United States Nuclear Regulatory Commission

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PROCEEDINGS OF THE WORKSHOP ON DIGITAL TWIN APPLICATIONS FOR ADVANCED NUCLEAR TECHNOLOGIES

Virtual Workshop
December 1–4, 2020

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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.

As part of the project, the Office of Nuclear Regulatory Research (RES) sponsored the Virtual Workshop on Digital Twin Applications for Advanced Nuclear Technologies. The workshop was hosted by Idaho National Laboratory in collaboration with Oak Ridge National Laboratory and was held on December 1-4, 2020.

The 4 days of the workshop comprised 13 technical and panel sessions with over 50 presenters from a wide range of national and international organizations, including universities, national laboratories, government agencies, nuclear vendors, advanced reactor vendors, and digital twin vendors. With over 400 participants across the globe, the workshop provided a forum for nuclear industry and digital twin stakeholders to discuss the state of knowledge and research activities related to digital twins and their application in the nuclear industry.

The workshop had two main purposes: (1) to review and exchange information on the current understanding of digital twin technologies, and (2) to identify the potential benefits, opportunities, and challenges of applying digital twin technologies to nuclear reactors. The workshop covered specific topics such as applications to advanced reactors, nonnuclear applications, cybersecurity, and regulatory impacts.

In the opening session, on Tuesday, December 1, Ms. Stephanie Coffin, Deputy Director of RES, made introductory remarks. Mr. Jeremy Bowen, Deputy Director of the RES Division of Engineering, moderated the opening plenary session, entitled “Reactor Digital Twins—Shifting the Paradigm.” Technical sessions on specific topics took place Tuesday through Friday. Each session consisted of technical presentations followed by question -and -answer periods. On Friday morning, Mr. Ray Furstenau, Director of RES, moderated the closing plenary session entitled “Digital Twin – Regulatory Discussion”.

The following are some major takeaways from the workshop:

- There is significant interest in digital twin technology because it affects many industries. Applications of digital twin technology in nuclear reactors are expected to increase; thus, early engagement with regulators is important.

- Digital twin technology is improving rapidly, with intense activity from a variety of stakeholders. Current efforts aim to establish proof -of -concept use cases, build consensus on definitions, develop advanced sensors to enable digital twin technology, establish best practices and standards, and define cybersecurity requirements.

- Digital twin technology holds promise of benefits such as improved design, reduced uncertainty (including regulatory uncertainty), reduced risk, and improved prognostics and diagnostics.

- Increased collaboration and coordination would allow digital twin stakeholders to share information, develop common solutions to shared challenges, and establish a community of practice for applications in advanced nuclear technologies. Collaborative research would help address unresolved issues.

- Digital twin technology could be a novel source of trusted information on plant design, performance monitoring and prediction, process optimization, and regulation. The technology serves as a tool for general integrated data -sharing among vendors, licensees, regulators, and the public. Such an information source could both build public trust and improve regulatory efficiency.

- Planned collaborative and informational activities include follow-on- workshops focused on technical issues, technological advances, industry plans, and regulatory topics.

- The NRC plans to issue several technical reports detailing the following:

  – the state of technology for applications of digital twins,
  – the state of the art, technical challenges, and gaps for using digital twins in data analytics, machine learning (ML), artificial intelligence (AI), and multiphysics models,
  – regulatory readiness levels and gaps in applying digital twins for nuclear reactor applications, and
  – a summary report of technical and regulatory gaps

- Workshop participants identified several topics related to digital twin technology and safety that would be of interest for collaborative research:

  – development of a common language or taxonomy for digital twin stakeholders to use in communication, collaboration, and research,
  – development of advanced sensors and an approach for sufficient instrumentation of nuclear plants to enable digital twin use,
  – development of holistic nuclear life cycle models that could be integrated within a digital twin, covering requirements, design, testing, implementation, and change management,
  – development of data types, aggregation methods, and abstractions needed to implement digital twin technology,
  – development of data driven- model technologies to allow continuous model updates in response to real-time- plant data,
  – development of tools to characterize the interface between digital twin technology and human operators, including possible effects on cost, efficiency, and plant processes,
  – establishment of a Community of Practice with specific focus on digital twin applications for advanced nuclear technologies, and
  – establishment of a crowdsourcing platform for sharing of models, algorithms, and best practices

All presentation slides from this workshop are available in the NRC's Agencywide Documents Access and Management System, under Accession Nos. ML20356A234, ML20356A235, ML20356A236, and ML20356A237.

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1 DAY 1 PRESENTATIONS

1.1 Session 1: Opening Plenary Session Summary

This session served as an introduction to the digital twin concept, as well as to potential applications in advanced nuclear technologies and regulatory viability. The speakers represented a wide spectrum of stakeholders: the NRC, universities, national laboratories, and digital twin developers. Specific applications discussed included PLM, operational improvement in asset intensive- businesses, additive manufacturing, digital engineering approaches, and predictive maintenance. Digital twins are by their nature diverse, as different applications call for different information. However, they all share the trait of using a digital representation of a physical thing to accomplish desired goals.

Participants in this session identified the following challenges:

- technology
- risk versus uncertainty
- cultural inertia
- needed tools and data

Participants in this session identified the following key takeaways:

- Recent advances in computing capabilities have enabled M&S and the use of AI.
- Standards are currently fragmented.
- Validation is critical.
- Digital twin technology offers the opportunity to shorten learning curves.

The presentations slides for Day 1 can be found here and in the Agency Documents Access and Management System (ADAMS) under ML20356A237.

Presentations

1.1.1 Nuclear Digital Twins

Michael Grieves, Chief Scientist of Advanced Manufacturing, Executive Vice President of Operations
Florida Institute of Technology

Presentation Overview: The first presentation of the opening plenary presents the origin, definition, application, and the recent propagation of digital twin technologies. Traditional digital twins as originated from the concept of product lifecycle management have enabled design, manufacturing, testing and operation of products or system in virtual space. The enabling technologies of digital twins comprise of digital instrumentation, computational hardware, data analytics, machine learning and artificial intelligence and physics-based simulation. As these technologies continue to mature, the digital twins from the past continue to evolve from passive, offline, goal-given and predictive into the digital twins of the future that are active, online, real-time, goal-seeking, and anticipatory.

1.1.2 IBM Digital Twin

Joseph Berti, Vice President of Offering Management
IBM

Presentation Overview: IBM and Rotterdam developed a HydroMeteo digital twin prototype. This twin fuse 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/levels, and tides/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 cargo arrives safely.

1.1.3 ORNL Resources to Support Digital Twin Applications for Nuclear Systems

Jeremy Busby, Division Director, Reactor and Nuclear Systems Division
Oak Ridge National Laboratory

Presentation Overview: The major science and technology initiatives or ORNL include materials and chemical processes, neutron science, computer and data analytics, nuclear fission and fusion, isotope research and production, biological and environmental systems and natural security. This presentation highlights the potential research and development in digital twin technologies that address several of the ORNL initiatives. The transformational challenge reactor (TCR) program is harnessing advances in additive manufacturing, materials and computational sciences, data analytics and machine learning to enhance efficiency and safety in advanced reactors.

1.1.4 National Reactor Innovation Center Digital Engineering

Ashley Finan, Director
National Reactor Innovation Center

Presentation Overview: The National Reactor Innovation Center at INL provides resources for testing, demonstration, and performance assessment to accelerate the deployment of new advanced nuclear technology concepts. In 2020, NRIC started transforming the traditional engineering design ecosystem from a document-centric paradigm to a digital engineering framework to increase collaboration and efficiency. NRIC has focused on MBSE tools, data models, and processes for the design of the facilities, components, and contractor interfaces to enable GenIV microreactors. NRIC utilizes the Deep Lynx framework from VTR to facilitate lifecycle communication between conceptual, functional, and detailed design data and information. This paradigm is currently being applied for the system-level artifacts for both the EBR-II and Zero Power Physics Reactor (ZPPR) demonstration testbeds at NRIC.

1.1.5 The GEMINA Program: What ARPA-E Is Doing and Broader Opportunities

Jenifer Shafer, Special Government Employee Consultant
Advanced Research Projects Agency–Energy

Presentation Overview: This presentation provides an overview of the ARPA-E programs of MEITNER, MEITNER-RT, LISE, OPEN-Fission, and GEMINA. The ARPA-E GEMINA program is focused on leveraging advanced technologies such as autonomy and machine learning so that advanced reactors can achieve operating and maintenance costs comparable to a natural gas combine cycle plant. The outcome of ARPA-E GEMINA are intended to be tools that can be used by the industry to predict and prevent failure, avoid plant trip, reduce maintenance and insurance cost, improve reliability and utilization without increasing risk. The FY21 GEMINA awardees are interdisciplinary teams that will build digital twins for advanced reactor systems, build cyber-physical hardware in the loop system, assess the needed signals and sensor modalities, gain data for validation of software for nuclear application, practice control operations for scenarios such as startup, shutdown and transient, and define standard approaches to handle uncertainty, fidelity and interface etc.

1.2 Session 2: Advanced Reactors

Representatives from several companies developing advanced reactors discussed their views on the appropriate uses for digital twins in the design stages for both reactor modeling and O&M.

Participants in this session identified the following challenges:

- identification of the most appropriate applications for twins in the design process
- verification and validation of twins for as-yet-unbuilt designs

Participants in this session identified the following key takeaways:

- Twins can be used for many purposes, each of which may call for different twins and different approaches, depending on the scope of the analyses required.

- Several applications have used machine learning algorithms with good results.

Presentations

1.2.1 Xe-100 Digital Technologies Overview

Ian Davis, Senior Digital Twin System Engineer
X-Energy LLC

Presentation Overview: X-Energy LLC (X-energy) is transforming the nuclear energy marketplace through the development of the Xe-100 advanced reactor, which is a Generation IV high temperature gas- -cooled reactor (HTGR). X-energy sees innovative digital technologies, especially the digital twin, as an integral part of that transformation. Unlike digital twin use cases in today's existing nuclear fleet, the Xe-100 digital twin will provide invaluable feedback for the design process. It will help shape our systems design, control strategy, operations and maintenance (O&M) programs, and much more.

1.2.2 Digital Twin Development for Advanced Reactors, Accelerating Time to Market, Increasing Safety Margins, Maximizing Value

Anthonie Cilliers, Senior Manager, Instrumentation, Controls, and Electrical

Kairos Power

Presentation Overview: The development of advanced reactors today coincides with the fast maturing of digital modeling tools, virtual reality, machine learning, and the ever -increasing computing power becoming available to reactor designers and operators. As advanced reactor developers, we have a unique opportunity to incorporate a number of digital twin use cases from the conception of each project. This discussion explores the fundamental use cases of digital twins and how they can impact and support advanced reactor designs.

1.2.3 Advanced Reactor Design Meets Silicon Valley

Clyde Huibregtse, Reactor/Software Engineer
Oklo, Inc.

Presentation Overview: Contrary to the conventional notion of a digital twin as a tool exclusively for simulating system dynamics, Oklo has adopted a methodology known as a surrogate model in the early stages of reactor design. Leveraging the containerization capabilities of Docker Engine, Oklo has constructed a virtualized analysis pipeline through which we can feed a large number of permutations of our nominal design, each of which outputs a scalar -valued performance metric. We train a surrogate model to map a vector of input dimensions to a performance value. With it, we can efficiently compute gradients of our performance function with respect to input parameters, allowing us to optimize our design's performance.

1.2.4 Revolutionary Reactor Designs for a Changing and Challenged World

Charles R. "Chip" Martin, Scientific/Technical Advisor
HolosGen, LLC

Presentation Overview: This presentation introduces microreactor designs that eliminate the traditional "balance of plant" through the integration of the power conversion components with the nuclear core. The designs use modern high-speed motors and generators to convert thermal energy from the nuclear core to load -following electricity, with simplifications that make them competitive with nonnuclear electricity -producing technologies. The Holos Quad design is modeled using high -fidelity simulators from the national laboratories and academia and a subscale helium closed -loop simulator. The further simplified Risk Reduction Demonstration Monolithic-Holos (M-Holos) design facilitates the "virtual build" through digital twins, leveraging national laboratory and industry expertise, to reduce risks and accelerate deployment.

1.3 Session 3: Nonnuclear Applications of Digital Twins Overview

There is a wide array of digital twin applications in other advanced fields, such as aviation, conventional power generation, and healthcare. These twins help optimize uptime, reduce unplanned disruptions, and optimize lean supply chains. Digital twins have also found application in the monitoring and improving of human performance.

Participants in this session identified the following challenges:

- maximizing value from scarce data

- verification to the level of accuracy required for application

Participants in this session identified the following key takeaways:

- Digital twins offer considerable savings and performance improvements in some applications.
- Advanced sensor technology presents new avenues for verifying digital twin accuracy and performance.

Presentations

1.3.1 Industrial Digital Twins: GE Experience and Perspectives

Abhinav Saxena, Senior Scientist, Machine Learning, GE Research
General Electric

Presentation Overview: This talk presents GE's definition of digital twins for industrial assets, with specific examples of applications in several industrial domains, such as aviation, healthcare, power, and transportation. Given GE's digital twin experience in the field, the talk also discusses current challenges and research directions.

1.3.2 Overcoming Digital Twin Data Scarcity and Accelerating the Journey To Predict

Chandler Maskal, Offering Manager, IBM AI Applications
IBM

Presentation Overview: This presentation discusses two of the greatest technical challenges in adopting digital twin technology and IBM's strategy for overcoming these challenges. This session introduces the challenges seen across many industries and discusses the technical steps that IBM is taking to drive the adoption of digital twin technology for equipment operations.

1.3.3 Pacing Optimization Enabled by a Human Thermoregulatory System Digital Twin

Mark Buller, Principal Investigator, Biophysics and Biomedical Modeling Division
U.S. Army Research Institute of Environmental Medicine

Presentation Overview: This presentation describes how physiological -feedback pacing enabled by a human thermoregulatory system digital twin can optimize both performance and safety for relevant military tasks. It shows that using a digital twin enables a simple Markov decision process (MDP) representation of military pacing problems. By solving these MDPs, we can construct pacing policies to optimize human physiological resources while minimizing thermal -work strain safety risks. What had been identified in the literature as expert "black box" pacing templates were successfully enumerated by the use of a digital twin and can now be applied by novices on new and novel tasks.

1.3.4 A Digital Twin Approach to Study Sensor Fused Additive Manufacturing Toward Smart Component Fabrications

Kevin P. Chen, Professor
University of Pittsburgh

Presentation Overview: One of the major challenges for metal -powder -based additive manufacturing is to design an optimized manufacturing strategy to mitigate the residual strain induced during the manufacturing processes. This talk discusses distributed fiber optic sensors embedded in Inconel alloy components as experimental means to validate numerical models of additive manufacturing processes. Using high -spatial -resolution data harnessed by distributed fiber sensors, digital twin models can accurately model the manufacturing process, leading to design and manufacturing optimization.

2 DAY 2 PRESENTATIONS

2.1 Panel Session: ARPA-E GEMINA Summary

The recent ARPA-E programs Modeling -Enhanced Innovations Trailblazing Nuclear Energy Reinvigoration (MEITNER), Leveraging Innovations Supporting Nuclear Energy (LISE), and GEMINA aim to apply data, physics -based models, and algorithms to increase operational efficiencies and reduce construction and O&M costs for current and future nuclear power plants. This panel discussion focused on the recently awarded R&D efforts within the GEMINA program. It included an overview of programs funded by ARPA-E and project -specific presentations by three of the awardees, followed by a question -and -answer session.

Participants in this session identified the following challenges:

- Verification and validation of AI and machine learning algorithms is a major challenge, especially in light of the lack or absence of data.

- Use of digital twins to reduce security, maintenance, and operational personnel would potentially require addressing major regulatory constraints.

Participants in this session identified the following key takeaways:

- ARPA-E envisions a reduction of O&M costs to $3 per megawatt -hour (a cost profile comparable to that of a natural gas combined -cycle plant).

- A GE project funded under GEMINA focuses on AI -enabled predictive maintenance of digital twins for advanced nuclear reactors.

- The X-energy GEMINA project focuses on reducing fixed O&M costs in Xe-100, targeting three labor -intensive areas: operators, maintenance personnel, and security personnel.

- The Kairos SAFARI project aims to deliver a capability enabling smart functionalities in advanced reactor systems, such as autonomous operations, flexible operations, and predictive maintenance.

- The Kairos MARS project aims to develop advanced distributed sensing and data generation techniques to characterize critical components and systems; increase sensor diversity and develop multifunctional sensors that measure several process variables simultaneously; automate maintenance tasks through machine -learning -enabled fault detection and diagnostics; and inform intelligent sensor placement to achieve autonomous operation.

The presentations slides for Day 2 can be found here and in the Agency Documents Access and Management System (ADAMS) under ML20356A234.

Presentations

2.1.1 ARPA-E Perspective: Digital Twins as an Enabler of Low Operations and Maintenance Costs

Joel Fetter, Lead Associate
ARPA-E

Presentation Overview: This presentation describes several examples on how the inclusion of digital twin technology can reduce operation and maintenance costs. In addition, a portfolio at a glance of currently digital twin funded programs are discussed.

2.1.2 Artificial -Intelligence -Enabled Predictive Maintenance Digital Twins for Advanced Nuclear Reactors

Abhinav Saxena, Senior Scientist, Machine Learning, GE Research
General Electric

Presentation Overview: This presentation gives a brief overview of GE's GEMINA project on AI -based digital twins for reducing O&M costs for advanced reactors. The presentation describes key project goals and technology R&D towards achieving O&M cost reductions.

2.1.3 Xe-100 ARPA-E GEMINA Program Overview

Yvotte Brits, Supply Chain Manager and Operator Training Simulator Program Manager
X-Energy LLC

Presentation Overview: X-energy is transforming the nuclear energy marketplace through the development of the Xe-100 advanced reactor, which is a Generation IV HTGR. Levelized fixed O&M costs of conventional energy -generating technologies, such as coal and gas, are lower than those of nuclear energy. The regulatory framework of traditional nuclear power requires a number of operators, security, and maintenance personnel, resulting in high levelized fixed O&M costs of approximately $14.5 per megawatt -hour for the Xe-100 plant. The presentation demonstrates the digital twin's ability to reduce levelized fixed O&M costs to a target of $2 per megawatt hour in the Xe-100 plant. The Xe-100's intrinsic passive safety features make it ideal to showcase the abilities of the digital twin.

2.1.4 ARPA-E GEMINA Projects:

Project SAFARI—Secure Automation for Advanced Reactor Innovation
Project MARS—Maintenance of Advanced Reactor Sensors and Components
Anthonie Cilliers, Senior Manager, Instrumentation, Controls, and Electrical
Kairos Power

Presentation Overviews:

SAFARI: This project will deliver a capability enabling smart functionalities in advanced reactor systems, such as autonomous operations, flexible operations, and predictive maintenance. This has the potential to dramatically lower O&M costs compared to those of currently operating LWRs.

MARS: This project will develop advanced distributed sensing and data generation techniques to characterize critical components and systems; increase sensor diversity and develop multifunctional sensors that measure several process variables simultaneously; and automate maintenance tasks through machine-learning-enabled fault detection and diagnostics and intelligent sensor placement to achieve autonomous operation.

2.2 Session 2: Industry Vision Overview

This session presented the industry vision of digital twin technology R&D, with a focus on current and future applications. Participants discussed the current state of the technology and its potential use in the nuclear industry, along with the industry's first impressions of the techniques. The session highlights included overviews from EPRI, BWX Technologies, Westinghouse, and Analysis and Measurement Services Corporation (AMS).

Participants in this session identified the following challenges:

- Use of a digital twin as a repository for the subject matter expert knowledge base is a challenge.

- Porosity is a challenge in metal powder bed additive manufacturing, and traditionally, the only nondestructive way to detect it is through expensive CT scanning. The digital twin approach could be much cheaper than these scans.

- Prohibitively large and unforeseen increases in construction cost are one of the greatest challenges for future nuclear reactors.

Participants in this session identified the following key takeaways:

- Westinghouse's current efforts in digital twin applications include eliminating destructive testing in fabrication processes, coupling machine learning with neutronics models, replacing reactor internal components, and identifying cracks in concrete structures.

- At BWX Technologies, digital twin efforts focus on the inspection of additively manufactured nuclear components to detect porosity.

- EPRI digital twin efforts aim to transition the nuclear industry from the current approach of "maintain and repair" to "replace and refurbish" life cycle management, and to lower construction costs.

- One of the current efforts at AMS is online monitoring to support the autonomous remote operation of advanced reactors.

Presentations

2.2.1 Synopsis of Westinghouse Machine Learning, Artificial Intelligence, and Digital Twin Developments for Nuclear Power Applications

Brian Golchert, Principal Engineer
Westinghouse Electric Company

Presentation Overview: This presentation gives an overview of digital-twin-related activities at Westinghouse, emphasizing current and future applications of digital twins.

2.2.2 Digital Twin for the Manufacture and Qualification of Additively Manufactured Nuclear Components

Matthew LeVasseur, Director of Research
BWX Technologies

Ryan Kitchen, Research and Development Data Scientist
BWX Technologies

Presentation Overview: This presentation shows a quality grade platform for digital twin inspection during build, how it works and the benefit of implement it. In addition, a quality assessment for digital twin is presented.

2.2.3 EPRI's Digital -Twin -Related Activities for the Nuclear Industry

Hasan Charkas, Principal Technical Leader
Electric Power Research Institute

Presentation Overview: This presentation gives an overview of EPRI's recent activities and research projects in digital twin technology.

2.2.4 Digital Twins for Advanced Reactor Applications

Hash Hashemian, President and CEO
Analysis and Measurement Services Corporation

Jacob Houser, Senior Research Engineer
Analysis and Measurement Services Corporation

Presentation Overview: This presentation covers the adaptation of digital twins for improved instrumentation and control maintenance in current and next -generation nuclear reactors. We have integrated process data from measurements collected in nuclear power plants with empirical and physical modeling to produce reliable predictions for process and sensor behavior, which can be used for anomaly detection, diagnostics, and prognostics.

2.3 Session 3: Applications of Advanced Technologies—Part I Overview

Individuals from ORNL, INL, and ANL summarized their use of digital twins in the development and management of research facilities (the Versatile Test Reactor, Transformational Challenge Reactor, and Spallation Neutron Source) and in the specific research areas of additive manufacturing and digital twin sensor deployment optimization.

Participants in this session identified the following challenges:

- collecting good data—sensor selection and placement
- uncertainty quantification
- obtaining explainable and trustworthy results
- validation and verification
- cybersecurity

Participants in this session identified the following key takeaways:

- We are at a tipping point for AI, and the future will see increasing use of AI in science and engineering.

- Digital twin technology may be able to dramatically reduce O&M costs through maintenance scheduling and the elevation of humans to oversight roles.

- Digital twins allow the integration of megaprojects to increase communication, document control, and scheduling to avert "failures."

- Digital twins can accelerate the manufacturing process by creating digital threads to track quality during component development and creation.

Presentations

2.3.1 On Artificial Intelligence Research at ORNL and Its Application at the Spallation Neutron Source

David E. Womble, Director of Artificial Intelligence Programs
Oak Ridge National Laboratory

Presentation Overview: This presentation describes the biggest challenges in the implementation of artificial intelligence (AI)/ machine learning (ML) and the strategic directions of ORNL regarding the topic. In addition, introduce "easy steps" for the anomaly detection in AI/ML systems.

2.3.2 Overview of Digital Twin Work at Argonne National Laboratory

Richard Vilim, Senior Nuclear Engineer; Manager, Plant Analysis and Control and Sensors Department, Nuclear Science and Engineering Division
Argonne National Laboratory

Presentation Overview: This presentation defines what is a digital twin and why is the interest in the topic. Introduces AI/ML as an enabler of autonomous operation and describe several examples of ANL digital twin projects.

2.3.3 Extending a Digital Engineering Framework through Operations

Christopher Ritter, Director, Digital Innovation Center of Excellence
Idaho National Laboratory

Presentation Overview: This presentation provides an explanation of the National Reactor Innovation Center (NRIC) at Idaho National Laboratory (INL) and discuss several examples of projects and applications that the center is currently working.

2.3.4 Digital Platform for the Transformational Challenge Reactor

Ben Betzler, Nuclear Engineer
Oak Ridge National Laboratory

Vincent Paquit, Senior Research Scientist, Electrical and Electronics Systems Research
Oak Ridge National Laboratory

Presentation Overview: This ORNL presentation gives an overview of how the Transformational Challenge Reactor (TCR) uses additive manufacturing and artificial intelligence to provide high performance materials and assess the quality of the component during the manufacturing process. ORNL is developing new certification methodologies for manufacturing technologies. The TCR Digital Platform uses data analytics for prototyping and evaluating the products to optimize the manufacturing process. ORNL continues to research in areas of data management, in-situ quality control, and sensor development.

2.4 Session 4: Applications of Advanced Technologies—Part II Overview

Experts from Framatome, ANL, and the University of Illinois detailed specific applications of digital twins in the nuclear field. The Framatome representative discussed the use of digital twins and AI in the development of reactor cooling models for HTGRs. The ANL representatives detailed digital twin use in the optimization of moisture carryover in boiling water reactors, as well as work on developing AI and machine learning tools as predictive tools for computational mechanics. The presenter from the University of Illinois proposed the use of digital twins as training tools in the nuclear field.

Participants in this session identified the following challenges:

- addressing more than a single steady -state system mode in the modeling of a reactor
- sensor identification
- generating meaningful data to validate failure modes
- obtaining data from actual reactor components

Participants in this session identified the following key takeaways:

- Digital twin technology can provide value in failure detection, regulatory basis verification, and cost savings.

- Digital twins and neural networks efficiently analyze parameters and evaluate models.

- Digital twin and virtual reality training tools can be valuable for dose reduction and operational efficiency.

Presentations

2.4.1 Digital -Twin -Based Asset Performance and Reliability Diagnosis for the HTGR Reactor Cavity Cooling System Using Metroscope

Eric Helm, Product Manager—Metroscope
Framatome

Presentation Overview: This presentation provides an overview of the technical and commercial challenges in using digital twins for system diagnostics, along with savings and regulatory basis considerations. It also discusses the initial project approach meant to address those challenges.

2.4.2 Data -Driven Optimization of Moisture Carryover in an Operating Boiling-Water Reactor

Richard Vilim, Senior Nuclear Engineer; Manager, Plant Analysis and Control and Sensors Department, Nuclear Science and Engineering Division
Argonne National Laboratory

Presentation Overview: Argonne National Laboratory (ANL) is exploring how historical operating data for moisture carryover gives data-driven model to guide and manage reactor operating conditions, so moisture carryover is acceptable. ANL uses machine learning model with applicable algorithms to perform an analysis of different functional forms including actual inputs and a neural network model. These models provide predictive capabilities to changes power up rates and new core loading patterns in a BWR.

2.4.3 Role and Status of Virtual Reality, Augmented Reality, and Mixed Reality in Digital Twins in the Nuclear Industry

Rizwan Uddin, Professor and Head of the Department of Nuclear, Plasma, and Radiological Engineering
University of Illinois at Urbana--Champaign

Presentation Overview: This presentation provides an overview of the current state of technology and future vision for application of virtual reality, augmented reality and mixed reality for potential application in the nuclear industry.

2.4.4 Online Artificial Intelligence/Machine Learning and Computational-Mechanics-Based Predictive Tools for a Digital Twin Framework

Subhasish Mohanty, Principal Research and Development Engineer
Argonne National Laboratory

Presentation Overview: The presentation focuses on various aspects of digital twins, with some example results related to laboratory-scale testing, three-dimensional finite-element modeling, online state estimation based on heterogeneous sensor measurements, and online condition-based state forecasting and remaining life estimations.

3 DAY 3 PRESENTATIONS

3.1 International Activities in Digital Twins Session Summary

This session focused on international activities in digital twin R&D, with four presentations on digital twin R&D in Canada, the United Kingdom, and Spain and at Euratom. The presentations covered diverse topics in digital twin research, including software qualification, the economic impact of introducing digital twins in the nuclear industry, the benefits of using digital twins for maintenance and surveillance in the nuclear industry, and Euratom activities on digitization in the nuclear industry.

Participants in this session identified the following challenges:

- Software qualification (i.e., demonstration that software tools will not fail) is a challenge.
- Quantifying the economic impact of introducing digital twins is a challenge.
- Developing digital twins for plant maintenance and surveillance is challenging because there are no high-fidelity models for many equipment degradation mechanisms.
- The models available for use in digital twins are often based on empirical dependencies, with parameters inferred from the data.
- The limited availability of experimental and plant data for digital twin development is a challenge.
- Information sharing, innovation sharing, and cost management are challenges in developing digital twins.

Participants in this session identified the following key takeaways:

- Some nuclear research and industry projects have used prototypes of digital twins.
- Efforts are in progress to develop digital environments to support the nuclear life cycle.
- An integrated approach for design modifications is being developed.
- International collaboration on digital twin development is underway in the European Union.
- The use of digital twins in the nuclear industry often depends on simulated data.
- Highly useful applications exist for small modular reactors and existing facilities; there are also links to the construction sector.
- Response.

The presentations slides for Day 3 can be found here and in the Agency Documents Access and Management System (ADAMS) under ML20356A235

Presentations

3.1.1 Qualification of the Pickering a Test Facility

Richard Henry, Section Manager, Computers and Control Design, Central Engineering
Ontario Power Generation

Presentation Overview: A software-based test facility can be used for the verification and validation testing of nuclear control computer software modifications. Ontario Power Generation successfully implemented this digital twin application at one of its plants. This presentation discusses regulatory requirements and software qualifications and gives an overview of the test facility.

3.1.2 The United Kingdom's Nuclear Virtual Engineering Capability

Albrecht Kyrieleis, Senior Consultant
Jacobs

Presentation Overview: This presentation gives an overview how the NVEC plans to deliver net zero carbon emissions by 2050. The NVEC plans to achieve this goal by developing a digital environment for the nuclear sector. The NVEC is in phase 2 of their plan in developing standards, guidance, and models. The NVEC will establish validation of the benefits of operation of a digital twin using case studies and further collaboration with the manufacturing and supply chain to reduce economic costs, improve accuracy, safety, and reliability.

3.1.3 Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

Susana López Lumbierres

Presentation Overview: Tecnatom designed, implemented, and tested a design modification for the online monitoring of the essential services water system in a boiling water reactor nuclear power plant by integrating it into the existing digital control system (DCS). Key system parameters were acquired in real time to be displayed in the human system interface and used in performing calculations, and their historical evolution was stored. The objective was to optimize the monitoring and surveillance of this system. Furthermore, Tecnatom developed an engineering simulator (a "what if" simulator) consisting of a hydraulic model of the system. This simulator takes as inputs the heat exchanger performance parameters from the plant DCS, allows the user to change the essential services water system configuration (valve positions, uniform hazard spectrum level), and calculates theoretical process values predicting the system's real behavior. In a second stage, more system instruments were wired to the DCS to verify compliance with technical specifications and provide automatic surveillance of opening and closing times of system valves.

3.1.4 Euratom Research and Training Programme—Fission Research

Panagiotis Manolatos

Presentation Overview: This presentation covers the modus operandi of the European Atomic Energy Community (Euratom) Research and Training Programme, examples of currently funded research projects in nuclear safety, the status of preparation of the next Framework Programme 2021–2027 (Horizon Europe), and opportunities for international cooperation.

3.1.5 European Research, Development, and Innovation Towards Digital Twins

Abderrahim Al Mazouzi

Presentation Overview: Within the Sustainable Nuclear Energy Technology Platform (SNETP), many collaborative technological and scientific projects (most of them sponsored by Euratom) are helping association members to progress toward building digital twins, from critical components up to the entire reactor. This presentation gives the flavor of some ongoing projects and highlights some examples considered by SNETP members.

3.2 Cybersecurity Session Summary

This session described the cybersecurity challenges that can arise when implementing digital twin techniques. It highlighted regulatory considerations for the development phase of digital twin technology and emphasized the importance of understanding the technology before procuring or using it.

Participants in this session identified the following challenges:

- Cybersecurity considerations could exponentially complicate any digital twin implementation; addressing cybersecurity issues before implementation is a significant challenge.

- Analysis of vulnerability to cyberattacks in nuclear power plants is a major challenge.

- Understanding the levels of granularity for cybersecurity modeling is a challenge.

Participants in this session identified the following key takeaways:

- AI holds potential for modeling cyberattacks in digital twins.

- An infrastructure developed to test against an AI attack could prove valuable for digital twins as well.

- Data exfiltration and supply chain threats are standard cybersecurity concerns, as is the potential for an attacker to contaminate the supply chain by altering a digital twin used for design.

- Digital twins and AI allow for automated vulnerability analysis.

- The selection of appropriate levels of granularity depends on the exploit and the hardware

Presentations

3.2.1 Digital Twins and Cybersecurity

Christopher Spirito, Nuclear Cybersecurity Consultant
Idaho National Laboratory

Presentation Overview: As digital twins are integrated into the systems used to control nuclear reactors and supporting systems, it is necessary to ensure that they are not vulnerable to manipulation by cyber means, but there is also an opportunity to use digital twins to support cybersecurity goals and objectives. This presentation gives a historical account of each of these problems, from how these systems have been envisioned through how they have been implemented. We also discuss how we believe they could be used in the future.

3.2.2 Cybersecurity for Digital Twins

Cynthia DeBisschop, Senior Cybersecurity Analyst
Oasis Systems, LLC (NRC contractors)

Presentation Overview: This presentation offers a regulatory perspective on cybersecurity considerations while digital twin technology is in development. Before the procurement or use of technology, the attack surfaces and environments associated with digital assets should be understood. Throughout the life cycle of digital assets, plant operators must maintain a defensive security architecture to address all attack surfaces and environments, as well as multiple layers of cybersecurity protections to establish sufficient defense in depth. Defense-in-depth protective strategies ensure the capability to detect, respond to, and recover from cyberattacks. Their effectiveness depends on thorough understanding and careful consideration of the technology before procurement or use.

3.2.3 The Asherah Nuclear Power Plant Simulator in a Closed-Loop Digital Twin Environment

Rodney Busquim e Silva, Computer Security Officer
International Atomic Energy Agency

Presentation Overview: Nuclear power plants consist of several complex industrial processes with a large number of information technology and automation systems, implementing process control, safety, and security functions. The need to understand the impacts of cyberattacks—and how they propagate—led to the development of a specific simulator, the Asherah Nuclear Power Plant Simulator, for an IAEA Coordinated Research Project. Digital twins open new possibilities for simulating, monitoring, estimating, and optimizing the state of nuclear energy systems. Within this scope, digital twins can be leveraged for computer security purposes when integrated into simulators like the Asherah Nuclear Power Plant Simulator.

3.3 Multiphysics Modeling Session Summary

This session addressed the role of advanced multiphysics M&S in the digital twin context, discussing M&S tools and frameworks for both LWR and non-LWR advanced reactor designs. M&S plays a pivotal role in the development and operation of digital twins: it fills gaps in knowledge or data and provides access to unmeasurable quantities.

Participants in this session identified the following challenges:

- Uncertainties from multiphysics M&S, data generation, and the training of machine learning algorithms or surrogate models are nonlinear and are amplified when we apply these tools in developing digital twins. How can we quantify such uncertainties?

- How can we efficiently perform predictions using digital twins?

Participants in this session identified the following key takeaways:

- Integrating high-fidelity, high-resolution M&S with advanced sensors yields unprecedented details of reactor behavior.

- The role of M&S is to provide access to a wealth of data. However, results must be obtainable and meaningful.

- We need to establish credibility and applicability of the M&S evaluation model in order to account for uncertainty and verify the trustworthiness of the tools.

- Digital twins must bridge the gap between model predictions (understanding) and observations (reality).

Presentations

3.3.1 Advanced Modeling and Simulation and Its Future Role in Nuclear Systems Digital Twin Technology

Dave Kropaczek, Director, Consortium for Advanced Simulation of Light Water Reactors (a DOE Energy Innovation Hub)
Oak Ridge National Laboratory

Presentation Overview: This presentation demonstrates how a digital twin virtual simulator gives reliable predictive capabilities for reactor quantities of interest based on multiphysics modeling. Formal calibration methods can address the uncertainties of the input parameters and closure relations. This presentation goes into how the Virtual Environment for Reactor Applications (VERA) give unprecedented reactor analysis. Through the integration of high fidelity, high resolution simulation along with advanced sensors results in accurate reactor behavior.

3.3.2 Modeling and Simulation to Support Digital Twins

Jeffrey W. Lane, Chief Engineer and Principal Consultant
Zachry Nuclear Engineering

Presentation Overview: This presentation discusses the role of advanced M&S in digital twin development and applications. It focuses on what advanced M&S can provide, and on the required attributes of an advanced M&S tool to support digital twin applications. This presentation also discusses challenges related to data assessment and credibility.

3.3.3 Multiphysics Modeling for Advanced Reactor Safety and Digital Twin Development

Rui Hu, Manager, Plant System Analysis Group
Argonne National Laboratory

Presentation Overview: Inherent safety is a key characteristic for various advanced reactor concepts; it requires an improved understanding of multiphysics phenomena and M&S capabilities. This talk gives an overview of the safety characteristics and the needs of multiscale multiphysics simulation. It provides an example of coupled multiphysics simulation of a heat-pipe-cooled microreactor and presents some thoughts on leveraging multiphysics simulations in digital twin development.

3.3.4 Hybrid Physics-Informed Neural Networks, Cumulative Damage Models, and Digital Twins

Felipe A. C. Viana, Assistant Professor
University of Central Florida

Presentation Overview: This presentation challenges the myth that building digital twins with machine learning requires large datasets. First, it addresses how physics-driven and data-driven kernels combine within deep neural networks. This framework, pioneered in the Probabilistic Mechanics Lab, allows for a neural network to directly implement differential equations while accounting for uncertainty in the model form as well as in observations. The presentation also gives an overview of the theoretical aspects and show engineering applications in digital twins for the failure prognosis of main bearings of wind turbines, aircraft fuselage panels, and batteries used to power electric vehicles

3.4 Diagnostics, Prognostics, and Condition Monitoring Session Summary

This session discussed diagnostics, prognostics, and condition monitoring using digital twins. Digital twins are an important tool in these applications, as they allow the modeling of different degradation and failure mechanisms without resorting to physical modeling. Also, digital twins can forecast the development of various failures and mitigate their consequences.

Participants in this session identified the following challenges:

- There are no high-fidelity models for many degradation and failure mechanisms present in nuclear equipment.

- Many existing degradation models are empirical and have little first principles support.
- Diagnostics is an ill posed problem, as similar symptoms (effects) can have different causes.
- Model comparison and validation are challenges for diagnostics and prognostics.
- In general, prognostics and diagnostics models need to be time dependent and adaptable.

Participants in this session identified the following key takeaways:

- Active and passive component models require different approaches for use in digital twins.
- It may be necessary to frequently update or even change models based on component condition. Digital twins are time dependent.
- Digital twin development should follow a data driven physics inspired approach.
- There is a tradeoff between early maintenance and failures due to a lack of maintenance.
- A useful concept is that of prognostic distance. Maintenance should be performed when remaining useful life is less than prognostic distance.
- Digital twins can contribute to information driven asset management.

Presentations

3.4.1 A Quantitative Framework to Assess Tradeoffs in Alternative Models and Algorithms for Prognostics and Health Management

Lance Fiondella, Associate Professor of Electrical and Computer Engineering
University of Massachusetts at Dartmouth

Presentation Overview: The field of PHM is transforming reliability engineering by pinpointing which components or subsystems require maintenance, as well as precisely predicting when maintenance actions should occur. While there are several metrics to quantitatively assess the accuracy of remaining-useful-life predictions, few studies have explicitly modeled the economic benefits of implementing PHM, such as return on investment, life cycle cost reduction, and average total cost over a period. Although simulation and probabilistic techniques have been developed to select a time horizon for use based on remaining-useful-life predictions, in order to guide maintenance decisions that minimize cost, these past techniques do not consider additional factors of interest. To overcome this limitation, we develop data-driven analogs to metrics from renewal theory, including average cost per unit time, utilization, safety, and availability, which are suitable for application in the context of PHM methods. Simultaneous consideration of multiple metrics leads to a multi-objective generalization of the cost minimization problem, necessitating a framework to compare alternative PHM methods. Therefore, we also explicitly decouple degradation models from the algorithms that iteratively update estimates of a model’s parameters. This decoupling enables the direct comparison of alternative combinations of models and algorithms, as well as provides a method to select a time horizon that balances tradeoffs between multiple competing metrics according to stakeholder preference. We apply this approach to lithium-ion batteries. The results indicate that the approach can be used to select a combination of model and algorithm that balances tradeoffs between competing objectives, such as cost and utilization. Moreover, the framework is general and accommodates both existing and future degradation models and algorithms.

3.4.2 Digital Twins in a Nearly Autonomous Management and Control System for Advanced Reactors

Linyu Lin, Postdoctoral Research Scholar, Department of Nuclear Engineering
North Carolina State University

Presentation Overview: This presentation introduces the implementation of a nearly autonomous management and control system with digital twins and machine learning algorithms. The presentation discusses four design principles for nearly autonomous management and control: three-layer architecture, modular frameworks, digital twin development and assessment processes, and digital twin trustworthiness assessment.

3.4.3 Digital Twins for Prognostic Health Management in Nuclear Energy: Opportunities and Challenges

Pradeep Ramuhalli, Distinguished Scientist
Oak Ridge National Laboratory

Presentation Overview: Oak Ridge National Laboratory (ORNL) is a key player for providing diagnostics, prognostics, and decision making using an intelligent digital twin. ORNL is leading in research in sensors, modeling, simulation, data analytics, and advanced manufacturing and communication technologies to make risk informed operational and maintenance decisions. Data driven with physics models allow diagnostics and predictive maintenance. The Bayesian method integrated with failure physics information minimizes uncertainties. Resulting technologies enable sustainable nuclear power by improving the reliability of nuclear plants.

4 DAY 4 PRESENTATIONS

4.1 Closing Plenary Session Summary

The closing plenary comprised technical presentations covering a wide variety of topics from a regulatory perspective, including risk in digital twins, regulations, and nonproliferation. A panel session followed with industry representatives, advanced reactor designers, and others. Dr. Raj Iyengar of the NRC presented the closing remarks.

Participants in this session identified the following challenges:

- Implementation of digital twins in the nuclear setting is increasingly complex, as nuclear power plant operational models are difficult to change.
- Real-time data management to support digital twin implementation is a challenge.
- It is a challenge to identify the areas in which digital twins can contribute to optimizing regulatory oversight.

Participants in this session identified the following key takeaways:

- Digital twin technology may be able to reduce the scope and cost of regulatory oversight.
- Digital twins can help identify the components that really matter for safety.
- It will be helpful if organizations turn over digital twins to the NRC to increase shared information and system knowledge. Sharing models directly with the NRC staff has already been fruitful. It has saved hundreds of hours by providing a platform for direct interactions with the digital twin finite-element models, allowing quick responses to questions.
- The IAEA is working on a plant taxonomy that may eventually support digital twins.
- It is important to learn from organizations in other regulated industries that use digital twins, such as self-driving car manufacturers and the Federal Aviation Administration. For example, the Food and Drug Administration uses risk-based information to determine how extensively to test a new drug.

The presentations slides for Day 4 can be found here and in the Agency Documents Access and Management System (ADAMS) under ML20356A236.

Presentations

4.1.1 Managing Regulated Change: An Enterprise-Level Digital Twin for the Nuclear Industry

Michael Mazzola, Executive Director, Energy Production and Infrastructure Center
University of North Carolina at Charlotte

Presentation Overview: An enterprise level-digital twin integrates all business, technical, and regulatory compliance on an enterprise wide-digital platform. Such a system would allow the NRC to participate more collaboratively in the process of making changes while maintaining the intent of the approved design control document. With adequate provision for the independence of the NRC's oversight, a certified enterprise-level digital twin would allow both the enterprise and the NRC to carry out efficient assessment and approval of changes while maintaining the as constructed- plant's performance to license.

4.1.2 Including Risk in Digital Twins

Michael Calley, Department Manager, Regulatory Support, Nuclear Safety and Regulatory Research Division
Idaho National Laboratory

Presentation Overview: This presentation looks at including risk in digital twin applications. Digital twin technology will be part of next generation-reactors. Risk in terms of performance shortfalls is a powerful way to characterize and understand complex systems, and public health frequency consequence- is a key part of a risk informed-- approach. Completeness in design and operation must account for uncertainties. If risk elements are taken into consideration, a digital twin approach can yield major efficiency improvements in the design, operation, and licensing of advanced reactors.

4.1.3 Towards a Digital Twin to Detect Nuclear Proliferation Activities

Christopher Ritter, Director, Digital Innovation Center of Excellence
Idaho National Laboratory

Presentation Overview: This project will develop technologies to enable digital engineering and digital twinning to assist in diversion pathway analysis and apply safeguards by design concept for advanced reactors and power plants. Digital twinning and digital engineering have produced significant performance improvements and schedule reduction in the aerospace, automotive, and construction industries. This integrated modeling approach has not been fully applied to nuclear safeguards programs in the past. Digital twinning combined with AI technologies can lead to innovations in process monitoring detection, particularly in event classification and data tampering.

4.2 Digital Twin Regulatory Discussion Panel

4.2.1 Bret Kugelmass, Managing Director

Energy Impact Center

4.2.2 Neil Olivier, Director of Corporate Services

NuScale Power

4.2.3 Pat Everett, Director of Thermal Engineering

Oklo, Inc.

4.2.4 Gregory A. Banyay, Modeling and Simulation Hub Technical Lead (Principal Engineer)

Westinghouse Electric Company

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APPENDIX A SPEAKERS BIOS

A.1 Day 1 Speaker Bios

Michael Grieves, Chief Scientist of Advanced Manufacturing, Executive Vice President of Operations
Florida Institute of Technology

Education/Experience: Dr. Michael Grieves is currently at the Florida Institute of Technology in Melbourne, FL, where he helped form the Center for Advanced Manufacturing and Innovative Design. He is an internationally renowned expert in product life cycle management (PLM) and originated the concept of the digital twin. His focus is on virtual product development and engineering; systems engineering and complex systems; manufacturing, especially additive manufacturing; and operational sustainment. Dr. Grieves wrote the seminal books on PLM, *Product Lifecycle Management* and *Virtually Perfect: Driving Innovative and Lean Products through PLM*. He has consulted with and done research at top global organizations, including the National Aeronautics and Space Administration (NASA), Boeing, Newport News Shipbuilding, and General Motors. Dr. Grieves has presented at industry and academic conferences worldwide.

Joseph Berti, Vice President of Offering Management
IBM

Education/Experience: Mr. Joseph Berti provides detailed direction on key technical and marketing tasks to launch offering features, offerings, or collections of offerings. He is accountable for key outcome metrics, including customer satisfaction, accessibility, and the revenue and profitability of assigned offerings. Mr. Berti also demonstrates offering capabilities and value propositions to external stakeholders (customers, partners, and analysts), analyzing feedback to identify potential gaps or opportunities, and recommending solutions. Mr. Berti has over 25 years of leadership experience in software and services in more than eight industries, with a focus on transforming industries using optimization technologies. As an experienced innovator, Mr. Berti has launched more than 10 products and services, transforming entire industries. Before joining IBM, Mr. Berti led the company Oniqua into a rapid -growth cycle while launching new products and achieving new levels of innovation. Since IBM acquired Oniqua, Mr. Berti has led the IBM Maximo® Inventory Optimization product offering. Mr. Berti received a bachelor’s degree in finance and management information systems from Ohio State University.

Jeremy Busby, Division Director, Reactor and Nuclear Systems Division
Oak Ridge National Laboratory

Education/Experience: Dr. Jeremy Busby’s research focuses on materials performance and the development of materials for nuclear reactor applications. While at Oak Ridge National Laboratory (ORNL), Dr. Busby has participated in materials research efforts for space reactors, fusion machines, advanced fast reactors, and light -water reactors (LWRs). Ultimately, the results of this diverse research will enable the development of operating criteria for structural materials in a variety of adverse environments, which will allow the design and operation of safe, reliable, and cost -effective nuclear systems.

From 2009 to 2015, Dr. Busby led the Materials Aging and Degradation Pathway for the Light Water Reactor Sustainability research and development (R&D) program at the U.S. Department of Energy’s (DOE’s) Office of Nuclear Energy. He also led the Materials Cross--Cut effort of the Nuclear Energy Enabling Technologies program, in addition to participating in several research tasks sponsored by the nuclear industry. As principal investigator for the DOE Office of Science ITER program, he led an investigation into the feasibility of using an innovative cast austenitic stainless steel for the first wall structure of the international ITER project. In 2010, following this effort, Dr. Busby received the Presidential Early Career Award for Science and Engineering for "excellence in research leading to the development of high -performance cast stainless steels, a critical part of the U.S. Contributions to ITER project, and for his mentoring of students both as an Adjunct Assistant Professor at the University of Michigan and at ORNL." In 2011, he received the Secretary of Energy Achievement Award for contributions to the DOE's response to the Fukushima Dai-ichi nuclear accident. The American Nuclear Society presented Dr. Busby with the Landis Young Member Achievement award in 2006, and in 2007 he received the ORNL Early Career Award for Engineering Accomplishment for his leadership in the cast stainless steel effort.

Ashley Finan, Director
National Reactor Innovation Center

<u>Education/Experience</u>: Dr. Ashley Finan is the director of the National Reactor Innovation Center. In this role, she oversees initiatives to provide reactor innovators with resources to test, demonstrate, and conduct performance assessments to accelerate the deployment of advanced nuclear technology concepts. Dr. Finan holds a bachelor's degree in physics as well as bachelor's and master's degrees in nuclear science and engineering from the Massachusetts Institute of Technology.

Dr. Finan earned her doctoral degree in nuclear science and engineering at the Massachusetts Institute of Technology. Her doctoral work focused on energy innovation investment and policy optimization, in both nuclear and renewable energy technologies. She has played a key role in studies of the use of advanced nuclear energy to reduce greenhouse gas emissions in several applications, including hydrogen production, coal -to -liquids processes, and oil production methods. She has worked as a strategy and engineering consultant, primarily on nuclear energy applications. She has also contributed to analyses of the technoeconomic potential of energy efficiency improvements in the residential and commercial sectors, and several related topics.

Jenifer Shafer, Special Government Employee Consultant
Advanced Research Projects Agency–Energy

<u>Education/Experience</u>: Dr. Jenifer Shafer currently serves as a special government employee consultant at the Advanced Research Projects Agency–Energy (ARPA-E). At ARPA-E, she focuses on developing innovative and proliferation -resistant technologies to manage nuclear waste and used nuclear fuel. She is an expert in nuclear separations, nuclear forensics, and the fundamentals of actinide chemistry. Before joining ARPA-E, Dr. Shafer served on the faculty at the Colorado School of Mines as an Associate Professor in the Chemistry Department and the Nuclear Science and Engineering Program. Before that, she worked for 2 years at Pacific Northwest National Laboratory.

Dr. Shafer received a bachelor's degree from Colorado State University in 2005 and a doctoral degree from Washington State University in 2010. She was a DOE Early Career Award winner and currently serves on the American Chemical Society's Committee on Science. She is the coauthor of several book chapters and nearly 60 technical manuscripts, and she has led or collaborated on several projects for the DOE, the U.S. Department of Homeland Security, and the U.S. Department of Defense, as well as the National Science Foundation.

Ian Davis, Senior Digital Twin System Engineer
X-Energy LLC

Education/Experience: Mr. Ian Davis holds both a bachelor's and a master's degree in nuclear engineering from the Pennsylvania State University. He is a nuclear engineer with over 6 years of experience in the nuclear power generation industry, specializing in the simulation of thermal hydraulics and neutronics, software programming, and data science.

Anthonie Cilliers, Senior Manager, Instrumentation, Controls, and Electrical
Kairos Power

Education/Experience: Dr. Anthonie Cilliers holds a doctoral degree in nuclear engineering and both a master's and a bachelor's degree in computer and electronic engineering. He has over 12 years of experience in nuclear -specific plant control and protection systems, specializing in model reference plant control and diagnostics and control system architecture.

Clyde Huibregtse, Reactor/Software Engineer
Oklo, Inc.

Education/Experience: Mr. Clyde Huibregtse holds a bachelor's degree in both mathematics for computer science and physics from the Massachusetts Institute of Technology. He has been with Oklo in some capacity for almost 3 years.

Charles R. "Chip" Martin, Scientific/Technical Advisor
HolosGen, LLC

Education/Experience: Dr. Charles R. Martin holds a doctoral degree in nuclear engineering from the U.S. Air Force Institute of Technology and a bachelor's degree in nuclear engineering from North Carolina State University. He is currently an executive consultant with Longenecker and Associates, but he has held many interesting positions over the years. In 2018, he was the Glenn T. Seaborg Science and Technology Policy Fellow for the American Nuclear Society and the American Association for the Advancement of Science. In this role, he served as a staffer in the U.S. House of Representatives. Before that, he was the chief nuclear officer for the Nevada National Security Site. He has served on the faculties of the University of Nevada, Las Vegas; the University of Maryland; and the U.S. Air Force Academy. He served as a technical specialist at the U.S. Defense Nuclear Facilities Safety Board; he was a nuclear research officer in the Office of the Secretary of the Air Force; he managed the U.S. Advanced Space Reactor Program at the DOE; and he served as technical director for three underground nuclear weapon tests.

Abhinav Saxena, Senior Scientist, Machine Learning, GE Research
General Electric

Education/Experience: Dr. Abhinav Saxena is a senior scientist in AI and learning systems at General Electric (GE) Research and the principal investigator for the GE -led Generating Electricity Managed by Intelligent Nuclear Assets (GEMINA) Award 2174-1511. Dr. Saxena is developing prognostics and health management (PHM) solutions based on machine learning and AI for various industrial systems at GE (aviation, nuclear, power, and healthcare) and is driving the integration of AI -based PHM analytics in GE's industrial systems. Before joining GE, Dr. Saxena worked as a research scientist at NASA Ames Research Center, carrying out fundamental research on prognostics methods and evaluation. Dr. Saxena has over 15 years of experience in developing predictive maintenance methods and technologies. He is also an adjunct professor in the Division of Operation and Maintenance Engineering at Luleå University of Technology, Sweden. His interests lie in developing PHM methods and algorithms with special emphasis on deep learning and data -driven methods in general for practical prognostics. Dr. Saxena has published over 100 peer -reviewed technical papers and has coauthored a seminal book on prognostics. He is a fellow of the PHM Society and actively participates in several SAE standards committees, the Institute of Electrical and Electronics Engineers (IEEE) prognostics standards committee, and various PHM Society educational activities. He has served as the chief editor of the *International Journal of Prognostics and Health Management* since 2011 and actively participates in organizing PHM Society conferences.

Chandler Maskal, Offering Manager, IBM AI Applications
IBM

Education/Experience: Ms. Chandler Maskal graduated from Rensselaer Polytechnic Institute in 2018 with bachelor's and master's degrees in information technology and Web science. She has worked for IBM for 2 years as an offering manager on multiple products in the enterprise asset management space. She most recently led the launch of IBM's digital twin initiative in May 2020.

Mark Buller, Principal Investigator, Biophysics and Biomedical Modeling Division
U.S. Army Research Institute of Environmental Medicine

Education/Experience: Dr. Mark Buller gained his doctorate in computer science from Brown University in the area of computational physiology. Dr. Buller has over 20 years of experience in designing and fielding ambulatory physiological monitoring systems for warfighters. Dr. Buller's current research interests are real--time algorithms that determine health state from wearable sensors and performance optimization from physiological feedback. Dr. Buller is currently the principal investigator of a multi--institute research study to identify noninvasive markers of exertional heat stroke. Dr. Buller has authored more than 100 publications and is currently serving as a chair for the North Atlantic Treaty Organization (NATO) working group "Development of a NATO STANREC for Physiological Status Monitoring to Mitigate Exertional Heat Illness."

Kevin P. Chen, Professor
University of Pittsburgh

Education/Experience: Dr. Kevin Chen received a doctoral degree in 2002 from the University of Toronto.

A.2 Day 2 Speaker Bios

Joel Fetter, ARPA-E, Lead Associate
Booz Allen Hamilton

Education/Experience: Over the past 9 years, Mr. Joel Fetter has focused primarily on the establishment of ARPA-E's Technology -to -Market capability, where he advises on the development and implementation of program structures that translate science into business concepts. To date, ARPA-E portfolios have accrued many billions of dollars in follow -on funding, extensive patent activity, and seminal research that has created new learning curves for advanced energy technologies. Most recently, Mr. Fetter advised on the creation of ARPA-E's initial suite of investments into advanced nuclear energy systems, which comprised nearly $100 million in enabling technologies, microreactors, and improved O&M technologies.

Before his engagement with ARPA-E, Mr. Fetter consulted to public, private, and nonprofit organizations across the energy landscape. He earned a master's degree in law and diplomacy from the Fletcher School at Tufts University and a bachelor's degree, summa cum laude, in international affairs from the University of Colorado at Boulder.

Abhinav Saxena, Senior Scientist, Machine Learning, GE Research
General Electric

Education/Experience Summary: Dr. Abhinav Saxena is a senior scientist in AI and learning systems at GE Research and the principal investigator for the GE -led GEMINA Award 2174-1511. Dr. Saxena is developing PHM solutions based on machine learning and AI for various industrial systems at GE (aviation, nuclear, power, and healthcare) and is driving the integration of AI -based PHM analytics in GE's industrial systems. Before joining GE, Dr. Saxena worked as a research scientist at NASA Ames Research Center, carrying out fundamental research on prognostics methods and evaluation. He has over 15 years of experience in developing predictive maintenance methods and technologies. He is also an adjunct professor in the Division of Operation and Maintenance Engineering at Luleå University of Technology, Sweden.

Yvotte Brits, Supply Chain Manager and Operator Training Simulator Program Manager
X-Energy LLC

Education/Experience: Mr. Yvotte Brits holds a master's degree in nuclear engineering and electric and electronic engineering. Mr. Brits is a nuclear engineer with 13 years of vital experience in the international nuclear industry, specializing in supply chain management, operator training simulator program management, energy plant transient analyses, instrumentation and control design, cost modeling, and plant system design for power plants.

Anthonie Cilliers, Senior Manager, Instrumentation, Controls, and Electrical
Kairos Power

Education/Experience: Dr. Anthonie Cilliers holds a doctoral degree in nuclear engineering and master's and bachelor's degrees in computer and electronic engineering. Dr. Cilliers has over 12 years of experience in nuclear -specific plant control and protection systems; he specializes in model reference plant control and diagnostics and control system architecture.

Brian Golchert, Principal Engineer
Westinghouse Electric Company

Education/Experience: Dr. Brian Golchert holds a doctorate in nuclear engineering from the University of Illinois. He has engineering work experience from Argonne National Laboratory (ANL), Fluent, GE Nuclear, and Westinghouse, as well as teaching experience at DePaul University (mathematics and statistics) and Purdue Calumet (engineering).

Matthew LeVasseur, Director of Research
BWX Technologies

Education/Experience: Mr. Matthew LeVasseur has been with BWX Technologies over 21 years; he previously spent 10 years with the U.S. Marine Corps as an aerospace officer. He holds degrees and qualifications from Duke University (Global Executive Management M.B.A., with honors, 2007), the University of Michigan (M.S. in aerospace science, 1995, and B.S. in astronomy, 1989); Six Sigma Qualtec (Master Black Belt, Process Analytics and Data Methods, 2006); and the U.S. Space Command (Space Control Qualification, Data Modeling/Infrastructure, 1997).

Ryan Kitchen, Research and Development Data Scientist
BWX Technologies

Education/Experience: Mr. Ryan Kitchen is the lead data scientist and innovator for BWX Technologies on a shared project with ORNL to develop digital twin technology for electron beam melt additive manufacturing as well as additional R&D for nuclear manufacturing. Mr. Kitchen brings expertise in high performance computing, GPU computing, biocomputing, and machine vision and instrumentation for integration into manufacturing systems. He received a bachelor's degree in computer science from Oregon State University in 2018.

Hasan Charkas, Principal Technical Leader
Electric Power Research Institute

Education/Experience: Dr. Hasan Charkas holds a doctoral degree in structural engineering and engineering mechanics. Dr. Charkas has been with the Electric Power Research Institute (EPRI) for almost 5 years. Previously, he worked for Areva/Framatome as an engineering supervisor in the component analysis and fracture mechanics group (specializing in stress analysis for nuclear steam supply system components and reactor vessel internals). Before working at Areva/Framatome, Dr. Charkas was a design engineer for a structural group (specializing in strengthening of deficient structures).

Hash Hashemian, President and CEO
Analysis and Measurement Services Corporation

Education/Experience: Dr. Hash Hashemian obtained a D.E. degree in electrical engineering from Lamar University, Beaumont, in 2009; a doctoral degree in nuclear engineering from Chalmers University, Gothenburg, in 2010; and a doctoral degree in computer engineering from Western University, London, in 2011.

Jacob Houser, Senior Research Engineer
Analysis and Measurement Services Corporation

Education/Experience: Dr. Jacob Houser holds doctoral and master's degrees in mechanical engineering from the University of Tennessee, Knoxville, and a bachelor's degree in mechanical engineering and management from the Rensselaer Polytechnic Institute.

David E. Womble, Director of Artificial Intelligence Programs
Oak Ridge National Laboratory

Education/Experience: Dr. David E. Womble received his doctoral degree in applied mathematics from Georgia Tech in 1986. Before joining ORNL in 2017, Dr. Womble served as the program deputy for Advanced Simulation and Computing at Sandia National Laboratories, responsible for developing and deploying modeling and simulation (M&S) capabilities. He also served as the senior manager for the Computational Simulation Group and for the Computer Science and Mathematics Group. His recognitions include two R&D 100 Awards and the Gordon Bell Award. Dr. Womble's research interests include numerical algorithms and methods for machine learning and high -performance computing, including the solution of linear and nonlinear systems, multigrid and multiscale algorithms, time-series analysis, and scalable algorithms in high -performance computing. Dr. Womble has also worked across several application domains, including seismic imaging, semiconductor device simulation, computational mechanics, and wind energy.

Richard Vilim, Senior Nuclear Engineer; Manager, Plant Analysis and Control and Sensors Department, Nuclear Science and Engineering Division
Argonne National Laboratory

Education/Experience: Dr. Richard Vilim has over 30 years of professional experience in the design and safety analysis of nuclear reactors, with ongoing research projects involving control system design, M&S of nuclear systems, the operation of advanced nuclear reactors employing load -following and load -leveling using energy storage, and AI and machine learning for plant performance improvement. He is an author on over 300 reports and publications and nine U.S. patents.

Christopher Ritter, Director, Digital Innovation Center of Excellence
Idaho National Laboratory

Education/Experience: With a bachelor's degree in computer science from Virginia Polytechnic Institute and State University, Mr. Christopher Ritter is a group lead with the Digital and Software Engineering Group at Idaho National Laboratory (INL). His expertise is in software engineering, software development, leading software teams, systems engineering software integration, and database management. Before coming to INL, he was director of software development at SPEC Innovations, where he was the chief architect of Innoslate. He also architected the software system and consulted on the data ontology for a centralized mission risk management system for the Joint Staff at the Pentagon and supported the Marine Corps business process reengineering for its Capability Portfolio Management processes. In addition, he has served as a computer programming teacher at St. Michael's Academy in Warrenton, VA.

Ben Betzler, Nuclear Engineer
Oak Ridge National Laboratory

Education/Experience: Dr. Benjamin R. Betzler is an outcome -focused reactor physics nuclear engineer with demonstrated experience and performance on R&D programs for a variety of sponsors; his experience includes leading diverse multiorganization teams. He has recognized expertise in both reactor analysis and methods development, with specialized knowledge of advanced reactor systems (e.g., molten -salt reactors, microreactors, HTGRs, and space propulsion systems) and Monte Carlo radiation transport methods (alpha -eigenvalue methods, time -dependent problems, and matrix methods and applications of Markov processes). Dr. Betzler received his doctoral degree in nuclear engineering and radiological sciences from the University of Michigan in 2014.

Vincent Paquit, Senior Research Scientist, Electrical and Electronics Systems Research
Oak Ridge National Laboratory

Education/Experience: Before joining ORNL, Dr. Vincent Paquit worked at the University of Burgundy (France), in the Laboratoire d'Électronique et d'Informatique de l'Image, as an engineer in technology transfer for all commercial and technical applications in the fields of electronics, computer science, and signal processing. Since then, Dr. Paquit has been an active member of the Imaging, Signals, and Machine Learning Group at ORNL, working on multiple projects and programs supporting two core missions of the DOE: energy sustainability and national security. He is contributing to ORNL's scientific endeavors by conceiving, designing, and implementing complex computer vision and multidimensional imaging systems—combining hardware and software development—to perform quantitative analysis of complex datasets and to make quantitative measurements of various objects. Currently, Dr. Paquit is the data analytics lead for the Manufacturing Demonstration Facility. His team is developing a data analytics framework aimed at better understanding of additive manufacturing processes for the purpose of process certification and control. His research interests include applied signal and image processing, algorithm development on GPU platforms, two- and three -dimensional image segmentation, multispectral and hyperspectral imaging, biomedical imaging, pattern recognition, remote sensing data understanding, and machine learning. He has published numerous peer -reviewed articles and one book chapter, submitted multiple invention disclosures, and served on program committees of several international conferences.

Eric Helm, Product Manager—Metroscope
Framatome

Education/Experience: Mr. Eric Helm holds a bachelor's degree in mechanical engineering and a master's in systems engineering. He has 5 years of experience in the automotive manufacturing industry and 15 years of experience at Framatome in a variety of engineering roles, including fuel fabrication, large projects, systems engineering methods, field service, equipment analytics, and advanced diagnostics with Metroscope.

Richard Vilim, Senior Nuclear Engineer; Manager, Plant Analysis and Control and Sensors Department, Nuclear Science and Engineering Division
Argonne National Laboratory

Education/Experience: Dr. Richard Vilim has over 30 years of professional experience in the design and safety analysis of nuclear reactors, with ongoing research projects involving control system design, M&S of nuclear systems, the operation of advanced nuclear reactors employing load-following and load-leveling using energy storage, and AI and machine learning for plant performance improvement. He is an author on over 300 reports and publications and nine U.S. patents.

Rizwan Uddin, Professor and Head of the Department of Nuclear, Plasma, and Radiological Engineering
University of Illinois at Urbana-Champaign

Education/Experience: Professor Rizwan Uddin is a fellow of the American Nuclear Society. He directs the Virtual Education and Research Lab and the Master of Engineering in Energy Systems program at the University of Illinois at UrbanaChampaign (UIUC). He received the American Society of Engineering Education's Glenn Murphy Award in 2015, the American Nuclear Society's Arthur Holy Compton Award for his teaching and research accomplishments in 2016, and UIUC's Campus Award for Excellence in Guiding Undergraduate Research in 2017.

Subhasish Mohanty, Principal Research and Development Engineer
Argonne National Laboratory

Education/Experience: Dr. Subhasish Mohanty is currently working as a principal R&D engineer at the Nuclear Science and Engineering division of ANL. Dr. Mohanty began working at ANL in 2010 after finishing his doctoral degree in aerospace engineering from Arizona State University. Dr. Mohanty also has 4 years of experience in the aerospace industry. His experience and interests primarily focus on structural mechanics and digital twins of nuclear reactor and aerospace systems; machine learning, AI, and data analytics techniques; and Internet -of -things concepts.

A.3 Day 3 Speaker Bios

Richard Henry, Section Manager, Computers and Control Design, Central Engineering Ontario Power Generation

Education/Experience: Mr. Richard Henry holds a bachelor’s degree in electrical engineering from McMaster University.

John Sladek, Specialist, Systems Engineering Division, Directorate of Assessment and Analysis Canadian Nuclear Safety Commission

Education/Experience: Mr. John Sladek holds a bachelor’s degree in electrical engineering from Queen’s University, Kingston.

Albrecht Kyrieleis, Senior Consultant, Jacobs

Education/Experience: With more than 10 years of experience in the nuclear industry and a background in physics, Dr. Albrecht Kyrieleis has worked on a broad range of projects in the areas of simulation software development, radiation shielding and protection, and nuclear physics and criticality. Involved in fission as well as fusion, he has led various R&D and application projects and is the technical lead for the United Kingdom’s Nuclear Virtual Engineering Capability project, responsible for the overall technical program.

Susana López Lumbierres, Senior Project Manager, Tecnatom

Education/Experience: Ms. Susana López Lumbierres is an industrial and simulation Engineer.

Panagiotis Manolatos, Project Officer, European Atomic Energy Community

Education/Experience: Dr. Panagiotis Manolatos is an engineer who holds a doctoral degree in materials sciences from the École des Mines in France. His experience includes 10 years in laboratory research on the behavior of materials and components at various European national laboratories (in France and the Netherlands), 5 years tutoring at the École Centrale de Paris in France, and 20 years coordinating research in nuclear safety at the European Commission’s Directorate General for Research and Innovation.

Abderrahim Al Mazouzi, Expert Group in charge of the European affairs of the research and development program on energy production EDF France

Education/Experience: Dr. Abderrahim Al Mazouzi acted as the general secretariat and as a member of the executive committee of the Nuclear Generation II & III Alliance (NUGENIA) for 7 years. After receiving his doctoral degree in materials science in 1989, he spent 3 years as a postdoctoral researcher at the Hahn Meitner Institute in Berlin, Germany, then held a position as visiting scientist at Kyoto University, Japan, from 1993 to 1995.

In 1995, he joined the Centre de Recherches en Physique des Plasmas at the École Polytechnique Fédérale de Lausanne (Switzerland) to work on fusion technology. He then moved to the Paul Sherrer Institute (Switzerland), where he acted as project manager at the hot-lab facility from 1999 to 2001. From 2002 until 2009, he served as a senior scientist and then group leader at SCK CEN, Belgium, before joining Électricité de France (EDF) R&D.

Christopher Spirito, Nuclear Cybersecurity Consultant, Idaho National Laboratory

Education/Experience: Mr. Christopher Spirito is a nuclear cybersecurity consultant with INL. He supports domestic and international programs with the DOE and the International Atomic Energy Agency (IAEA). For the past 7 years he worked closely with the Korea Atomic Energy Research Institute and the Korea Institute of Nuclear Nonproliferation and Control through the U.S.–Republic of Korea bilateral relationship, as well as on international research projects through the IAEA. Mr. Spirito is also a visiting professor in the Faculty of Law at the University of Tartu, Estonia, and a board member for WiRED International, a global health NGO providing support to underserved regions of the world. Mr. Spirito graduated from Boston College with a degree in mathematics and attended graduate school at Worcester Polytechnic Institute and the Harvard School of Public Health. Before joining INL, Mr. Spirito was the International Cyber Lead for The MITRE Corporation.

Cynthia DeBisschop, Senior Cybersecurity Analyst Oasis Systems, LLC (NRC contractors)

Education/Experience: Dr. Cynthia DeBisschop holds a bachelor's degree in chemical engineering from Drexel University and master's and doctoral degrees in engineering sciences and applied mathematics from Northwestern University. Inspired by computational mentors at the Mobil Research and Development Corporation, where she worked as a cooperative education student early in her career, she pursued graduate research focused on the mathematical modeling of physical processes at Northwestern as a National Science Foundation Graduate Research Fellow. She engaged in computational interdisciplinary research as a postdoctoral researcher in the Department of Mathematical Sciences at the University of Delaware and as a professor in the Department of Mathematics and Statistics at Old Dominion University. In 2009, Dr. DeBisschop began work as a research analyst for CNA's Institute for Public Research under contract to the Federal Aviation Administration, where she conducted research in data and information management and in systems engineering for the NextGen modernization effort. While at CNA, she coauthored a paper that won two David Lubkowski Memorial Best Paper Awards in 2011.

Since 2017, Dr. DeBisschop has supported the cybersecurity program at the U.S. Nuclear Regulatory Commission (NRC) and has conducted and supported 18 cybersecurity inspections of nuclear power plants. She assisted in the presentation of the Advanced Cyber Security Inspection training course at the NRC Technical Training Center in Chattanooga, TN. More recently, she assisted in the development of NRC regulatory guidance.

Rodney Busquim e Silva, Computer Security Officer, International Atomic Energy Agency

Dave Kropaczek, Director, Consortium for Advanced Simulation of Light Water Reactors (a DOE Energy Innovation Hub) Oak Ridge National Laboratory

Education/Experience: Former president and CEO of Studsvik Scanpower, the nuclear software division of Studsvik AB, Dr. Dave Kropaczek holds a bachelor's degree in engineering science from the New Jersey Institute of Technology and master's and doctoral degrees in nuclear engineering from North Carolina State University. He has over 27 years of experience in the nuclear industry, with areas of expertise including fuel cycle and plant optimization, computational reactor physics and thermal hydraulics, and numerical algorithm development. Previous experience includes positions in research, product development, and management, including 9 years with GE Global Nuclear Fuel, developing methods and software for boiling water reactor fuel technology; 12 years with Studsvik Scanpower, developing methods for real-time kinetics simulation and multicycle optimization; and 3 years with Westinghouse Fuels, focusing on core design and monitoring applications. In addition, Dr. Kropaczek spent 3 years as a research assistant professor at North Carolina State University, working with students and on R&D projects sponsored through the Electric Power Research Center. Dr. Kropaczek serves as the American Nuclear Society Reactor Physics Division Chair for the Advances in Nuclear Fuel Management topical meetings, and as technical reviewer for several journals, including *Nuclear Technology* and *Nuclear Science and Technology*.

Jeffrey W. Lane, Chief Engineer and Principal Consultant, Zachry Nuclear Engineering

Education/Experience: Dr. Jeffrey W. Lane has 15 years of software development experience in computational thermal hydraulics and reactor safety analysis for existing LWRs, as well as for next generation small modular reactor and non-LWR concepts. His expertise is in multiphysics and multiscale methods; verification, validation, and uncertainty quantification; and software quality assurance. Dr. Lane has also taken part in digital twin development, autonomous control, and data driven modeling. Currently, he is the technical lead and program manager for the GOTHIC coarse grid computational fluid dynamics software. Dr. Lane worked for the Bettis Atomic Power Laboratory, where he was responsible for advancing simulation capabilities to support existing and future applications in the Naval Nuclear Propulsion Program, including the safety analysis for the Ford class aircraft carrier, multiphysics methods development, and integrated plant analysis development. Dr. Lane received his doctoral degree from the Pennsylvania State University, where he studied under the Rickover Fellowship Program in nuclear engineering.

Rui Hu, Manager, Plant System Analysis Group, Argonne National Laboratory

Education/Experience: Dr. Rui Hu holds a doctoral degree in nuclear engineering from the Massachusetts Institute of Technology.

Felipe A. C. Viana, Assistant Professor, University of Central Florida

Education/Experience: Before joining the University of Central Florida, Dr. Felipe A.C. Viana was a senior scientist at GE Renewable Energy, where he led the development of computational methods for improving wind turbine performance and reliability. Before that role at GE, he spent 5 years at GE Global Research, where he led and conducted research on design and optimization under uncertainty, probabilistic analysis of engineering systems, and services engineering. Dr. Viana holds a doctoral degree in aerospace engineering from the University of Florida and both a doctoral and a master's degree in mechanical engineering from the Federal University of Uberlândia (Brazil).

Lance Fiondella, Associate Professor of Electrical and Computer Engineering at University of Massachusetts in Dartmouth

Education/Experience: Dr. Lance Fiondella holds a doctoral degree in computer science and engineering from the University of Connecticut.

Linyu Lin, Postdoctoral Research Scholar, Department of Nuclear Engineering of North Carolina State University

Education/Experience: Dr. Linyu Lin holds a doctoral degree in nuclear engineering.

Pradeep Ramuhalli, Distinguished Scientist at Oak Ridge National Laboratory

Education/Experience: Over the last 18 years, Dr. Pradeep Ramuhalli has led and contributed to advances in systems resilience and reliability, with current research focused on developing technologies that enable robust digital twins, and on applying these technologies to improve the economics of nuclear power, enhance the reliability of renewable energy systems, and support cybersecurity and international safeguards. Relevant technology areas include sensors and algorithms for the continuous online monitoring of stressors and systems for degradation detection and characterization, physics informed machine learning algorithms for prognostic assessment of system and component remaining useful life, and risk informed methodologies to ensure the reliability of measurements and resilience of degraded systems. Dr. Ramuhalli has coedited a book on integrated vision and imaging techniques for industrial inspection and has authored or coauthored four book chapters, over 175 technical publications in peer reviewed journals and conferences (including over 35 peer reviewed journal publications), and over 90 technical research reports. He is a senior member of IEEE and a member of the American Nuclear Society.

A.4 Day 4 Speaker bios

Michael Mazzola, Executive Director, Energy Production and Infrastructure Center, University of North Carolina at Charlotte

Education/Experience: Dr. Michael Mazzola attended the University of North Carolina at Charlotte; he received a doctoral degree in electrical engineering from Old Dominion University in 1990. From 1990 to 1993, Dr. Mazzola was employed by the U.S. Navy at the Naval Surface Warfare Center Dahlgren. From 1993 to 2017, he served on the faculty in the Electrical and Computer Engineering Department at Mississippi State University. In 2009, he was appointed Associate Director for Advanced Vehicle Systems at the Center for Advanced Vehicular Systems, a unit of the High-Performance Computing Collaboratory at Mississippi State University. In July 2017, Dr. Mazzola was appointed the executive director of the Energy Production and Infrastructure Center, as well as the Duke Energy Distinguished Chair in Power Engineering Systems, at the University of North Carolina at Charlotte.

Michael Calley, Department Manager, Regulatory Support, Nuclear Safety and Regulatory Research Division Idaho National Laboratory

Education/Experience: Mr. Michael Calley has over 31 years of experience in probabilistic risk assessment (PRA), safety evaluations, and hazards assessments, including project management. His experience includes performing PRAs for both commercial nuclear power plants and nuclear research and test reactors, supporting the NRC on inspections at commercial nuclear power plants, and providing PRA technology transfers both domestically and internationally. He has knowledge of preparing hazards assessments, developing guidelines for the preparation of safety analysis reports, and resolving concerns about the adequacy of safety analysis reports. Mr. Calley's background also includes the comprehensive use of PRA software. He holds a master's degree in nuclear science and engineering and a bachelor's degree in general engineering from Idaho State University.

Christopher Ritter, Director, Digital Innovation Center of Excellence of Idaho National Laboratory

Education/Experience: Mr. Christopher S. Ritter is a group lead with the Digital and Software Engineering Group at INL. His expertise is in software engineering, software development, leading software teams, systems engineering software integration, and database management. Before coming to INL, he directed software development at SPEC Innovations, in Manassas, VA. He served as the chief architect of Innoslate, a popular system engineering tool that leverages elastic cloud technologies and AI and neurolinguistic programming for high scalability and advanced analytics. Mr. Ritter architected the software system and consulted on the data ontology for a centralized mission risk management system for the Joint Staff at the Pentagon and supported the Marine Corps business process reengineering for its Capability Portfolio Management processes. He was also a computer programming teacher at St. Michael's Academy in Warrenton, VA, and developed an elementary school computer programming curriculum. He holds a bachelor's degree in computer science from Virginia Polytechnic Institute and State University.

