleet levels, providing a significant benefit for the licensees, regulators, and the public.

The application of digital technologies such as digital twins to nuclear reactors could address one of the biggest challenges faced by the current fleet of U.S. commercial NPPs, the prohibitively high cost of O&M [2]. Recognizing the potential for digital technologies to reduce O&M costs in NPPs, the U.S. Department of Energy's (DOE) Advanced Research Project Agency – Energy (ARPA-E) has initiated competitively funded research efforts in this field. In recent years, ARPA-E has established the following three programs with a specific focus on using digital technologies to increase efficiencies in the design, construction, and O&M of advanced reactors: 1) Modeling-Enhanced Innovations Trailblazing Nuclear Energy Reinvigoration (MEITNER), 2) Leveraging Innovations Supporting Nuclear Energy, and 3) Generating Electricity Managed by Intelligent Nuclear Assets (GEMINA) [5–7]. The projects awarded

within these programs are collaborative efforts across national laboratories, universities, digital technology vendors, utilities, and advanced reactor developers. They are working together in performing high-impact research supporting the use of digital technologies for safe, reliable and economic operation of a nuclear reactor. Of these programs, GEMINA focuses specifically on the application of digital twin technology [7].

One of the premier global research and advisory firms, Gartner Inc., has recognized digital twin technology as globally emerging technology. In its 2018 Hype Cycle for Emerging Technologies, Gartner placed digital twin as a technology that would reach the plateau of productivity between 2023 and 2028 [8]. This Gartner assessment positions digital twin as a technology that is expected to grow and experience wide industry adoption by the next decade.

The Office of Nuclear Regulatory Research of the U.S. Nuclear Regulatory Commission (NRC) has initiated an effort to assess the regulatory viability of digital twins for NPPs. This effort is led by Idaho National Laboratory (INL) in collaboration with Oak Ridge National Laboratory (ORNL). The objective of the NRC's digital twins project is the identification and evaluation of technical challenges associated with the application of digital twins in reactors that would impact the regulatory outcomes, with the goal of developing a regulatory infrastructure for the use of digital twins as part of the regulatory programs. This effort allowed the Virtual Workshop on Digital Twin Application for Advanced Nuclear Technologies in December 2020 [9, 12]. The purpose of the workshop was to assess the current understanding of digital twins and identify their potential benefits, opportunities, and challenges for nuclear reactors. The workshop provided a forum for the nuclear industry and digital twin stakeholders to discuss the state of knowledge and research activities related to digital twin and their application in the nuclear industry.

This report documents the assessment of the state of digital twin technology with a particular focus on their nuclear reactor applications. The scope of this report is to 1. provide background on DTs, 2. introduce the DT enabling technologies, and 3. provide nuclear and nonnuclear applications of DTs. This report is intended for the NRC staff and the digital twin vendors and professionals associated with the nuclear industry, such as reactor designers and manufacturers, plant operators and engineers, plant or utility managers, researchers at universities and laboratories, regulators.

The assessment was undertaken by teams at INL and ORNL comprising scientists and experts in a wide variety of fields, such as reactor design, nuclear engineering, thermal-hydraulics, fuel performance, multi-physics modeling, data analytics, machine learning (ML) and artificial intelligence (AI), safety and reliability, policy and regulations, digital I&C, computer hardware and software, and data management. The state-of-the-art assessment was broadly aimed at finding answers to the following questions:

- 1. What are digital twins?
- 2. What are the applications of digital twins in nonnuclear industries?
- 3. What are the applications of digital twins or associated technologies in the current fleet of nuclear reactors?
- 4. What are the current efforts and future vision of applying digital twins in the next generation of nuclear reactors?

The answers to the above questions are discussed in this report as follows. Section 2 presents a discussion about the current definition, understanding, and perception of what a digital twin is. Section 3 highlights the current efforts undertaken by the global digital twin technology companies and presents some notable applications of digital twins in nonnuclear industries. Section 4 is dedicated to a comprehensive discussion of digital twin in the nuclear reactor applications in two parts: for the current fleet and next generation reactors. Section 5 presents an assessment of data analytics, ML, AI, and advanced modeling, the enabling technologies of digital twins.

2 What are Digital Twins?

The term "digital twin" evolved from the concept of product lifecycle management (PLM) and can be attributed to the work of Michael Grieves and John Vickers [15-19] over the last two decades. The first instance of the term digital twin, coined by John Vickers, is found in their presentation [19]. In [19], the digital twin model is comprised of the physical product, its virtual representation as a digital twin, data flowing from the physical to the digital twin, and information flowing from the digital to the physical twin [53].

Figure 1 illustrates this digital twin system for a typical nuclear power plant. In Figure 1, the physical space for an NPP consists of

- The SSCs, such as the reactor, turbine, steam generator, pumps, motors, valves, and others,
- ➤ Other infrastructures such as sensors and instrumentation, and computing hardware and software.
- Plant operations and processes, and
- > Human operators.

To enable a continuous and real-time flow of plant performance and other data and information to the virtual space, the physical space is equipped with an infrastructure of digital, wired or wireless sensors and instrumentation that acquire the data on health and operating condition of the SSCs. The virtual space can comprise of all or several of the following:

- 1. A virtual representation of the SSCs as computer models ranging from simplified representations, such as block diagrams to high-fidelity 3D CAD models,
- 2. Data handling and management framework that receives data from the plant sensors and enables data storage and data sharing,
- 3. Data preprocessing capabilities, such as data cleaning, completeness evaluation, consistency checks, and others, to ensure data are ready and usable,
- 4. Data analytics comprising of ML or AI algorithms aimed at health and performance trending, anomaly detection, diagnostics, prognostics, and predictions, and
- 5. Advanced models such as multi-physics modeling and simulation capabilities such as neutronics, fuel performance, and thermal-hydraulics; traditional and dynamic probabilistic risk assessment (PRA) models, etc.

The information flowing out of the virtual space consists of insights, such as the outcomes and results of the various modeling, simulations, and algorithms that can be utilized by human operators for decision making or in autonomous controls such that the plant operations are optimum, safe, reliable, and economical.

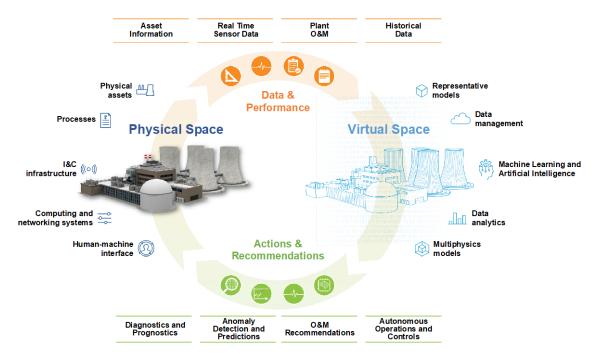


Figure 1. The digital twin system for an NPP, consisting of the physical systems, structures and components, and their digital twin representations in virtual space, connected through the flow of data and information.

There are many answers to the question "What is a digital twin?". A recent survey of the literature found 46 different definitions for a digital twin [14]. In this report, instead of defining, we describe a digital twin, including key components, functions, and provide examples to give the reader a better understanding of how both the nuclear and nonnuclear fields are using the term. For the purpose of clarity, we will use the following terminology throughout this report:

Digital Twin Technology: when referencing generally the approaches and technologies used to implement a digital twin,

[Specific instance name] digital twin: when referencing a particular instance or implementation of a digital twin, e.g., a pump digital twin, a sensor digital twin, a ship digital twin, a design digital twin, a operational digital twin, etc. Note that an instance digital twin can exist in the absence of one of the above elements of Figure 1, for instance, a design digital twin of a product may exist even though the physical system, the product itself, currently does not exist.

Digital twin system: when referencing the overall system that comprises at a minimum the physical system, the virtual system, and the relationships between physical and virtual systems, e.g., information and data flows. Figure 1 presents a digital twin system for a nuclear power plant.

While the nuclear industry has years of experience with technologies that may be used as elements of a future nuclear digital twin 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 digital twin system. As illustrated by our example in Figure 1, generally a nuclear digital twin system must have a physical system, a virtual system, and a set of relationships (as well as a means of maintaining the relationships) between the two.

Additionally, a number of technologies and industry approaches can be enablers for digital twins, such as the following:

Digital Engineering: The Department of Defense defines digital engineering as "an integrated digital approach that uses authoritative sources of system data and models as a continuum across disciplines to support lifecycle activities from concept through disposal." This approach requires the design to use models or data instead of documents, the integration of data across models, new deployment ecosystems, such as cloud and high-performance computing, and the culture change across project teams to realize digital engineering ecosystems [52].

Digital Thread: The digital thread is a software data architecture that provides an integrated view, connection, and common framework for access to data throughout a system's lifecycle. These technologies typically use web protocols to communicate between IoT devices, engineering databases, and modeling software.

IoT: Internet of Things is an enabling technology to bind a physical asset into the digital world with near real-time data streaming. IoT devices and sensors use a transmission control protocol to connect and exchange data over the internet.

Model-Based Systems Engineering: Model-based systems engineering (MBSE) is a methodology that focuses on the use of systems-level data-driven models to capture systems information instead of document-centric engineering. MBSE is used to define functions (activity diagram), requirements (requirement diagram), physical blocks (block definition diagram), and interfaces between blocks (internal block diagram). MBSE focuses on the concept and development stages. Detailed design, verification events, and operational data warehouses are a focus of digital engineering but are not directly a focus of MBSE.

Product Lifecycle Management: Consulting firm CIMdata defines PLM as a "strategic business approach that applies a consistent set of business solutions in support of the creation, management, dissemination, and use of product definition information across the extended enterprise." Unlike digital engineering, PLM does not require a data transfer at the object level; however, it can be a crucial enabler in designing digital engineering and digital twins.

Dassault Systemes (Dassault) sponsored an industry-wide survey on digital twin technology conducted among professionals working across eight different industries: engineering, manufacturing, aerospace, education, oil and gas, construction, automotive, and medical equipment and devices [10]. Figure 2 shows one of the interesting observations of the survey in which the responders were asked the question: "What does digital twin primarily mean for you?" The combination of the top two responses indicates that digital twin is a fully defined model that is able to simulate the full behavior of a product and receive data from the sensors on the real product.

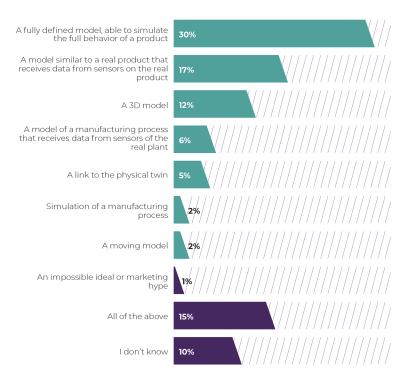


Figure 2. Responses to the question "What does digital twin primarily mean for you?" as part of a survey on digital twins by Dassault Systemes [10].

While defining a digital twin can be subjective, the classification of digital twins is straightforward. Figure 3 shows some of the classifications of digital twins by IBM. Based on the different areas of application, digital twins can be appropriately classified as operational twin, maintenance twin, simulation twin etc. or an overlap or combination of two or more such digital twins. Based on scalability, digital twins can be classified as a part twin, a product twin, or a system twin [11]. A part twin can be a digital twin of a small but critical component, such as the bearing of a coolant pump, the failure of which can have a critical adverse impact on plant operations. The part twin would utilize sensor data aimed at condition monitoring and failure estimation for the specific part. A product twin is a twin of a component made up of several parts, such as a twin of the coolant pump, and captures the interaction of several part twins. A system twin comprises of several product twins to recreate the virtual model and operation of an entire system, such as a coolant system comprising of pumps, motors, pipes, and valves. For a nuclear power plant, a system twin might reflect the historic and current state and predict the future state of a particular system of the plant, a generating unit, or the whole power plant.



Figure 3. The different forms of possible digital twins. Credit: IBM [9].

3 Digital Twins in Nonnuclear Industries

This section provides a review of the current application of digital twin technologies in nonnuclear industries. The review focuses mainly on the major technology companies of IBM, General Electric (GE), Siemens, ANSYS, and Dassault, which are well-known for providing turn-key solutions for complex industrial applications. Some of these companies have recently been involved with nuclear application of digital twins as well. Those nuclear applications are discussed in the Section 4.

Key highlights of the review presented in this section are:

- IBM's Watson AI platform is being widely applied across diverse industrial applications such as manufacturing, transportation, healthcare, energy, etc.
- Recent application of IBM Watson for vessel management at Port of Rotterdam, the largest seaport in Europe, is described in detail in this section.
- The "HydroMeteo" digital twin prototype developed by IBM and Rotterdam utilizes weather and water conditions from real-time sensor data for predicting future weather and water conditions aimed at determining optimal moor and departure times. This real-time twin enables Rotterdam to facilitate cost-effective vessel management and can help ensure that cargo arrives safely.
- The GE digital twin technologies applied extensively across complex industrial applications such as aviation, energy, grid, healthcare, and rail-transport etc., for anomaly detection, failure prediction, process optimization, workflow improvements and increasing operational efficiencies.
- Digital twin technologies by Dassault Systemes have been applied with specific focus on manufacturing industry with applications such as flexible production systems, process improvements, virtual testing, virtual process alterations and iteration, improved human factors and enhanced connectivity.
- To address the challenge of time and resource intensive physics-based simulations integrating with digital twin technologies, ANSYS is implementing linear and nonlinear response surface based reduced-order models that are ideal for digital twin applications.
- Newport News Shipbuilding is implementing Siemens' solutions, such as NX and Teamcenter, to transform the shipbuilding process to a model-based enterprise and digital twin-based approach that range from design and manufacturing of ship parts to operation and maintenance of an entire ship.
- Additionally, this section provides a review of digital twin technology applications in the areas of manufacturing, product design, aerospace and aviation, smart automobile, farming and healthcare.

Because digital twin technologies are variously conceived, this section discusses self-described examples of DT technology and its applications to provide a broad context for what the industry considers DT technology. This discussion will highlight certain features of these technologies that may be significant to our understanding of future DT capabilities.

3.1 IBM

Under the aegis of its Watson AI platform, IBM has been at the forefront of implementing digital twin technologies in wide-ranging applications, such as manufacturing, transportation, healthcare, and energy [9]. Figure 4 illustrates some of IBM's digital twin application areas, along with the level of complexity expected in developing and applying those digital twins. Notice the applications, such as creating and maintaining a bill of materials or developing and evolving the stocking strategy for logistics

management have a lower level of complexity. Some of the more complex applications of digital twins are forecast and prediction models and asset health scoring methods, which are expected to involve a challenging integration of various technologies, such as data analytics, ML and AI, and physics-based modeling.

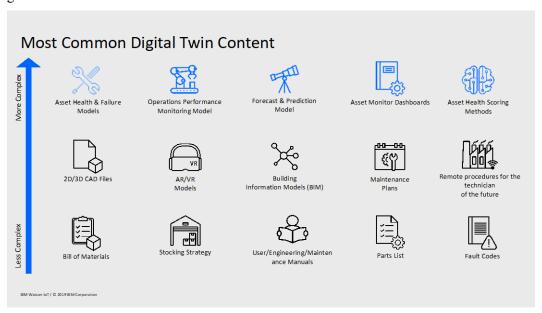


Figure 4. The complexity grid of applying digital twins across several potential applications, as envisioned by IBM [9].

One of the notable use cases of the IBM Watson digital twin application is for vessel management at the Port of Rotterdam. The Port of Rotterdam is the largest seaport in Europe and covers an area over 41 square miles. This port serves 30,000 vessels every year and manages a staff of nearly 400,000 people. A port of this size has a maintenance budget of \$60 million; accordingly, a single hour reduction in vessel berthing time saves \$80,000 [9]. The port has 70,000 in or out of port movements annually, and the average fuel cost per vessel is \$2 million; thus a 4% fuel cost savings results in a cumulative \$5.6 billion savings annually [9].

Various environmental factors lead to unplanned costs for sea vessels. For example, bad weather can add an additional day to the vessel's schedule. A change in tides or traffic can prevent vessel berthing. A broken post vertical on the wharf bollard can prevent docking. Or finally, a broken traffic sign can cause a detour, resulting in further delays. These delays cause additional fuel burn, resulting in increased costs and CO₂ emissions [9].

IBM and Rotterdam developed a HydroMeteo digital twin prototype. This twin fuses sensor weather and water conditions predicted sensor and water conditions (predictive digital twin), and anomaly detection for sea vessel traffic management (simulated digital twin). These sensors continuously capture data on air temperature, wind speed, relative humidity, water salinity, water flow and levels, and tides and currents. This data is used to predict optimal moor and departure times at Rotterdam. This real-time twin enables Rotterdam to facilitate cost-effective vessel management and can help ensure that cargo arrives safely [9].

Port of Rotterdam



Autonomous behavior of Smart connected objects (or Assets)

0 | 0 | | 0 | 0 | 0 | 0 | | 0 | 0

Integrating legacy IT and unlocking true value of (more) data



Intelligent workflows and process optimization



Environment integrated with external data sources



The operating model in asset intensive industries is changing





Figure 5. The IBM Watson digital twin application at the Port of Rotterdam [9].

This digital twin enabled new technologies, which make this technology stand out in comparison to past implementations. The twin fused environmental data with onsite environment data, enabled asset autonomous behavior, integrated legacy information technology, and enabled intelligent workflows and process optimization (Figure 5). This combination of physical and virtual data streams, autonomous behavior (AI), and visualization (Figure 6) became the key ingredients for Rotterdam's digital twin. In the future, this port twin can be integrated with autonomous ships (e.g., IBM Watson Mayflower) to further reduce total operational costs [9].

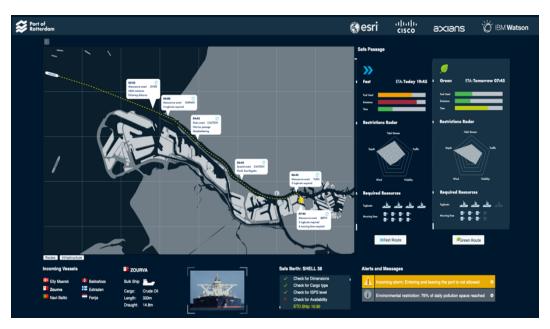


Figure 6. Rotterdam twin visualization [9].

IBM identifies key challenges to digital twin success as follows: digital asset data availability, complex integration and lack of infrastructure or standardization, and missing data and models to drive actionable insights with AI (Figure 7). Data availability issues can stem from an inaccurate bill of materials, missing structure or classification of parts and equipment, missing vendor data, missing equipment tags, or data quality issues. A complex integration can be caused by sites lacking infrastructure for the twin's data, lack of sensing and monitoring, provider commitment issues, or complex relationships across operators. Lastly, missing data and models can be caused by absence of data, too little data, an overwhelming set of data, data not integrated with O&M, or absence of data.

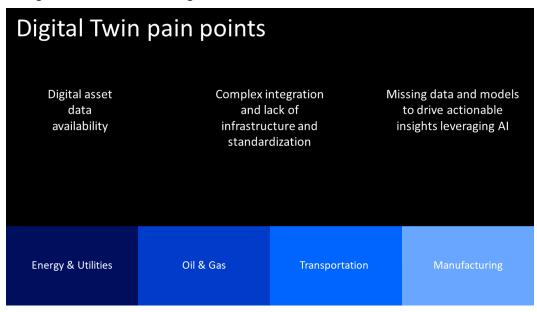


Figure 7. Digital twin pain points (IBM) [9].

3.2 GE

GE has experience across infrastructure that powers key assets around the world. Their infrastructure technologies support approximately one-third of the world's power, their engines fly 300,000 passengers per hour, and their medical scanners support millions of patients per day [9]. At this scale, GE must support changes in customer demand, changing regulatory policies, and lower the total cost to remain commercially competitive.

Sufficient Early Warning **Continuous Prediction Dynamic Optimization** DOMAIN KNOWLEDGE Condenser vacuum, Cooling water temperature, ST MW Generator load, frequency, transmission line flow (MW/MVAR), etc. Wind speed, temperature, turbine KW, speed, etc INDUSTRIAL DATA Load forecast, transmission constraints, Fouling prediction, anomaly score Pitch, TSR & Yaw optimal setpoints BUSINESS OUTCOME ETPO - Performance optimization Higher grid utilization, lower cost Increased lead detection time >150GW footprint enabled >1% AEP improvement 11 days \$ Millions saved per year \$ Millions saved per year

Energy Customer Outcomes with Digital Twin

Figure 8. GE energy customer digital twin outcomes [9].

GE sees a digital twin as continually improving business outcomes through a build-the-model (either as new or improved), deploy-the-model, scale-the-model, and then adapt-(manage)-the-digital twin model feedback loop [9]. The twin generates insights to business process actions and outcomes relevant to operational or financial performance in a variety of industrial applications, such as aviation, energy, and healthcare. The energy sector program goals are an early warning of a fouling anomaly, the optimization of pitch and yaw set points through continuous prediction, and the dynamic optimization of high grid utilization (Figure 8) [9]. Healthcare follows the same pattern, with the early warning of filament failure in diagnostic machines, the continuous prediction of an optimal scan plan, and dynamic workflow improvements as outcomes of digital twins.

In aviation, the goals are to provide sufficient early warning (e.g., predict compressor issues), continuous predictions to optimize the maintenance schedule, and a dynamic fleet optimization. GE is flying about 64,000 engines globally, and uptime is of critical importance. This is achieved through operational monitoring data and physical models to predict Stage 1 shroud oxidation [9]. This is also fused with environment data, configuration data, city pair data, original design data, and inspection data from on and off wing inspection. This inspection is also used to continuously improve the digital twin model.