Bret Kugelmass, Managing Director of Energy Impact Center

Education/Experience: Mr. Bret Kugelmass holds a master's degree in mechanical engineering from Stanford University and is a former robotics entrepreneur.

Neil Olivier, Director of Corporate Services at NuScale Power

Education/Experience: Mr. Neil Olivier, who has over 25 years of experience, began his career as a nuclear submarine mechanic in the U.S. Navy, and then went on to work as an operator of multiple commercial pressurized water and boiling water reactors. Mr. Olivier has an NRC reactor operator license at Columbia Nuclear Generating Station, an NRC senior reactor operator license at Limerick Nuclear Generating Station, a bachelor's degree in nuclear engineering technology, and a master's degree in business administration.

In his current position, Mr. Olivier leads the Document Control and Records Management Group, the Engineering Support Group, Facilities Management, and the Performance Improvement Group at NuScale Power. These groups administer multiple programs for compliance with Nuclear Quality Assurance1, including Engineering Design Control, Document Control and Records Management, and the Corrective Action Program. Mr. Olivier also currently heads NuScale's new PLM implementation, which will enable the digital twin and digital thread.

Pat Everett, Director of Thermal Engineering Oklo, Inc.

Education/Experience: Mr. Pat Everett holds a bachelor's degree in nuclear and mechanical engineering from the Massachusetts Institute of Technology. He leads the technical design of Oklo's advanced reactor systems and is an active developer of Oklo's advanced reactor analysis infrastructure. He led the safety analysis of the Aurora, as described in the Aurora combined license application to the NRC, which is the first and only non-LWR and microreactor combined license application submitted to and accepted for review by the NRC. He is actively supporting the NRC's technical review of the Aurora.

Gregory A. Banyay, Modeling and Simulation Hub Technical Lead (Principal Engineer)

Education/Experience: Dr. Gregory A. Banyay received a doctoral degree in civil and environmental engineering from the University of Pittsburgh in 2019; he also holds master's and bachelor's degrees in mechanical engineering from Ohio University. Since 2010, he has worked at Westinghouse Electric Company as a computational mechanics analyst with an emphasis on flow induced vibration, acoustics, and probabilistic analysis. From 2006 to 2010, Dr. Banyay worked at Parker Hannifin as a design engineer for aerospace fuel pumps and pneumatic valves. Currently, Dr. Banyay focuses on the intersection of data driven and physics-based modeling for objectives related to structural health monitoring and PHM for nuclear power plants.

APPENDIX B
WORKSHOP ATTENDEES

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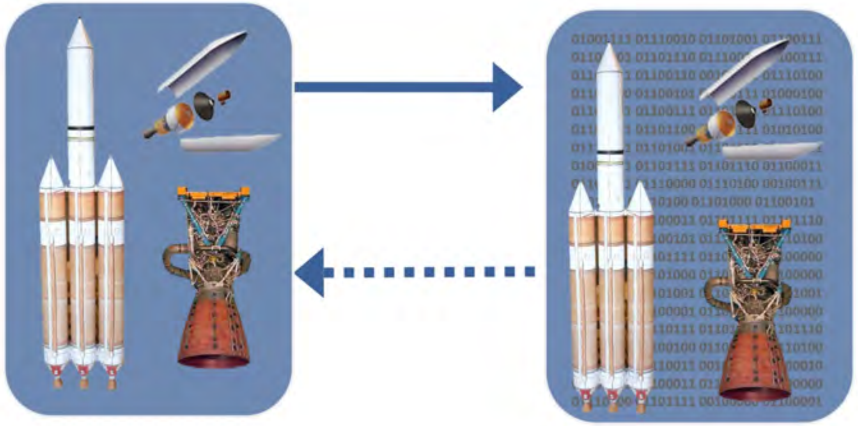
APPENDIX C
PRESENTATION SLIDES



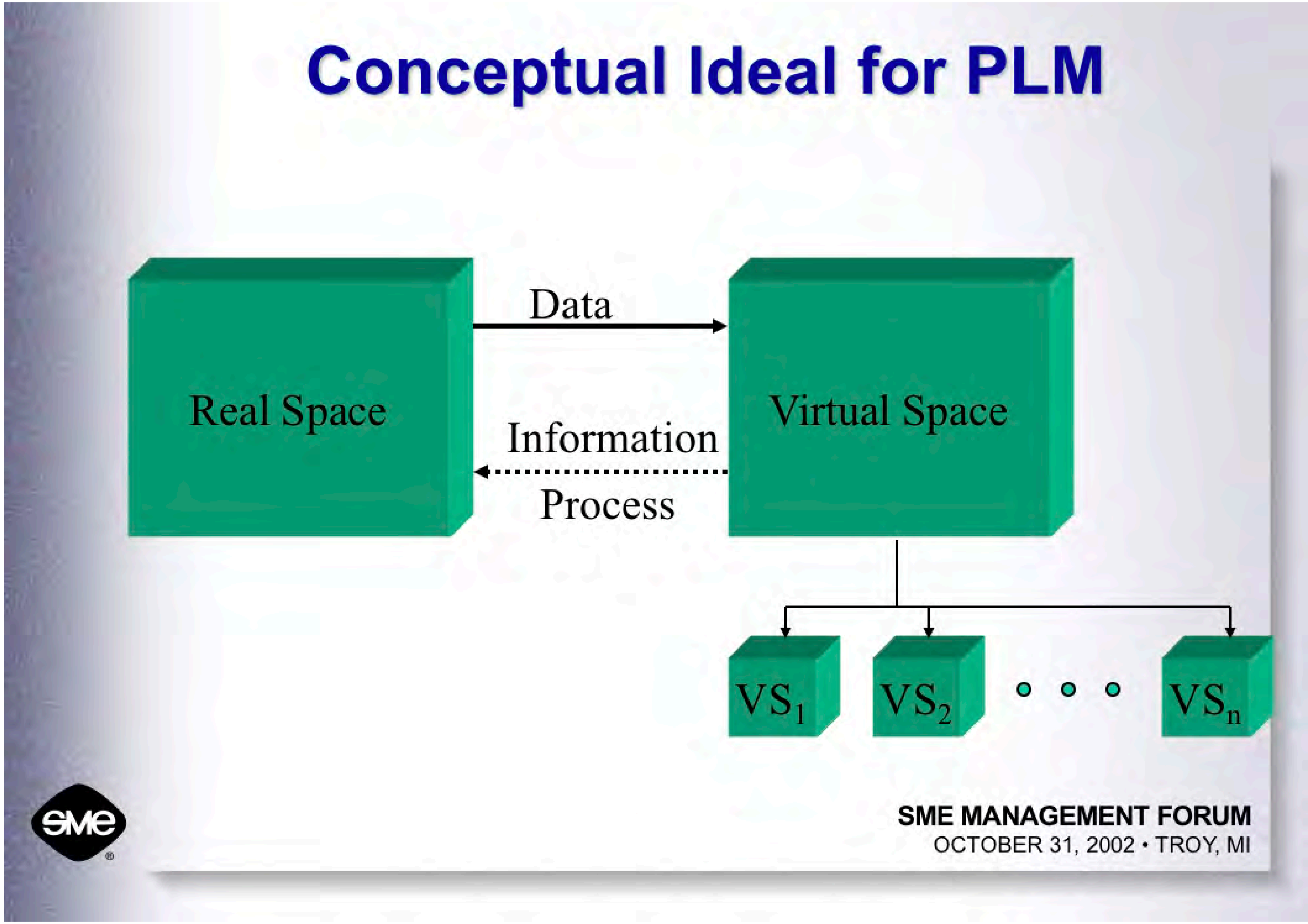
Nuclear Digital Twins

Dr. Michael Grieves

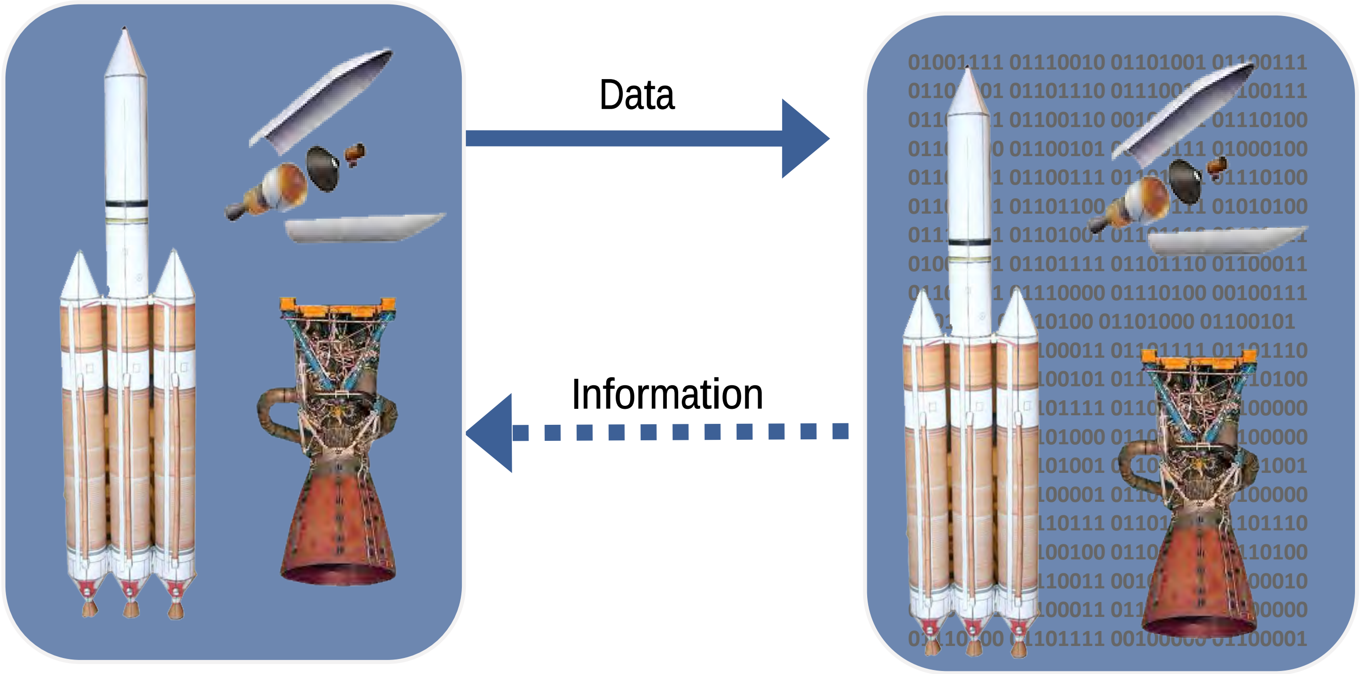
Chief Scientist of Advanced Manufacturing

Florida Institute of Technology


FLORIDA TECH
PRODUCT LIFECYCLE MANAGEMENT
MICHAEL GRIEVES
Virtually Perfect


Conceptual Ideal for PLM
Real Space
Data
Information
Process
Virtual Space
VS_1
VS_2
VS_n
SME MANAGEMENT FORUM
OCTOBER 31, 2002 • TROY, MI

Digital Twin Model



Physical Space

Virtual Space

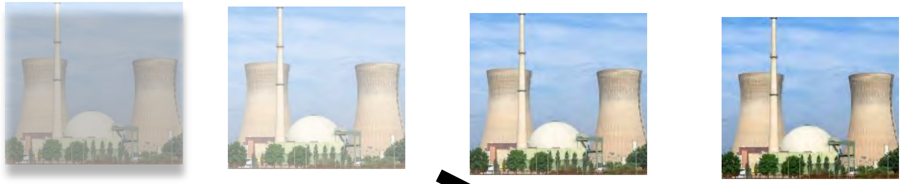
20th Century — Work Activity → 21st Century

Substituting information for wasted physical resources

Digital Twin Types (DT)

Digital Twin Prototype (DTP)

All Products that CAN BE made



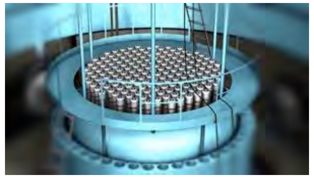
Digital Twin Aggregate (DTA)

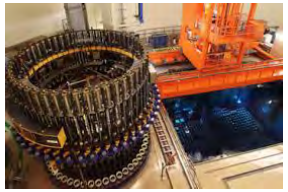
All Products that HAVE BEEN made

Digital Twin Instance (DTI)

Individual Products that ARE made

Physical Twin (PT)

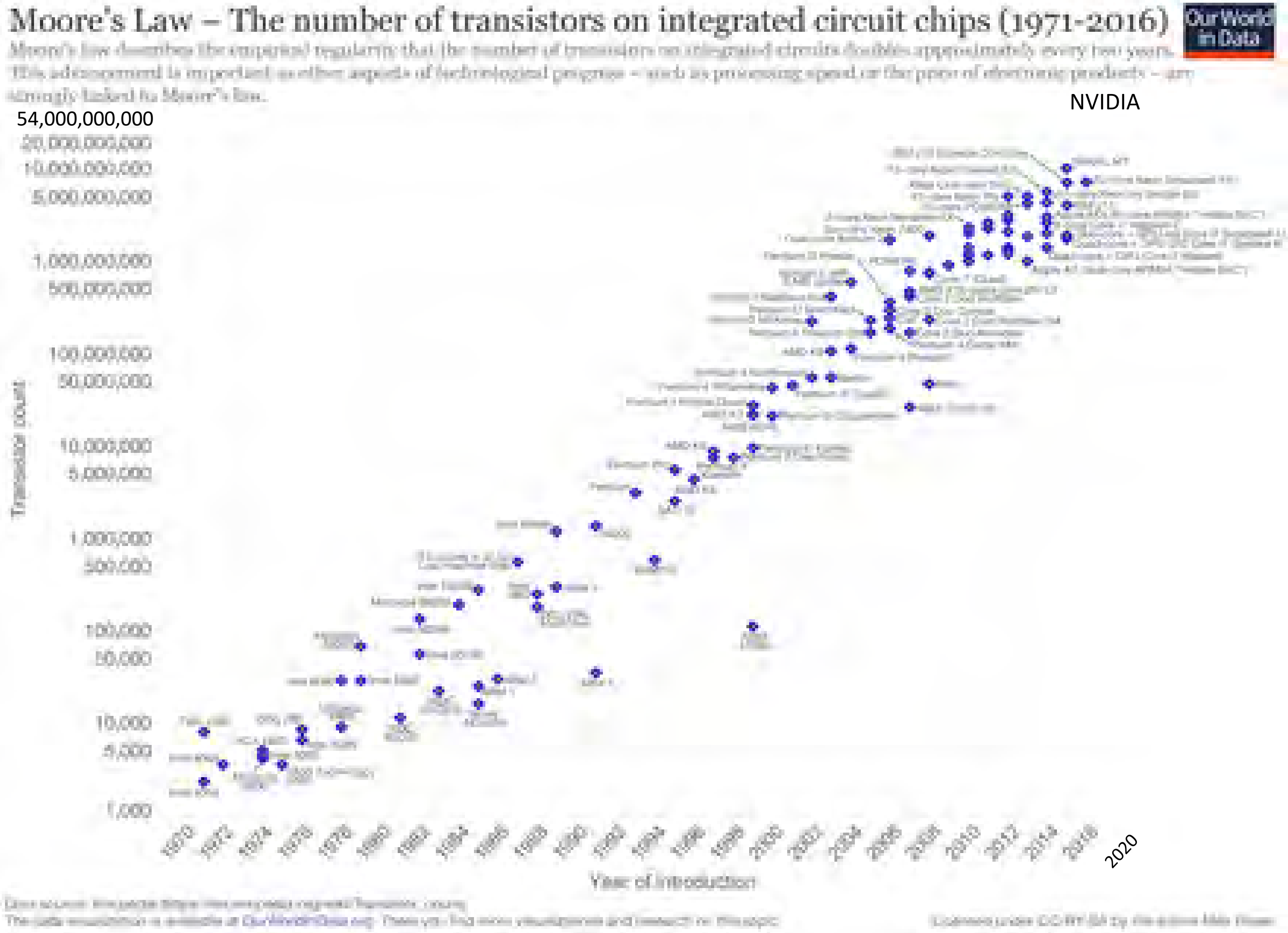


- Smart
  - Sensing
  - Translating
  - Comparing
  - Reacting
- Smart, Connected
  - Communicating, Assessing, Response
  - Protecting

Grieves, M., *Virtually Intelligent Product Systems: Digital and Physical Twins*, in *Complex Systems Engineering: Theory and Practice*, S. Flumerfelt, et al., Editors. 2019, American Institute of Aeronautics and Astronautics. p. 175-200.

FLORIDA TECH

Computing Capability Enabling M&S and AI



2040 – 885T - 16,000x Increase

2030 – 7T - 128x Increase

Modeling and Simulation
M&S

- Increase in granularity
- Increase in fidelity
- Increase in cohesion (integration)
- Improved physics modeling

Artificial Intelligence (AI)

- On a spectrum – Expert Systems to Singularity
- Intelligence – Goal seeking while minimizing scarce resources
- Dramatically different hardware
- Human assistance (cued availability) vs. human replacement

AI Spectrum

Digital Twin vs. Intelligent Digital Twin

Digital Twin (DT)

- Passive
- Offline
- Goal given
- Predictive

Intelligent Digital Twin (IDT)

- Active
- Online
- Goal Seeking/Minimizing Resources
- Anticipatory

Grieves, M., Intelligent Digital Twins and the Development and Management of Complex Systems, Forthcoming, 2021.

Digital Twin

Virtual

Front Running Simulation (FRS)

Replication

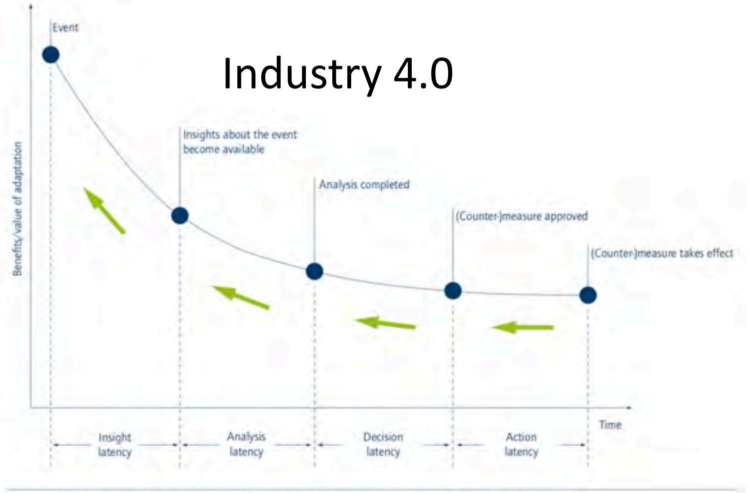


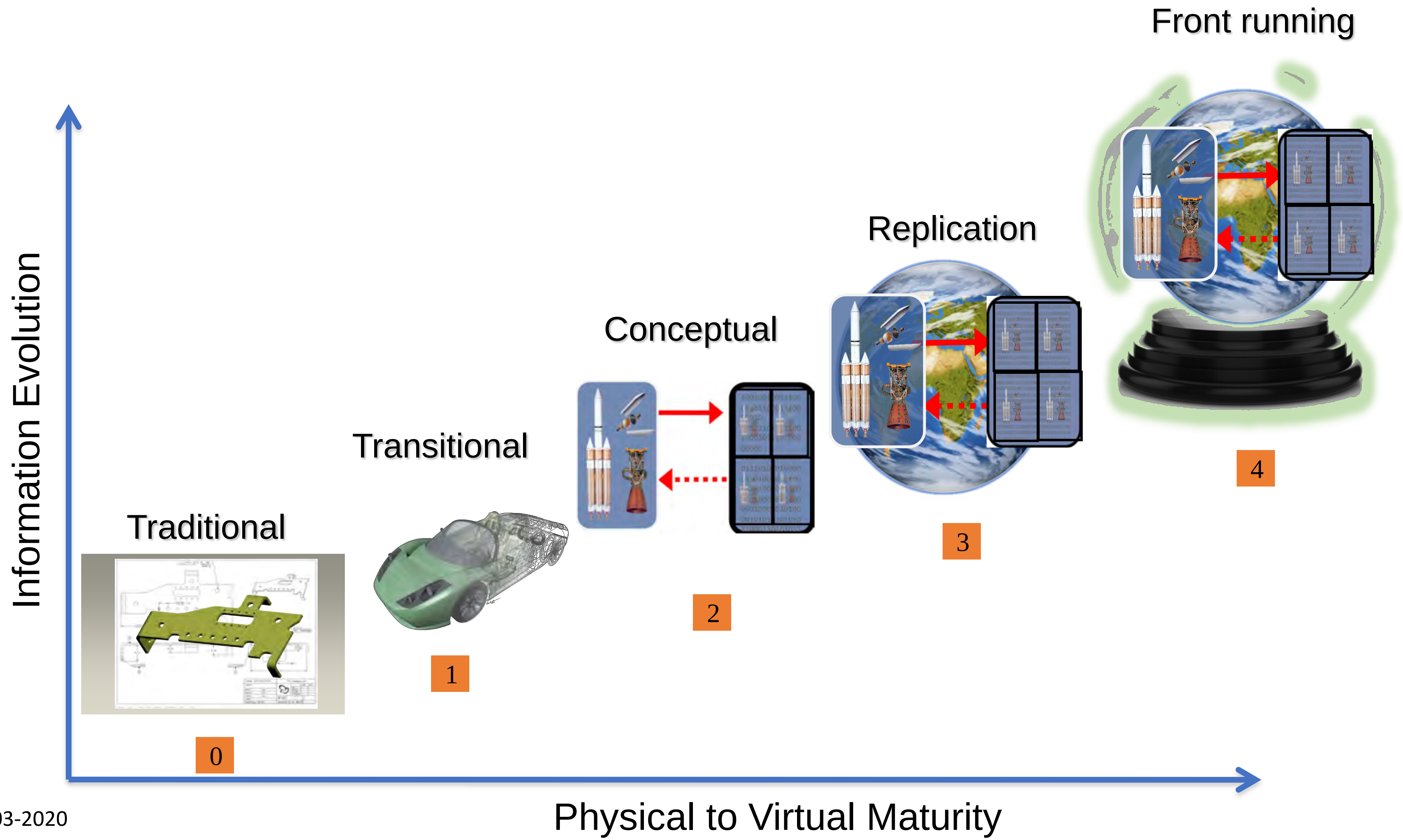
Figure 1: Corporate adaptation processes (source: based on Hackathom 2002; Muehlen/Shapiro 2010)

Physical

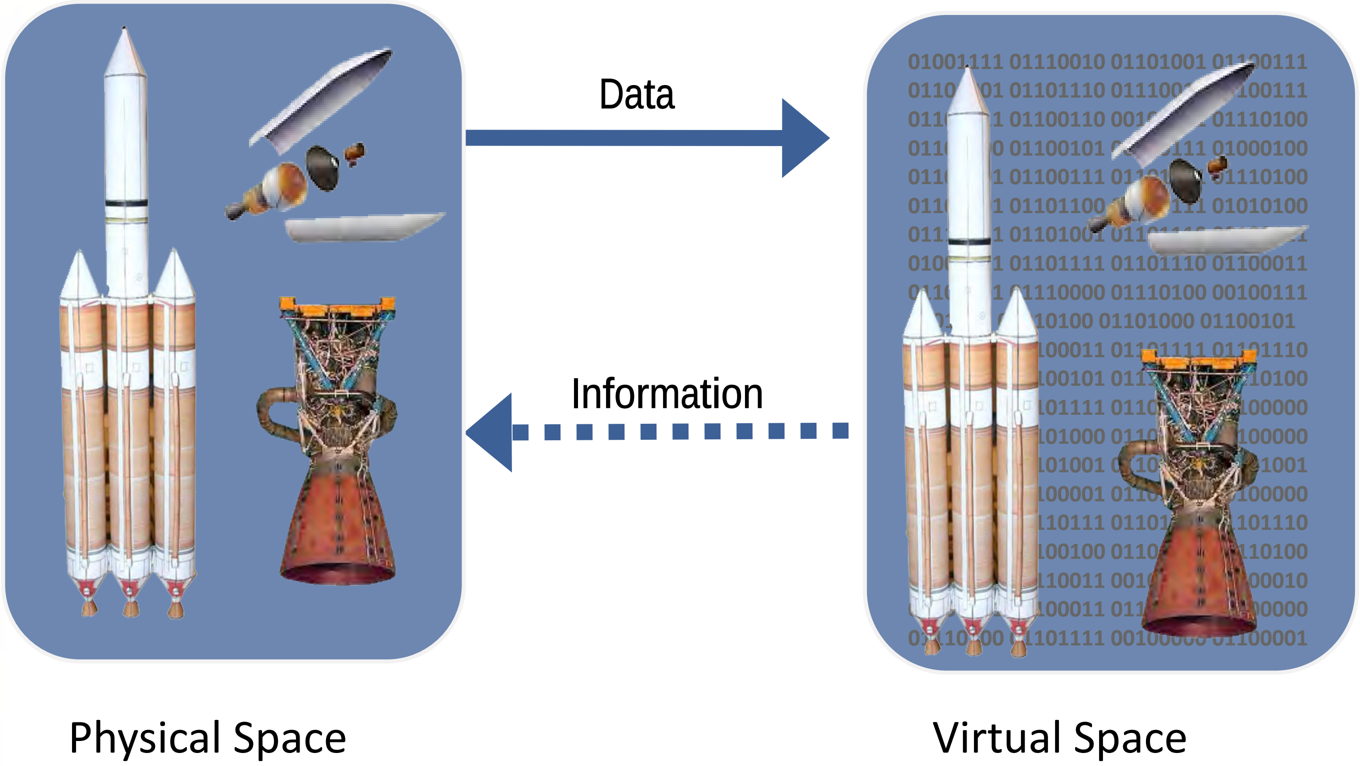
Time – t_0

Time - T_x

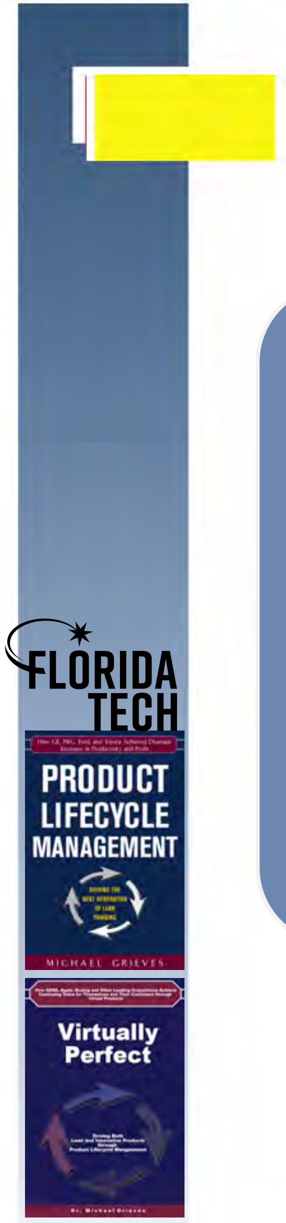
Digital Twin Evolution



Intelligent Digital Twin (IDT)
ML/AI

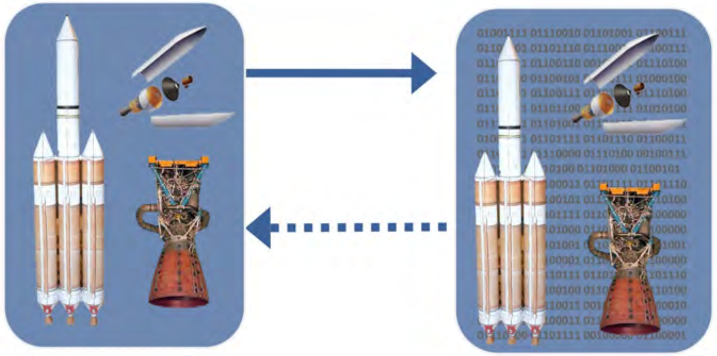


- Capture lessons learned
- Cued Availability
- Sensemaking
- FRS Multi-Scenario
- Decision Assistance /Making



Digital Twin Impediments

- Technology
  - Hardware
  - Software
  - Physics
- Risk vs. Uncertainty
- Cultural inertia



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IBM Digital Twin

December 1, 2020

–

Joe Berti
VP of Offerings Management, AI Applications

Breaking Through
To True Operational Success

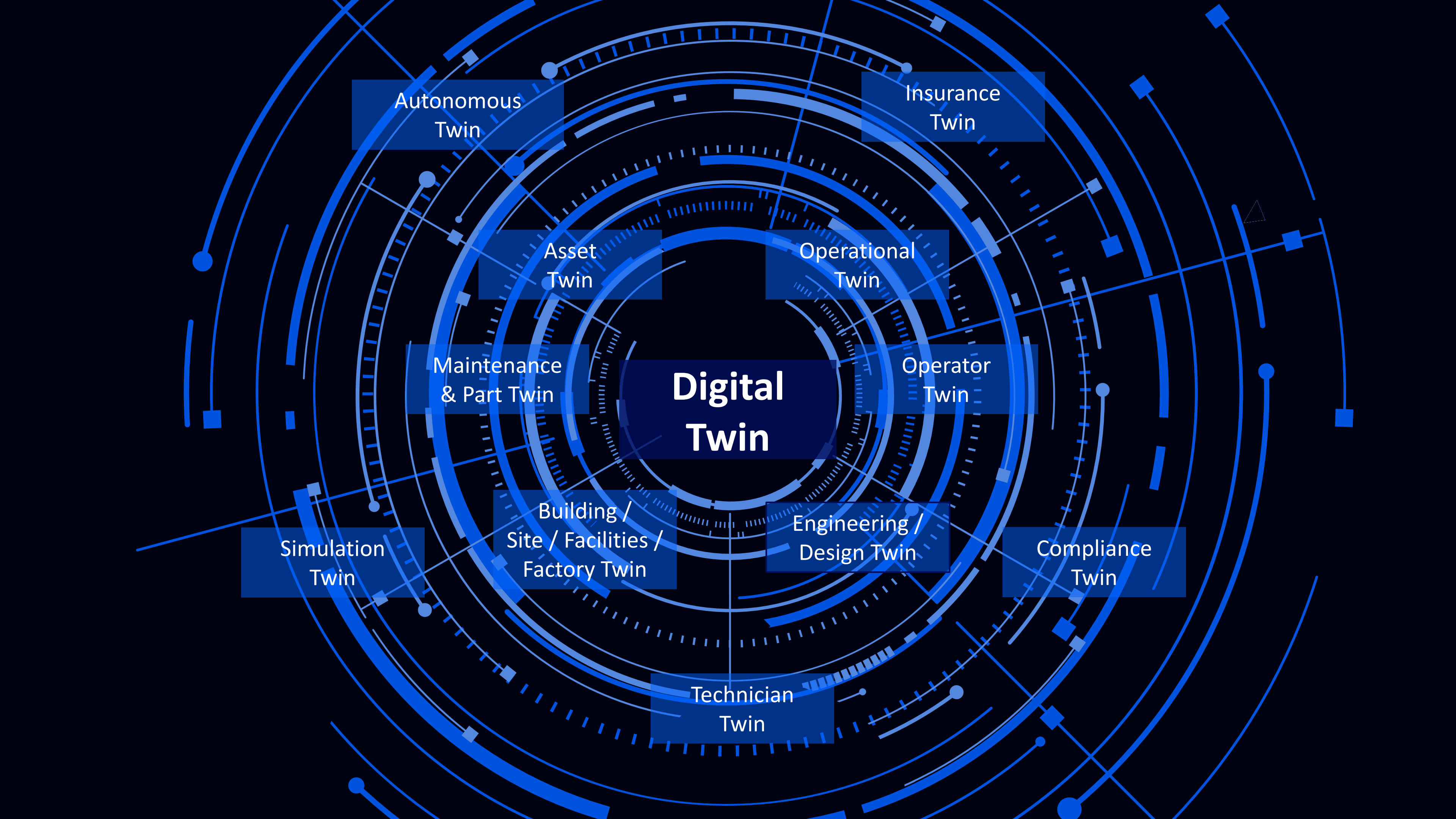
The time and need for *going digital* is more pressing as the move to AI occurs. Going digital has become a *top strategic goal* but getting there is *a daunting challenge*, especially for asset-intensive industries struggling with fundamental data and business process issues that are not designed for the digital age.

IBM digital twin immediately provides a complete digital solution for operational performance: *lack of data* and *business practices* that are *counter-productive* to going digital. IBM provides a process for *managing* digital asset content and *shortening the timeframe* to be *digitally enabled* quickly yielding *significant operational returns*.

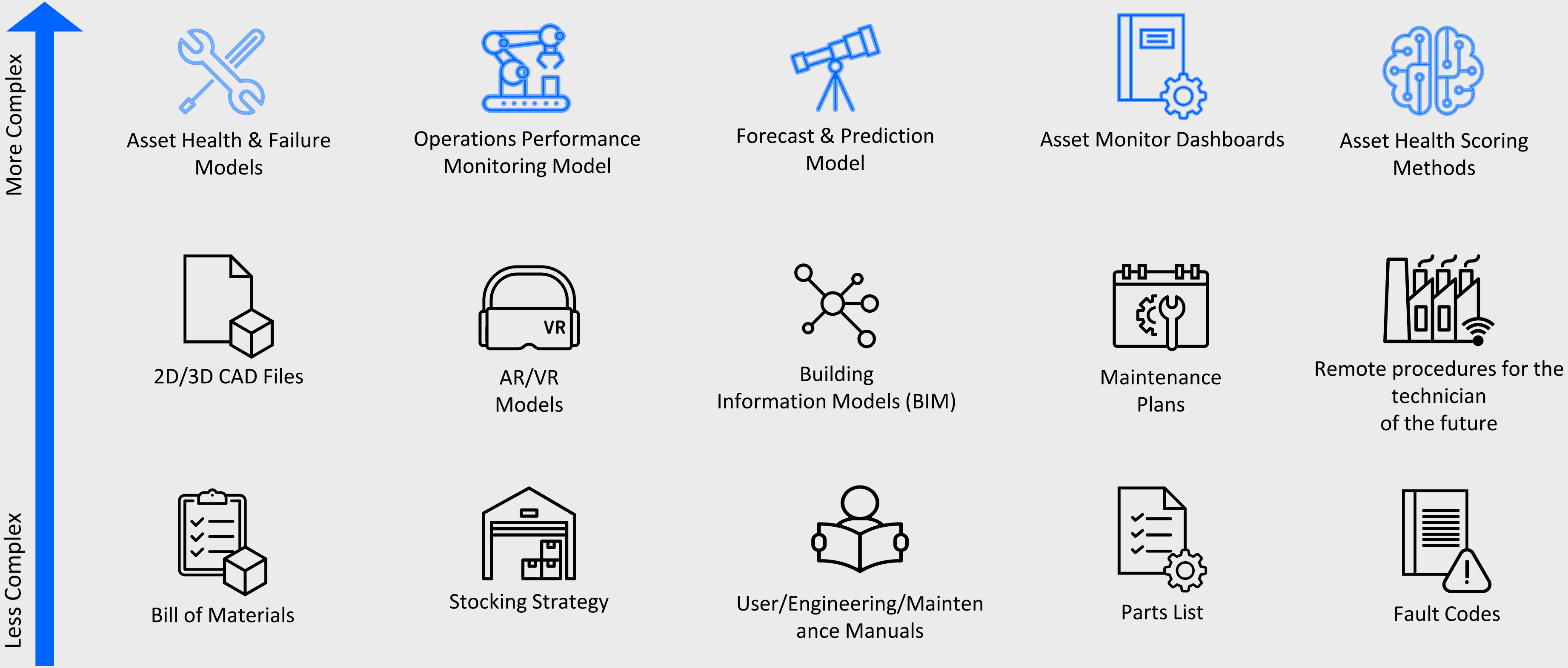
IBM digital twin strives to be a *"no brainer" investment* that is an end to end *consulting, software and digital content solution.* IBM provides a compelling alternative to the more common approaches: numerous tactical solutions and projects *scattered* across the organization. In todays business environment, boil the ocean strategies are a non starter. IBM is especially attractive for eliminating the alternative: *"throwing money and people at the problem."*

dig·i·tal twin

A digital representation of a physical thing. Combined with IoT, digital twins come alive, evolving into a living virtual model that mimics the experiences of it’s physical twin.


Autonomous Twin
Insurance Twin
Asset Twin
Operational Twin
Maintenance & Part Twin
Digital Twin
Operator Twin
Building / Site / Facilities / Factory Twin
Engineering / Design Twin
Simulation Twin
Compliance Twin
Technician Twin

Most Common Digital Twin Content



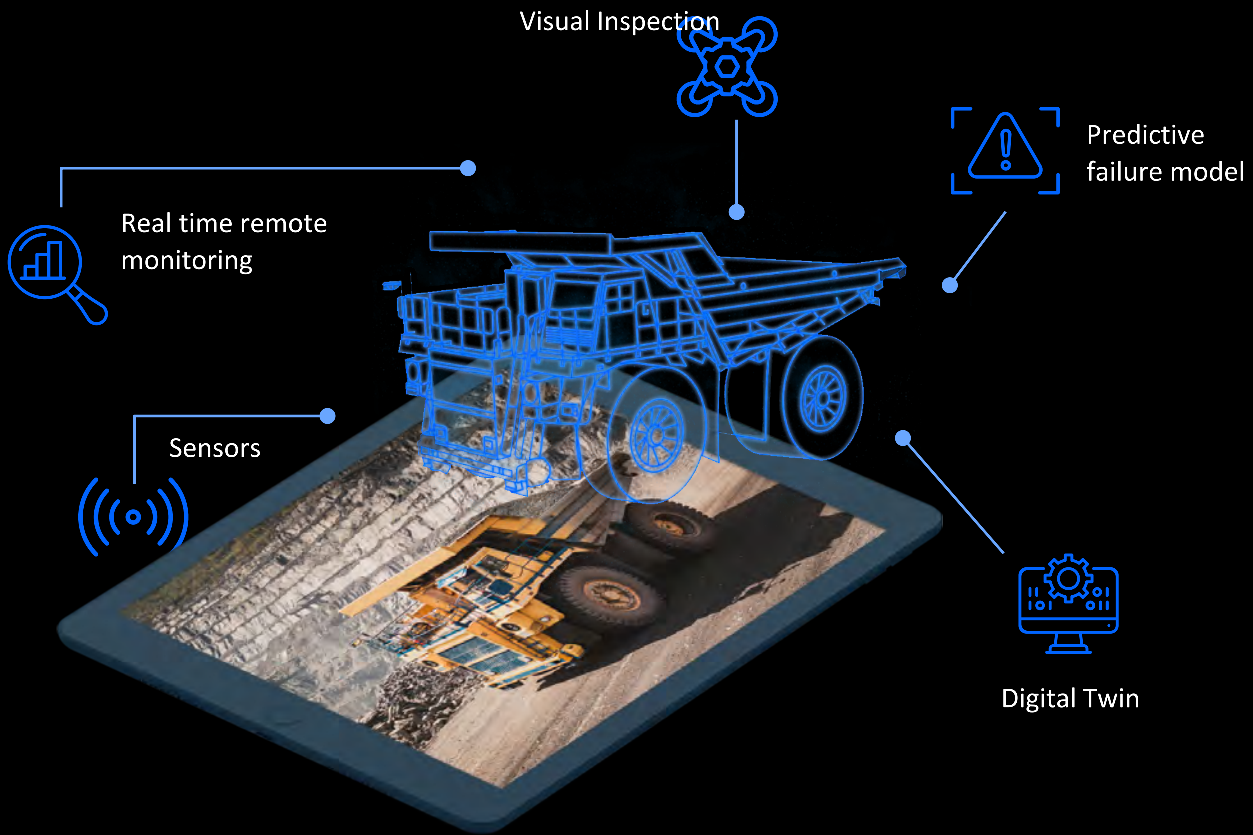
The operating model in asset intensive industries is changing

IoT is no longer a novelty

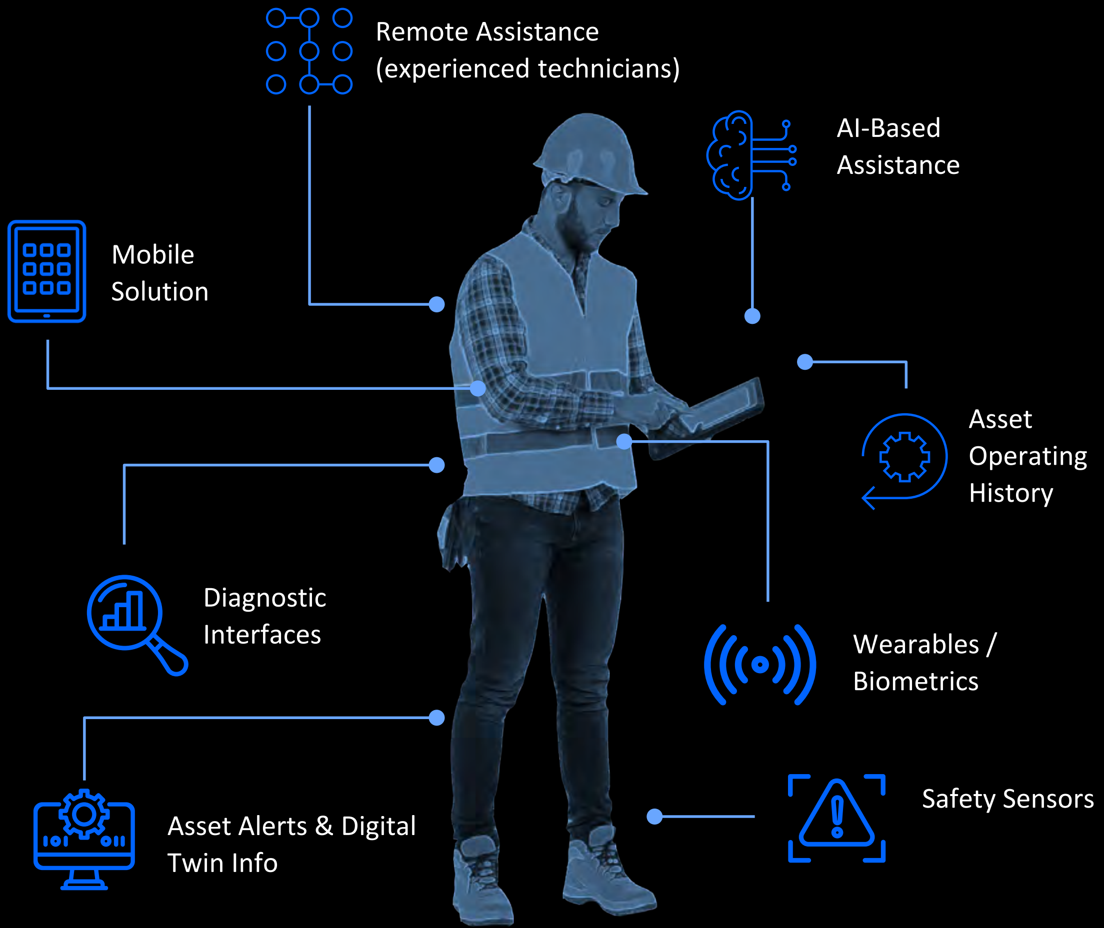
15%-50%
Reduced Operational Cost

5%-10%
Increased Up time
& Availability

Up to 15%
Increased Asset Life



The operating model change also applies to technicians



Port of Rotterdam

Information

12 hours

earlier means

134.000

tons of CO^2 reduction (4%)

Reducing waiting times can result in additional

188.000

tons of CO^2 reduction

Average household produces **4** tons of CO^2 per year

---

42 km long
12,686 ha of which 64% is land

$60M
Annual maintenance budget (USD)

#1
Netherlands has the best quality of port infrastructure in the world

Trimming **one hour** of berthing time for a single vessel results in

$80,000/ hr

70,000 sea-going ship movements (in- or out of Port) per year. One-way trip from Singapore to Rotterdam costs
$5-6M (USD) in fuel cost.
Assume average fuel cost per ship movement to be $2M (USD).

Based on this assumption a 4% fuel cost savings for ships using Port of Rotterdam results in a total

$5,6 Bn (USD)

savings per year

That is why their clients would want to choose Port of Rotterdam over their competitors.

Day in the life of… A containervessel’s captain

Departure Singapore, planned for 35 days

Full speed ahead! (but **burning fuel**)

Surprise 1: Bad **weather**!

Surprise 2: **Tides** and **traffic** so **not allowed** to berth

Angry customer

Surprise 3: **Broken bollard**, needs to be fixed first

Surprise 4: **Broken traffic sign** was not replaced, **detour** or **accident** also causing delay

Everything fixed, but tired captain returns **late, tired and having burned too much fuel** along the way.

Day in the life in… the Digital Twin 4.0

How is this different?

Environment integrated with external data sources

Autonomous behavior of Smart connected objects (or Assets)

Intelligent workflows and process optimization

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

The operating model in asset intensive industries is changing

Digital Twin 4.0
From Prototype to MVP

Based on this Digital Twin vision we just described the Port of Rotterdam resulted in a phase I prototype: Building the foundation SmartInfra IoT platform and first use case HydroMeteo.

HydroMeteo: Realtime data processing of sensor and predicted weather and water data, with anomaly detection to support harbour traffic management. With 70.000 sea-going ship movements a year and a cost of $80,000 per hour per ship, optimizing the traffic has a huge impact on Rotterdam's competitive position.

http://port-of-rotterdam.eu-gb.mybluemix.net/

How the Port of Rotterdam is using IBM digital twin technology to transform itself from the biggest to the smartest

Business problem

- The Port of Rotterdam covers an area of over 41 square miles, employs close to 400,000 people, and serves nearly 30,000 sea-going vessels each year

- Needed to operate optimally within the Global Hub and within Europe’s Industrial Cluster and become the world’s first digital port

Solution

- Sensors throughout the dock facility to continuously gather real-time data about air temperature, wind speed, (relative) humidity, turbidity and salinity of the water, water flow and levels, tides and currents, smart quay walls, and sensor-equipped buoys

Business Value Delivered

- Reduce waiting times and costs by predicting more accurately what the best time is to moor and depart

- Real-time access to information enables the Rotterdam Port Authority to better predict visibility and water conditions, lower fuel consumption rates, facilitate cost-effective per-ship payloads and ensure the safe arrival of cargo

- Shipping companies and the port may save up to one hour in berthing time, and enable more ships to pass through the port each day by using a digital dashboard for operations

The Solution: Strategic Digital Management

Initiate Escrow/Tracking → Encryption Key Passed to Trusted Participants in Escrow →

BC or Encryption Repository	**Asset / Equipment / Building / Vehicle Data**	**Change in Ownership and Purchase Costs**	**Maintenance Performed**	**Criticality & Reliability Data**	**Reported Equipment Failures**	**Warranty Claims**	**Change History**	**Operating Conditions, and History**	**Overhaul/ Decommission/ Scrap**
	Asset/Equipment/Building/ Vehicle Description Serial/Equipment/VIN number Manufacturer/Build Date Equipment Attributes Bill of Material (parts) Recommended Maintenance 3D Part Specifications	Dealer Ownership Purchased by Customer Leased Purchase Price Lease Price	Type of Maintenance Labor Hours Parts Used Performed By Date Performed	Part Criticality Usage Rates	Failure Type Part/Equipment Age Failure Impact	Claim Type Claimed By Claim Date	Configuration Change Parts Added/Removed	Operating Condition Date of Reported Condition	Date Event Type Scrap Value Sold to (Scrapper)
Solutions Involved	Digital Escrow Digitization Factory	Digital Escrow	Digital Escrow Digital Connect Maximo TRIRIGA Connected Vehicle	Digital Escrow Digital Connect MRO IO Maximo TRIRIGA	Digital Escrow Digital Connect Maximo TRIRIGA	Digital Escrow Digital Connect	Digital Escrow Digital Connect Continuous Engineering	Digital Escrow Digital Connect	Digital Escrow Digital Connect
Parties Involved (sample)	Manufacturer Dealer Equipment Reseller Construction company	Manufacturer Dealer Equipment Reseller Construction company	Equipment Owner Dealer 3rd Party Maintainer Property manager	Equipment Owner 3rd Party Operator Manufacturer Dealer	Equipment Owner 3rd Party Maintainer Dealer Service/Repair	Manufacturer Dealer	Equipment Owner 3rd Party Maintainer Dealer Service/Repair Property manager	Equipment Owner 3rd Party Operator Sensor Data	Equipment Owner Dealer Reseller Third parties

ORNL Resources to Support Digital Twin Applications for Nuclear Systems

Nuclear Energy and Fuel Cycle Division

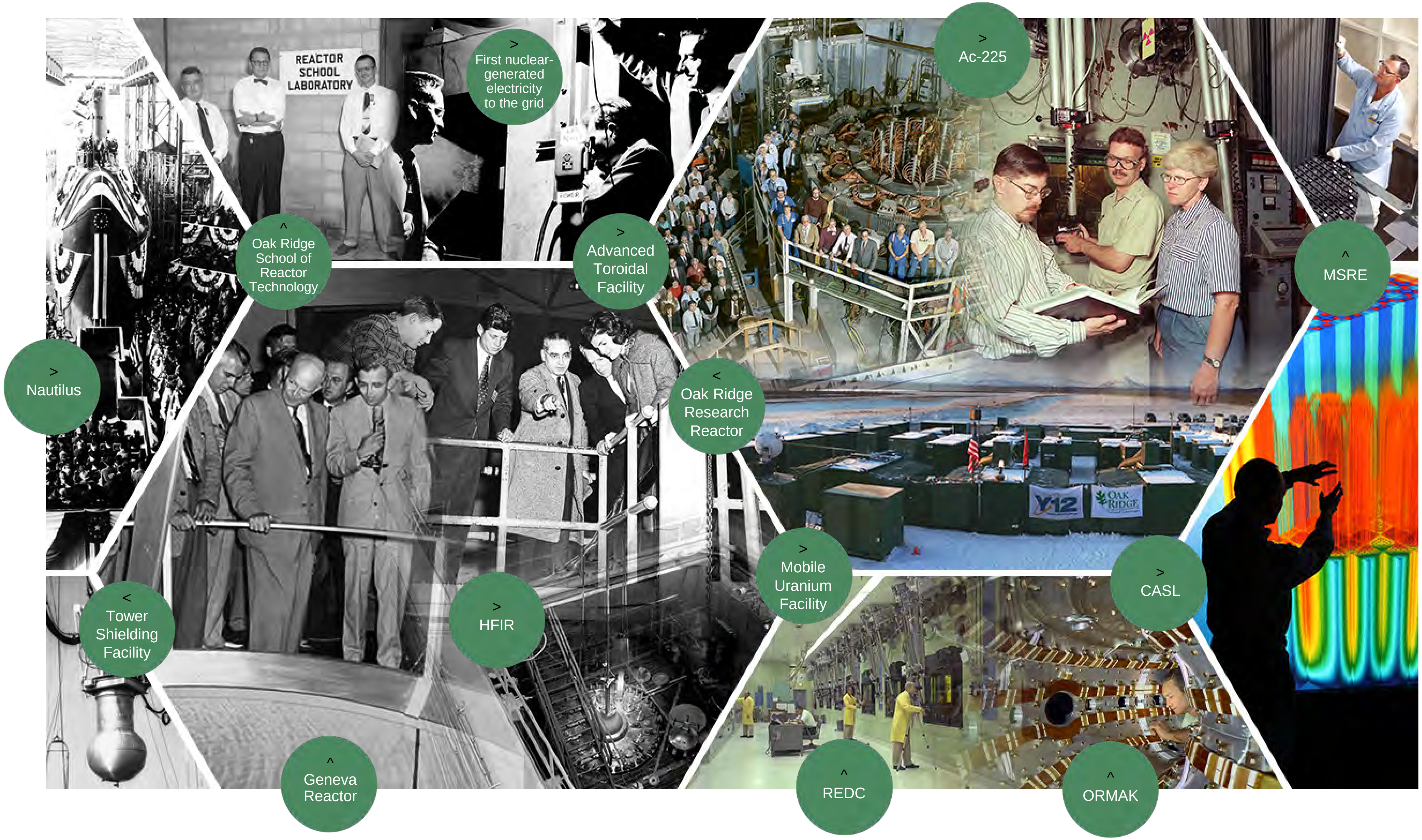
Jeremy Busby and Prashant Jain

December 1, 2020

The historic beginnings of ORNL

The Graphite Reactor: A solid foundation and true legacy

Expanding nuclear impact through the decades



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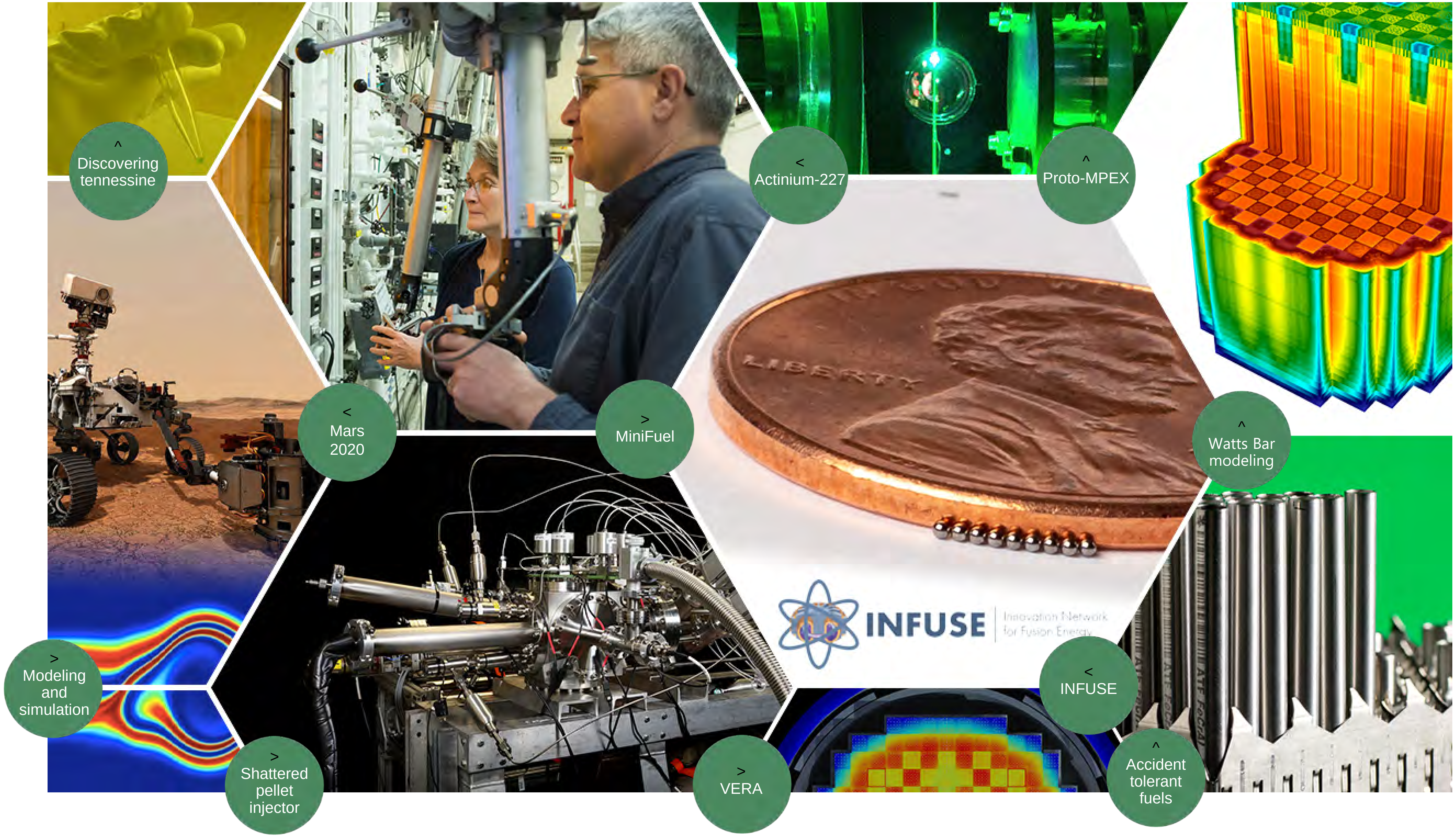
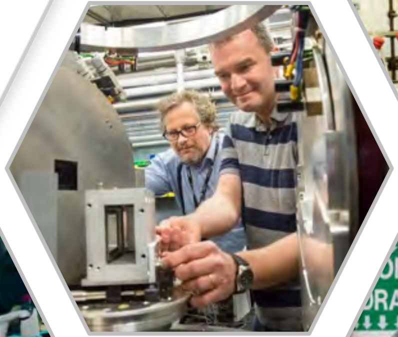
Today's innovation in nuclear science and technology



Our vision for ORNL: World's premier research institution

Focus on the most difficult problems

Conduct world-leading research

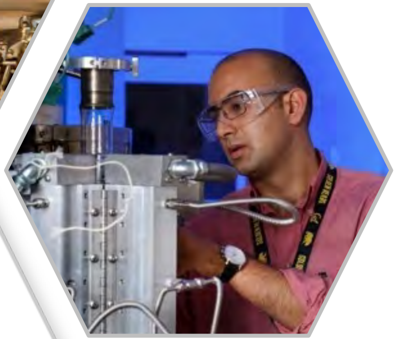


Ensure the nation's energy future

Relentlessly pursue institutional effectiveness

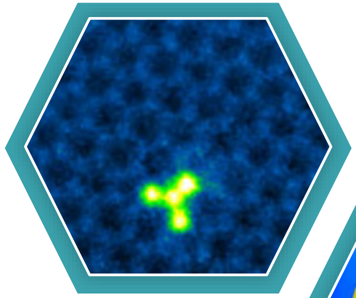
Deliver innovative break-throughs

Strengthen national security



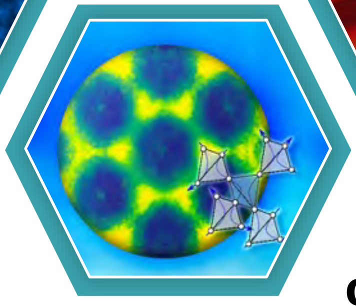
OAK RIDGE National Laboratory

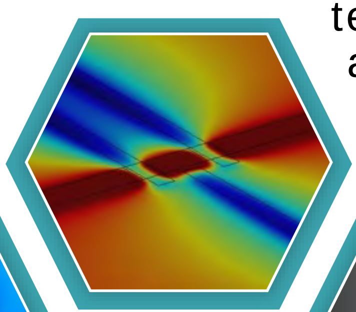
ORNL’s major science and technology initiatives



Discover and design next-generation **materials and chemical processes** for energy

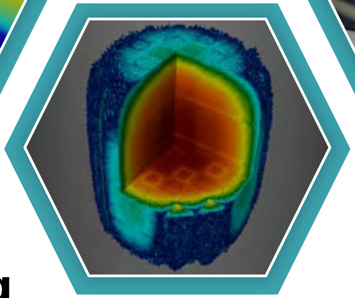
Advance the impact and application of **neutron science**





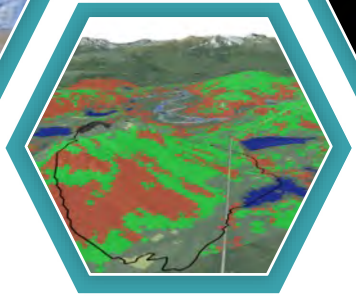
Scale **computing and data analytics** to exascale and beyond for energy

Achieve breakthroughs in **nuclear** science, technologies, and systems



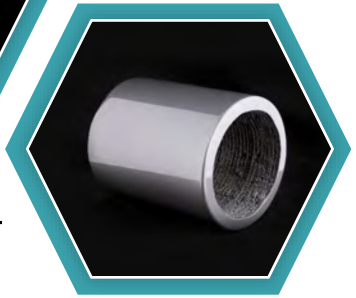
Provide strategic capabilities in **isotope R&D and production**

Understand complexity in **biological and environmental systems**



Deliver S&T to address pressing **national security** challenges

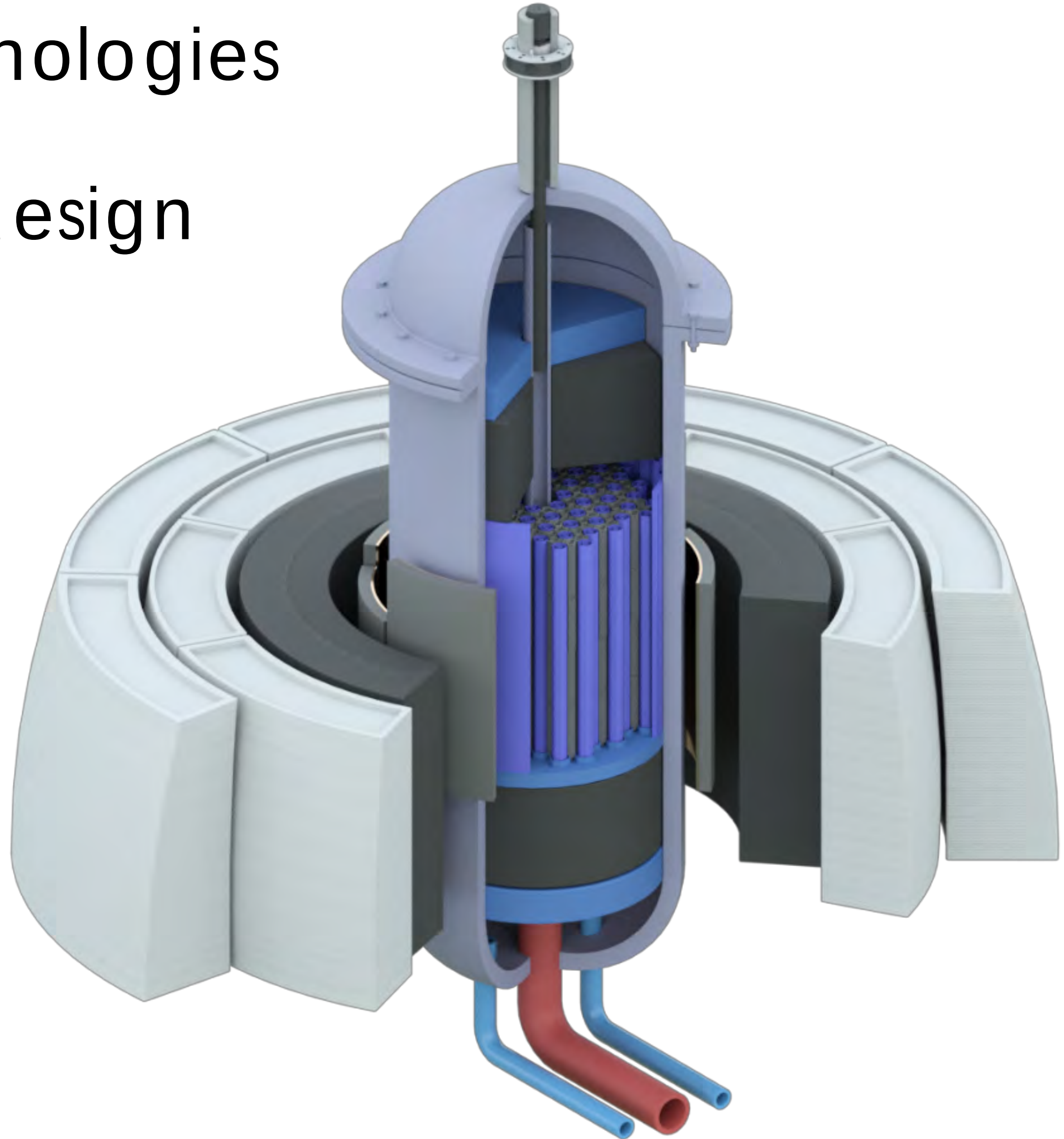
Deliver transformational R&D on integrated **energy systems**



The Transformational Challenge Reactor (TCR) Program

Demonstrating a new approach to design and deployment

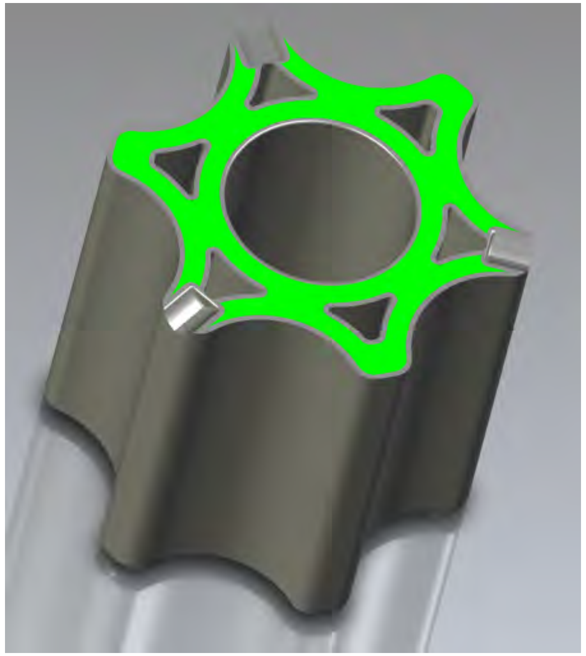
- Apply additive manufacturing technologies that enable rapid prototyping and geometric control to nuclear core design
  - Core *design* is driven by *manufacturing*
  - *Demonstration* with reactor deployment and successful operation is centric to showing the value of this approach



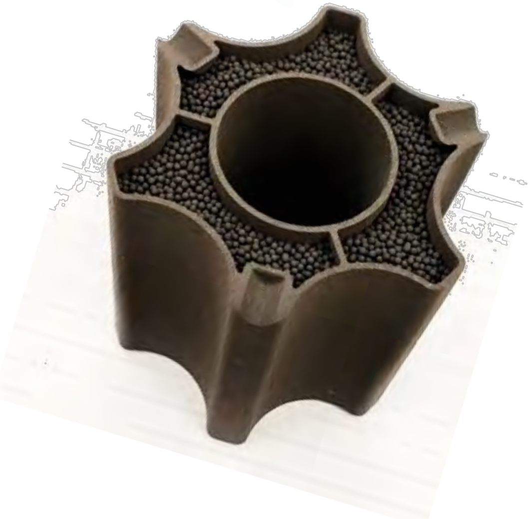
https://tcr.ornl.gov/

TCR is harnessing advances in manufacturing, materials, and computational sciences to enable advanced reactors

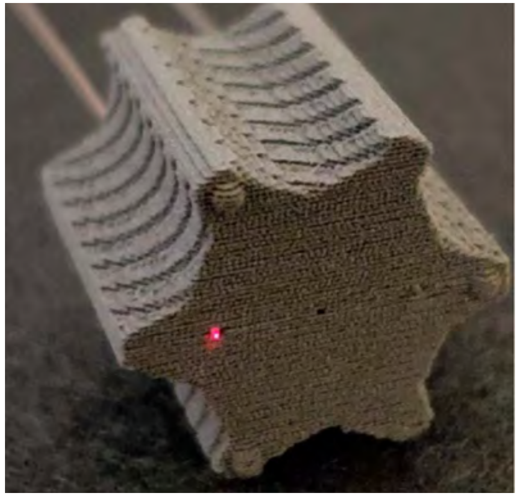
Design for advanced manufacturing



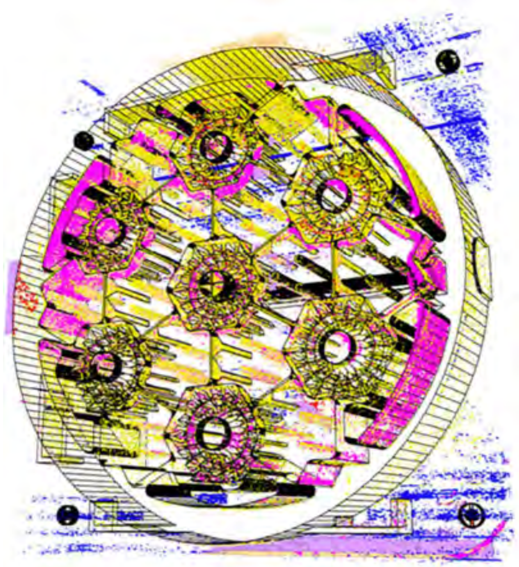
Advanced high-performance Materials



Distributed sensing towards autonomy



On the fly certification of critical components



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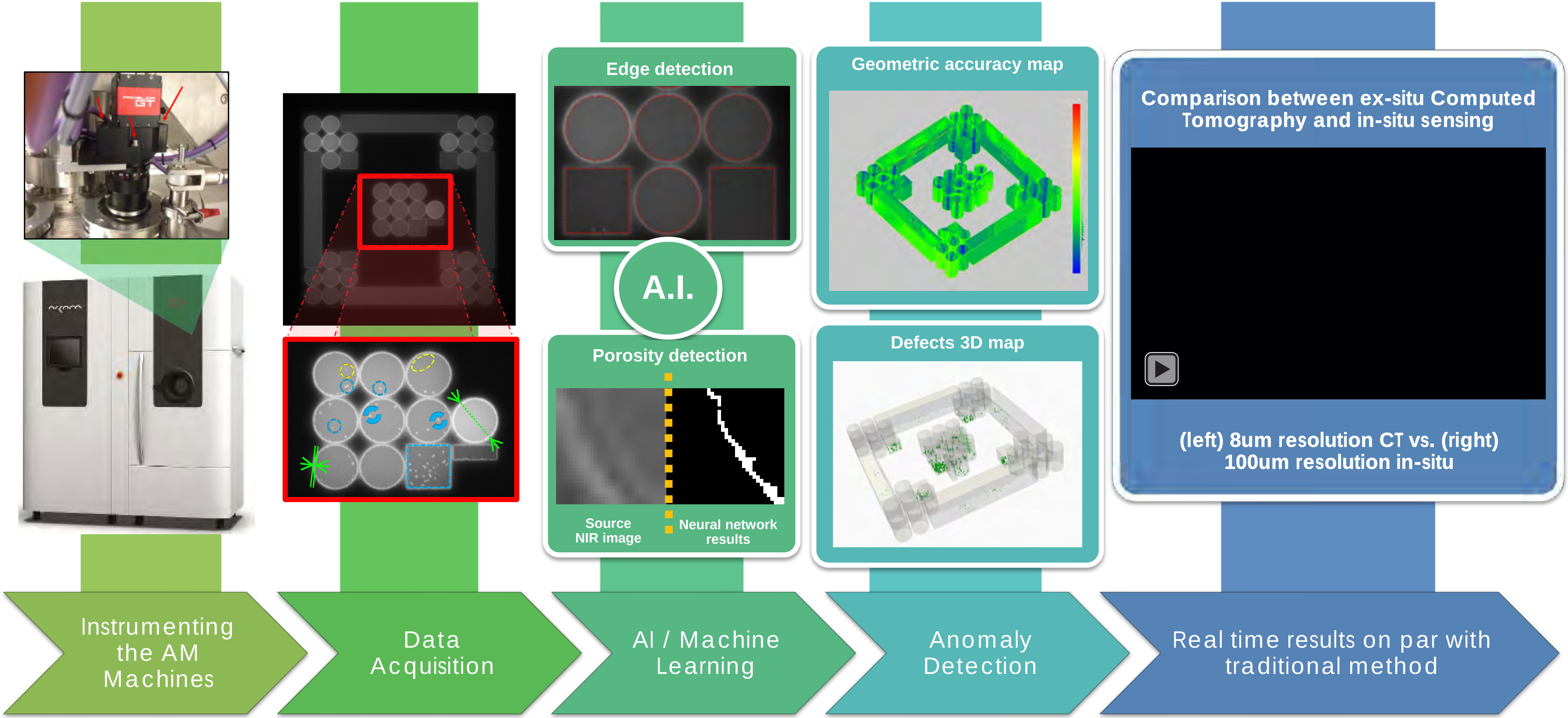
TCR Developed "In-Situ" Quality Control of AM Processes using AI



Developing Digital Twins for Nuclear Can Build On Expertise in many areas

- ORNL has spent decades working in a number of key areas for nuclear applications
  - Fission energy systems to sustain the existing fleet and accelerate deployment of advanced reactors;
  - Fusion energy systems to improve understanding of plasma physics and accelerate facility design and safety assessment;
  - Isotopes and neutron sciences to accelerate design and improve efficiencies; and
  - Nuclear security solutions to support detection of proliferation support application of safeguards, and determine provenance of nuclear threats.

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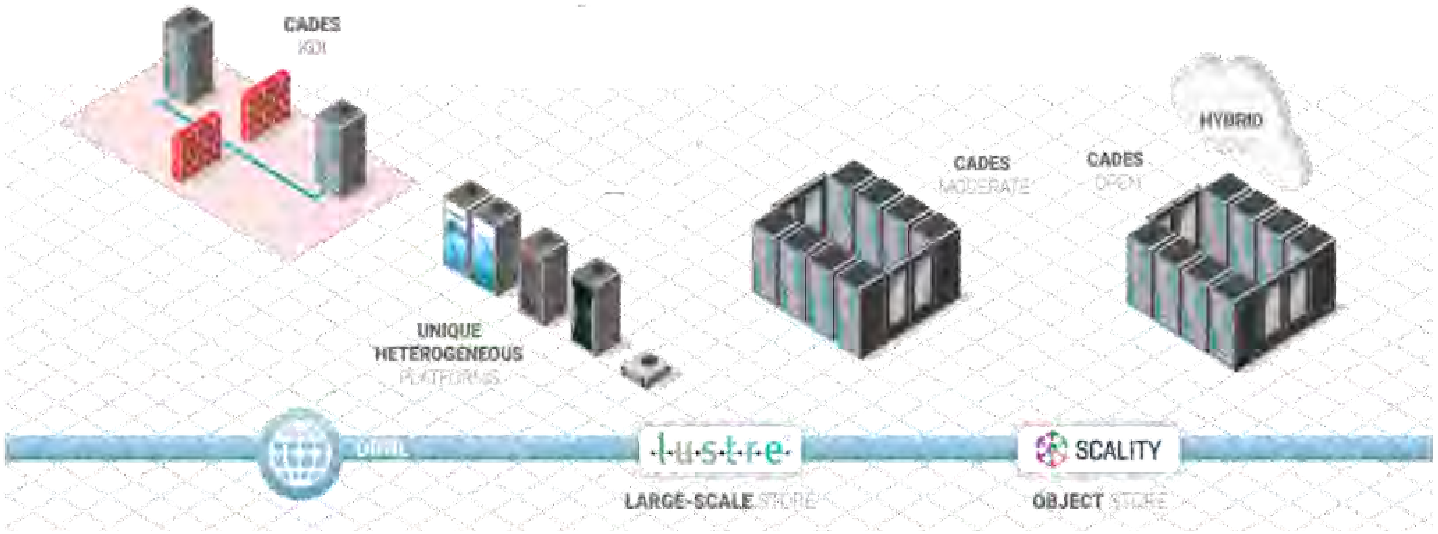
Computing Resources

- Commodity clusters for production calculations
- Secure cloud computing
- Compute and Data Environment for Science (CADES)



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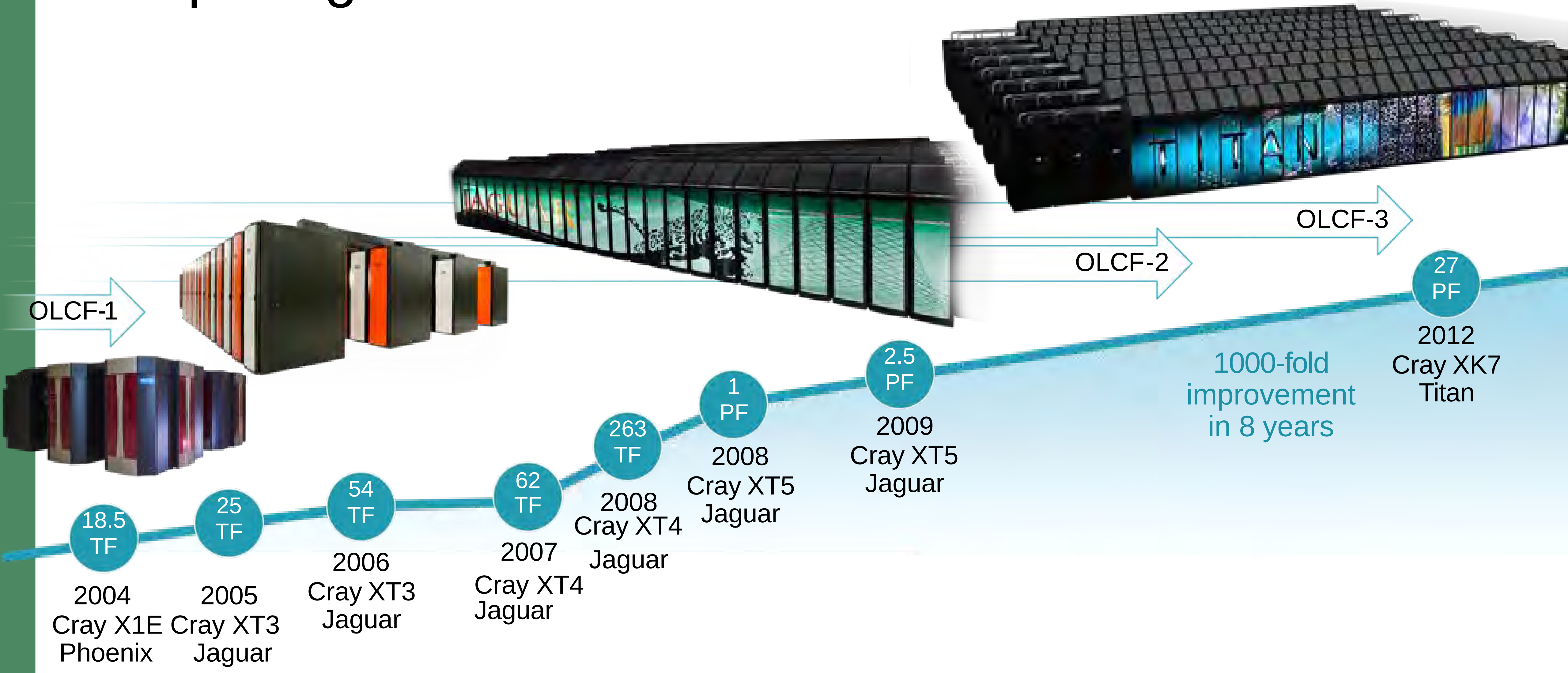
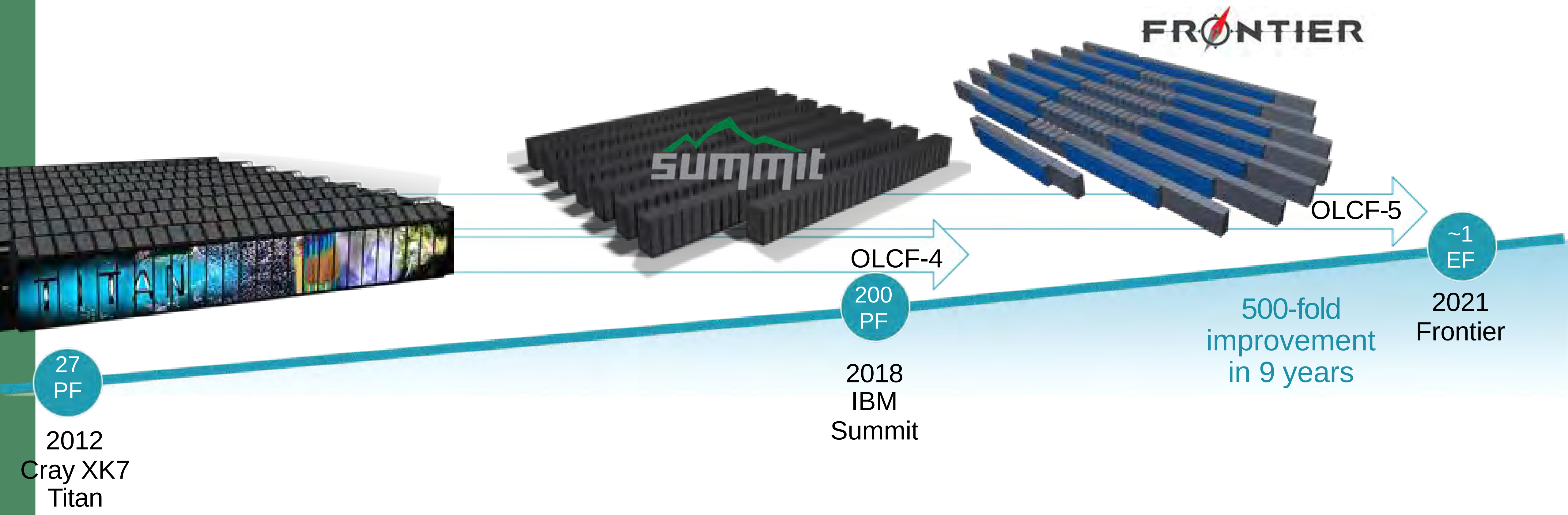
ORNL has been pushing the limits for leadership computing



We are building on this record of success to enable exascale in 2021



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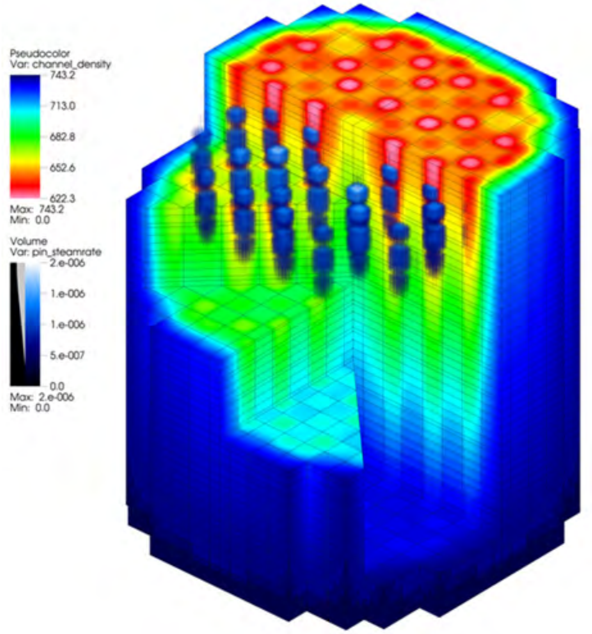
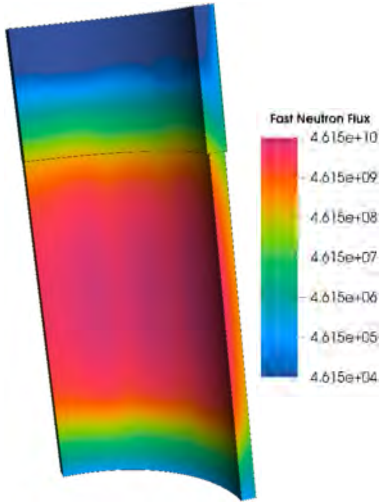
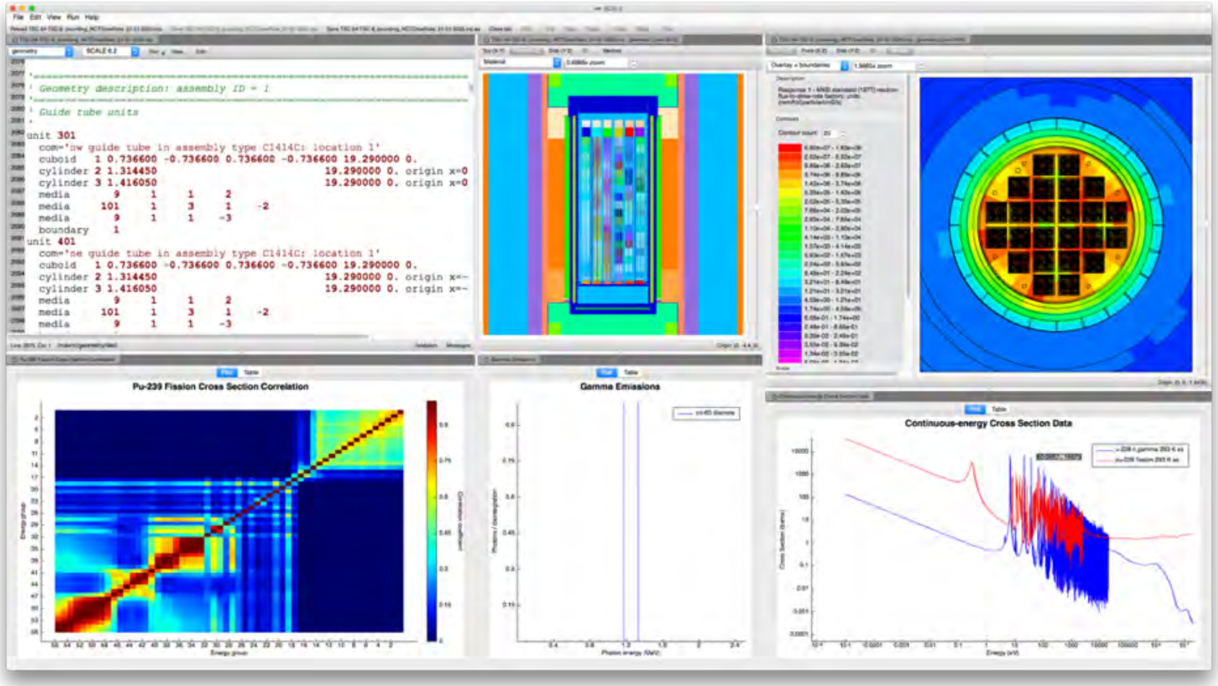
Production Tools

Tools distributed under license from RSICC

- SCALE Code System
- CASL VERA
- CTF
- ADVANTG
- AMPX
- SAMMY
- RPS-DET





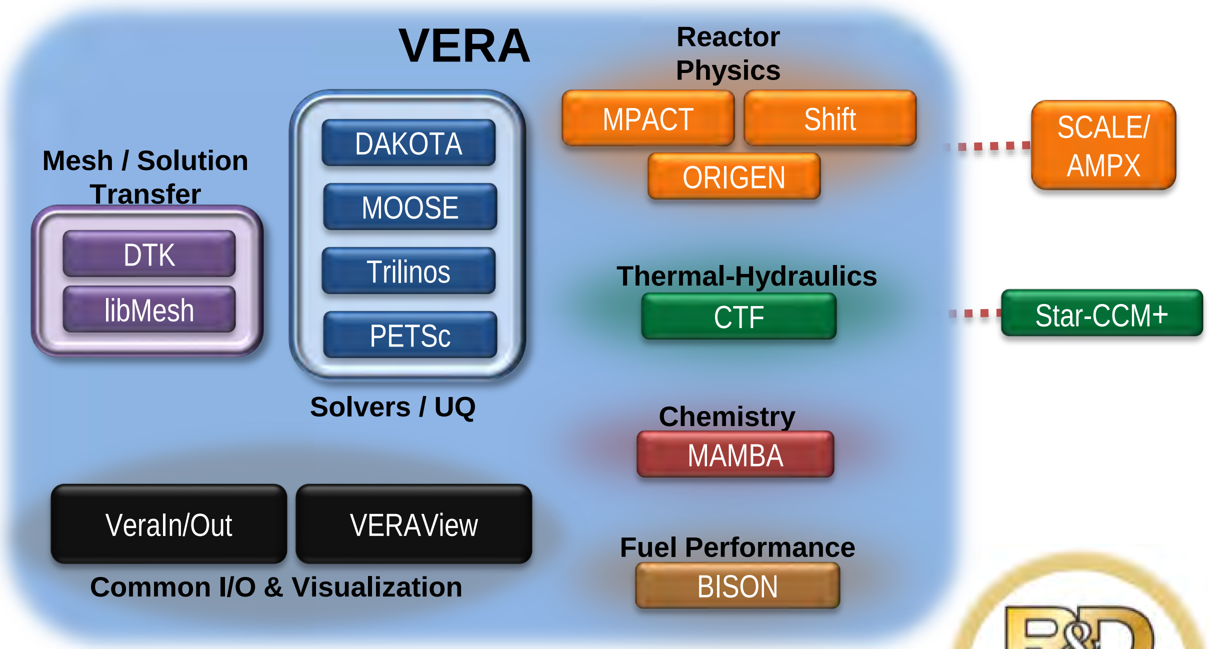


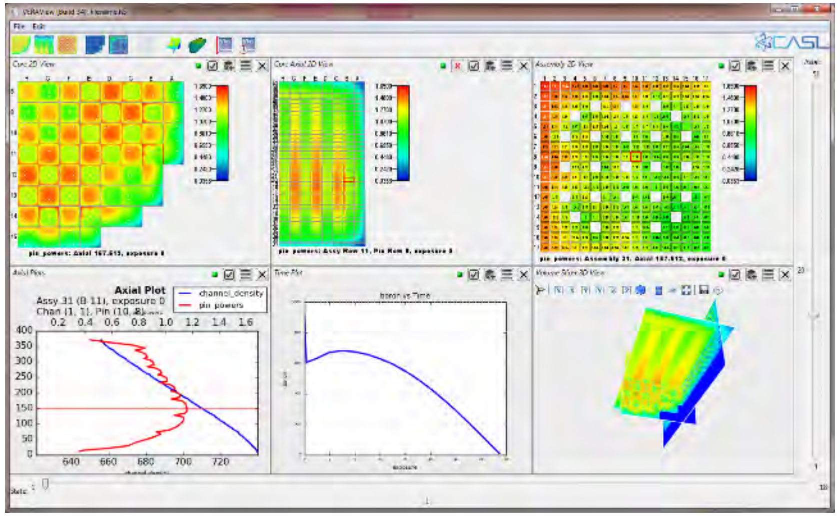
CASL VERA – End User Product

Virtual Environment for Reactor Applications

https://www.casl.gov/

- **High Resolution:**
  - Fully coupled and pin-resolved neutronic, T/H, and crud growth physics
  - Detailed rod-wise fuel performance analyses
- **Integrated Applications:**
  - Modeling in-core and ex-core detector prediction of axial offset anomaly(AOA) due to CRUD deposition
  - Identification of Pellet Clad Interaction (PCI) failure risk during load follow operation with Accident Tolerant Fuels
  - Accumulation of vessel fluence damage over the reactor operating history
  - Prediction of cladding integrity during reactivity-initiated transients
- **Performance & Usability:**
  - User-friendly I/O (e.g. automated mesh generation and data transfers)
  - Integrated visualization tools



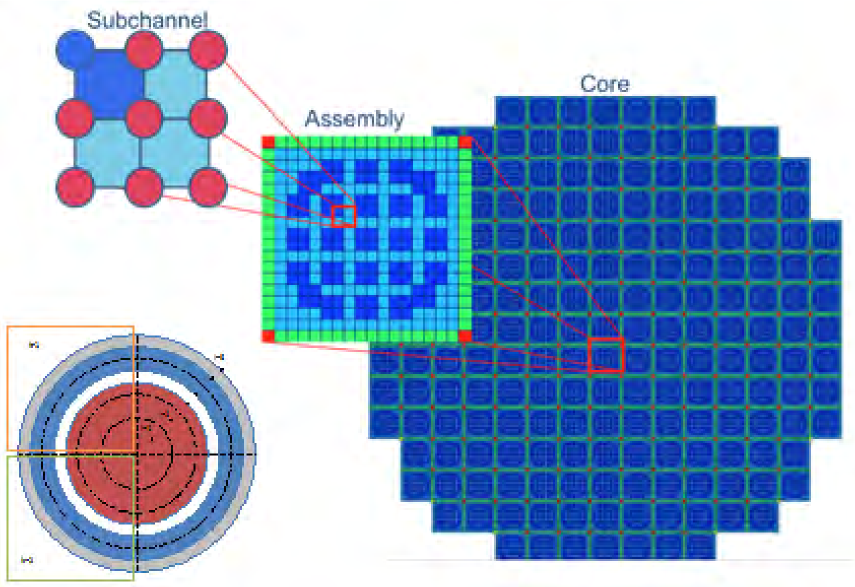


VeraView

CTF: Whole-Core Thermal Hydraulics Subchannel Code

- Two-fluid, three-field representation of the two-phase flow
  - Continuous vapor (mass, momentum and energy)
  - Continuous liquid (mass, momentum and energy)
  - Entrained liquid drops (mass and momentum)
  - Non-condensable gas mixture (mass)
- Cross flow between channels, Spacer grid models
- Internal pin conduction with dynamic gap model
- Parallel Solution = ~5 secs per solve

https://www.ornl.gov/onramp/ctf



CTF enables in-line T/H analyses and direct local feedback to neutronics

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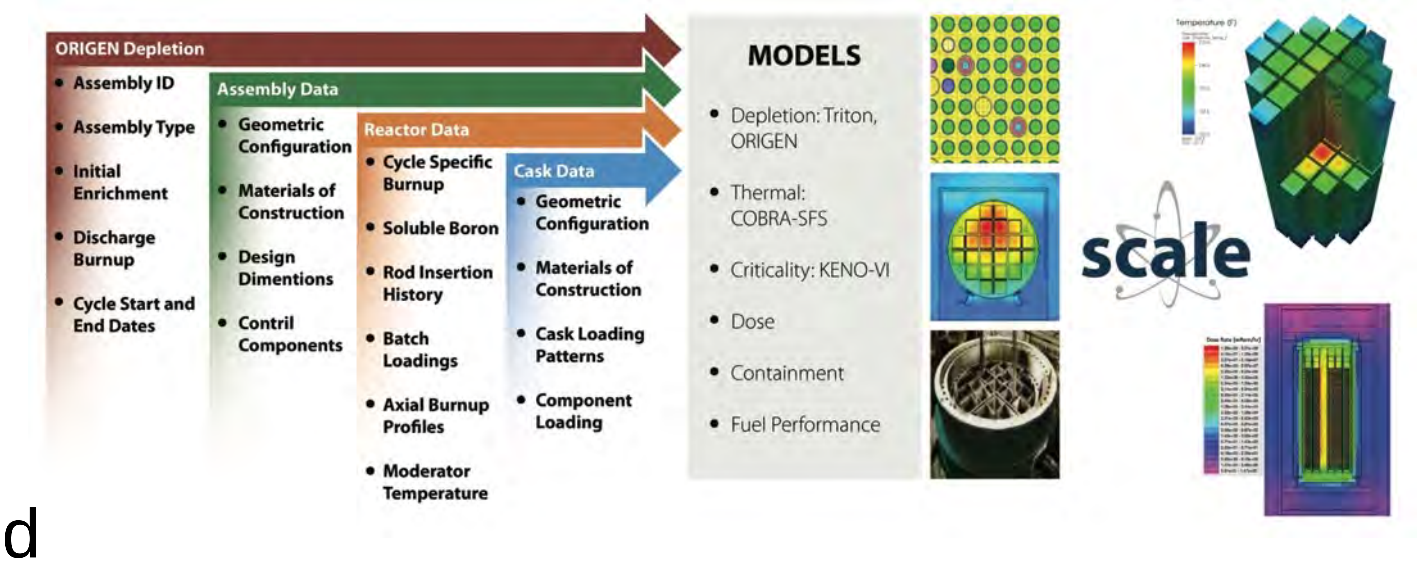
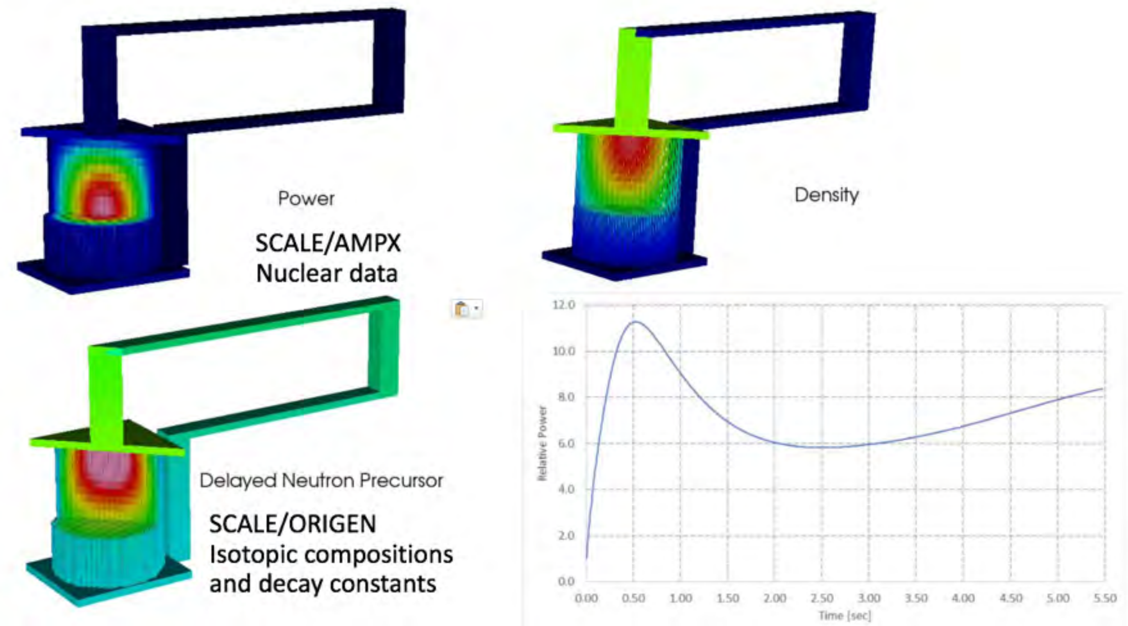
Custom-Developed Tools and Data

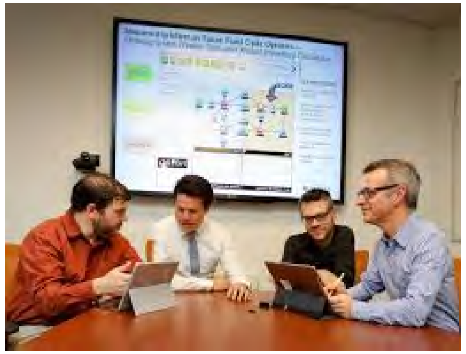
- UNF-ST&DARDS
- NEAMS Workbench
- TRANSFORM
- SCALE and VERA Enhancements for Advanced Nuclear Energy Systems
- Fusion Plasma Physics
- Nuclear Security
- Exascale Computing Project
- Software Development and Testing Environment

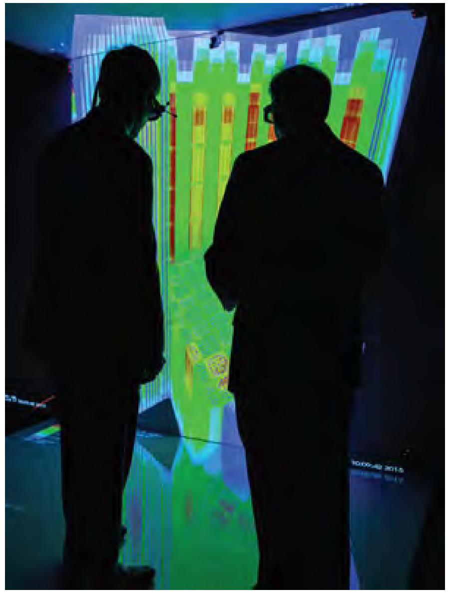


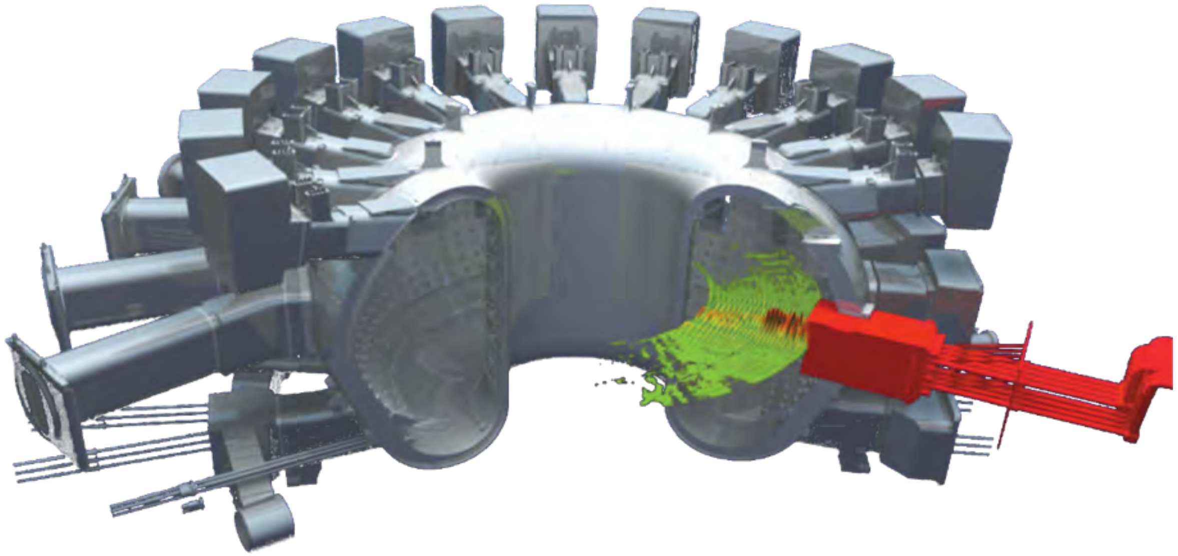


Analysis Expertise

- Nuclear data
- Radiation shielding and criticality safety
- Reactor neutronics
- Thermal hydraulics
- Nuclear materials
- Thermomechanics and fuels
- Reactor core analysis
- Accident analysis
- Fusion plasma physics
- Nuclear safeguards and security
- Fuel cycle analysis
- High-performance computing



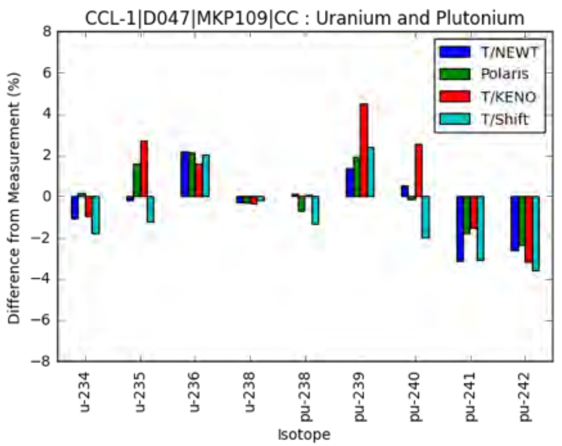


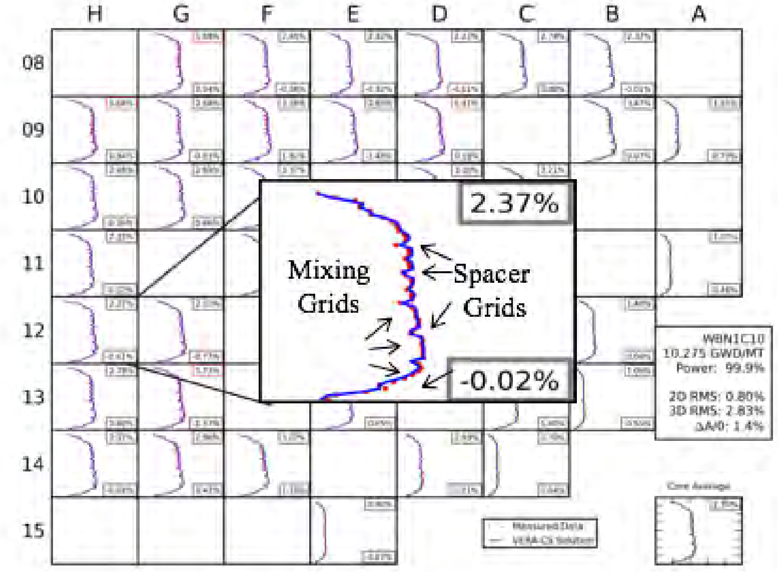


Validation

- *Validation* is the characterization of the suitability of a selected mathematical model and data to correctly predict and describe real-world physical phenomena. This places validation at the intersection of modeling, simulation, and experimental methods.

- ORNL has broad validation experience, including the collection and qualification of experimental validation data, leadership in international benchmark handbooks, development of problem-specific validation criteria, as well as comparison and visualization of large data sets.



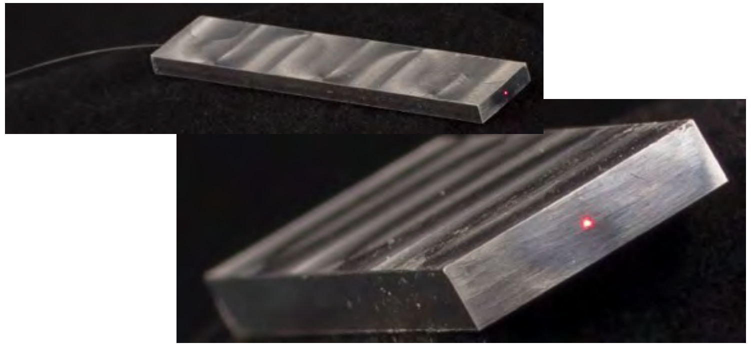


Experiment Design and Operation

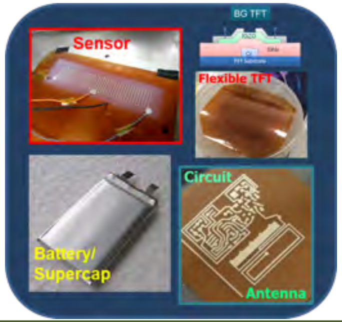
- Irradiation experiments
- Thermal hydraulics experiments
- Nuclear data measurements
- Nuclear criticality experiments
- Fusion experimental capabilities

Instrumentation and Control: Capabilities

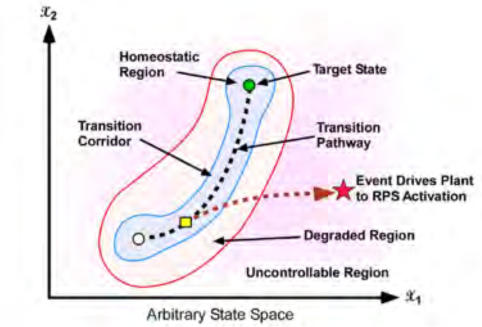
Measurements and Sensors



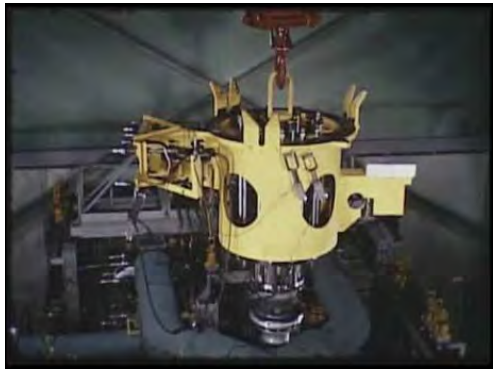
High Temperature Compatible and Embedded Sensors for Nuclear Process and Component Health Monitoring



Advanced Controls

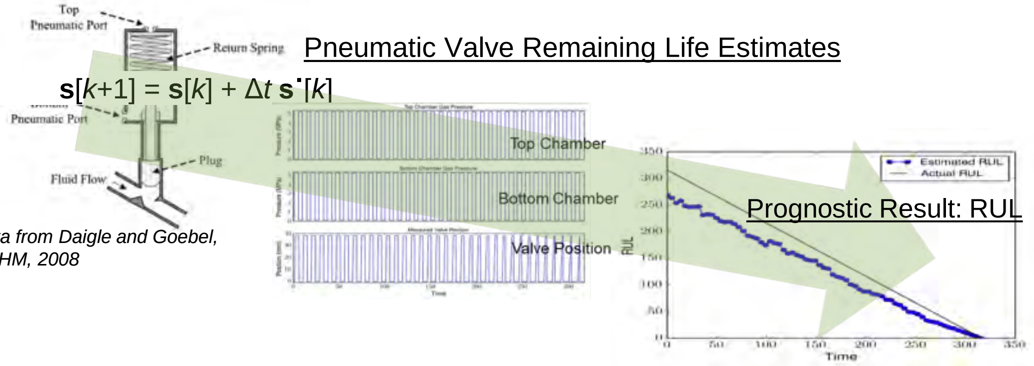


Autonomous Reactor Control and Operations Concept



Remote Maintenance

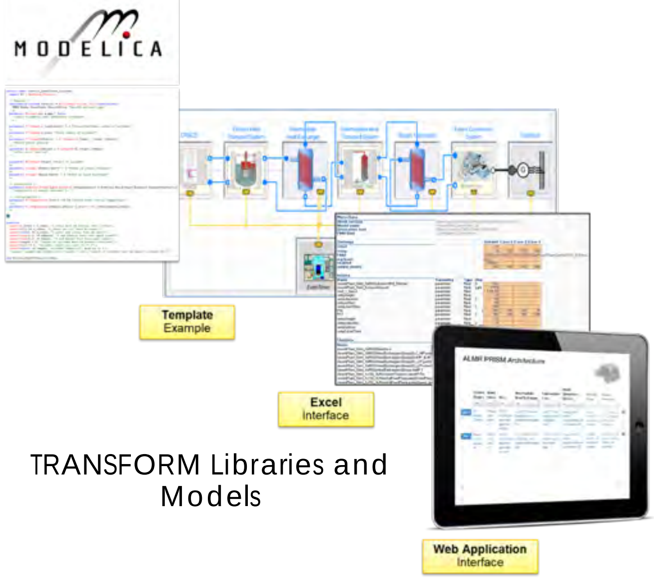
Data Analytics and Computing



Data from Daigle and Goebel, IJPHM, 2008

Predictive Health Management and Maintenance: Online Monitoring, Diagnostics and Prognostics

Models and Testbeds

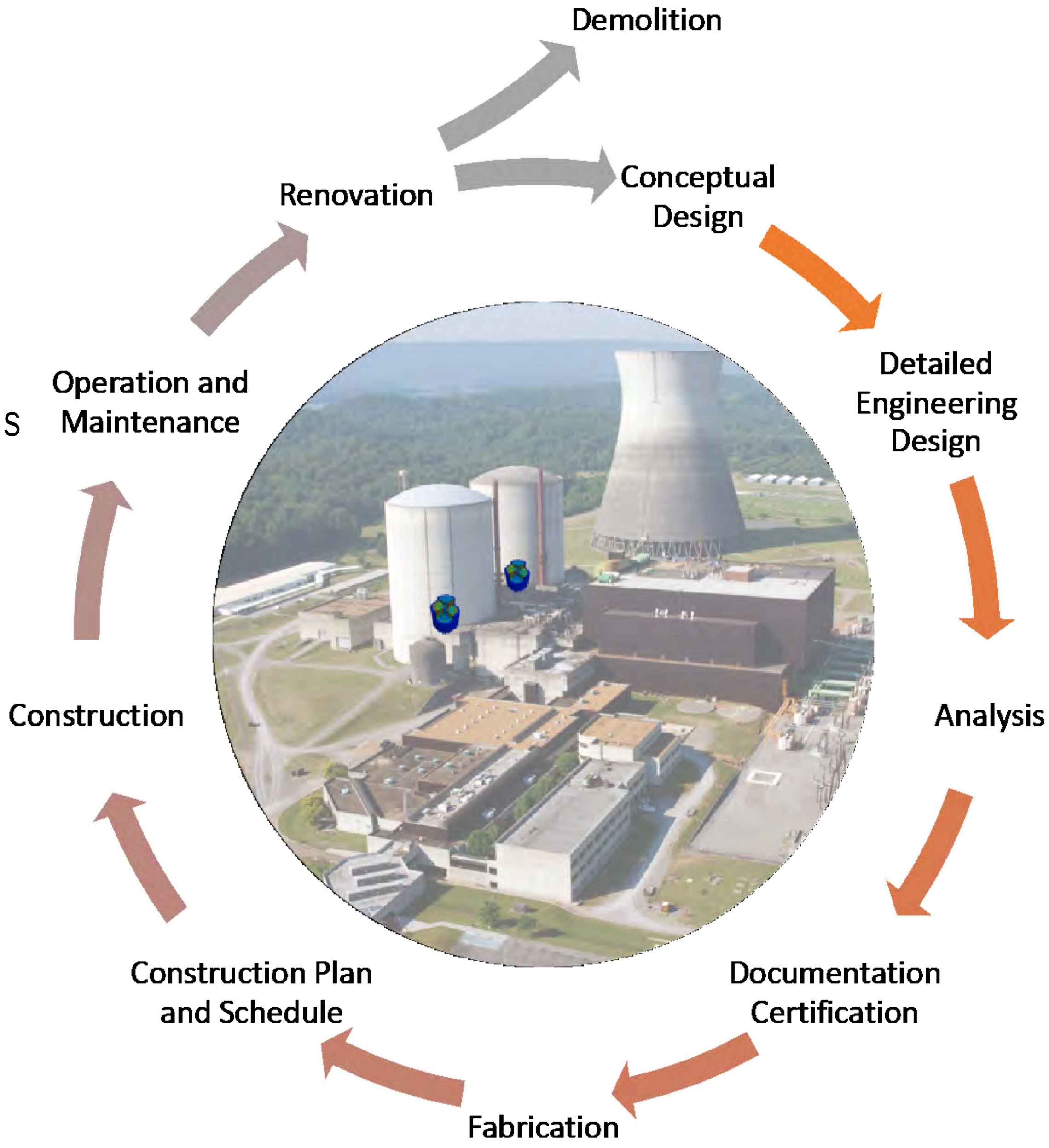


TRANSFORM Libraries and Models

Molten Salt Flow Calibration Facility (Under Development)

Diverse ORNL Technologies Can Enable Advanced Reactor Deployment

- High fidelity core simulations enabling powerful digital twins
- Model based system engineering approach to plant design
- Consideration of integrated energy system
- Siting database integration
- Optimization of operation and maintenance cycles
- Wholistic consideration of safety and security
- Building information model approach to construction cycle optimization
- Testing to grow confidence in advanced component performance
- New understanding of fundamental materials
- Deployment of new sensors and measurement methods
- AI enabled autonomous control
- Licensing



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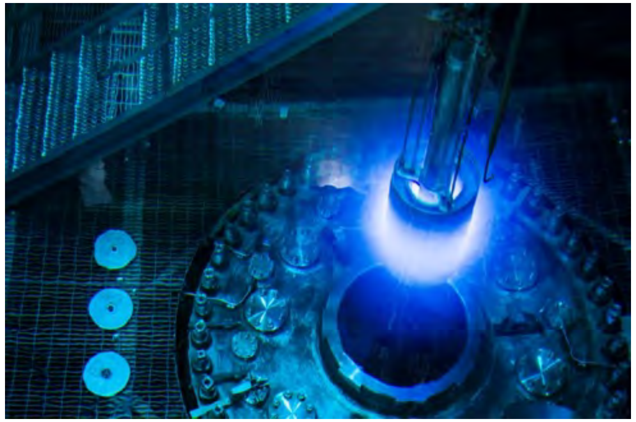
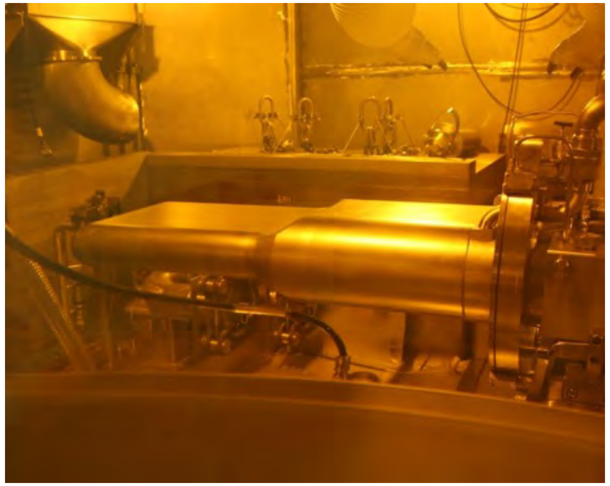
Facility Operation Support

- Safe, reliable operation of a nuclear facility requires facility-specific modeling and analysis tools and expertise.
- Nuclear modeling and analysis tools are used for many facility needs, including but not limited to establishing, maintaining, and implementing the safety basis; redesigning components; designing, optimizing, and qualifying experiments; and upgrading instruments.

HFIR



SNS
SPALLATION NEUTRON SOURCE



OAK RIDGE
National Laboratory

ORNL's High Flux Isotope Reactor can Provide a Test Bed to Mature Digital Twin Technology

- Located at Oak Ridge National Laboratory
- Achieved criticality / full power in 1965 / 1966
  - Has decades of remaining life
- Supports several high-impact scientific missions
  - World class capabilities serving a variety of national missions
  - Neutron scattering, isotope production, materials irradiation, ...
- Beryllium-reflected flux trap-type research reactor
  - 85 MW nominal full power (1.7 MW/L average power density)
  - 2.5×10^{15} n/cm^2/s peak thermal neutron flux
  - 23-26-day-long fuel cycles
- Downflowing light-water cooled and moderated
  - Primary coolant flow of 16,000 GPM
  - Inlet temperature / pressure of 120 °F / 468 psig
  - Outlet temperature / pressure of 156 °F / 358 psig

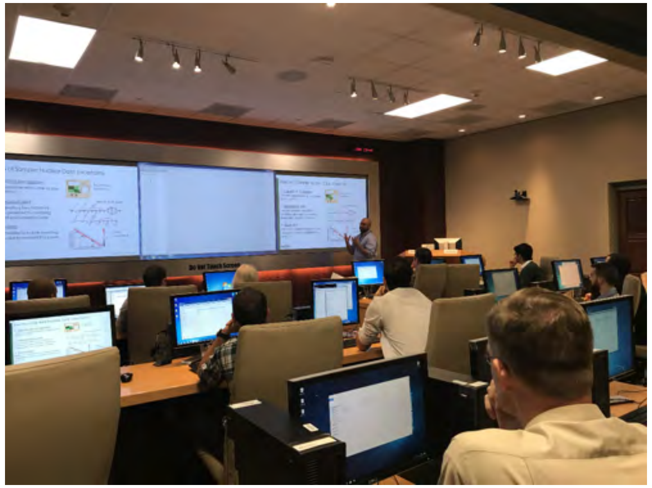
https://neutrons.ornl.gov/hfir

Workshops and Training

- ORNL workshops attract the global community to a venue that encourages innovation and excitement in a place where so much nuclear history has evolved. Recent meeting series that are especially applicable to ONRAMP include:
- Recurring workshops:
  - CASL/VERA Users Group (annual)
  - MSR Workshop (annual)
  - SCALE Users Group (annual)
- Possible future topics may include, but are not limited to:
  - CFD community of practice (broader than nuclear)
  - Experimental facilities, validation, and experiment design
  - HPC in nuclear applications
  - Hybrid variance reduction techniques
  - Modeling and simulation for advanced reactors
  - Modeling and simulation for fusion plasma physics and neutronics
  - Modeling and simulation for neutron science facilities
  - Modeling and simulation for research reactors
  - Nuclear data needs and opportunities
  - Nuclear security modeling
  - Sensitivity analysis and uncertainty quantification

Workshops and Training

- Training is provided by developers and expert users from our teams to address a variety of technical areas including but not limited to the following:
  - Nuclear criticality safety
  - LWR and advanced reactor modeling
  - Reactor safety analysis;
  - Radiation shielding
  - Spent nuclear fuel characterization for transportation/storage package designs, decommissioning and disposal
  - Verification, validation, and uncertainty quantification
  - Nuclear safeguards and security applications
  - Nuclear data processing and libraries generation



- New courses in FY19/20
  - Nuclear Data Fundamentals and AMPX Libraries Generation
  - VERA
  - ADVANTG
- Training presented at ORNL, NEA (Paris), NRC headquarters, utilities, nuclear suppliers, or R&D organizations.
- Additionally, many related workshops are presented at conferences and universities.

Partnerships

- **Inform:**
  - Participate in workshops and symposia to present current approaches and find out what is possible using ORNL's advanced techniques and computing. Tour ORNL facilities to observe state-of-art practices in facility operation and experimentation.
- **Educate:**
  - Choose from a wide array of training courses to gain hands-on experience using advanced tools.
- **Analyze:**
  - Partner with ORNL for specialized analysis of your systems, working in our collaboration space, and accessing world class computing resources.
- **Enhance:**
  - Establish partnerships to develop enhanced computational methods and data to better meet specialized needs and to realize the possibilities of HPC.
- **Validate:**
  - Quantify your validation basis by applying advanced approaches to assess available experiments and then enhance understanding through the design and operation of new benchmark quality experiments for licensing.
- **Deploy:**
  - Reap the benefits of quality assurance and archival analysis for licensing and deployment.
- **Commercialize:**
  - In certain cases, commercial licensing opportunities are available. These agreements may be on an exclusive or non-exclusive basis provided they are limited to a specific field of use. Said licenses are technologies that are bound by export control obligations which are available via RISCC.

Thank you for your attention!

NRIC National Reactor Innovation Center

NRIC Digital Engineering

December 1, 2020

Ashley E. Finan, Ph.D., NRIC director
ashley.finan@inl.gov

inspire

empower

deliver

NRIC

5-Year Program Objectives

Enable demonstration of at least 2 advanced reactors

- Make available infrastructure, sites, materials, expertise
- Provide regulatory support and coordination
- Best practices in public engagement

Prepare DOE/labs for continuing innovation and demonstration

- Develop best practices for planning/construction/demonstration of nuclear projects
- Develop enduring infrastructure and expertise
- Establish methods for efficient coordination among laboratories

NRIC

WE'VE DONE THIS BEFORE

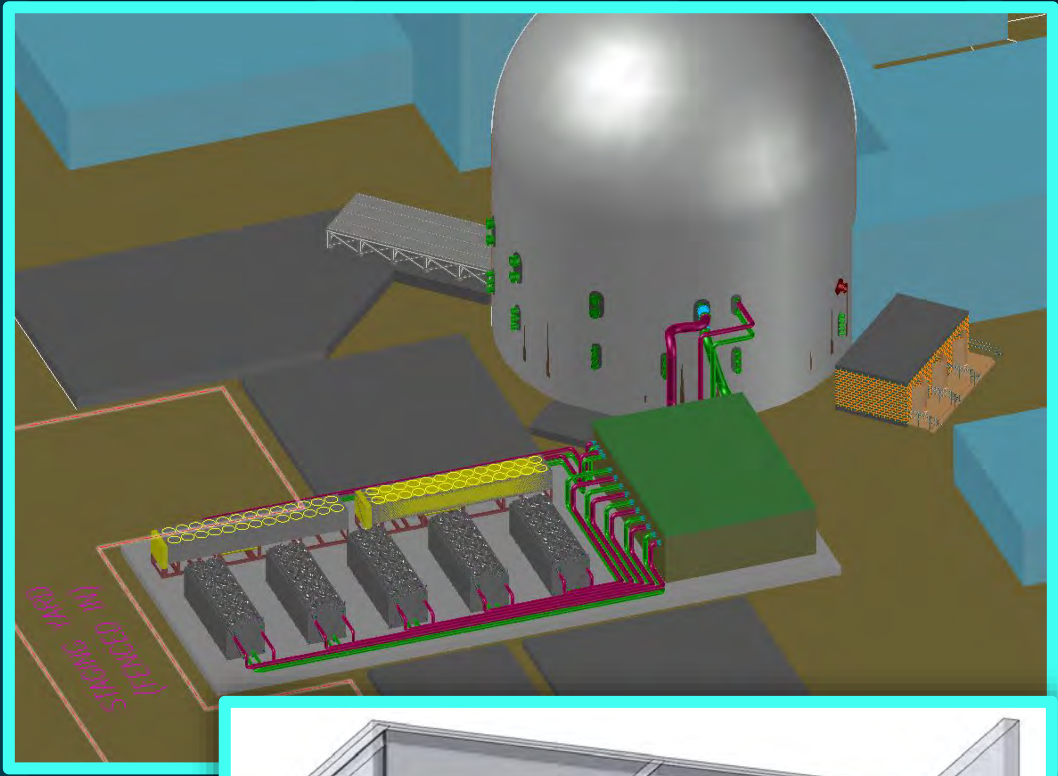
WE'RE GOING TO DO IT AGAIN

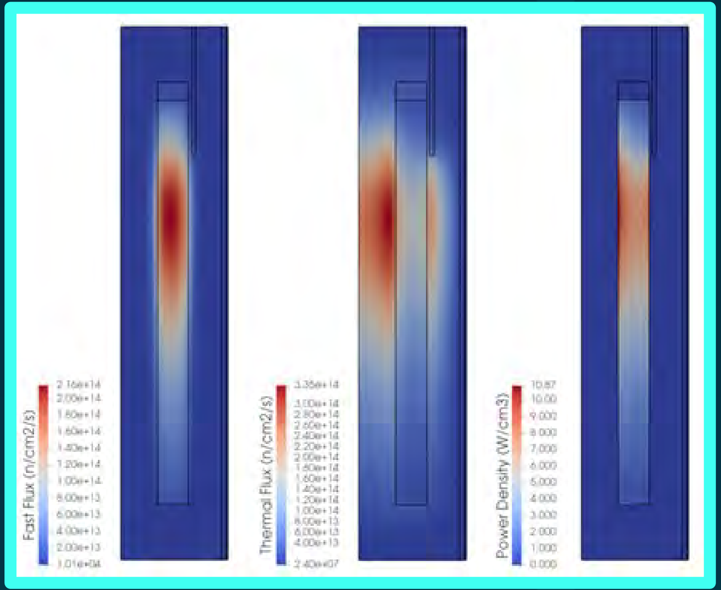
WITH SOME *refinements*

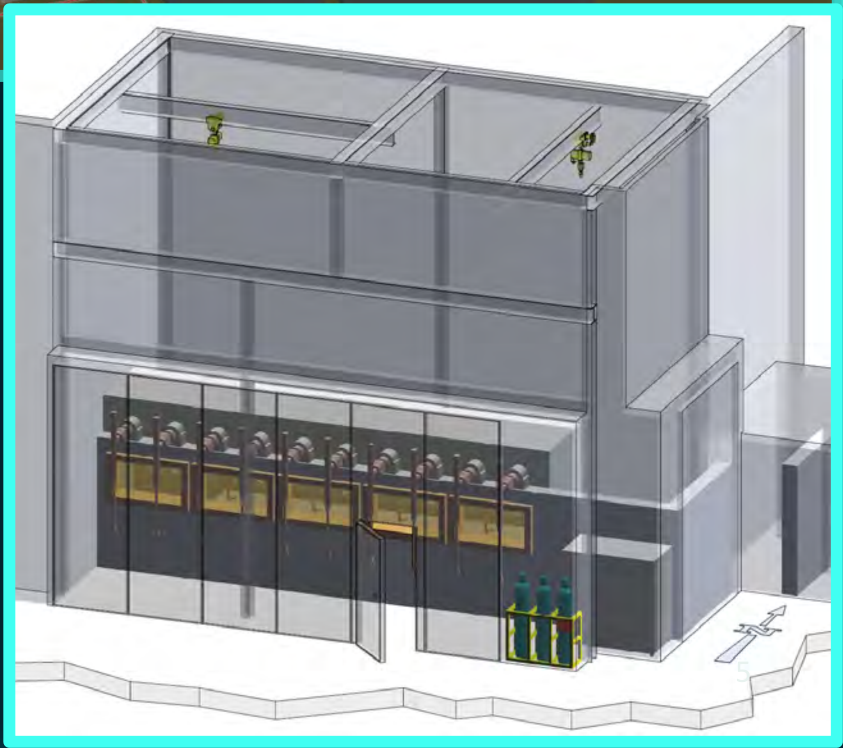
NRIC

Mod. # 1 Empowering Innovators

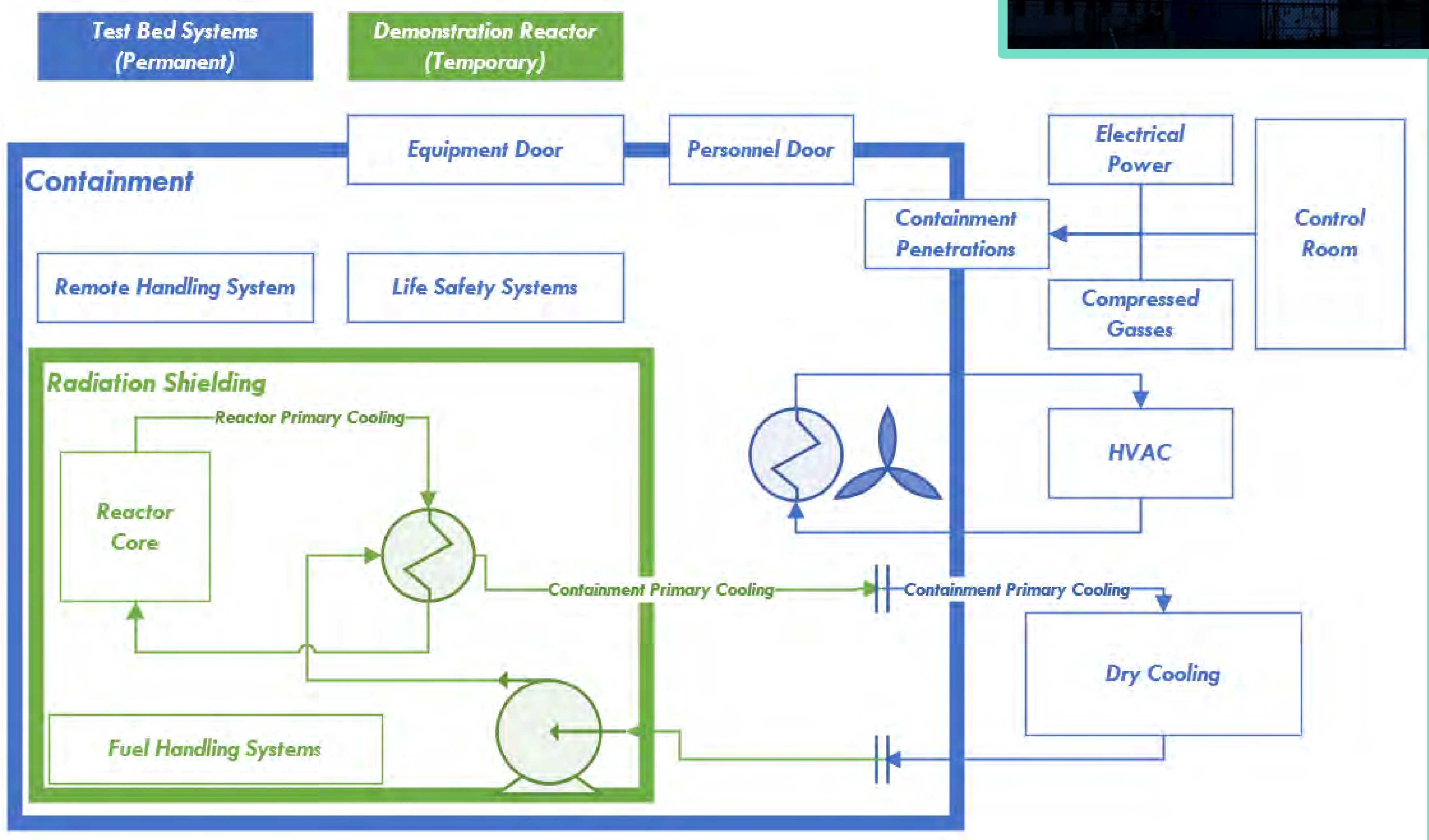
- Private Sector Driven Effort
- NRIC Resource Team
- Virtual Test Bed
- Demonstration Resource Network
  - Experimental facilities
  - Fuel facilities
  - Test beds
  - Demonstration sites







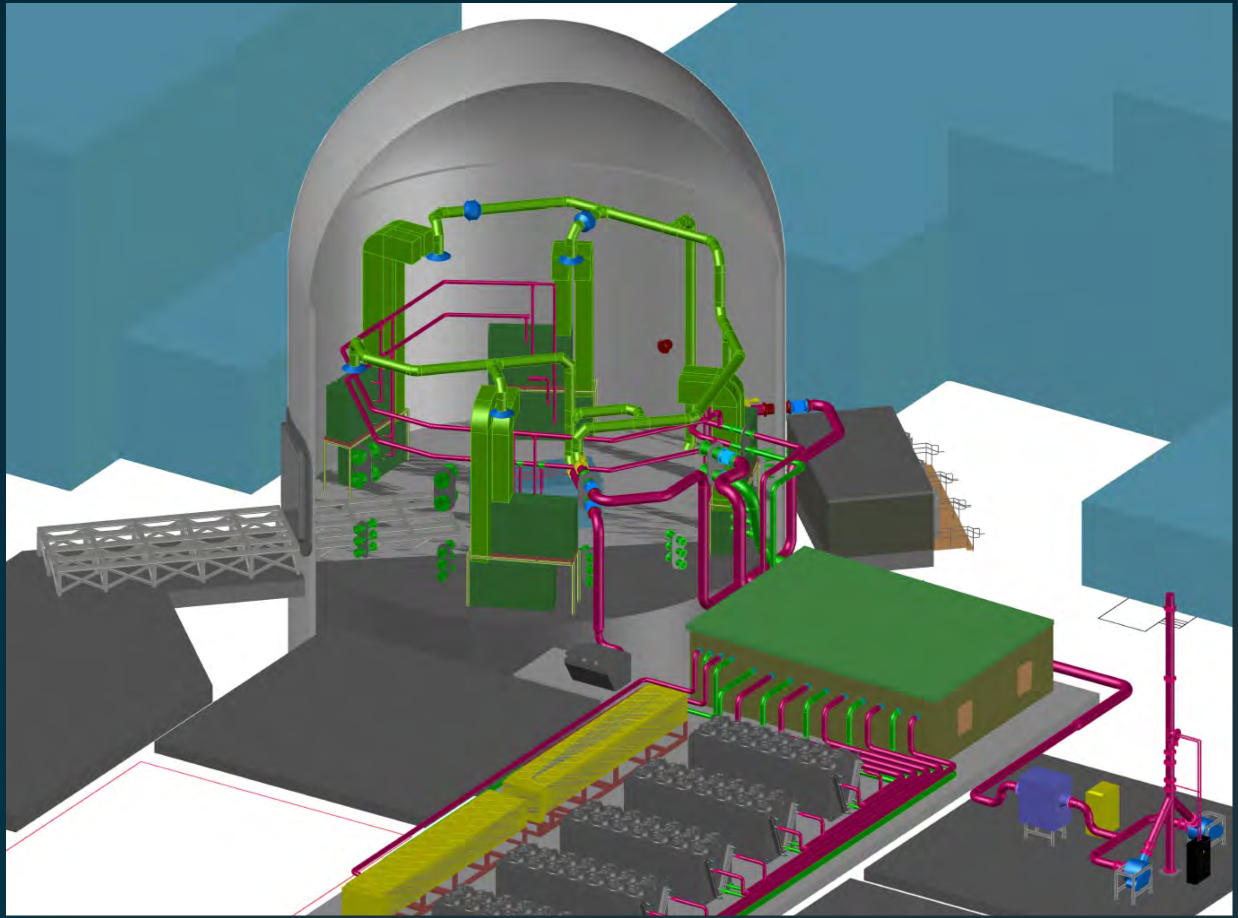
Demonstration Test Beds In Development



- User input received
- Functional and Operational Requirements Defined
- Concept of Operations Defined
- Digital engineering implemented
- Preconceptual design complete
- Request for Expressions of Interest released July 21 for A-E firm to complete design work in FY21

Pre-Conceptual Design
NRIC-DOME Demonstration Reactor Test Bed

- Reactors producing less than 10MWt power
- Use of Safeguards Category IV fuels
- Modifications to equipment door to enable loading of Conex containers
- Cooling, electrical, ventilation, process fluid penetrations
- Ventilation system upgrades
- Electrical power system including safety class battery backup
- Control Room for ETB operations



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Digital Engineering in Design - NRIC

- **National Reactor Innovation Center:** The National Reactor Innovation Center (NRIC) at Idaho National Laboratory provides resources for testing, demonstration, and performance assessment to accelerate deployment of new advanced nuclear technology concepts
- **State of the Art**: Document centric exchange of reactor design documents and information
- **Scope**: Transform the traditional engineering design ecosystem from a document-centric paradigm to a digital engineering framework to increase collaboration and efficiency.
- **Opportunity**: Powerful new software allows for the development of new products, services, and capabilities by using digital tools to improve real world outcomes. Industries ranging from construction to aerospace have implemented these techniques to bring down costs and increase productivity. NRIC is leading the way to begin applying these digital tools to advanced nuclear concepts.

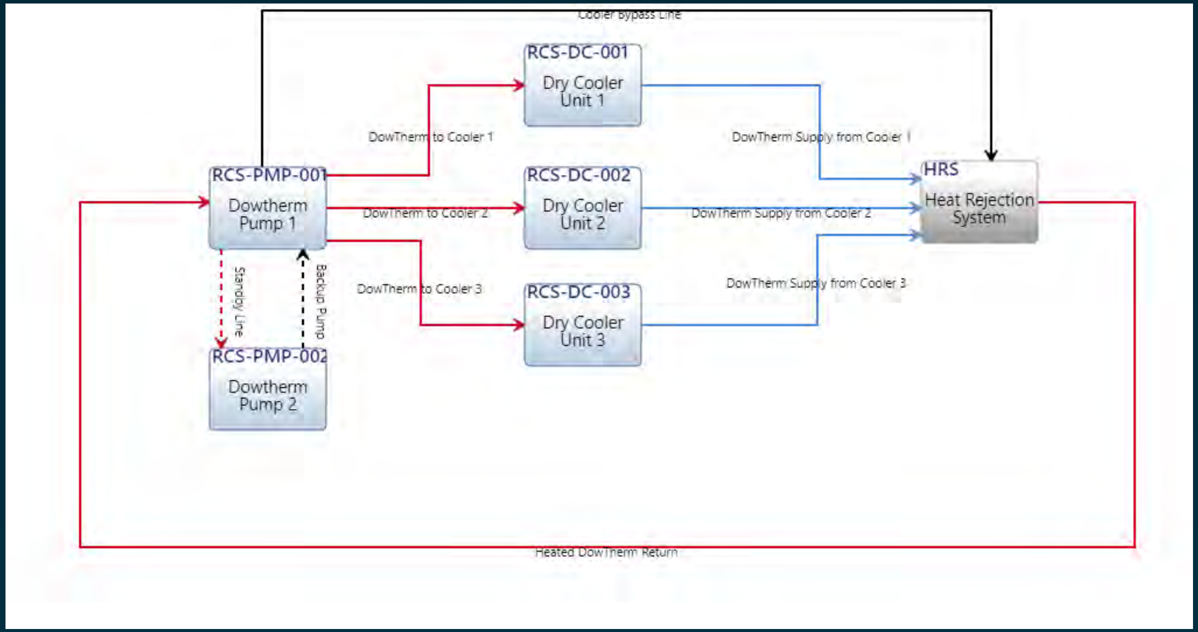
Complete Systems Level MBSE Architecture of Demonstration Test Bed

	Functional	System/Structure	Product
Conceptual	**Approved**	Preliminary	Preliminary for long-lead and key components
Preliminary	Updates as required	**Approved**	Preliminary
Final	Updates as required	Updates as required	**Approved**

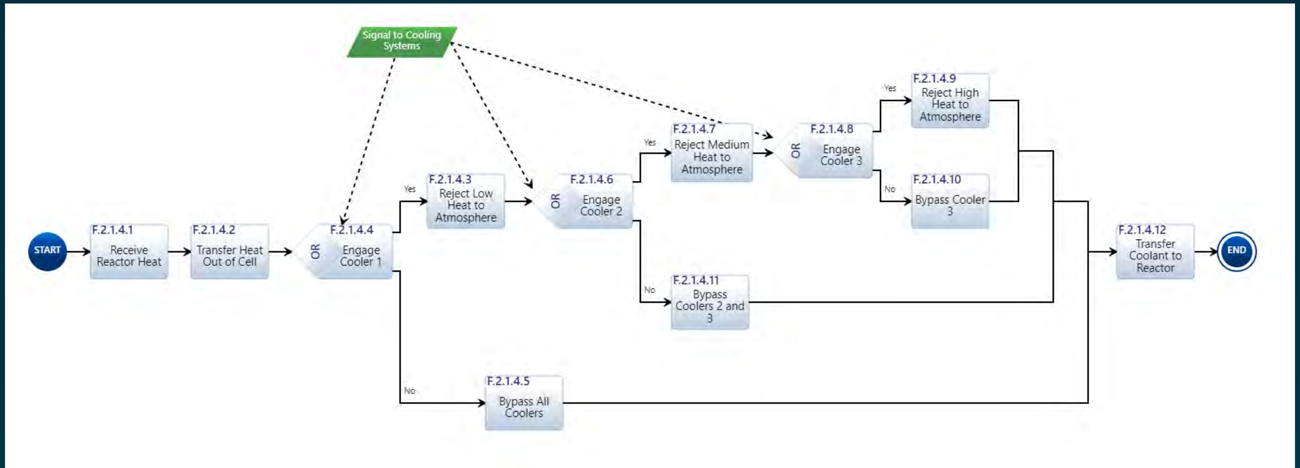
NRIC

Model-Based Systems Engineering (MBSE) Environment for NRIC Test Beds and Industry Teams

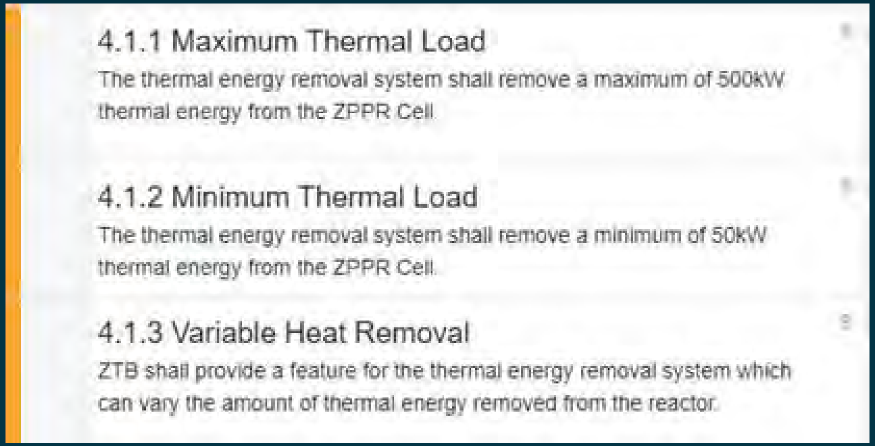
- Emphasis on development of functional analysis (activity diagrams) and physical analysis (asset, internal block diagrams) over document creation
- System models (SysML/LML) are linked to the requirements document in the same tool environment to provide system-level traceability
- Models are integrated across teams (from NRIC test beds through contractor design teams)



Physical: Reactor Cooling System (RCS) Asset Diagram (gray box indicates live contractor input)



Functional: Remove 50 - 500 kW Reactor Thermal Energy



4.1.1 Maximum Thermal Load

The thermal energy removal system shall remove a maximum of 500kW thermal energy from the ZPPR Cell.

4.1.2 Minimum Thermal Load

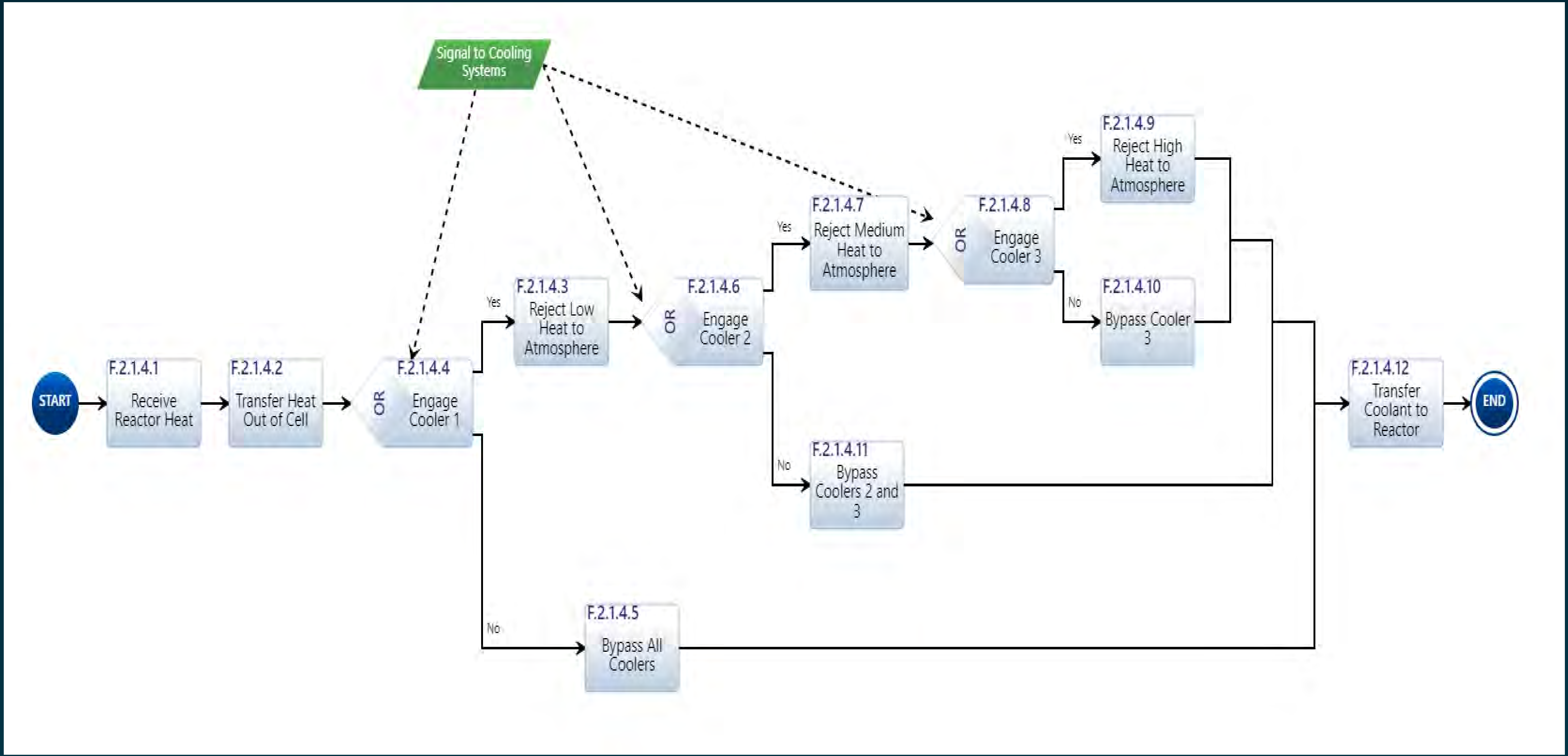
The thermal energy removal system shall remove a minimum of 50kW thermal energy from the ZPPR Cell.

4.1.3 Variable Heat Removal

ZTB shall provide a feature for the thermal energy removal system which can vary the amount of thermal energy removed from the reactor.

Requirements integrated with MBSE model

NRIC

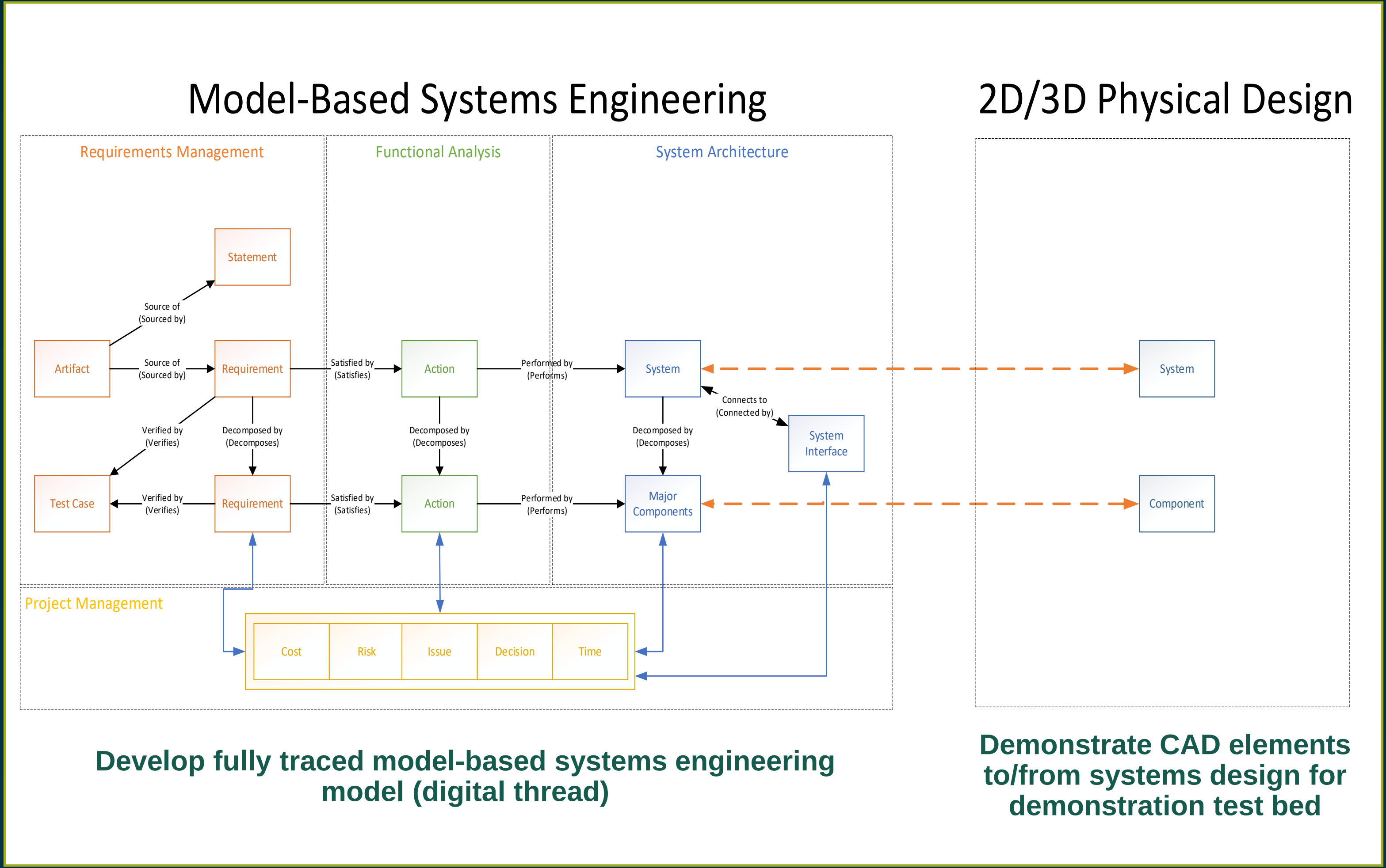


NRIC

Functional Requirement: Remove 50 - 500 kW Reactor Thermal Energy

Building the Digital Thread with Model-Based Systems Engineering (MBSE) and digital engineering

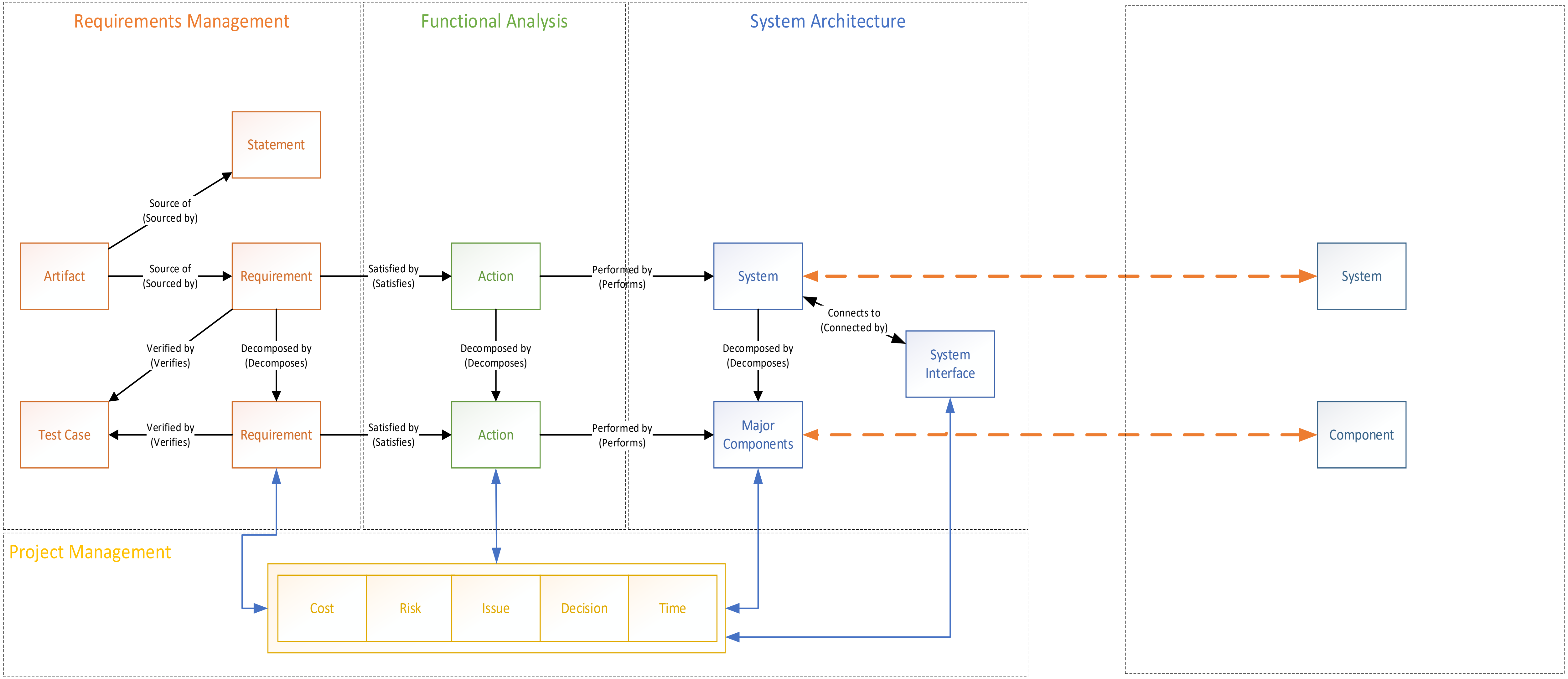
- Computer Aided Design (CAD) bidirectional integration with MBSE models to reduce error transferring from systems through detailed design (leveraging existing laboratory university research on Deep Lynx)
- Generating reports in INL- and NRIC-compliant formats to automate documentation needs at the system level
- Integration with the overall digital engineering ecosystem which will provide analysis integrations at the system, civil design physics, and nuclear physics codes
- Overall plan to integrate this system (used in design) with operating facilities to enable a full digital twin



NRIC

Model-Based Systems Engineering

2D/3D Physical Design



Develop fully traced model-based systems engineering model (digital thread)

Demonstrate CAD elements to/from systems design for demonstration test bed

NRIC

Key Goals of NRIC Digital Engineering Approach

- Efficient and accurate interface between NRIC and industry partners
- Improved project outcomes through digital thread & MBSE approach
- Foundation design framework to enable digital twin
- Ultimate cost and schedule reductions in deployment through use of tools/methods demonstrated through NRIC

Thank you!

Questions?

NRIC

The GEMINA Program:

What ARPA-E is Doing and Broader Opportunities

Jennifer Shafer

Dec 1, 2020

First, Thanks to a Great Team!