Research Focus: Advancing Digital Twin and Al for Adoption and Scale

Explainability

Humble AI

Safety & Robustness to put information to work

Information to work

RISK MANAGED OPTIMALITY

Realizing full value of data-driven analytics by putting information to action

Security

Multiple modes of learning

Learn from
Lea

Figure 9. AI technologies to support digital twins at GE [9].

In AI technologies, GE prides on the "explainability" in its models. Traditionally, deep neural networks are a black box, with a human understanding of an AI's decision impossible to decipher [9]. GE uses an explainable approach to allow for a greater human understanding of the AI model's decision process (Figure 9). This is expanded further with a "humble AI" approach where outcomes are predicted with quantifiable uncertainty. These principles are combined with multiple sources of training data, including humans, simulations, and operational fleet data, leading to continuous improvement. GE has also invested into real-time continuous defense in the cybersecurity domain with a "digital ghost" technology [9].

GE's technologies have been deployed on edge devices in plant operations. Edge devices are hardware components that control data flow at the boundary between two networks where they serve as network entry or exit points. At the 6FA Turbine Combined Cycle Plant, GE gathered plant operational data from edge devices, weather forecast data from external sources, and targets for production and fuel usage to generate operational set points as a digital twin for plant optimization. This optimizer, combined with digital twin targeting, led to a 1% gain in fuel efficiency. In locomotive rail, GE gathered train weight, rail topology data, and locomotive operational data to derive the optimal speed and horsepower [9]. This optimization is able to minimize fuel consumption by 32,000 gallons per year per locomotive and decrease a cumulative 174,000 tons of CO₂ emissions.

3.3 Dassault

Dassault is one of the leading 3D modeling and simulation solution providers with products and solutions being employed globally by original equipment manufacturers in complex industries, such as automobiles and aviation. A Dassault report [20] highlights the challenges faced by the ever-expanding manufacturing industries worldwide and presents potential solutions based on Dassault's digital twin technologies. Proactive flexible production systems of the future call for faster process improvement in manufacturing that can be achieved by virtual testing and virtual process alteration and iteration using digital twins of the manufacturing processes [20]. Using the Dassault digital twin technologies, the manufacturers can create "virtual factories" and perform "what if" experiments aimed at process optimization. Such a digital twin–based approach promises unlimited iterations, better process-insights,

improved human factors, increased flexibility, real-time and enhanced connectivity, and knowledge retention.

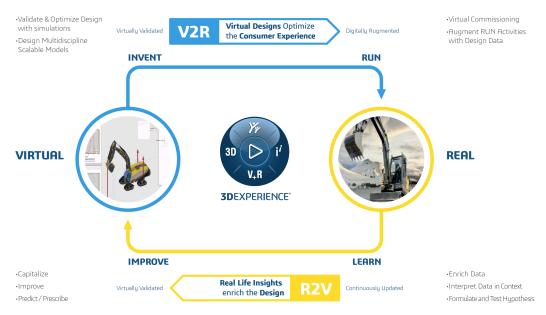


Figure 10. The virtual twin experience concept of Dassault Systemes [20].

3.4 ANSYS

ANSYS is a global leader in digital twin initiatives and is one of the founding members of the Digital Twin Consortium [21], an emerging standards body to drive the development and adoption of digital twin technologies. One of the key strengths of ANSYS is in providing high-fidelity physics-based simulation software across almost all applications. The high-fidelity physics simulation of complex models faces well-known challenges of long and highly intensive computations and large storage requirements. This could prove to be a major impediment in integrating physics-based simulations with digital twins for realtime applications involving complex physical phenomenon, such as 2D and 3D fluid flow, thermal models, solid mechanics, electromagnetism, etc. Recognizing this major challenge, ANSYS is implementing reduced-order models (ROMs) as the leaner and more efficient substitutes for physicsbased simulations to integrate with digital twin-based applications [22]. ROMs are simplification of physics-based models that preserve the key properties, behaviors, and responses of complex models for the purpose of reducing computational time and storage capacity. Some of the linear and nonlinear response surface-based ROMs reduce the computational time by orders of magnitude and achieve the same accuracy as physics-based simulations, making them ideal for digital twin applications. A white paper on digital twin technology by ANSYS [23] delineates the process of implementing digital twins into a three-step process - build, validate, and deploy - which can be achieved by the ANSYS Twin Builder software solution (Figure 11).

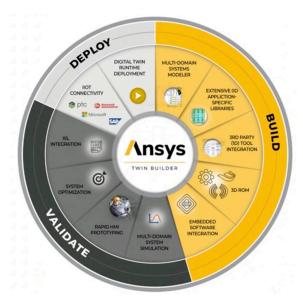


Figure 11. Illustration of the three-step process of Build-Validate-Deploy for digital twin implementation using ANSYS Twin Builder [23].

In a recent case study, researchers applied deep learning to the complex task of computational fluid dynamics (CFD) simulations. Solving fluid flow problems using CFD demands not only extensive computational resources, but also time for running long simulations. Artificial neural networks (ANNs) can learn complex dependencies between high-dimensional variables, which makes them an appealing technology for researchers who take a data-driven approach to CFD. In this case study, researchers applied an ANN to predict fluid flow, given only the shape of the object to be simulated. The goal of the study was to use ANN to solve fluid flow problems with significantly decreased time to solution (by the order of 1,000 times), while maintaining the accuracy of a traditional CFD solver.

3.5 Siemens

Siemens has collaborated with America's oldest and largest shipbuilding company, Newport News Shipbuilding (NNS), and has digitized the entire shipbuilding process from design and manufacturing to operations and service to achieve the first paperless ship [24]. NNS is implementing Siemens' solutions, such as NX and Teamcenter, to transform the shipbuilding process to a model-based enterprise and digital twin–based approach [24]. Figure 12 shows the digital environment architecture vision of NNS for the Ford Class aircraft carrier Gerald R. Ford. It comprises more than three-million-piece parts manufactured across more than 2,000 suppliers and over 70,000 part numbers [25]. The ship assembly comprises over 50 tons of fabricated steel assemblies, nine million feet of cable, and four million feet of fiber. This particular aircraft carrier has a build cycle of more than ten years and is designed to last a lifecycle of 50 years that must include obsolescence management and continuous modernization considerations. It is extremely challenging to manage the magnitude and complexity of manufacturing and O&M of the aircraft carrier while being able to implement disruptive technologies.

The strategy of NNS for what they refer to as an "intelligent digital twin" is based on the following five foundational elements [25]: 1) formalize the development, integration, and use of models to inform enterprise and program decision making (NNS-Strategy for Digital Thread and Digital Twin), 2) provide an enduring, authoritative source of truth (NNS-Configuration Managed Links between Navy Databases and Digital Product Model), 3) incorporate technological innovation to improve the engineering practice (NNS-Implementation of AR/VR, laser scanning, IoT and other technologies into production processes), 4) establish a supporting infrastructure and environment to perform activities, collaborate, and

communicate across stakeholders (NNS-Integrated, Secure Cloud Environment), and 5) transform the culture and workforce to adopt and support digital engineering across the lifecycle (NNS-integrated Digital Shipbuilding (iDS) for digital manufacturing).

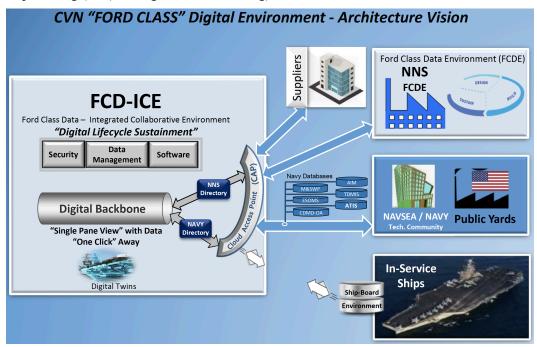


Figure 12. The digital environment architecture vision of NNS to achieve a digital twin of the design, manufacturing, and O&M of a Ford Class aircraft carrier [25].

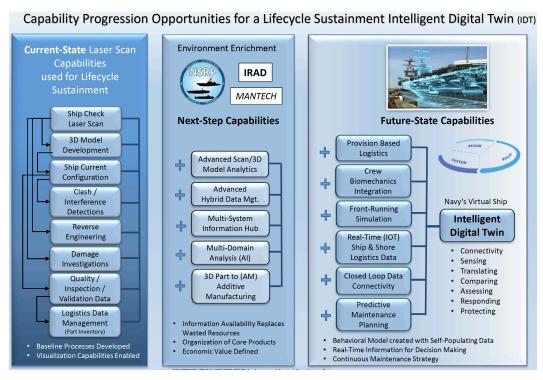


Figure 13. The intelligent digital twin strategy vision for the next-step, and potential future-state capabilities of NNS [25].

Figure 13 shows the current-state capabilities, next-step capabilities, and potential future-step capabilities to be achieved in the lifecycle sustainment of an aircraft carrier using an intelligent digital twin [25]. The capabilities progression opportunities range from the current-state capabilities that are mainly focused on achieving design and manufacturing goals using technologies, such as laser scanning, to future-state capabilities centered around the O&M of the entire ship.

3.6 Others

Manufacturing: As digital twin owes its advent to the manufacturing industry; a majority of current applications of digital twins are found in manufacturing [26]. A comprehensive survey of digital twins in the manufacturing industry [27] identifies the major areas of digital twin application as production planning and control, maintenance, PLM, process design, and layout planning. Utilizing advanced sensors, wireless communication, discrete event simulation, plant simulation, e-Robotics, and automation, the manufacturing industry is realizing the vision of "smart factories," applying digital twin to increase production efficiencies, optimizations, and cost reduction. However, the development and application of digital twin in manufacturing are still considered to be in infancy [27].

Product design: The ability to virtually operate and predict anomalies or failures in a product before operating the physical product is one of the most attractive prospects of the digital twin application. The product design industry boasts of mature technologies, such as computer-aided design, finite-element analysis, static and dynamic simulations, computer visualization, and other applications that have been successfully in use for several years now. With the introduction of a real-time digital thread connecting the physical product and its computer modeling and simulation, the digital twin application seems fairly straightforward compared to other industries [28-29].

Aerospace and aviation: NASA is the pioneer of a successful real-world application of digital twins to rescue members of the Apollo 13 mission when it experienced technical issues [35]. In 2012, Edward Glaessgen had presented NASA's vision of the application of digital twin technology in space exploration [36]. The commercial aviation industry has long been at the forefront of adopting the real-time performance and health monitoring of aircraft components. Engine manufacturers, such as GE and Siemens, and aircraft manufacturers, such as Boeing, have been using real-time component health monitoring aimed at predictive maintenance [34, 37].

Smart automobiles: Automobiles in recent times have seen a rich application of a variety of sensors and instrumentation, such as on-board sensors monitoring component performance, steering wheel feedback, environmental data for failure prediction, anomaly detection, and predictive maintenance [33, 38]. Combined with data analytics and ML, the automobile industry is moving toward a wider application, such as autonomous driving, navigation support, reducing distracted driving, enhancing safety in lane changing, parking, night driving, etc.

Farming: The farming, agriculture, and dairy sector has recently been adopting advanced sensors and real-time communication technologies from the farm to refrigerators. Recent publications [39, 40] provide an interesting account of digital twins of farm machinery, silos, transportation, supply chain, and other applications. The farming industry presents a vision of adopting digital twins for applications such as weather monitoring, produce quality monitoring, farm animal health and behavior monitoring, nutrition monitoring, output increase, autonomous farming, theft prevention, pest and infection monitoring and prevention, crop management, and economics.

Healthcare: The medical and healthcare industry has traditionally been one of the fastest in adopting advanced and digital technologies in patient monitoring, testing, diagnostics, and treatment. In [41], the authors envision the use of digital twin in surgical practice to plan and practice on a digital twin of the patient in a simulator. This enables the surgical staff to verify anatomy, engage remote experts, avoid inadvertent damage to the patient, and minimize risk to the patient. Q Bio, a healthcare startup company is

building a clinical digital twin platform called Q Bio Gemini which can be created by scanning a human body [31]. This clinical digital twin of a human is aimed at combining an individual's genetics, chemistry, anatomy, lifestyle, and medical history and correlate these with the individual's health risk factors.

The American Society of Mechanical Engineers has established a committee to develop a neutral standard for the design of chemical, fossil, nuclear, and petrochemical facilities. The standard will provide "processes and procedures for design organizations to (a) integrate process hazard analysis in the early stages of design; (b) incorporate and integrate existing systems engineering design processes, practices and tools with traditional architect engineering design processes, practices and tools; and (c) to integrate risk-informed probabilistic design methodologies with traditional deterministic design. The focus is to provide requirements and guidance for design processes, methodologies and tools that will provide a safer and more efficient system and component designs with quantified safety levels." Committee membership includes nuclear domain experts from Bechtel, INL, NuScale, Sargent & Lundy, TerraPower, and many others.

4 Digital Twins in Nuclear

This section presents a comprehensive review of the state of technology of nuclear reactor application of digital twins. The first part of this section presents the ongoing efforts of applying enabling technologies of digital twins in the current fleet of light water reactors. Several enabling technologies such as advanced sensors, ML/AI, data analytics and others are currently being either explored or starting to be implemented for wide applications in the operating NPPs. The second part provides an exhaustive compilation of current efforts undertaken by advanced reactor developers for applying digital twins ranging from design, prototyping and licensing to product lifecycle management. The third part of this section summarizes the key focus areas of digital twin application across current and advanced reactor applications.

Following are the main observations from the review presented in this section:

- Application of digital twin technologies in nuclear is currently an active area of research, development and demonstration evident from several collaborative efforts across utility companies, advanced reactor developers, digital twin vendors, universities, national laboratories and other R&D centers.
- Several current nuclear utilities have initiated implementing commercial business integration software solutions that allow integration of digital twin enabling technologies
- The current efforts of applying digital twin technologies in current fleet and advanced reactor are focused commonly on the following areas of application
 - o Plant-referenced simulators
 - Condition monitoring
 - Failure degradation prediction
 - Predictive maintenance
 - Analysis of historical plant data
 - Design, prototype development, and rapid demonstration
- Several current nuclear utilities have initiated implementing commercial business integration software solutions that allow integration of digital twin enabling technologies
- Some less common areas of application of digital twin technologies in nuclear are onsite staff-reduction, crew deployment optimization, multifunctional sensors, quick load following, creating event databases and fault libraries, optimizing sensor and instrumentation infrastructure, risk-based maintenance, virtual testing and maintenance, eliminating destructive testing, severe accident management, aging and degradation management, fuel performance enhancement, refueling management and optimization, virtual sensors, and intelligent autonomous control.

4.1 Elements of Digital Twin Technologies in the Existing Light Water Reactor Fleet

The existing light water reactor (LWR) nuclear power industry, in general, has lagged behind other industries in adopting modern data analytics to improve O&M. There are many contributing factors, including the prevalence of analog I&C, the lack of key sensors and the associated costs of installation,

limitations on data storage and analysis capabilities, and the lack of regulatory acceptance of such technologies within nuclear applications. In recent years, progress is being made in the introduction and use of digital models and data analytics. Current digital twin technology implementations are limited with a data connection between the physical asset and the digital model being exclusively one-directional and not always real-time. However, the increasing use of both digital systems and models in the existing LWR fleet does provide an experience base for next generation design, operation, and regulation. These are discussed further below.

Plant-Referenced Simulators: The use of plant-referenced simulator for operator training and testing is addressed in 10 CFR 55.46 [46]. The simulator features a physical replica of a plant control room and interfaces via an input/output (I/O) system with a plant simulation. The simulation executes models that replicate plant systems, functions, and the underlying physical phenomena that drive plant performance. Such models include electrical systems, analog and digital control systems, hydraulic systems, radiation detection systems, alarms, emergency response systems, thermo-hydraulic response, core physics, and various other models as required to present plant operators with an integrated operational environment identical to that of the physical plant modeled. The simulator must demonstrate expected plant response to operator input and to normal, transient, and accident conditions with a level of fidelity specified by federal regulations. Recently, NPPs have begun supplementing their plant-referenced simulators with entirely digital glass panel simulators (GPS). A GPS uses the same simulation and models as the plant-referenced simulator but replaces the physical panels and I/O system with an entirely digital graphical interface. While a GPS is currently not authorized for plant operator qualification training, it provides additional capability for general staff training and, in some cases, evaluation of plant changes. Companies such as CORYS, GSE Systems, Inc., L3 MAPPS, and Western Services Corporation provide plant-referenced and GPS to the nuclear industry.

Plant-referenced simulators can be characterized as "limited simulation and modeling" digital twins. That is, a plant-referenced simulator maintains only the scope and fidelity with respect to the physical plant required to train plant operators, and is a small subset of the scope and fidelity typically envisioned for a full-scale nuclear power plant digital twin environment [56]. Fidelity to the physical plant is maintained through modifications to the physical panels or digital displays and periodic mapping of plant response and design data onto the plant models through an update of the simulator model code and variables, and validation of response as required by 10 CFR 55.46 and associated regulations [46]. In addition to operator training and testing, most operating LWRs use the simulator to aid in the design, give problem resolution, and provide post trip analysis of equipment and operator response. Next generation reactor designers are using simulators extensively to aid in design, including the man-machine interface, and to understand and validate expected plant response to normal, transient, and accident conditions. Modern nuclear plant simulators can achieve levels of fidelity and performance suitable for engineering design work that was not feasible in earlier generation simulators.

The digital reactor restructuring project, "le Project Structurant Pour la Competitivite" [32] is a fouryear effort launched in September 2020 to create digital twin of every nuclear power unit in France. This collaborative project involves EDF Group, Framatome, French Alternative Energies and Atomic Energy Commission and six additional organizations from academia and the French nuclear industry. The project goal is to develop reactor digital twins that will serve as training simulators for operators and provide simulation environment for engineering studies [32].

Condition Monitoring: Historically, online performance/condition monitoring primarily relied upon the data collection, organization, and analysis performed manually by engineering and operations personnel. This was due to the lack of key sensors and limitations on data storage and analysis capabilities. Plant modernization efforts, in response to aging, obsolescence, and increasing maintenance costs, have resulted in continuing upgrades to the existing LWR fleet.

The installation of high-capacity fiber and Wi-Fi networks within the plants are resulting in the installation of additional wireless and wired vibrations sensors, thermal cameras, acoustics monitors, and wireless digital gauge readers, including vibration, acoustics, radio frequency identification, multi-gas detection, thermal cameras, and wireless digital gauge readers. These additional devices increase the available direct data to assess and monitor plant performance and failure modes not previously monitored. Additionally, plant process computer replacements have increased data storage and analysis capabilities.

Many utilities have established monitoring & diagnostic (M&D) centers that monitor plant equipment and provide early warning to the station for equipment anomalies, often well before plant alarms or traditional performance monitoring and trending systems. Examples of utilities that have implemented an M&D center include Duke Energy, Tennessee Valley Authority, Public Service Enterprise Group, Florida Power and Light, Arizona Public Service (APS), Xcel Energy, Exelon, and EDF Energy. In many cases, the nuclear M&D centers are integrated or shared with fossil M&D centers, permitting information sharing and expertise on balance-of-plant components [47-50].

At the U.S. NRC's Regulatory Information Conference 2021, APS and Exelon presented the current efforts at their respective plants that use data analytics and ML and AI to support O&M decision making [42-43]. APS relies on the ML and AI algorithms developed in-house that utilize component monitoring data to enable anomaly detection and work management automation and optimization [42]. Exelon is using data analytics to identify maintenance rule functional failures from the historical maintenance data of its plants [43]. Maintenance rule functional failures comprises around 0.1% of total incident reports, which are manually processed, amounting to around one hundred every day for every Exelon site. It is important to identify, study, and learn from the past maintenance rule functional failures. Exelon uses natural language processing (NLP) and ANNs to automatize the process of identifying maintenance rule functional failures from the large number of incident reports (Figure 14) [43]. Additionally, Exelon is focusing an advanced pattern recognition effort that utilizes component monitoring data, such as bearing metal temperature, oil-drain temperature, vibrations, suction-pressure, steam pressure and shaft pressure, to enable real-time component health monitoring and maintenance scheduling optimization [43].

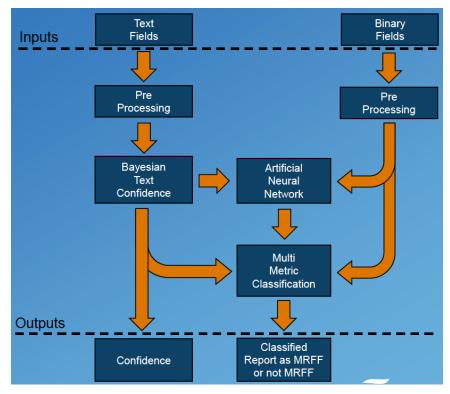


Figure 14. Structure of the maintenance rule analyzer based on artificial neural network being used by Exelon Energy for classification of maintenance rule functional failures from incident reports at its NPPs [43].

Currently, Advanced Pattern Recognition (APR) software is the primary tool used by the M&D centers. Models are created for each monitored asset using physics-based models and available equipment sensors. These models are "trained" to recognize normal equipment performance based on historical data (baseline performance). The APR software analyzes real-time data and compares it to the baseline performance. As flags are generated for calculated anomalies, invalid flags (false positives) are used to tune the models and improve performance. M&D center personnel review the flags for validity and refer valid anomalies to station personnel for review and concurrence. Upon validation, action is taken to investigate and resolve adverse conditions prior to plant impact. Current APR software vendors used by the existing LWR fleet include PRISM, Smart Signal, OSIsoft PI, and National Instruments InsightCM.