Joel Fetter, T2M

Curt Nehrkorn,
Tech SETA

Ray Duthu,
Tech SETA

Lakshana Huddar,
(former) Fellow

Caitlin Zoetis,
Proj. Manag. SETA

Geoffrey Short,
Tech SETA

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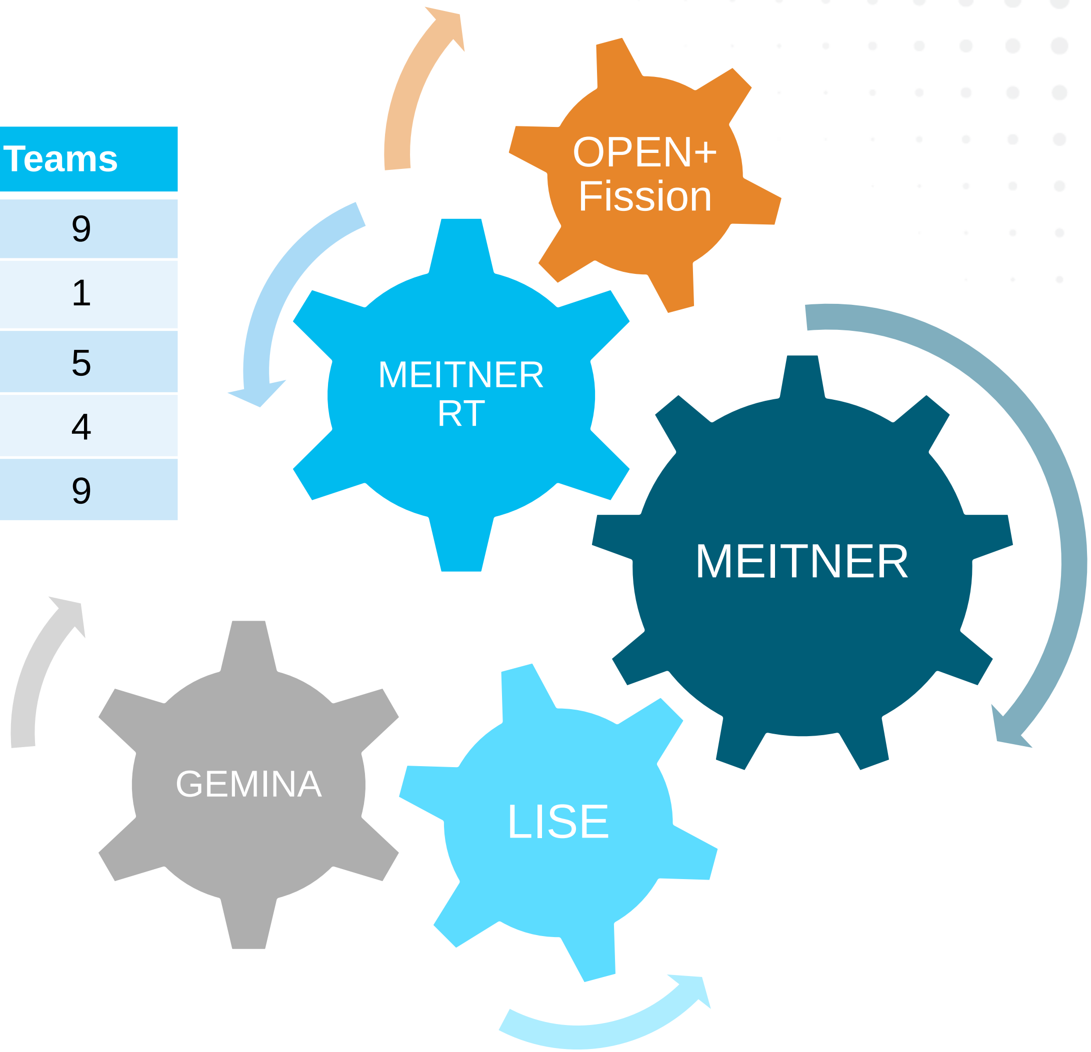
ARPA-E Nuclear Fission Landscape

Program/Cohort	Budget	Teams
MEITNER	~$30M	9
MEITNER Resource Team	~$10M	1
OPEN + Fission	~$12M	5
LISE	~$8M	4
GEMINA	~$35M	9

Multiple groups of fission teams, all managed together to achieve economically viable nuclear power



U.S. Reactors are Shutting Down from O&M

Category	Fuel	Capital	Operating	Total
All U.S.	6.44	6.64	20.43	33.50
Single-Unit	6.42	8.92	27.32	42.67
Multi-Unit	6.44	5.99	18.46	30.89

- Table in 2017 $/MWh
- Minimal staffing across best performing plants: ~750 FTEs
- Operations and Maintenance are the largest addressable categories

FTEs at a 1 GWe Reactor

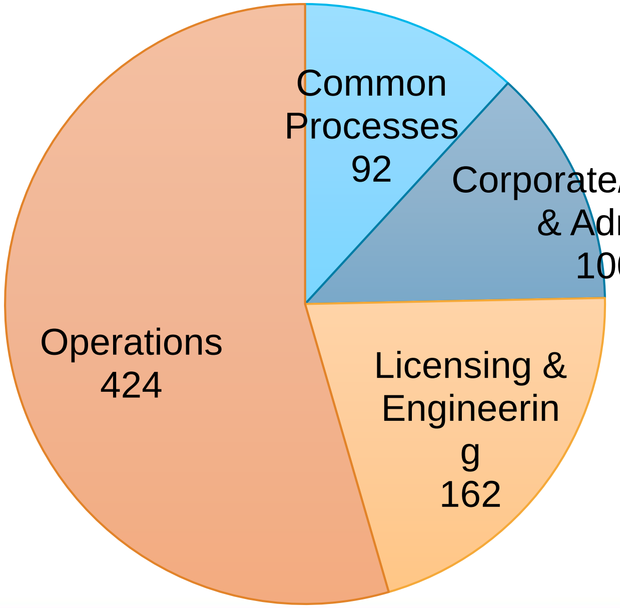


Table: https://www.nei.org/CorporateSite/media/filefolder/resources/reports-and-briefs/nuclear-costs-context-201810.pdf
Pie chart: https://www-pub.iaea.org/MTCD/Publications/PDF/te_1052_prn.pdf

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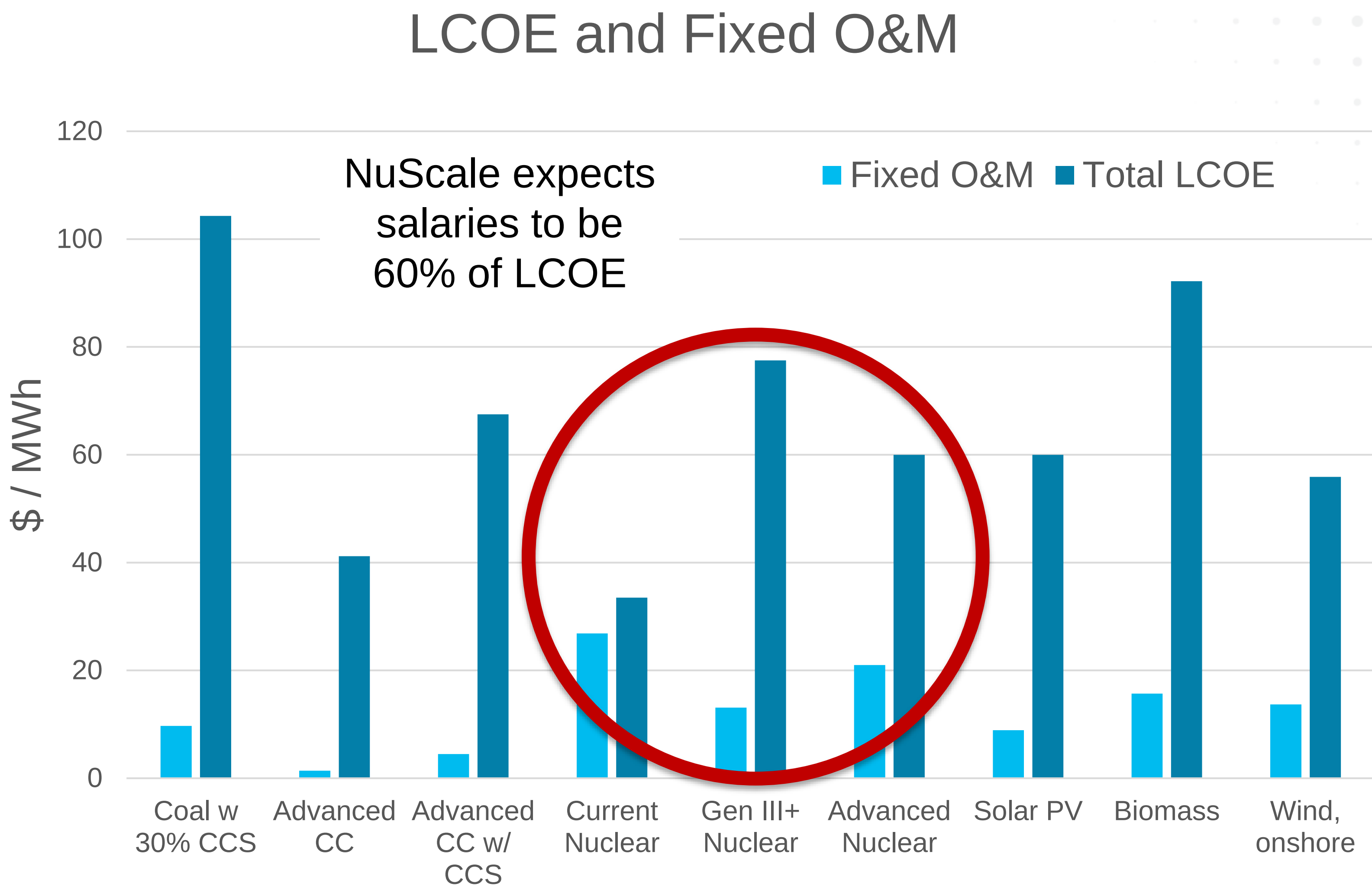
What Are the Costs? What About Next Gen?



https://www.eia.gov/outlooks/aeo/pdf/electricity_generation.pdf, https://www.innovationreform.org/wp-content/uploads/2018/01/Advanced-Nuclear-Reactors-Cost-Study.pdf

Features of Advanced Reactor Designs Lead to New Requirements for On Line Monitoring

Reduced accessibility
- pool-type designs
- sealed systems
- remote siting

→

- *In situ* monitoring systems
- Long-lived, harsh-environment sensors
- Centralized off-site monitoring

New component designs
- Longer periods between inspection and maintenance opportunities

→

- Greater situational awareness
- Physics-of-failure simulation models
- Real-time, continuous monitoring and condition assessment

New concepts of operation
- multi-modular operation
- fluctuating generation demands
- co-generation

→

- Integrate into supervisory control and O&M planning
- Accurately quantify and manage uncertainty throughout lifecycle

Credit: Jamie Coble

Challenge:

*Can we operate advanced reactors with a cost profile comparable to a natural gas combined cycle plant?
(a 15x reduction)*

What this really means:
Can we get ARs up to the leading edge of development to make them nearly autonomous – which is what the rest of the industrial world is doing?

Leverage New Ideas and Sort it out NOW

- Lots of industries are developing better controls, better models, better data, better algorithms

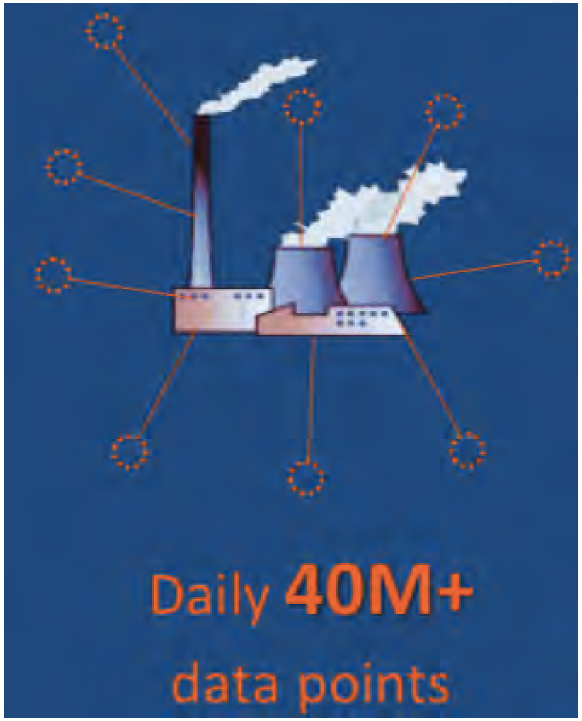
- Focus on autonomy and machine learning (ML) is getting many questions answered
- Answer those questions specific for nuclear and prove out ideas in our systems and with our software; aid in code validation
- Have tools the industry and the regulator can use

This Is an Essential Need

- Many developers have identified they need to develop these technologies
- In a test plan from an example company, Human-Machine Interface is an essential need that “would take full advantage of the technology advances since early LWRs were deployed.” It includes things like:
  - Remote maintenance
  - All ops activities, from cold shutdown to full power operation of all integrated systems
  - Recovery from off-normal conditions

Lots of People Are Working to Improve Industrial Performance

- How do we know when plant conditions are becoming riskier?
- How can we avoid a plant trip or component failure?
- How can we reduce maintenance and insurance costs?
- How can we improve reliability and utilization without increasing risk?



Alarms / Operating Limits

Asset Monitoring / Predictive Analytics

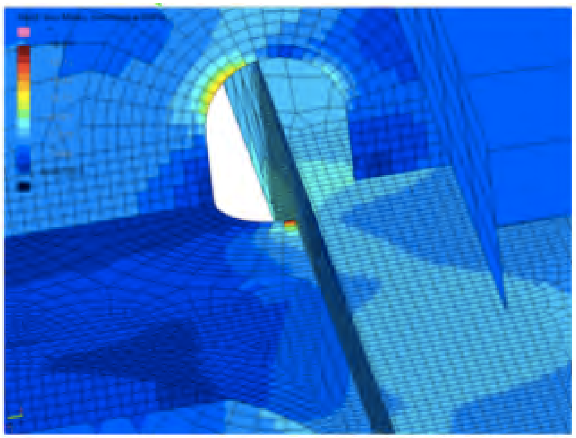
Self Service Analytics

Autonomous Risk Detection Systems

Source: Near-Miss Management, "Maximizing Uptime, Efficiency, and Safety of Industrial Operations through Early Risk Detection." AiChE

Lots of great results

Uptake reduced preventative maintenance work hours by 37% at Palo Verde nuclear plant

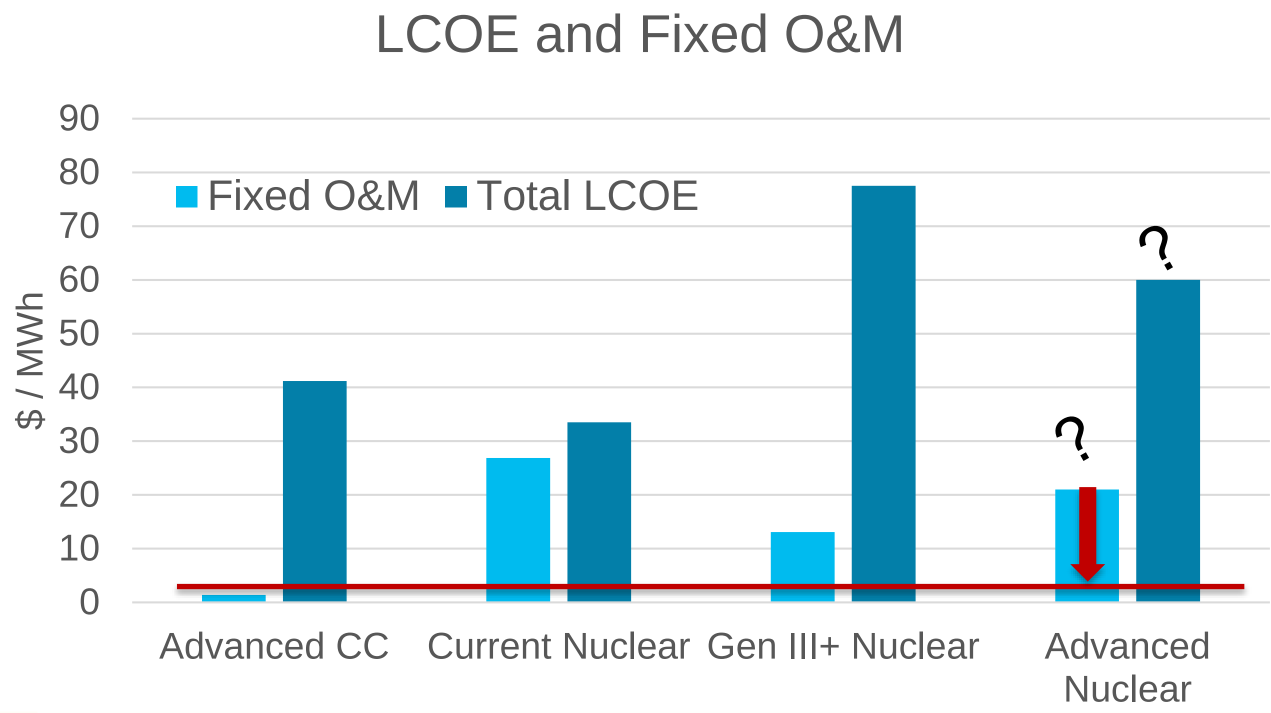


4x increase in predicted fatigue life without changing safety factors

Halliburton builds models of wells to help construct them (using physics models and data gleaned from other wells). Can cut well design time by 80%.

Program Framing and Goals

- **Goal:** Advanced Reactor (AR) O&M cost of no more than 10% more than an advanced combined cycle plant
- **Pathway:** personnel reduction through automation, autonomy, and enhanced safety case
- **Needs:**
  - Operations
  - Maintenance
  - Targeted "gap filling"



Potential Impact

- Detailed plan and reasonably vetted tech for low O&M costs for advanced reactors: **strong basis for cost estimates**
- Substantially autonomous reactor operation:
  - Software and algorithms developed and ready for demo
  - Tools for design and regulation to accelerate deployment
- Significant reduction in staff for maintenance:
  - Map of task allocation and minimum staff required
  - Designs updated to integrate with autonomy needs
- Opportunities for demo: Existing test facilities, Southern Co's Large Component Test Facility, Micro reactors, NuScale, Versatile Test Reactor

Operating Advanced Reactors

Interdisciplinary teams will

- Build a digital twin for an advanced reactor system
- Build a cyber-physical / hardware in the loop[1] system at an existing non-nuclear test loop
- Assess what signals are needed with what accuracy; develop new inference methods as needed
- Gain validation data for nuclear software
- Practice control operations with injected signals: startup, shutdown, and transient scenarios
- Define a standard interface / approach for how to deal with uncertainty, simulation fidelity needs, inputs / outputs, signal measurement, etc.
- Examine impact of changes and feedback learning into design needs
- Wash, rinse, repeat

[1] HIL: real signals from a controller are connected to a test system that simulates reality, tricking the controller into thinking it is in the assembled product

New tech seeing some use in the field

- Accenture: Applying advanced analytics to the predictive maintenance of assets could save…up to 12% on scheduled repairs and lower overall maintenance costs up to 30%
- Exelon is using GE Predix to provide predictive assessments of key power plant components such as turbines
  Collect and analyze sensing information from equipment to determine whether the probability threshold of that equipment failing has been breached
- Framatome + IBM Watson IoT to use N-Vision data analytics service: proactive approach in maintenance and operations strategy

https://analysis.nuclearenergyinsider.com/industrial-internet-turns-big-data-boom-operator-profits
http://www.framatome.com/solutions-portfolio/media/products/prodshts/A0816-PS_US_648_ENG_03-18-_NVision_Data_Analytics_Solutions_IBM.pdf

LISE Teams

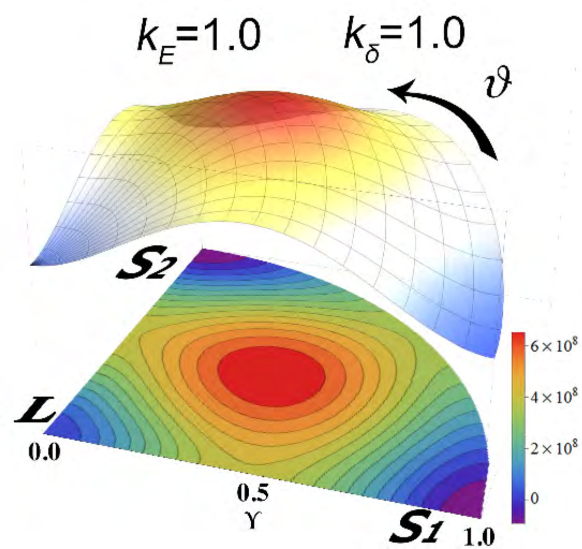
Sensing for Operations	Construction	Autonomous Maintenance
National Energy Technology Laboratory	NC State University; Idaho National Laboratory	Southern Research; PAR Systems

Fuels

Idaho National Laboratory; OKLO

OPEN+ 2018: Five Teams, $11.7M Fed

- CMU: Additive Manufacturing of Spacer Grids for Nuclear Reactors
- LBNL: MEMS RF Accelerators for Nuclear Energy and Advanced Manufacturing
- LANL: Advanced Manufacturing of Embedded Heat Pipe Nuclear Hybrid Reactor
- MIT: Multimetallic Layered Composites for Rapid, Economical Advanced Reactor Deployment
- UW-Madison: Accelerated Materials Design for Molten Salt Tech. Using Innovative High-Throughput Methods



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MEITNER Teams

Microreactor
- Westinghouse — INNOVATION YOU CAN BE SURE OF
- Los Alamos National Laboratory
- Stony Brook University
- HolosGen™

Construction
- moltex energy — safer, cheaper, nuclear
- University at Buffalo — The State University of New York
- EPRI

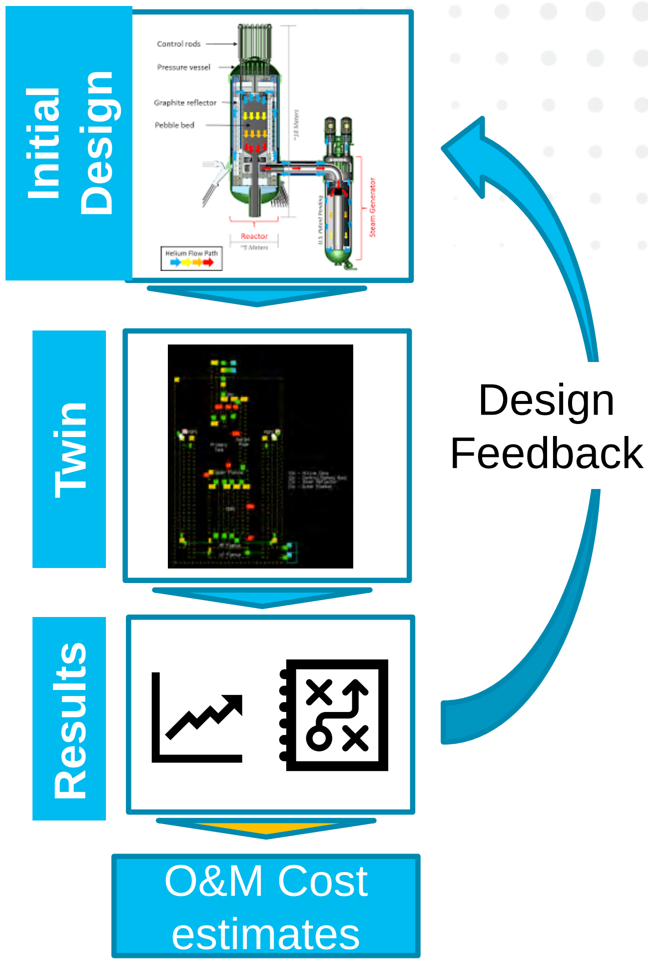
Safety
- YELLOWSTONE ENERGY
- NC STATE UNIVERSITY
- ZACHRY

Components
- THE UNIVERSITY OF TENNESSEE KNOXVILLE
- OAK RIDGE National Laboratory

Load Following
- ILLINOIS

Objectives and Measures

- Measures of success:
  - System provides correct recommendations for startup and shutdown; system avoids or mitigates accidents in off-normal scenarios
  - Ability to implement a change in the models and investigate the tradeoffs
- Provide authoritative data to regulators that leads to credible, expedited design and operator approvals
- Create knowledge of advanced nuclear system O&M that provide the basis for advanced reactor operating standards



Tools and Data Are Needed As Well

- We already know some of the knowledge and capability gaps that will prevent deployment of the first two efforts
- If we solve them concurrently, we'll be that much closer to deployment into test systems coming online in the early 2020s where they can be fully derisked
- Operations needs:
  - Data, e.g., thermophysical properties of molten salts; high temperature materials behavior
  - Key sensors, e.g., flow meter for molten salt
- Maintenance needs:
  - Some things must be done by robots

Sources: NRC, Southern Company

AR O&M: Opportunity to Do Things Differently

- <u>Now</u> is the time: no O&M plans, unfinished designs, no regs
- Implement “design for maintenance”
- ARs have a much stronger safety case, this opens the door to more change and more flexibility
- Most ARs have or will have different refueling schedules
  - Currently, maintenance is done during outage
  - Without outage, removal of time pressure
- A fleet of small, distributed reactors could have remote operators and one maintenance crew between them
- We need to generate tools and data to support licensing and fast learning

Key Points

LWR operations are dialed in after decades of experience

- New reactors need long uptime right away -> use tech to change the learning curves

LWRs have refueling outages every 18 months when lots of maintenance is done

- New reactors may refuel on much longer time scales (5-30 years), so new paradigm for maintenance

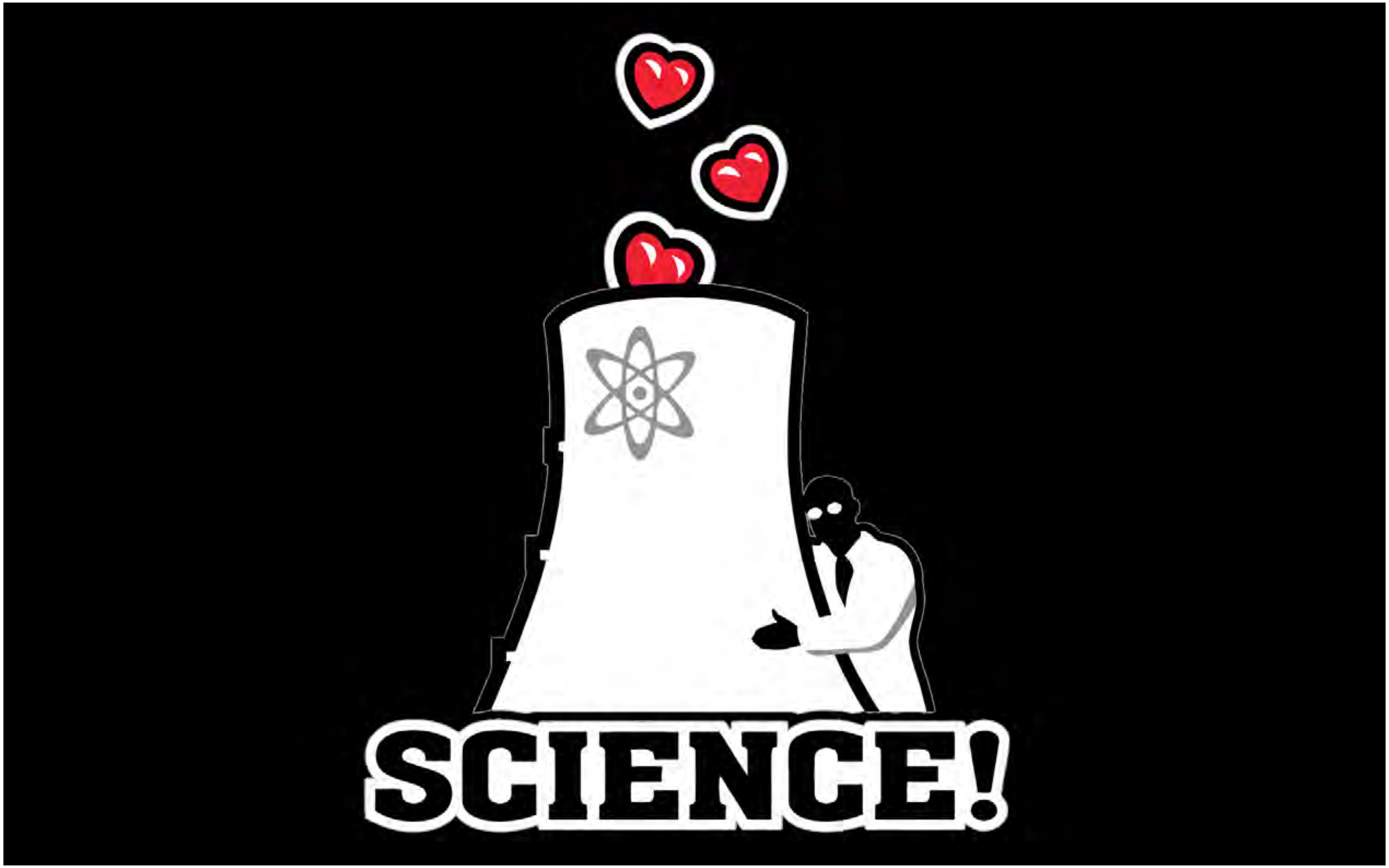
Cost profiles for LWRs are locked in via nuclear quality assurance procedures

- These haven't yet been developed / don't exist for advanced reactors yet

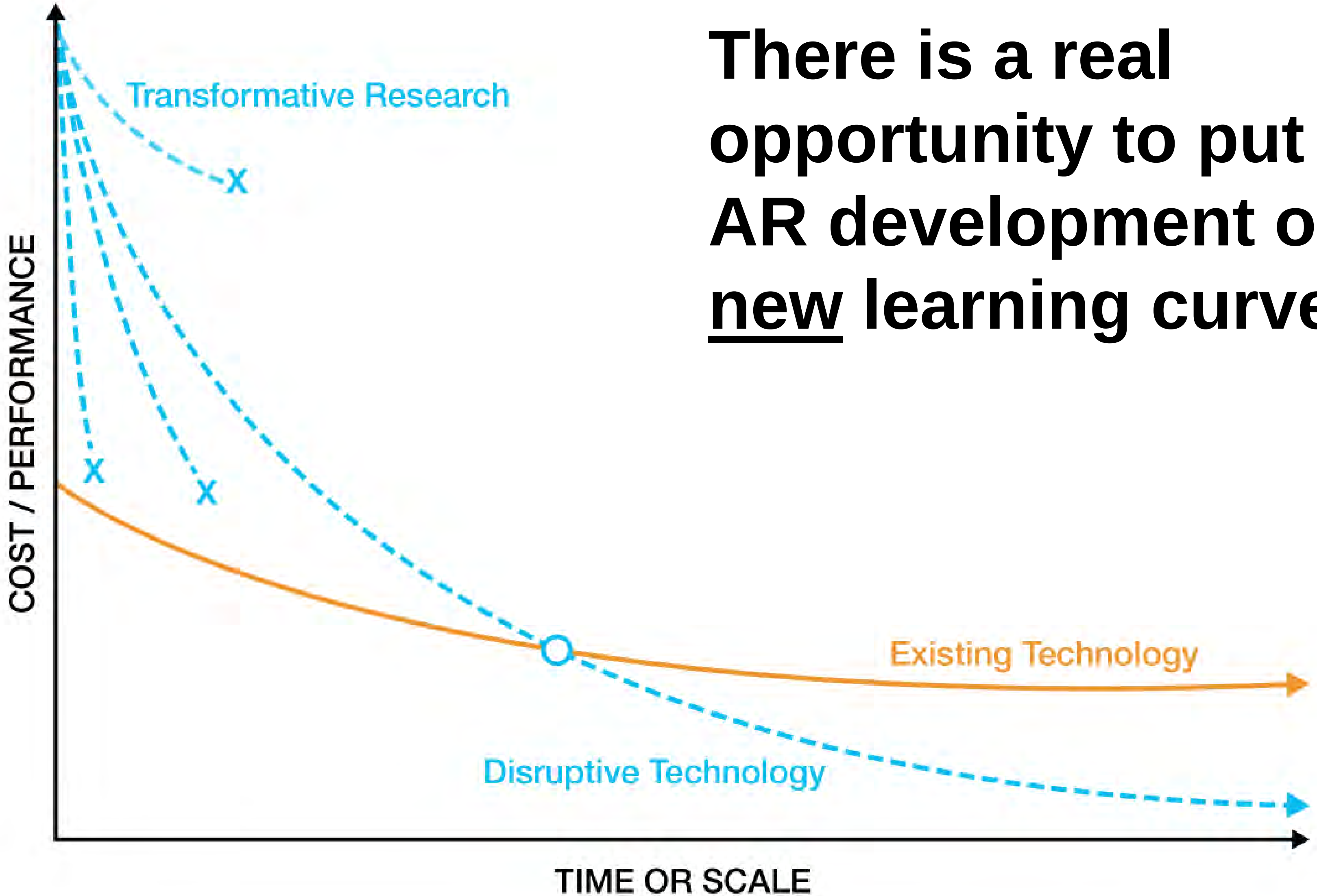
There are lots of technologies being developed to take advantage of and become just another industrial customer

Source: Near-Miss Management, "Maximizing Uptime, Efficiency, and Safety of Industrial Operations through Early Risk Detection." AiChE

NE Questions?

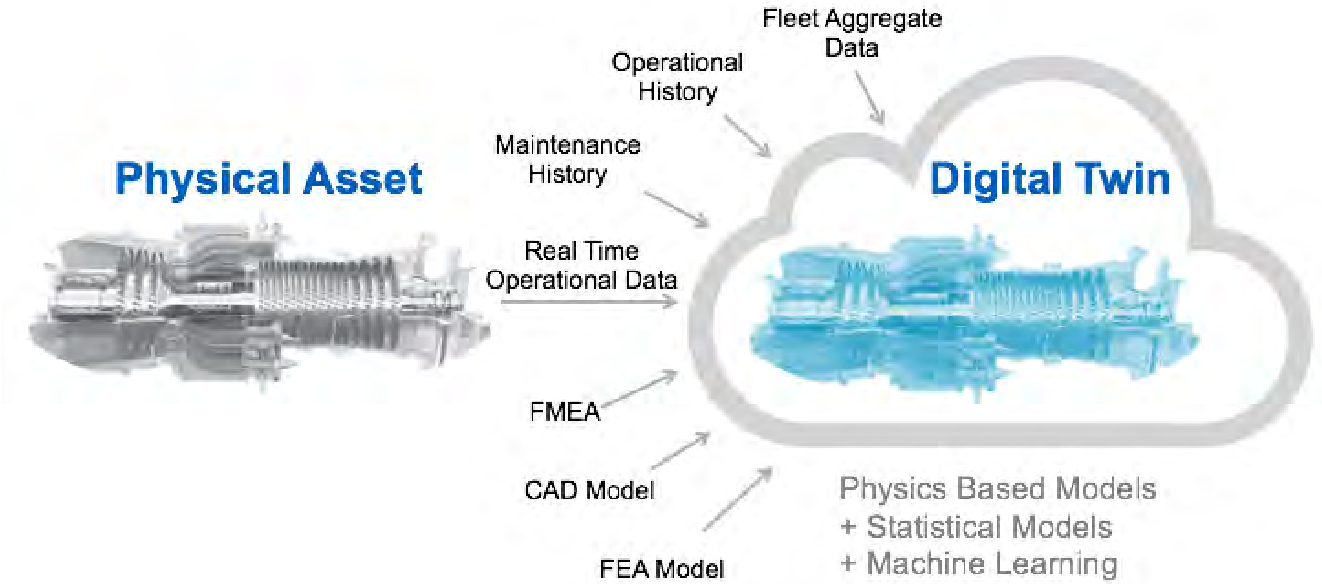


There is a real opportunity to put AR development on <u>new</u> learning curves



Digital Twins

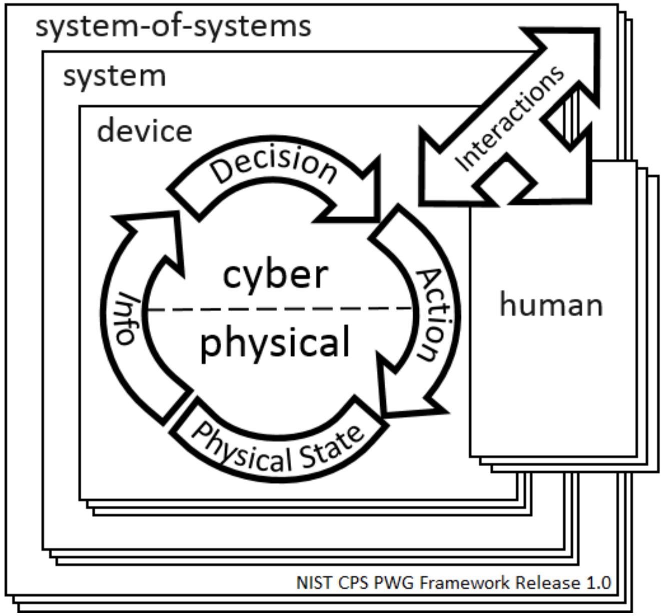
- Digital Twin:
  - "A 'digital twin' is a physics-based, or data science-based, model of an asset that exists in real life. It should mirror digitally the exact characteristics and operating performance of the real device, so that operators can understand the…asset"



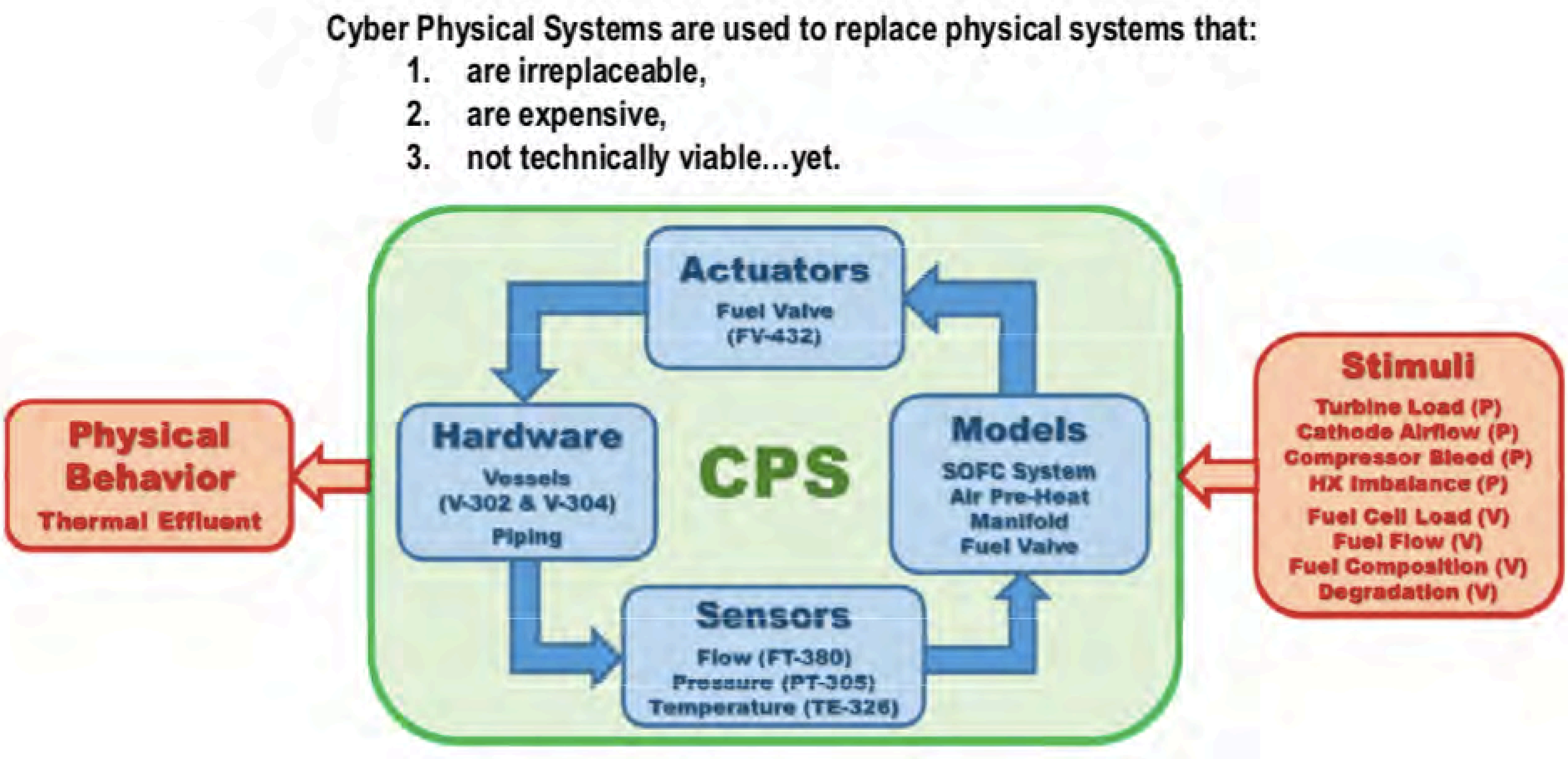
BNEF, Digital Twin Edition, Nov 7 2018, https://www.bangkokbankinnohub.com/digitaltwin/

Cyber-Physical Systems

- Cyber-physical system:
  - "integrations of computation, networking, and physical processes…with feedback loops where physical processes affect computations and vice versa…
  - CPS integrates the dynamics of the physical processes with those of the software and networking…"



Cyber Physical System Example: Hyper



What Might "Optimal Operations" Mean?

- Lower direct personnel costs
- Eliminate radiation to workers
- Reduce cost / amount of maintenance
- Reduce risk of human error
- Increase operational excellence
- Increase margin / safety envelope

However,

- Increase cost of sensors / equipment / software?
- Shift problems and cost from one place to another?
- Increase need for certain highly specialized staff?
- How do we get the relevant innovators to think about nuclear?

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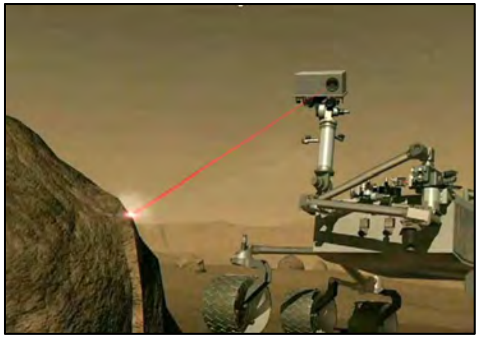
Some Places to Draw Inspiration

- JPL currently deploys autonomous systems that:
  - Protect systems from detected faults and hazardous conditions (fault protection)
  - Perform critical events despite the presence of failures (orbit insertion; entry, descent and landing)
  - Increase mission effectiveness and return (auto-navigation, feature detection and science observation re-targeting)



Curiosity Rover

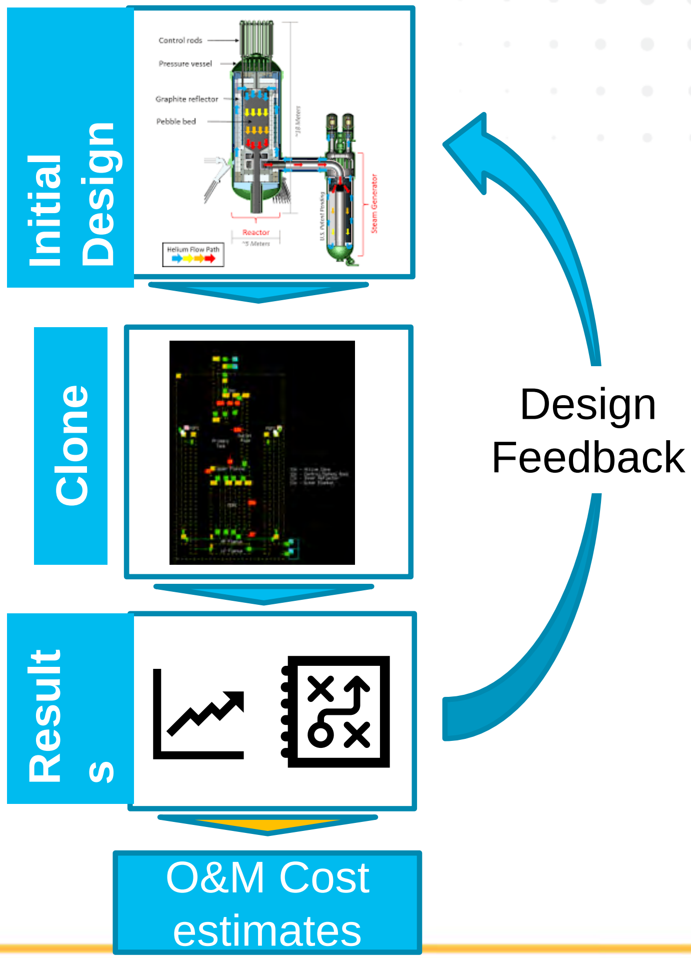
- ExxonMobil has signed collaboration agreements with six other companies to accelerate the development of Open Process Automation (OPA) systems.
- Autonomous vehicles, Oil & Gas, DoD, jet engines, etc. (most industries are developing or adopting this stuff)

Credit: John Day
https://www.marketwatch.com/press-release/exxonmobil-signs-collaboration-agreement-to-accelerate-development-of-open-process-automation-systems-2019-07-18

Learning feeds back into the design

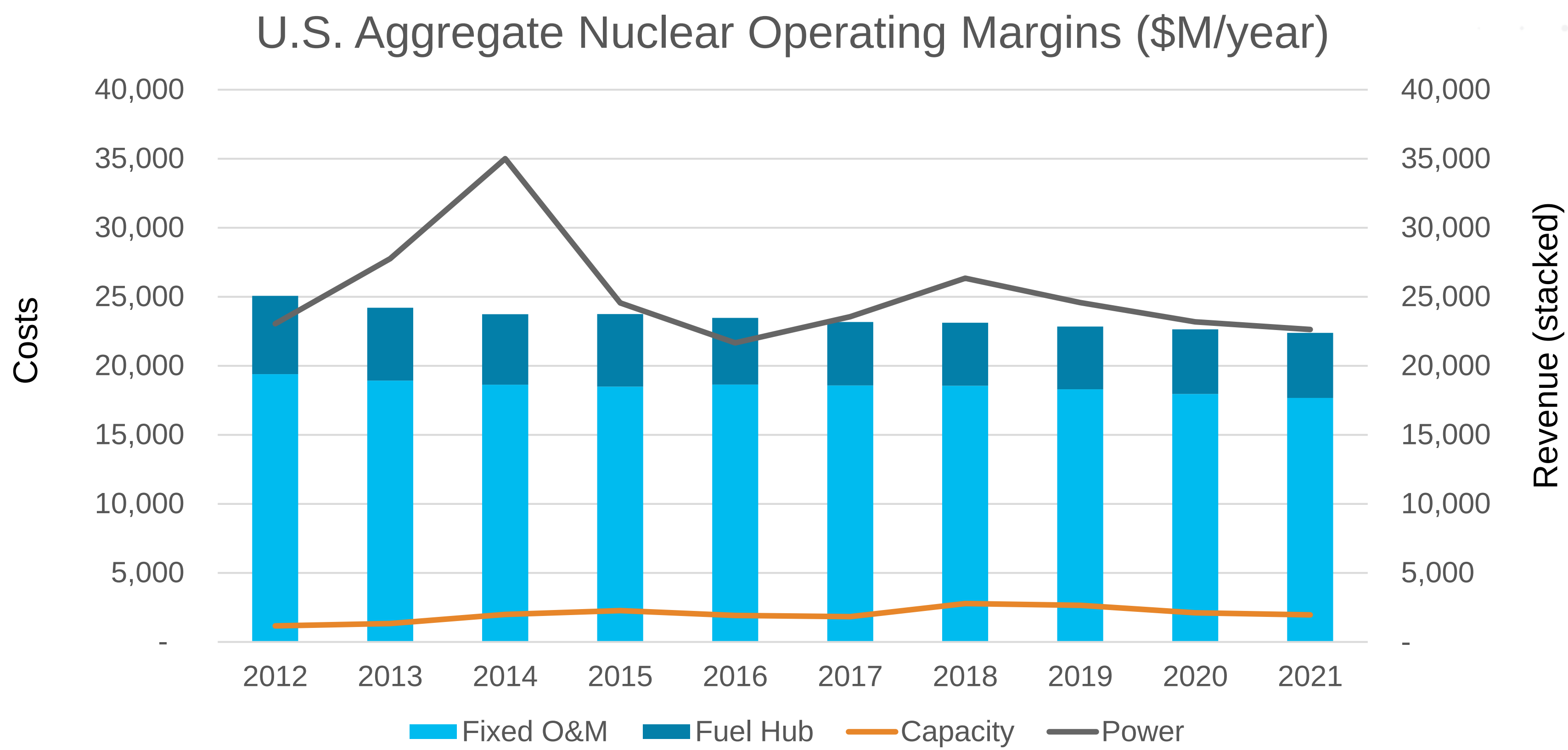
- **Purpose:** Use the model to inform O&M costs and practices.
  - Determine the necessary O&M staffing profile
  - Understand reactor dynamics in order to inform design enhancements
  - Document pro forma O&M costs

- **Lead:** Ideally, a reactor vendor and/or build contractor
- **Key issues:**
  - Further development will almost certainly be needed – “month 37” is especially important
    - → Ensure a home for the generic devices, perhaps at a laboratory.
  - Regulator input should be solicited to inform next stage development requirements
    - → Look to aviation sector for approaches to certifying simulators



U.S. Reactors are Shutting Down

- 5 reactors closed in the last 5 years
- 14 more scheduled to close by 2025



Source: Bloomberg New Energy Finance, Reactors in the Red: Margins for U.S. Nukes. May 15, 2018

CHANGING WHAT'S POSSIBLE

Southern nuclear challenge

- Second half of 2016, approached by a number of vendors for new data analysis techniques
  - 6 months of computer data (1 TB) available to each vendor
  - Develop and train over 1 month where issues are pre-identified
  - New dataset (6 months) with no issues pre-identified, 2 months to analyze
  - Vendors reported findings
  - With lack of training information, similar results to deterministic approach

Digital Twin Applications for Advanced Nuclear Technologies

Xe-100 Digital Technologies Overview

Ian Davis, *Senior Digital Twin Systems Engineer*

December 1, 2020

X-energy was Created to Change the World

Dr. Kam Ghaffarian,
Founder and Executive Chairman

"President Kennedy once said that we are in a space race and my work with NASA reflects the progress he had hoped for.

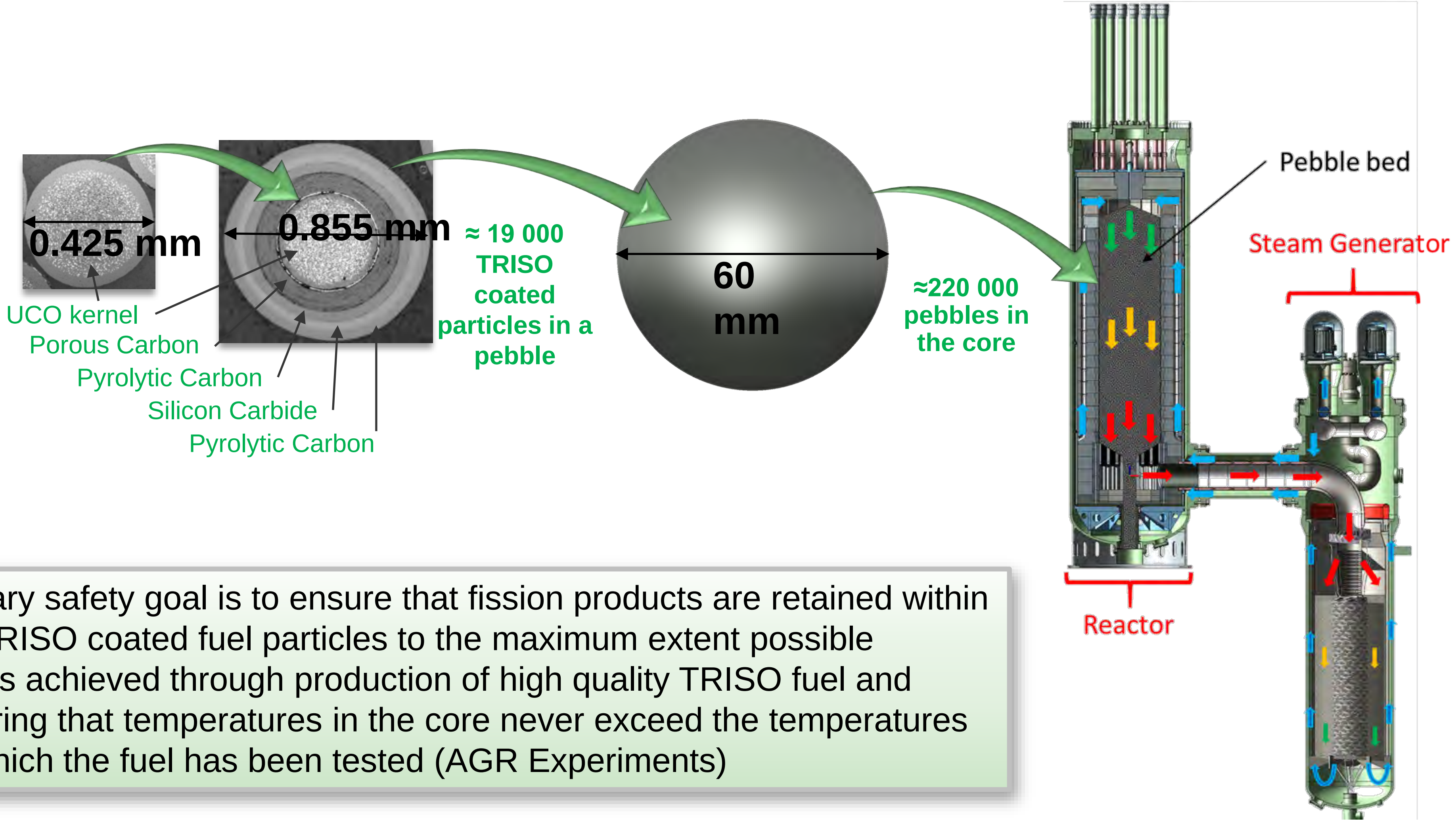
Today, I believe we are in an energy race. Providing clean energy across the world is my vision for X-energy and I believe that clean, safe, reliable nuclear energy is necessary to making this possible."

- Dr. Kam Ghaffarian is a globally recognized technology visionary across energy, space and information technology.
- Created and grew Stinger Ghaffarian Technologies (SGT), Inc. to $650 million in annual revenue and 2,400 employees. SGT was ranked as the U.S. National Aeronautics and Space Administration's second largest engineering services company prior to being acquired by KBRwyle, subsidiary of KBR, Inc.
- Founded X-energy in 2009 to address innovation in critical energy solutions. X-energy was awarded ~$60M from DOE to focus on an advanced nuclear reactor and TRISO fuel.
- Began Intuitive Machines in 2016 to leverage NASA technologies for commercial space and terrestrial applications. Intuitive Machines won its first Commercial Lunar Lander Contract from NASA in 2018.
- Began Axiom Space in 2017 to develop the first commercial space station, to be launched by 2021.

Agenda

1. Company Introduction
2. Xe-100 Overview
3. Digital Twin Overview
4. Anomaly Detection in Systems & Components

UCO TRISO Particle – Primary Fission Product Barrier

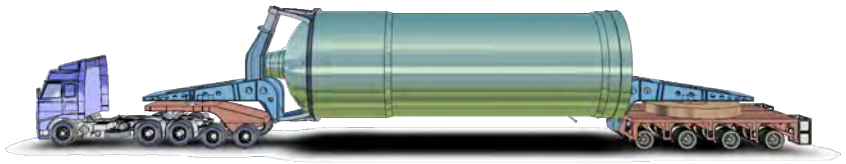


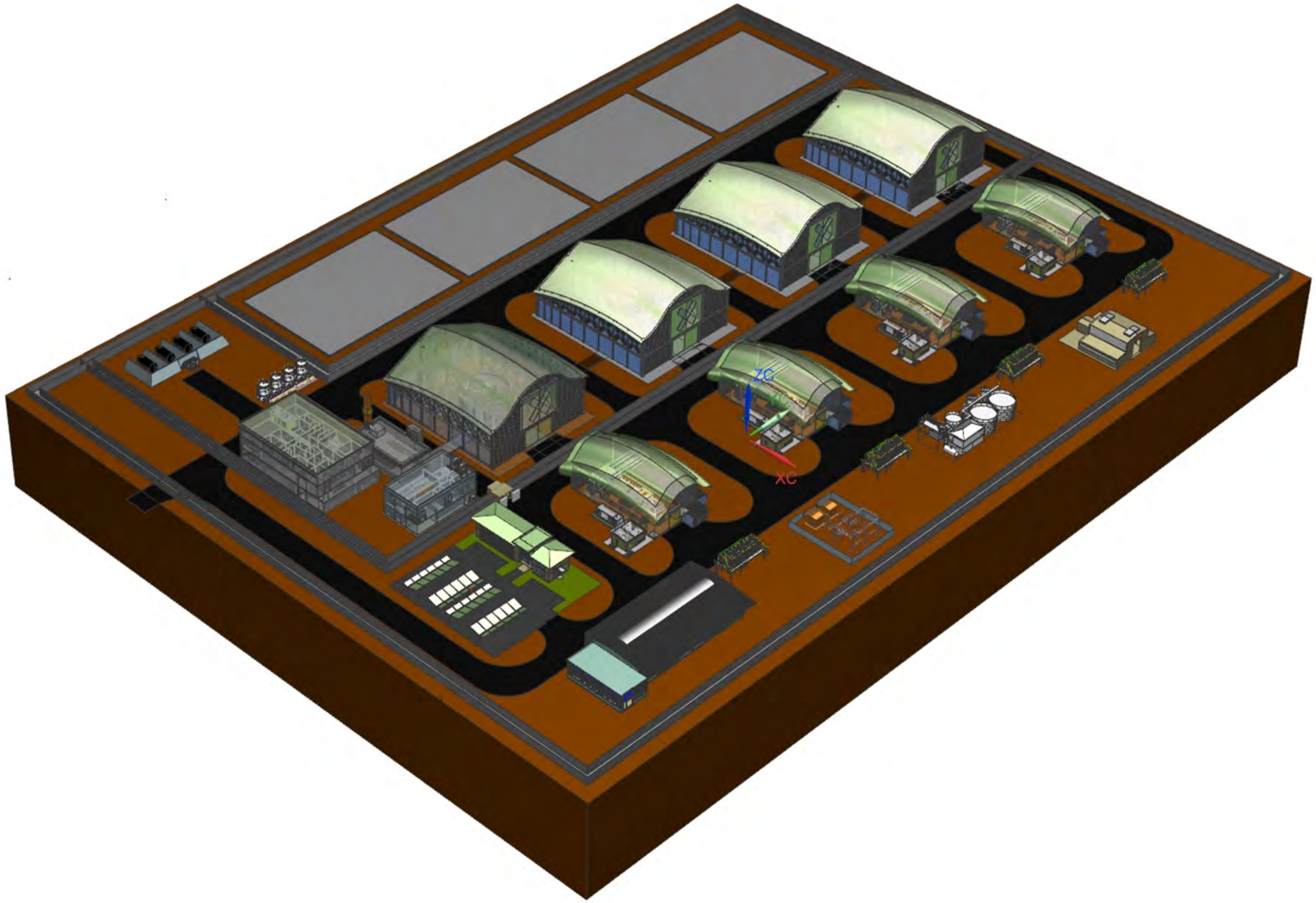
- Primary safety goal is to ensure that fission products are retained within the TRISO coated fuel particles to the maximum extent possible
- This is achieved through production of high quality TRISO fuel and ensuring that temperatures in the core never exceed the temperatures for which the fuel has been tested (AGR Experiments)

Xe-100 Plant Overview

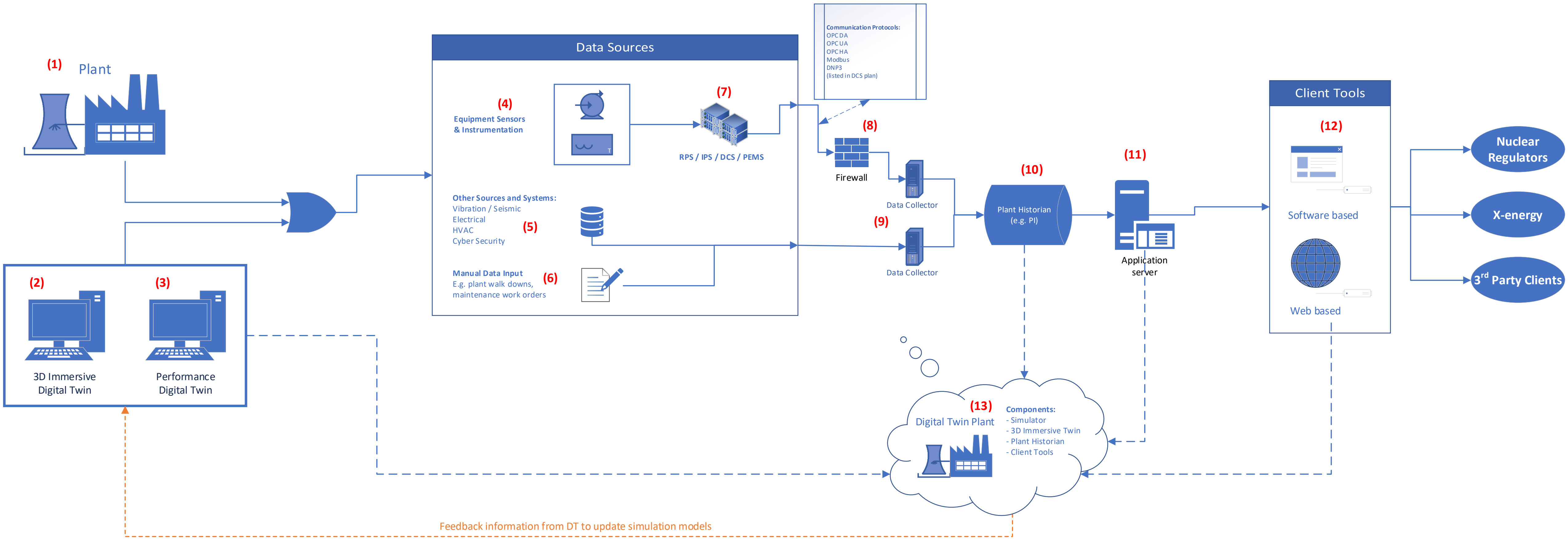
Standard X-energy plant have 4 Reactors - 4 Turbines producing 320 MWe, attributes include:

- 200MWth/80MWe Per Module
- Process heat applications
- Proven intrinsically safe
- Meltdown proof
- Walk-away safe
- Modular construction
- Requires less time to construct (2.5-4 years)
- Road transportable for diverse geographic areas
- Uses factory-produced components
- Load-following to 40% power within 15 minutes
- Continuous fueling; resilient on-site fuel storage

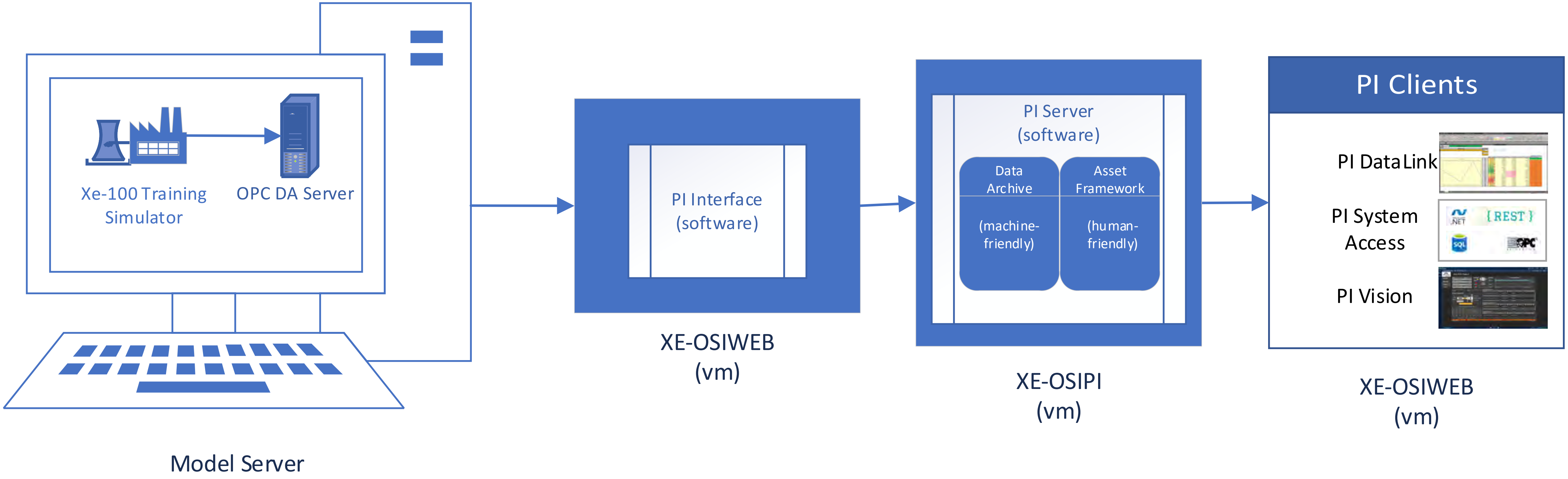




Xe-100 Digital Twin Overview

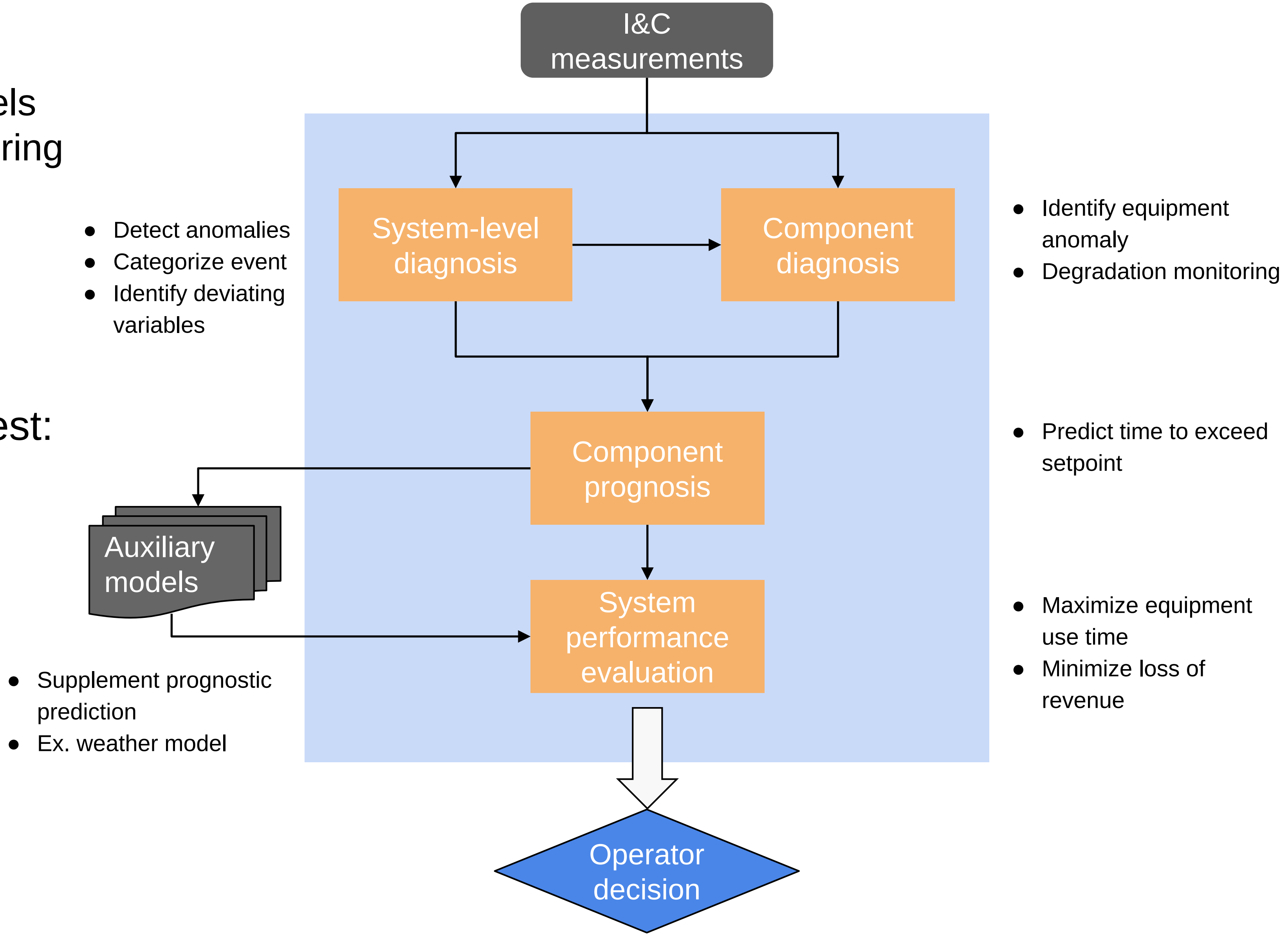


Training Simulator Integration with the PI System



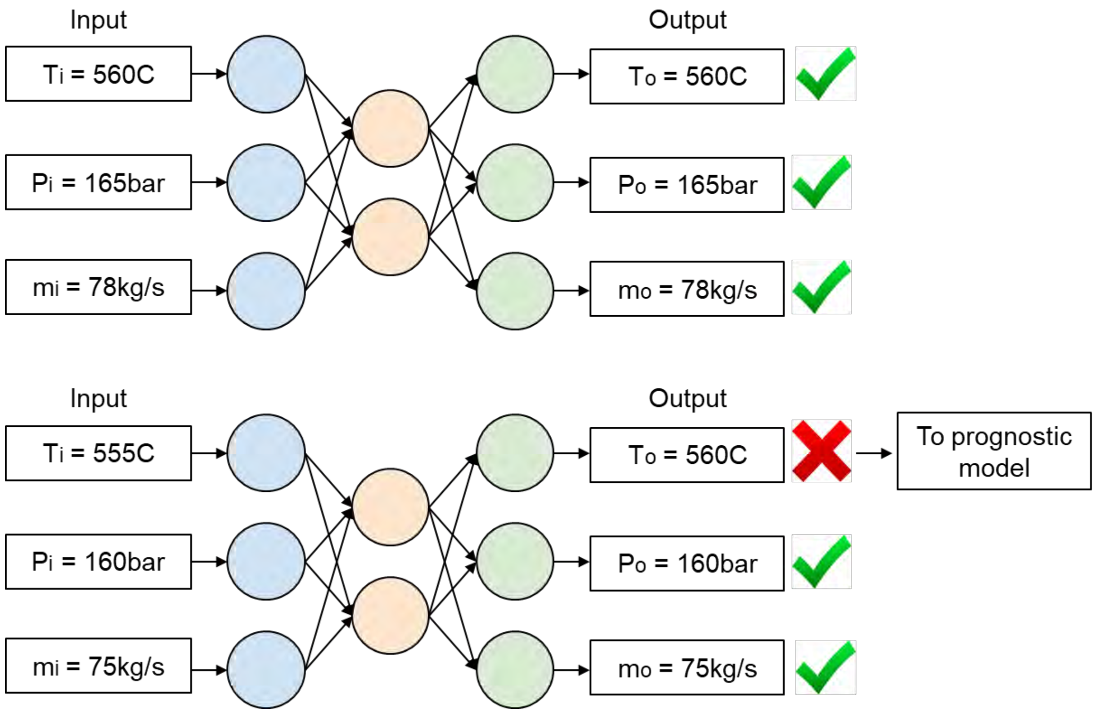
Anomaly Detection with Machine Learning

- Central Maintenance Model
  - Predictive Maintenance Models
  - Thermal Performance Monitoring
  - System/Component Performance Monitoring
- Machine Learning
  - Diagnostic Models
  - Prognostic Models
- Systems/Components of interest:
  - Reactor
  - Steam Generator
  - Turbine
  - Helium Circulators
  - Feedwater Pumps



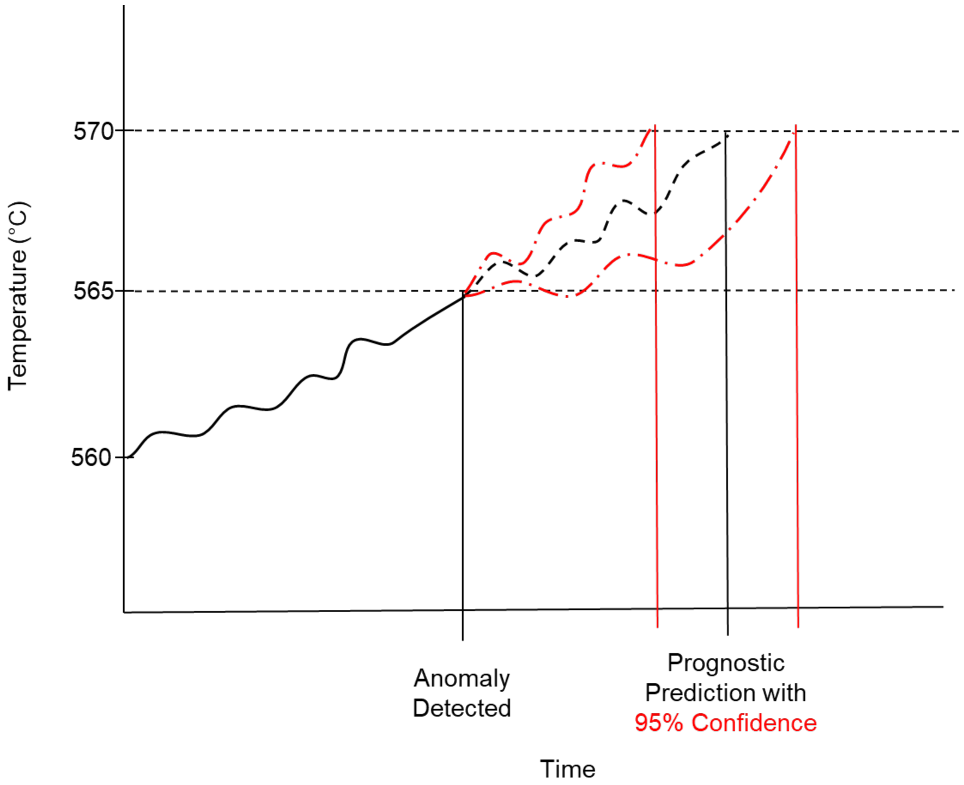
Diagnostic Model

- The diagnostic model aims to
  - Detect system component anomalies
  - Identify deviating variables
  - Initiate the correct prognostic model
  - Be continuously trained online
- Machine learning algorithms include
  - *Auto-Encoder* (AE) for feature extraction
  - *Long-Short Term Memory* (LSTM) for temporal data



Prognostic Model

- The prognostic model aims to
  - Predict time to abnormal condition
  - Provide time window to auxiliary models
- Machine learning algorithms include
  - *Bayesian Neural Network* (BNN) for uncertainty
  - AE-LSTM for input space reduction and temporal data
  - *Convolutional Neural Network* (CNN) for efficient spatiotemporal data processing



Kairos Power

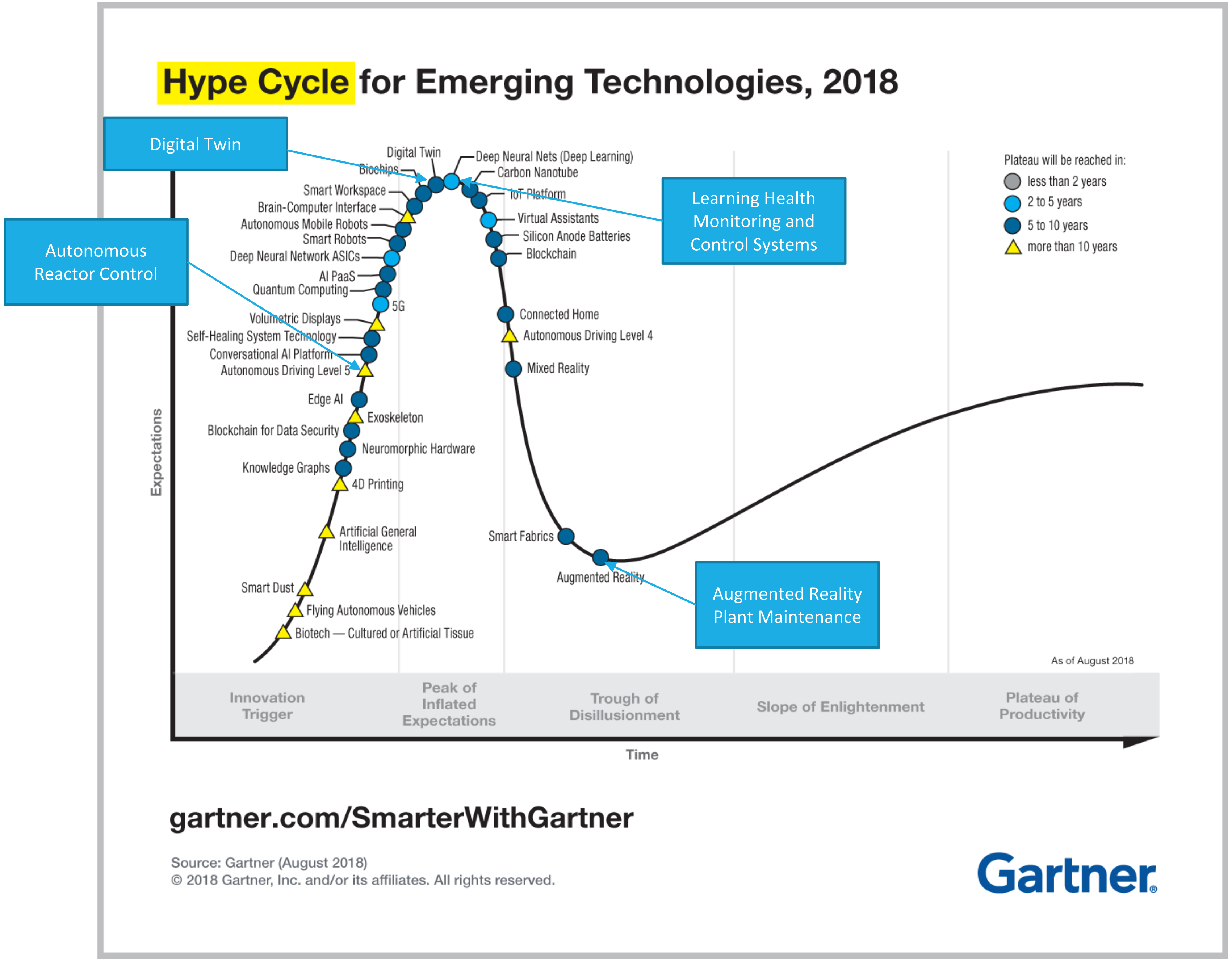
Digital Twin development for Advanced Reactors: Accelerating time to market, increasing safety margins, maximizing value.

DR. ANTHONIE CILLIERS

DECEMBER 1ST 2020

Kairos Power's mission is to enable the world's transition to clean energy, with the ultimate goal of dramatically improving people's quality of life while protecting the environment.

In order to achieve this mission, we must prioritize our efforts to focus on a clean energy technology that is *affordable* and *safe*.


Hype Cycle for Emerging Technologies, 2018
Digital Twin
Autonomous Reactor Control
Learning Health Monitoring and Control Systems
Augmented Reality Plant Maintenance
Expectations
Digital Twin
Biochips
Deep Neural Nets (Deep Learning)
Carbon Nanotube
IoT Platform
Smart Workspace
Brain-Computer Interface
Autonomous Mobile Robots
Smart Robots
Deep Neural Network ASICs
AI PaaS
Quantum Computing
5G
Volumetric Displays
Self-Healing System Technology
Conversational AI Platform
Autonomous Driving Level 5
Edge AI
Exoskeleton
Blockchain for Data Security
Neuromorphic Hardware
Knowledge Graphs
4D Printing
Artificial General Intelligence
Smart Dust
Flying Autonomous Vehicles
Biotech — Cultured or Artificial Tissue
Virtual Assistants
Silicon Anode Batteries
Blockchain
Connected Home
Autonomous Driving Level 4
Mixed Reality
Smart Fabrics
Augmented Reality
Plateau will be reached in:
less than 2 years
2 to 5 years
5 to 10 years
more than 10 years
As of August 2018
Innovation Trigger
Peak of Inflated Expectations
Trough of Disillusionment
Slope of Enlightenment
Plateau of Productivity
Time
gartner.com/SmarterWithGartner
Source: Gartner (August 2018)
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Gartner

Digital Twin and simulator focus

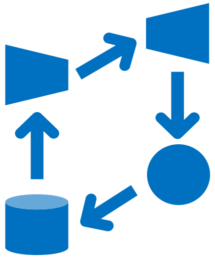
A Digital Twin consists of sophisticated models or system of models based on deep domain knowledge of specific industrial assets. The Digital Twin is informed by design, manufacturing, inspection, repair, online sensor and operational data. It employs a collection of high-fidelity computational physics-based models and advanced analytics to forecast the health and performance of operating assets over their lifetime.

Lifing

Capital equipment predictive reliability **models** for personalized intervals, dispatch tradeoffs & long-term outage planning.

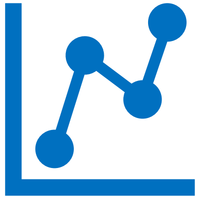
Anomaly

Physics & data driven **models** for prognostics, early fault detection & asset specific failure mode management to reduce unplanned downtime.



Thermal

Plant thermal cycle **models** to make informed operational tradeoffs, manage degradation and improve efficiency over the load profile.