Physics-based digital models exist for an increasing percentage of critical assets, such as pumps, turbine generators, compressors, and diesels. The Electric Power Research Institute (EPRI) Preventive Maintenance Basis Database provides failure modes and effects analysis for a variety of plant components [51]. Vendors and engineering firms continue to develop digital models for their products or to aid in plant issue resolution.

ML algorithms and models improve their ability to recognize patterns with increased amounts of reference data. The use of ML will further improve the effectiveness of performance monitoring analysis and reduce false positives. Tools, such as FAMOS/PMAX (Curtis Wright) and Metroscope (EDF), utilize physics-based modeling and ML to either compliment or replace APRs.

Exelon is using the physics-based analytics suite FAMOS/PMAX to model and optimize thermal performance monitoring. EDF is using Metroscope (which combines AI and physics-based models) for performance monitoring analysis. GE Hitachi and Exelon are implementing the Predix analytics suite to manage and predict asset performance and enable condition-based maintenance.

PKMJ Services is working with INL and Public Services Enterprise & Group Nuclear, LLC under a DOE Office of Nuclear Energy Industry Funding Opportunity Announcement Award to develop and demonstrate a fully integrated risk-informed condition-based maintenance capability on an automated platform [44]. Figure 15 shows the overview of this effort that utilizes real-time sensor data, data analytics, ML and AI, and risk-modeling aimed at transitioning the NPP O&M from the current laborcentric approach to an efficient technology driven approach [44].



Figure 15. An overview of the research and development effort of INL, the Public Service Enterprise Group, and PKMJ aimed at transitioning the NPP O&M from the current labor-centric approach to a technology driven approach [44].

This effort developed ML models using heterogeneous plant process and vibration data, collected at different spatial and temporal resolutions from the Salem NPP's circulating water system (CWS), to diagnose a circulating water pump failure based on salient fault signatures. Diagnostic models are extendable to other faults associated with circulating water pumps and their motors, given associated fault signatures [44]. This effort also developed an NLP technique based on a convolutional neural network to automatically classify the Work Order (WO) data into different categories. The developed an NLP technique was validated on independent WO data. This automates the tedious, time-consuming mining and classifying of WOs by subject matter experts. The mean time between downtimes estimation framework is developed to establish the reliability of CWS components using unstructured WO data along with CWS plant process data fostering risk-informed decision making for predictive maintenance [44].

Business Integration Software: The use of business integration software by both existing LWR utilities and next generation reactor designers is continuing to evolve. For digital twins, digital thread, and MBSE to be effective data from various direct and indirect sources must be automatically gathered and organized. All existing LWR utilities have transitioned from a manual document-based system and component health report and operator logs. Electronic operator rounds (eSOMS), electronic work packages and procedures, and condition monitoring databases are in wide use.

Continued integration efforts include Duke Energy's integration of PRISM, NI InsightCM, CAS, and Power BI to manage condition-based maintenance. Exelon and Southern Company's development and integration of improved processes include analytic tools for data transfer and integration of PRA, maintenance rule, and Mitigating Systems Performance Index (MSPI) or Safety System Performance Indicator (SSPI) unavailability calculations. Component unavailability data transmitted into the station's

configuration risk management program software is improved by the use of a single-entry point (eSOMS) to ensure consistent equipment entries and include error checking rules to eliminate duplicate data entry and reduce data entry errors. eSOMS transmits unavailability data to an online risk monitoring software, such as Equipment-Out-Of-Service (EOOS), Paragon, or EPRI Phoenix Risk Monitor, which updates with "actual" times, providing more accurate Core Damage Frequency (CDF) trending [54]. CDF trending provides an aggregate assessment of the balance between reliability and availability by looking at the risk impact associated with both planned and unplanned maintenance, considers the impact of failures as failures that occur at power result in unplanned maintenance, and provides an aggregate assessment of maintenance planning and execution.

Preventive Maintenance is a cornerstone of equipment reliability, and also a resource intensive task in the existing LWR fleet. In addition to the online performance/condition monitoring and condition-based maintenance advancements described above, many existing LWRs are implementing value-based maintenance initiatives to evaluate the most cost-effective maintenance strategies. This involves taking into consideration the cost of preventive maintenance, the cost of corrective maintenance, and the cost of unacceptable consequences to maintain the appropriate level of reliability consistent with sound business principles. Value-based maintenance utilizes Power BI software for data transfer of component reliability and maintenance cost. Data comes from station databases and analyses using EPRI's WO Data Visualization Tool (QlikView), Cost Analysis Tool, and Preventive Maintenance Basis Database [51].

4.2 Digital Twin in Next Generation Nuclear Projects

4.2.1 Kairos Power

Kairos Power is using and developing digital twins through two separate GEMINA awards. Their overall approach is to quickly iterate through successive developmental prototypes of key reactor plant subsystems in order to most directly reduce the uncertainty that is at the root of most cost overruns in nuclear projects. Digital twins play a key role in capturing the results of these prototypes and scaling them to the following demonstrations.

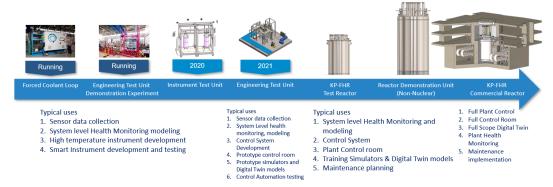


Figure 16. The Kairos Power approach to technological innovation is to perform the rapid iteration of developmental prototypes in order to quickly reduce uncertainty and thereby reduce risk [9].

The Secure Automation for Advanced Reactor Innovation (SAFARI) project partners with University of Michigan and seeks an AI framework to enable autonomous operations, flexible operations (i.e. load following), and efficient predictive maintenance (Figure 17). These capabilities work together to greatly reduce the O&M costs associated with the system by reducing the need for an onsite staffing and enabling maintenance crews to service multiple units, rather than being dedicated to a single site [9].

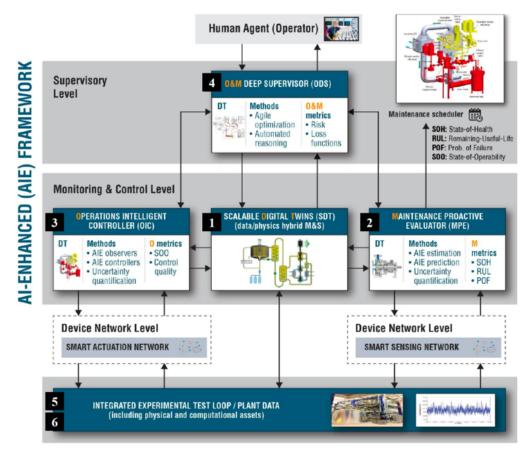


Figure 17. The SAFARI project combines multiple aspects of digital twinning to reduce O&M costs for future advanced reactor designs [9].

The Maintenance of Advanced Reactor Sensors and Components (MARS) project aims to improve the maintainability of advanced reactor designs through the development of multifunctional sensors to inform machine learning—enabled predictive maintenance algorithms (Figure 18). These sensors are tested and applied on various components through the rapid demonstration process in order to qualify both the sensors and the digital twins used to extend their usage to parts of the system that are not directly monitored. This reduces the overall number of sensors required, thereby reducing costs [9].

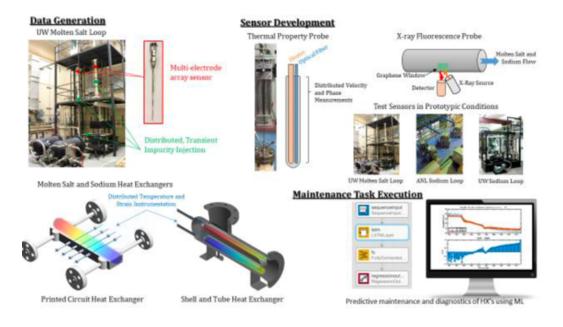


Figure 18. The MARS project focuses on predictive maintenance and sensor technology [9].

4.2.2 GE

GE, through an ARPA-E GEMINA project has been investigating and developing digital twins for use with their BWRX-300 small modular reactor design. By leveraging the digital twin experience gained through their jet engine and power turbine business, they aim to gain significant cost reductions for both capital and operating expenses on the BWRX-300 (Figure 19). The usage of digital twins for this project falls into three categories, operational, health, and decision, and they span over a range of coverages, from parts, to products, to processes, and to systems (Figure 20). Furthermore, these twins incorporate AI technologies that are being designed to be "humble"—they incorporate uncertainty into all of their estimates—and explainable (Figure 21). These twins will be used for optimizing plant health monitoring, scheduling maintenance, and feedback into the reactor design process, leading to lower overall costs [9].

Predictive Maintenance Digital Twins (PMDT)



Figure 19. Overview of the predictive maintenance digital twins approach for the GE Hitachi BWRX300 reactor within the GEMINA project [9].

Digital TwinsGE Experience

Parts Twins
Rotor failure prediction

Product Twins
Steam turbine performance

Process Twins
Field engineer scheduling

System Twins
Performance optimizer

Figure 20. Digital twins exist across multiple scales within the GE system [9].

Research Focus: Advancing Digital Twin and AI

for Adoption and Scale

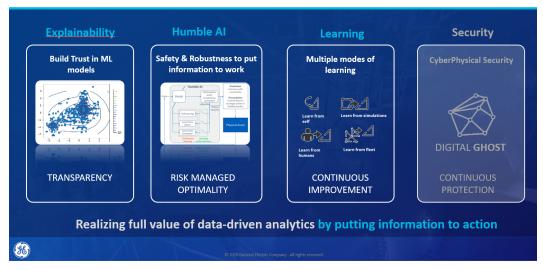


Figure 21. GE digital twins utilize AI to achieve transparency, optimality, and continuous improvement [9].

4.2.3 HolosGen

HolosGen was awarded an ARPA-E MEITNER project in 2018 to develop a transportable, gas-cooled nuclear reactor with a load following ability. Their scalable family of conceptual modular nuclear generators eliminates the balance of plants, responds quickly for load following, and packaged in a standard shipping container [9]. The goal of the ARPA-E project is to demonstrate the viability of this concept using multi-physics modeling and simulation tools and validating the models using a nonnuclear prototype [9].

The HolosGen team includes Siemens Digital Industries, which has developed digital twin and data analytics for multiple nuclear vendors, and ORNL, which is leveraging the Consortium for Advanced Simulation of Light Water Reactors (CASL) to develop M-Holos digital twins. The subscale simulator Holos-QUAD, and demonstration M-Holos serve as hardware data generators coupled to a digital twin. The digital twins developed by Siemens and ORNL will assist real-time decisions in both the virtual and physical worlds throughout the lifecycle of the asset. They will leverage a "virtual build" approach to realize continuous optimization and visualize, simulate, and optimize project designs, construction execution, and operational performance [9].

4.2.4 Framatome

Framatome was awarded an ARPA-E GEMINA project in 2020 to develop two digital twins for use with Metroscope, an EDF-developed diagnosis software for operations and condition-based maintenance of nuclear plants [9]. Metroscope connects digital twins and their associated fault libraries and monitors them with an algorithm to detect problems early on. The digital twins will simulate Argonne National Laboratory's (ANL's) Natural Convection Shutdown Heat Removal Test Facility, with one twin for the passive cooling system with internal thermal-hydraulic faults and one twin for the cooling circuit with different operating modes and control states.

Framatome's vision for the project (Figure 22) is to develop the generic capability to determine needed sensors and find faults with no operating fault data. Digital twins will allow for sensor sensitivity and reliability to be characterized and optimized. Ultimately, the system will allow for the automated

diagnosis and visualization of fault characteristics and will support the deployment of different maintenance regimes (e.g., risk-based), making the plants more cost effective [9].

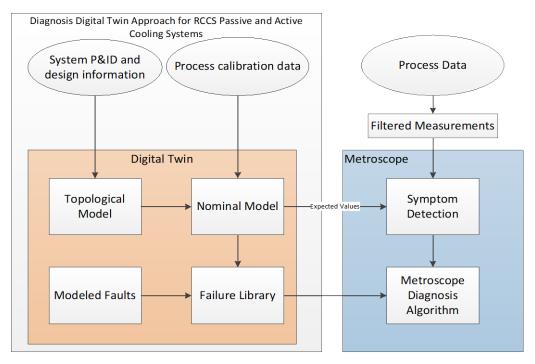


Figure 22. Overview of the Framatome vision of digital twin aimed to determine needed sensors and find faults with no operating fault data [9].

4.2.5 Westinghouse

Westinghouse is a leading infrastructure services provider to the power generation industry. Westinghouse has a long history of applying new technology and ideas to the nuclear industry, such as being the first nuclear company to use a commercial finite-element analysis code, pressurized thermal shock, accident tolerant fuel, and AP1000 passive safety plant technology [9]. Current emphasis in Westinghouse is on digital twin applications that build upon their experience and leverage operational data. Selected areas where digital twins (in conjunction with ML and AI) have been or will apply to Westinghouse include the: (1) reduction of physical testing and maintenance, exemplified by destructive test elimination at a manufacturing facility and baffle-former bolt predictions; (2) automated analysis of inspection or monitoring data, exemplified by concrete crack detection using drones, neutron noise monitoring of reactor structures aging, and managing a reactor severe accident in real-time; and (3) process optimization, exemplified by component condition monitoring and fan operation. Future work in digital twin development at Westinghouse will extend to advanced reactors (e.g., eVinci, Lead Fast Reactor); entire reactor systems, such as steam generators and pump seals; advanced manufacturing (e.g., fuels, additive manufacturing); fatigue and probabilistic fracture mechanics applied to systems; and source tracing for environmental substrate contamination [9].

4.2.6 BWXT

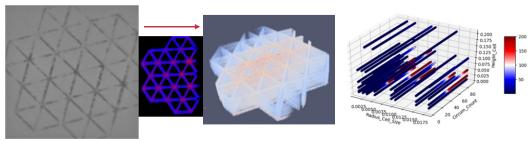
BWX Technologies, Inc. (BWXT) is a leading supplier of nuclear components, precision manufactured components, and fuel to commercial NPPs and provides technical, management, and site services in the operation of complex facilities. BWXT is collaborating with ORNL on developing and demonstrating digital twin technologies for additive manufacturing. The current additive manufacturing

technologies build one layer over another. BWXT efforts utilize in situ imaging during fabrication to for a layer-by-layer 3D representation of not only the build but also the study and modeling of its features, such as cracks, pores, and stress features. Computer vision, ML, and deep neural networks are then used across the 3D representation to discover indicative patterns and anomalies (Figure 23). BWXT and ORNL envision that the manufacturing of advanced reactors and microreactors can benefit from such techniques to achieve optimized geometries, shapes, and material behavior. Accurate digital twins of additively manufactured nuclear components could potentially replace or augment destructive and nondestructive testing, inspection, and quality assessment, increasing efficiencies in manufacturing and O&M [9].

Digital Twin (as-built) as input to multiphysics simulation

Merging data and physics: feed digital twin as-built data model back into design simulation to guide design-for-manufacturing and predictive component test (e.g. additive manufacturing):

- See effects of true geometry, defects, fuel and moderator placement
- Neural networks + computer vision: supporting build technique development, physics simulation, design, predictive test and performance validation



Example: digital twin based on in-situ melt pool to predict thermally induced stresses and other properties. This as-built model may then be fed back into simulation tools.

Example: Reactivity comparisons of as-built



Figure 23. Overview of the digital twin technologies of BWXT for additive manufacturing [9].

4.2.7 X-Energy

X-Energy is nuclear reactor and fuel design company that is currently developing high-temperature gas-cooled nuclear reactor. X-energy's Xe-100 plant is planned to be four helium-cooled pebble-bed reactors and four turbines producing around 320 MWe at about 40% efficiency. The intrinsically meltdown proof, walkaway safe reactor design is intended to provide applications for both electricity as well as heat applications. The advanced operation & maintenance techniques implemented in the Xe-100 plant digital twin to reduce the fixed O&M cost will use "human factors engineering, probabilistic risk assessment, hazard analysis, and security and maintenance evaluations to identify areas for optimization".

X-Energy is involved in both an ARPA-E GEMINA project and a DOE Advance Reactor Demonstration Project, both of which are focused on their Xe-100 modular gas-cooled reactor design. This plant design utilizes a tristructural isotropic (TRISO) fuel form to ensure fission product retention under accident scenarios to help reduce both the likelihood of adverse consequences and the costs associated with mitigating adverse situations [9]. The GEMINA project focuses on reducing costs by optimizing the staffing levels for O&M activities (Figure 24). These optimizations are possible through the development of an immersive digital twin environment that allows humans factors, maintenance, and security experts to examine plant operational needs in order to find where cost reductions can be safely achieved [9]. The digital twins are being further developed in order to enable improved predictive maintenance capabilities; these twins are able to track the usage and operating conditions of critical parts in order to forecast when plant maintenance will be required. By anticipating these needs ahead of time, parts may be ordered, and work may be planned to occur during scheduled windows, rather than simply

waiting for a failure to occur and be handled reactively. Through the Advanced Reactor Demonstration Program Award, X-Energy will deploy a demonstration reactor unit for testing prior to 2030.

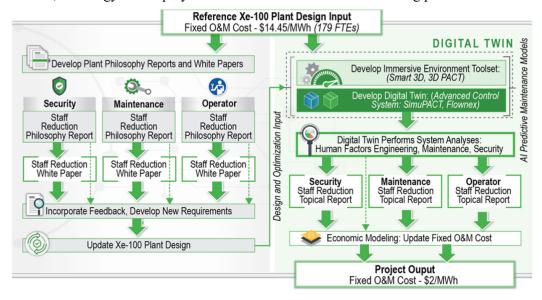


Figure 24. Xe-100 digital twins are being developed to address O&M costs through the ARPA-E GEMINA Project [9].

4.2.8 Radiant

Radiant is a private company currently designing and developing portable microreactors that are aimed at delivering one megawatt electricity for up to 8 years, promising remote monitoring, and centralized refueling and maintenance [30]. Radiant is developing a digital twin architecture using hardware-in-the-loop concepts from the aerospace and automotive industries [30]. The digital twin being developed by Radiant is aimed to test blended configurations of real and simulated hardware operating against either real-time simulations or live instruments. Tests can inject real-world risks, failure rates, and load profiles. This paradigm holds promise to reduce development, schedule, and cost risk by engaging all engineering disciplines with real hardware as early as possible [30]. Radiant has completed a small-scale digital twin with some physical components, assemblies, and controls from Kaleidos, an in-development portable micro-HTGR (Figure 25). It uses analytical models and prototype control software to manage neutronics, thermal fluids, and electrical power generation and consumption.

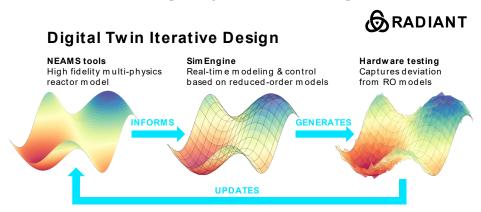


Figure 25. Overview of digital twin for iterative design by Radiant.

4.2.9 EPRI

EPRI is an American nonprofit organization that conducts research and development related to electrical power generation, delivery, and use. EPRI has a long history supporting innovation and modernization for the nuclear power industry. EPRI has recently launched two projects: a study of best practices for the use of digital twins in advanced reactors and a study of the use of digital twins in nuclear plant water chemistry. The advanced reactor study seeks to explore the benefits of digital twins, summarize the available tools, establish industry guidelines, and estimate the cost savings associated with the use of digital twins [9]. Recently initiated efforts at EPRI are exploring the use of digital twins in design, construction, and O&M of advanced nuclear plants. EPRI is also exploring the use of digital twins in the development of updated water chemistry tools. An update will combine two existing tools and incorporate water chemistry simulation and real-time data importing to model the plant steam heat balance that matches the current plant conditions.

ARPA-E has awarded EPRI the "Build-to-Replace: A New Paradigm for Reducing Advanced Reactor O&M Costs" project, which will use a proof-of-concept study to decide if "replace and refurbish" can replace the current "maintain and repair" approach in nuclear power O&M. If successful, this research could allow for shorter but predictable equipment timelines reducing unplanned outages.

4.2.10 INL

Idaho National Laboratory is nation's leading center for nuclear energy research and development, and works on each of the strategic goal areas of the US DOE: energy, national security, science and environment. This section describes the various INL projects related to DT technology.

National Reactor Innovation Center (NRIC) is tasked with the demonstration of two advanced nuclear reactors by 2025. NRIC's mission is to inspire stakeholders, empower nuclear energy innovators, and deliver success by demonstrating and deployment of advanced nuclear technologies [3]. NRIC is a DOE-NE program led by INL to realize a demonstration by the end of 2025. NRIC has two test beds, the Zero Power Physics Reactor (ZPPR) test bed, for reactor designs with less than 500 kWt power production and the EBR-II Dome test bed, for reactors producing less than 10,000 kWt in power. The NRIC DOME will allow the use of safeguards for category IV fuels, loading of Conex containers, control rooms for EBR-II Dome test bed (ETB) operations, and electrical power, including safety class backup. These facility upgrades are currently under design to allow for the reactor demonstration.

NRIC has digital engineering goals to enable the efficient and accurate exchange of information and data between NRIC and industry partners, improved project outcomes through digital thread and MBSE approaches (Figure 26), foundational design for a digital twin, and, importantly, cost and schedule reduction by using these technologies. NRIC has deployed commercial MBSE tools to a shared environment in the cloud to allow for the industry partner collaborative development of advanced reactors and the interface between both the facilities and asset design.