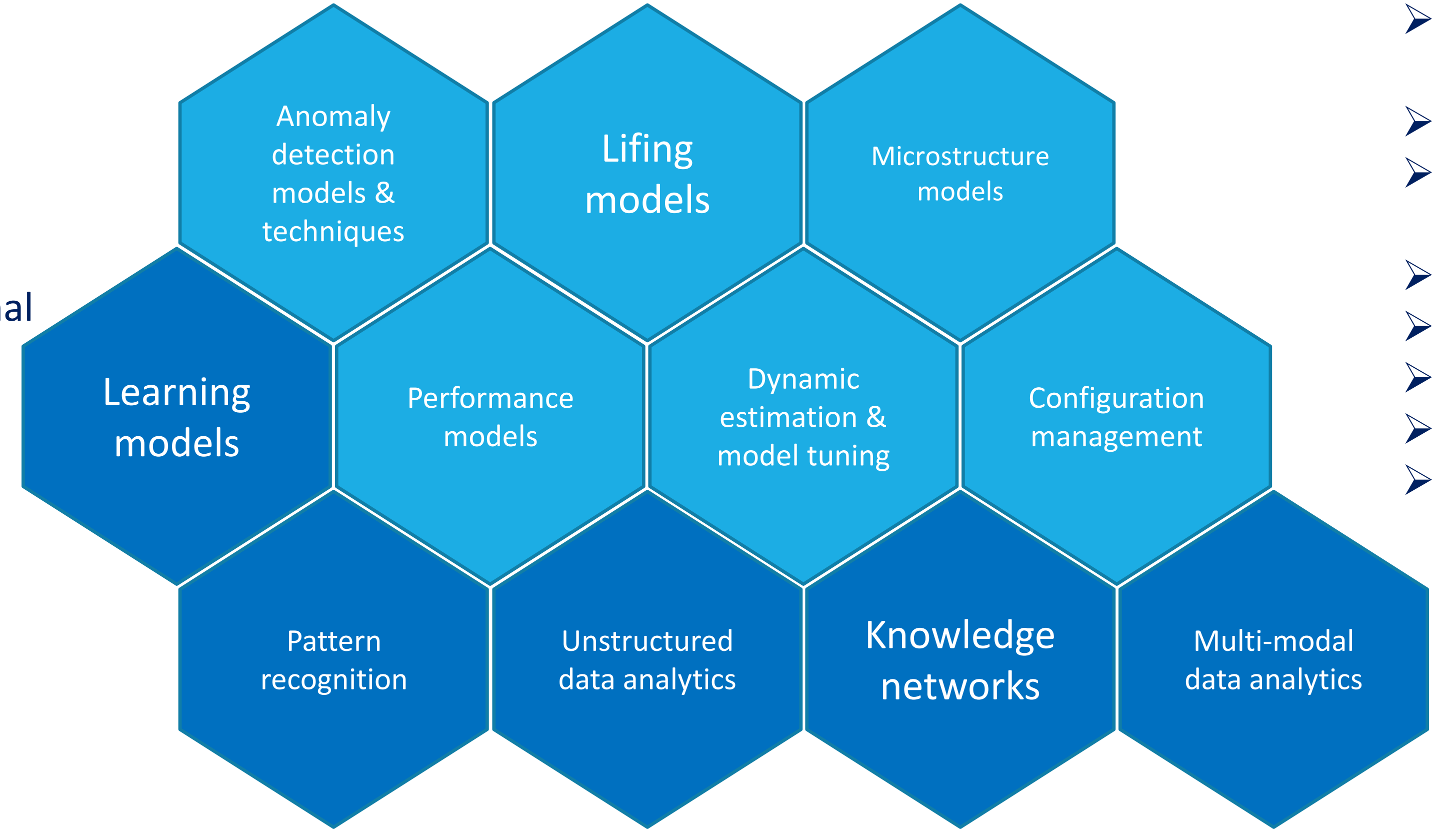


Transient

Physics & predictive **models** for achieving best plant operational flexibility while managing equipment & site constraints.

Fundamental Digital Twin uses

Physics based models



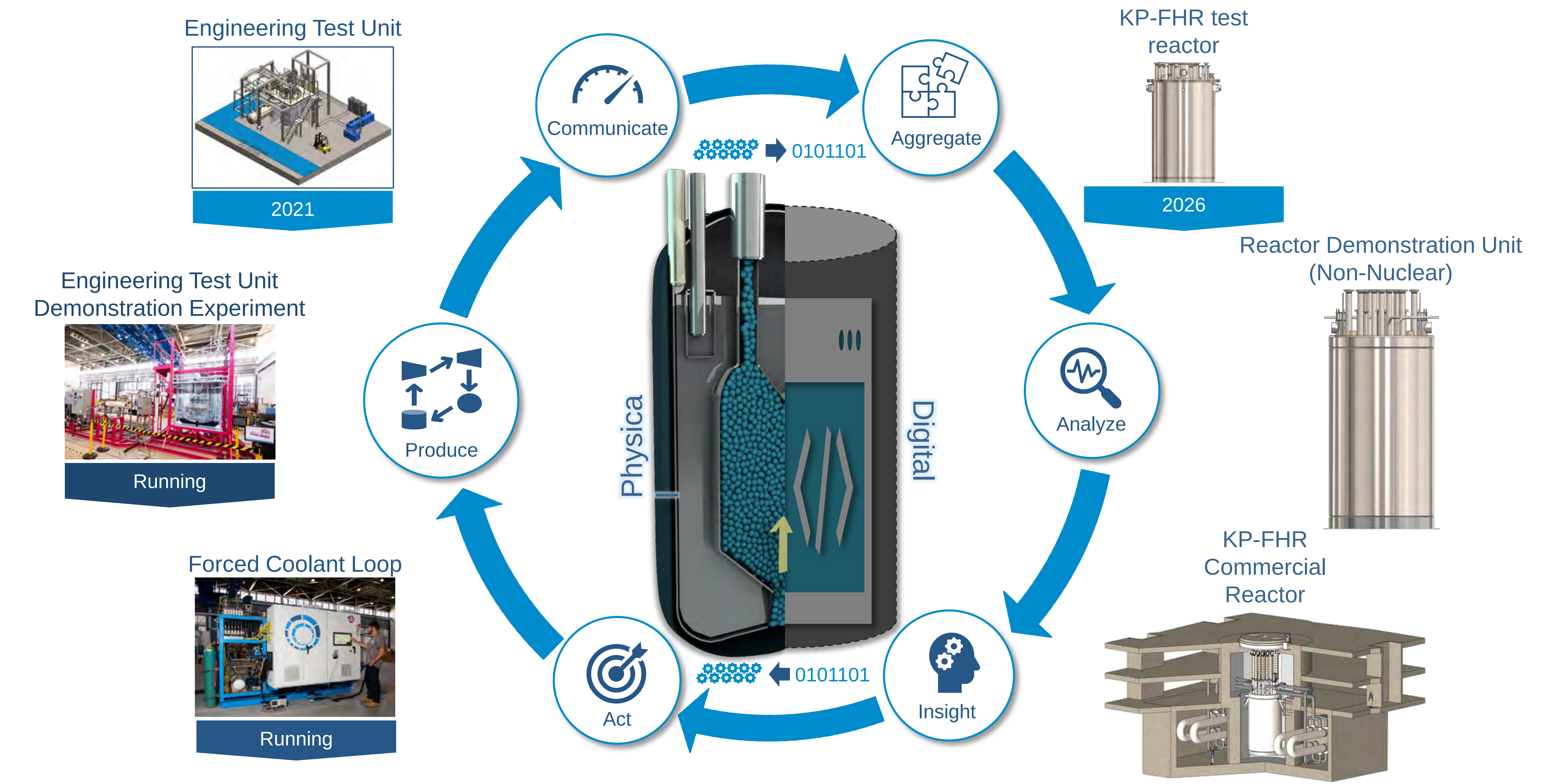
Artificial intelligence

Inputs

- Environmental data/external inputs.
- Sensors/operational data
- Experimental data
- Maintenance actions

Outcomes

- Online performance monitoring
- Zero unplanned downtime
- Analytics based maintenance
- Operational flexibility
- Life optimizing control
- Plant dispatch optimizer
- Economic dispatch
- Reduced load on safety related equipment


Engineering Test Unit
2021
Engineering Test Unit
Demonstration Experiment
Running
Forced Coolant Loop
Running
Communicate
Aggregate
0101101
Produce
Physica
Digital
Analyze
Act
0101101
Insight
KP-FHR test
reactor
2026
Reactor Demonstration Unit
(Non-Nuclear)
KP-FHR
Commercial
Reactor

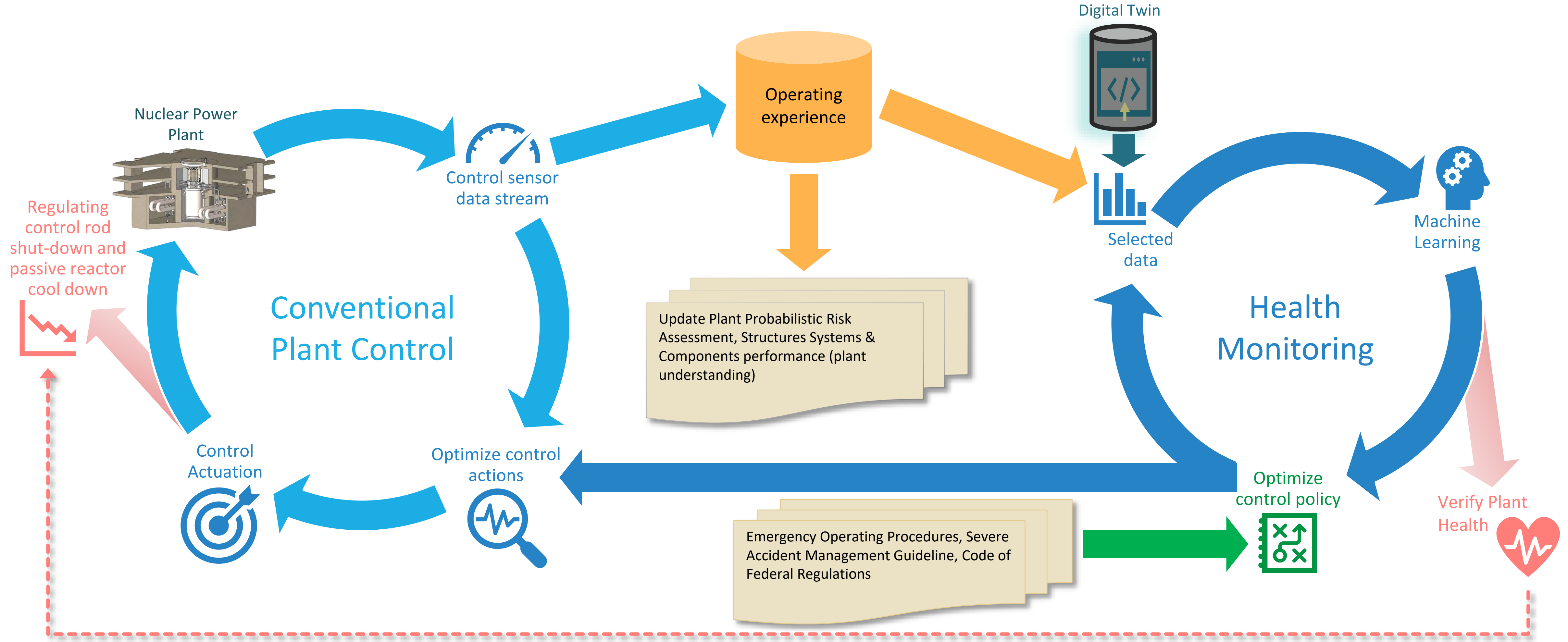
Digital Twins: Increasing Safety Margins

Outcomes

- Digital Twin Operating Point creates a virtual reference for plant operations.
- Identifies abnormal operations early before challenging System, Structure, Component integrity.
- Increases reliability of Non-Safety Related control systems.
- Reduces frequency of Safety Related system operation.
- Increases safety margin.

Source: Cilliers A.C., A deterministic approach for establishing a narrow band dynamic operating envelope to detect and locate hardware deterioration in nuclear power plants, North West University, South Africa, 2013

Digital Twins, maximizing operational value



Adapted from source: Singh. G., Gas Turbine Auto Tuner, Siemens Digital Innovation, MIT: The Digital Nuclear Power Plant: Design, License and Operate at Minimal Cost, April 30 - May 1, 2019

Thank You

Advanced Reactor Design Meets Silicon Valley

Digital twins as early design tools

Clyde Huibregtse, Oklo Inc.

How do we scope the design problem?

What we have:

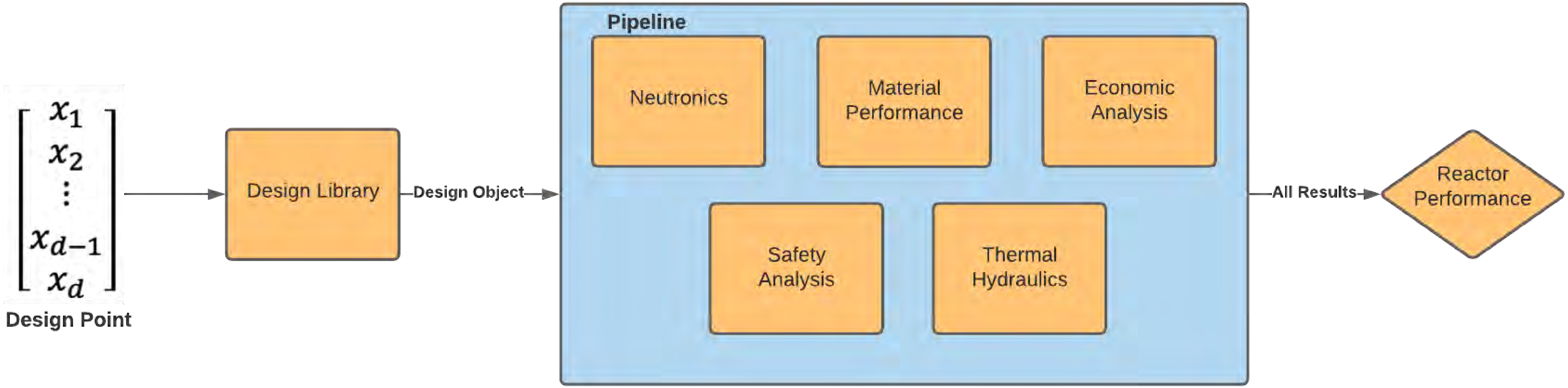
- High-level reactor concept and use-case (power, coolant, fuel type, etc.)
- Rough design and operating limits (material limits, peak temperatures, size)
- Ability to evaluate a design's **performance** based on economics, safety and operating state

What we want:

- Low-level choices for design parameters (design dimensions, material selections, operating conditions, etc.)
- Performance sensitivity to design parameter changes
- Ability to limit design search space by highly non-linear customizable acceptance criteria

Surrogate Model

The Pipeline

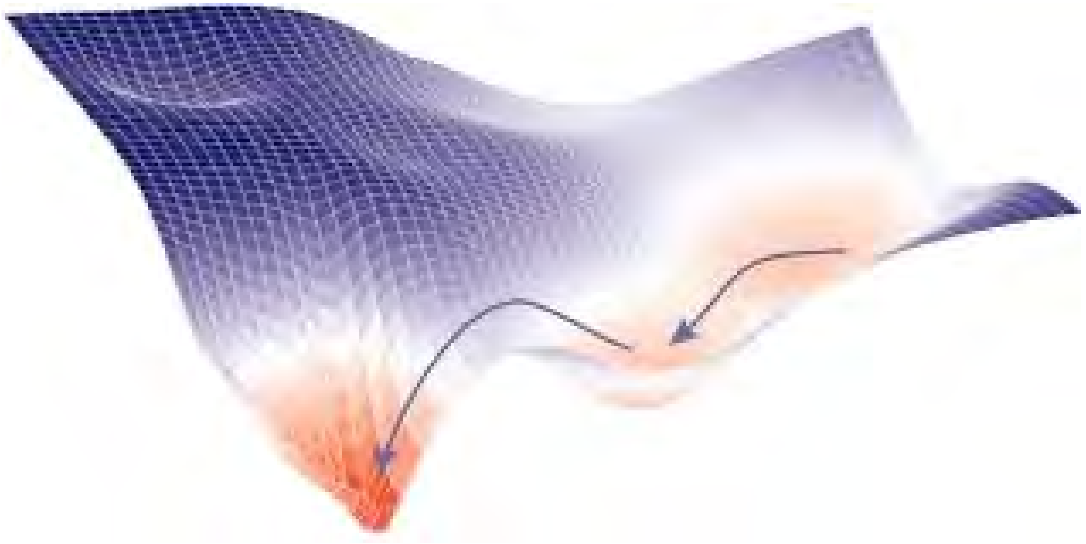


docker

IPoIB

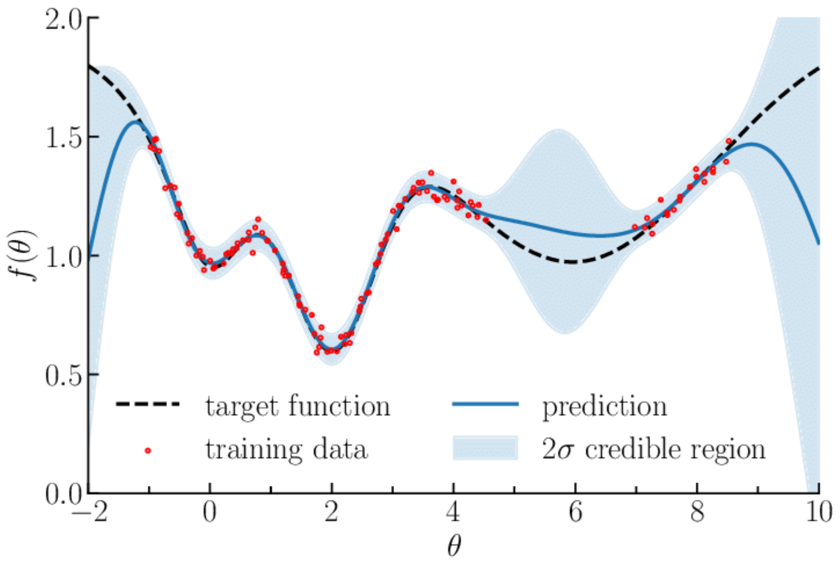
Our Holy Grail: The partial derivative

- "By how much does my reactor performance change as I tweak one of my dimensions?"
- Critical in modern convex optimization methods; Industry is dominated by gradient-based approaches
- **Computing a derivative through a large, heterogenous computational stack is difficult, if not impossible**
- (Industry is moving towards full-stack, algorithmic differentiation. Zygote.jl)

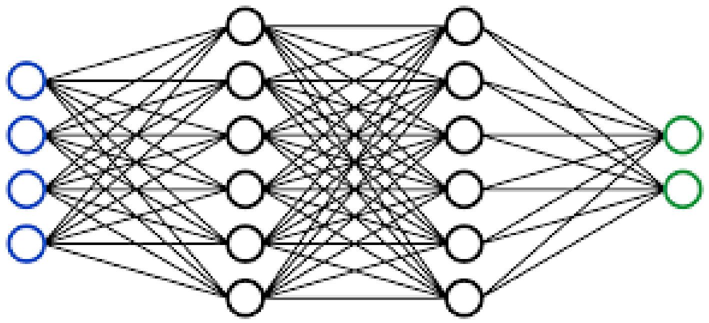


$$\frac{\partial \text{ perf.}}{\partial x_i}$$

Surrogates make computing derivatives easy



Gaussian Process



Artificial Neural Network

- Mimic the diverse, expensive computational stack with a **surrogate model**

- Surrogate should be:
  - Accurate – surrogate should closely match the objective on unseen data points
  - Fast – calls to the surrogate should be computationally cheap
  - Statistics informed – surrogate should report the quality of its predictions

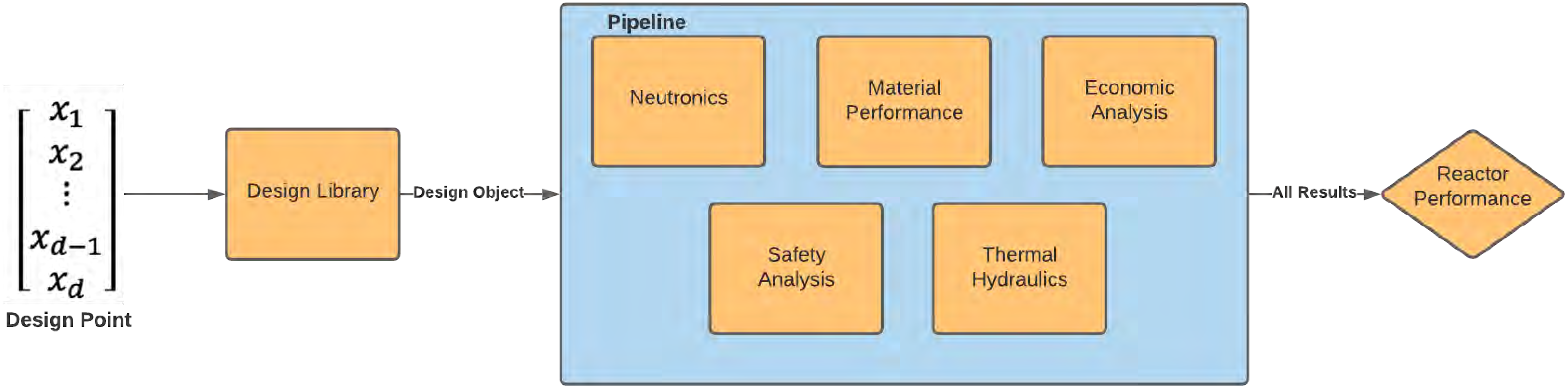
- Surrogate can be Neural Network, **Gaussian Process**, regression, etc.

Surrogate formalism

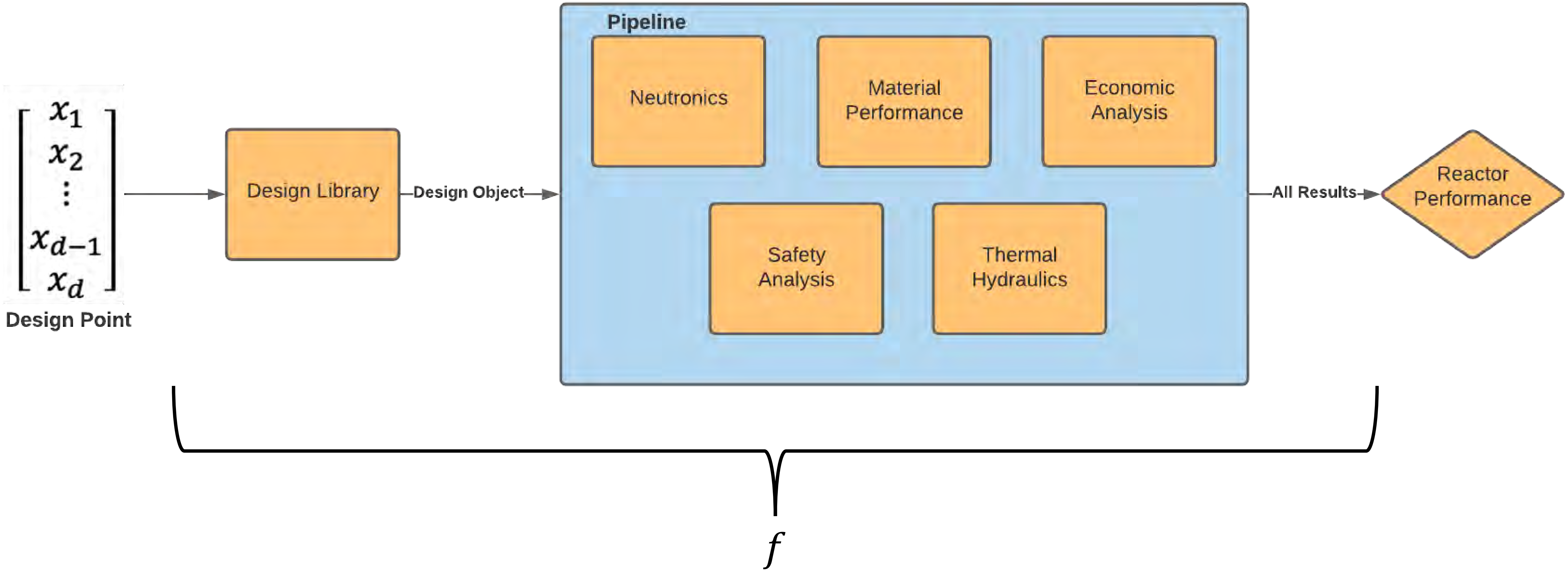
- Let $\vec{x}$ be a vector of d dimensions - **design point**
- Let f represent the stack of codes that computes the **performance** of a given design point
- Therefore, $y = f(\vec{x})$ is the scalar output of our performance function

- **Goal**: create **surrogate**, f^* such that $f^*(\vec{x}) \approx y$, and find minimum of f^*
  - f^* trained by collecting many $(\vec{x}, y)$ pairs
  - Ideally, f^* responds to queries in the form: $f^*(\vec{x}) = y \pm \sigma$

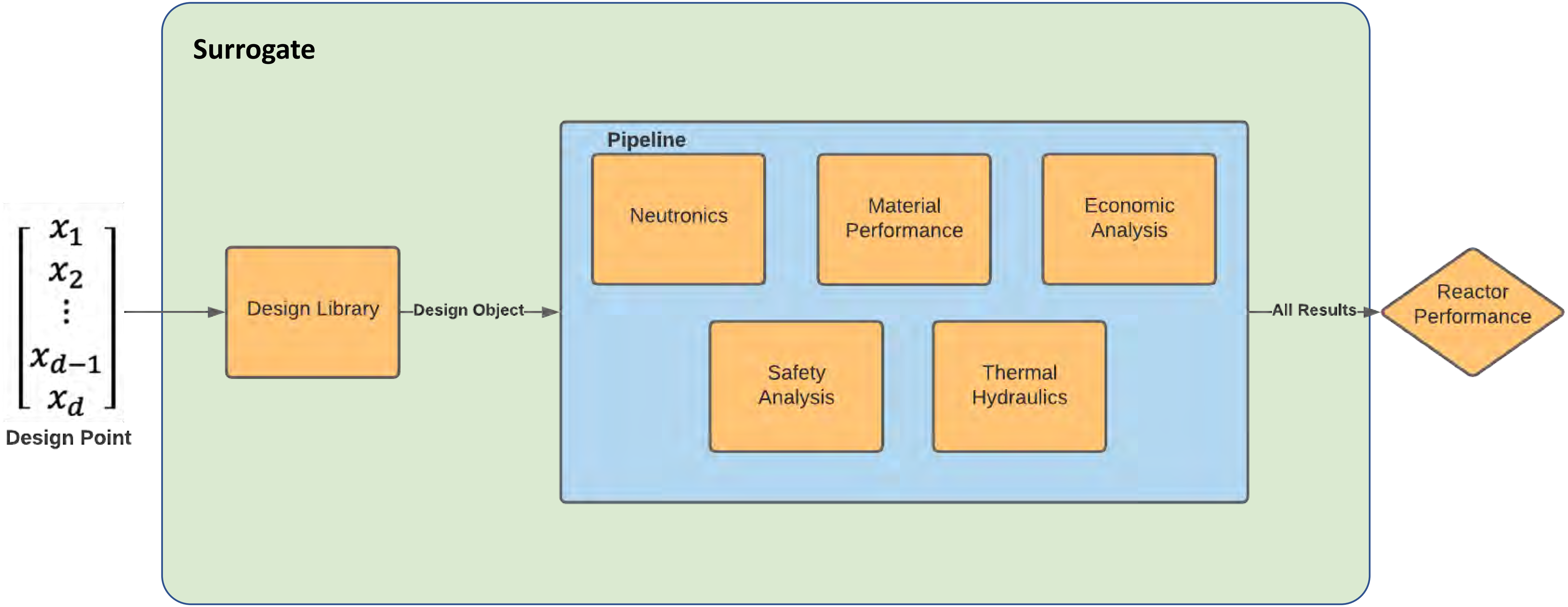
Surrogates in our pipeline



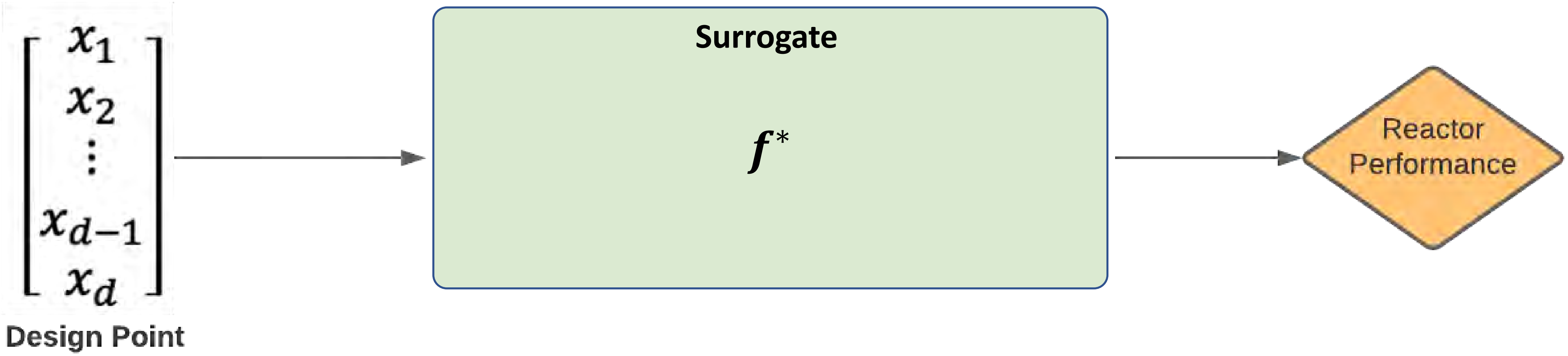
Surrogates in our pipeline



Surrogates in our pipeline



Surrogates in our pipeline



Training a surrogate

- $\mathbb{R}^d$ is too large to search in earnest
- But we do have some intuition:
  - Most dimensions positive
  - Sense for relative scale given the use-case of the design

- Intuition gives a bounding **hyperspace** for the location of the optimal design point
- How do we efficiently span this hyperspace? Ensure surrogate is accurate where we need?
  - Grid in d dimensions?
  - Monte Carlo?
  - **Low Discrepancy Sequences (LDSs)!**

Generating efficient training data

- What is "efficient"? Low error in numerical integration

$$\int_{C^d} f(u)du \approx \frac{1}{N}\sum_{i}^{N} f(\vec{x}_i)$$

$$I(f) \approx \hat{I}(f;\vec{x}_1^N)$$

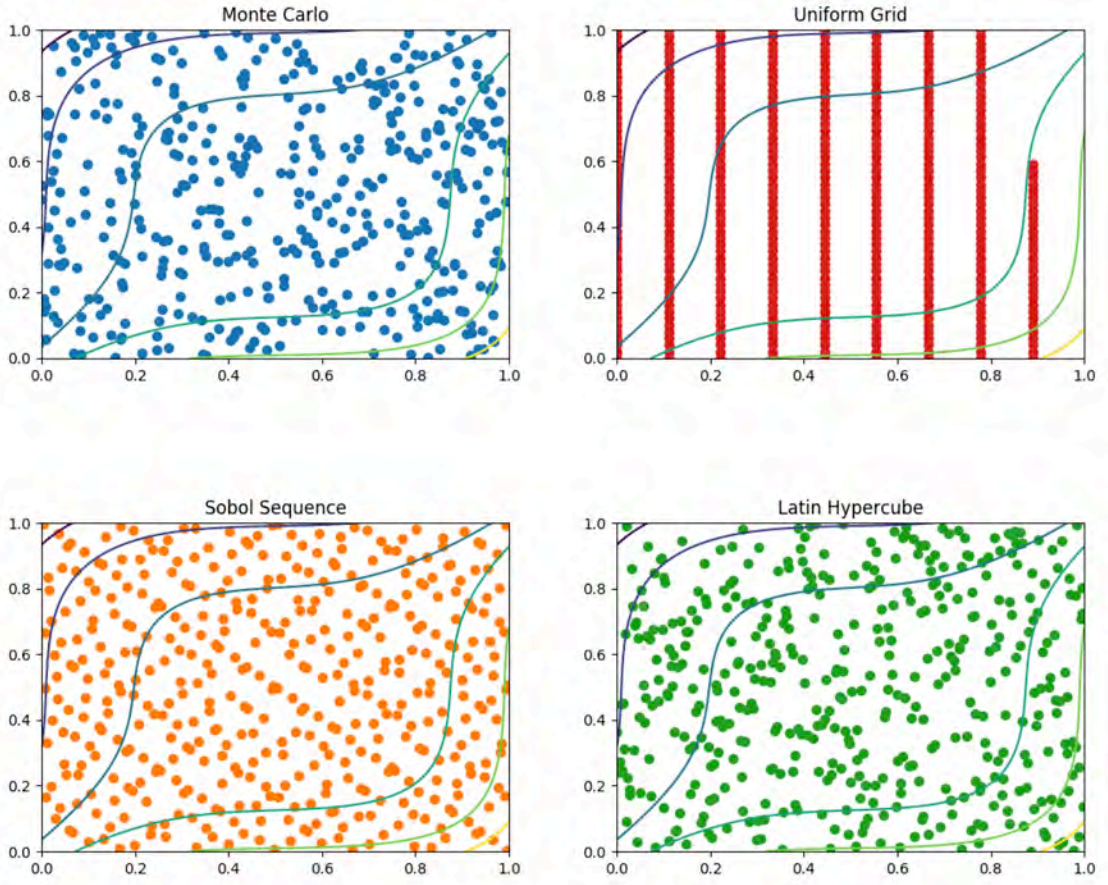
where,

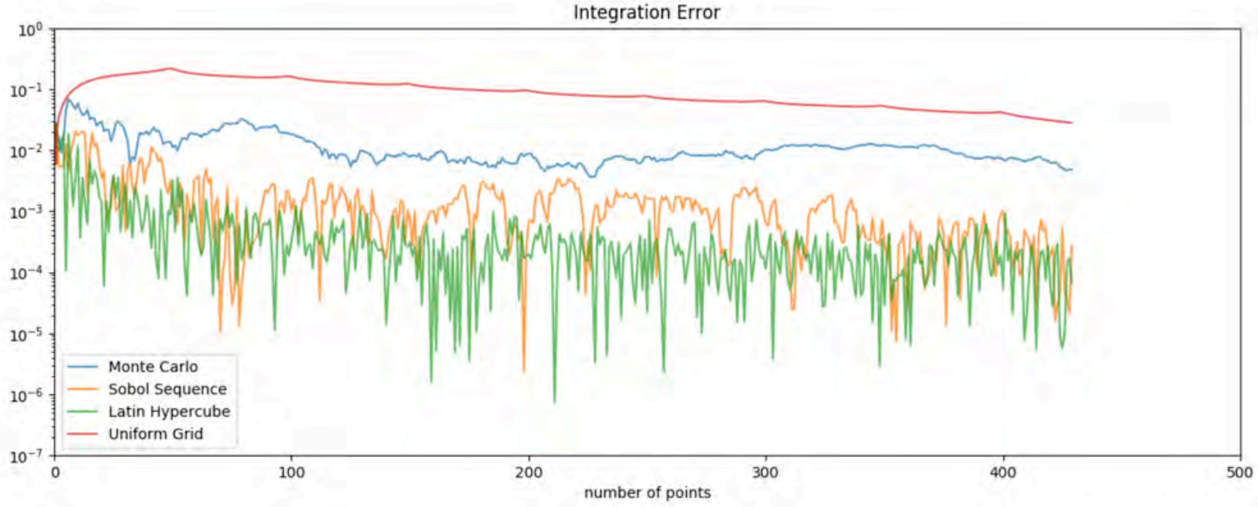
$$C^d = \prod_{j}^{d}[0,1)$$

$$\{\overrightarrow{x_1}, \overrightarrow{x_2}, \dots, \overrightarrow{x_N}\} = P$$

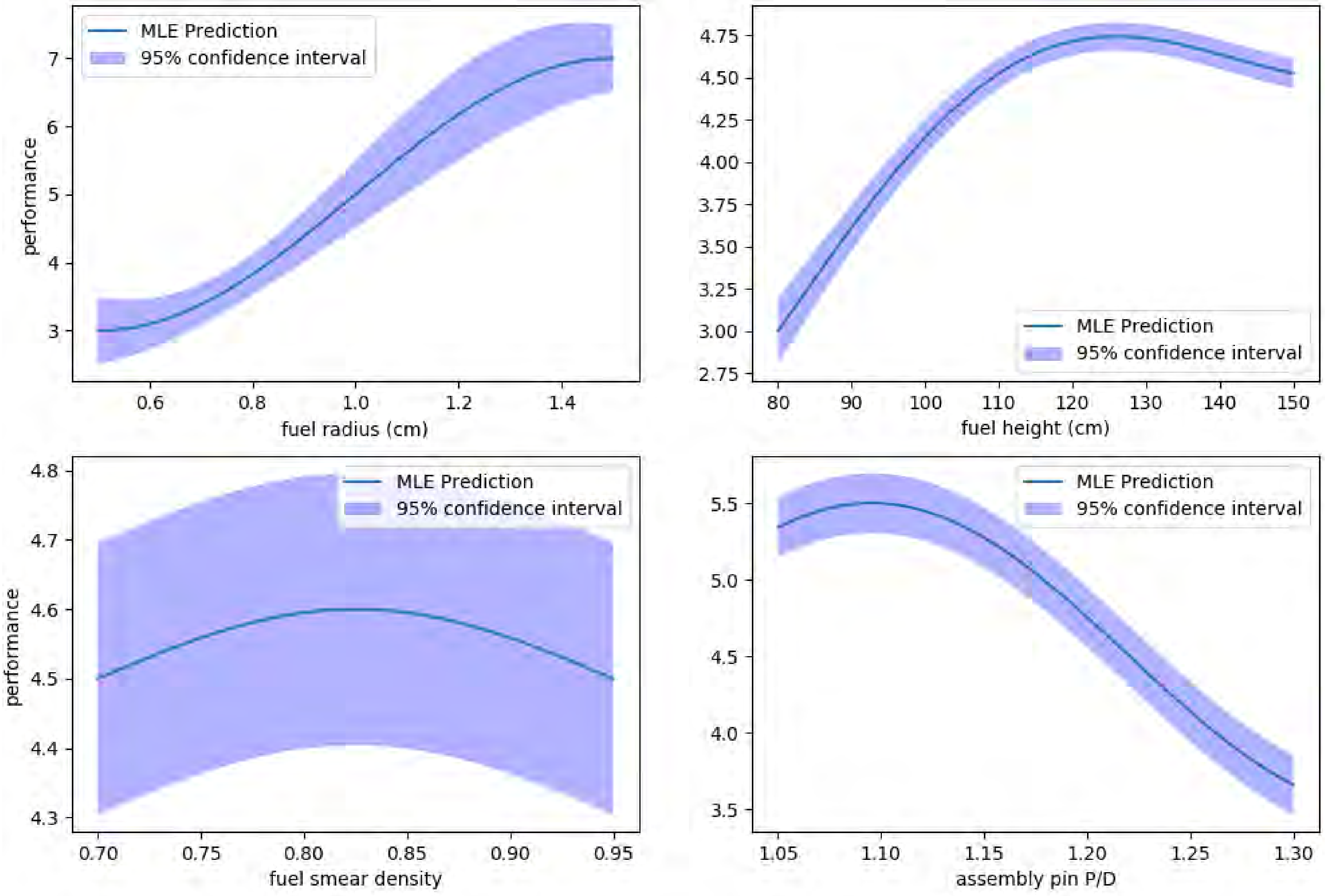
- What is the smallest P such that $\left|I(f) - \hat{I}(f;P)\right|$ is minimized?
- "How well does our training data set P represent the important regions of f's domain?"
- Remember that each evaluation of $f(\overrightarrow{x_i})$ is **expensive**!

Choice of P matters!

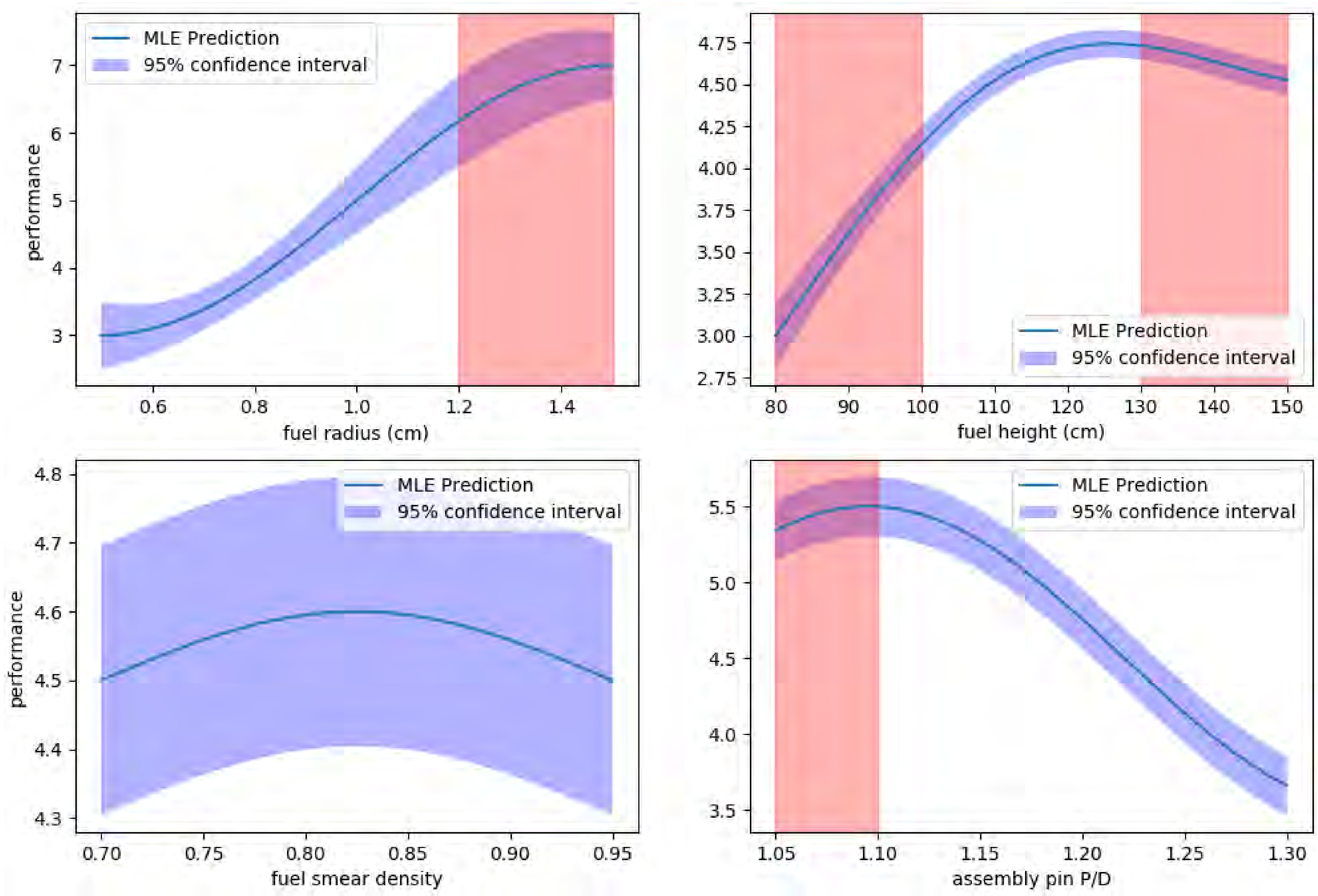




Sample partial derivatives



Sample partial derivatives




Thank you

GE Research

Industrial Digital Twins: GE Experience and Perspectives

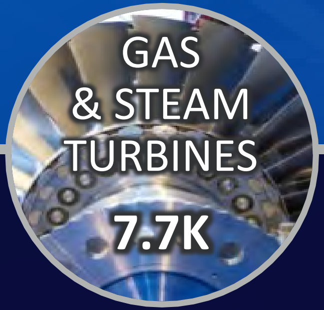
Achalesh Pandey
Research Director- AI

Abhinav Saxena, PhD
Senior Scientist – Machine Learning

Digital Twin

GE Experience

KEEP 300K PEOPLE IN THE SKY/HR. | 1/3 OF THE WORLD ELECTRICITY | 16K SCANS PER MINUTE



DRIVERS

1 INCREASED PRODUCTIVITY

2 FASTER GROWTH

3 RISK-MANAGED ADAPTABILITY

4 IMPROVED SAFETY

DYNAMICS

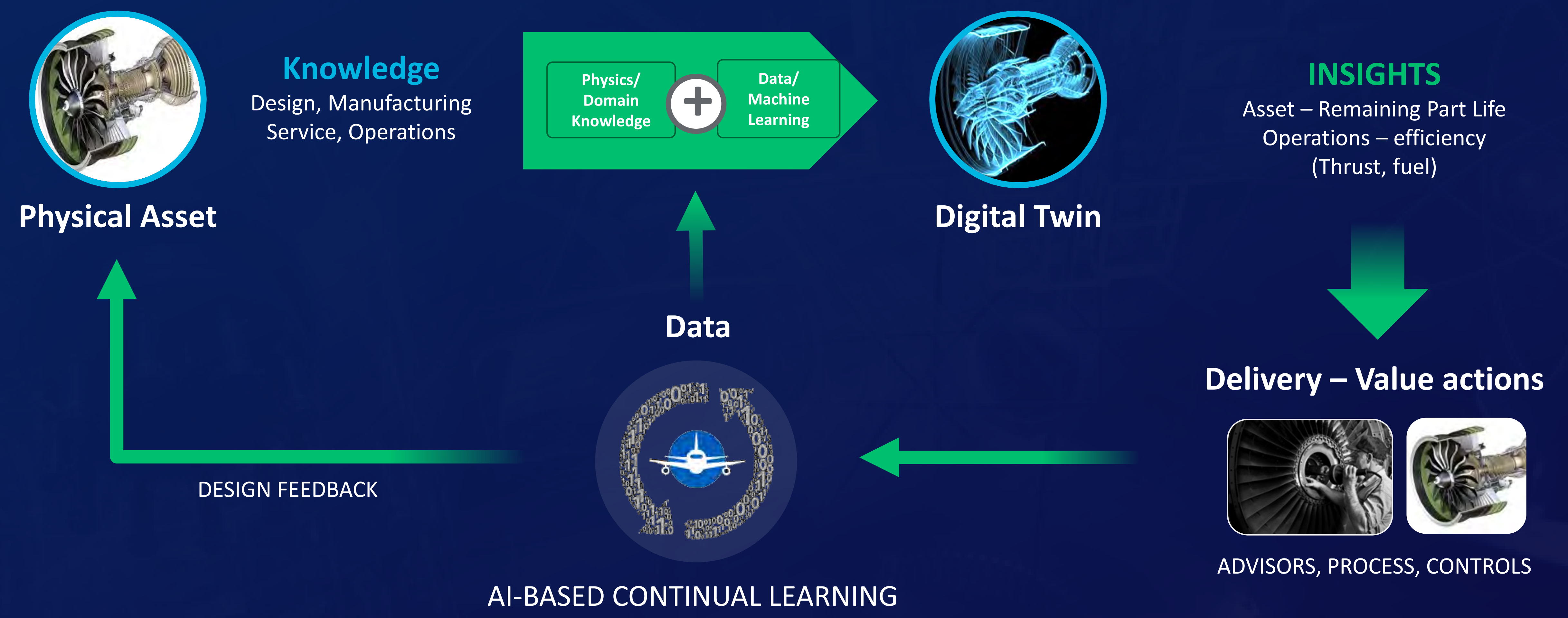
CHANGES IN CUSTOMER DEMAND
e.g. seasons, economy, …

BLURRING COMPETITIVE MARKETS AND REGULATORY/ GOVERNMENT INFLUENCES
e.g. Policy, regulations, …

↑ DIGITAL CAPABILITIES @ LOWER COST
e.g. autonomous, tele, online, …

Digital Twin

A personalized, living, learning, model

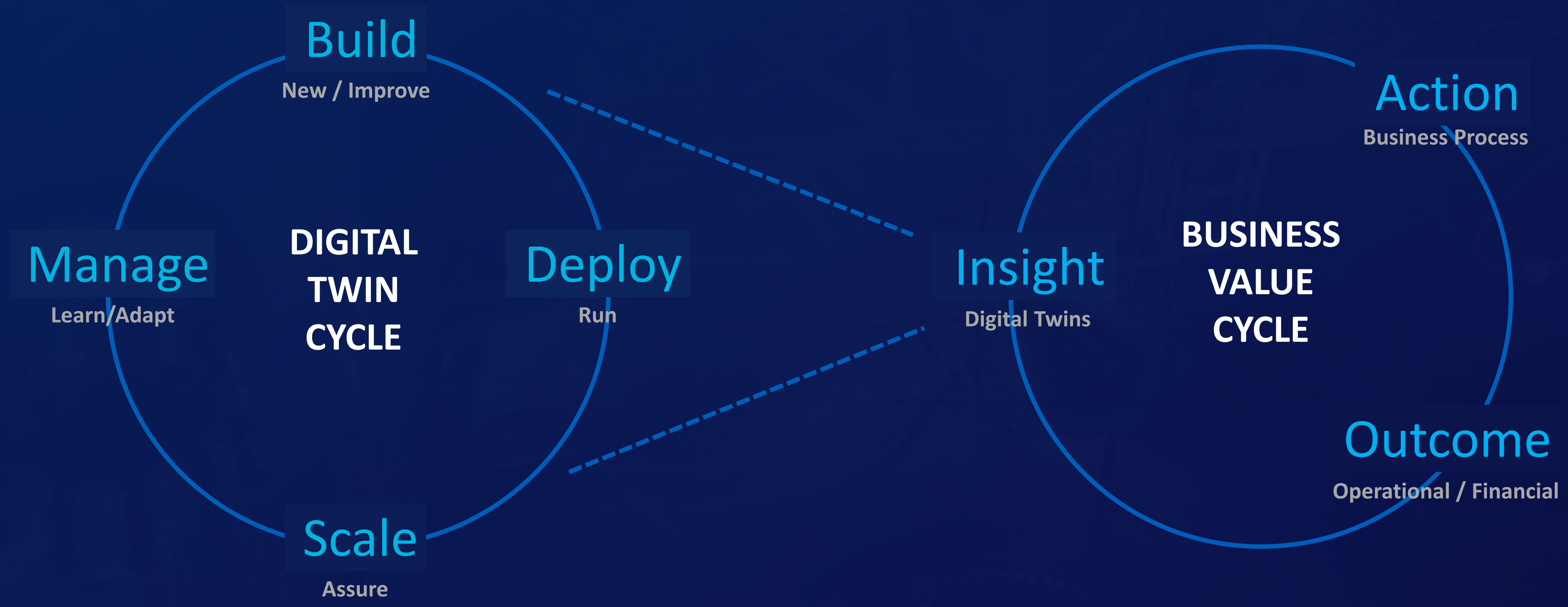


CONTINUOUSLY IMPROVING BUSINESS OUTCOMES

A framework for

Adopting Digital Twins to Deliver Business Value

LEARNING FROM OUR TWINS AT SCALE | **USING LEARNINGS TO DELIVER BUSINESS OUTCOMES**



Continuous feedback loop to further advance Digital Twin capabilities

Aviation Customer Outcomes with Digital Twin

DOMAIN KNOWLEDGE

+

INDUSTRIAL DATA

BUSINESS OUTCOME

Sufficient Early Warning

Compressor pressure, temperature, Exhaust gas temperature (EGT)

Predict Probability of Failure

Predict Compressor Issues

>30 days advanced warning

Continuous Prediction

Critical Engine Parts; TB Coating, EGT Environmental Parameters

Critical Engine Parts; Cumulative Damage

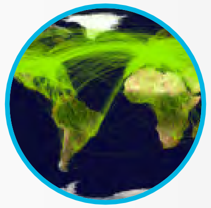
Optimized Inspection Schedule

>50% planned outage reduction
$10Ms saved per year

Dynamic Optimization

Fleet Engines, Routes, Environmental Data, CDM

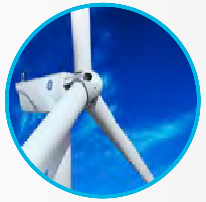
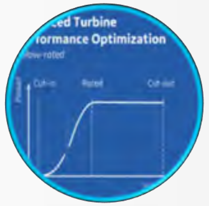
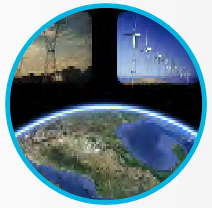
Scenario Analysis and Optimization



Fleet Optimization

$10Ms saved per year in lease costs

Energy Customer Outcomes with Digital Twin

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

Healthcare Customer Outcomes with Digital Twin

DOMAIN KNOWLEDGE

+

INDUSTRIAL DATA

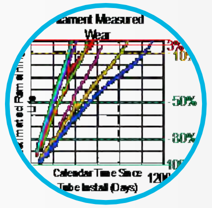
↓

BUSINESS OUTCOME

Sufficient Early Warning

CT Tube voltage, current, etc.

Predict probability of filament failure



>5% decrease in overtime cost
$100Ks of savings per hospital system per year

Continuous Prediction

Brain MR Imaging, MR physics

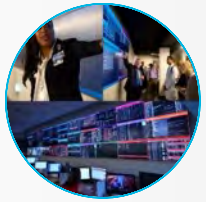
Anatomy detection, optimal scan plane

Improved consistency, better image quality and reduced scan time (**40-50%**)
2X throughput

Dynamic Optimization

Hospitals & Health Systems

Scenario Analysis and Optimization

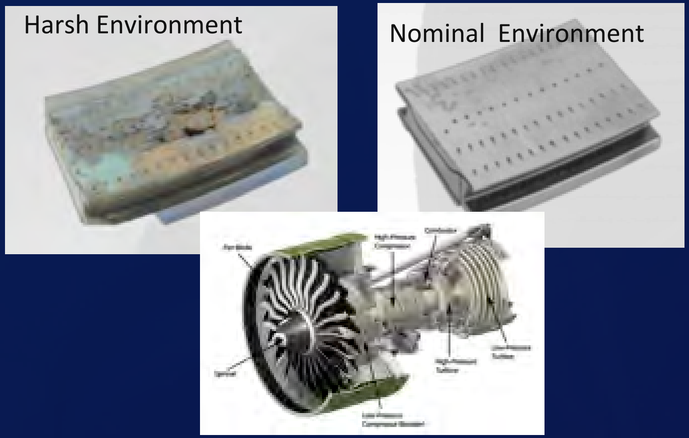


45% workflow improvement, **2X** growth
$ Millions saved per year

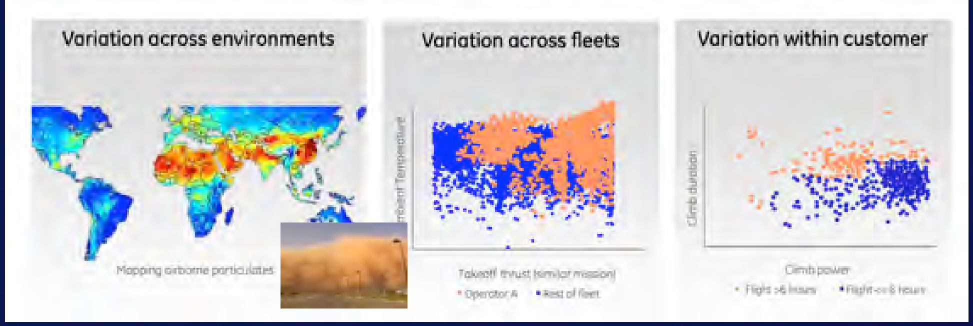
Digital Twin Example

Aviation Continuous Prediction Use Case

GE 90 HPT Stage-1 Shroud (Oxidation Failure)

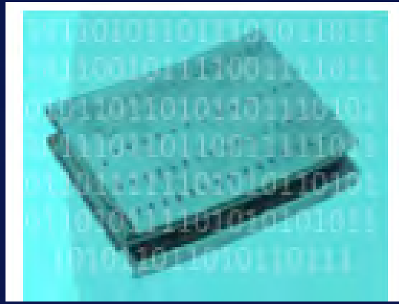


Operational & Environmental Variation

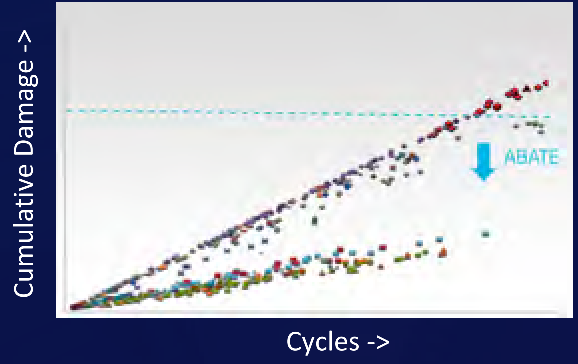


Environmental Data, Engine Operation Data, Configuration Data, City Pair Data, Design Data, Inspection Data

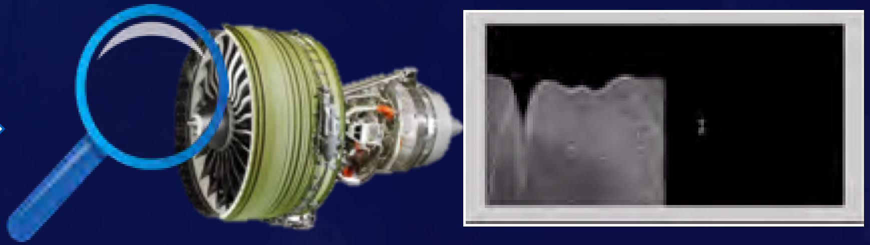
S1S Oxidation Digital Twin (Physics + Data Driven)



Analytics Based Removal



On/Off- Wing Inspection



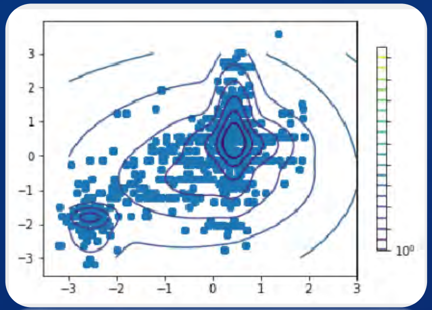
Feedback is used to continuously update Digital Twin Model

Research Focus: Advancing Digital Twin and AI

for Adoption and Scale

Explainability

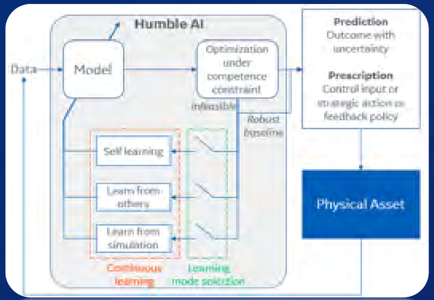
Build Trust in ML models



TRANSPARENCY

Humble AI

Safety & Robustness to put information to work



RISK MANAGED OPTIMALITY

Learning

Multiple modes of learning

Learn from self

Learn from simulations

Learn from humans

Learn from fleet

CONTINUOUS IMPROVEMENT

Security

CyberPhysical Security

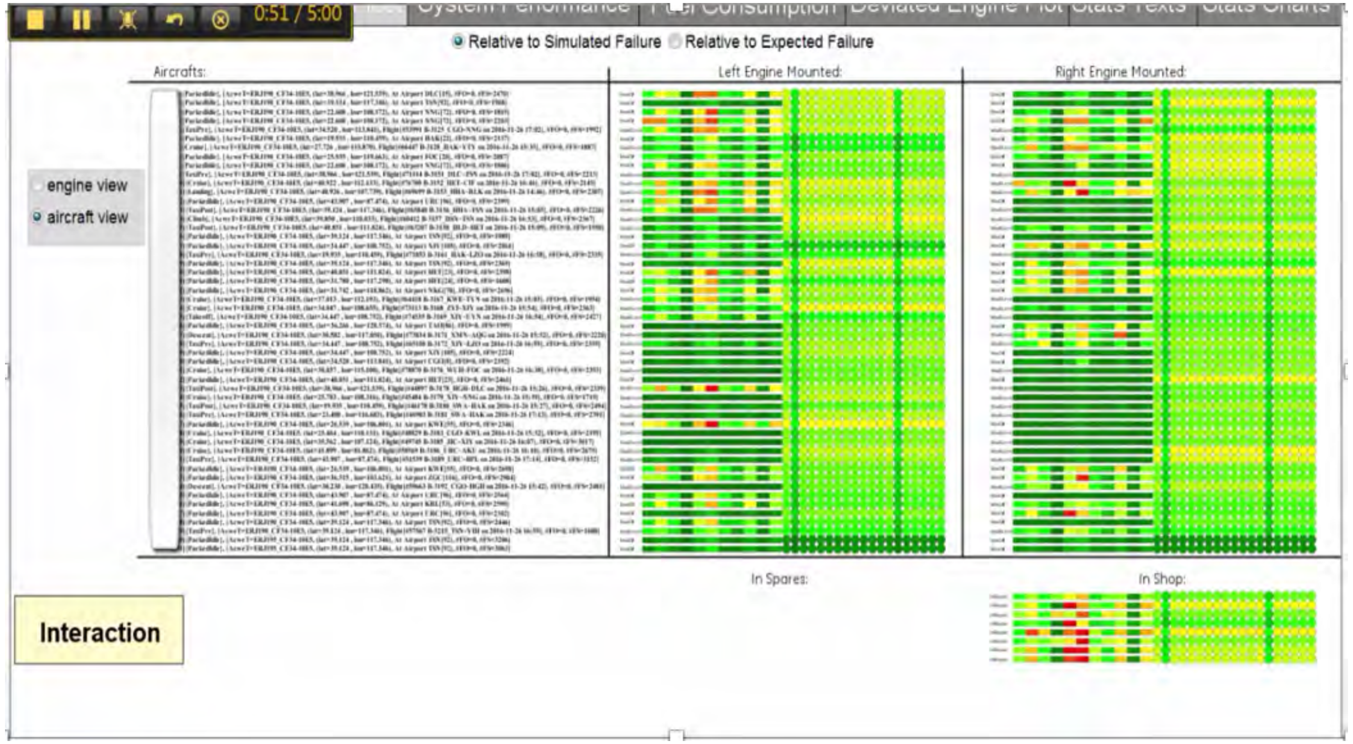
DIGITAL GHOST

CONTINUOUS PROTECTION

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

Systems Level Digital Twin for Optimization

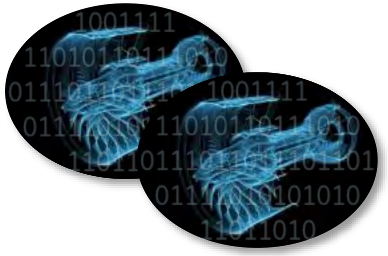
Understand and create fleet conditions for business flexibility



PHYSICAL ASSET AND STATE

Engine life and performance, flight schedules, operator details - thrust, etc.

DIGITAL TWIN



MRO Service data
- Simulated 'What-if' Futures: Operations, Spares/MRO TAT, Financials

VALUE OUTCOMES

Optimal engine assignment to routes, on-wing operations and MX

Realtime Optimization@ Edge

CCGT Plant Optimization

6FA Turbine Combined Cycle Plant

Plant operational data, Weather forecasts

Objectives; Production target, Fuel usage

Operational set points

Plant Twin Optimization

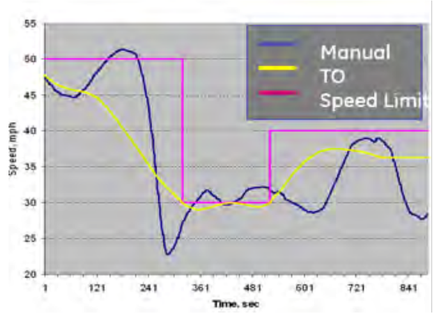
Continuously tuned combined cycle plant model

Automated Optimizer + Twin targeting > 1% fuel efficiency boost scalable across all turbine types

Evo Locomotive Trip Optimization

Train weight; Rail topology; Locomotive data

Optimal speed and horsepower



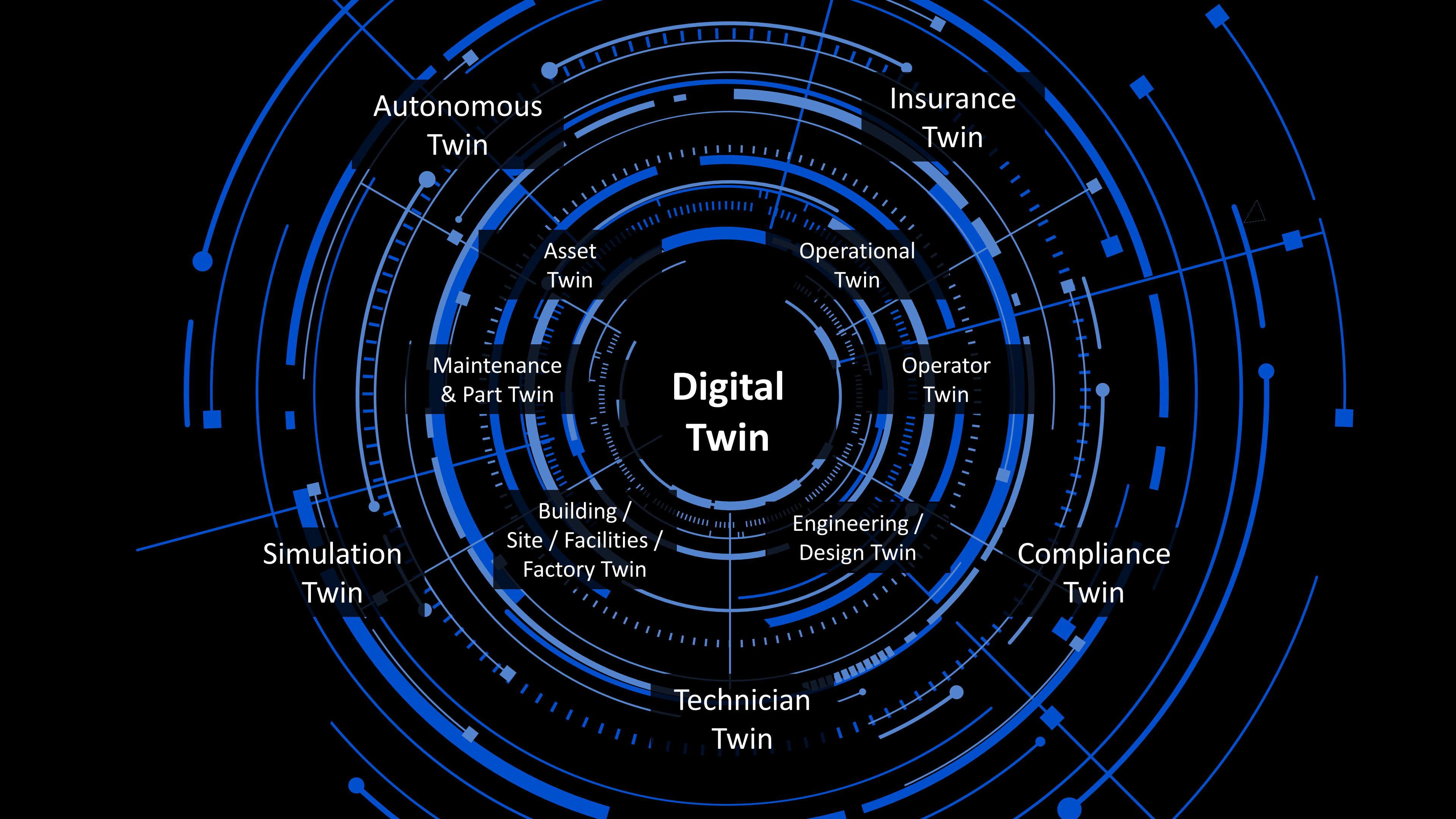
Minimize fuel consumption and emissions – generated per trip.

32K gallons / locomotive and 174K tons emissions decreased per year

IBM Digital Twin

Overcoming Digital Twin Data Scarcity and Accelerating the Journey to Predict

Presented By:
Chandler Maskal Offering Manager, Digital Twin Exchange


Autonomous Twin
Insurance Twin
Asset Twin
Operational Twin
Maintenance & Part Twin
Digital Twin
Operator Twin
Building / Site / Facilities / Factory Twin
Engineering / Design Twin
Simulation Twin
Compliance Twin
Technician Twin

Digital Twin pain points

Digital asset data availability

Complex integration and lack of infrastructure and standardization

Missing data and models to drive actionable insights leveraging AI

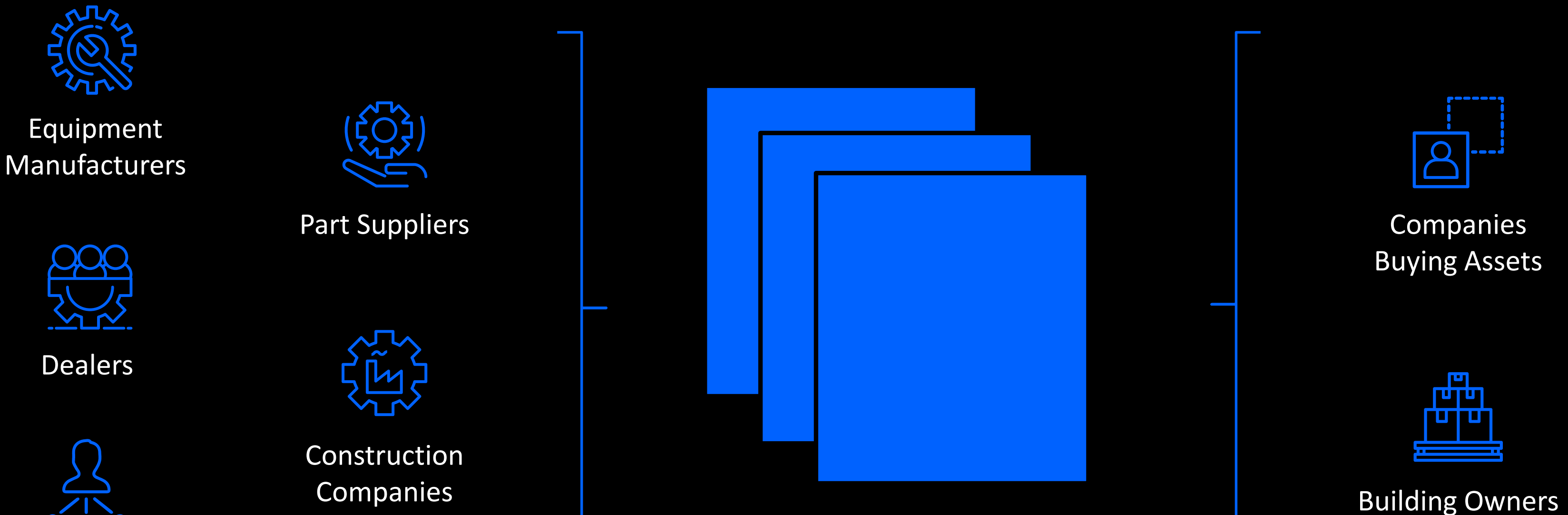
Energy & Utilities

Oil & Gas

Transportation

Manufacturing

The Solution:
Strategic Digital Management



Agreement Type

- Requires Transfer of Digital Twin
- Defines Digital Requirements

The Operational Performance Breakthrough:
Strategic Digital Management

What's needed to drive "breakthrough" success:

Short time-to-implementation
- days and weeks

Rapid ROI
- A system that immediately begins to pay-for-itself

Proven solution, team and team that:
- Has global deployment experience
- Is used to demanding customers demanding hard-dollar savings

A strategic platform that will grow as technology proliferates and data grows

A focus on biggest data improvement paybacks first

A platform that drives your key strategies/ initiatives to effective action

Backed by consulting services and a digital factory to transform your business

Solution Overview

Digital Twin Content

More Complex

Asset Health & Failure Models

Operations Performance Monitoring Model

Forecast & Prediction Model

Asset Monitor Dashboards

Asset Health Scoring Methods

2D/3D CAD Files

AR/VR Models

Building Information Models (BIM)

Maintenance Plans

Remote procedures for the technician of the future

Bill of Materials

Stocking Strategy

User/Engineering/ Maintenance Manuals

Parts List

Fault Codes

Less Complex

Establishing digital twin standardization for easy deployment

Phase 1

Creation

–

Promote existing digital twins, formats and manual integration

Drive the creation of complex digital twins

Phase 2

Integration

–

Create automated integration capability to ingest digital twin data

Phase 3

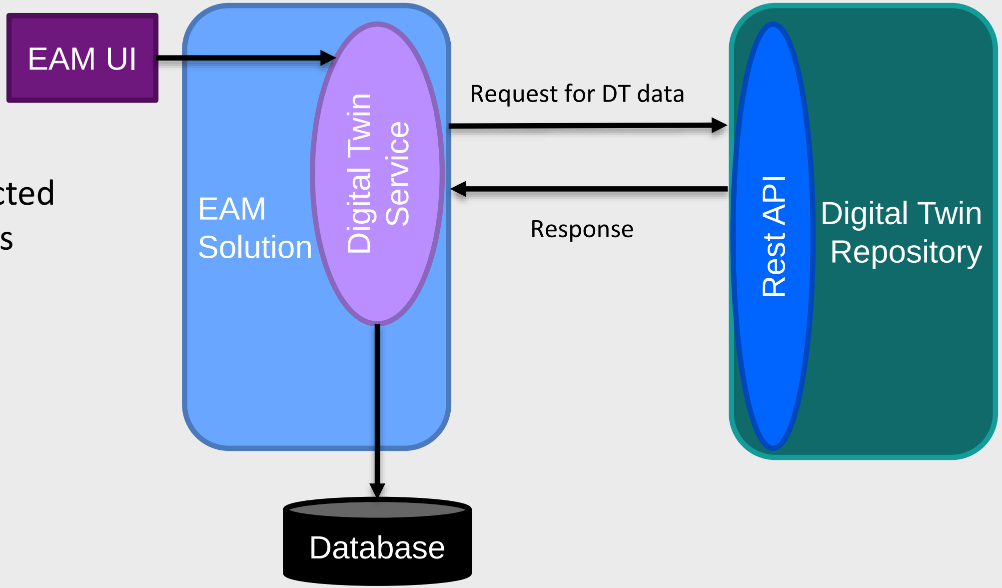
Established Standards

–

Create format standard for use by OEMs and industry stakeholders aligned with industry specific use cases

Digital Twin Integrations – Spare Parts List into EAM Solution

A repository of asset related digital data that are provided by various sources including the manufacturers is needed



<Architecture>

<u>Data objects created with the integration</u>

- Item records with images
- The asset with Spare part records for the selected digital twin product with images and attachments
- Job plan and Job tasks with asset link record
- Json format

<u>Custom Integration Mapping</u>

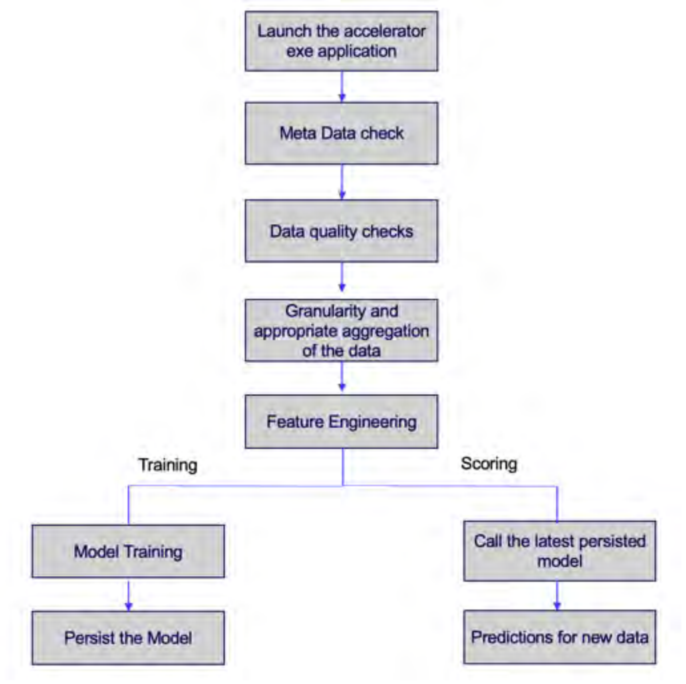
- Additional fields can be mapped between EAM platform and digital twin repository
- An automation script can be used to customize mapping for an integration point in the integration.

AI/ML Accelerators – Enabled Accelerator for Air Compressors

Accelerators analyze parametric data from assets like air compressors and predicts imminent failures thereby helping plant maintenance engineers/technicians plan the maintenance activity without disrupting plants operations

Air compressor downtime impeller failure/breakdown is critical, the event could impact the operations of a plant for days

- Generalized to work with air compressors that have an impeller - Rotary and Centrifugal air compressors
- Can predict impeller failure/breakdown
- The accelerator is based on the experiences with several customers across industries - from air compressor manufacturers to industries that heavily rely on availability of air compressors for their day to day operations
- Validated with multiple datasets from Compressors deployed in different geographies. The analytic model predicts the time to failure of the compressor (in days)



Architecture

Pacing Optimization Enabled by Human Thermoregulatory System Digital Twin

Mark Buller, PhD
U.S. Army Research Institute of Environmental Medicine

December 2020

Motivation: Why is Pacing Important

"Hawkins made his move in the race around Mermaid Beach, 20km into the 42km Commonwealth Games marathon. Despite the stifling heat that would hit **29 degrees** and that would cause such distress later on, the Scot began to turn it on and ease clear."

60% Humidity: Full Sun

Remember Callum Hawkins is from Scotland (not too warm or humid)

"His **lead was approaching two minutes** with only seven kilometres to run. … *[His coach]* was excited but concerned. There was something about Hawkins' running style that perturbed him. There was a **little wobble** that he'd spotted that few others had spotted."