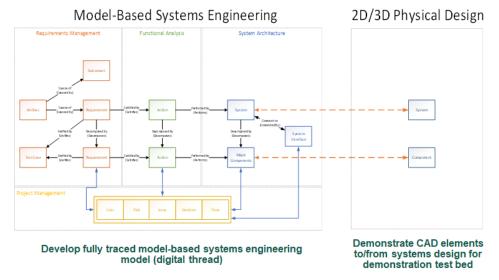


Figure 26. The fully traced MBSE model at NRIC [3].

The digital engineering environment at NRIC consists of commercial-off-the-shelf tools, custom integrations between commercial-off-the-shelf tools, and a Microsoft Azure for Government cloud environment authorized by DOE for export-controlled and official use only information. The custom integrations enable a digital thread throughout the design of new GEN IV reactors at NRIC and utilize a hub-spoke model for integration, reducing the custom point-to-point adapters needed to build a thread. NRIC's custom integrations are open-sourced and developed openly on GitHub for other reactor designers to utilize and are compatible with efforts on other DOE-NE programs, using the same hub technology, Deep Lynx. This platform is planned to be used as the basis for NRIC's digital twins when each reactor starts operations.

VTR: The Versatile Test Reactor (VTR) is a proposed 300 MWt, sodium-cooled fast reactor that will support materials research and testing under closely controlled environmental conditions. The VTR team is implementing digital engineering and digital twin strategies to predict reactor performance and design issues early in the process, minimizing the cascading risk. The VTR project follows the Department of Defense strategy for digital engineering:

- Development and Integration of Models: To capture integrated 2D and 3D models of the plant, the VTR uses a virtual design construction and building information management tool from conceptual design through construction. Physics models for the experiment design are integrated using TerraPower's Advanced Reactor Modeling Interface (ARMI). Requirements are managed at the object level within the IBM Jazz DOORS Next requirements management tool.
- Authoritative Source of Truth: To integrate data from engineering tools, the physics code, and analysis tools, VTR developed a data warehouse linking technology, Deep Lynx. The Deep Lynx integration platform allows for an integrated platform during the design and operations of megaprojects using web protocols (REST) and graph queries (GraphQL). This framework was open-sourced [36] and is in use on the Microreactor AGile Nonnuclear Experimental Testbed (MAGNET), NRIC, the National Nuclear Security Administration, and the Transformational Challenge Reactor digital twin programs.
- Technological Innovation: The VTR team is comprises of laboratories, universities, and industry partners. Key university AI and laboratory multi-physics assets are being utilized throughout the digital engineering ecosystem.

- Infrastructure and Environment: VTR uses the Microsoft Azure for Government cloud-based platform for real-time collaboration across geographic regions so that national laboratory, industry, and university partners can access VTR information quickly and securely. This technology reduced latency by a factor of 100 during peak use when systems were migrated from onsite technologies.
- Culture/Workforce: To introduce these new data-driven, data-first concepts, the VTR project
 holds regular training on building information management and data-driven requirements
 management. Additionally, workflows and data models are tuned to meet the engineering
 existing standards processes.

The advanced reactor design and development creates new challenges in the application of nuclear safeguards and the ability for the timely detection of diversion and misuse to deter and prevent nuclear proliferation, as these technologies get deployed more broadly. These new nuclear reactors are using digital engineering and digital twin technologies. Leveraging digital thread technologies currently under development to support the VTR Program, current research efforts within the National Nuclear Security Administration are developing a system to support diversion detection for item (LWR, sodium-cooled fast reactors, etc.) or bulk (molten-salt reactor) type advanced reactors. The availability of these unique and comprehensive data streams opens the opportunity for a comprehensive understanding of all aspects of nuclear fuel cycle facility operations to significantly strengthen nuclear safeguards and the nonproliferation regime in general.

MAGNET: A digital twin of the MAGNET with a single heat pipe test article is under development at INL, providing the capabilities for remote monitoring and unattended operation (autonomous control) of the system. This digital twin is a digital replica of an operating asset that can display data received from live sensors, update a physics model for the asset with the received data, compute predictive results of operational status with AI to aid in optimizing asset use, and apply asset control accordingly. This will be developed through the integration of Deep Lynx (a data warehouse technology), the Multi-physics Object-Oriented Simulation Environment (MOOSE), physical asset sensors, and physical asset controls. This will forward research regarding how to best integrate these software systems with physical sensors and asset controls. The project team is performing AI model training and experimentation to determine what models and features are most important for enabling intelligent autonomous control as well as evaluate and determine best practices for a digital twin feedback loop.

Transformational Challenge Reactor: To achieve a paradigm shift in new nuclear costs, the Transformational Challenge Reactor Program will design, build, and operate a microreactor using a rapid advanced manufacturing approach. The program will accelerate innovation by: 1) establishing advanced nuclear energy system designs unconstrained by conventional manufacturing, 2) developing processes for the advanced manufacturing of nuclear reactors, 3) embedding sensors into key structures to obtain real-time information about their health for enhanced diagnostic and prognostic assessments, 4) building a sound process for automated operating procedures to establish a pathway for autonomous operations, 5) creating a digital platform by coupling data analytics with design and manufacturing information for the rapid quality evaluation of manufactured products, 6) demonstrating the value of integrating technology advances through the operation of an additively manufactured microreactor, and 7) engaging with industry, standards development organizations, and regulatory bodies to enable the broad adoption of this new approach. The demonstration delivers two distinct outcomes: a set of technological advancements at the ripe readiness level for adoption by industry, reestablishing the credibility of the national complex to undertake and deploy advanced nuclear energy systems at a low cost and reduced timeline.

4.2.11 ORNL

Developing and deploying digital twins for nuclear reactor systems will require leveraging resources and technical expertise in many different areas, such as high-performance computing systems, advanced

multi-physics simulation tools and technologies, data-driven hybrid approaches, and subject matter expertise on various nuclear system components. The hybrid digital twin models and procedures must also be validated through carefully planned experiments to support their qualifications. Over the last several decades, ORNL has pushed the leadership computing limits. The Frontier supercomputer, being launched in 2021, will enable exascale computing at ORNL and support the deployment of large digital twin applications for nuclear systems. For example, ORNL's Virtual Environment for Reactor Application (VERA) code suite is a candidate for building fully coupled pin-resolved neutronics and thermal-hydraulics digital twins for existing light water reactors [78].

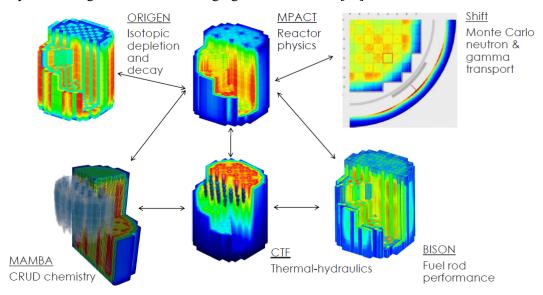


Figure 27. Key physics codes of VERA [78].

This software suite is a collection of interfacing codes that can simulate reactor core behavior from the large-scale down to the molecular scale. VERA has accurately simulated the entire 20-year history of the Tennessee Valley Authority's Watts Bar nuclear reactor, proving the software's capabilities. Industry adoption of CASL's evolving modeling and simulation capabilities helps address the long-standing and future operational and safety challenges of the nuclear fission industry.

Another area of active research at ORNL is the development of a digital platform (Figure 28) to couple data analytics with the design and manufacturing data for use in rapid prototyping and quality evaluations of additively manufactured products. This research is supported through the U.S. DOE's Transformational Challenge Reactor Program, which aims to develop, qualify and demonstrate the use of additively manufactured components in advanced nuclear reactors. Advanced manufacturing technologies produce valuable datasets at every stage of the manufacturing workflow. Collecting, structuring, and analyzing such data is paramount to understanding, optimizing, and validating the manufacturing process.

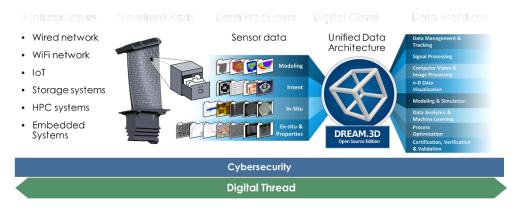


Figure 28. Digital platform being developed for the Transformational Challenge Reactor Program at ORNL.

ORNL's strategic direction in ML and AI spans research in data infrastructure, learning methods, scalability of techniques, assurance (including uncertainty quantification and explainability), and scientific workflows (edge AI to high-powered computing and human-computer interfaces and augmented intelligence). Research in these pillars is being applied to solve fundamental problems in digital twins. A digital twin is a model that captures the current state of a system (continuously updated and individualized to a specific system), is causal, and can be used to assess system health, system control, and decision making. ORNL's research in digital twins distinguishes between as designed, as manufactured, and as operating systems, with the challenge that either equation cannot completely characterize most systems once put into operation. Data collected from the operating system can, however, serve to provide a clearer understanding of the system's behavior. Challenges in this context that are being addressed at ORNL include informed learning (incorporating physics information and blending traditional models with ML models), determining the right data sets, modeling systems with widely varying temporal and spatial scales, causal analysis, and stochastic nature of the problem. Assurance, in particular, is a significant challenge.



Figure 29. Digital twin pipelines envisioned in research at ORNL.

A major part of ORNL research is developing and applying digital twins for prognostic health management. This addresses a specific need for information-driven asset management technology and spans the range from traditional models to entirely data-driven models at the necessary level of fidelity. Research in this area encompasses data through new, extreme environment sensor and instrumentation development, methods to physics-inform ML models for high-fidelity, low-complexity diagnostic and system health prognostic models, strategies to ensure data quality through sensor reliability estimation, and risk-informed methods for integrating the diagnostic and prognostic result into a robust decision-making framework (Figure 30). Applications of this workflow have been demonstrated for both active (pumps, valves, etc.) and passive (structures/structural health monitoring) components in nuclear power, with integrated solutions established for risk-informed cost-benefit analyses in O&M decision making.

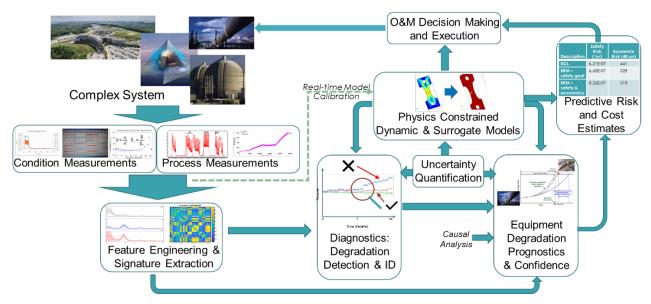


Figure 30. Process flow for digital twin–based diagnostics and prognostics integration with decision making.

4.2.12 ANL

Several research groups across ANL are co-investigators in four recent ARPA-E GEMINA awards titled: Automated Power Plants: Intelligent, Efficient and Digitized; MARS; Digital Twin-Based Asset Performance and Reliability Diagnosis for the High Temperature Gas-cooled Reactor Cavity Cooling System Using Metroscope; and Project SAFARI – Secure Automation for Advanced Reactor Innovation. Current research efforts at ANL focus on the development and application of digital twin framework for the structural state and life prediction of reactor components. The proposed digital twin framework, shown in Figure 31, consists of a hybrid approach, which combines first principles – based models with data-driven modeling. The data for the data-driven components of the digital twin is expected to be historical operational data collected either from physical or virtual sensors. The development of digital twin starts with laboratory-scale tests for understanding and modeling the material-damage time evolution over the entire fatigue life. The following reasons are listed for using laboratory-scale data for initial digital twin development instead of actual reactor components include: reaching the reactor components can be expensive and inaccessible, component may not be currently instrumented, and regulatory hurdles for putting in a new sensor. On the other hand, laboratory-scale (e.g., fatigue test) data could generate the required historical data since it is relatively inexpensive, and it is possible to capture different failure modes over the entire fatigue life from start to final failure. For data-driven modeling, we propose using different libraries and approaches, such as TensorFlow, Kerras, and Scikit-Learn, Apache Spark, Python, and Gaussian processes.

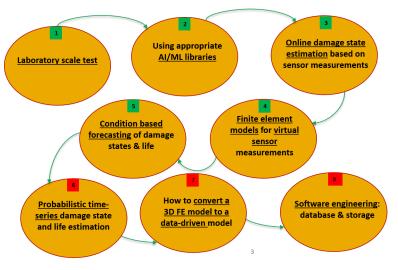


Figure 31. Building blocks of digital twin framework envisioned in research at ANL [9].

4.2.13 NCSU

The nearly autonomous management and control system [45] (NAMAC) developed at North Carolina State University is a comprehensive control system to assist plant operations by furnishing recommendations to operators. Such recommendations are derived by integrating knowledge from scenario-based models of plant, plant operating procedures, real-time measurements, etc. NAMAC is an intelligent operational software, whose goal is not to replace human operators but to try and make use of as much broader knowledge as possible, especially during emergent and difficult situations.

To better extract and store knowledge, NAMAC uses digital twin technology. The objective is to provide better understanding and insights about the operation and maintenance of physical objects by having an accurate virtual representation for a specific function in a specific operating environment. In the NAMAC context, digital twins are defined as a knowledge acquisition system from the knowledge base to support the intended use, including diagnosis, prognosis, strategy inventory, and so on. Figure 32 shows the development process of digital twins to support NAMAC operation.

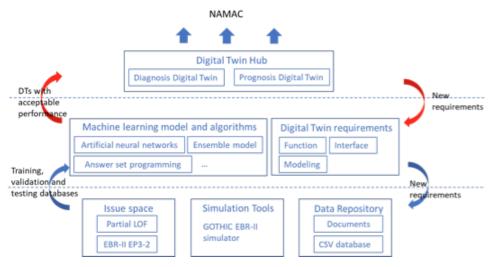


Figure 32. Development scheme for diagnosis and prognosis digital twins to support NAMAC operations [45].

The bottom layer is the knowledge base, which contains information from the issue space, simulation tools, documents, and data repository. Because of the rareness of accident and advanced reactor data, simulation data are the key contributor to the knowledge base. In NAMAC, a GOTHIC simulator for the Experimental Breeder Reactor II (EBR-II) is coupled with the Risk Analysis and Virtual Environment code for the generation of training, validation, and testing databases.

The middle layer is to develop different digital twins with various ML algorithms based on the requirements in digital twin's function, interface, and modeling. The function refers to the intended uses of a digital twin. In NAMAC, there are two major types of digital twin functions—diagnosis and prognosis. The modeling refers to techniques and algorithms that describe a virtual representation that duplicates or twins the physical system. Generally, there are four classes of options—model-free methods, model-based methods, hybrid methods, and reasoning-based methods. At last, the interface refers to the digital twin information transmission that is directly related to the human operator, a part of the physical system.

After the implementations, the digital twins will be stored in the digital twin hub and further used to support NAMAC operations on the EBR-II reactor simulator. Presently, the proof-of-concept for NAMAC has been performed for a complex loss-of-flow scenario; NAMAC is able to make reasonable recommendations, which are consistent with operator norms as in emergency procedure 3-2 (EP3-2) for EBR-II. The recommendations are derived from a multi-attribute decision-making scheme, where component reliability, reactor safety, and performance are considered simultaneously. Meanwhile, a class of digital twins are implemented mostly by feedforward and recurrent neural networks, and they are connected by an operational workflow for assimilating the knowledge base with the real-time information from the plant simulator.



Figure 33. The experimental flow loop at the University of Michigan will be used to demonstrate the SAFARI digital twin model on a molten-salt demonstration loop [7].

4.2.14 University of Michigan

The University of Michigan and a group of partners at ANL, INL, Kairos Power, and Curtiss wright were awarded an ARPA-E GEMINA award in 2020 for project SAFARI [7]. The University of Michigan is directing the project, which will leverage the expertise and facilities of the University and partners to accomplish six tasks: 1) development of a digital twin module; 2) development of a maintenance evaluation program; 3) development of an operations controller module; 4) development of an O&M supervisor module; 5) demonstration of capabilities on a molten-salt loop; and 6) application of the capability to the Kairos-FHR reactor design. Project SAFARI seeks to apply digital twins primarily to the maintenance, normal operation (to include load following), and accident scenarios of an advanced nuclear plant.

4.2.15 MIT

The Massachusetts Institute of Technology was awarded two ARPA-E GEMINA projects in 2020 to develop high-fidelity CFD digital twin models, develop a digital twin of the BWRX-300 small modular reactors to model mechanical and thermal fatigue for O&M activities, and generate molten-salt irradiation data to inform molten-salt reactor digital twins [7]. The high-fidelity CFD will use AI digital twins to inform predictive maintenance models to reduce operating costs and will apply to any technology with a flowing coolant. The development of a digital twin for the BWRX-300 will include the assembly, validation, and demonstration of the reactor systems. The collection of irradiation data from molten-salt samples for entry into a digital twin system is intended to model fuel salt behavior in molten-salt reactors.

4.3 Summary of Planned and Potential Use Cases of DT in Nuclear

Following are the areas of application of digital twins in the nuclear industry, either currently planned within ongoing research and development efforts for near term implementation or envisioned for medium to long term:

- Plant-referenced simulators: In addition to operator training and testing, most operating LWRs use the simulator to aid in the design, give problem resolution, and provide post trip analysis of equipment and operator response. Next generation reactor designers are using simulators extensively to aid in design, including the man-machine interface, and to understand and validate expected plant response to normal, transient, and accident conditions.
- Condition monitoring: Backed by the installation of advanced sensors and instrumentation, data transfer and computing infrastructure, many current utilities have established condition monitoring capabilities that monitor plant equipment and provide early warning to the station for equipment anomalies, often well before plant alarms or traditional performance monitoring and trending systems. Examples of utilities that have implemented a dedicated monitoring and diagnostics center include Duke Energy, Tennessee Valley Authority, Public Service Enterprise Group, Florida Power and Light, APS, Xcel Energy, Exelon, and EDF Energy.
- Failure and degradation prediction: Several NPPs are implementing APR software tools that are "trained" to recognize normal equipment performance based on historical data (baseline performance). The APR software analyzes real-time data and compares it to the baseline performance. As flags are generated for calculated anomalies, invalid flags (false positives) are used to tune the models and improve performance. M&D center personnel review the flags for validity and refer valid anomalies to station personnel for review and concurrence. Upon validation, action is taken to investigate and resolve adverse conditions prior to plant impact. The use of ML will further improve the effectiveness of performance monitoring analysis and reduce false positives.

- Predictive maintenance: Public Services Enterprise & Group Nuclear (PSEG) is working with INL and PKMJ to develop and demonstrate a fully integrated risk-informed condition-based maintenance capability on an automated platform. This effort developed ML models using heterogeneous plant process and component performance data to diagnose component failures based on salient fault signatures. These output from these models are used by optimizing the scheduling of preventive and corrective maintenance of components at a plant. Exelon is focusing an APR effort that utilizes component monitoring data, such as bearing metal temperature, oil-drain temperature, vibrations, suction-pressure, steam pressure and shaft pressure, to enable real-time component health monitoring and maintenance scheduling optimization. Many existing LWRs are implementing value-based maintenance initiatives to evaluate the most cost-effective maintenance strategies.
- Analysis of historical plant data: Utilities such as PSEG and Exelon are using NLP for
 analyzing and gaining insights from the rich source of historical plant data. PSEG is using
 NLP based on convolution neural network to automatically classify the WO data into
 different categories, automating the tedious, time-consuming mining and classifying of WOs
 by subject matter experts. Exelon uses NLP and ANNs to automatize the process of
 identifying maintenance rule functional failures from the large number of historical incident
 reports.
- **Design and prototype development**: Several advanced reactor developers envision using digital twins in prototype development enabling quick iteration through successive developmental prototypes of key reactor plant subsystems, reducing uncertainties, increasing efficiencies in design, licensing and construction process.

In addition, the current fleet and advanced reactor developers envision using digital twin for a wideranging areas of application such as additive manufacturing, design optimization, rapid demonstration, onsite staff-reduction, crew deployment optimization, multifunctional sensors, quick load following, creating event databases and fault libraries, optimizing sensor and instrumentation infrastructure, riskbased maintenance, virtual testing and maintenance, eliminating destructive testing, downtime reduction, severe accident management, aging and degradation management, fuel performance enhancement, refueling management and optimization, virtual sensors, assist plant operator, and intelligent autonomous control.

5 Enabling Technologies for Digital Twin

Using the knowledge gained by reviewing the above applications of digital twins technologies, our discussions with experts in digital twins technology and nuclear power, and a review of relevant literature, we identify in this section several key technologies that will be needed to enable a nuclear digital twin: advanced sensors and instrumentation, data analytics, ML and AI, and advanced modeling.

Main observations of the review presented in this section are as follows:

- The advanced sensors and instrumentation efforts across national laboratories, university research centers and reactor developers are focusing on development and demonstration of following types of advanced sensors:
 - Thermocouples that are aimed at high-temperature irradiation resistant thermocouples
 - Acoustic sensors based on advanced acoustics and ultrasonic technology for multimodal measurements
 - Neutron flux sensors that are self-powered and provide are more reliable compared to existing standard ex-core power monitors
 - Optical fiber-based sensors have been popular in several complex applications and are now being developed and tested for a variety of nuclear applications
 - Wireless sensors offering enhanced functionalities such as self-powered, economical production, direct sensing, and multi-modal sensing
- A variety of data analytics, ML, and AI techniques such as shallow and deep neural network, artificial neural network, convoluted neural network, support vector machines, clustering, filtering, NLP, and others are being developed from historical and real-time plant data for reactor applications such as anomaly detection, failure prediction, predictive maintenance, WO classification, predicting accident scenarios, reactor safety, component and sensor degradation prediction etc.
- Traditionally in the nuclear industry multi-physics modeling and simulation have been extensively in use in the form of physics-based models for several phenomenon such as thermal-hydraulics, neutronics, fuel performance etc. The computational tools for multi-physics modeling have evolved and developed considerably in last several years, the capabilities of these tools are discussed briefly in this section and a comprehensive compilation of the multi-physics tools currently applied in the nuclear industry is presented in Appendix A.
- The section presents a review of methodologies, computational tools, and potential application of dynamic PRA, enabled through digital twin technologies that combines multi-physics modeling, safety system response, and operator action with traditional PRA.

5.1 Advanced Sensors and Instrumentation in Nuclear

Sensors and instrumentation form the backbone of monitoring and controls capabilities at NPPs. While most of the sensors are already in place as part of the existing control system, advanced systems of sensors are under development to allow for better tracking and predicting of conditions, real-time data transfer, extended longevity of sensors, and detection of incipient sensor failure, all without requiring a disproportionately large number of sensors. Following is an overview of the current research, development, and deployment of advanced sensors and instrumentation for both current and advanced reactor operations.

The U.S. DOE's Office of Nuclear Energy's Advanced Sensors and Instrumentation (ASI) program has spurred innovation in the measurement science field by funding research to advance the nuclear

industry's monitoring and control capability [55]. The ASI program has identified the following four crosscutting research areas (Figure 34) aimed at responding to the nuclear industry's needs: 1. Sensors and Instrumentation, 2. Communication, 3. Big Data, ML/AI, and 4. Advanced Control Systems.



Figure 34. Areas of research, development, and demonstration within the U.S. DOE's ASI program [55]

Following are the types of advanced sensors currently undertaken for development and demonstration as part of ASI program:

Thermocouples: Real-time temperature measurements is one of the most significant modalities for reactor performance monitoring during normal operations and during any potential post-accident conditions. There have been recent advances in developing high-temperature irradiation resistant thermocouples that address the requirements of low-drift and high-neutron flux environment [55]. These advanced thermocouples push the operating temperature limit to more than 1650°C achieving measurements of direct fuel temperature, cladding-surface temperature, and micro-fuel [55].

Acoustic sensors: The advanced acoustic and ultrasonic sensors can be used for measuring wideranging parameters including temperature, gas pressure, vibration etc. Ultrasonic sensors offer an attractive capability of making multiple, spatially resolved and multiplexed measurements without direct access to the sample to be measured [55]. Recent efforts at INL are developing and testing additively manufactured surface acoustic wave devices fabricated using stainless steel, zircaloy-4, molybdenum, and tungsten aimed at high-temperature and pressure applications [55]. The Acousto-Optic Smart Multimodal Sensors project is developing an integrated sensor concept, based on the use of surface acoustic wave devices, that enables simultaneous measurements of temperature, pressure, and gas composition using a single sensor platform, thereby limiting the number of penetrations in a reactor vessel [55].

Neutron flux sensors: Current efforts are focused on demonstration and qualification of self-powered neutron detectors that will provide real-time measurements [55]. These advanced neutron flux sensors improve upon the standard methods of determining spatially resolved neutron flux by providing exact flux measurements at key locations in-core that are more reliable than standard ex-core power monitors [55]. These self-powered neutron detectors have recently been deployed in the transient test reactor facility at INL achieving a crucial step toward qualification [55].

Optical fiber-based sensors: Optical fibers have traditionally been popular in several complex applications such as mining, aerospace and medical. They hold promise for wide application in the

nuclear industry such as component and structural health monitoring, spent fuel storage monitoring, and irradiation testing [55]. Radiation hardened optical fibers are currently under development, testing and qualification for in-pile temperature measurement application.

Wireless sensors: Wireless sensor technology is currently being developed at ORNL with the goal to deploy network of wireless sensors at NPPs. The network would comprise of digitally printed radio frequency surface acoustic wave devices that are fabricated by additive manufacturing technologies [55]. These advanced wireless sensors offer enhanced functionalities such as being self-powered, produced economically, direct sensing, and multi-modal sensing. Such wireless sensor network when deployed will enable real-time, multi-modal data stream, component health monitoring, and faster component failure detection.

5.2 Data Analytics and Machine Learning and Artificial Intelligence Applications in Nuclear

The existing LWR nuclear power industry, in general, has lagged behind other industries in adopting modern data analytics to improve O&M, power generation, safety and reliability. However, in recent years, the industry is making progress in the introduction and use of digital models and data analytics. This section provides an overview of the past and current research efforts in the area of data analytics, ML, and AI specific to nuclear reactor applications. A comprehensive review of recent research efforts using ML/AI for various nuclear application is presented in [57]. The report in [57] was created as part of the research conducted at INL for the U.S. NRC and presents the recent and ongoing efforts of the most widely used ML/AI algorithms specifically applied in reactor system design and analysis, plant operation and maintenance, and nuclear safety and risk analysis.

In the past few decades, AI and machine learning—based computing technologies, specifically, shallow and deep neural networks, support vector machines, and other data-driven techniques have been investigated for application to NPPs [58-69]. A combination of convoluted neural networks, denoising autoencoders, and k-mean clustering is used in [58] for anomaly detection using pressurized-water reactor data. The data was simulated using diffusion theory to perform a low-order approximation of the angular moment of the neutron flux along with simulated noise and perturbation. A well-known limitation of component degradation modeling is the lack of a physics-based degradation model, which is addressed in [59]. The authors present an anomaly detection algorithm for the condition monitoring of components in an NPP, while modeling sensor degradation as well. The efficient symbolic dynamic filtering—based anomaly detection algorithm is implemented and validated on the data simulated via the International Reactor Innovative and Secure NPP simulator.

Critical heat flux is one of the criteria for safe reactor performance that limits the maximum heat flux in the reactor core. An adaptive neuro-fuzzy inference system is developed in [60] to predict critical heat flux using publicly published data from experimental observations and critical heat flux lookup tables. In [61], auto-associative kernel regression and sequential probability ratio tests are used in conjunction for the condition monitoring of sensors, followed by verification with a baseline sensor measurement to diagnose component performance. The performance of the condition monitoring algorithm is validated using a full-scope NPP simulator.

Artificial neural network—based methodology is developed in [62] for the prediction and identification of accident scenarios in NPPs and for diagnosing transients in [68]. Training and testing of the algorithm are performed using a simulator for identifying a large break loss-of-coolant accident with and without an emergency core cooling system. Simple techniques for principal component analysis and Fisher discriminant analysis are presented in [63] for fault detection in control rod withdrawal and external reactivity insertion. This work is unique in that the data is obtained not from a simulator but from a low power research reactor.

A prototype system for diagnosing the likely states of nuclear reactor systems using a dynamic Bayesian network is presented in [64]. The prototype system utilizes the observed plant performance parameters for a better understanding of the state of a reactor during an accident when only a subset of data might be available [64]. An artificial neural network—based model of a pressurized-water reactor pressurizer is developed in [66] along with a fuzzy controller. The training and validation are performed using a Westinghouse 3-loop pressurized-water reactor simulator.

One of the earliest works was published in 2000 [67] in which a genetic algorithm was employed for optimizing the preventive maintenance scheduling of the standby systems of an NPP and was applied to optimize the existing periodic maintenance schedule of auxiliary feedwater system components. One of the recent works in [69] present an extensive study to explore the application of ML methods, particularly neural networks for predictive analytics in nuclear reactor applications.

A common limitation in a majority of current works developing ML and AI algorithms for nuclear applications is that the data used for the training and validation of the algorithms are mostly generated using simulators. Algorithms developed and validated without using actual plant data must be critically assessed for accuracy, validity, and uncertainty in their outcomes.

5.3 Advanced Models in Nuclear

5.3.1 Multi-physics Modeling and Simulation

Modeling and simulations have been an integral part of the licensing and operations of NPPs. Due to the limited computing power in the past, the modeling and simulation tools have been historically developed in standalone mode to solve the governing equations of individual physics. The feedback between various physical phenomenon has been either omitted or loosely considered. With the advent of advanced reactor designs, the feedback between different physical phenomenon is an important phenomenon that must be accounted for in the safety analysis and operations of NPPs. For example, the thermo-mechanical expansion of core structural materials in fast reactors can have a significant impact on neutron leakage and hence in reactivity control, and the power distribution in the core is also affected by the distribution of fuel and coolant temperature. Therefore, fast reactors require a tight coupling between neutronics and thermal-hydraulics to account for rapid changes in power due to the reactivity feedback that can occur with changes in temperature. As a result, multi-physics modeling and simulations play an essential role in digital twin technologies that enable the development and licensing of advanced nuclear reactor designs and can be used to simulate various accident scenarios to assess the risk and consequence. Historically, multi-physics simulations have been segregated into different areas of focus or disciplines. The disciplines include: 1) cross section generation, 2) core neutronics and kinetics, 3) core thermalhydraulics or thermodynamics, 4) system analysis, and 5) fuel performance. The multi-physics simulations could also include additional disciplines, when needed, such as CFD, structural analysis, and source terms. Within the context of digital twin technologies, the multi-physics simulation toolkit should have the following desired characteristics:

- Centralized databases that store and unite data from suppliers, clients, multi-physics simulators, and onsite information. The centralized databases provide the capability to streamline the data flow and reduce the chance of errors in the multi-physics simulations. The databases must evolve to reflect the state of the plant given the 40 plus years of the expected lifecycle of an NPP.
- The multi-physics simulation tools with varying degrees of pedigree and fundamental
 assumptions must be integrated to perform the intended consequence analyses. The interfaces
 between simulation tools must be standardized to ensure the interoperability of computer
 codes.

• The multi-physics models should have the quality, verification and validation, and uncertainty quantification to comply with regulatory requirements.

There are many advanced reactor concepts being developed and designed. These concepts, in general, fall into one of the following advanced reactor categories:

- High-temperature gas-cooled reactors (HTGR): There are prismatic core and pebble-bed core designs for HTGRs. The spectrum can be thermal or fast. X-energy (Xe-900) is a pebble-bed core with a thermal spectrum design. Framatome's HTGR design has a prismatic core with a thermal spectrum. The fuel for both X-energy and Framatome's HTGR is TRISO fuel, either in plates or pebbles. General Atomics' gas-cooled fast reactor has a prismatic core with fast-spectrum neutrons.
- Molten-salt-cooled high-temperature reactors (MSR) Karios Power's fluoride-salt-cooled high-temperature reactor falls into this category.
- Liquid-metal-cooled fast reactors (LFR)— The designs can be further classified as sodium-cooled fast reactors (SFR) and lead-cooled fast reactors (LFR). DOE's VTR and TerraPower's Natrium sodium-cooled fast reactor design fall into the SFR category. LFR includes design variants from Westinghouse, Columbia Basin, and Hydromine.
- Liquid-fuel molten-salt reactors Many design variations are being studied within this category. The designers include Terrestrial, TerraPower, Elysium, Thorcon, Muons, Flibe, Alpha Tech, and Moltex Energy SSR-W.
- Microreactors Oklo Power LLC's Aurora and Westinghouse's eVinci are fast microreactors.

These reactor concepts have diverse designs with various fuel forms, coolant types, plant configurations, and neutron spectrum. Consequently, various computer codes with varying maturity levels are either already developed or still being developed to support the analyses of different reactor designs. The detailed assessment of some of the typical computer codes used in the multi-physics simulations is provided in Appendix A.

Table 1. Summary of typical computer codes used in multi-physics simulations.

	HTGR	MSR	LMFR	Liquid- Fuel MSR	Microreactors
Cross Section Generation	SCALE, SERPENT, DRAGON	SCALE, SERPENT	MC2-3	SCALE	SERPENT
Core Neutronics	PARCS, Griffin MCNP5	PARCS, Griffin MCNP5	DIF3D, REBUS-3 Griffin MCNP5	SCALE	MCNP5, Griffin
Core Thermal Hydraulics	AGREE, PRONGHORN	PRONGHORN	SE2-ANL		SAM
System Analysis	RELAP5, SAM, TRACE, TRANSFORM	RELAP5, SAM, TRACE, TRANSFORM	SASSYS/ SAS4A, RELAP5, TRACE, SAM,	SAM, TRANSFO RM	SAM, TRANSFORM

			TRANSFORM	
Fuel Performance	PARFUME, BISON	PARFUME, BISON	LIFE-METAL, FAST, BISON	FAST, BISON

5.3.2 Dynamic PRA

Hsueh and Mosleh had envisioned in 1996 [70] dynamic accident simulation for dynamic probabilistic risk assessment such that the plant thermal-hydraulic behavior, safety system response, and operator interactions could be modeled and simulated together. The lack of computational resources at the time limited the scope and extent of modeling and simulating such a dynamic PRA. However, digital twin technology that combines multi-physics modeling with safety system responses as well as operator actions, together in real-time can enable dynamic PRA for NPPs. Integration with traditional PRA and dynamic PRA opens the digital twins to make decisions and recommendations associated with mitigation and safety systems. Recent efforts on dynamic PRA have focused on data generation and data analysis for dynamic PRA [71], modeling control room operator actions [72], severe accident management [74], and integrating traditional PRA with dynamic PRA [75].

Event Modeling Risk Assessment using Linked Diagrams (EMRALD) is a software tool developed at INL for researching the capabilities of dynamic PRA [73]. In order to promote the effective use of dynamic PRA by the general community, EMRALD focuses on the following key aspects: simplifying the modeling process by providing a structure that corresponds to traditional PRA modeling methods; providing a user interface to model and visualize complex interactions; allowing coupling with other analysis applications such as physics-based simulations; and providing the sequence and timing of events that lead to the specified outcomes. The Risk Analysis and Virtual ENviroment (RAVEN) developed at INL provides a full and comprehensive set of capabilities to build analysis workflows based on state-of-the-art and advanced UQ, PRA, optimization, and ML techniques [77]. The primary objectives of the software is to assist users to: (1) improve the performance of their physical design; (2) estimate the likelihood of undesired outcomes (risk analysis); (3) identify main parameters and events affecting the behavior of the model and their impact; and (4) construct analysis flows combining multiple physical models and analysis procedures.

6 Conclusions and Future Work

This report presents an assessment of the state of digital twin technology in nuclear reactor applications. The assessment encompasses the history, current state, and future vision associated with the technology, applications, and regulations of digital twin technologies. The assessment was undertaken by teams at INL and ORNL comprised of scientists and experts in a wide variety of fields, such as reactor design, nuclear engineering, thermal-hydraulics, fuel performance, multi-physics modeling, data analytics, ML and AI, safety and reliability, policy and regulations, digital I&C, computer hardware and software, and data management. The state-of-the-art assessment was broadly aimed at finding answers to the following questions:

- 1. What are digital twins?
- 2. What are the applications of digital twins in nonnuclear industries?
- 3. What are the applications of digital twins or associated technologies in the current fleet of nuclear reactors?
- 4. What are the current efforts and future vision of applying digital twins in the next generation of nuclear reactors?

Five global digital twin technology companies were reviewed for their current digital twin capabilities and future vision. This report includes a discussion on their notable digital twin applications in nonnuclear industries. The assessment of digital twin applications in the nuclear industry presents the effort undertaken by U.S. commercial utilities to implement various elements of technologies that can potentially form digital twins. This discussion highlights the efforts of commercial NPPs in collaboration with digital twin vendors and university and national laboratory researchers to implement digital twins aimed at achieving operation efficiency, enhanced safety, and reliability. This report presents an assessment of digital twin for next generation nuclear reactor applications in form of the efforts undertaken at fourteen entities across the nation, including advanced reactor designers and developers, nuclear technology vendors, national laboratories, and universities.

Following are the key observations from the assessment across the spectrum of digital twin technologies in general and their nuclear reactor applications in particular:

- Digital twins 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 digital twin technologies continues to grow and the technology is expected to experience rapid and wide industry adoption by the next decade.
- Current efforts in the nuclear industry are focused on specific enabling technologies that form digital twin, such as advanced sensors, digital computing and communication infrastructure, hi-fidelity models, data analytics, ML and AI, and multi-physics modeling and simulation.
- In future the above discrete enabling technologies will coalesce to form a unified system or
 plant digital twin. To pave way for a smooth and successful application of digital twin in
 nuclear, it is imperative to understand and address the challenges and gaps associated with
 specific enabling technologies.
- Some of the focus areas of applying digital twins in 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 analysis.

- The main topics related to digital twin application in nuclear that need to be addressed in near term are:
 - O Development of a common understanding, including an agreeable definition, of the structure and functions of a digital twin,
 - o Identification of technical challenges and potential solutions related to implementing the digital twin enabling technologies in nuclear,
 - o Identification of regulatory readiness levels and gaps in applying digital twins for nuclear reactor applications, and
 - Engagement with stakeholders to identify the digital twin implementations in the current fleet and their potential regulatory impact.

7 References

- 1. Thomas, Kenneth D. 2016. "First-of-a-Kind Control Room Modernization Project Plan." INL/EXT-16-38026, Idaho National Laboratory.
- 2. S. Lee, Y. T. Yoon, S. Moon and J. Park, "Smart grid based nuclear load-following operation strategies in the South Korean power system," 2013 IEEE Power & Energy Society General Meeting, 2013, pp. 1-5, doi: 10.1109/PESMG.2013.6672241.
- 3. National Reactor Innovation Center. "National Reactor Innovation Center Homepage." Accessed April 6, 2021. https://nric.inl.gov.
- 4. Ford, Neil. 2019. "PG&E seeks decommissioning head start as cost estimates rise." Reuters, May 13, 2019. https://analysis.nuclearenergyinsider.com/pge-seeks-decommissioning-head-start-cost-estimates-rise.
- 5. Advanced Research Project Agency Energy. 2021. "ARPA-E Homepage." Accessed April 6, 2021. http://arpa-e.energy.gov.
- 6. Advanced Research Project Agency Energy. 2018. "Modeling-Enhanced Innovations Trailblazing Nuclear Energy Reinvigoration." Accessed by April 6, 2021. https://arpae.energy.gov/technologies/programs/meitner.
- 7. Advanced Research Project Agency Energy. 2019. "Generating Electricity Managed by Intelligent Nuclear Assets." Accessed April 6, 2021. https://arpae.energy.gov/technologies/programs/gemina.
- 8. Panetta, Kasey. 2018. "5 Trends Emerge in the Gartner Hype Cycle for Emerging Technologies, 2018." Gartner, Accessed April 6, 2021. https://www.gartner.com/smarterwithgartner/5-trends-emerge-in-gartner-hype-cycle-for-emerging-technologies-2018.
- 9. Vaibhav Yadav, et al. 2021. "Proceedings of the Workshop on Digital Twin Applications for Advanced Nuclear Technologies." ML21083A132, U.S. Nuclear Regulatory Commission.
- 10. "Dassault Systems. "Can digital twin software be the salvation of your supply chain?" Accessed by April 6, 2021. https://www.3ds.com/3dexperience/cloud/digital-transformation/digital-twin-software.
- 11. Kienzler, Romeo. 2019. "Digital Twins and the Internet of Things." IBM, May 13, 2019. https://developer.ibm.com/articles/digital-twins-and-the-internet-of-things.
- 12. Digital Innovation Center of Excellence. 2020. "Digital Twin Application for Advanced Nuclear Technologies." Accessed April 6, 2021. https://dice.inl.gov/digital-twin-workshop.
- 13. U.S. Nuclear Regulatory Commission. 2019. "Integrated Action Plan to Modernize Digital Instrumentation and Controls Regulatory Infrastructure." ML19025A312, U.S. Nuclear Regulatory Commission.
- 14. VanDerHorn, Eric, and Sankaran Mahadevan. "Digital Twin: Generalization, characterization and implementation." Decision Support Systems (2021): 113524.
- 15. Grieves, Michael. 2002. "PLM Initiatives." Paper presented at the Product Lifecycle Management Special Meeting, University of Michigan Lurie Engineering Center, December 2002.
- 16. Grieves, Michael. 2005. "Product Lifecycle Management: the new paradigm for enterprises." International Journal of Product Development 2 (1/2): 71 –84. http://doi.org/10.1504/IJPD.2005.006669.