"I just wanted to keep pushing. I probably wasn't in the right mind to make the decision."
– Callum Hawkins

USARIEM

Military Relevance of Pacing

- Timed 8 mile road march
  - US Army Ranger Students
  - Part of a week-long **series of pass/fail events**
  - Must complete in 2 hrs. 10 min. or **fail class**
  - Carried ~32 kg (70 lb)
  - Warm (25 ºC) and Humid (85% RH)
- Thermal illness risk elevated
- Students selected their own pacing strategy

Background

Ranger 8 mile timed Ruck March

Hot group, Warm group

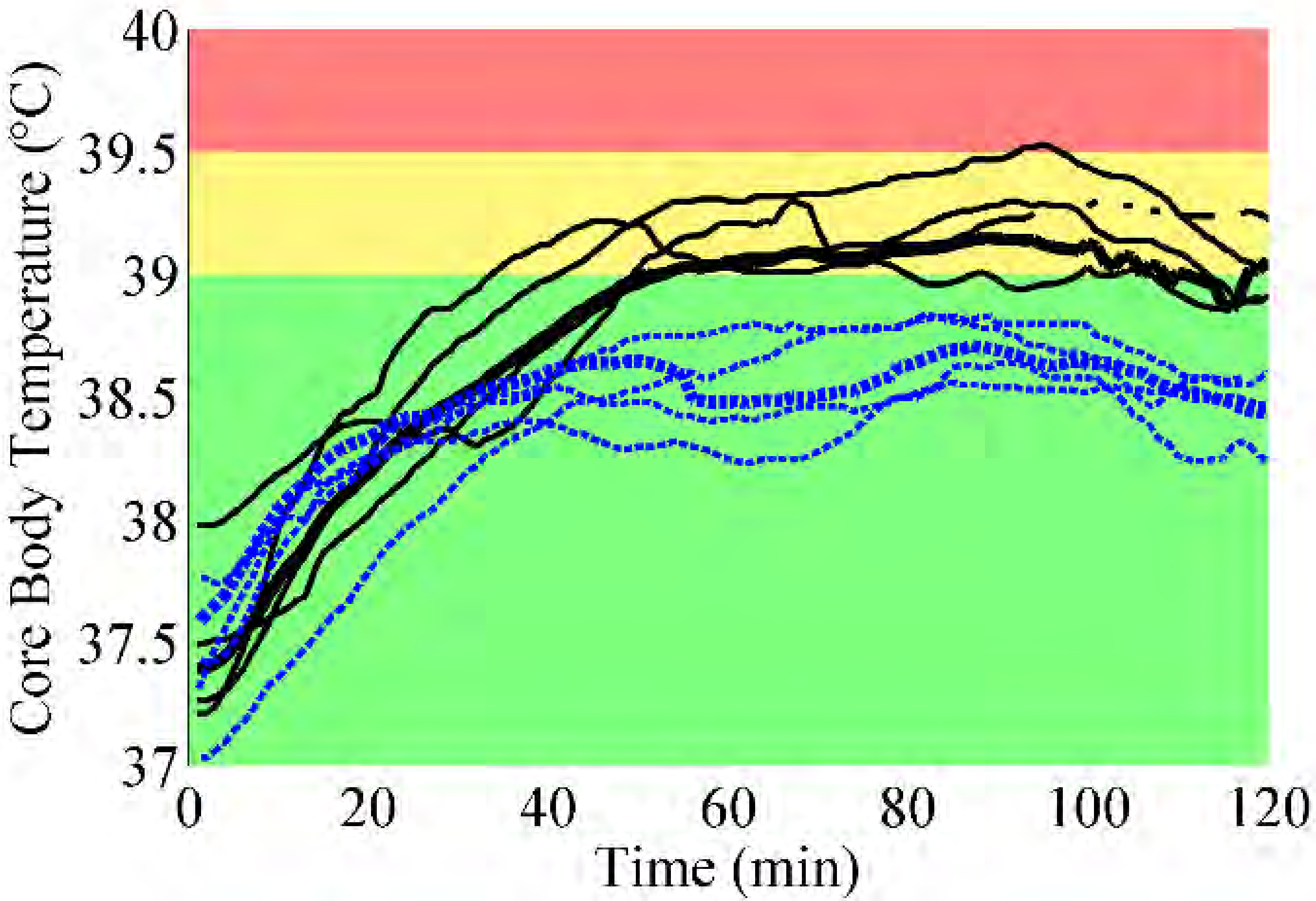
No difference in:

  Height, Weight, Fitness,

  Completion Time, Load

Only know difference:

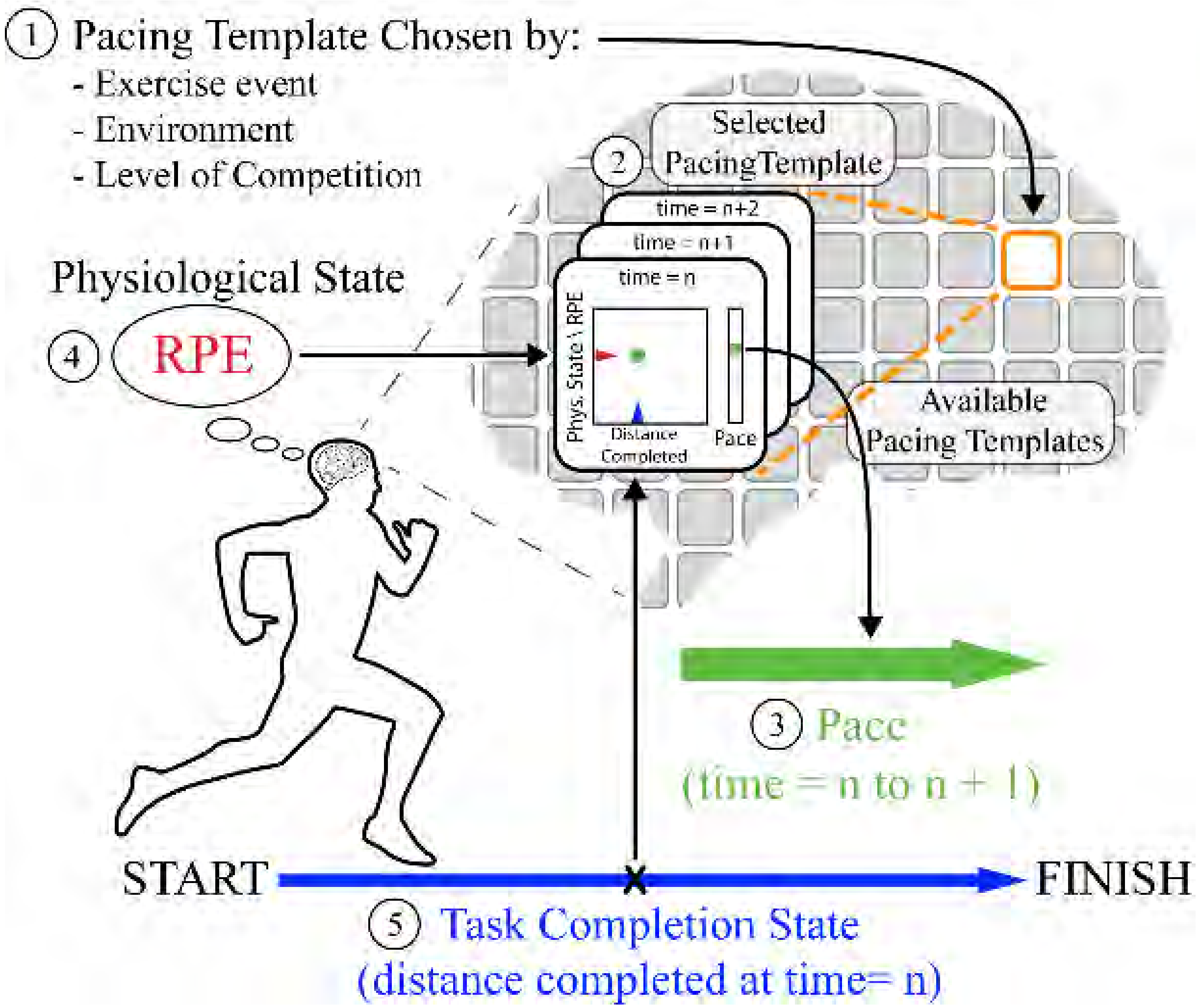
  Pacing Strategy



Background

Black Box, Expert Learned Pacing Templates: Tucker (2009)

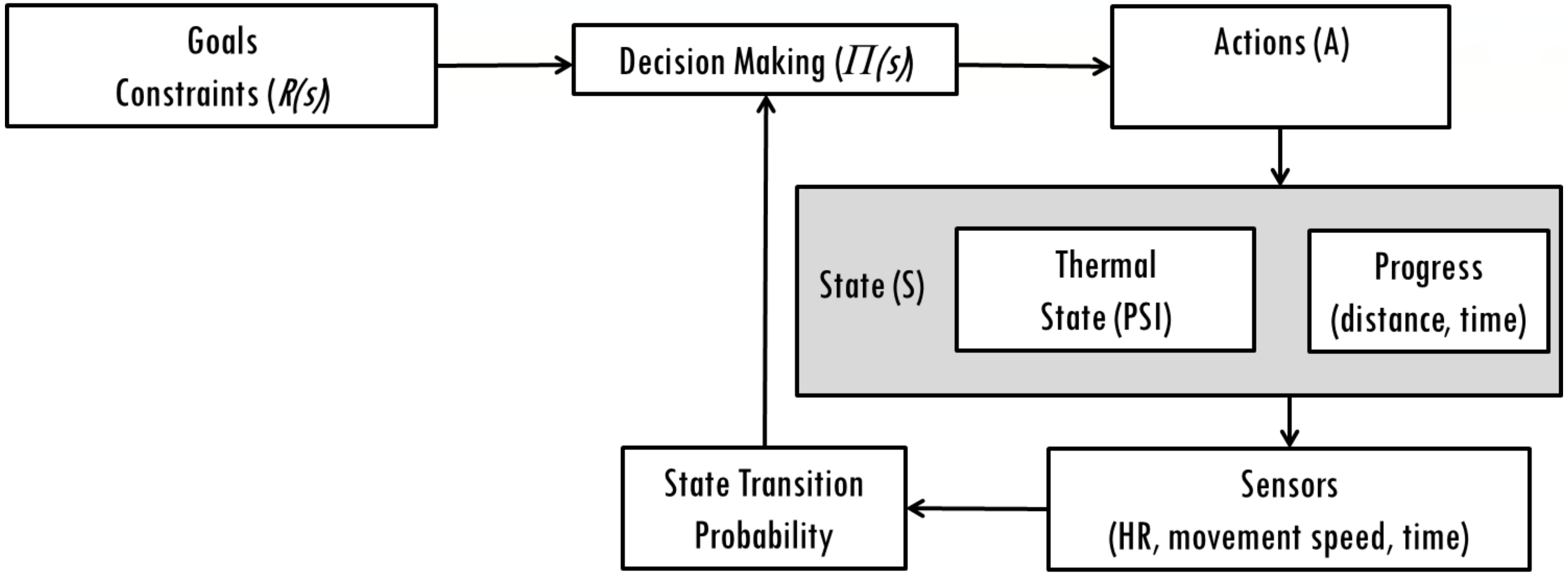
Athletes, use distance to goal, time remaining, and current RPE to optimally pace a race.



Pacing Control System

Markov Decision Process (MDP)

- State (S) :
  - Physiological Strain Index (PSI), distance remaining, time
    - PSI calculated from HR and estimated core temperature
- Actions (A) :
  - movement speed
- State Transition probability :
  - *P(S'| A, S)*
  - *Likelihood of transitioning to a state (i.e., PSI value, distance, time) given current state and an action.*
- Reward function *R(s)* :
  - *Describes goals and constraints using "points"*



$$PSI = 5\left(\frac{CT_t - CT_{rest}}{39.5 - CT_{rest}}\right) + 5\left(\frac{HR_t - HR_{rest}}{180 - HR_{rest}}\right)$$

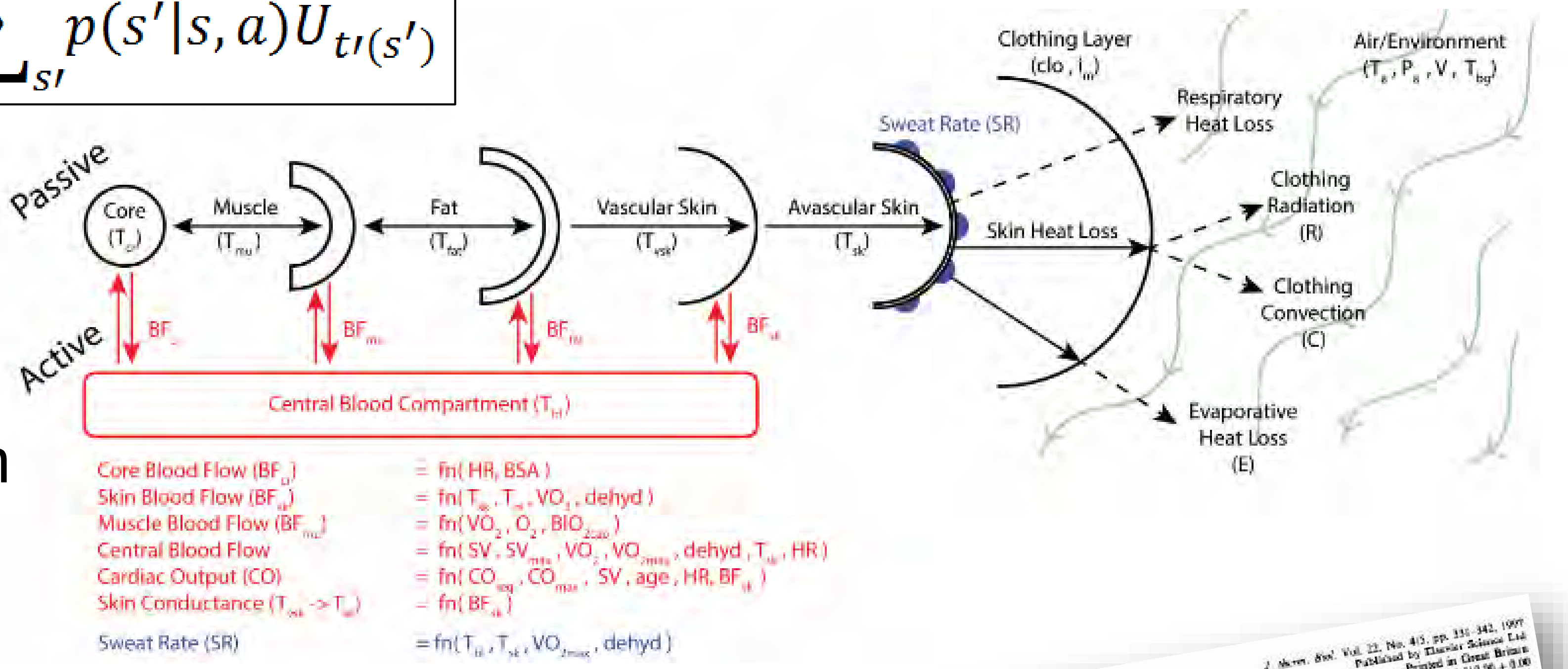
PSI	
<5	Low
5-6	Moderate
7-8	High
9-10	Very High
>10	Extreme

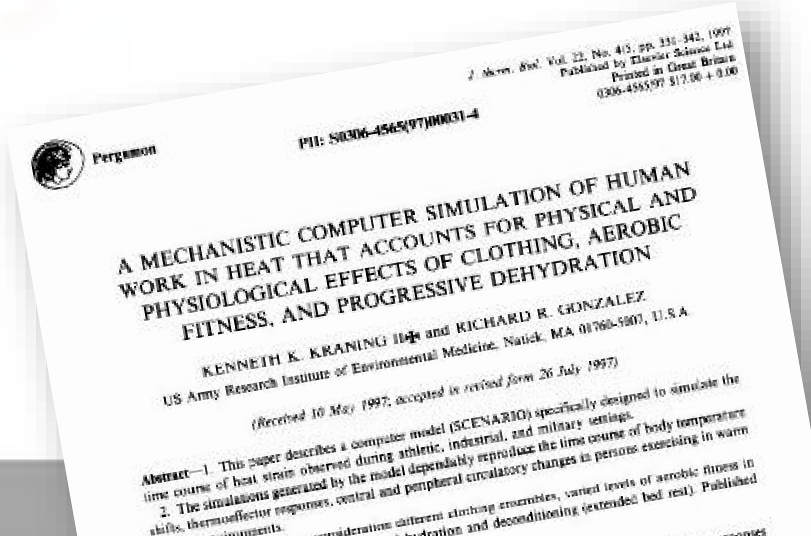
USARIEM

Human Thermoregulatory System – Digital Twin

$$\pi_t^*(s) = \operatorname{argmax}_{a \in A(s)} R(s) + \sum_{s'} p(s'|s,a)\, U_{t'(s')}$$

- $P(PSI' \mid PSI, A)$
  - Non-trivial
  - Affected by work rate, environment, clothing, individual
  - Monte Carlo approximation (10,000 iters) using human thermo-regulatory model (SCENARIO)
    - Inputs: metabolic rate, clothing, environment, height, weight





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A MECHANISTIC COMPUTER SIMULATION OF HUMAN WORK IN HEAT THAT ACCOUNTS FOR PHYSICAL AND PHYSIOLOGICAL EFFECTS OF CLOTHING, AEROBIC FITNESS, AND PROGRESSIVE DEHYDRATION

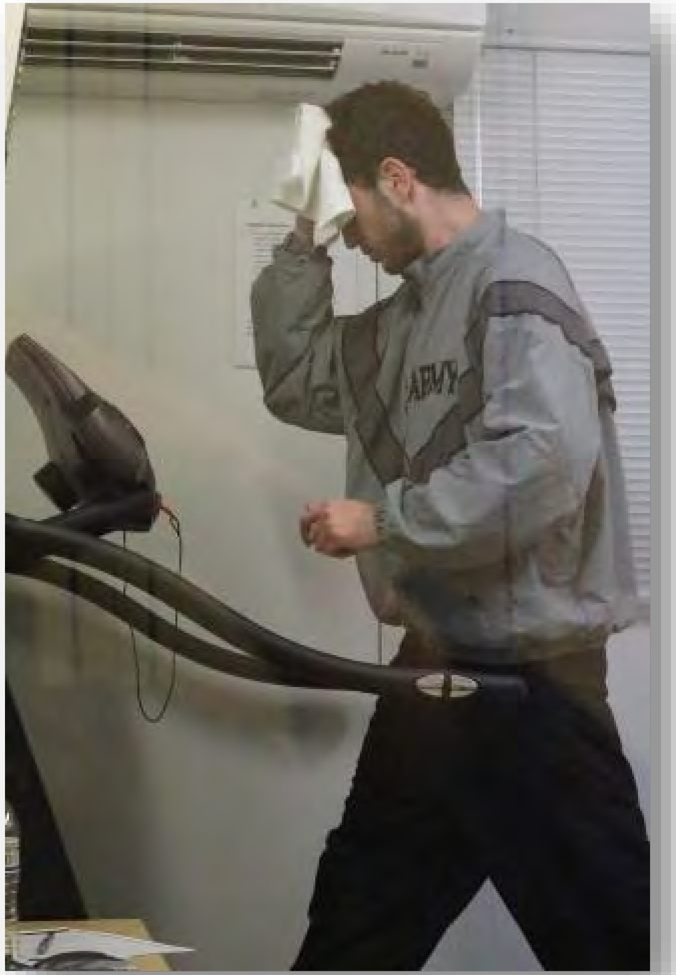
KENNETH K. KRANING II and RICHARD R. GONZALEZ
US Army Research Institute of Environmental Medicine, Natick, MA 01760-5007, U.S.A.

(Received 10 May 1997; accepted in revised form 26 July 1997)

Abstract—1. This paper describes a computer model (SCENARIO) specifically designed to simulate the time course of heat strain observed during athletic, industrial, and military settings.
2. The simulations generated by the model dependably reproduce the time course of body temperature shifts, thermoeffector responses, central and peripheral circulatory changes in persons exercising in warm ...

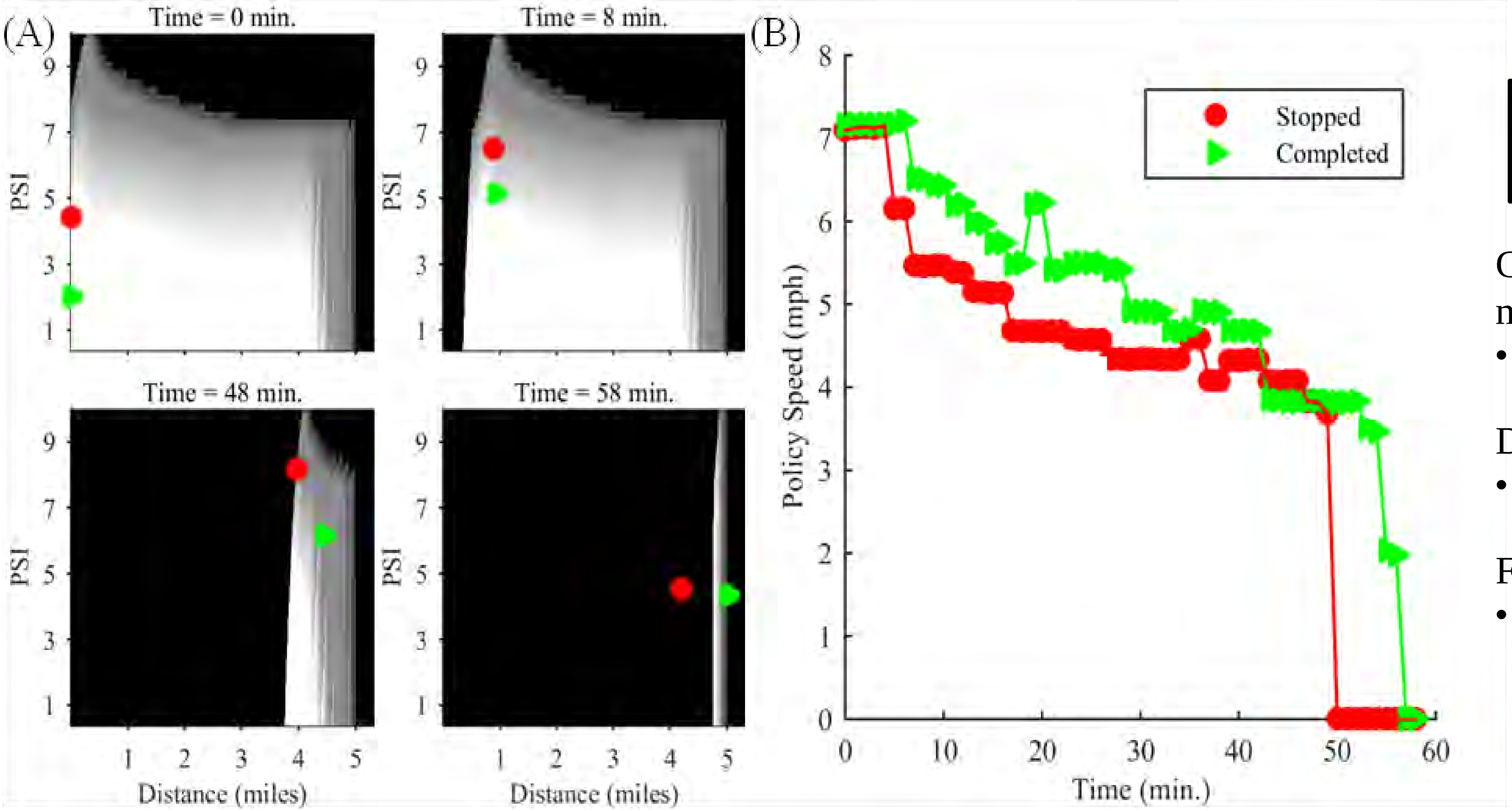
Real-Time Human Laboratory Experiment

- 16 Volunteers (11 M, 5 F)
  - » Fit: Able to run 3.2 km (2 miles) in 16 minutes
  - » Age 23 ± 3 yrs., Wt. 67 ± 9 kg
  - » Collected: HR, T_{SK}, T_{CR}, VO_2, movement speed
- Two trials:
  - SELF-PACED/UNGUIDED (1^{st} trial) Instructions:
    - Complete 8.04 km (5 miles) in 60 minutes
    - Don’t get too hot
    - Complete the 60 minutes as cool as possible
  - GUIDED (2^{nd} Trial) Instructions:
    - Follow MDP application guidance as best you can
    - App designed to stop participants if their projected PSI was predicted to create to large a penalty
  - Environment:
    - 22 °C, 50% RH, minimal air movement
  - Hot Clothing:
    - U.S. Army Winter tracksuit (nylon)



USARIEM

Pacing Templates - No Longer a Black Box



Goals
Constraints (R(s))

Complete 8.04 km (5 miles) in 60 mins

- heavy penalty/negative points for failure

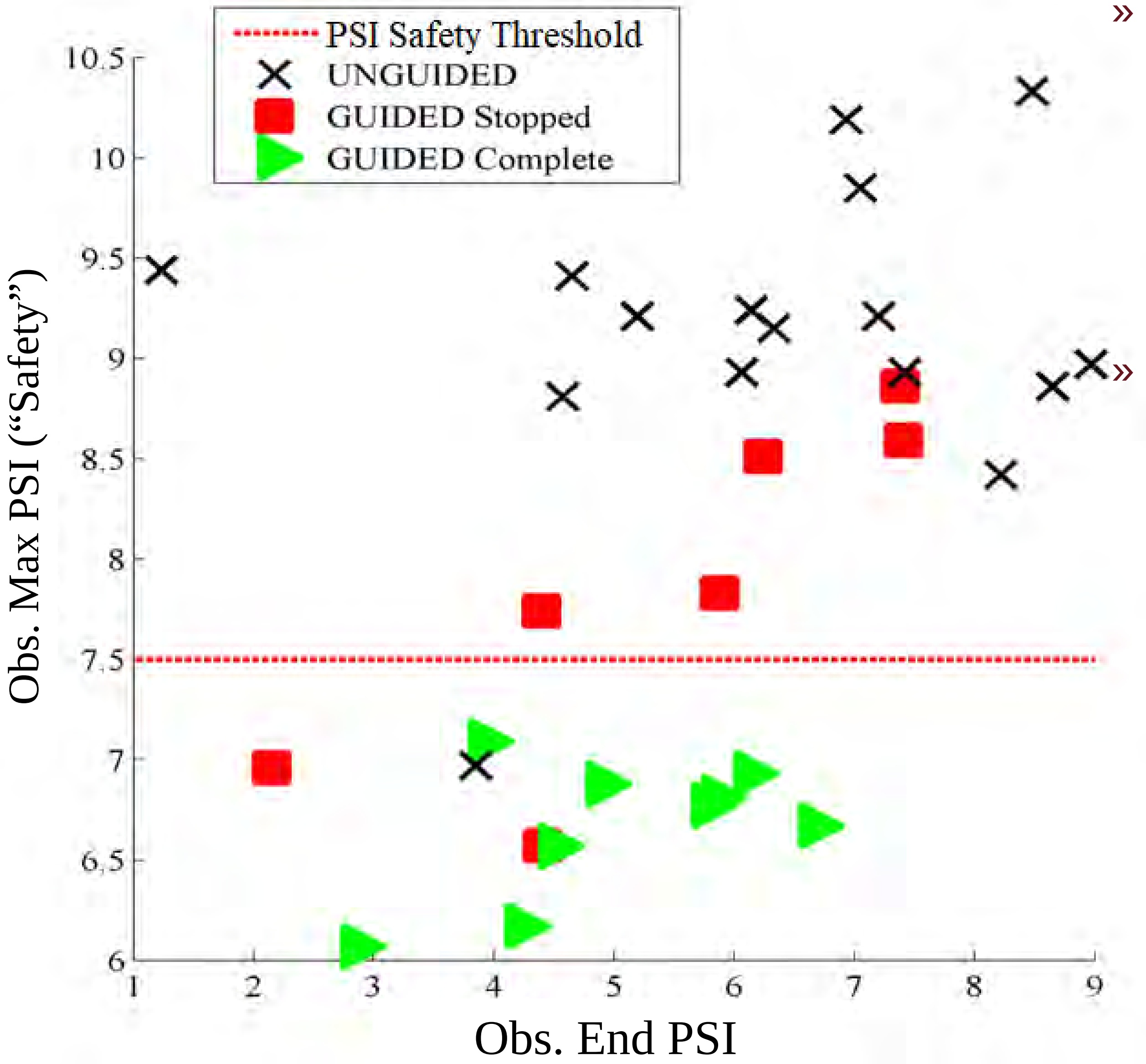
Don't get too hot "Safety"

- Heavy penalty/negative points for exceeding PSI of 7.5

Finish with a low PSI "End PSI"

- The lower the ending PSI the more "bonus" points.

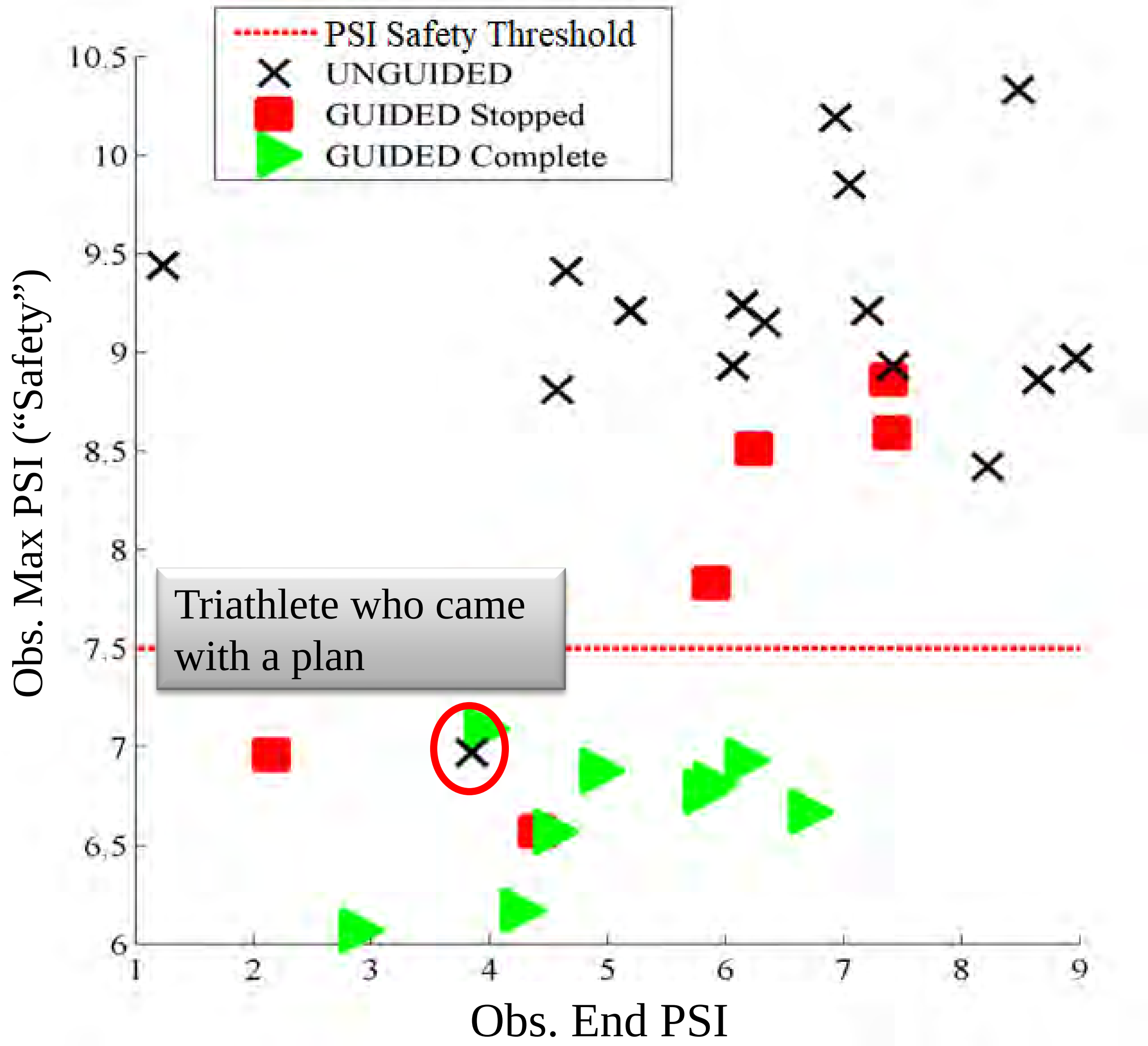
Results



- UNGUIDED (Self Paced)
  - 15 completed in 60 min
  - 1 stopped as they got too hot
- GUIDED (MDP Policy)
  - 9 guided to completion
  - 7 guided to stop

PSI	
<5	Low
5-6	Moderate
7-8	High
9-10	Very High

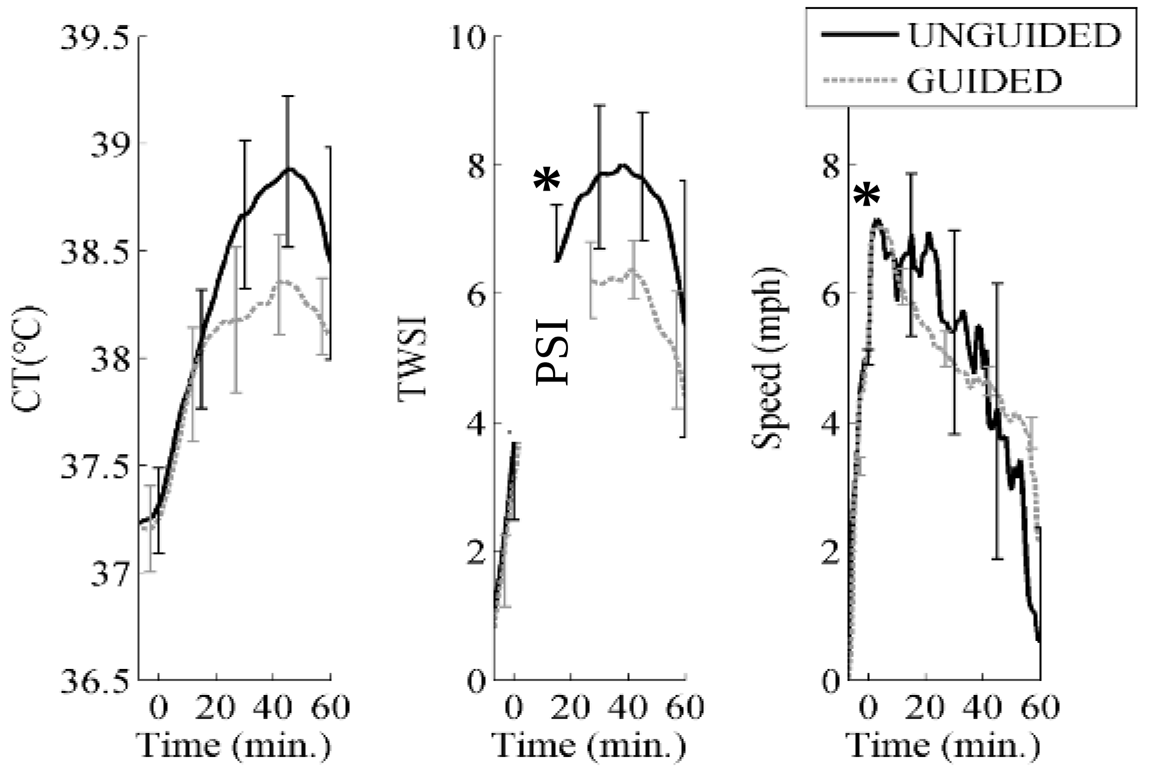
Results



PSI	
<5	Low
5-6	Moderate
7-8	High
9-10	Very High

Physiology Comparison (n=8†)

- T_{CR} and PSI (max and mean) significantly lower when GUIDED
- Total Energy Expenditure: GUIDED = 599 ± 84 W, UNGUIDED = 617±104 W



** Paired t-test $p<0.01$*

PSI	
<5	Low
5-6	Moderate
7-8	High
9-10	Very High

†1 subject dropped as they completed an old policy computed from incorrect transition probabilities

Conclusions

- Guidance effective at reducing PSI on novel task
- Only triathlete with a plan matched guidance policy performance
- Digital Twin shed light on a black box control surface
- Physiological feedback allowed machine pacing to the same level as an expert on a novel task

Distributed Fiber Sensor Enabled Digital Twin Modeling

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University of Pittsburgh

December 2, 2020

Digital Twin Applications for Advanced Nuclear Technologies Workshop

Motivation

Computer Modeling can generate high resolution Digital Twin Models but…

- **Are they real?**

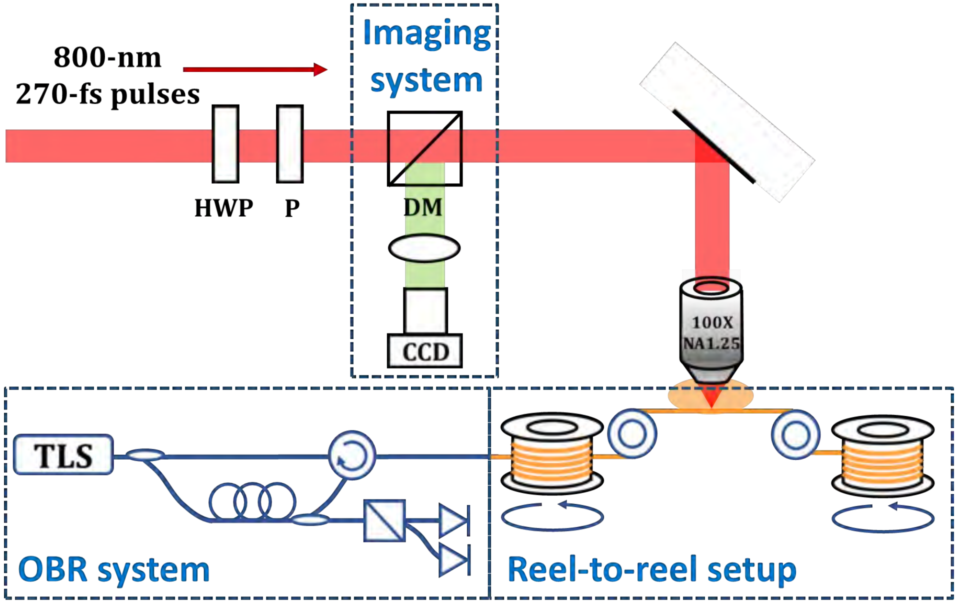
Spatial/Temporal Resolutions of Digital Twin Modeling Scale with Moore's Law…

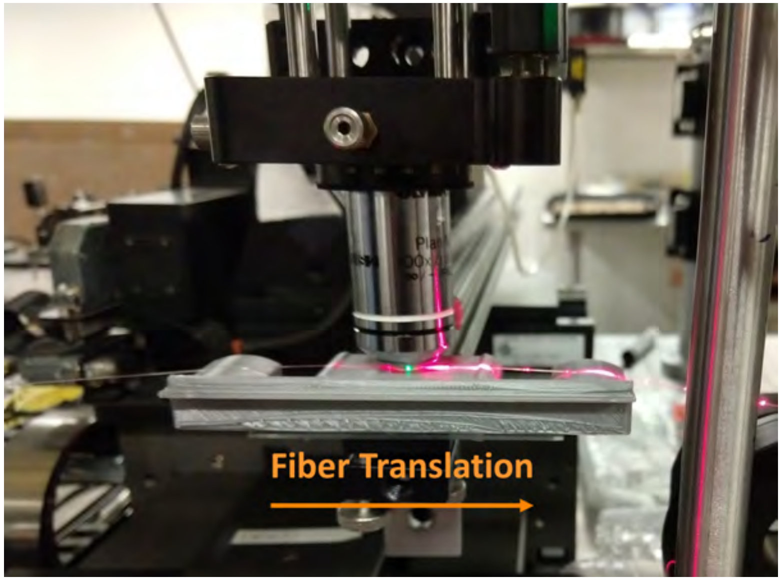
- **Is measurement devices scalable in similar fashion?**

Outline

- Developing distributed fiber sensor technology to harness high spatial resolution data for NE applications
- Provide direct measurements to support the development of highly accurate Digital Twin (DT) models.
- Using sensor data to shed light on design optimization
  - High spatial resolution temperature measurements in reactor core.
  - High spatial resolution monitoring of solid oxide fuel cell
  - High resolution sensor data enabled DT modeling of additive manufacturing

Femtosecond Laser Fabrication for Sensor for NE Applications



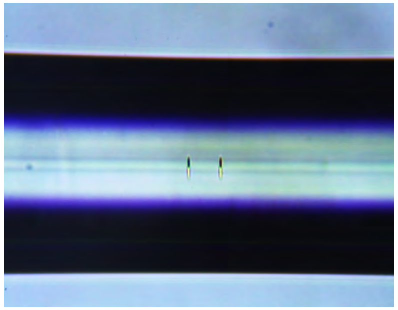


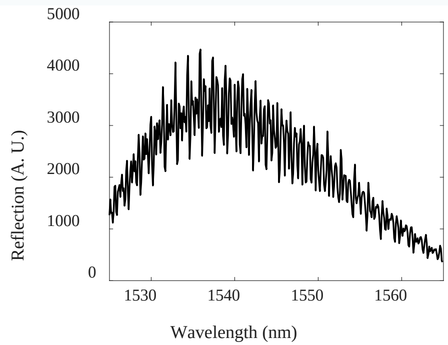
Reel-to-reel oil-immersion fiber writing setup

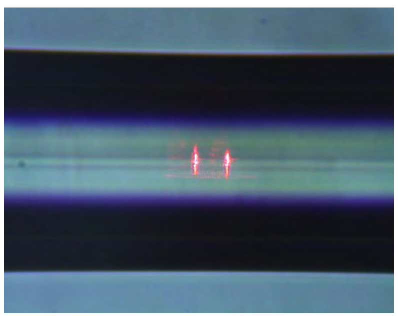
- Fast and simple fabrication of meters of fiber
- Can inscribe sensors on meters of optical fibers
- Real-time monitoring using an Optical Backscattering Reflectometer (OBR)

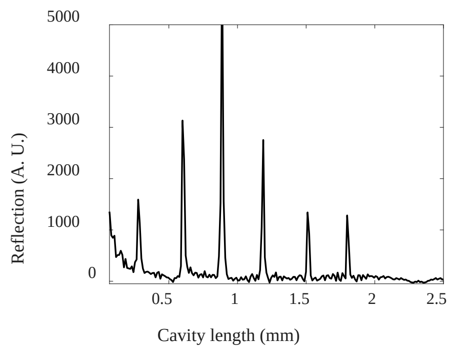
Reel-to-Reel Sensor Fabrications

Fs-laser inscription of Type-II IFPI Sensor Array

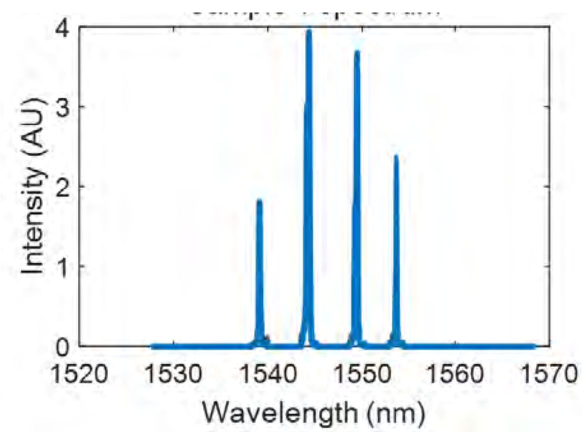




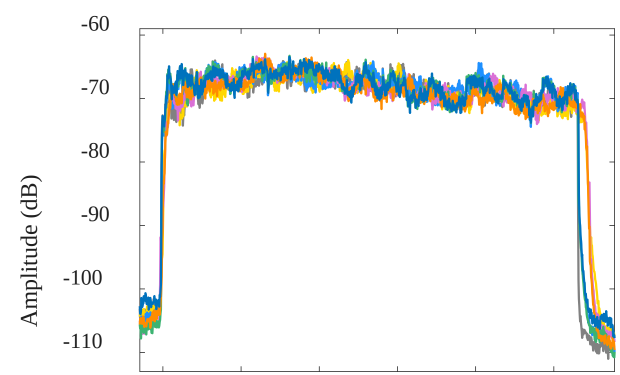




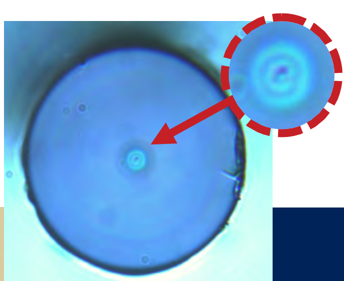
FBG Sensor String

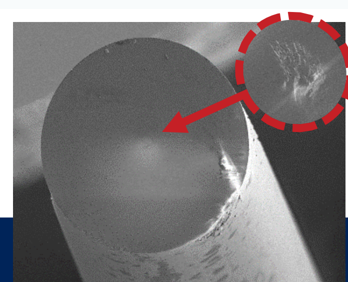


Laser Enhanced Rayleigh Scattering Profile



Precision Control of Formation of Nanograting

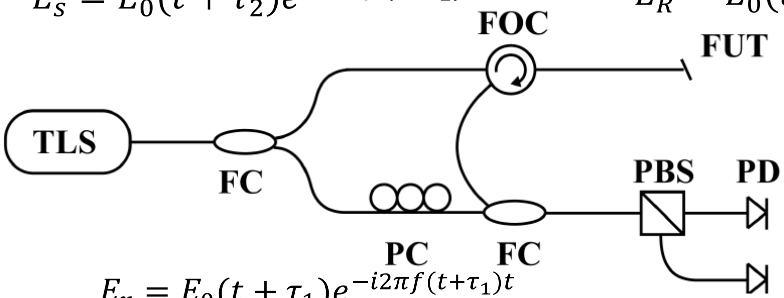




Optical Frequency Domain Reflectometry

$E_s = E_0(t+\tau_2)e^{-i2\pi f(t+\tau_2)t}$

$E_R = E_0(t+\tau_2)\rho(2\pi f)e^{-i2\pi f(t+\tau_2)t+i\varphi(f)}$



TLS: Tunable Laser Source
FUT: Fiber Under Test
FC: Fiber coupler
PD: Photo-detector

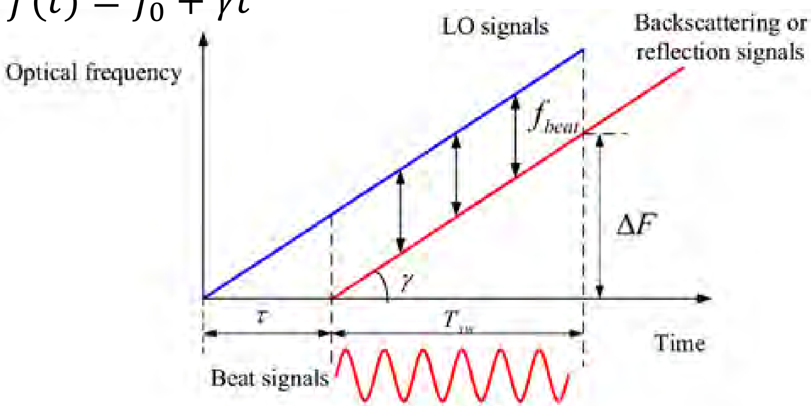
$E_r = E_0(t+\tau_1)e^{-i2\pi f(t+\tau_1)t}$

$$I_{out} = |E_0(t)|^2 + |E_0(t-\tau)\rho(f)|^2 + 2\rho(f)E_0(t)E_0(t-\tau)\cos[w(f)\tau - \varphi(f)]$$

$E_{in} = E_0(t)e^{-i2\pi f(t)t}$

$f(t) = f_0 + \gamma t$

$I_{out}(\tau) = FFT[I_{out}(f)]$



Spectral Domain → **FFT** → **Temporal Domain**

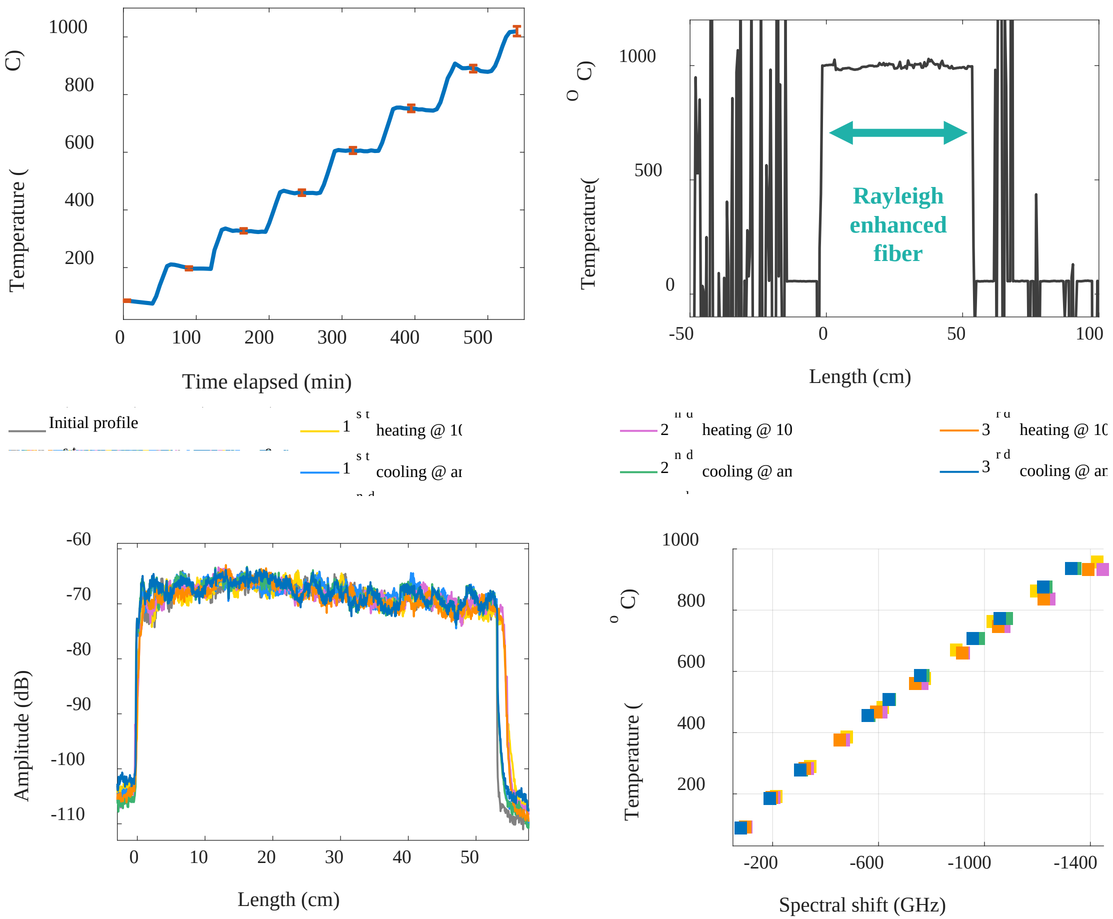
$$-\frac{\Delta\nu}{\nu} = \frac{\Delta\lambda}{\lambda} = K_T\Delta T + K_\varepsilon\Delta\varepsilon$$

Spectral Domain — **Auto-correlation** → **Physical Change**

Challenges of Previous methods

- **Limited harsh environment stability**
- **High insertion loss lead to low spatial resolution**

Temperature Sensing Performances



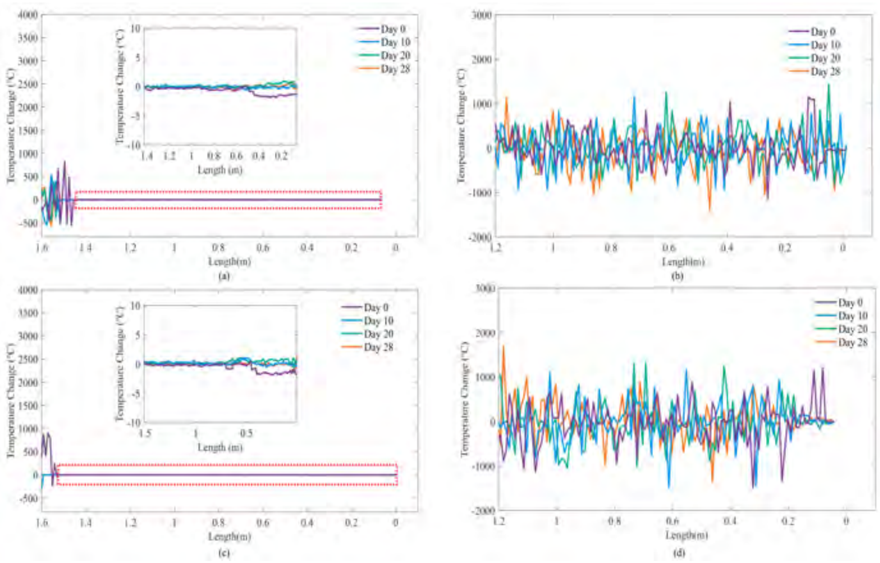
- **After 16 hours under 1000°C, the processed fiber section still functional compared to the unmodified fiber**
- **Robust and consistent operation after repeated heating and cooling cycles**

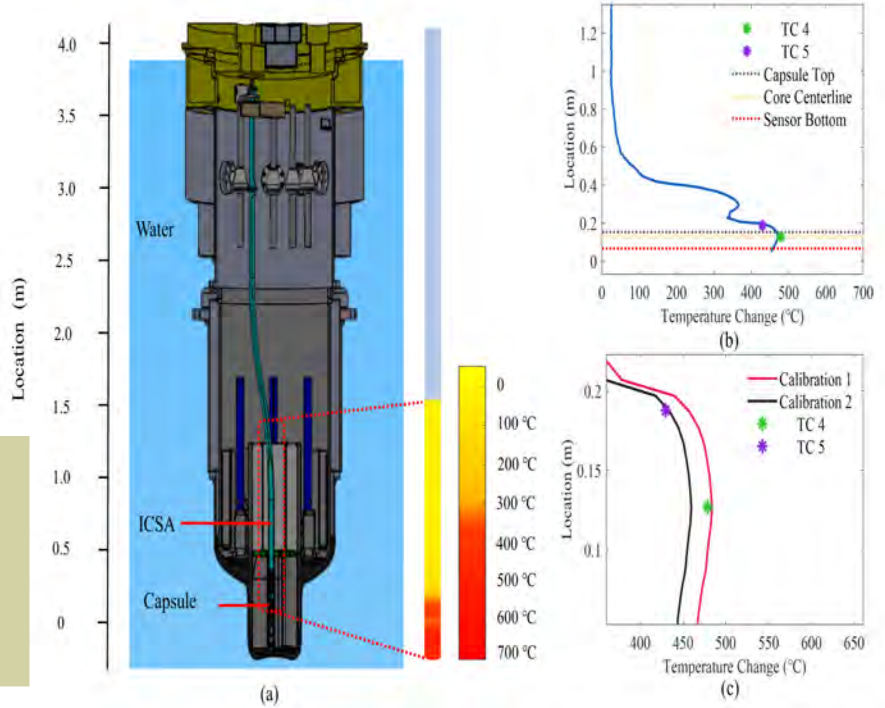
M. Wang, et al. “Reel-to-reel Fabrication of In-fiber Low-loss and High-temperature Stable Rayleigh Scattering Centers for Distributed Sensing,” IEEE Sensors Journal (2020).

First High Spatial Resolution Temperature Profile Measurements of a Reactor Core

Laser Enhanced Fibers

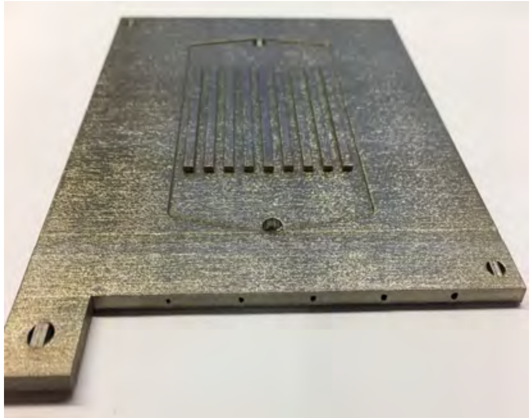
Pristine Fiber

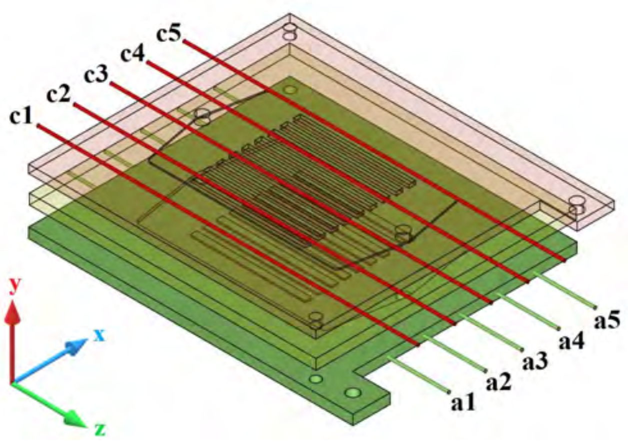


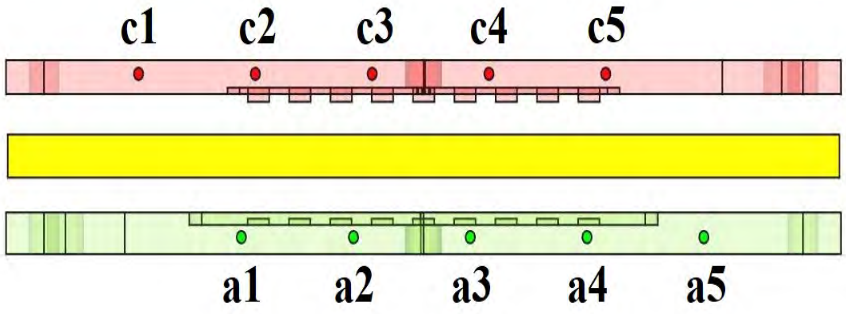


- **In-pile measurements at (560°C, 1.4×10^{14} f n/s/cm^2)**
- **1.6-m core profile, 3-cm resolution, 1-s update rate.**
- **Laser enhancement critical**

In-Vivo Monitor of SOFC and DT Modeling

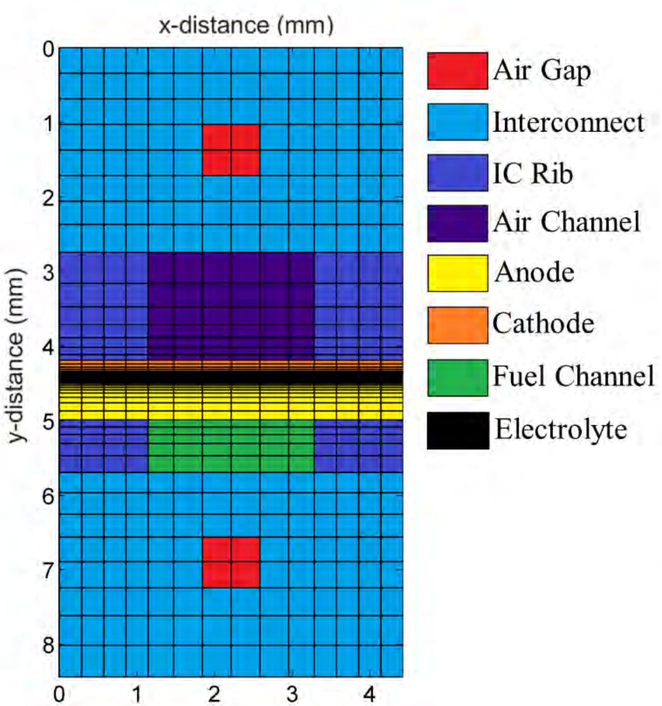


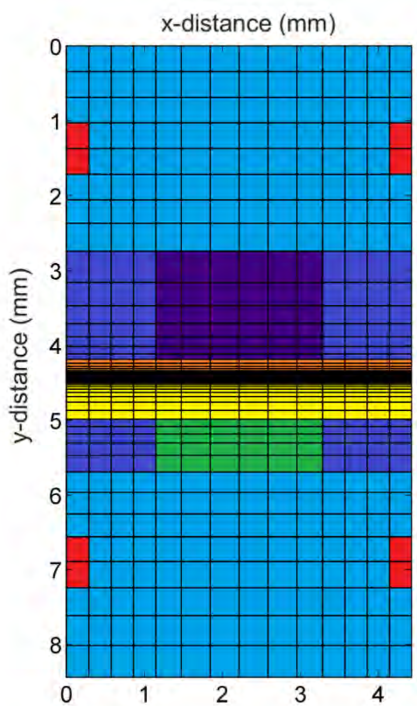


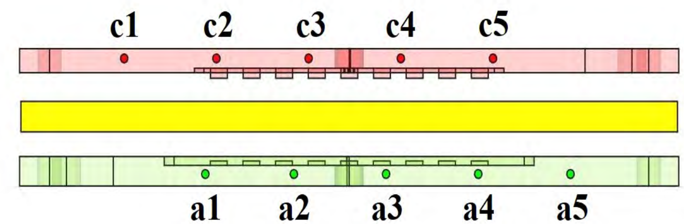


Digital Twin Modeling

- $$\frac{\partial}{\partial t}(\varepsilon_k \rho_k \phi_k) + \nabla \cdot \left(\varepsilon_k \rho_k \vec{u}^{eff} \phi_k\right) = \nabla \cdot \left(\varepsilon_k \Gamma_\phi^{eff} \nabla \phi_k\right) + \varepsilon_k \rho_k S_\phi + f_{kl}$$



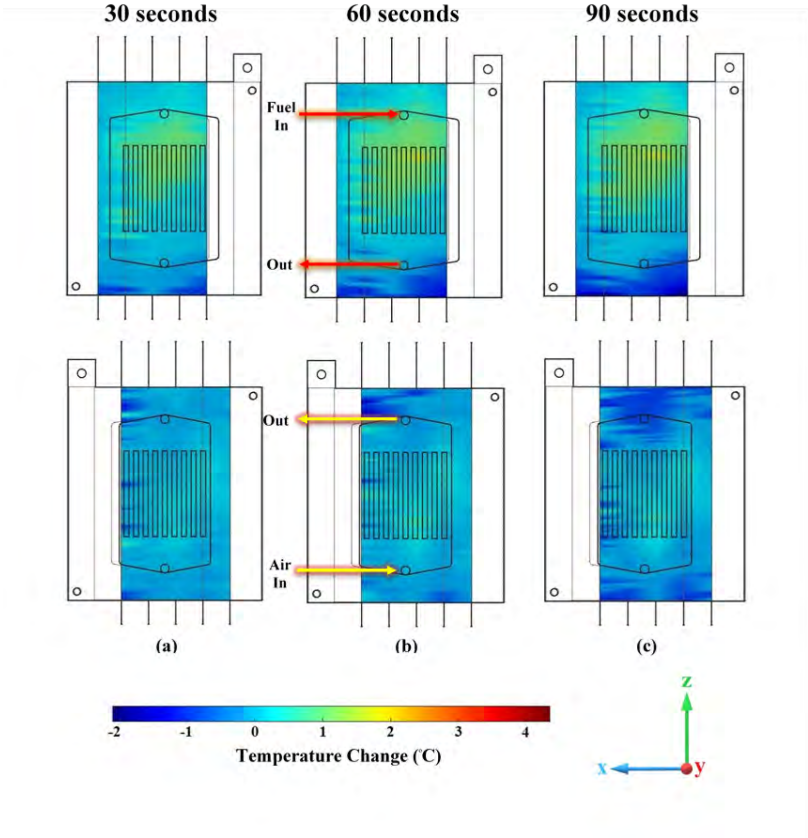




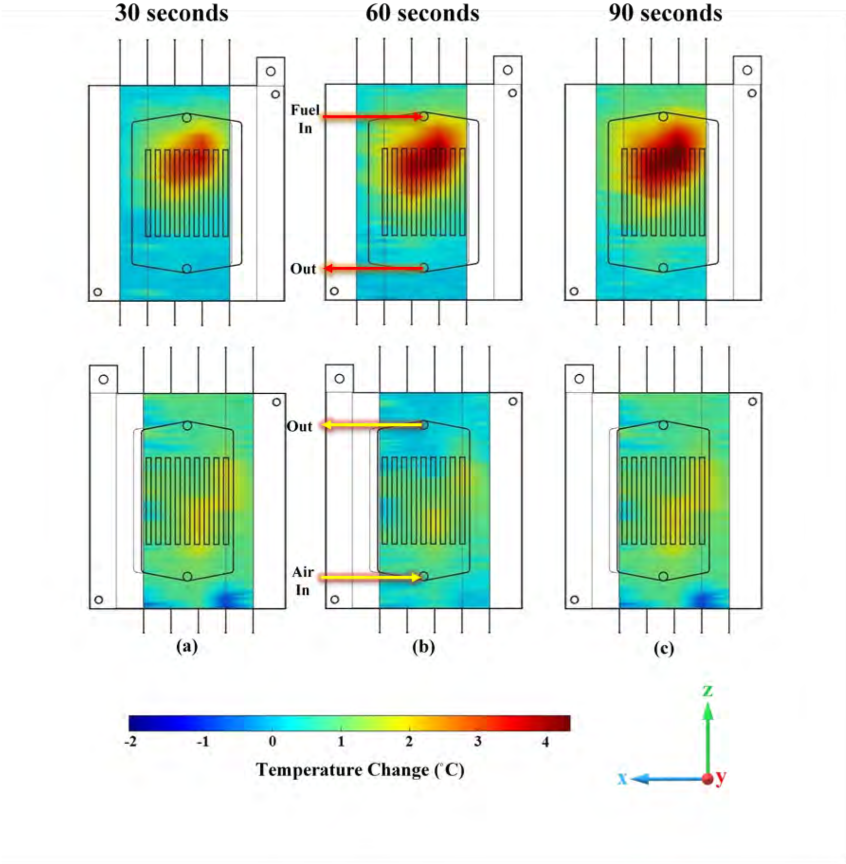
- **2D modeling using transport model**
- **Temperature**
- **Charge transport**
- **Fuel consumption rate**
- **Direct comparison with measurements**

Sensor Measurements

750C, 100 sccm, 10% H2, 1A

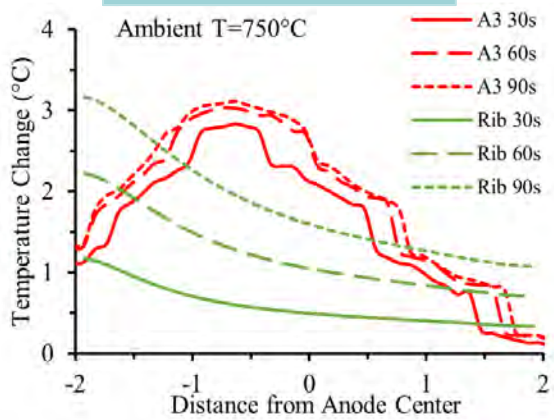


750C, 100 sccm, 50% H2, 2A

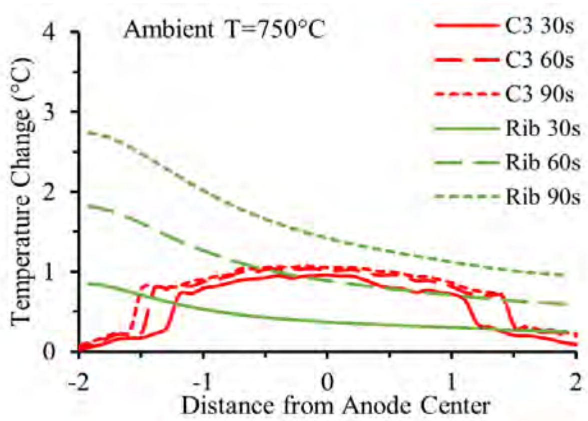


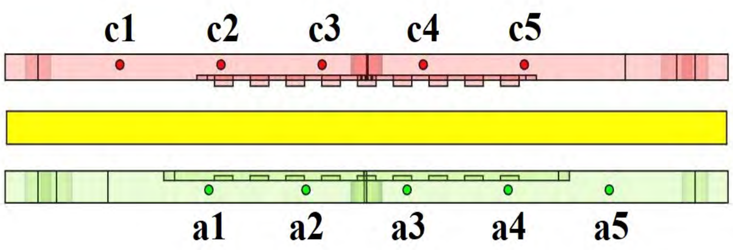
DT-Experiment Comparison

Anode

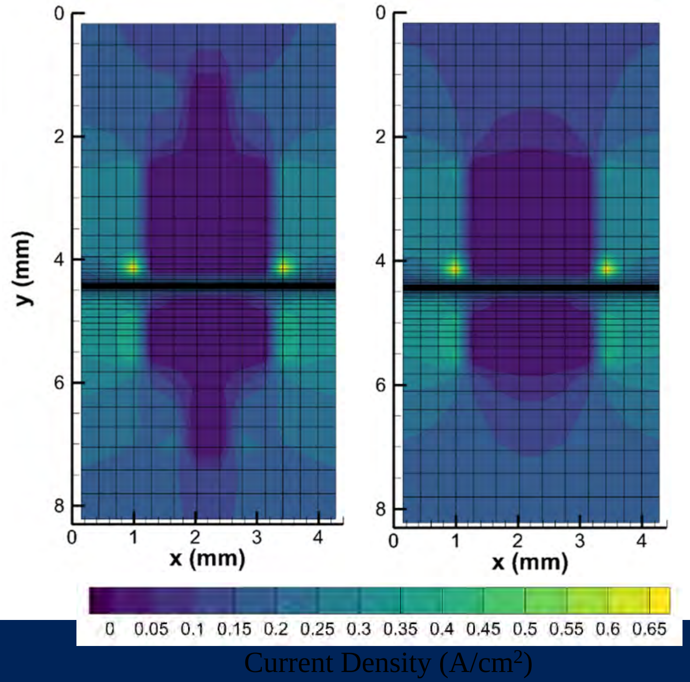


Cathode



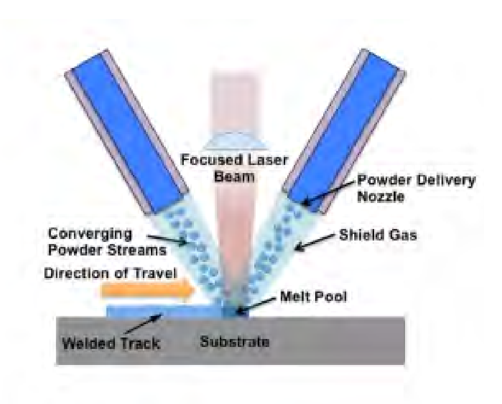


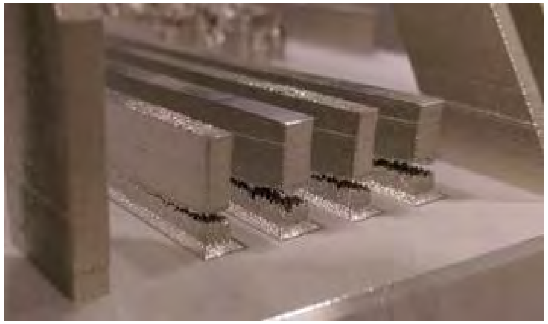
Current Distributions



DT for Additive Manufacturing

Power Bed Based Additive Manufacturing

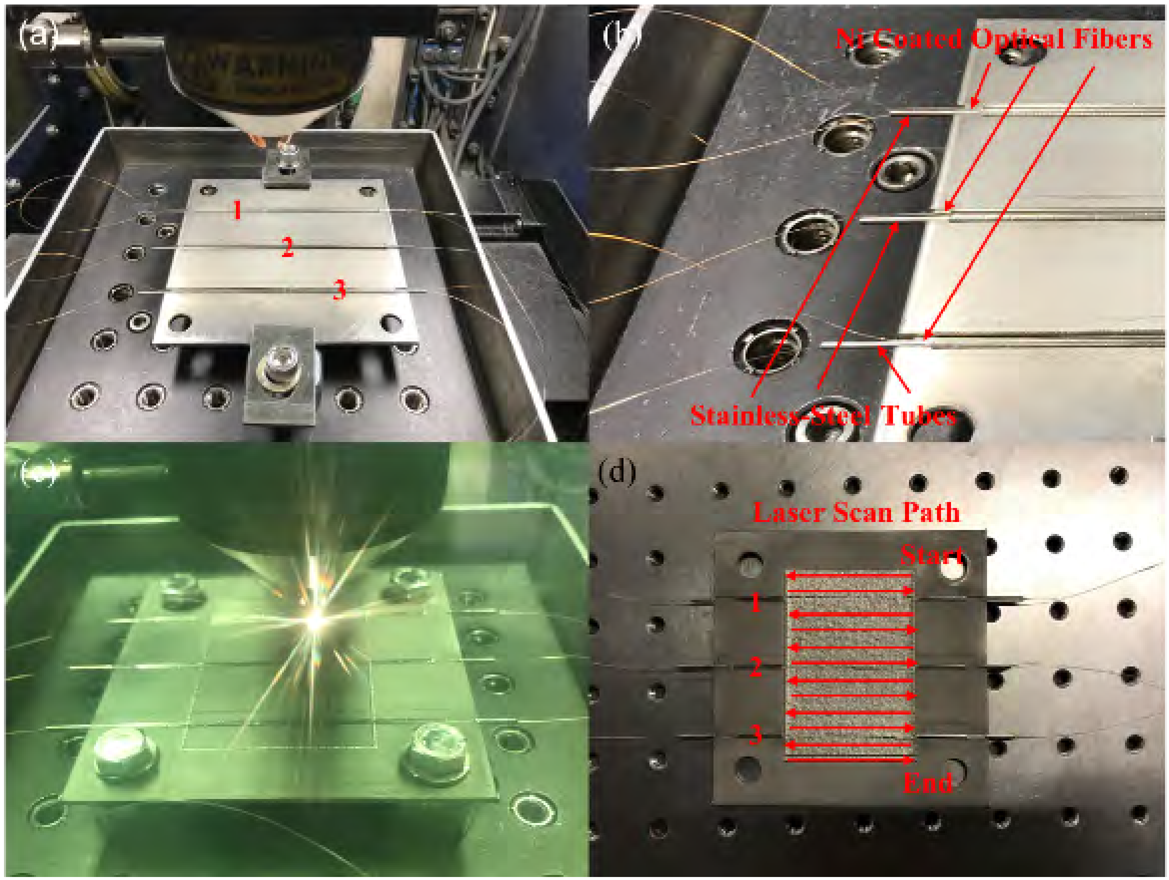




Can we develop an accurate DT models to predict, design, and optimize AM process for engineering

- **High-T AM process are for NE**
- **Residual stress is a key road block**
  - **Corrosion performance**
  - **Manufacturing accuracy**
  - **High-term stability**
- **DT can be critical to design optimize AM process to minimize residual stress**
- **How to validate our DT model???**

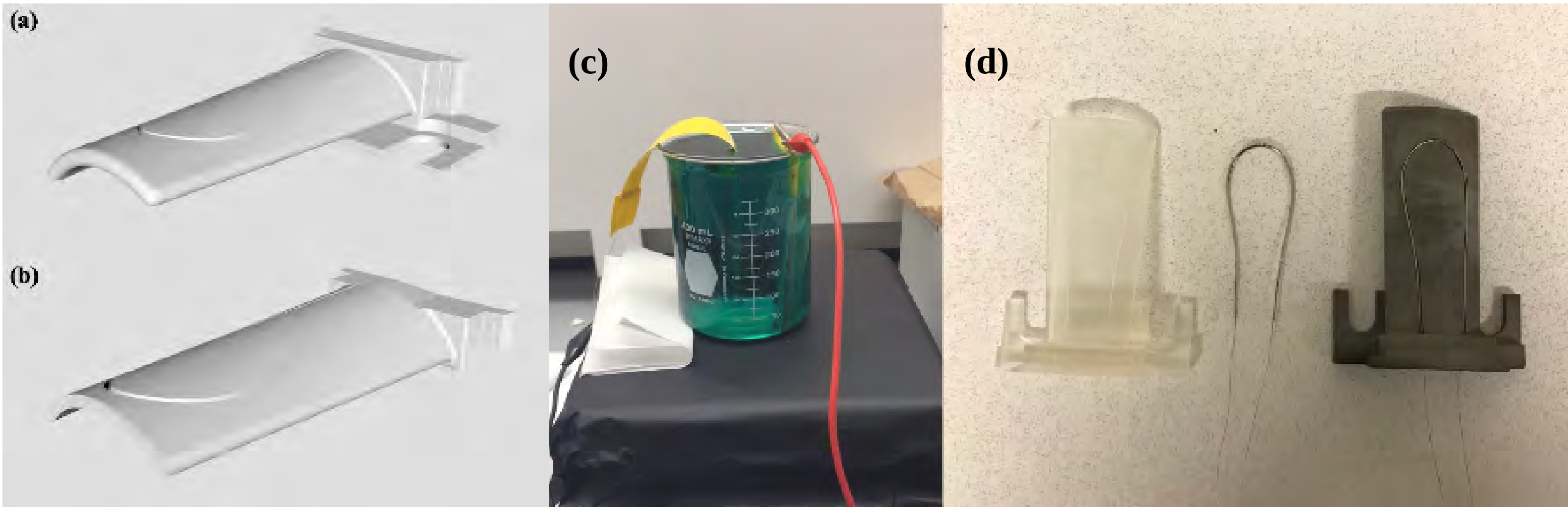
Sensor-Fused AM Process

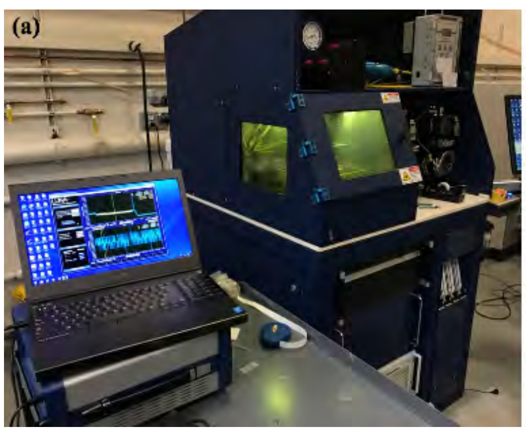


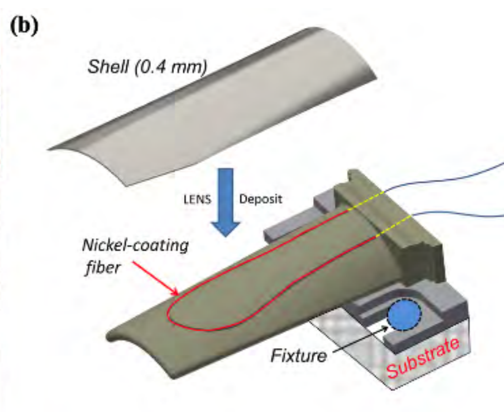
Sensor Fused AM Process

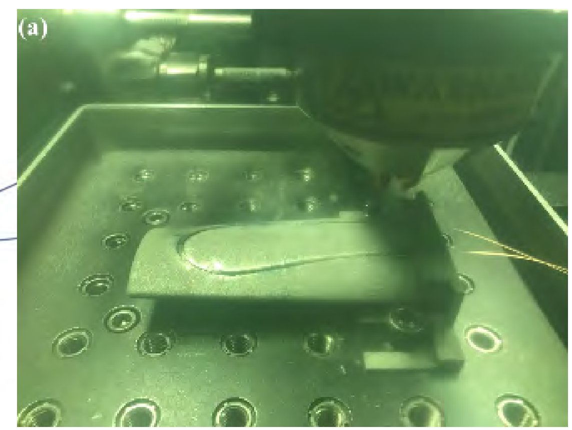
- High resolution real-time T & $\mu\varepsilon$ measurements
- Design proper structures to embed sensors without disturbing AM process and part itself
- Real-time measurements to study AM process itself
- Post-process monitoring to study residual strain formation and relaxation.
- Compare, correct, and validate DT

Embedding Fiber Sensor on Turbine Blade

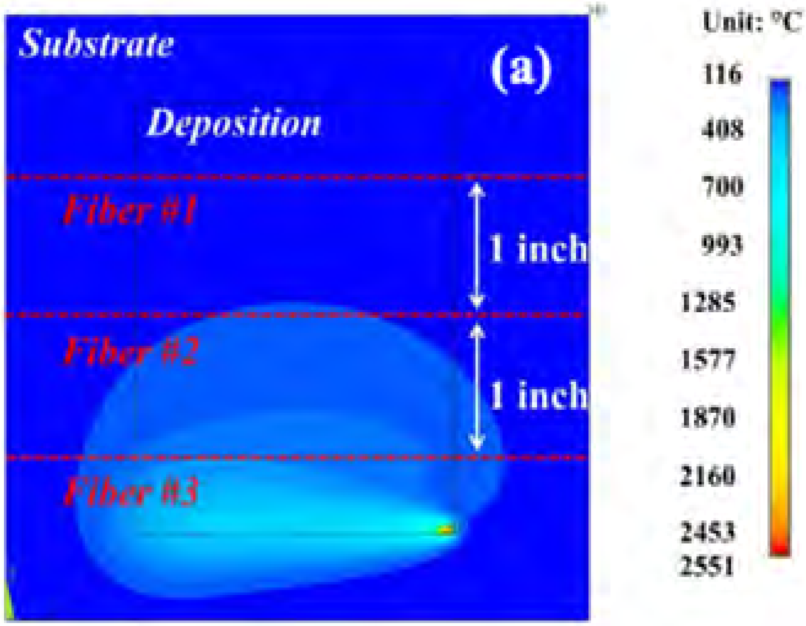








Temperature Modeling vs. Measurement



$$\rho C_p \frac{dT(\boldsymbol{r},t)}{dt} = -\nabla \cdot \boldsymbol{q}(\boldsymbol{r},t) + Q(\boldsymbol{r},t), \boldsymbol{r} \in \boldsymbol{V}$$

Dirichlet boundary conditions

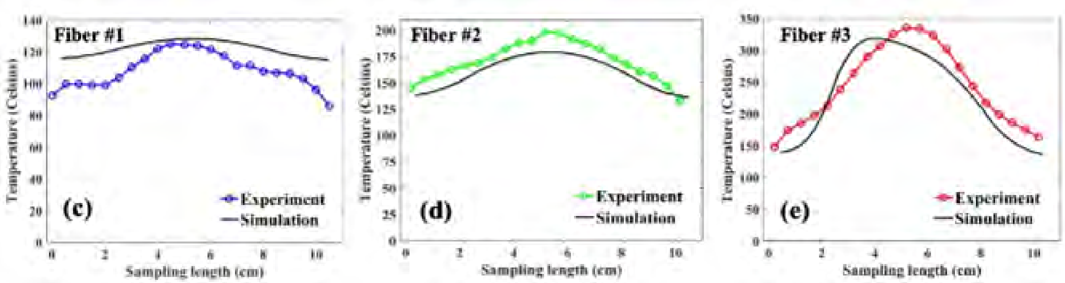
$$T = \bar{T}, \qquad \boldsymbol{r} \in S_D^T$$

Neumann boundary conditions:

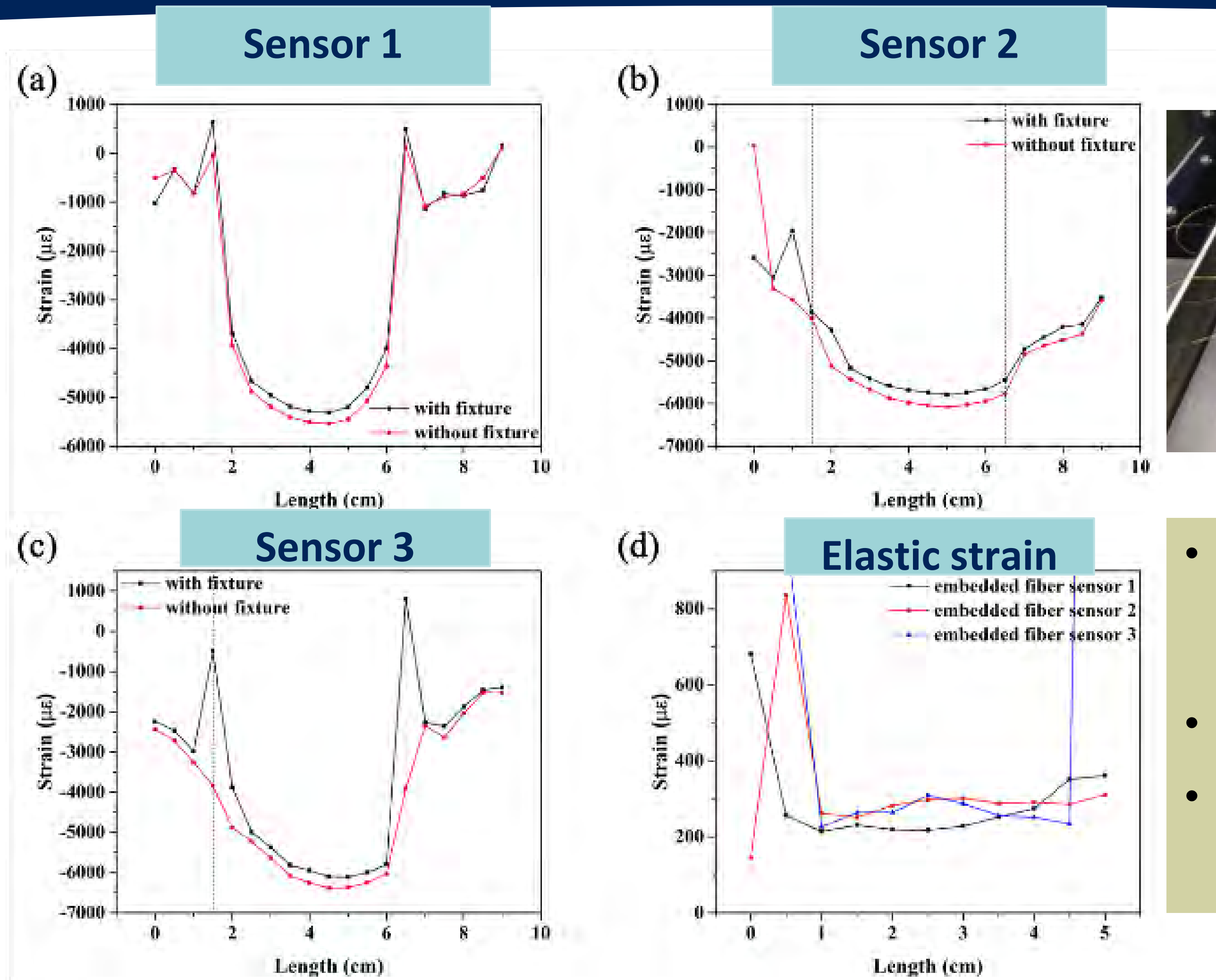
$$-k\nabla T \cdot \boldsymbol{n} = \overline{q}, \ \boldsymbol{r} \in S_N^T$$

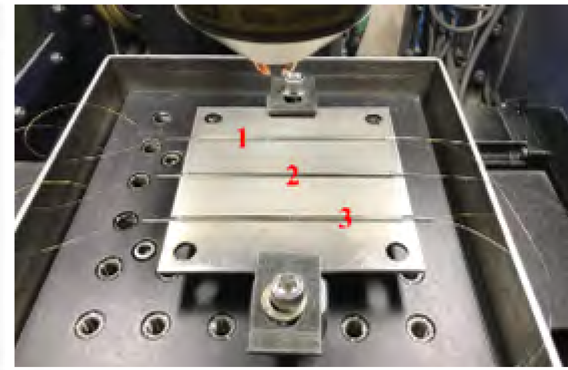
Robin boundary conditions:

$$-k\nabla T \cdot \boldsymbol{n} = h(T - T_a), \boldsymbol{r} \in S_R^T$$



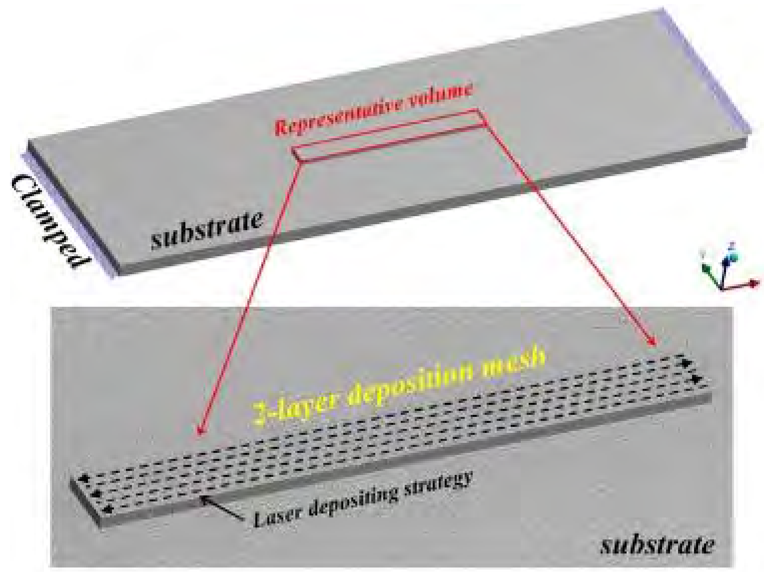
Elastic Strain vs Plastic Strain

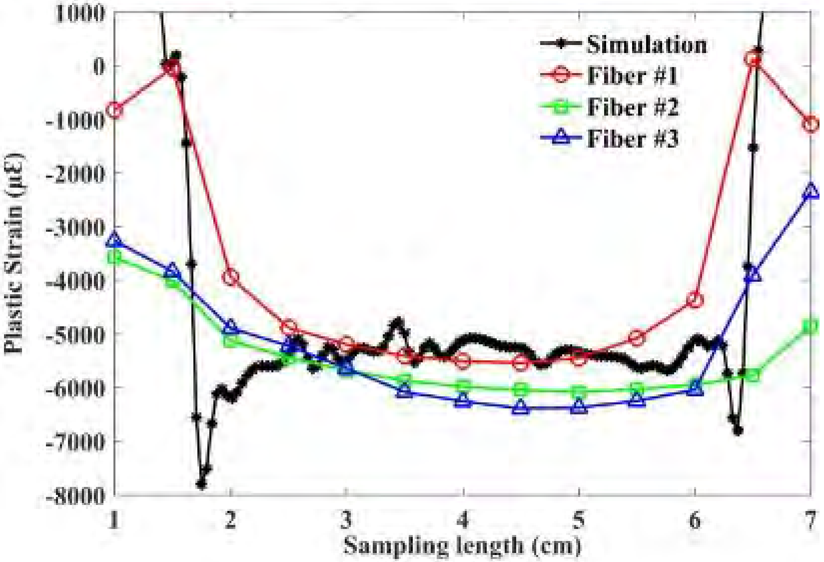




- Distributed strain measurement after the fabrication
- 4-mm spatial resolution
- 3 locations along the deposition path.