- 17. Grieves, Michael. 2005. *Product Lifecycle Management: Driving the Next Generation of Lean Thinking*. New York: McGraw-Hill.
- 18. Grieves, Michael. 2011. Virtually Perfect: Driving Innovative and Lean Products through Product Lifecycle Management. New York City: McGraw-Hill.
- 19. Grieves, Michael. 2014. "Digital twin: manufacturing excellence through virtual factory replication." White paper 1: 1–7.
- 20. Dassault Systems. 2021. "Beyond Digital Twin Convergence of the Virtual and Real Worlds." Accessed April 6, 2021. https://discover.3ds.com/beyond-digital-twin.
- 21. Digital Twin Consortium. 2021. "Digital Twin Consortium Homepage." Accessed April 6, 2021. https://www.digitaltwinconsortium.org.
- 22. ANSYS. 2019. "What is Reduced Order Model and Response Surface Model?" Accessed April 6, 2021. https://www.ANSYS.com/blog/what-is-a-reduced-order-model-response-surface-model.
- 23. ANSYS. 2021. "Digital Twins: Making the Vision Achievable." Accessed April 6, 2021. https://www.ANSYS.com/resource-center/white-paper/digital-twins-making-vision-achievable.
- 24. Nercesian, Jeffrey. 2017. "Newport News Shipbuilding Launches the Digital Shipyard." Siemens, April 12, 2017. https://blogs.sw.siemens.com/thought-leadership/2017/04/12/newport-news-shipbuilding-launches-the-digital-shipyard.
- 25. Debbink, Mark and Carla Coleman. 2019. "Strategy for an Intelligent Digital Twin. NIST Model Based Enterprise Summit." Presented at NIST Model Based Enterprise (MBE) Summit, Gaithersburg, MD, April 2019. https://www.nist.gov/system/files/documents/2019/04/05/13d_strategy_for_an_intelligent_digital_twin_03-04-2019_-_mark_debbink.pdf.
- 26. Jones, David, Chris Snider, Aydin Nassehi, Jason Yon, and Ben Hicks. 2020. "Characterizing the Digital Twin: A systematic literature review." CIRP Journal of Manufacturing Science and Technology 29 (A): 36–52. http://doi.org/10.1016/j.cirpj.2020.02.002.
- 27. Kritzinger, Werner, et al. 2018. "Digital Twin in manufacturing: A categorical literature review and classification." IFAC-PapersOnLine 51 (11): 1016-22. https://doi.org/10.1016/j.ifacol.2018.08.474.
- 28. Ferguson, Stephan, Edward Bennett, and Artem Ivashchenko. 2017. "Digital twin tackles design challenges." World Pumps 2017 (4): 26–28. https://doi.org/10.1016/S0262-1762(17)30139-6.
- 29. Tao, Fei, et al. "Digital twin-driven product design framework." International Journal of Production Research 57 (12): 3935–3953. https://doi.org/10.1080/00207543.2018.1443229.
- 30. Radiant Digital Twin. The Digital Thread Imperative for New Growth in Digital Twins and Augmented Reality. https://radiant.digital/the-digital-thread-imperative-for-new-growth-in-digital-twins-and-ar/
- 31. Q Bio Gemini Clinical Digital Twin. https://www.businesswire.com/news/home/20210429005437/en/Q-Bio-Announces-First-Clinical-%E2%80%9CDigital-Twin%E2%80%9D-Platform-and-Novel-Whole-Body-Scanner-and-Major-Investment-From-Kaiser-Foundation-Hospitals

- 32. World Nuclear News. "Project launched to digitally clone all French reactors". September 2020. https://world-nuclear-news.org/Articles/Project-launched-to-digitally-clone-all-French-rea
- 33. Tharma, Rajeeth, Roland Winter, and Martin Eigner. "An approach for the implementation of the digital twin in the automotive wiring harness field." In proceedings of the DESIGN 2018 15th International Design Conference, Dubrovnik, Croatia, May 21–24, 2018. http://doi.org/10.21278/idc.2018.0188.
- 34. NEC Corporation. 2021. "The Future of Digital Twins." Accessed April 6, 2021. https://www.nec.com/en/global/insights/article/2020022510/index.html.
- 35. Ferguson, Stephan. 2020. "Apollo 13: The First Digital Twin." Siemens, April 14, 2020. https://blogs.sw.siemens.com/simcenter/apollo-13-the-first-digital-twin.
- 36. Glaessgen, Edward and David Stargel. 2012. "The digital twin paradigm for future NASA and U.S. air force vehicles." http://doi.org/10.2514/6.2012-1818.
- 37. Hilton, Gary and James Needham. 2019. "Welcome to Boeing's factory of the future." Boeing, Accessed April 7, 2021. https://www.boeing.com/features/innovation-quarterly/feb2019/btj-global.page.
- 38. Damjanovic-Behrendt, Violeta. 2018. "A digital twin-based privacy enhancement mechanism for the automotive industry." Presented at 2018 International Conference on Intelligent Systems (IS), Madeira, Portugal, September 2018. http://doi.org/10.1109/IS.2018.8710526.
- 39. Verdouw, C.N. and J.W. Kruize. 2017. "Digital twins in farm management: illustrations from the FIWARE accelerators SmartAgriFood and Fractals." Presented at 7th Asian-Australasian Conference on Precision Agriculture Digital, Hamilton, New Zealand, October 2017. http://doi.org/10.5281/zenodo.893662.
- 40. Hofmann, Thomas. 2017. "Integrating nature, people, and technology to tackle the global agri-food challenge." Journal of Agricultural and Food Chemistry 65 (20): 4007 –4008. http://doi.org/10.1021/acs.jafc.7b01780. http://doi.org/10.1021/acs.jafc.7b01780.
- 41. Ahmed, Hanad and Laurence Devoto. 2020. "The Potential of a Digital Twin in Surgery." Surgical Innovation (December). https://doi.org/10.1177/1553350620975896.
- 42. Lacal, Maria. 2021. "Analytics, Machine Learning, and Artificial Intelligence for Nuclear Power Plants." Presented at the 33rd NRC Regulatory Information Conference, Virtual, March 2021." https://ric.nrc.gov/docs/abstracts/lacalm-th22-r1-hv.pdf.
- 43. Retzer, Matthew. 2021. "Exelon Use of Analytics." Presented at 33rd NRC Regulatory Information Conference, Virtual, March 2021. https://ric.nrc.gov/docs/abstracts/retzerm-th22-hv.pdf
- 44. Agarwal, Vivek, et al. 2021. "Machine Learning and Economic Models to Enable Risk-Informed Condition Based Maintenance of a Nuclear Plant Asset." INL/EXT-21-61984, Idaho National Laboratory.
- 45. Lin, Linyu, et al. 2021. "Development and assessment of a nearly autonomous management and control system for advanced reactors." Annals of Nuclear Energy 150 (January): 107861. https://doi.org/10.1016/j.anucene.2020.107861
- 46. U. S. Nuclear Regulatory Commission. 2000. "Operator License Eligibility and Use of Simulation Facilities in Operator Licensing." Code of Federal Regulations, title 10, part 5, section 46. https://www.govinfo.gov/content/pkg/FR-2000-07-03/pdf/00-16751.pdf.

- 47. Stankorb, Sarah. 2019. "New EPRI Tool Enables Nuclear Plants to Save Millions in Maintenance Costs." EPRI Journal January 29, 2019. https://eprijournal.com/new-epri-tool-enables-nuclear-plants-to-save-millions-in-maintenance-costs.
- 48. Electric Power Research Institute. 2019. "Continuous Online Monitoring Pilot Study: Quick Guide Pilots Show Real Savings." EPRI Technical Report 3002012785, Electric Power Research Institute.
- 49. Electric Power Research Institute. 2019. "Methods for Developing Decision-Making Software for Cost-Effectively Managing Balance-of-Plant Components in Nuclear Power Plants." EPRI Technical Report 3002015922, Electric Power Research Institute.
- 50. Electric Power Research Institute. 2020. "Plant Modernization Business Case: Monitoring and Diagnostic (M&D) Program Development: Cost-Benefit Analysis of Implementing Online Monitoring (OLM) and an M&D Program to Reduce Operating Costs and Avoid Outage and Derate Costs." EPRI Technical Report 3002018424, Electric Power Research Institute.
- 51. Electric Power Research Institute. 2019. "Preventive Maintenance Basis Database (PMBD)". https://www.epri.com/research/products/00000003002007394.
- 52. Darrington, John, Jeren Browning, and Christopher Ritter. "Deep Lynx: Digital Engineering Integration Hub." Computer software. USDOE Office of Energy Efficiency and Renewable Energy (EERE), Web. https://doi.org/10.11578/dc.20200929.1.
- 53. Grieves, Michael, 2019. "Virtually Intelligent Product Systems: Digital and Physical Twins." InComplex Systems Engineering: Theory and Practice, edited by Shannon Flumerfelt, Katherine G. Schwartz, Dimitri Mavris, and Simon Briceno, 175–200. Reston: American Institute of Aeronautics and Astronautics. http://doi.org/10.2514/5.9781624105654.0175.0200.
- 54. Electric Power Research Institute. 2019. "Phoenix Risk Monitor (RM) Version 2.0a". https://www.epri.com/research/products/00000003002011626.
- 55. U.S. Department of Energy. "Advanced Sensors and Instrumentation Project Summaries". https://www.energy.gov/sites/prod/files/2020/09/f79/ne-asi-project-summaries-2020.pdf.
- 56. International Atomic Energy Agency. 2019. "Classification, Selection, and Use of Nuclear Power Plant Simulators for Education and Training." IAEA-TECDOC-1887, International Atomic Energy Agency.
- 57. Ma, Zhegang; Bao, Han; Zhang, Sai; Xian, Min; Mack, Andrea. 2020. "Exploring Advanced Computational Tools and Techniques for Operating Nuclear Plants". INL/LTD-20-61117. Idaho National Laboratory.
- 58. Caliva, Francesco, et al. "A deep learning approach to anomaly detection in nuclear reactors." In proceedings of 2018 International Joint Conference on Neural Networks (IJCNN), Rio de Janeiro, Brazil. 2018. http://doi.org/10.1109/IJCNN.2018.8489130.
- 59. Jin, Xin, et al. "Anomaly detection in nuclear power plants via symbolic dynamic filtering." IEEE Transactions on Nuclear Science 58 (1): 277–288. http://doi.org/10.1109/TNS.2010.2088138.
- 60. Zaferanlouei, Salman, Dariush Rostamifard, and Saeed Setayeshi. 2010. "Prediction of critical heat flux using ANFIS." Annals of Nuclear Energy 37 (6): 813–821. http://doi.org/10.1016/j.anucene.2010.02.019.

- 61. Wei Li, Wei, et al. 2017. "Design of comprehensive diagnosis system in nuclear power plant." Annals of Nuclear Energy, 109: 92–102, 2017. http://doi.org/10.1016/j.anucene.2017.05.024.
- 62. TV Santosh, et al. 2009. "Diagnostic system for identification of accident scenarios in nuclear power plants using artificial neural networks. Reliability Engineering & System Safety, 94 (3): 759–762. https://doi.org/10.1016/j.ress.2008.08.005.
- 63. Jamil, Farhan, Muhammad Abid, Inamul Haq, Abdul Qayyum Khan, and Masood Iqbal. 2016. "Fault diagnosis of Pakistan research reactor-2 with data-driven techniques." Annals of Nuclear Energy 90 (April): 433–440. https://doi.org/10.1016/j.anucene.2015.12.023.
- 64. Jones, Thomas B., Michael C. Darling, Katrina M. Groth, Matthew R. Denman, and George F. Luger. 2016. "A dynamic bayesian network for diagnosing nuclear power plant accidents." In proceedings of the 29th International Florida Artificial Intelligence Research Society Conference, Key Largo, Florida, May 2016.
- 65. Gatto, L. B. S. et al. 2013. "Virtual Simulation of a Nuclear Power Plant's Control Room as a Tool for Ergonomic Evaluation." Progress in Nuclear Energy 64 (April): 8–15 (2013). https://doi.org/10.1016/j.pnucene.2012.11.006.
- 66. de Oliveira, Mauro Vitor and José Carlos Soares de Almeida. 2013. "Application of Artificial Intelligence Techniques in Modeling and Control of a Nuclear Power Plant Pressurizer System." Progress in Nuclear. Energy 63 (March): 71–85. https://doi.org/10.1016/j.pnucene.2012.11.005.
- 67. Lapa, Celso M. F., Cláudio M. N. A. Pereira, and Antônio Carlos de A. Mol. 2000. "Maximization of a Nuclear System Availability Through Maintenance Scheduling Optimization Using a Genetic Algorithm." Nuclear Engineering and Design 196 (2): 219–231. http://doi.org/10.1016/S0029-5493(99)00295-2.
- 68. Santosh, T. V., Gopika Vinod, R. K. Saraf, A. K. Ghosh, and H. S. Kushwaha. 2007. "Application of artificial neural networks to nuclear power plant transient diagnosis." Reliability Engineering and System Safety 92 (10): 1468 –1472. https://doi.org/10.1016/j.ress.2006.10.009.
- 69. Mario, Fernandez Gomez, Akira Tokuhiro, Kent Welter, and Qiao Wu. 2017. "Nuclear energy system's behavior and decision making using machine learning." Nuclear Engineering and Design 324: 27–34. https://doi.org/10.1016/j.nucengdes.2017.08.020.
- 70. Hsueh, Kae-Sheng, and Ali Mosleh. "The development and application of the accident dynamic simulator for dynamic probabilistic risk assessment of nuclear power plants." Reliability Engineering & System Safety 52, no. 3 (1996): 297-314.
- 71. Mandelli, D., C. Smith, C. Rabiti, A. Alfonsi, R. Youngblood, V. Pascucci, B. Wang et al. "Dynamic PRA: an overview of new algorithms to generate, analyze and visualize data." Proceeding of American Nuclear Society (2013).
- 72. Coyne, Kevin, and Ali Mosleh. "Nuclear Plant Control Room Operator Modeling Within the ADS-IDAC, Version 2, Dynamic PRA Environment: Part 1-General Description and Cognitive Foundations." International Journal of Performability Engineering 10, no. 7 (2014).
- 73. Idaho National Laboratory. "Event Modeling Risk Assessment using Linked Diagrams (EMRALD)." https://emrald.inl.gov/SitePages/Overview.aspx.
- 74. Groth, Katrina M., Matthew R. Denman, Jeffrey N. Cardoni, and Timothy A. Wheeler. "Smart Procedures": Using dynamic PRA to develop dynamic context-specific severe accident

- management guidelines (SAMGs). No. SAND2014-2207C. Sandia National Lab.(SNL-NM), Albuquerque, NM (United States), 2014.
- 75. Mandelli, D., Wang, C., Parisi, C., Alfonsi, A. "Integration of Classical PRA models into Dynamic PRA." https://lwrs.inl.gov/Newsletter%20Articles/Issue%2028/Issue_28-Article 04.pdf
- 76. Argonne National Laboratory. 2021. "Software." Accessed April 7, 2021.
- 77. Idaho National Laboratory. 2021. Risk Analysis and Virtual ENviroment (RAVEN). https://raven.inl.gov.
- 78. Consortium for Advanced Simulation of Light Water Reactors. 2015. "VERA Common Input User Manual, Version 2.0.0, Revision 2, CASL, 2015a." February 2015. CASL-U-2014-0014-002, Consortium for Advanced Simulation of Light Water Reactors.
- 79. Consortium for Advanced Simulation of Light Water Reactors. 2015. "MPACT User's Manual Version 2.0.0, CASL, 2015b." CASL-U-2015-0077-000, Consortium for Advanced Simulation of Light Water Reactors.
- 80. Consortium for Advanced Simulation of Light Water Reactors. 2015. "CTF A Thermal-Hydraulic Subchannel Code for LWRs Transient Analysis, CASL, 2015c." CASL-U-2015-0055-000, Consortium for Advanced Simulation of Light Water Reactors.
- 81. Hales, J. D., et al. 2016. "BISON Theory Manual, The Equations behind Nuclear Fuel Analysis." INL/EXT-13-29930, Idaho National Laboratory.
- 82. Knoll, D.A. and D. Keyes. 2004. "Jacobian-free Newton-Krylov Methods: A Survey of Approaches and Applications." Journal of Computational Physics 193 (2): 357–397. https://doi.org/10.1016/j.jcp.2003.08.010.
- 83. Marleau, G., A. Herbert, and R. Roy. 2016. "A User Guide for DRAGON Version4." IGE–294, Ecole Polytechnique de Montreal.
- 84. Gaston, Derek R., et al. 2015. "Physics-based multiscale coupling for full core nuclear reactor simulation." Annuals of Nuclear Energy 84 (October): 45–54. https://doi.org/10.1016/j.anucene.2014.09.060.
- 85. Martineau, R. et al. 2020. "Multi-physics for nuclear energy applications using a cohesive computational framework." Nuclear Engineering and Design 367 (October): 110751.
- 86. Miller, G.K., et al. 2018. "PARFUME Theory and Model Basis Report." INL/EXT-08-14497, Idaho National Laboratory.
- 87. Touran, Nicholas W., et al. 2017. "Computational Tools for the Integrated Design of Advanced Nuclear Reactors." Engineering 3 (4): 518–526.
- 88. Hu, G., et al. 2019. "Multi-Physics Simulations of Heat Pipe Micro Reactor." ANL-NSE-19/25, Argonne National Laboratory. https://doi.org/10.2172/1569948.
- 89. Idaho National Laboratory. n.d. "RELAP5-3D." Accessed April 7, 2021. https://relap53d.inl.gov/SitePages/Home.aspx.
- 90. Leppänen, J., et al. 2015. "The Serpent Monte Carlo code: Status, development and applications in 2013." Annals of Nuclear Energy 82 (August): 142–150. https://doi.org/10.1016/j.anucene.2014.08.024.
- 91. Permann, Cody J., et al. 2020. "MOOSE: Enabling massively parallel multi-physics simulation." SoftwareX 11 (January–June): 100430.

- 92. Wieselquist, W. A., R. A. Lefebvre and M. A. Jessee, eds. 2020. "SCALE Code System, Version 6.2.4." ORNL/TM-2005/39, Oak Ridge National Laboratory.
- 93. Oak Ridge National Laboratory. n. d. "Impact." Accessed April 7, 2021. https://casl.gov/impact.
- 94. Advanced Reactor Modeling Interface. n.d. "Armi." Accessed April 7, 2021. https://terrapower.github.io/armi.
- 95. Rearden, B. T. and M. A. Jessee, eds. 2016. "SCALE Code System, Version 6.2." ORNL/TM-2005/39, Oak Ridge National Laboratory. https://doi.org/10.2172/1424483.
- 96. U. S. Nuclear Regulatory Commission. 2019. "NRC Non-Light Water Reactor (Non-LWR) Vision and Strategy, Volume 1 Computer Code Suite for Non-LWR Design Basis Event Analysis." ML19093B322, U. S. Nuclear Regulatory Commission.
- 97. Geelhood, K. J., W. G. Luscher, and P. Raynaud. 2014. "FRAPCON-3.5: A Computer Code for the Calculation of Steady-State, Thermal-Mechanical Behavior of Oxide Fuel Rods for High Burnup, Vol 1, Rev 1." NUREG/CR-7022, U. S. Nuclear Regulatory Commission.
- 98. Geelhood, K. J., et al. 2011. "FRAPTRAN 1.4: A Computer Code for the Transient Analysis of Oxide Fuel Rods, Vol. 1." NUREG/CR-7023, U. S. Nuclear Regulatory Commission.
- U. S. Nuclear Regulatory Commission. n.d. "DRAFT TRACE V5.0 Theory Manual: Field Equations, Solution Methods, and Physical Models." ML071000097, U. S. Nuclear Regulatory Commission.
- 100. Brunett, J., and T. Fanning. 2017. "U.S. Sodium Fast Reactor Codes and Methods: Current Capabilities and Path Forward." In proceedings of 2017 International Conference on Fast Reactors and Related Fuel Cycles: Next Generation Nuclear Systems for Sustainable Development, FR17, Yekaterinburg, Russian Federation, June 2017.
- 101. Zhang, Hongbin, et al. 2017. "Industry Application ECCS/LOCA Integrated Cladding/Emergency Core Cooling System Performance: Demonstration of LOTUS-Baseline Coupled Analysis of the South Texas Plant Model." INL/EXT-17-4246, Idaho National Laboratory.
- 102. Oak Ridge National Laboratory. "ORIGEN." Accessed April 7, 2021. https://www.ornl.gov/division/rnsd/projects/origen.
- 103. Oak Ridge National Laboratory. "SCALE." https://www.ornl.gov/scale.
- 104. X-5 Monte Carlo Team. 2008. "MCNP--A General Monte Carlo N-Particle Transport Code, Version 5, Volume I: Overview and Theory." LA-UR-03-1987, Los Alamos National Laboratory.
- 105. Xu, Y., T. J. Downar, A. Ward, T. Kozlowski, and K. Ivanov. 2006. "Multi-Physics Coupled Code Reactor Analysis with the U.S. NRC Code System TRACE/PARCS." In PHYSOR 2006, Paper D026. La Grange Park: American Nuclear Society.

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Appendix A Assessment of Multi-physics Modeling and Simulation Tools

AGREE: AGREE is a 3D thermal-hydraulics code that solves the energy, mass, and momentum balance equations for both steady-state and time-dependent analyses.

BISON: BISON [81] is a finite-element based nuclear fuel performance code applicable to a variety of fuel forms, including LWR fuel rods, TRISO particle fuel, and metallic rod and plate fuel. It is an advanced fuel performance code being developed at INL and offers distinctive advantages over FRAPCON/FRAPTRAN, such as a 3D simulation capability, etc. BISON solves the fully coupled equations of thermomechanics and species diffusion, for either 1D spherical, 2D axisymmetric, or 3D geometries. Fuel models are included to describe temperature and burnup dependent thermal properties, fission product swelling, densification, thermal and irradiation creep, fracture, and fission gas production and release. Plasticity, irradiation growth, and thermal and irradiation creep models are implemented for clad materials. Models also are available to simulate gap heat transfer, mechanical contact, and the evolution of the gap and plenum pressure with plenum volume, gas temperature, and fission gas addition. BISON has been coupled to the mesoscale fuel performance code MARMOT, demonstrating a fully coupled multiscale fuel performance capability. BISON is based on the MOOSE framework and can therefore efficiently solve problems using standard workstations or very large high-performance computers. BISON is currently being validated against a wide variety of integral LWR fuel rod experiments.

DIF3D: DIF3D [76] is a code system using variational nodal methods and finite-difference methods to solve neutron diffusion and transport theory problems. Cross sections used in the DIF3D nodal solver must be processed into multigroup cross sections for each node. The nodal option of DIF3D solves the multigroup steady-state neutron diffusion equation in 2D and 3D hexagonal and Cartesian geometries and solves the transport equation in 2D and 3D Cartesian geometries. The VARIANT option solves the multigroup steady-state neutron diffusion and transport equations in 2D and 3D Cartesian and hexagonal geometries using variational nodal methods. The transport approximations involve complete spherical harmonic expansions up to order P99.

DRAGON: DRAGON is an open-source lattice neutron transport code developed at Ecole Polytechnique de Montreal (83). DRAGON solves the integral transport equation with methods ranging from a simple collision probability method coupled with the interface of the current method to the full collision probability method. DRAGON can model the double heterogeneity self-shielding effect with the Hebert double heterogeneity model (collision probability) or the Sanchez-Pomraning double heterogeneity (method of characteristics) model.

FAST: FAST is an NRC fuel performance computer code that combines FRAPCON/FRATRAN which is a suite of codes developed by Pacific Northwest National Laboratory for the U.S. NRC for the purposes of performing fuel performance analyses under steady-state (FRAPCON) and transient (FRAPTRAN) conditions.

FRAPCON [96] is a computer code that calculates the steady-state response of LWR fuel rods. The code calculates the temperature, pressure, and deformation of a fuel rod as functions of time-dependent fuel rod power and coolant boundary conditions. The phenomena modeled by the code include: 1) heat conduction through the fuel and cladding to the coolant, 2) cladding elastic and plastic deformation, 3) fuel-cladding mechanical interaction, 4) fission gas release from the fuel and rod internal pressure, and 5) cladding oxidation. The code contains necessary material properties, water properties, and heat transfer correlations.

FRAPTRAN: The Fuel Rod Analysis Program Transient (FRAPTRAN [96]) is a Fortran language computer code that calculates the transient performance of LWR fuel rods during reactor transients and hypothetical accidents, such as loss-of-coolant accidents (LOCAs), anticipated transients without scram, and reactivity-initiated accidents. FRAPTRAN calculates the temperature and deformation history of a fuel rod as a function of time-dependent fuel rod power and coolant boundary conditions. Although FRAPTRAN can be used in "standalone" mode, it is often used in conjunction with, or with input from, other codes. The phenomena modeled by FRAPTRAN include a) heat conduction, b) heat transfer from cladding to coolant, c) elastic-plastic fuel and cladding deformation, d) cladding oxidation, e) fission gas release, and f) fuel rod gas pressure.

Griffin: Griffin is a MOOSE-based reactor physics tool. It integrates MAMMOTH/Rattlesnake (INL) and MC2-3/PROTEUS (ANL) capabilities, which is being developed jointly by ANL and INL under the DOE-NE Nuclear Energy Advanced Modeling and Simulation (NEAMS) program. Griffin is also part of the U.S. NRC's Comprehensive Reactor Analysis Bundle (CRAB). The emphasis of Griffin is to address the challenges of multi-physics modeling and simulations imposed by advanced reactor designs and to support users (industry and government organizations) more practically and timely. Griffin is multi-physics-oriented with great flexibility and extendability that meets NQA-1 requirements. It allows users adaptable computer systems ranging from laptops to super-computers. Griffin has been applied to the analysis of the Advanced Test Reactor, VTR (versatile test reactor), TREAT (transient reactor test facility), NRAD at INL and of various advanced reactor designs including PBR, HTTR, VHTR, MSR, and microreactor, etc.

LIFE-METAL: The LIFE-METAL code [100] represents the metallic fuel version of the LIFE series of fuel performance codes that have been developed in the U.S. to evaluate the thermo-mechanical behavior of fuel elements in fast reactors. Development of LIFE-METAL continued up to the termination of the Integral Fast Reactor program in the early 1990s. The recent interest of academia and industry in the development of advanced SFR has renewed interest in these fuel performance codes, as they can be utilized for design and licensing activities as well as for the verification and validation of other newly developed fuel performance codes. Over the past decade, the LIFE-METAL code has been used extensively to support design evaluation and licensing efforts by Toshiba and KAERI in relation to the licensing of the 4S and Prototype Gen IV sodium-cooled fast reactor (PGSFR) reactors, respectively. LIFE-METAL includes physical, mechanical, thermal, and irradiation property correlations for test and design cladding materials, such as SS316, D9, and HT9 alloys. The code also includes correlations for wastage due to the sodium-cladding interaction as well as time and strain failure correlations. Models were developed for Ni depletion from D9 cladding and carbon depletion from HT9 cladding due to fuelcladding chemical interaction. Code predictions that are of interest to nuclear design are changes in fuel length and fissile content with burnup. Thermal predictions of the fuel temperature and design margins to fuel melting are also of interest, in addition to predictions of the fuel-cladding chemical interaction. Mechanical predictions that are useful to designers are the fuel-cladding mechanical interaction, cladding deformation and design margin to significant coolant flow area reduction, and cladding damage and design margin to cladding failure due to fuel and fission gas pressure loading.

MC2-3: MC2-3 [76] is a code to calculate fast neutron spectra and multigroup cross sections. The MC2-3 code is developed by improving the resonance self-shielding and spectrum calculation methods of MC2-2 and integrating the 1D cell calculation capabilities of SDX (a space dependent cross section generation capability) for fast reactor analysis. The code solves the consistent P1 multigroup transport equation using basic neutron data from ENDF/B data files to determine the fundamental mode spectra for use in generating multigroup neutron cross sections.

MCNP5: MCNP5 is a continuous-energy general-purpose Monte Carlo neutral particle transport code that can assess the criticality of nuclear systems [104]. MCNP5's geometry engine defines arbitrary volumes between first-, second-, and third-degree surfaces or fourth-degree elliptical tori. Nuclear reaction rates (fission, capture, particle production, and neutron damage) can be estimated with flux

tallies. Furthermore, MCNP is seen as a reliable, well understood code for performing high-fidelity neutron transport in the nuclear engineering community, so it is often utilized to produce reference values against which to benchmark results from new methods. MCNP5 accounts for the double heterogeneity effect by explicitly modeling fuel particles of the lattices of repeated structures and can stochastically translate the TRISO particles on a regular lattice. As stated earlier, this approach is the most accurate and fundamental way to account for the double heterogeneity energy self-shielding.

PARCS: PARCS [105] is a U.S. NRC-approved 3D reactor core simulator that solves the steady-state and time-dependent, multigroup neutron diffusion and SP3 transport equations using a coarse mesh finite-difference solver in Cartesian, hexagonal, and cylindrical geometries. It can perform depletion calculations and can track the evolution of various nuclide populations over time, including short-lived fission products (Xe, Sm) in reactor transients. PARCS represents the full core as a collection of homogenized nodes. PARCS has been coupled to RELAP5 and TRACE to perform spatial kinetics and thermal-hydraulic calculations.

PARFUME: PARFUME [86] is a fuel performance modeling code that simulates the mechanical, thermal, and physic-chemical behavior of the coated fuel particles during normal irradiation and accident conditions. It contains various capabilities that include:

- 1) various options for calculating CO production and fission product gas release
- 2) an analytical solution for stresses in the coating layers that accounts for irradiation-induced creep and swelling of the pyrocarbon layers
- 3) a thermal model that calculates a time-dependent temperature profile through a pebble-bed sphere or a prismatic block core as well as through the layers of each analyzed particle
- 4) simulation of the multidimensional particle behavior associated with cracking in the IPyC layer, partial debonding of the IPyC from the SiC, particle asphericity, and kernel migration (or amoeba effect)
- 5) two independent methods for determining particle failure probabilities
- 6) a model for calculating release-to-birth ratios of gaseous fission products that accounts for particle failures and uranium contamination in the fuel matrix
- 7) the evaluation of an accident condition, where a particle experiences a sudden change in temperature following a period of normal irradiation.

The accident condition entails the diffusion of fission products through the particle coating layers and through the fuel matrix to the coolant boundary.

PRONGHORN: PRONGHORN is a multi-physics reactor analysis application built based on the MOOSE framework. PRONGHORN was developed at INL to model the pebble-bed and prismatic gascooled reactor using an arbitrary number of groups neutron diffusion model and a porous media flow model. PRONGHORN can be run in serial or on massively parallel computers with one-, two-, three-, or axisymmetric R-Z geometry. Current capabilities of PRONGHORN include solving steady-state and transient-coupled, homogenized, fluid flow heat transfer problems and standard multigroup diffusion problems (fixed source, criticality, and time-dependent).

REBUS-3: REBUS-3 [76] is a system of codes designed for the analysis of fast reactor fuel cycles and can perform depletion analysis on systems with multi-batch fuel management schemes. Two basic types of problems are solved: the infinite-time, or equilibrium, conditions of a reactor operating under a fixed fuel management scheme and the explicit cycle-by-cycle, or nonequilibrium operation of a reactor under a specified periodic or non-periodic fuel management program. REBUS-3 can:

1) adjust the cycle length to impose a specific burnup

- 2) adjust the enrichment to impose a specific k-effective at a particular point in burnup
- 3) adjust the poison concentration to maintain a k-effective throughout the fuel cycle
- 4) adjust the cycle length to impose a specific k-effective at the end of the equilibrium cycle.

RELAP5-3D: The RELAP5-3D [89] code has been developed for best-estimate transient simulations of LWR coolant systems during postulated accidents. Specific applications of the code have included simulations of transients in LWR systems, such as loss-of-coolant, anticipated transients without scram, and operational transients, such as loss of feedwater, loss of offsite power, station blackout, and turbine trip. RELAP5-3D, the latest in the series of RELAP5 codes, is a highly generic code that, in addition to calculating the behavior of the reactor coolant system during a transient, can be used for the simulation of a wide variety of hydraulic and thermal transients in both nuclear and nonnuclear systems involving mixtures of vapor, liquid, noncondensable gases, and nonvolatile solutes.

RELAP5-3D is suitable for the analysis of all transients and postulated accidents in LWR systems, including both large- and small-break LOCAs as well as the full range of operational and postulated transient applications. Additional capabilities include space reactor simulations, gas-cooled reactor applications, fast breeder reactor modeling, and cardiovascular blood flow simulations. The RELAP5-3D code is based on a nonhomogeneous and nonequilibrium model for the two-phase system that is solved by a fast, partially implicit numerical scheme to permit the economical calculation of system transients. The objective of the RELAP5-3D development effort from the outset was to produce a code that included important first-order effects necessary for an accurate prediction of system transients but that was sufficiently simple and cost effective so that it would be possible to conduct parametric or sensitivity studies.

The code includes many generic component models from which general systems models can be developed and the progress of various postulated events simulated. The component models include pumps, valves, pipes, heat releasing or absorbing structures, reactor kinetics, electric heaters, jet pumps, turbines, compressors, separators, annuli, pressurizers, feedwater heaters, ECC mixers, accumulators, and control system components. In addition, special process models are included for effects, such as form loss, flow at an abrupt area change, branching, choked flow, boron tracking, and noncondensable gas transport.

The mathematical system models are coupled into an efficient code structure. The code includes an extensive input checking capability to help the user discover input errors and modeling and input inconsistencies. Also included are free-format input, restart, renodalization, and variable output edit features. These user conveniences were developed in recognition that the major cost associated with the use of a system transient code is generally in the engineering labor and time involved in accumulating system data and developing system models, while the computational cost associated with the generation of the final result is usually small.

SAM: The System Analysis Module (SAM) is a modern system analysis tool being developed at ANL for advanced non-LWR safety analysis. It aims to provide a fast-running, whole-plant transient analyses capability with improved fidelity for SFR, LFR, and MSR/FHR. SAM takes advantage of advances in physical modeling, numerical methods, and software engineering, to enhance its user experience and usability. It utilizes MOOSE, its underlying meshing and finite-element library (libMesh), and linear and nonlinear solvers (PETSc) to leverage the modern advanced software environments and numerical methods.

SAS4A/SASSYS-1: The SAS4A/SASSYS-1 [76] computer code is developed for thermal, hydraulic, and safety analysis of power and flow transients in liquid-metal-cooled nuclear reactors. SASSYS-1 is used to assess the safety margins in design-basis accidents and the consequences of beyond-design-basis accidents. SAS4A is used to analyze the consequences of severe accidents with coolant boiling or fuel

failures, which are initiated by a very low probability coincidence of an accident precursor and the failure of one or more safety systems.

SCALE: The SCALE code system [95] is a widely used modeling and simulation suite for nuclear safety analysis and design that is developed, maintained, tested, and managed by ORNL's Reactor and Nuclear Systems Division and deployed to over 9,000 users in 59 nations. SCALE provides a comprehensive, verified and validated, user-friendly toolset for criticality safety, reactor physics, radiation shielding, radioactive source term characterization, and sensitivity and uncertainty analyses. Since 1980, regulators, licensees, and research institutions around the world have used SCALE for safety analysis and design. The NRC is the primary sponsor of SCALE for its application in licensing current and advanced reactors, fuel cycle facilities, and radioactive material transportation and storage. An additional 33 international regulatory bodies are included in the thousands of SCALE users.

SCALE provides a modern, integrated framework with dozens of computational modules, including four deterministic solvers and three Monte Carlo radiation transport solvers from which the user selects based on the desired solution strategy. SCALE includes current nuclear data libraries and problem-dependent processing tools for continuous-energy and multigroup neutronics and coupled neutron-gamma calculations, as well as activation, depletion, and decay calculations. SCALE provides unique capabilities for automated variance reduction in shielding calculations as well as sensitivity and uncertainty analysis. SCALE's graphical user interfaces assist with accurate system modeling and provide convenient access to desired results. SCALE 6.2 (Figure 35) is one of the most comprehensive revisions in the history of SCALE, providing several new capabilities and significant improvements in many existing features.

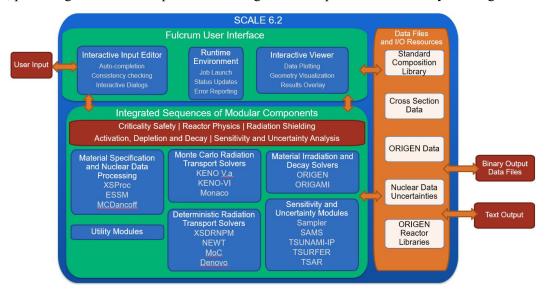


Figure 35. SCALE 6.2 capabilities with features and interdependencies of the user interface (top left), modular computational sequences and modules (bottom left), and data libraries (right).

SE2-ANL: SE2-ANL [76] is a modified version of the SUPERENERGY-2 thermal-hydraulic code, which is a multi-assembly, steady-state subchannel analysis code developed at MIT for an application to fast reactor (wire-wrapped and ducted) rod bundles. At ANL, the code was coupled to heating calculation methods based on the DIF3D code system, and models were added for hot spot analysis, fuel element temperature calculations, and allocation of coolant flow subject to thermal performance criteria.

SERPENT: SERPENT [90] is a multipurpose 3D continuous-energy Monte Carlo particle transport code, developed at the VTT Technical Research Centre of Finland, Ltd. Serpent started out as a simplified reactor physics code, but the capabilities of the current development version, Serpent 2, extend well beyond reactor modeling. The applications can be roughly divided into three categories: 1) traditional

reactor physics applications, including spatial homogenization, criticality calculations, fuel cycle studies, research reactor modeling, validation of deterministic transport codes, etc.; 2)multi-physics simulations (i.e., coupled calculations with thermal-hydraulics, CFD, and fuel performance codes); and 3) neutron and photon transport simulations for radiation dose rate calculations, shielding, fusion research, and medical physics.

TRACE: The TRAC/RELAP Advanced Computational Engine is a modernized thermal-hydraulics code designed to consolidate the capabilities of the NRC's three legacy safety analysis codes: TRAC-B (BWR), TRAC-P (PWR), and RELAP. It is able to analyze a full spectrum of transients and accidents, including large- and small-break LOCAs in both boiling-water reactors and pressurized-water reactors. The capability also exists to model thermal-hydraulic phenomena in both 1D and 3D. TRACE is currently the NRC's primary thermal-hydraulics analysis tool. A comprehensive validation matrix, including separate and integral effect tests, has been developed for the overall code assessment and validation.

As part of the international CAMP-Program sponsored by the U.S. NRC, the TRACE best-estimate thermal-hydraulics code system has been coupled with the Purdue Advanced Reactor Core Simulator (PARCS). The coupling of TRACE and PARCS accounts for the interaction of the plant dynamic thermal-hydraulic performance and the neutron kinetics for the reactor core.

TRANSFORM: The Transient Simulation Framework of Reconfigurable Modules (TRANSFORM) is an ORNL-developed component library created using the Modelica programming language for the investigation of dynamic thermal-hydraulic systems and other multi-physics systems. The TRANSFORM library allows for rapid development of energy systems with a focus on enabling the modeler to customize the components for any application, including instrumentation and control design. The TRANSFORM library has been successfully used for a variety of nuclear applications, including investigations into the performance of nuclear hybrid energy systems, nuclear thermal propulsion systems, liquid-metal and gascooled reactors, and molten-salt applications, including kinetic behavior and fission product transport (e.g., neutron precursors, xenon, and tritium).

Modelica is a nonproprietary, object-oriented, equation-based programming language used to conveniently model complex physical and cyberphysical systems to include systems containing mechanical, electrical, electronic, hydraulic, thermal, and control components. A key advantage of Modelica is its separation of physical models and the solvers of the models. This separation enables the rapid generation of complex physical systems and control design in a single language without deep knowledge of numeric solvers, code generation, etc.

Coupling of Models

A defining feature of a digital twin is its ability to pass configuration and scenario data from an authoritative data source to the relevant physics models and to receive verifiable analysis results. While early simulation models were designed around a standalone, batch execution model—largely due to the limits of available computational power—much progress has been made over the past decade in the development of common data interface standards to enable high-fidelity, coupled multi-physics simulations to be performed on large-scale computing clusters. These code interfaces provide an initial basis from which a digital twin may be more easily created. One of the most well-known nuclear simulation systems is MOOSE [91]. This environment consists of an interconnected set of simulation codes utilizing a common data and computation framework such that numerical methods, spatial meshing, and other functions are all commonly abstracted in such a way as to allow components of various types to be interchanged, enabling multiscale and multifidelity computation. Further, these components are rigorously tested to ensure a high level of quality to the obtained results. One drawback of this tightly coupled approach to integration is that new modules must often be developed with future integration into the framework in mind; it is not a simple task to integrate existing modeling or simulation tools.

At the other end of the spectrum is the SCALE code system [95]. While these codes are also developed with a high level of rigor, most were developed independently and are able to be used independently of each other, each to solve problems within a particular domain. More recent updates have revamped the code base in order to increase the utilization of common, interchangeable data formats; likewise, the introduction of the NEAMS Workbench provides a common user interface for many of the codes. Further coupling of certain codes in the SCALE system is accomplished by the VERA code that was developed through CASL. As the name implies, this model focuses on achieving extreme high-fidelity results for certain challenging modeling issues specific to LWRs (crud deposition, two-phase flow, fuel performance modeling, etc.)[78].

The ARMI code—developed by TerraPower LLC—sets out a common Python API through which users may combine many common reactor design calculations into a single suite [94]. While its capabilities are primarily targeted toward fast-spectrum, sodium-cooled reactor designs, its open-source implementation provides avenues for interested parties to extend it, as necessary.

The methods used in coupling one model to another vary from one application to another depending on the nature of the phenomena to be modeled. For example, under rapid transient conditions in a light water reactor, the neutronic behavior depends greatly on the state of the coolant in the core and vice versa. In these situations, the radiation transport and thermal-hydraulics calculations must be nearly fully integrated, directly passing data at the time-step level or finer. Other calculations might require only a single exchange of data at the beginning and end of the calculation. The coupling of the latter type of analysis to a center can be accomplished rather more simply, either through a RESTful API or other standardized asynchronous methods.

As the development of digital twins moves forward, several responsibilities that typically fall to the analyst will need to be generalized and automated in a robust manner. First, the translation of modeling data from engineering specifications down to the specific inputs for a given model requires detailed knowledge of both the design under consideration as well as the limitations and domains of operation of the codes themselves. Secondly, the evaluation and translation of the code outputs can likewise require complicated expert judgment in order to discern when results are truly representative of the physics involved. Finally, while the data passed from one model into the next might be sufficient for the immediate purposes of the second model, there must also be an awareness of how further follow-on analyses will depend upon the assumptions made in the first interface, as complex and unpredicted behaviors may result. The following two subsections have more detailed discussions of the loose coupling and tight coupling approaches.

Loose Coupling

Loose coupling is done based on solving respective governing equations (e.g., neutronics and thermal-hydraulics) independently and data exchange is done externally between codes used to solve these equations. Under most circumstances, such as steady-state operations) loose coupling, or iterative modeling, will most likely be sufficient. The advantage of loose coupling is that only robust interfaces between existing computer codes have to be developed within a proper framework. This approach can take advantage of the many mature computer codes that have been developed and validated.