Strain Modeling vs. Measurements





- Two-layer deposition (red box) as the representative volume of the large deposition area (upper).
- Laser scanning strategy in the laser fusion process (lower) Modelled.

- Measurements performed at 4-mm spatial resolution.
- Simulation consistent with modeling, provide confidence for model-based optimization.

Summary: Sensor-Fused DT Modeling

- Radiation-harden and high-T stable distributed fiber sensors provide mean to harness high spatial/temporal resolution data
- Providing direct measurements to support the development of highly accurate Digital Twin (DT) model.
- Sensor-fused DT modeling useful for several DT scenarios
  - Validate and provide accurate boundary conditions
  - Test DT model developed for extreme environments
  - Provide most relevant evidence for DT-based design optimization
  - … many more


Thank you!
Email: pec9@pitt.edu

ARPA-e perspective: Digital twins as an enabler of low O&M costs

Or: If You Build It, Can You Run It?

Joel Fetter, Adviser to ARPA-e

Workshop on Digital Twin Applications for Advanced Nuclear Technologies

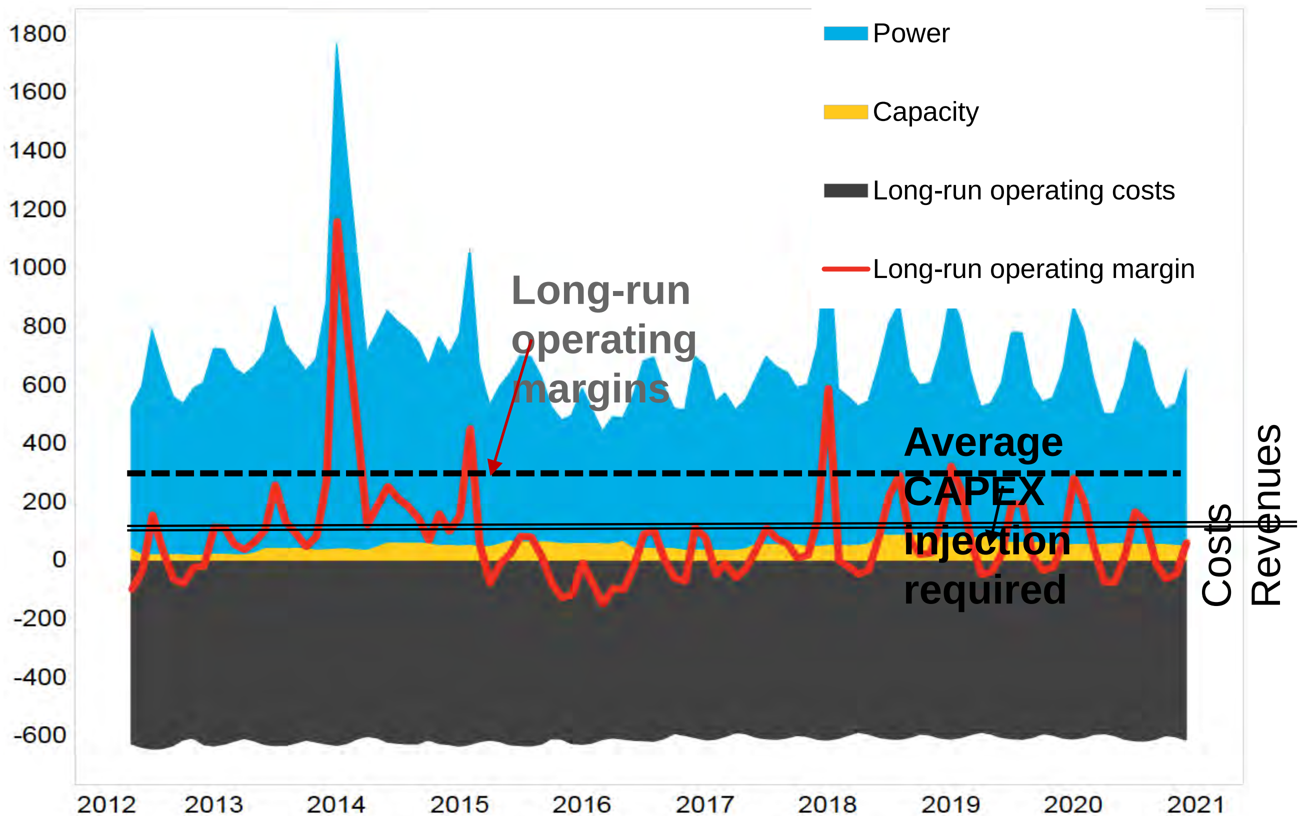
December 2020

Provocation #1: LWR O&M costs are high: What are AR developers doing to reduce O&M costs?

Long-run operating margin = **Power revenues** + **Capacity revenues (resource adequacy)** + State subsidies* - **Long-run operating costs (including fuel)** - CAPEX injections for upgrades*

*Excluded from margin estimates

Quarterly revenues, costs, and long-run operating margins ($/MW-day)



- Developer 1: (~1 GWe) +/- $40/MWh estimate uses the same **O&M costs as proposed for the current PWRs**
- Developer 2: (multiple 10's Gwe modular reactor) **0.7 FTEs/MWe** is not radically different either

Source: Bloomberg New Energy Finance, EIA, FERC Form 1 Note: Capital expenditures for uprates, enhancements, or regulatory compliance are not included. Those CAPEX injections averaged almost $6.74/MWh in 2016, or approximately $150/MW-day, according to the Nuclear Energy Institute. In previous analyses, we included these costs as part of the long-run margin estimates.

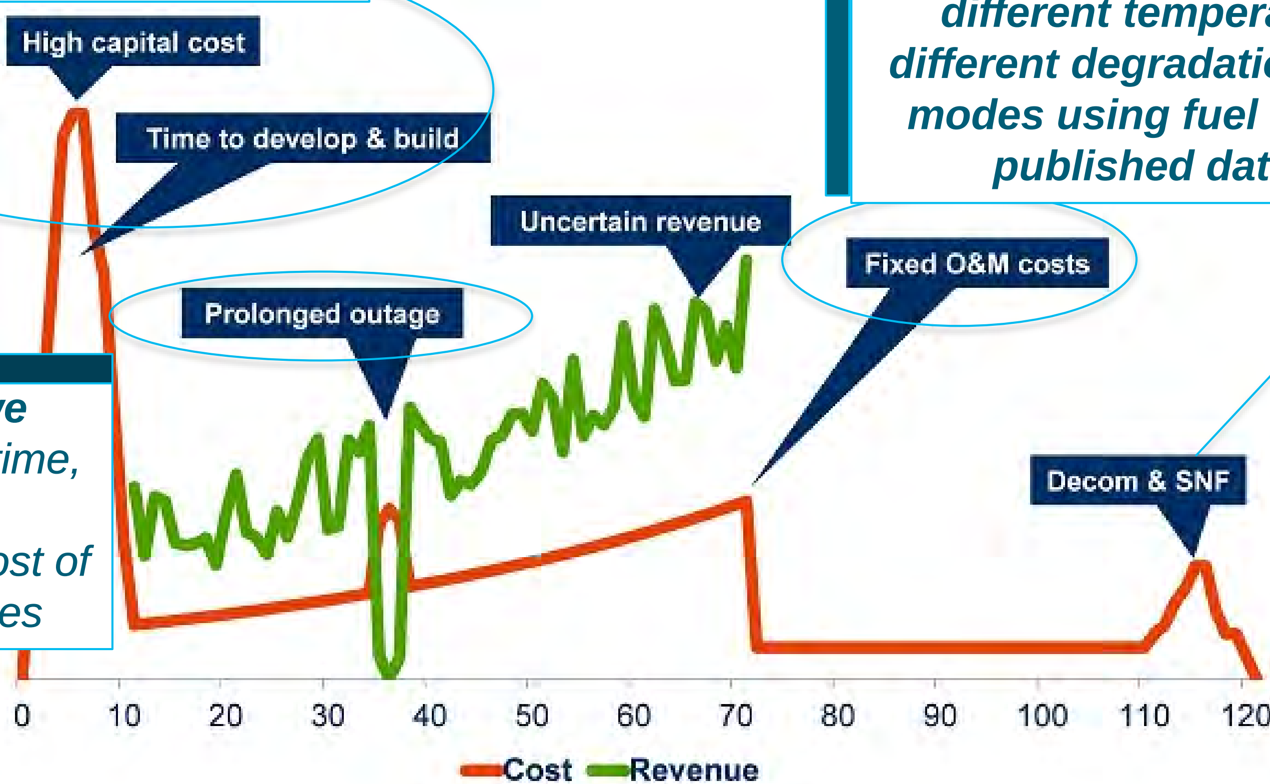
Provocation #2: Pro-forma financials need better data inputs – what really is the cost?

Nuclear power plant cash flow

1 *Design + MEITNER + LISE + OPEN 18*

2 *Dependent upon novel components operating at different temperatures with different degradation and failure modes using fuel for which no published data exists.*

3 *How do we Maximize uptime, minimize opportunity cost of lost revenues*



Stay tuned for this one

Graphic: https://nuclear-economics.com/5-revenue-certainty/

Provocation #3: The designs are maturing, but still optimizable for O&M

- Lots of industries are developing better controls, better models, better data, better algorithms

- Focus on autonomy and machine learning (ML) is getting many questions answered
- Answer those questions specific for nuclear and prove out ideas in our systems and with our software; aid in code validation
- **Have tools the industry and the regulator can use**

Portfolio-at-a-glance

Funded programs

- BWRX 300
  - GE research
  - MIT / GE, focus on Thermal-hydraulics
- Kairos
  - Argonne National Lab (sensors)
  - University of Michigan
- X-energy: O&M for XE-100
- Moltex USA: O&M for SSR
- Framatome (Metroscope)
- EPRI: Optimal component design life
- MIT: Irradiation data for MSRs
- (other portfolios) Southern Research (Robotics), NC State (construction)

Outcomes we're striving for

Digital twins of emerging advanced nuclear reactors (AR) that:

- Enable *flexible and economic operation* for the meeting needs of the future grid
- *Provide foundational insight* into the implications of new operating paradigms on proposed AR designs – early enough to modify them inexpensively
- Improve the *safety*, *reliability*, and *cost effectiveness* of emerging designs
- Provide *data-driven, design-specific foundations* for AR staffing and cost profiles
- *Support private markets* to identify and finance lowest cost, highest value designs
- *Accelerate* what are now extended and costly regulatory approval processes.

Parting thought: program takes inspiration from aerospace

Design

Digital design accelerated the 777 development process

Boeing 777: First new Boeing aircraft in 10 years:

- First jetliner 100% digitally designed
- Pre-assembly done digitally, eliminating need for costly pre-production mock-ups
- Five years from project launch to production, and 8 years from launch to commercial flight

Operational Simulation

Simulators support design of new aircraft, pilot training,

Based on flight equations and matches with physical data, simulators:

- Provide developers with insights into aircraft design trade-offs.
- Teach pilots – especially in advanced aircraft – how to assimilate data from new/unique systems (e.g. F22 Raptor)
- Offer “Extended envelope” training teaches pilots, regulators how systems perform in extreme conditions.

What is Possible Now That Wasn't Before?

- From 1985: "Future nuclear power plants are projected to be highly modularized, with the possibility of several plants being operated from one control room. AI-based diagnostics and control systems can make this possible by taking over the mundane day to day oversight tasks that the operators must perform to keep the plant running."

U.S. Department of Energy Assistant Secretary for Nuclear Energy Technology Transfer Artificial Intelligence Task Team. "Artificial Intelligence and Nuclear Power". June, 1985, p. 10

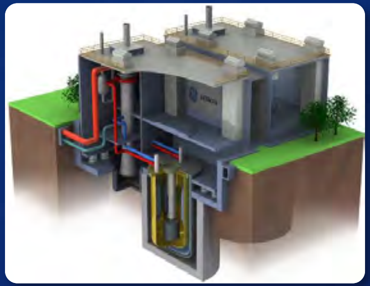
GE Research

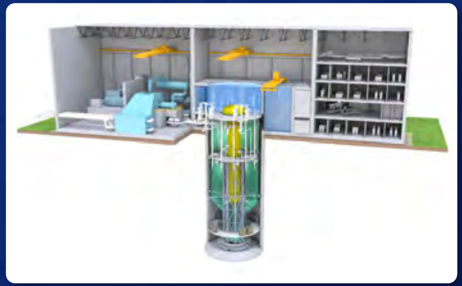
AI Enabled Predictive Maintenance Digital Twins for Advanced Nuclear Reactors

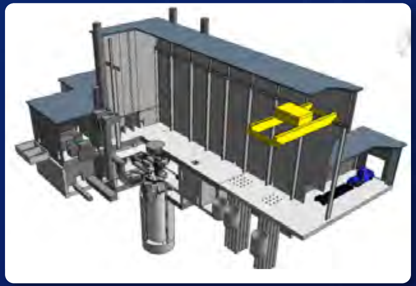
Abhinav Saxena, PhD
Senior Scientist – Machine Learning
PI - GEMINA Award 2174-1511

Decades of New Plant Innovation

Rich history of nuclear innovation ready to support advanced reactor market







OVER 80 YEARS OF NUCLEAR EXPERIENCE AND INNOVATION

- **1939** – First GE involvement in nuclear physics
- **1951** – Aircraft nuclear propulsion
- **1955** – GE Atomic Division established
- **1957** – Vallecitos BWR AEC License #1
- **1981** – PRISM development commences
- **1996** – 1st ABWR built on time on budget
- **2014** – ESBWR NRC License
- **2017** – BWRX-300 launched
- **2018** – VTR Contract PRISM

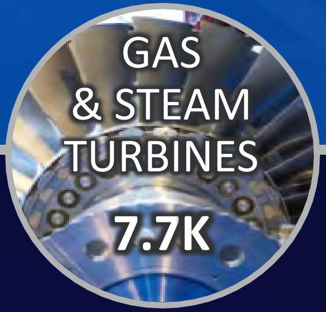
Digital Twins

GE Experience

KEEP 300K PEOPLE IN THE SKY/HR.

1/3 OF THE WORLD ELECTRICITY

16K SCANS PER MINUTE



DRIVERS

1 INCREASED PRODUCTIVITY

2 FASTER GROWTH

3 RISK-MANAGED ADAPTABILITY

4 IMPROVED SAFETY

OUTCOMES

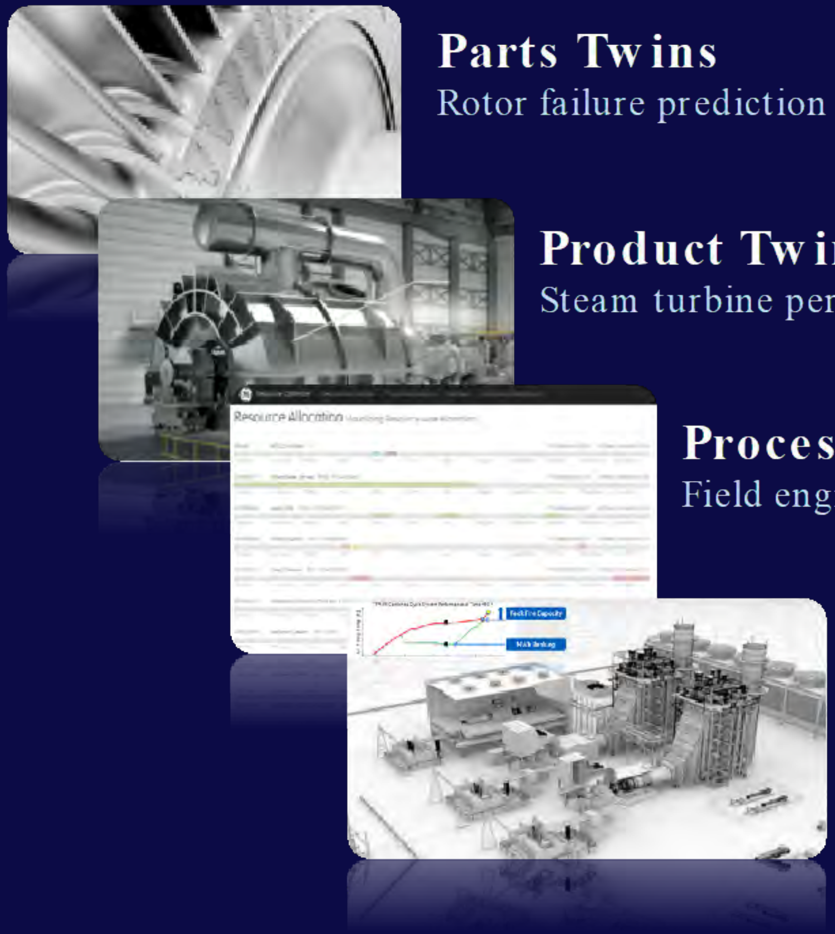
Digital Twins

GE Experience

KEEP 300K PEOPLE IN THE SKY/HR.

1/3 OF THE WORLD ELECTRICITY

16K SCANS PER MINUTE



Parts Twins
Rotor failure prediction

Product Twins
Steam turbine performance

Process Twins
Field engineer scheduling

System Twins
Performance optimizer

Industrial Digital Twins

Predictive Maintenance Digital Twins

Summary

Team

GE Research & GE Hitachi

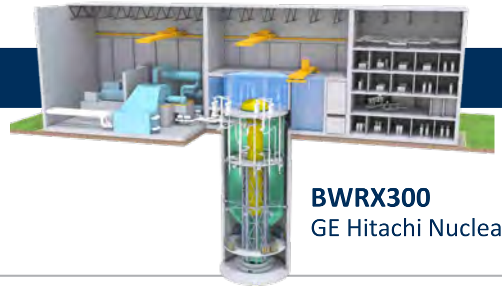
UT Knoxville

Oak Ridge Natl. Lab

Exelon Energy Corp.

Program Impact

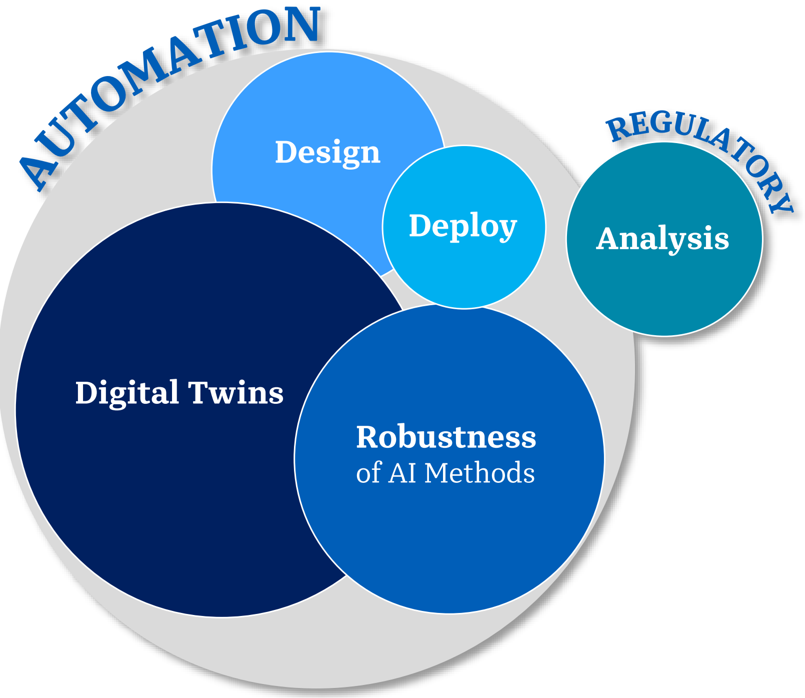
AI-enabled predictive maintenance **to ↓ O&M labor costs from \$15/MWh to \$3/MWh** in an Advanced Nuclear Reactor



BWRX300
GE Hitachi Nuclear

Program Targets

Metric	From	To
Automation ↓ labor costs	*None*	Automated workorders … ↓ Planning staff Online calibration … ↓ Tech and admin staff
Predictive Maintenance ↓ labor & mat'l	*Alarms*	↓Forced outages & trips … AI-driven predictive algorithms → ↓ Labor headcount
Trust	*Human*	Humble & explainable AI … quantify uncertainty to establish trust in the models & encourage automation



Technology Summary

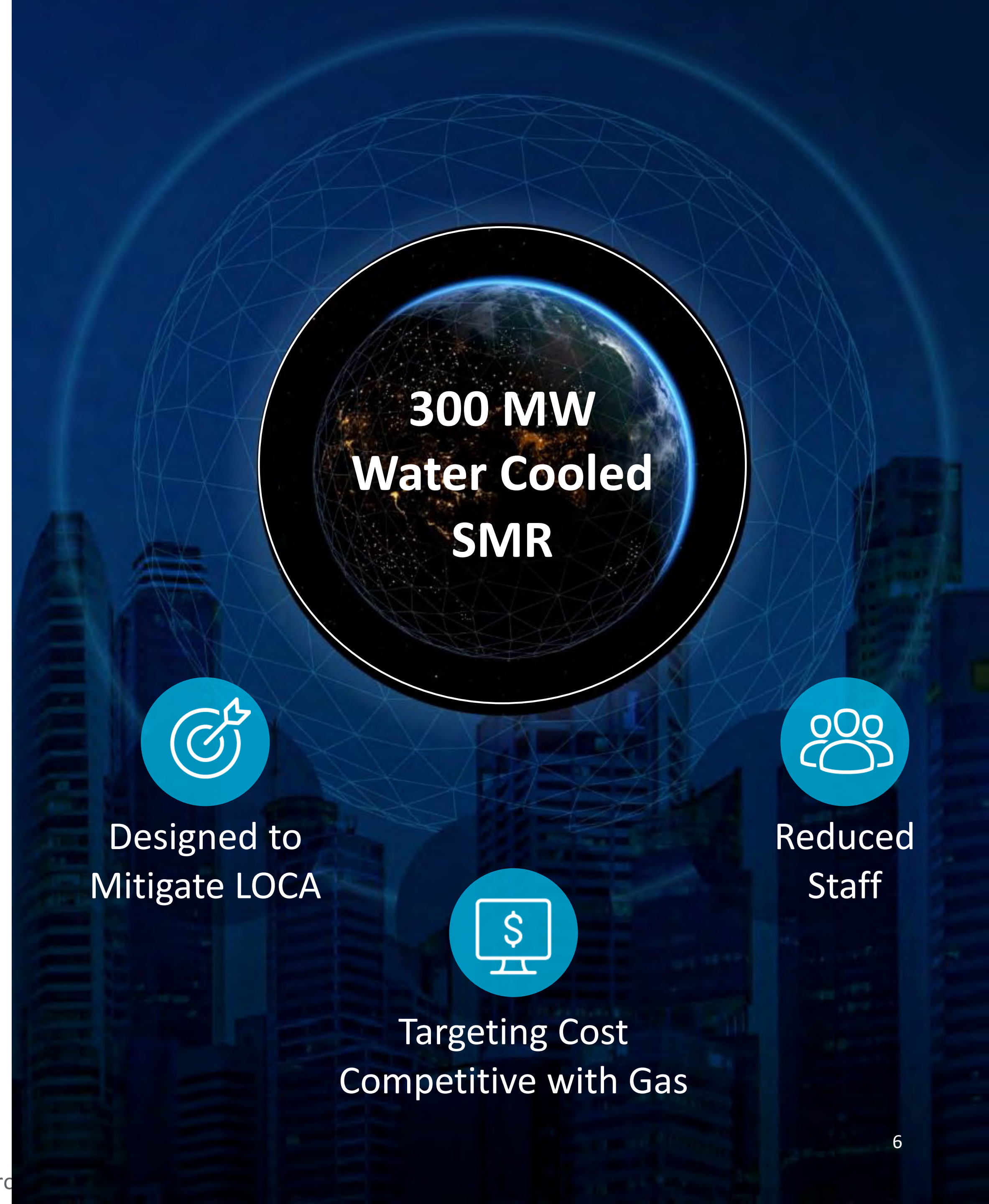
- **Reactor Operations** – Physics-informed machine learning, sensor optimization
- **Reactor Health –** Causal, humble & explainable AI for predictive maintenance
- **Decision Making –** Autonomous risk-informed decisions for reconfiguration & maintenence

AI-based predictive maintenance for lower O&M costs

BWRX300

- 10th generation BWR
- 300 MWe SMR
- World class safety
- Targeting LCOE competitive with gas
- Significant capital cost reduction per MW
- Scaled from licensed ESBWR
- Design-to-cost approach: targeting <$1B total and <$2,250/kW for NOAK
- Capable of load following
- Ideal for industrial applications … district heating, desalinization and process heat
- Constructability integrated into design
- Initiated licensing in the U.S. and Canada

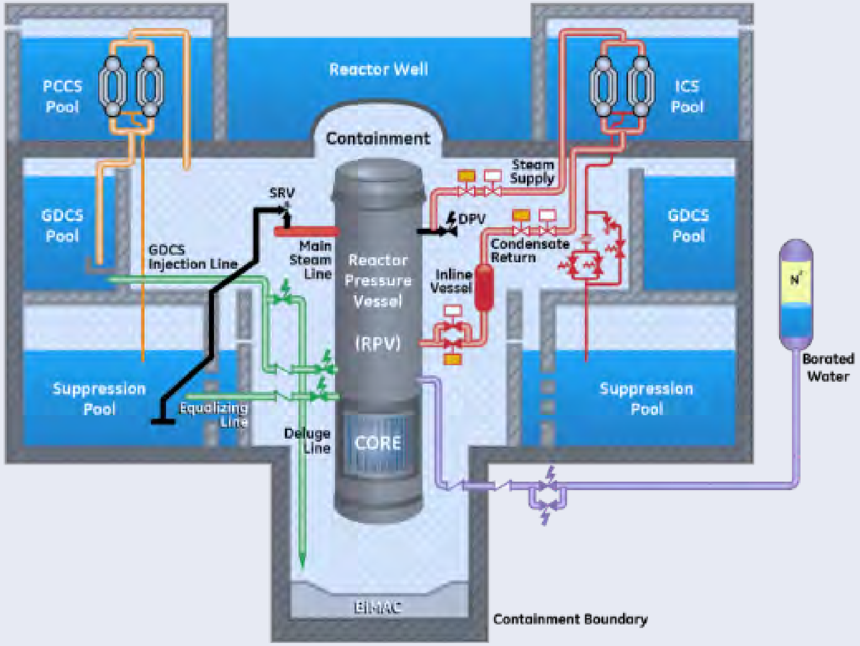
Operational by 2027



HITACHI

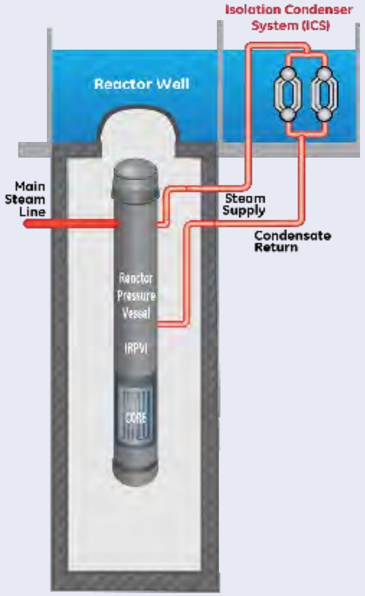
BWRX-300 Design Simplification

ESBWR



90% volume reduction

BWRX300



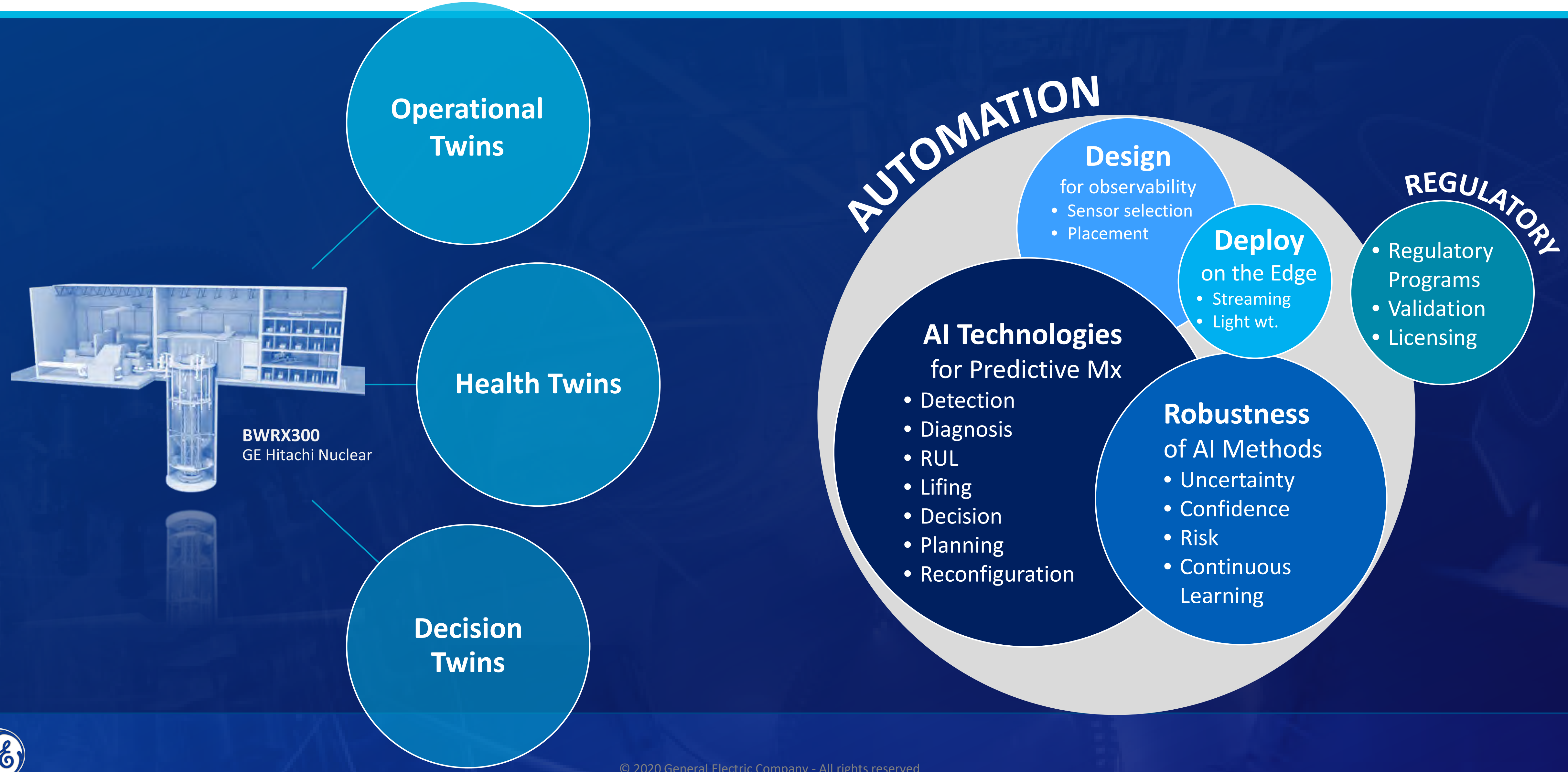
LOCA mitigation enables dramatic simplification

- LTR submitted to NRC and accepted for review
- Engineering design work confirmed 90% reduction in concrete vs. ESBWR

>50% building volume reduction/MW
>50% less concrete/MW

Predictive Maintenance Digital Twins (PMDT)

Technical Approach

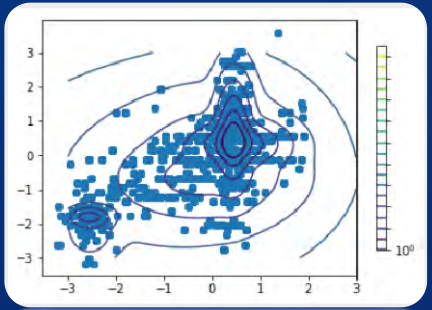


Research Focus: Advancing Digital Twin and AI

for Adoption and Scale

Explainability

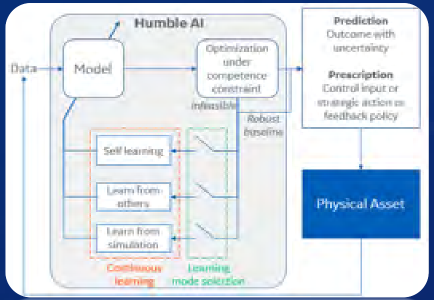
Build Trust in ML models



TRANSPARENCY

Humble AI

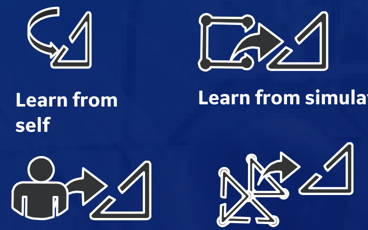
Safety & Robustness to put information to work



RISK MANAGED OPTIMALITY

Learning

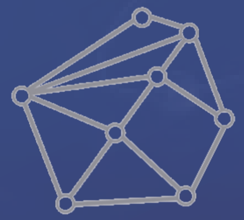
Multiple modes of learning



CONTINUOUS IMPROVEMENT

Security

CyberPhysical Security



DIGITAL **GHOST**

CONTINUOUS PROTECTION

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

Project Outcomes

GEMINA PMDT Project

DTs

1. Development of operational and health digital twins for
   - High value plant systems/components (low hanging)
   - Reactor core critical components (challenging)

Demo

2. Demonstration of automation
   - Online sensor calibration – use flow-loop HIL testbed
   - Work order automation – APM cloud deployments

R&D

3. Research to address gaps and challenges
   - Humble AI (challenging – technical development)
   - Risk and Uncertainty - (challenging – integration)

Analysis

4. Analyses
   - Cost reduction opportunities and entitlements in SMR systems
   - Regulatory needs and constraints

X energy

Digital Twin Applications for Advanced Nuclear Technologies

Xe-100 ARPA-E GEMINA Program Overview

Yvotte Brits, ***Senior Nuclear Systems Engineer***

December 2, 2020

Agenda

1. X-Energy Introduction
2. Xe-100 Plant Overview
3. Xe-100 ARPA-E GEMINA Program Overview

X-energy was Created to Change the World

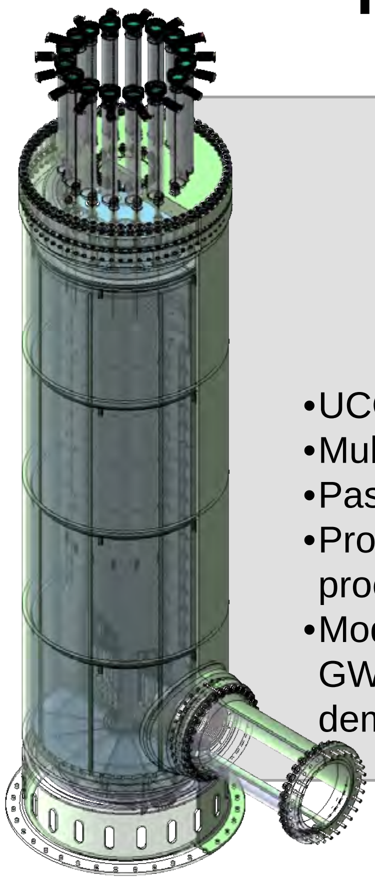
Dr. Kam Ghaffarian,
Founder and Executive Chairman

"President Kennedy once said that we are in a space race and my work with NASA reflects the progress he had hoped for.

Today, I believe we are in an energy race. Providing clean energy across the world is my vision for X-energy and I believe that clean, safe, reliable nuclear energy is necessary to making this possible."

- Dr. Kam Ghaffarian is a globally recognized technology visionary across energy, space and information technology.
- Created and grew Stinger Ghaffarian Technologies (SGT), Inc. to $650 million in annual revenue and 2,400 employees. SGT was ranked as the U.S. National Aeronautics and Space Administration's second largest engineering services company prior to being acquired by KBRwyle, subsidiary of KBR, Inc.
- Founded X-energy in 2009 to address innovation in critical energy solutions. X-energy was awarded ~$60M from DOE to focus on an advanced nuclear reactor and TRISO fuel.
- Began Intuitive Machines in 2016 to leverage NASA technologies for commercial space and terrestrial applications. Intuitive Machines won its first Commercial Lunar Lander Contract from NASA in 2018.
- Began Axiom Space in 2017 to develop the first commercial space station, to be launched by 2021.

Reactor Solutions for Multiple Markets

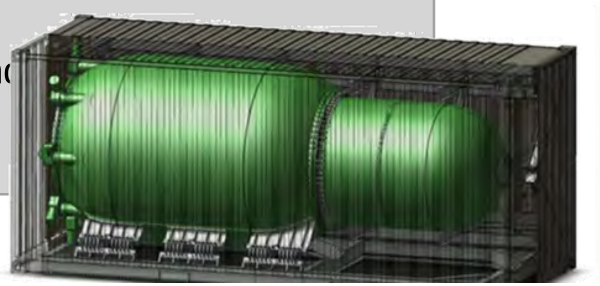


Xe-100
For commercial power and process heat applications
80 MWe

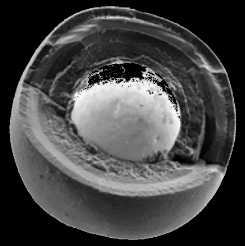
- UCO TRISO fuel in pebble fuel elements
- Multi-pass online refueling
- Passive safety
- Produces steam for electricity and/or process heat applications
- Modules can be combined to generate GW-level power for large electricity demand

Xe-Mobile
For remote locations and micro-grids
1-3 MWe

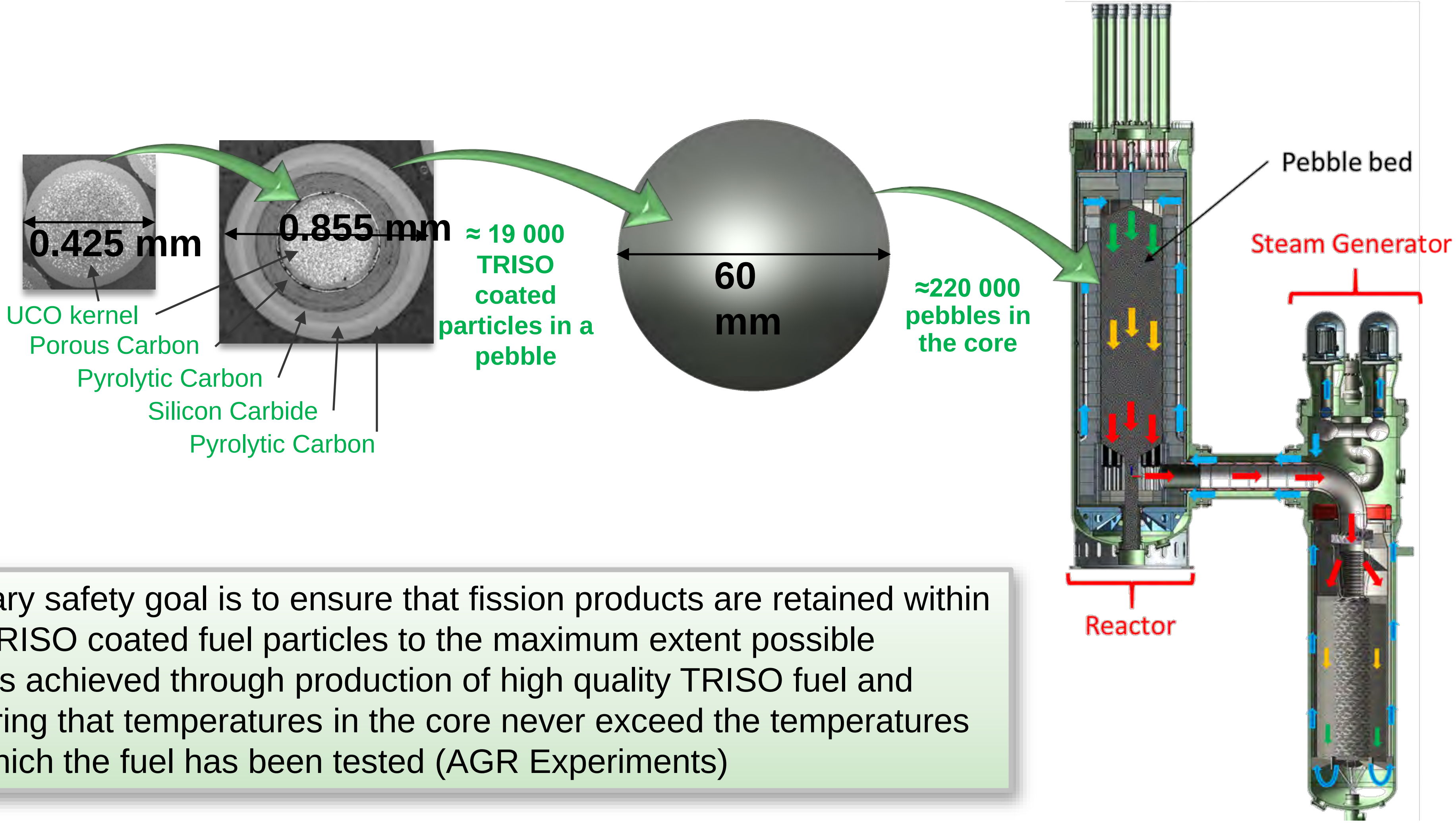
- UCO TRISO fuel in pebble fuel or prismatic elements
- Power conversion via gas or steam turbine generator
- 2-10+ year fuel cycles
- Passive safety
- Applicable for forward bases and disaster relief needs



TRISO Fuel



UCO TRISO Particle – Primary Fission Product Barrier

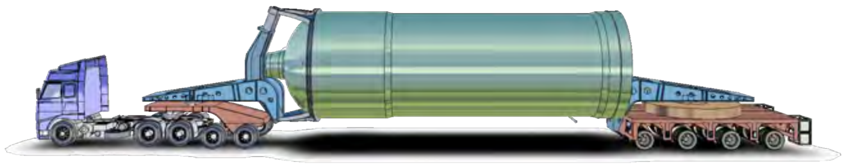


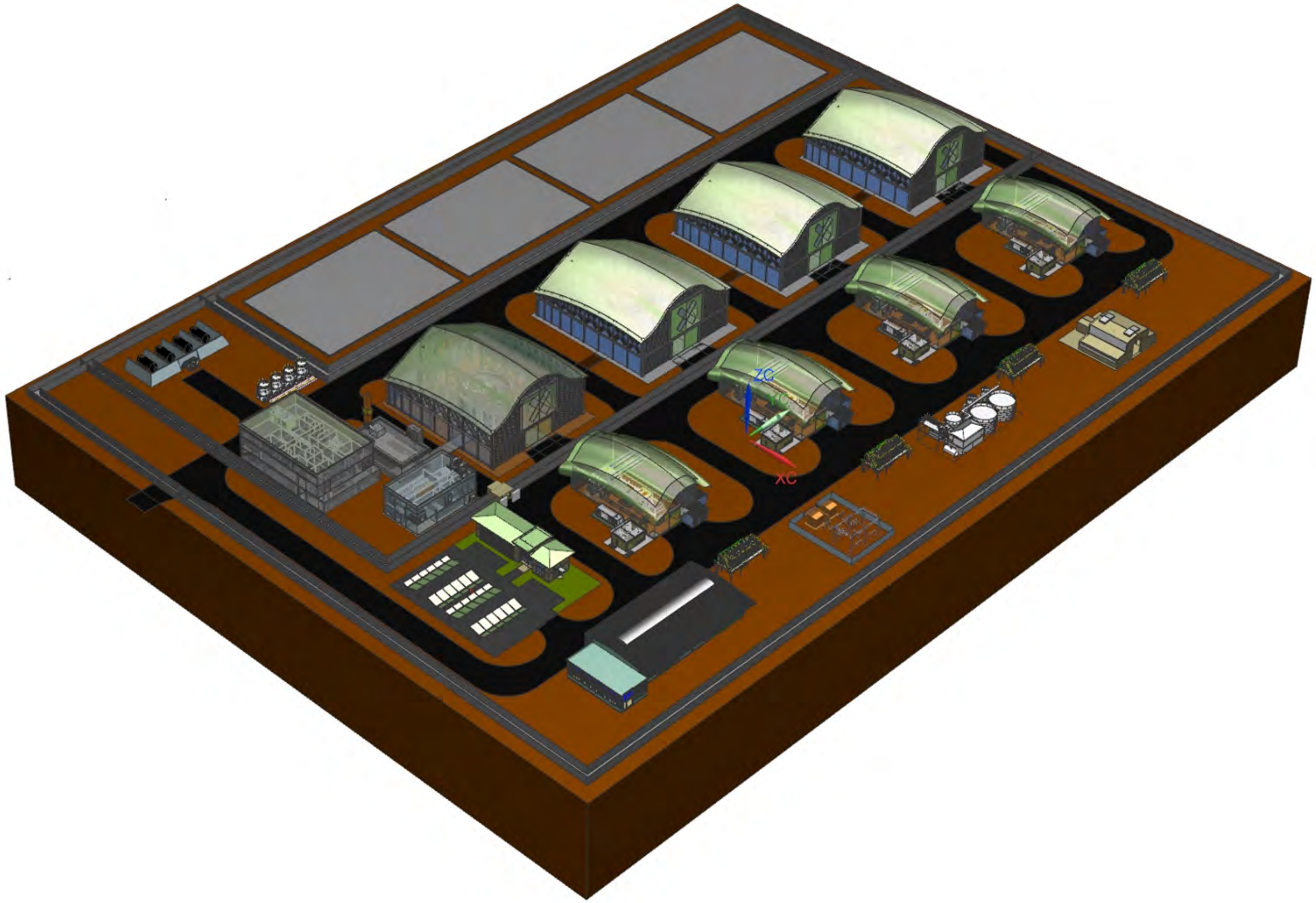
- Primary safety goal is to ensure that fission products are retained within the TRISO coated fuel particles to the maximum extent possible
- This is achieved through production of high quality TRISO fuel and ensuring that temperatures in the core never exceed the temperatures for which the fuel has been tested (AGR Experiments)

Xe-100 Plant Overview

Standard X-energy plant have 4 Reactors - 4 Turbines producing 320 MWe, attributes include:

- 200MWth/80MWe Per Module
- Process heat applications
- Proven intrinsically safe
- Meltdown proof
- Walk-away safe
- Modular construction
- Requires less time to construct (2.5-4 years)
- Road transportable for diverse geographic areas
- Uses factory-produced components
- Load-following to 40% power within 15 minutes
- Continuous fueling; resilient on-site fuel storage





Xe-100 ARPA-E GEMINA Project Objective

Current Xe-100 Plant Staff

Division Nr	Number of Modules	Plant Staff
1	Plant Management	4
2	Operations Division	40
3	Security Division	50
4	Maintenance Division	52
5	Engineering Division	21
6	Administration Division	12
	Total	179

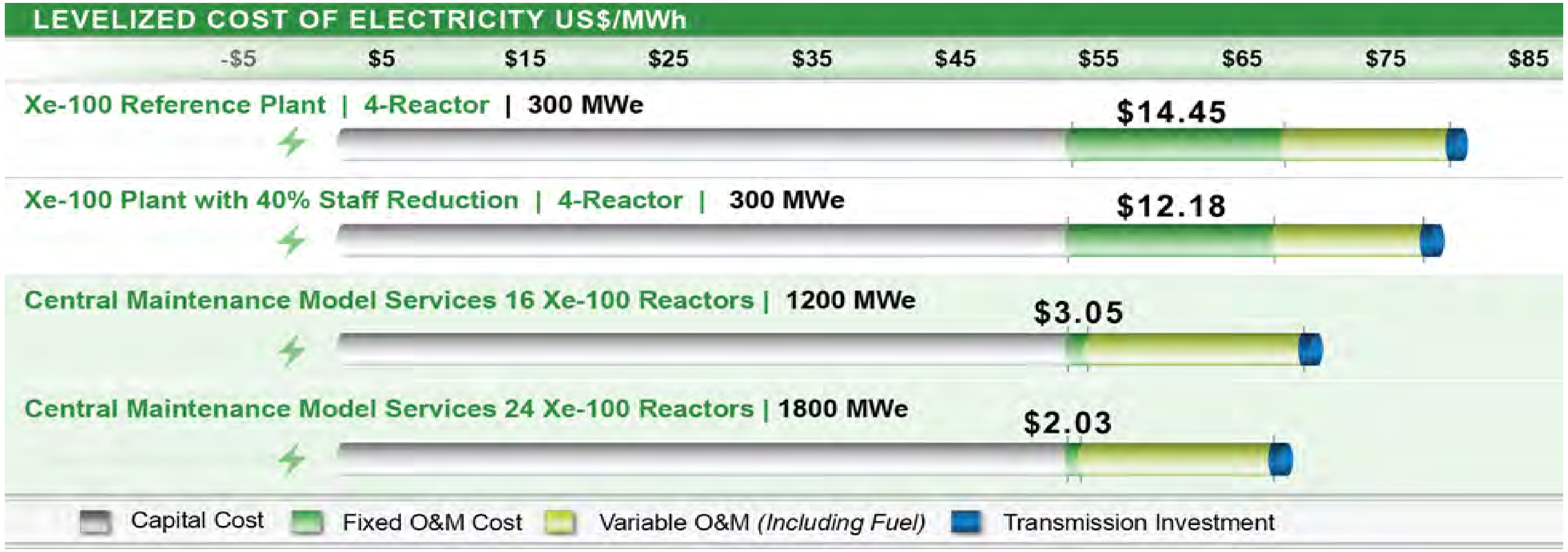
ARPA-E Xe-100 Plant Staff Target

Conservative

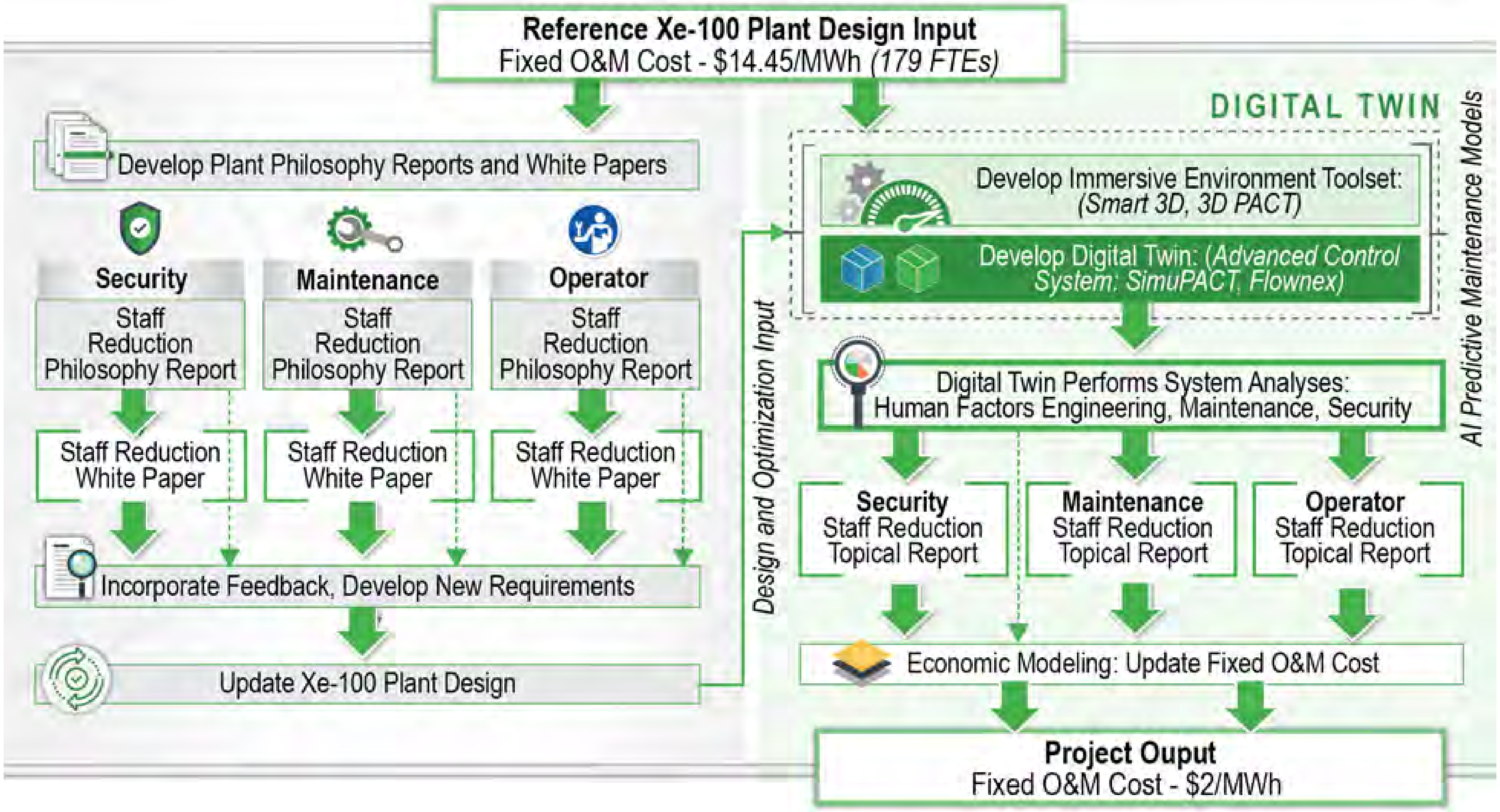
Plant Staff
4
30
20
20
21
12
107

Aggressive

Plant Staff
4
18
20
20
10
12
84



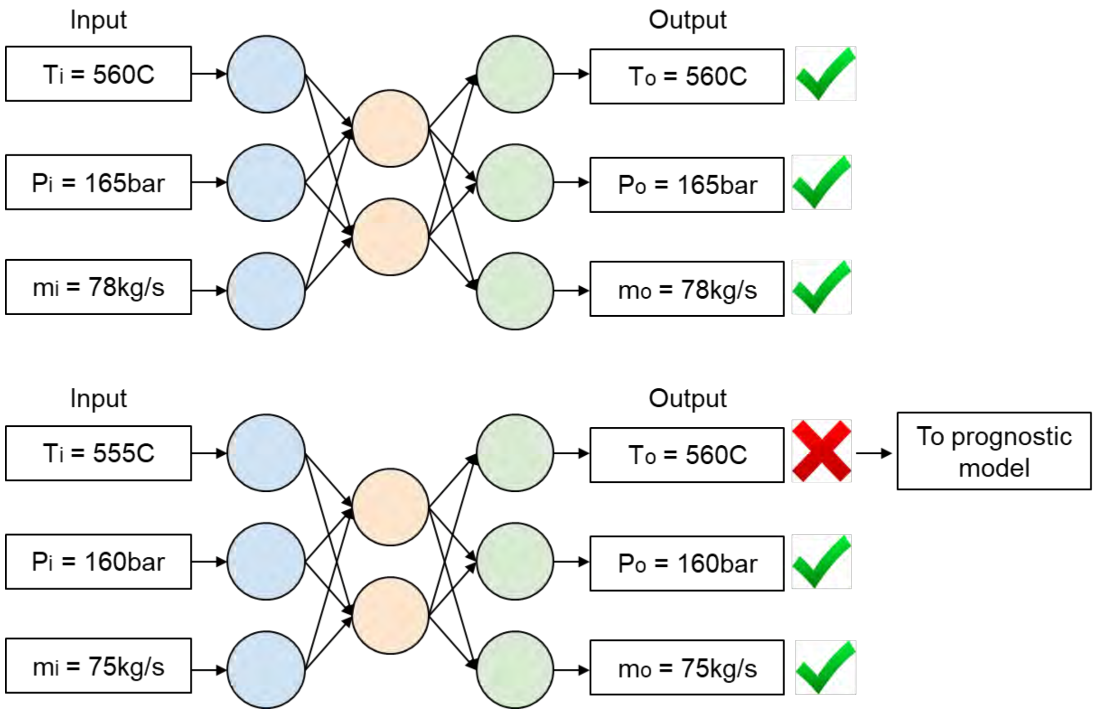
Overall Project Lifecycle (24 months)



Xe-100 Digital Twin for Operator Staff Reduction in progress…

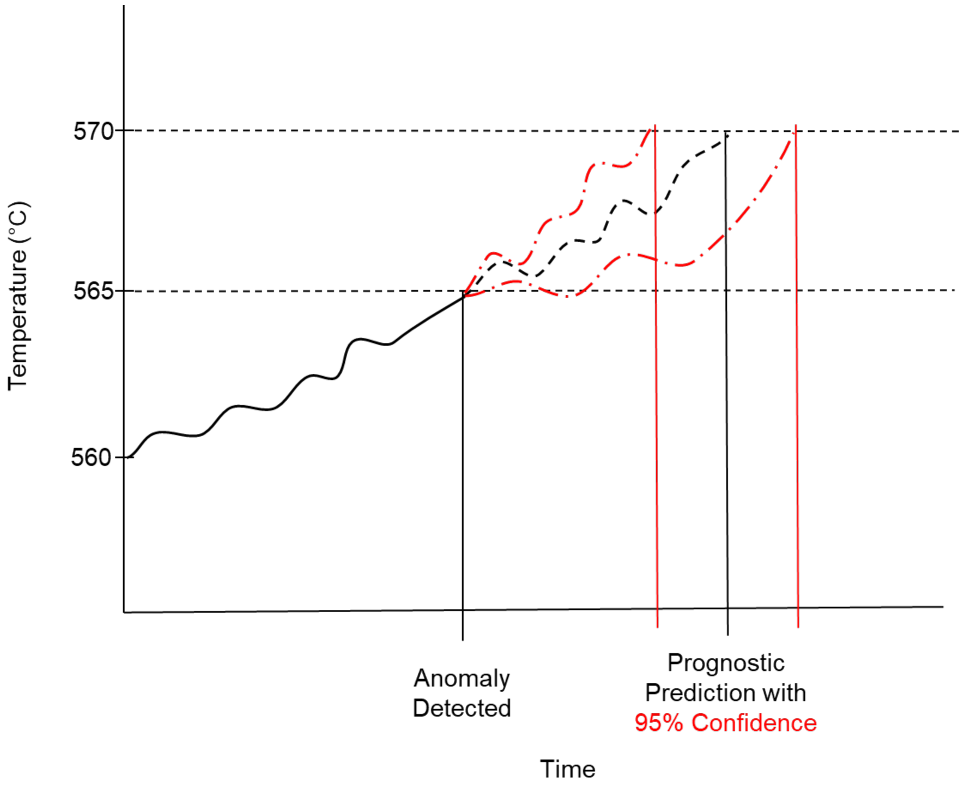
Diagnostic Model

- The diagnostic model aims to
  - Detect system component anomalies
  - Identify deviating variables
  - Initiate the correct prognostic model
  - Be continuously trained online
- Machine learning algorithms include
  - *Auto-Encoder* (AE) for feature extraction
  - *Long-Short Term Memory* (LSTM) for temporal data

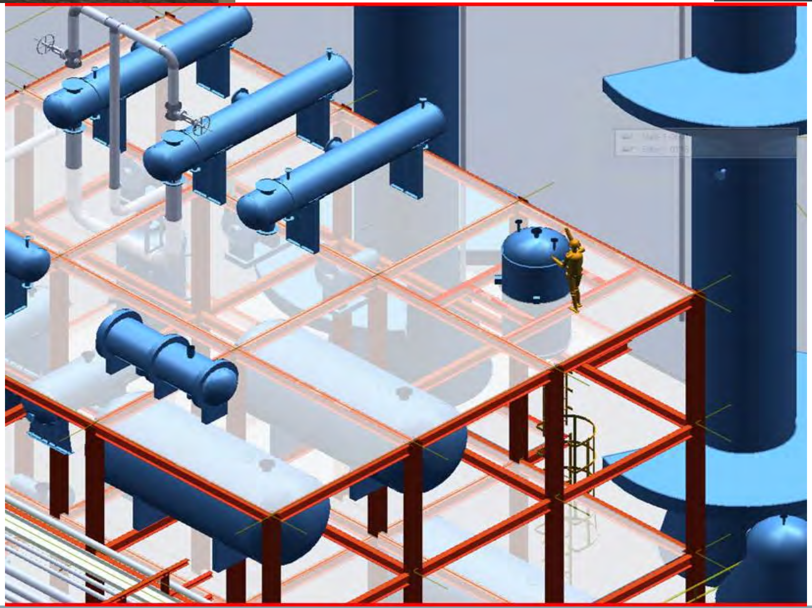


Prognostic Model

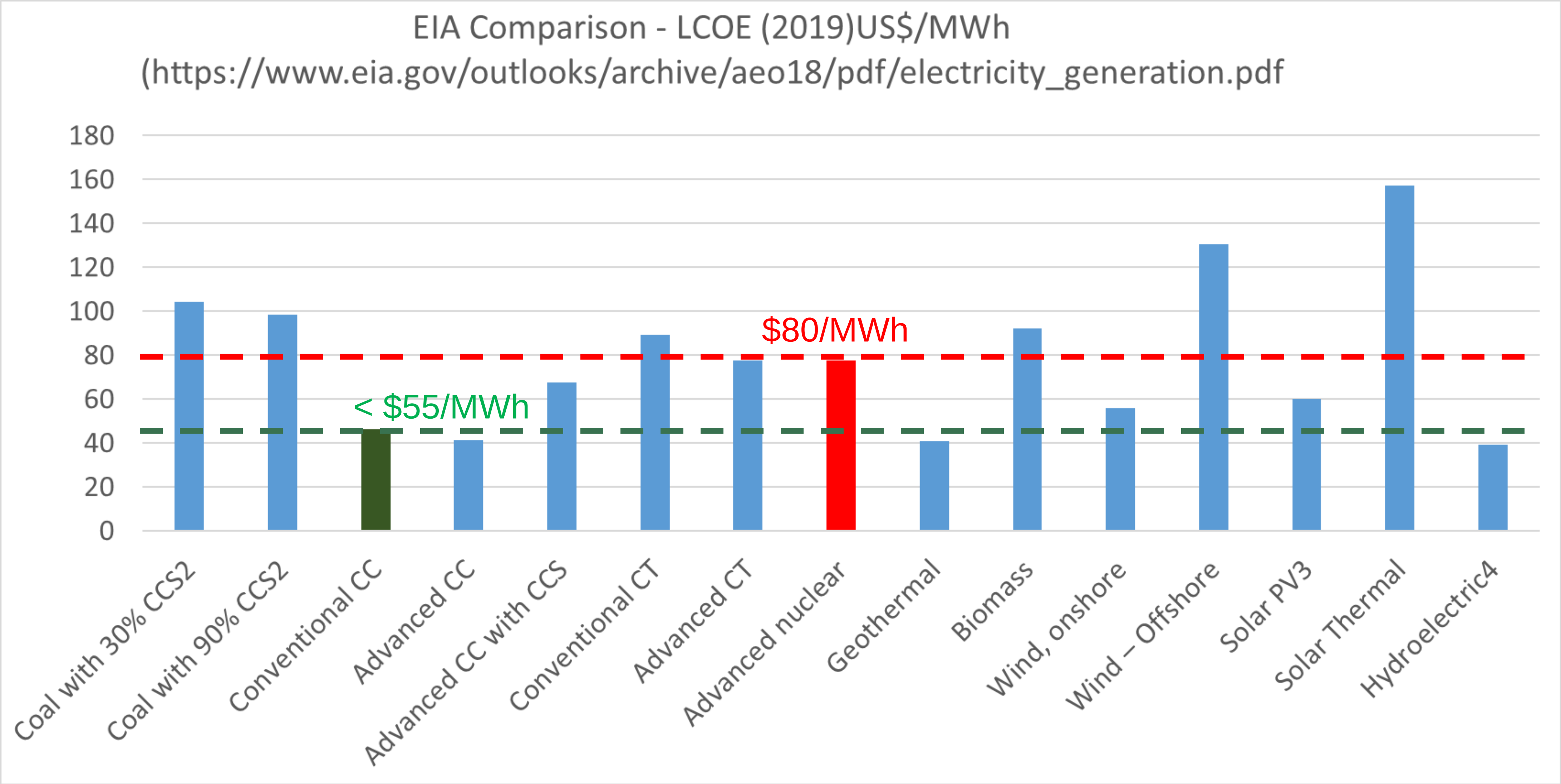
- The prognostic model aims to
  - Predict time to abnormal condition
  - Provide time window to auxiliary models
- Machine learning algorithms include
  - *Bayesian Neural Network* (BNN) for uncertainty
  - AE-LSTM for input space reduction and temporal data
  - *Convolutional Neural Network* (CNN) for efficient spatiotemporal data processing



Xe-100 Immersive Environment Toolset for Security and Maintenance Staff in progress…



Successful deployment of Advanced Reactors in the US requires lower plant cost



Questions

Kairos Power

Kairos Power ARPA-E Gemina Projects:
Project “SAFARI” – Secure Automation for Advanced Reactor Innovation
Project “MARS” – Maintenance of Advanced Reactor Sensors and Components.

DR. ANTHONIE CILLIERS

DECEMBER 2ND 2020

Kairos Power's mission is to enable the world's transition to clean energy, with the ultimate goal of dramatically improving people's quality of life while protecting the environment.

In order to achieve this mission, we must prioritize our efforts to focus on a clean energy technology that is *affordable* and *safe*.

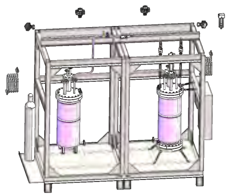
Iterative systems supporting Digital Twin development projects

Running

Forced Coolant Loop

Running

Engineering Test Unit
Demonstration Experiment



2020

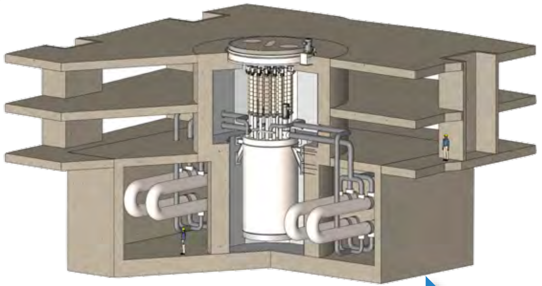
Instrument Test Unit

2021

Engineering Test Unit

KP-FHR
Test Reactor

Reactor Demonstration Unit
(Non-Nuclear)



KP-FHR
Commercial Reactor

Typical uses

1. Sensor data collection
2. System level Health Monitoring modeling
3. High temperature instrument development
4. Smart Instrument development and testing

Typical uses

1. Sensor data collection
2. System Level health monitoring, modeling
3. Control System Development
4. Prototype control room
5. Prototype simulators and Digital Twin models
6. Control Automation testing

Typical uses

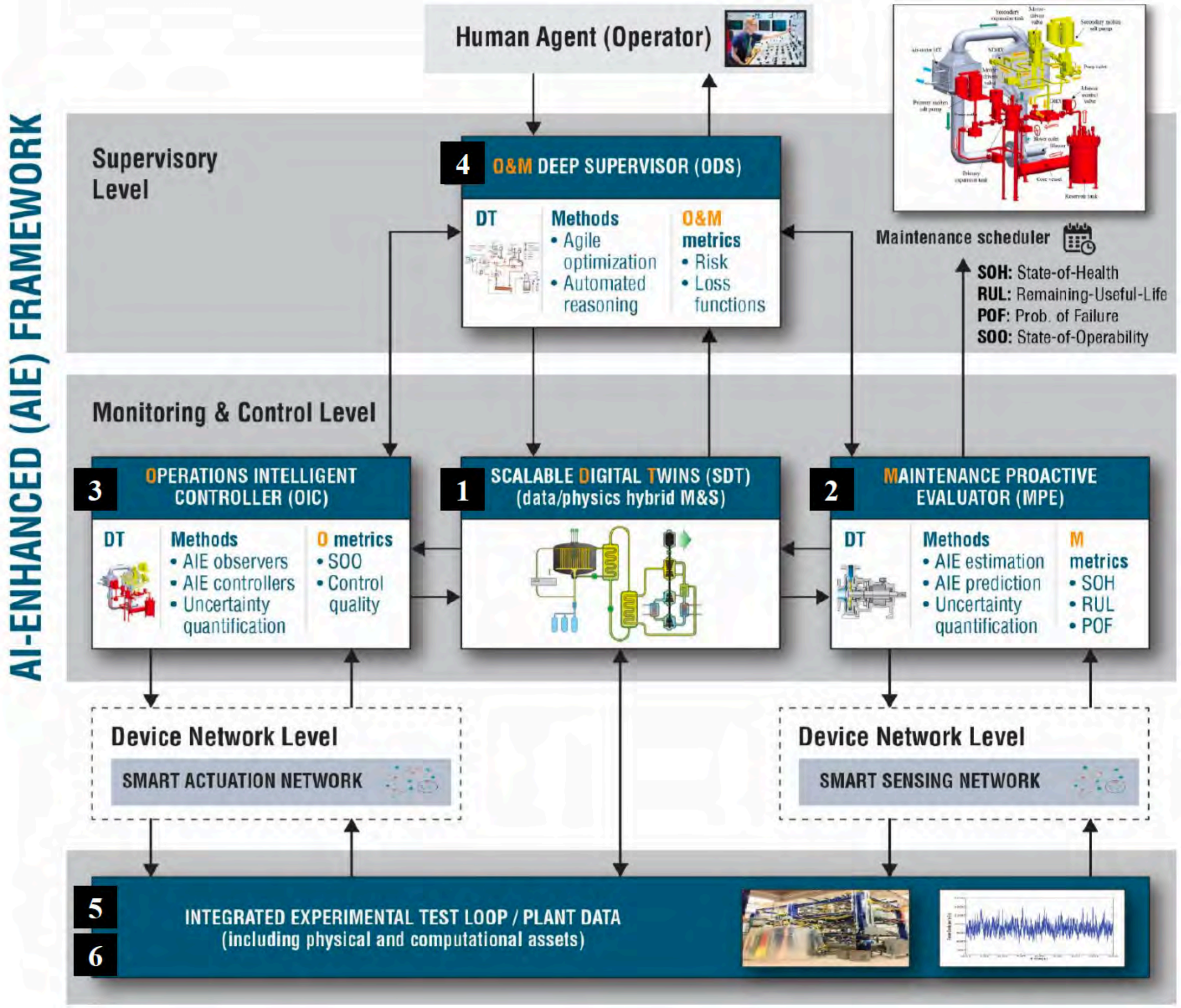
1. System level Health Monitoring and modeling
2. Control System
3. Plant Control room
4. Training Simulators & Digital Twin models
5. Maintenance planning

1. Full Plant Control
2. Full Control Room
3. Full Scope Digital Twin
4. Plant Health Monitoring
5. Maintenance implementation

Project “SAFARI” – Secure Automation for Advanced Reactor Innovation
&
Project “MARS” – Maintenance of Advanced Reactor Sensors and Components.