Traditionally, the analyses involving multiple disciplines, including core design, fuel-clad performance, systems analysis, containment analysis, and radioactive material release, and consequence analysis were performed sequentially. This means that the analysis performed to address one portion of the physics does not necessarily provide sufficient consideration for the downstream analyses that need to be performed. As a result, the boundary conditions used for one set of analysis frequently assume conservative values from the upstream analyses. As a minimum, this sequential processing of information is inefficient and results in excess expenditures of time and resources. This is often exacerbated by the need to revise previous analyses due to results obtained during later analyses. This need to operate in a cyclical manner can add significantly to the expense and time required to conduct these analyses. In

addition, different models and assumptions went into the computer codes developed for each of the physics being analyzed. As a result, the conventional approach and methods are strongly "code-oriented." The analyst has to be familiar with the details of the codes utilized, in particular with respect to their input and output structures. This represents a significant barrier for widespread use outside of the small pool of experts that develop and apply the codes. It has become apparent how difficult it is to make changes and accelerate progress under such a paradigm, especially in a heavily regulated environment where even a single line change in a code can carry a high cost of bookkeeping and regulatory review. This "divide-and-conquer" approach currently adopted in the industry where every physics is resolved independently, and coupling is addressed by complex interface procedures. The current process is labor-intensive and inefficient. There are significant assumptions and engineering judgments used in setting up those procedures that make the propagation of uncertainties across the disciplines complex and potentially prone to errors. More importantly, the continued use of these current methods has a significant bias to retain excess analytical margins, which cannot be exploited at a later time to enhance operational and economic performance.

To address the conservatisms built into the current practice, it is essential to propagate uncertainties across the stream of physical disciplines and manage the data stream. The use of an integrated approach in managing the data stream is realized through the loose coupling of computer codes. This is also well suited to the current trends in the industry to enhance automation and develop integrated databases across their organizations. There is a trend to move toward a "plug-and-play" or task-oriented approach, where the codes are integrated together under one roof and each code is simply treated as a module "under the hood" that provides the input-output relationship for a specific analytical discipline. The "plug-and-play" multi-physics environment is essentially a workflow engine with the capability to drive physics simulators, model complex systems, and provide risk assessment capabilities. The DOE's LWRS-developed LOTUS framework represents such progress.

Tight Coupling

When strong nonlinear interdependencies exist between reactor physics, thermal-hydraulics, fuel performance, coolant chemistry, etc., tightly coupled calculations are required to resolve nonlinear dependencies. There are two approaches to perform tight coupling calculations. The first one is to solve simultaneously a system of equations that governs the behavior of more than one major distributed parameter. This method is also referred to as full coupling. For example, for a reactor core analysis, this approach usually means the simultaneous solution of neutron flux, heat transfer, and coolant flow through the core. The ability to solve these equations simultaneously avoids the introduction of errors that often arise from solving the equations separately and coupling them explicitly via "split-operator" techniques. Multi-physics codes can be used to investigate phenomena too complex for system codes, especially fast-evolving transients where neutronic and thermal-hydraulic phenomena are tightly coupled, such as anticipated transients without scram. INL's MOOSE framework is developed to perform the full coupling of multi-physics calculations.

The other approach is the "operator split" approach with which disparate physics codes of different software design, code languages, and spatial and temporal integration schemes are coupled together with relatively complex data passing interfaces. This is often realized using tightly coupled schemes, such as a Picard iteration, with which each separate application must be completely solved multiple times to fully converge the coupled solutions. This type of a coupling approach allows the opportunity to take advantage of more mature computer codes with which a significant amount of investment has already been made. These type of tightly coupled calculations is often required for a certain type of analyses. For example, to obtain a more detailed and realistic assessment of the fuel rod's behavior under transient conditions, coupled RELAP5-3D/BISON calculations are required. For non-LOCA transients for an LWR where the departure from nucleate boiling ratio has to be evaluated, a more detailed subchannel analysis (e.g., using a code such as COBRA-TF) has to be performed and coupled calculations, such as RELAP5-3D/COBRA-TF calculations, will be required.

Existing Frameworks to Perform Multi-physics Simulations

Various frameworks are developed or still being developed to perform multi-physics simulations. This subsection provides summarized descriptions for a few representative multi-physics frameworks.

MOOSE Framework

MOOSE [84] is being developed at INL to provide a multiscale (in space and time), multi-physics simulation capability based on a greater understanding of fundamental physical phenomena and enabled by the latest in software design, numerical methods, and advanced architecture. The design objective of MOOSE is to develop multi-physics software based upon mathematically and numerically consistent formulations to achieve converged solutions of important interdependent physics at all scales. Inside MOOSE, the physical systems are generally represented (modeled) as a system of fully coupled nonlinear partial differential equations. The Jacobian-Free Newton Krylov [82] method is implemented as a parallel nonlinear solver that naturally supports implicit coupling between physics equation systems. Extensive research in Jacobian-Free Newton Krylov preconditioning has been conducted and implemented into MOOSE to improve the parallel performance of large-scale multi-physics calculations. Since 2011, both national and international laboratories and universities have stood up more than 60 known MOOSE-based applications and over 58,000 known MOOSE framework build package downloads [85]. Because of using the same programming interfaces, following identical software design and library dependencies, MOOSE provides a simplified path to tightly couple physics that have vastly different space and time scales (multiscale, multi-physics) through a unique data transfer system, called "MOOSE MultiApps and Transfers," specifically designed for multiscale simulations employing multiple software applications. This multiscale approach has been extensively employed in the numerical investigation of nuclear fuel performance, where the physics vary in space and time by many orders of magnitude, and functionally coupled to reactor physics, radiation transport, and thermal fluids [Martineau et al., 2020].

MOOSE also has a feature called "MOOSE-Wrapped Apps" which utilizes MOOSE MultiApps and Transfers, along with a minimal application programmer interface (API), to treat external codes as if they were MOOSE-based. This feature allows some of the more mature computer codes, such as TRACE, RELAP5, etc., to be coupled with MOOSE-based computer codes, such as BISON, or other computer codes not based on MOOSE.

NRC's Comprehensive Reactor Analysis Bundle

The U.S. NRC is adopting the advanced software being developed by DOE-NE NEAMS program for regulatory and licensing efforts for non-LWR advanced reactor concepts and accident tolerant fuel concepts. Codes used by the NRC for confirmatory analysis have been designed and assessed for LWRs and are not immediately extendable to non-LWR designs. The NRC is developing a strategy where MOOSE coupling strategies would be applied to NRC LWR codes. In addition, advanced simulation tools developed by NEAMS for non-LWR reactor concepts would be adapted and coupled to NRC codes, as necessary. The full suite of non-LWR codes for confirmatory analysis at NRC is known as CRAB. It makes use of existing NRC codes and integrates them with several codes developed through the DOE-NE's NEAMS program. Within CRAB, MOOSE is currently being used to couple other codes. MOOSE provides a fully coupled, fully implicit solver that allows independent codes to be coupled and exchange information. Figure 36 illustrates the computer codes used in CRAB.

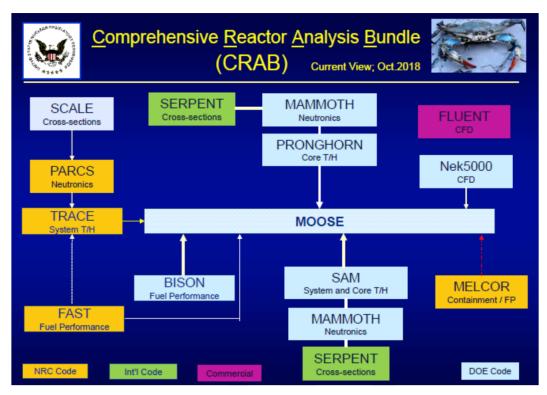


Figure 36. CRAB for analysis of design-basis events in non-LWRs [96].

CRAB was applied to demonstrate the application of coupled TRACE and BISON calculations to simulating the INL's Loss of Fluid Test Facility and simulated the L2-5 experiment [85].

ANL [88] applied CRAB to demonstrate the modeling and simulation of the heat pipe microreactor in a 3D fully coupled method. The heat pipe microreactor is modeled by three modules of CRAB, including MAMMOTH, SAM [88], and Tensor Mechanics [84]. MAMMOTH has been renamed to Griffin. The MAMMOTH module is used to simulate the reactor kinetics behavior of the microreactor; the SAM module is used to simulate the heat conduction in the reactor core and heat removal through the heat pipe heat exchangers and Reactor Cavity Cooling System (RCCS); the Tensor Mechanics module in MOOSE is used to simulate the thermal expansion of the reactor cores. The different submodels are coupled together using MOOSE's MultiApp system and executed using the BlueCrab Application (the executable of the combined CRAB code suite). The coupled multi-physics simulation capability is demonstrated with a steady-state operation analysis, a failure of a single central heat pipe transient analysis, and a loss of secondary flow transient analysis.

LOTUS - LOCA Toolkit for the U.S. NPPs

LOTUS [101] is a multi-physics best-estimate plus uncertainty (MP-BEPU) analysis framework being developed at INL. It established the automation interfaces among the various disciplines such that uncertainties can be propagated consistently in multi-physics simulations. These disciplines include: 1) core design automation, which focuses on automating the cross section generation, core design, and power maneuvering process; 2) fuel performance, which focuses on automating the interface between core design and fuel performance calculations and the interface between fuel performance and systems analysis; 3) components aging and degradation, which focuses on automating the interface between core design and systems analysis with component aging and degradation; 4) system analysis, which focuses on automating the process required to set up large numbers of system analysis code runs needed to facilitate Risk-Informed Systems Analysis (RISA) applications on LOCA and other accident scenarios; 5) uncertainty quantification and risk assessment, which focuses on the uncertainty quantification and

sensitivity analysis in multi-physics simulations and on establishing the interfaces to enable combined deterministic and probabilistic analysis; and 6) core design and plant systems optimization, which focuses on developing a core design and plant modifications optimization tool that can perform in-core and out-of-core design optimization.

LOTUS integrates existing computer codes as well as advanced computer codes that are being developed under various DOE programs to provide feedback and guide the development of advanced tools. Regardless of the specific codes used to model the physics, the methodology discussed here is a paradigm shift in managing the uncertainties and assessing risks.

Conventional methods are strongly "code-oriented." The analyst has to be familiar with the details of the codes utilized, in particular with respect to their input and output structures. This represents a significant barrier for widespread use. It becomes apparent how difficult it is to make changes and accelerate progress under such a paradigm, especially in a heavily regulated environment where even a single line change in a code carries a heavy cost of bookkeeping and regulatory review.

LOTUS's vision is to move toward to a "plug-and-play" approach where the codes are simply modules "under the hood" that provide the input-output relationships for a specific discipline. The focus shifts to managing the data stream at a system level. LOTUS is essentially a workflow engine with the capability to drive physics simulations, model complex systems, and provide risk assessments. A plug-and-play approach will enable plant owners and vendors to consider and further customize the LOTUS framework for utilizing their established codes and methods. Therefore, it could potentially become the engine for license-grade methodologies. In other words, it is possible that LOTUS technology could be advanced in the future to a level of fidelity and maturity such that it could be used for licensing or regulatory applications.

CASL's VERA

The CASL Challenge Problems range from CRUD to pellet-clad interaction and require validated, high-resolution multi-physics predictions of nuclear reactor operation and fuel performance throughout the life of an NPP. The VERA [78] is an ORNL-led collaboration with the University of Michigan, North Carolina State University, Core Physics LLC, and the Idaho and Sandia National Laboratories, with contributions from many other partners in academia, industry, and the national laboratory system (Figure 37).

The CASL tool sets are built on the validated foundation of the SCALE system (Figure 38), and they have rapidly enhanced the state-of-the-practice for advanced multi-physics simulation of LWRs. Integrating high-resolution neutronics using the MPACT code [79] with a subchannel two-phase flow with COBRA-TF [80] and a high-fidelity depletion with ORIGEN provides fully coupled estimates of the state of every pin and coolant channel in a pressurized-water reactor's core without traditional homogenizing of materials. Coupling with CRUD chemistry (MAMBA) and fuel performance (BISON) codes enable advanced solutions to complex industry problems.

Prediction of CRUD-Induced Power Shift and pellet-clad mechanical interaction, along with their effects on operational limits, may enable utilities to safely operate at higher power for longer periods of time with lower enrichment costs, resulting in great returns.

The ORNL-developed Shift Monte Carlo code provides solutions for high-fidelity reactor physics and radiation transport and shielding solutions within VERA. The Shift Monte Carlo code and the Denovo deterministic transport code are part of the Exnihilo massively parallel radiation transport framework. In addition to using Shift for benchmark-quality high-fidelity solutions, the Shift and Denovo capabilities are used with the hybrid methods pioneered by ORNL to provide advanced variance reduction capabilities for ex-core applications. The combination of these technologies is being used to develop the state-of-the-art capability for high-fidelity simulation pressure vessel and concrete bioshield fluence of entire reactor operational lifetimes.

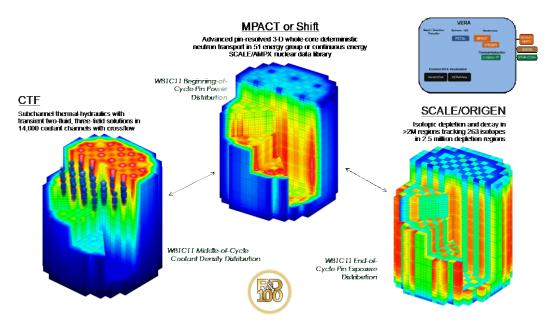


Figure 37. CASL's VERA.

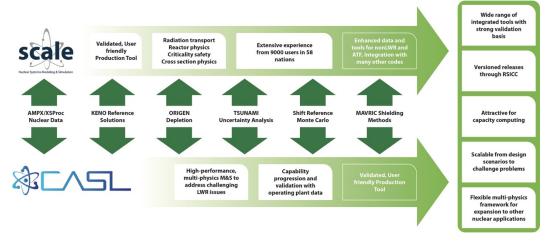


Figure 38. Capabilities jointly developed with SCALE and CASL.

MPACT

As stated in the MPACT Theory Manual [79], MPACT is a 3D whole core transport code that is capable of generating sub-pin-level power distributions. This is accomplished by solving an integral form of the Boltzmann transport equation for the heterogeneous reactor problem in which the detailed geometrical configuration of fuel components, such as the pellet and cladding, is explicitly retained. The cross section data needed for the neutron transport calculation are obtained directly from a multigroup cross section library, which has traditionally been used by lattice physics codes to generate few-group homogenized cross sections for nodal core simulators. Hence, MPACT involves neither a priori homogenization nor group condensation to achieve the full core spatial solution.

The integral transport solution is obtained using the method of characteristics (MOC) and employs discrete ray tracing within each fuel pin. MPACT provides a 3D MOC solution; however, for practical reactor applications, the direct application of MOC to 3D core configuration requires considerable amounts of memory and computing time associated with a large number of rays. Therefore, an alternative

approximate 3D solution method is implemented in MPACT for practical full core calculations, based on a "2D/1D" method in which MOC solutions are performed for each radial plane and the axial solution is performed using a lower order 1D diffusion or SP3 approximation. The core is divided into several planes, each on the order of 5–10 cm thick, and the planar solution is obtained for each plane using 2D MOC. The axial solution is obtained for each pin, and the planar and axial problems are coupled through transverse leakage. The use of a lower order 1D solution, which is most often the nodal expansion method with the diffusion or P3 approximation, is justified by the fact that most heterogeneity in the core occurs in the radial direction rather than the axial direction. Alternatively, a full 3D MOC solution can be performed, if necessary, if the computational resources are available.

The coarse mesh finite-difference (CMFD) acceleration method, which was originally introduced to improve the efficiency of the nodal diffusion method, is used in MPACT for the acceleration of the whole core transport calculation. The basic mesh in the CMFD formulation is a pin cell, which is much coarser than the flat source regions defined for MOC calculations. (Typically, there are approximately 50 flat source regions in each fuel pin.) The concept of dynamic homogenization of group constants for the pin cell is the basis for the effectiveness of the CMFD formulation to accelerate whole core transport calculations. The intracell flux distribution determined from the MOC calculation is used to generate the homogenized cell constants, while the MOC cell surface-averaged currents are used to determine the radial nodal coupling coefficients. The equivalence formalism makes it possible to generate the same transport solution with CMFD as the one obtained with the MOC calculation. In addition to the acceleration aspect of the CMFD formulation, it provides the framework for the 3D calculation in which the global 3D neutron balance is performed through the use of the MOC-generated cell constants, radial coupling coefficients, and the nodal expansion method-generated axial coupling coefficients.

In the simulation of depletion, MPACT can call the ORIGEN code, which is included in the SCALE package. However, MPACT has its own internal depletion model, which is based closely on ORIGEN, with a reduced isotope library and number of isotopes. The internal depletion model will be used in the use case applications where MPACT is applied.

COBRA-TF

Coolant Boiling in Rod Arrays – Two Fluid (COBRA-TF) [80] is a transient subchannel code based on the two-fluid formulation, in which the conservation equations of mass, energy, and momentum are solved for three fields, namely the vapor phase, continuous liquid, and entrained liquid droplets. The conservation equations for the three fields and for heat transfer from and within fuel rods are solved using a semi-implicit finite-difference numerical scheme, with closure equations and physical models to account for interfacial mass transfer, interfacial drag forces, interfacial and wall heat transfer, interchannel mixing, entrainment, and thermodynamic properties. The code is applicable to flow and heat transfer regimes beyond critical heat flux, and is capable of calculating reverse flow, counter flow and crossflow with either 3D Cartesian or subchannel coordinates for thermal-hydraulic or heat transfer solutions. It allows for full 3D LWR core modeling and has been used extensively for LWR LOCA and non-LOCA analyses, including the departure from nucleate boiling analysis.

The COBRA-TF (CTF) code was originally developed by the Pacific Northwest Laboratory and has been updated over the last few decades by several organizations. CTF is being further improved as part of the VERA multi-physics software package as part of the CASL DOE Modeling and Simulation Hub. These enhancements include:

- Improvements to the user-friendliness of the code through the creation of a preprocessor utility
- Code maintenance, including source version tracking, bug fixes, and transition to modern Fortran
- Incorporation of an automated build and testing system using CMake/CTest/Tribits

- Addition of new code outputs for better data accessibility and simulation visualization
- Extensive source code optimizations and full parallelization of the code, enabling the fast simulation of full core subchannel models
- Improvements to closure models, including Thom boiling heat transfer model, Yao-Hochreiter-Leech grid heat transfer enhancement model, and Tong factor for the W-3 critical heat flux correlation
- Addition of consistent set of steam tables from the IAPWS-97 standard
- Application of an extensive automated code regression test suite to prevent code regression during development activities
- Code validation study with experimental data.

In a steady-state or transient CTF simulation subchannel data, such as flow rate, temperature, enthalpy, pressure, and fuel rod temperatures are projected onto a user-specified or preprocessor generated mesh and written to files in a format suitable for visualization (Figure 39). The freely available Paraview software is used for visualizing the 3D data that results from large, full core models and calculations.

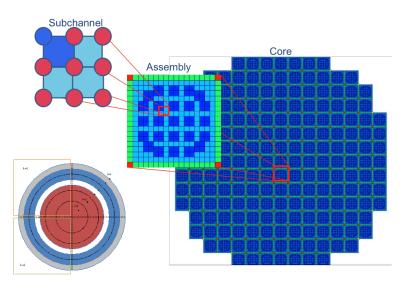


Figure 39. CTF models fluids and solids at pin-level resolution.

Advanced Reactor Modeling Interface

ARMI is an open-source tool that is maintained by TerraPower LLC (Figure 40). ARMI streamlines nuclear reactor design and analysis processes for professional reactor analysis teams. ARMI aims to enhance the quality, ease, and rigor of computational nuclear reactor design and analysis. ARMI is an integrated reactor modeling framework that enables seamless communication, coupling, automation, and continuous development that brings significant new capabilities and efficiencies to the practice of reactor design. In such a system, key performance metrics (e.g., optimal fuel management, peak cladding temperature in design-basis accidents, levelized cost of electricity) can be explicitly linked to design inputs (e.g., assembly duct thickness, tolerances), enabling an exceptional level of design consistency. ARMI:

1) Provides a hub-and-spoke mechanism to standardize communication and coupling between physics kernels and the specialist analysts who use them

- 2) Facilitates the creation and execution of detailed models and complex analysis methodologies
- 3) Provides an ecosystem within which to rapidly and collaboratively build new analysis and physics simulation capabilities
 - 4) Provides useful utilities to assist in reactor development.

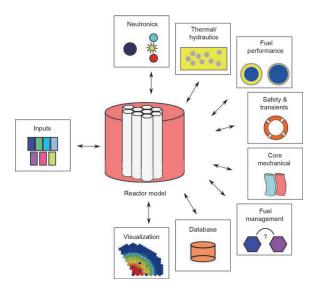


Figure 40. The schematic representation of the ARMI data model [76].

NEAMS Workbench

The NEAMS Workbench facilitates the use of multiple tools in analysis, including production tools and high-fidelity tools developed in the CASL and NEAMS programs, by providing a common user interface for model creation, review, execution, output review, and visualization for integrated codes (Figure 41). The workbench can provide a common user input, including engineering-scale specifications that are expanded into code-specific input requirements through the use of customizable templates. The templating process enables multifidelity analysis of a system from a common set of input data. Expansion of the codes and application templates and automated workflows available in the NEAMS Workbench facilitates system analysis and design (Figure 41). While users of the workbench are required to license and install the appropriate computational tools, the workbench will provide a more consistent user experience and will ease the transition from one tool to the next.

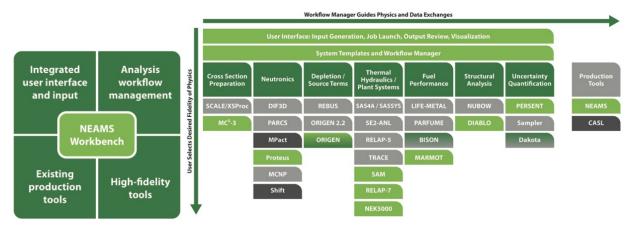


Figure 41. NEAMS Workbench concept for integrated multi-physics workflows with multiple levels of fidelity.