TWO COMPLEMENTARY PROJECTS SUPPORTED BY THE KAIROS TEST PROGRAM

Project "SAFARI" – Secure Automation for Advanced Reactor Innovation (University of Michigan)



Deliver a capability enabling smart functionalities in advanced reactor systems (ARS) such as

- autonomous operations (AO),
- flexible operations (FO), and
- predictive maintenance (PM).

This has the potential to dramatically lower operations and maintenance (O&M) costs compared to currently operating LWRs.

Project “SAFARI”: Partners

Kairos Power

EPRI

sas

ADVISORS
B.Haugh (Kairos Power)
C. Kerr (EPRI)
P.Tomski (SAS)

CURTISS-WRIGHT

COMMERCIALIZATION
S. Fueller (CW)

PROJECT DIRECTOR
A. Manera (UM)

Deputy Administrative Director
T. Downar (UM)

Deputy Technical Directors
H. Garcia (INL), R. Vilim (ANL)

UNIVERSITY OF MICHIGAN

Argonne NATIONAL LABORATORY

INL Idaho National Laboratory

Task 1: Digital Twins
Lead: K. Duraisamy (UM)

Task 2: MPE module
Lead: H. Garcia (INL)

Task 3: OIC module
Lead: R. Vilim (ANL)

Task 4: ODS module
Lead: H. Garcia (INL)

Task 5: Molten Salt Loop
Lead: X. Sun (UM)

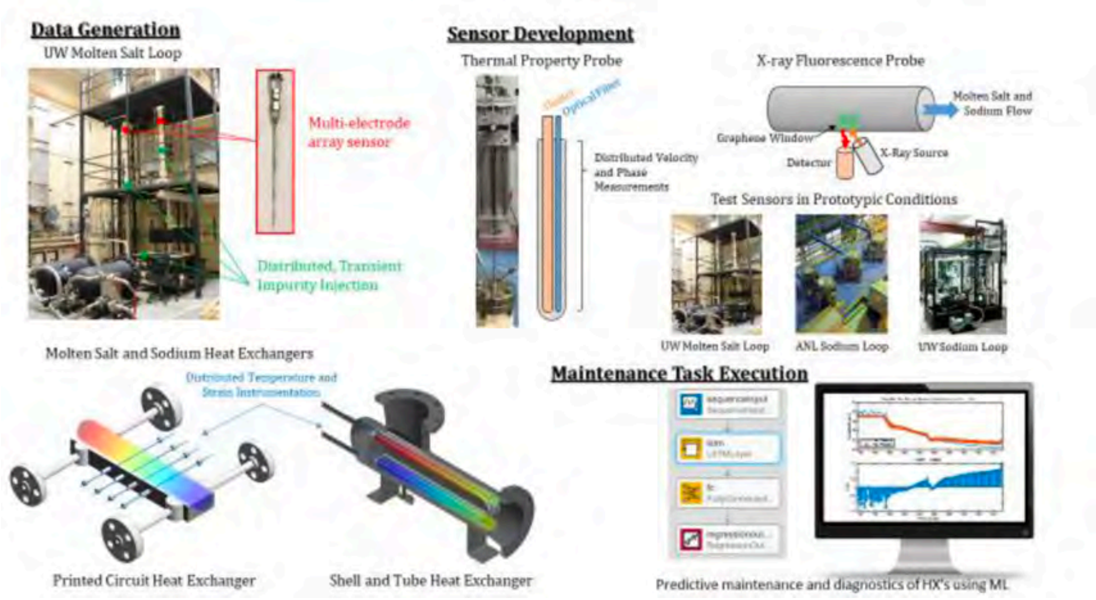
Task 6: Demo on FHR
Lead: T. Downar (UM)

Kairos Power

Project “SAFARI”: Activities

- The work is organized into 6 main tasks:
- Task 1 Development of Scalable Digital Twin (DT) module and SAFARI interface
- Task 2. Development of the Maintenance Proactive Evaluator (MPE)
- Task 3 Development of Operations Intelligent Controller (OIC) module
- Task 4 Development of O&M Deep Supervisor (ODS) module
- Task 5 Demonstration of Developed Capability using a Molten Salt Loop with Feedbacks
- Task 6 Application of the developed capability to Kairos-FHR

Project "MARS" – Maintenance of Advanced Reactor Sensors and Components (Argonne National Laboratory)



Develop advanced distributed sensing and data generation techniques to

- characterize critical components and systems,
- increase sensor diversity,

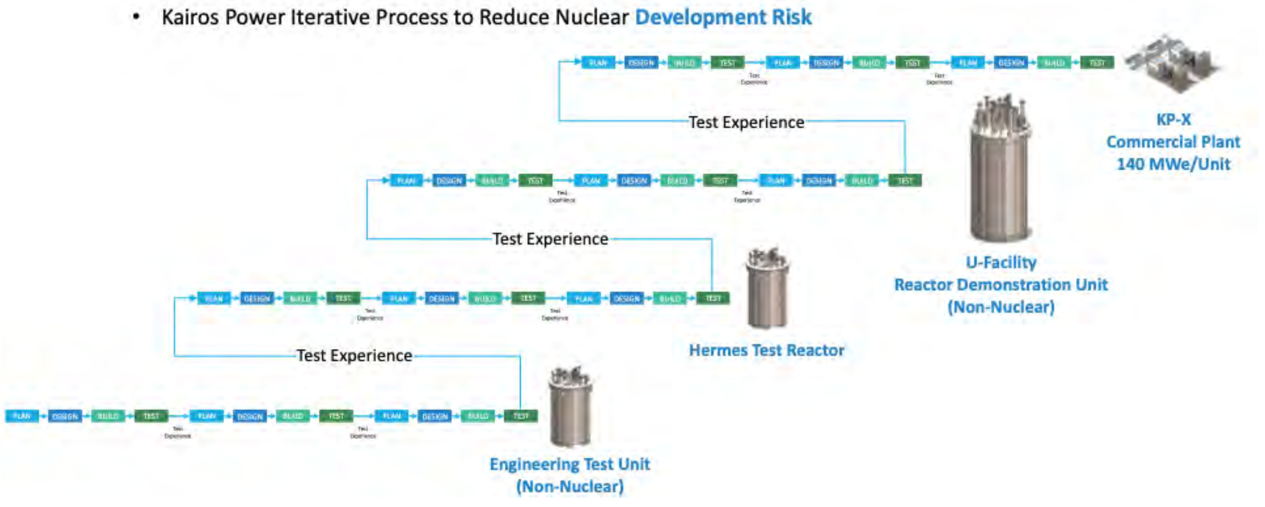
Develop multifunctional sensors which

- measure several process variables simultaneously,
- automate maintenance tasks through machine learning-enabled fault detection and diagnostics, and
- informs intelligent sensor placement to achieve autonomous operation.

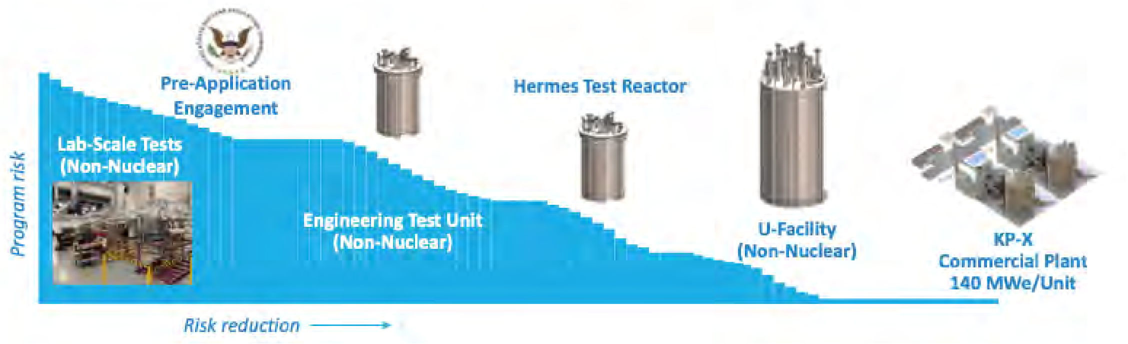
Project "MARS": Kairos Power Development Strategy

Develop O&M cost-saving solutions for the Kairos Power fluoride salt-cooled high temperature reactor.

- Kairos Power is a mission-driven engineering company focused on the delivery of a clean, affordable and safe energy solution through the integrated design, licensing and demonstration of advanced reactor technology.
- Focused on reducing technical risk through a novel approach to test iteration often lacking in the nuclear space.
- Constructing a non-nuclear research and development laboratory in Albuquerque, designed to test the high-temperature salt technology. Technologies demonstrated to be successful in reducing O&M costs, will be incorporated into the KP-FHR design.
- The licensing strategy reduces licensing risk and facilitates licensing certainty for customers via active pre-application engagement with the Nuclear Regulatory Commission (NRC) during the design process prior to plant construction.
- Licensing process improvements are anticipated by implementation of the Licensing Modernization Project (LMP), which provides a methodology for the identification and focus on safety significant portions of the design and safety analysis during the licensing review.



Risk Reduction



Project “MARS”: Outcome

- The proposed technology will decrease the O&M costs through automation of maintenance and increasing durability of components through better sensing.
- Characterization of critical components, such as the heat exchangers, combined with automation of maintenance task execution through machine learning and early detection of faults is expected to reduce staffing requirements and reduce the O&M cost.
- Early and distributed detection of oxide impurities will reduce the risk of corrosion of components.
- Multifunctional sensors will reduce the number of sensing units while providing requisite information about coolant process variables.
- Reactor maintenance will be enhanced through early detection of adverse thermal hydraulic effects, such as thermal stratification in the reactor vessel.

Thank You

Synopsis of Westinghouse Machine Learning, Artificial Intelligence, and Digital Twin Developments for Nuclear Power Applications

for the Workshop on Digital Twin Applications for Advanced Nuclear Technologies, December 2020

Brian M. Golchert, Ph.D.
Gregory A. Banyay, Ph.D., P.E.

WESTINGHOUSE
VISION & VALUES

Leading Infrastructure Services Provider to the Power Generation Industry

Outline

- Definition / History
- Selected areas where digital twins (in conjunction with Machine Learning (ML) / Artificial Intelligence (AI)) have been or will be applied at Westinghouse:
  1. **Reduction of physical testing & maintenance**
     - Destructive test elimination at our manufacturing facility
     - Baffle-former bolt predictions
  2. **Automated analysis of inspection or monitoring data**
     - Concrete crack detection using drones
     - Neutron noise monitoring of reactor structures
     - Reactor failure prediction
  3. **Process optimization**
     - Component condition monitoring
     - Fan operation
- Looking ahead

Items are briefly discussed at a high level in subsequent slides, emphasizing relevance to advancing digital twins

Background on Digital Twins

"A rose by any other name would smell as sweet"

What are digital twins?

- Digital twins (DT) are software that combine:
  - Plant data
  - Numerical models (CFD, FEA)
  - Statistical analysis (predictions)
- DT provides a virtual simulation of what is being modeled:
  - Components
  - Systems
  - Processes
- Current commercial analysis software provides more detail faster (close to real time) than ever before
  - This is key to the implementation and use of DTs

WEC has been doing 'DT' for years

- The following examples of high value services offered by Westinghouse are essentially digital twins:
  - WESTEMS
  - MAAP
  - BEACON
  - RESM
  - POMS
  - PFM
  - Simulators

Digital twins have been around for a long time. They are just getting a lot better!

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A Brief History of Westinghouse Innovation

“Brevity is the soul of wit”

- Westinghouse has a long history of applying new technology and ideas to the nuclear industry such as:
  - First nuclear company to use a commercial finite element analysis (FEA) code
  - Pressurized thermal shock
  - Accident tolerant fuel (ATF)
  - CVAP for AP1000®
  - AP1000 passive safety plant technology
- This presentation will focus on recent activities involving digital twins with emphasis on those applications that employ advanced analytics and simulation methods

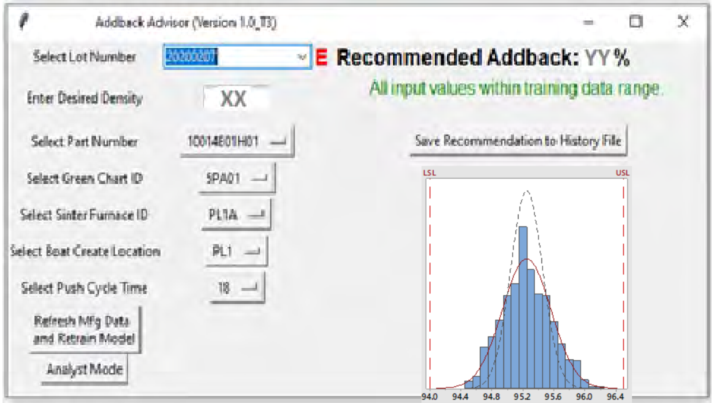
Westinghouse

Current emphasis in Westinghouse is on digital twin applications that build upon Westinghouse experience and leverages operational data

Area 1: Destructive test elimination

“By indirections find directions out”

Status	**Complete**
Issue	Part of the fuel fabrication facility at Westinghouse was experiencing large amounts of scrap due to poor prediction of fuel pellet composition and pellet testing. In part, the pellet composition was determined by subject matter expert input.
Value Proposition	ML model used to replace costly fuel pellet pre-production process **Project paid for itself in less than a year!!**
Plan	Exposed WEC to potential value of ML. Built trust in ML. Inspired and enabled new applications. Developed generic tool accessible to all WEC engineers.
Application	Almost any type of production process.



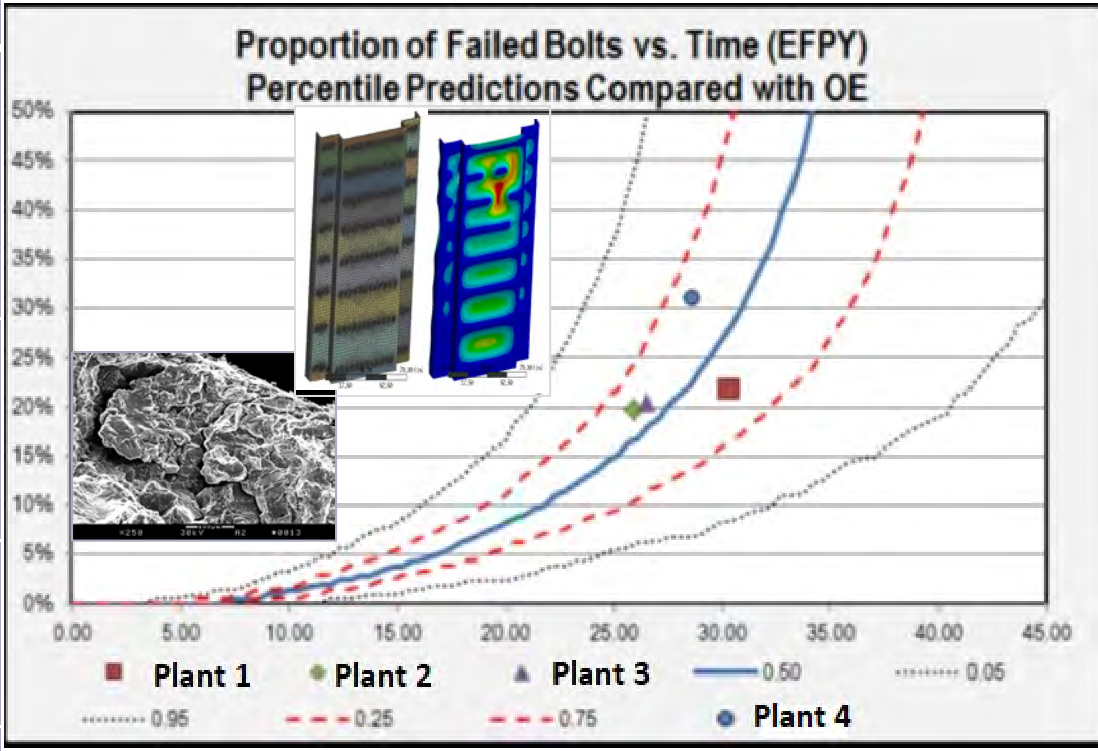
Machine learning methodology eliminated costly part of manufacturing process saving $1M+ /yr

Westinghouse

Area 1: Baffle-Former Bolt Predictions

"Better three hours too soon than a minute too late"

Status	Complete
Issue	Irradiation assisted stress corrosion cracking (IASCC) imparts damage to baffle-former bolts that hold together core support structures necessary for the structural integrity of the reactor assembly.
Value Proposition	Semi-empirical predictive methodology used analysis of operating experience data in conjunction with mechanics-based modeling (for stress re-distribution).
Plan	Deployed predictive methodology for >5 plants to improve model validation and assist in decision making for inspection timing & replacement part purchases.
Application	Probabilistic reliability analysis served to prognosticate remaining time to significant degradation, to assist in maintenance planning.



IASCC susceptibility can be exacerbated by dynamic stress, such as that due to flow-induced vibration

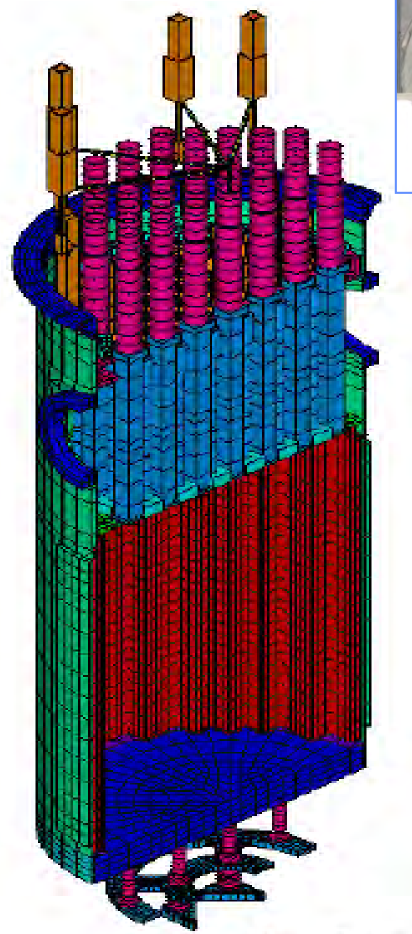
Westinghouse

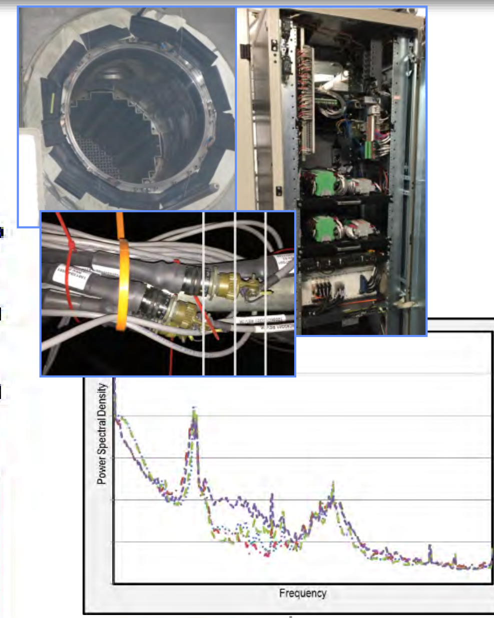
Area 2: Structural aging monitored by neutron noise

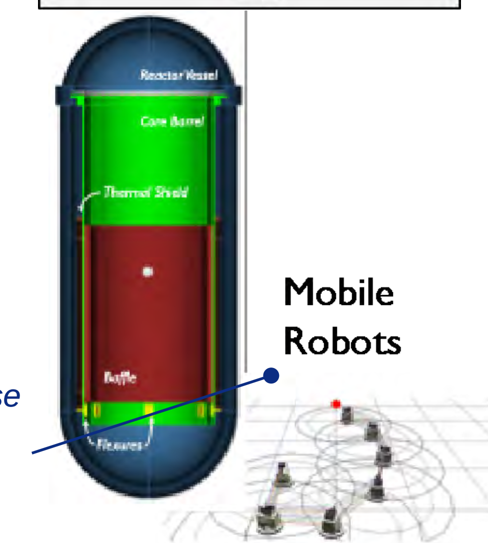
"…with a team of little atomies…"

Status	**On going**
Issue	Reactor internals degrade over time and it is necessary to know the current condition of these components.
Value Proposition	Use ML/Digital Twins to evaluate diagnostic certainty to assess reactor internals degradation due to aging. This will help reduce engineering cost to perform analysis.
Plan	Create a <u>condition</u>-based monitoring digital twin with machine learning that can be used to evaluate primary equipment, to enable movement away from <u>time</u>-based paradigm by EPRI MRP** requirements.
Application	Any reactor type internals

Reactor Internals structural dynamics are observable from neutron fluence signal due to **turbulent and acoustic excitation**







Visionary extension of this work to couple a computational Inverse problem (i.e., damage identification) with mobile active sensing (i.e., robotics) being researched via DOE funding with Duke U. & Sandia Nat'l Lab!

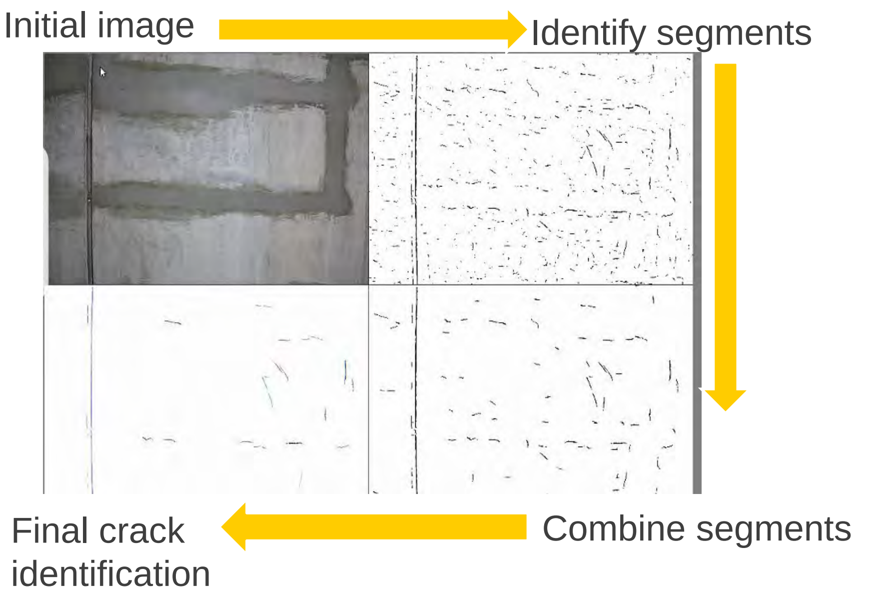
Westinghouse

** Electric Power Research Institute Materials Reliability Program

Area 2: Concrete crack detection using drones

"Once more unto the breach…"

Status	**On going**
Issue	Human inspection of large nuclear buildings is very slow, time consuming, and requires subject matter expert evaluation.
Value Proposition	Machine learning of drone-captured images to significantly reduce cost of concrete crack identification.
Plan	Develop machine vision system and skillset that can help automate visual inspections inside and outside the nuclear industry. Use subject matter expert elicitations to help train the ML algorithm.
Application	Wide range of nuclear and non-nuclear



Use images from drone surveillance and machine vision to locate potential cracks

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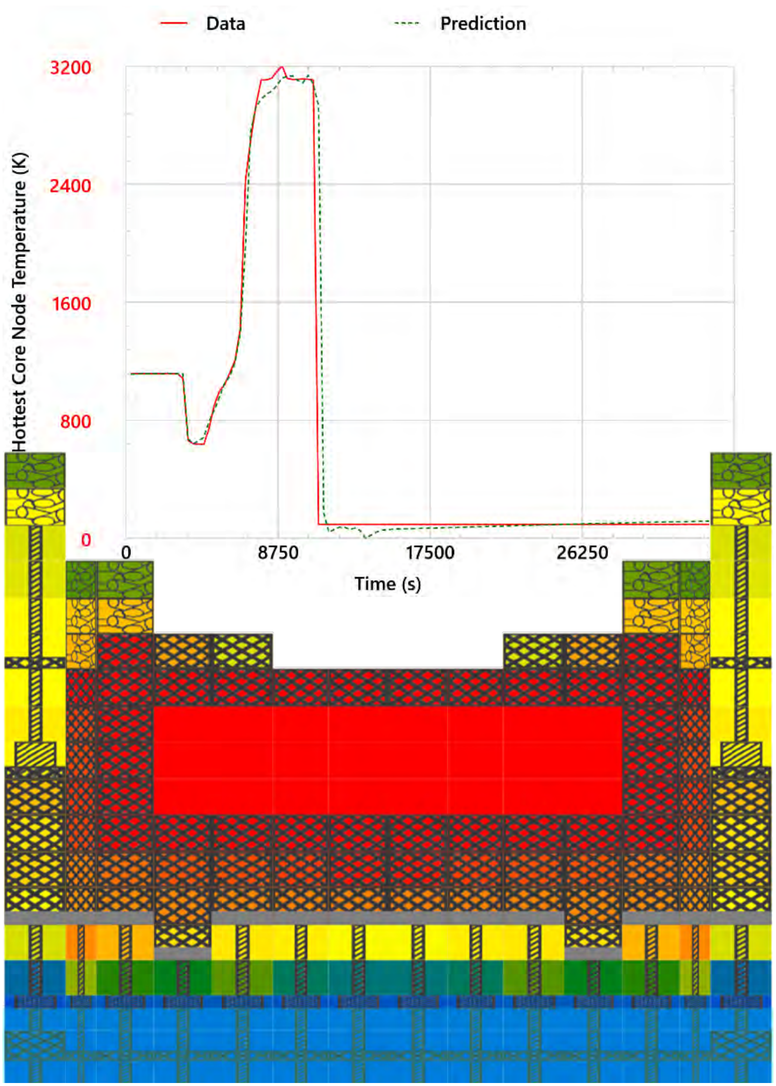
Area 2: Manage a Severe Accident in Real Time

"…melt, thaw, and resolve itself into a dew!"

Status	Completed
Issue	Using conventional means, it was difficult to initialize the state of a digital twin corresponding to a plant in the midst of a severe accident.
Solution	A deep, recurrent neural network was developed to identify the state of an ongoing accident when provided with either plant data or simulator data. The items calculated by the neural network include the core mass distribution, fission product releases, and the size of a vessel failure that may be present.
Application	Initialize a digital twin in the midst of a PWR severe accident to perform faster than real-time evaluation of the impact of various accident management strategies. Principles involved include multiple physics, including nuclear phenomena and fluid dynamics
Value Proposition	Reduce cost associated with an accident by improving the outcome due to increased knowledge of the accident state.

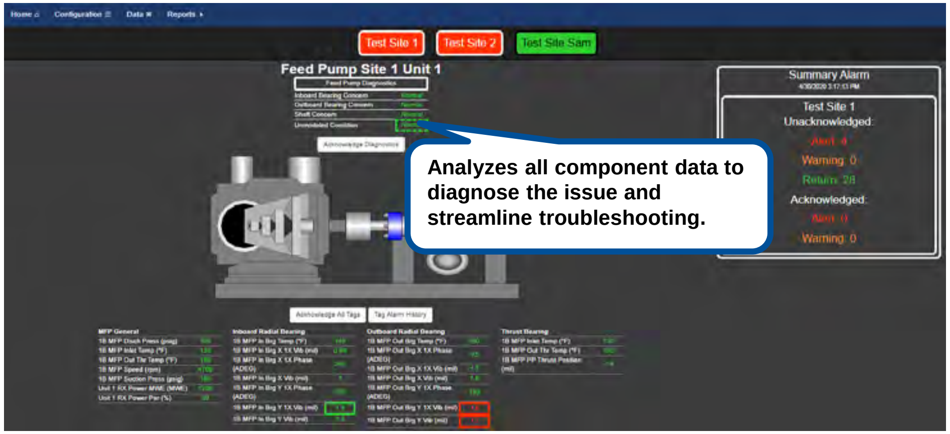


Product of Fauske and Associates, a Westinghouse subsidiary

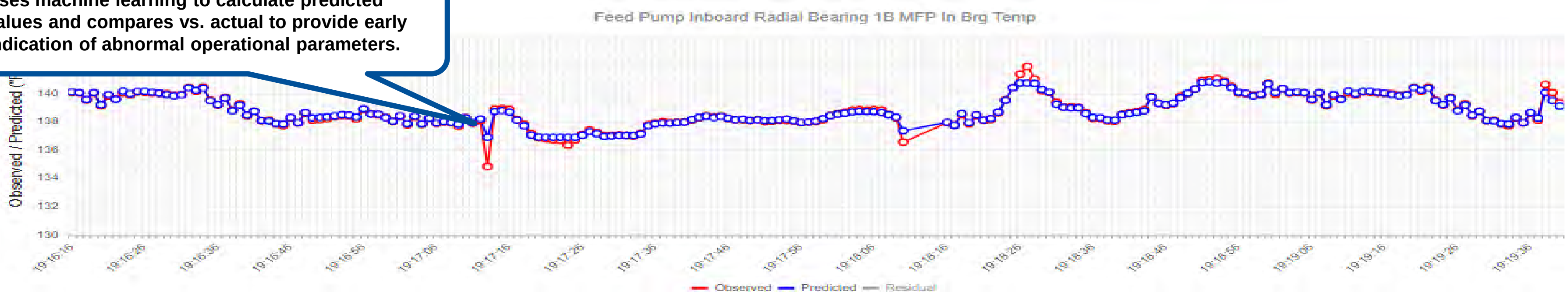
Area 3: Optimization through Component Condition Monitoring

"Though this be madness, yet there is method in it"

- Mission: improve plant economics by reducing O&M costs
- Developing predictive maintenance software to monitor component health and optimize maintenance activities:
  - Rapid to deploy and easy to use
  - Component agnostic
  - Anomaly detection, diagnostics, and remaining useful life
  - Utilizes data from diverse sources and sampling rates
- Partnered with experienced Advanced Pattern Recognition Software provider.



Uses machine learning to calculate predicted values and compares vs. actual to provide early indication of abnormal operational parameters.



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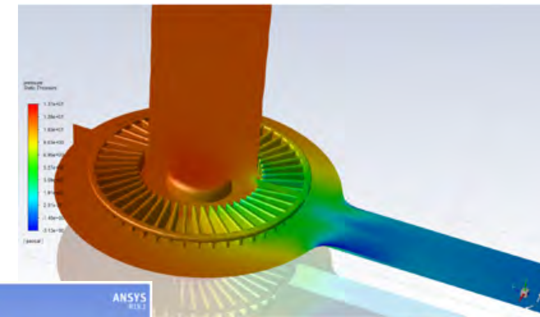
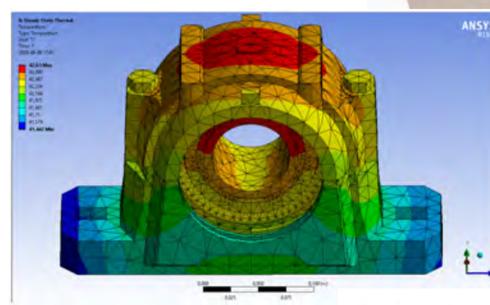
Emphasis on not only anomaly detection, but also **diagnostics** and **prognostics**

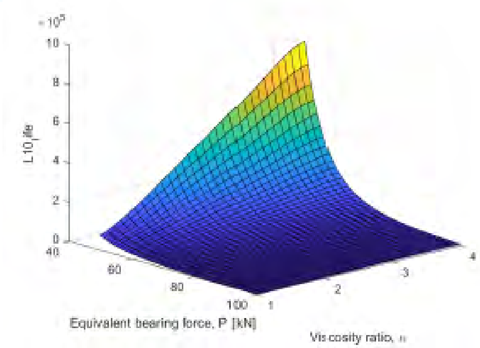
Area 3: Swedish Fan Optimization

“No, Iago, I’ll see before I doubt”

Status	**On going**
Issue	Fans in a Swedish factory were experiencing significant down time which led to lost production.
Value Proposition	A Digital Twin/ML condition monitoring model created to minimize fan downtime.
Plan	Development of methodology for integrating **physics-based reduced order models** in Westinghouse condition monitoring platform.
Application	Almost any type of manufacturing facility.







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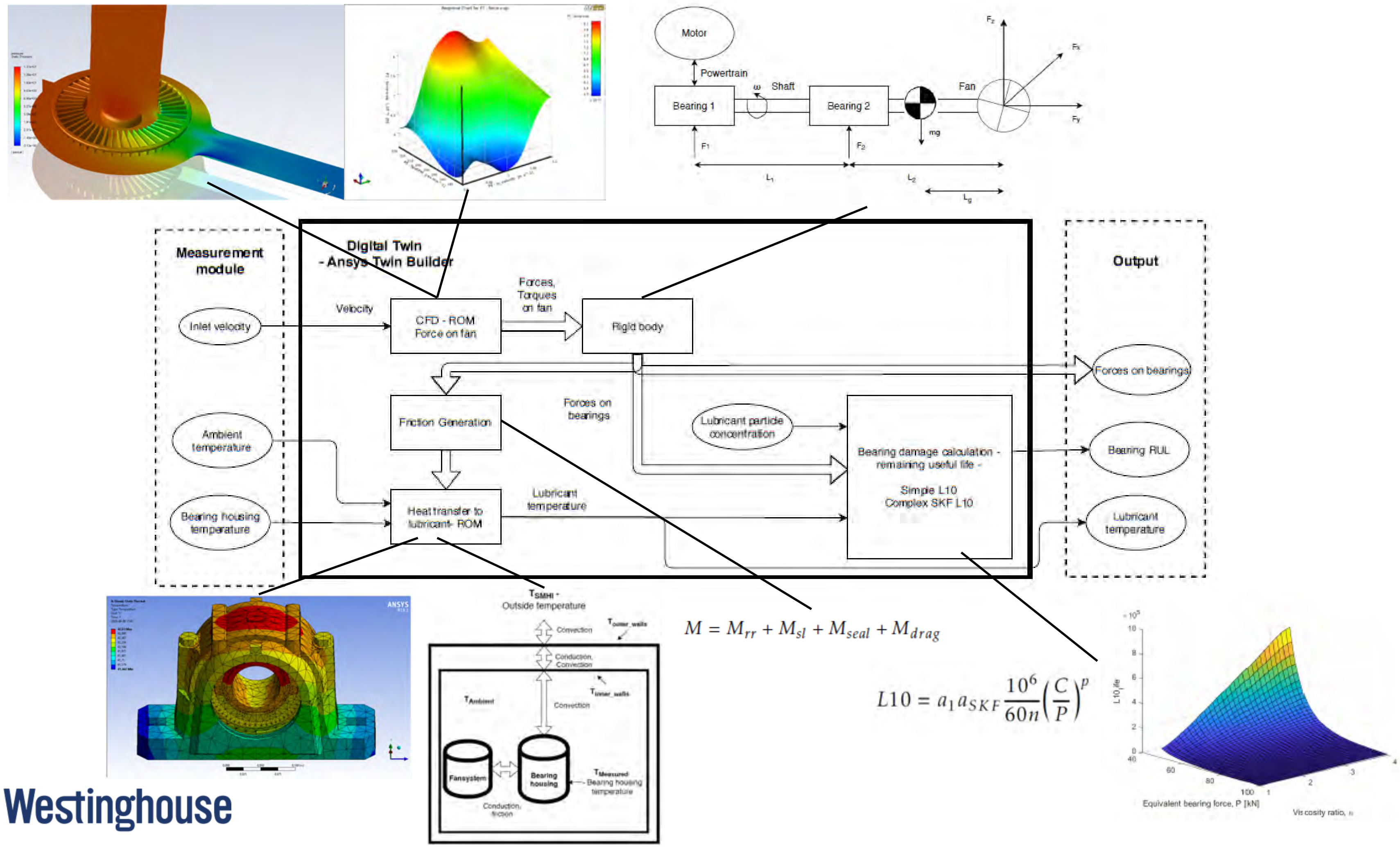
A Digital Twin Enhances Condition Monitoring capabilities by using **simulation as a virtual sensor** in real-time

Area 3: Swedish Fan Optimization



Looking Ahead

"Was this ambition?"

- Future works in progress or being considered
  - Extension of Digital Twins 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
    - Source tracing for environmental substrate contamination
- Working together to help nuclear thrive
  - Westinghouse continues its history of working with its customers, regulators, academia, and national laboratories to apply new technology in order to improve our understanding of nuclear power operations
  - We welcome any dialogue regarding mutual research or development activities.

Westinghouse

Nearly all nuclear analyses can be enhanced through their incorporation into digital twins

Questions?

- For further information, please contact:

Brian M. Golchert, golchebm@Westinghouse.com
Digital Twin Project Technical Lead

Gregory A. Banyay, banyayga@Westinghouse.com
Modeling & Simulation Hub Technical Lead

BWX Technologies, Inc.

Digital Twin for the Manufacture and Qualification of Additively Manufactured Nuclear Components

Matt LeVasseur, Director of Research

Ryan Kitchen, Data Scientist

Quality-grade Digital Twin to inspect-during-build

How it Works

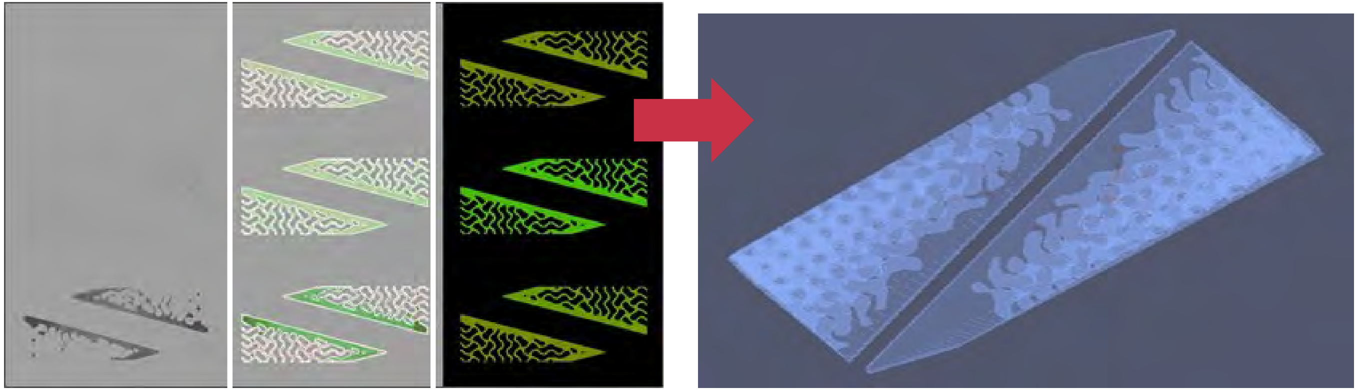
- Many additive manufacturing (AM) technologies build layer-by-layer
- A camera may be used to take images in-situ (during fabrication).
- Images between layers may be restacked to form a 3D representation
  - Becoming common to visualize AM parts, and many machines include a camera for calibration or general process quality
  - A true "digital twin" if it actually represent the as-built for inspection purposes
- Imagery reveals some features directly, and some are inferred computationally
  - Features may change, form, or heal later in processing (cracks, pores, stress features)
  - Computer vision and ML/deep networks are used to discover indicative patterns

The Benefit

- Additive manufacturing is most economic for low-volume, customized and complex geometries
  - Hard-to-Source replacement components
  - Manufacture of advanced reactor and microreactor designs, that take advantage of optimized geometries
- Qualification of AM nuclear components
  - Accurate digital twins could replace or augment DE and NDE inspection, streamlining cost of qualifying nuclear components
  - Digital twins may be used as simulations of as-built components, in place of as-designed
- Algorithms can relate as-built digital twin to mechanical properties

BWXT

Objective: reduce cost of development for novel components



Raw image (detected features on slices)

Computer Vison (enhanced detection)

ML algorithms infer final features (over 3D stack)

Digital Twin using Imagery, Data, and Computation Actuals

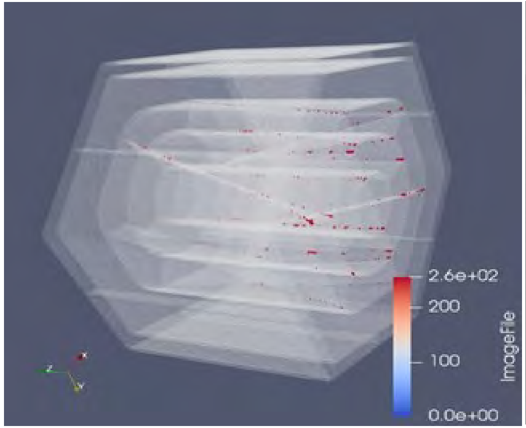
The Need

- Advanced nuclear concepts suffer from cost to qualify and deploy a technology
  - Reducing costs of testing combined with increased fidelity of data on the as-built can change the economics of nuclear and additively built development
  - Suited to creative microreactor design and deployment

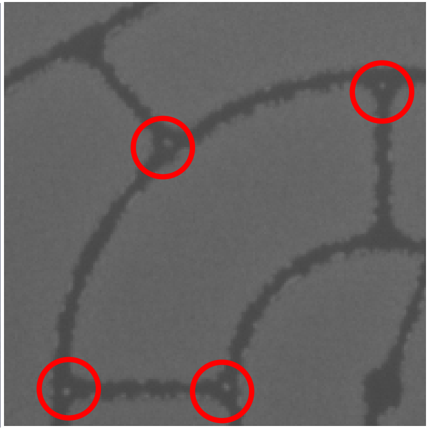
BWXT

Digital Twin for Quality Assessment

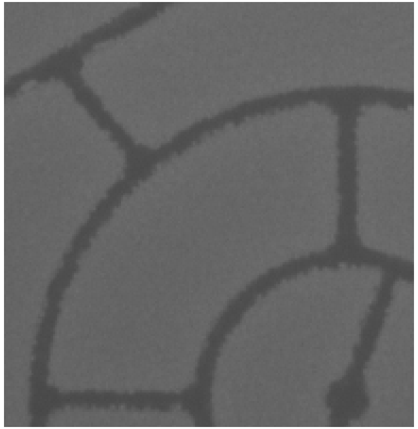
CT-scan of as-built part, for inspection and algorithm training (rendered transparent)



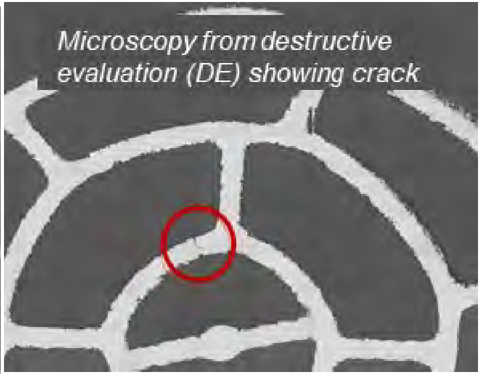
Algorithm-generated digital twin data model, identifying porosity



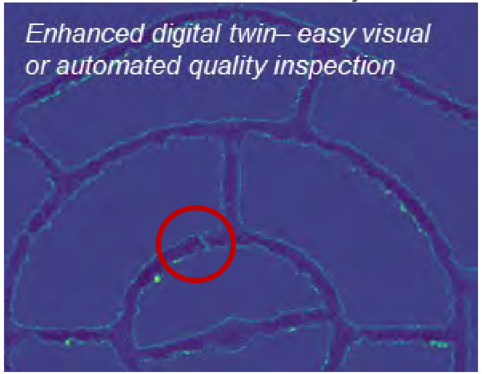
Build 23:
Pores in junctions



Build 26: based on improved AM technique, no pores in junctions



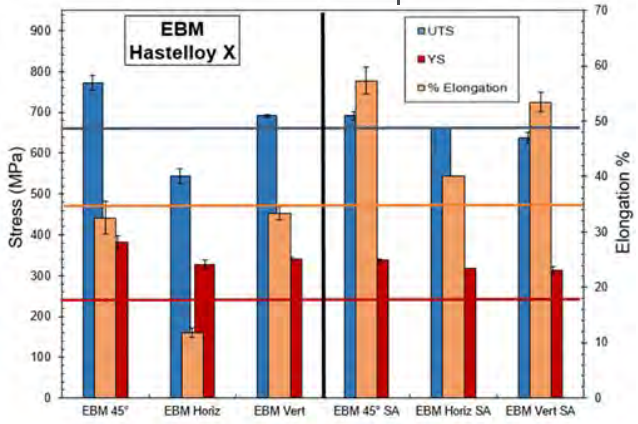
Microscopy from destructive evaluation (DE) showing crack



Enhanced digital twin– easy visual or automated quality inspection

Features of Interest

Mechanical Properties



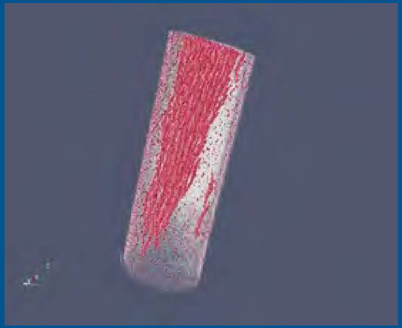
Digital Twin algorithms help infer/predict mechanical properties.

This above chart shows the results of an AM component after tensile strength testing.

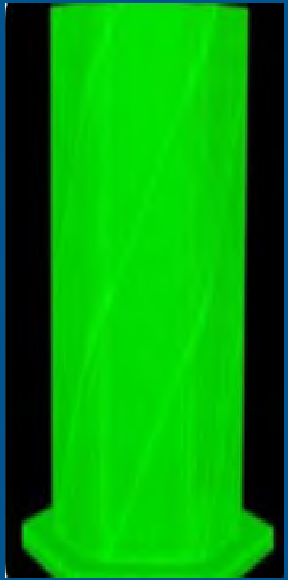
Color-coded horizontal thresholds represent ASTM B572 standards for rod N06002 (Hastelloy X).

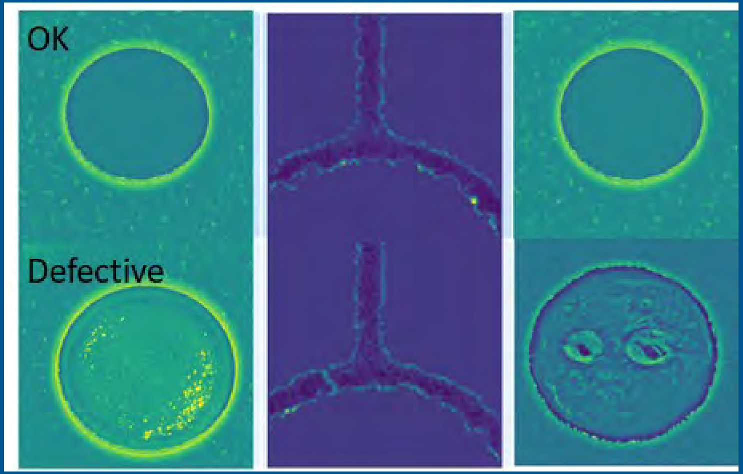
Geometry

Pore Propagation



Scoring



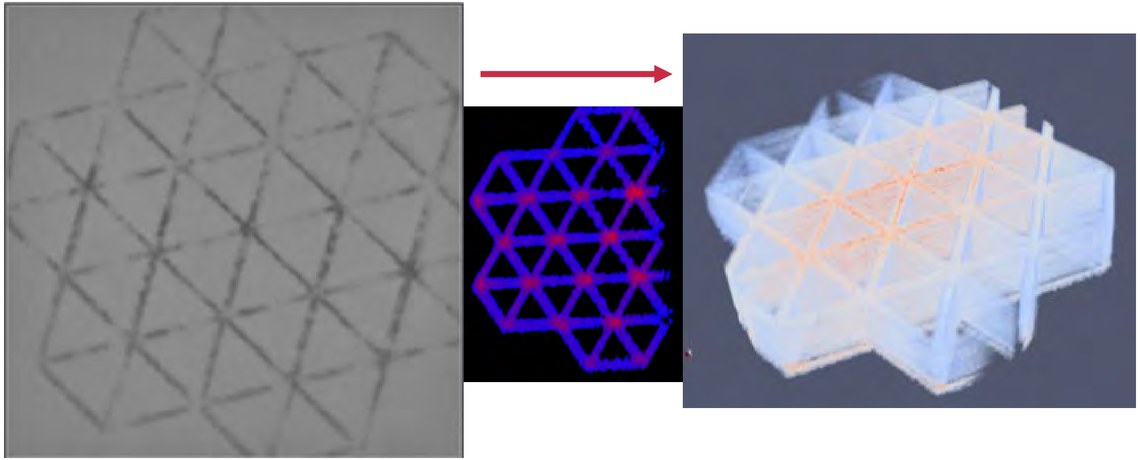


BWXT

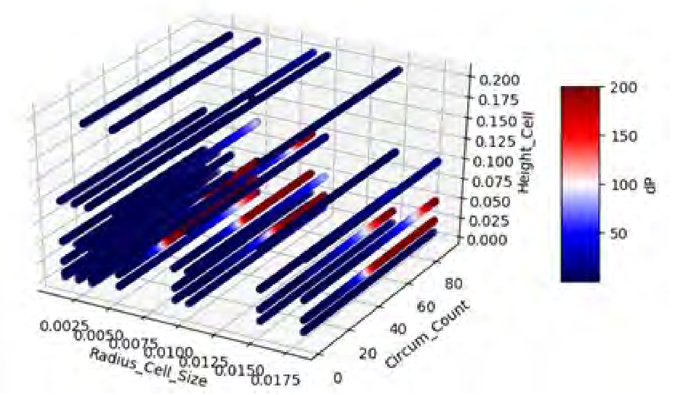
Digital Twin (as-built) as input to multiphysics simulation

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

End of Slides

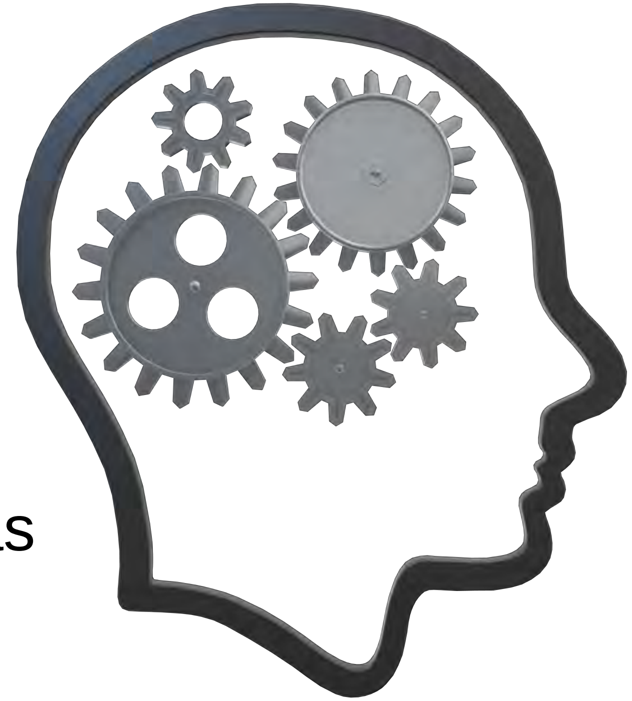
EPRI's Digital Twin Related Activities for Nuclear Applications

Hasan Charkas
Principal Technical Leader

Digital Twin Applications in the Nuclear Industry
Dec 1-4, 2020

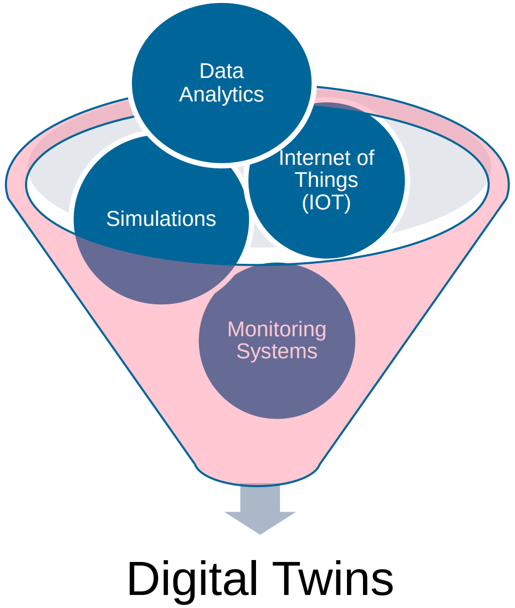
EPRI Digital Twin Engineering Overview

- Rapid advancement in 3D visualization and modeling technologies can lead to opportunities for using digital twins (DT) in managing the lifecycle of nuclear assets
- Formed an internal cross-cutting team for collaboration
- Near term the team is working on the following:
  - What impact do DT applications have on nuclear power plants construction, operation, maintenance and decommissioning?
  - What DT applications can be deployable in the near future?
- Launched 2 projects: advanced reactors and chemistry areas
- Developed a technical insight document (3002020014) and working on technical videos – targeted first video release in December 2020
- On going discussions in several technical virtual meetings with industry stakeholders to identify opportunities for coordination or collaboration



EPRI Digital Twin Engineering – Path forward

- Establish industry guidelines, best practices, and recommendations for DT implementation
- Informative videos and a series of coordination and collaboration webcasts with utilities, regulators, and vendors
- Project collaborate with Artificial Intelligence (AI) and Data Driven Decision Making (3DM) initiatives at EPRI
- Additional questions:
  - What research is needed for the industry to advance the use of DT?
  - How can DT optimize the life cycle of nuclear assets? Predictive maintenance, risk management, informed decisions?

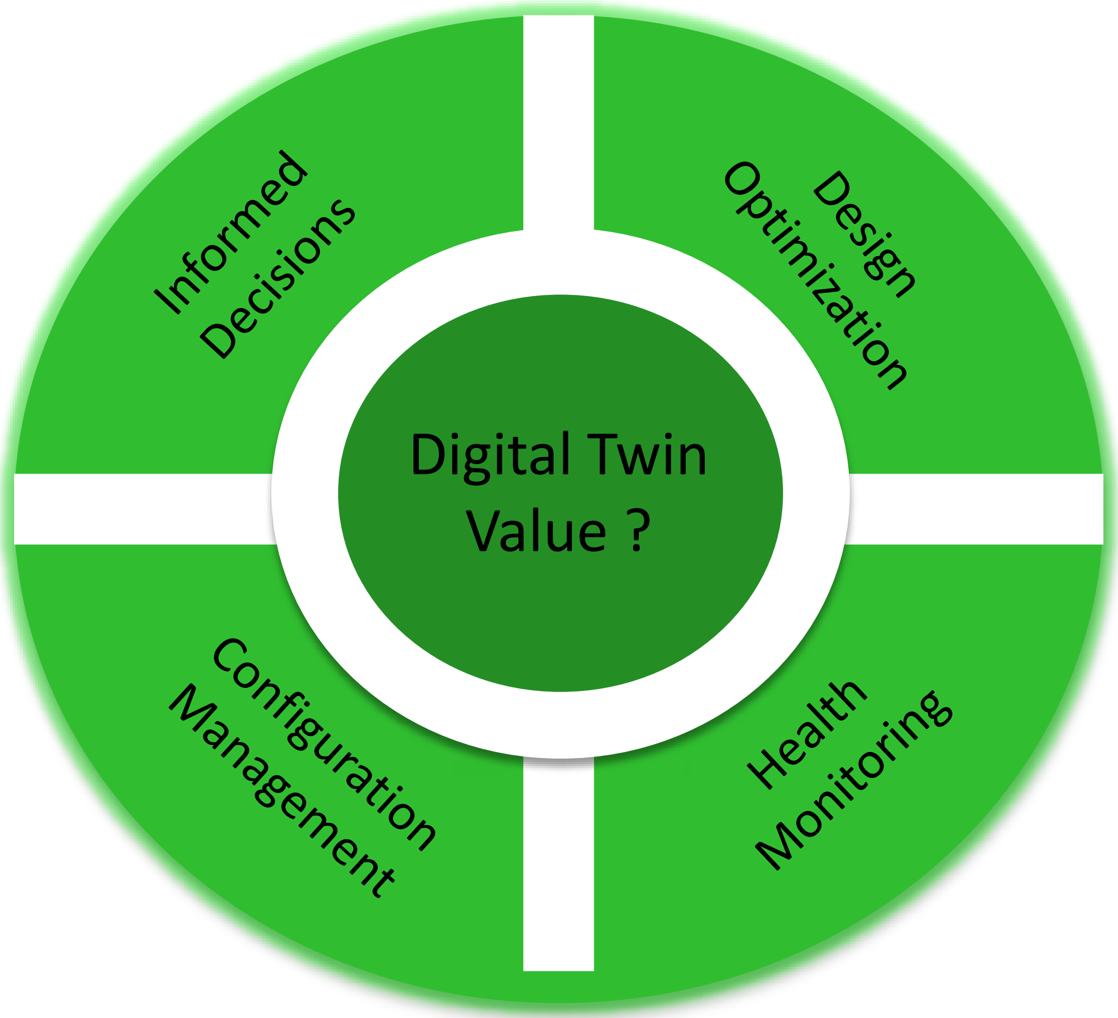


Digital Twin Project Phases

Discovery and Design	Establish Infrastructure	Identify Technologies	Digital Twining	Lifecycle Management
				
- Work with the engineering team to achieve common understandings and goals - Establish digital engineering roadmap	- Select technology platforms - Configure technology platforms and offer training to users - Provide a common plan for management and team members	- Identify supporting techs (sensors mixed reality, remote sensing) - Evaluate these technologies and establish the business case for using them	- Establish DT systems - Manage interfaces and data flow - Launch the system - Provide training to staff	- Manage all phases of the project - Analyze data and manage information flow - Leverage data for decision making (repair, maintenance and operations)

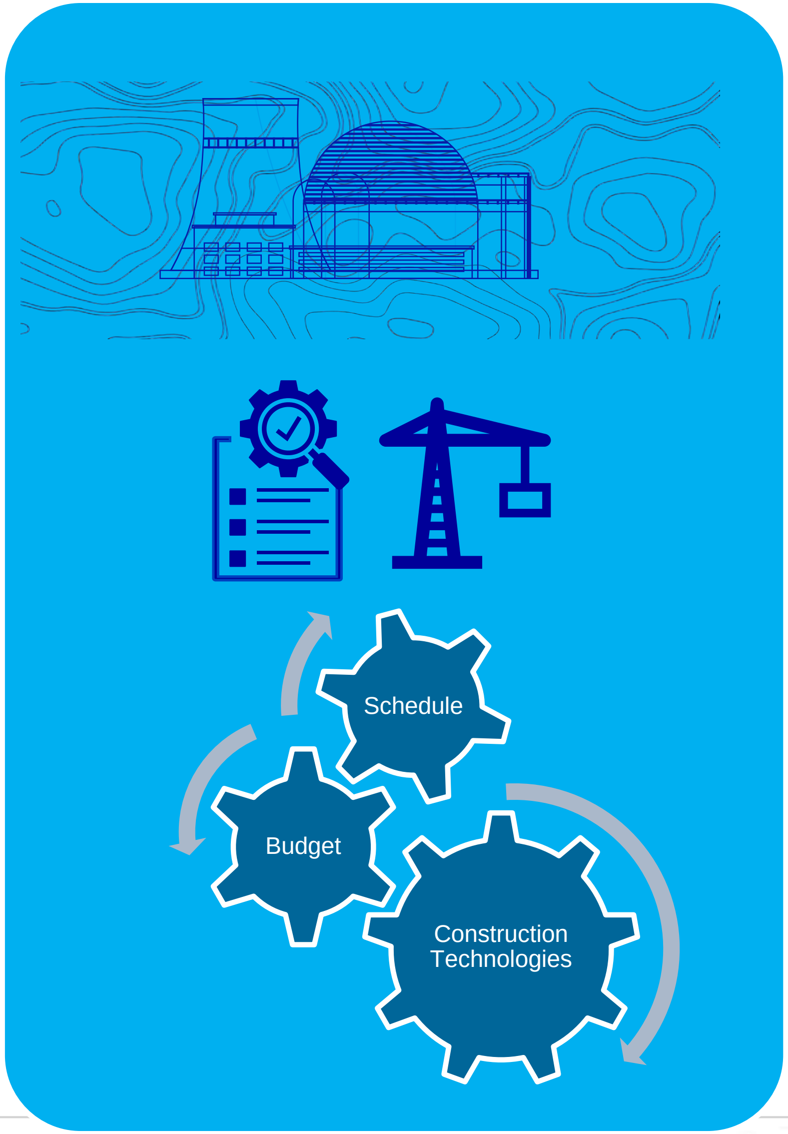
Digital Twin Applications for Advanced Reactors (ARs)

- Objectives:
  - Explore benefits, challenges and potential AR applications.
  - Summarize available tools, software, sensing technologies and monitoring strategies for equipment, structures and components (SSCs)
  - Establish industry guidelines, best practices and recommendations for implementing DTs in ARs life cycle management
  - Estimate costs and potential savings of implementing digital twin technology
- Value:
  - Help answer the question of where it makes sense to use DTs in ARs



Digital Twin Applications for Construction

- Holistic view of projects activities
- Effectiveness assessment of new construction techniques through progress monitoring
- Simulate what-if scenarios and run through steps of construction to identify challenges
- Automated progress reports, as-built configurations, including deviation from design, faster response to field changes
- Other reachable applications
  - ✓ Advanced manufacturing and fabrication
  - ✓ Performance of steam generators



EPRI | ELECTRIC POWER RESEARCH INSTITUTE

Together…Shaping the Future of Electricity

INNOVATING NUCLEAR TECHNOLOGY

Digital Twins for Advanced Reactor Applications

Presented by:

Jake Houser, Ph.D.
Senior Research Engineer, AMS

Hash Hashemian, Ph.D.
President, AMS

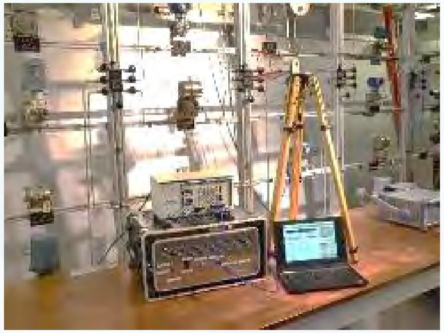
AMS Corporation
9119 Cross Park Drive,
Knoxville, TN 37923
www.ams-corp.com

December 2, 2020

About AMS

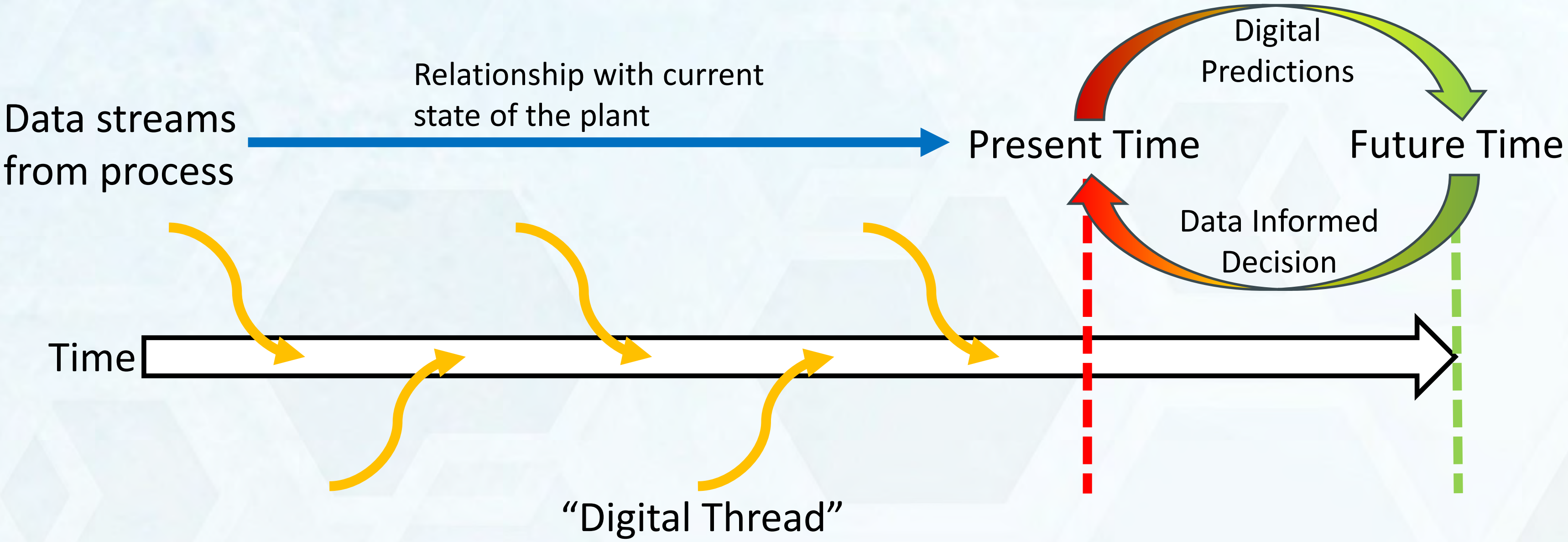
We Test the Instrumentation and Control Systems of Nuclear Facilities

- *I&C Testing*
- *Rod Control*
- *Cable Testing*
- *Software Reliability*
- *EMC/Wireless*
- *Reactor Diagnostics*
- *On-Line Monitoring*
- *Custom Data Acquisition*



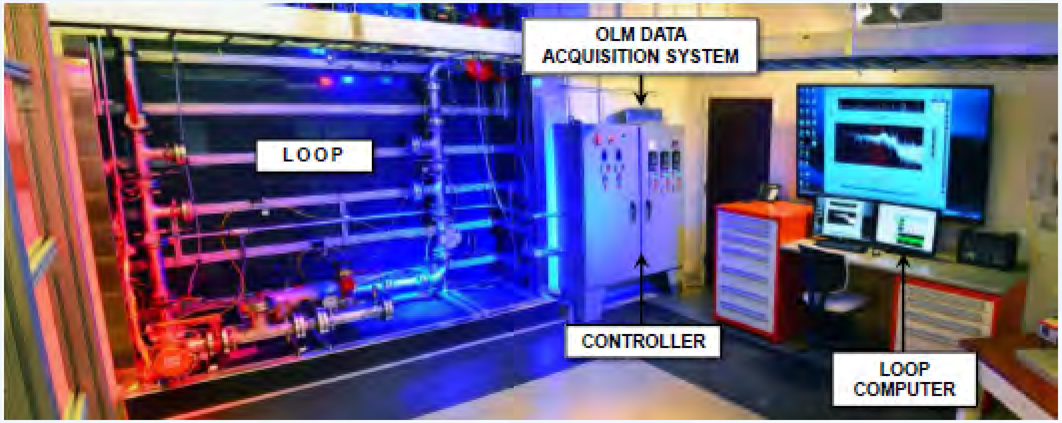
AMS Role in Adaption of Digital Twin

- Digital Twins are living, data informed models of complex systems



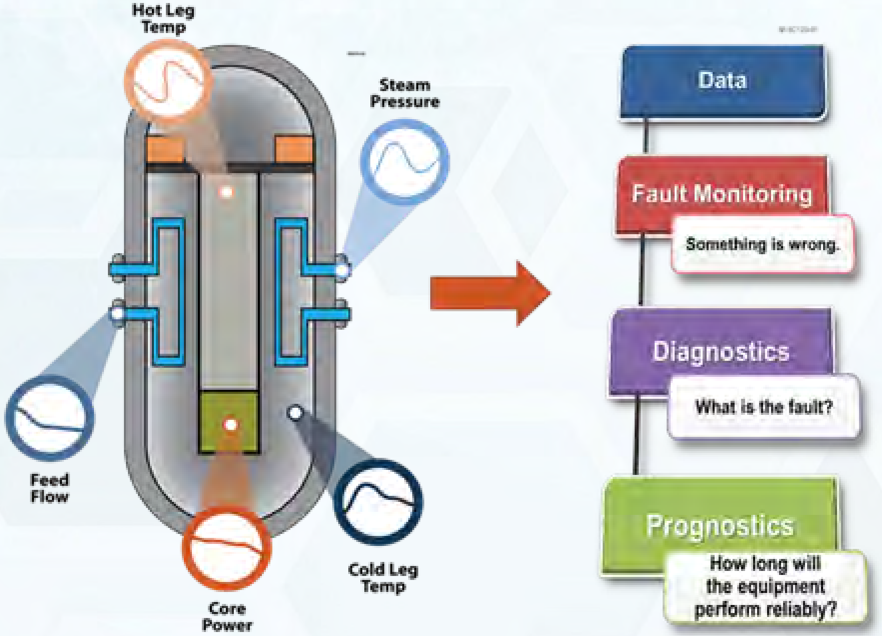
On-line Monitoring (OLM) for New Generation of Reactors

- Constructed flow loop to mimic SMR thermal-hydraulics
- Developed empirical and first principles models
- Compared data informed model results to experimental measurements



Takeaways from OLM for New Generation of Reactors

- **Four critical components in developing OLM for new reactors:**
  - For monitoring I&C performance, sampling frequency must be >1000 Hz
  - Redundancy helps verify calibration and separate process problems from I&C system issues
  - OLM can verify that response time of process sensors remains intact and sensors can register process changes
  - Algorithm/software package depends on I&C system architecture, sensor location, redundancy, and sampling frequency
    - Highly redundant systems → straight and weighted averaging of signals
    - No redundancy → process modeling needed to establish process state



Online Monitoring System to Support Autonomous Remote Microreactor Operations

- Establish I&C system sensors for process measurements and structural health monitoring (SHM)
- Determine ability of embedded sensors to provide quality measurement data
- Develop AI / ML based online monitoring (OLM) technologies for autonomous operation and predictive maintenance of microreactors

Regulatory Challenges

AMS has been working with the industry for over 30 years to extend safety related pressure transmitters calibration intervals. Attempts to do this using modeling techniques have been challenging.

- Working with NRC to approve simple averaging technique through DOE Pathway III grant

- NRC is currently more receptive to working to facilitate both efficiency and safety

- Safety related applications are always more difficult and will be challenging for Digital Twin implementation

→ Regulatory issues should be addressed in conjunction with development of Digital Twin architecture. Applications targeting efficiency, maintenance, and troubleshooting are promising.

INNOVATING NUCLEAR TECHNOLOGY

Thank You

Questions?

On AI Research at ORNL and its application at SNS

David Womble

AI Program Director

Oak Ridge National Laboratory

We are at a “tipping point” in AI/ML

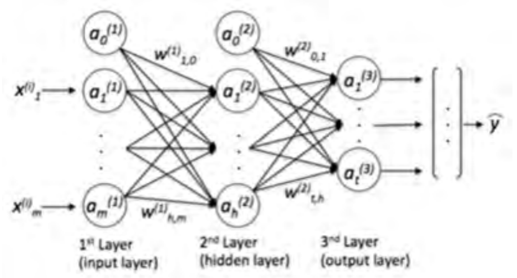
Data

- Facilities distinguish DOE
- Sensors are ubiquitous
- Data is plentiful. We are “bit-rich”

Computing

- DOE has an HPC mission
- Computing is “exaflop scale”
- Specialized HW for data analytics and “edge” applications

Algorithms



- Pre-defined models
- Computationally tractable training for ML

Accessibility

- Everyone has a PC and internet access
- A lot of data and SW are open-source

- Foundational research needed to bring AI/ML to DOE mission

AI won’t replace the scientist, but scientists who use AI will replace those who don’t.*

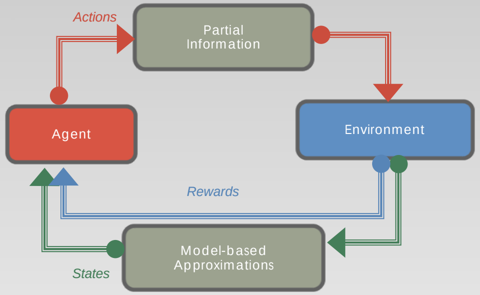
*Adapted from a Microsoft report, “The Future Computed”

ORNL Strategic Directions and in AI/ML

Data

- Facilities operation and control
- Experimental design
- Data curation and validation
- Compressed sensing

Learning

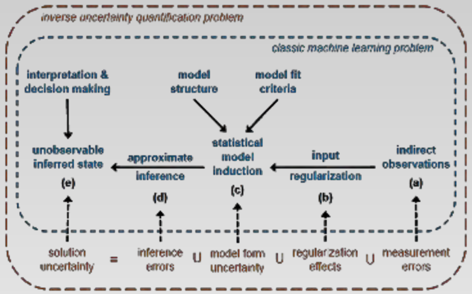


- Physics informed
- Accelerating learning
- Stability and robustness
- Foundations of ML formulations - RL, GANs, GNNs, BNNs
- Dimension reduction and encoding

Scalability

- Algorithms, complexity and convergence
- Levels of parallelization
- Mixed precision arithmetic
- Communication
- Implementations on accelerated-node hardware

Assurance



- Uncertainty quantification
- Robustness
- Explainability and interpretability
- Validation and verification
- Causal inference and hypothesis generation

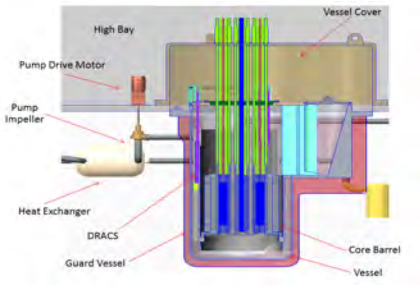
Workflow

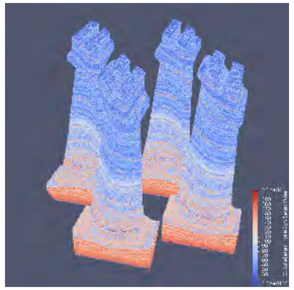
- Edge AI
- Compression
- Online learning
- Federated learning
- Infrastructure
- Augmented intelligence and HCI

What do I mean by "digital twin"

- A model that
  - Captures the current state of a system, — Engineered or natural system
    - Continuously updated
    - Is individualized to a specific system,
  - Can be used
    - to assess the health of the system,
    - In system control
    - And in making decisions, e.g., maintenance
  - Is "causal"

As designed ⇨ As manufactured ⇨ As operating



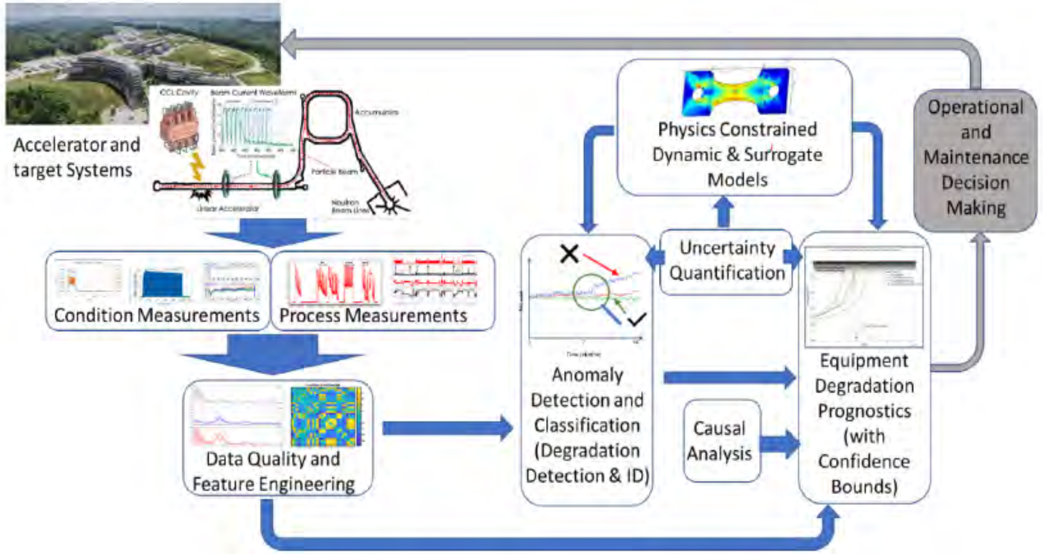


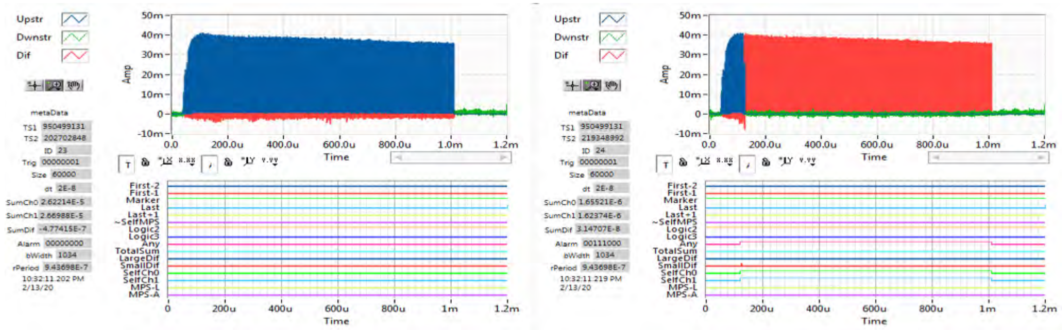
“As operating” is inherently a machine learning problem

- Most systems cannot be “completely characterized” by either equations or observations once they are put in operation.
- But we can collect data.
- Challenges
  - “Informed” learning
    - How do we incorporate physical “constraints” (physics-informed)
    - How do we blend traditional models with ML models/updates
  - Getting the right data
  - Widely varying temporal and spatial scales
  - Stochastic nature of the problem
  - Causal analysis
  - ASSURANCE

An “easy” first step is anomaly detection

- Is there something wrong with the system?
- Need a baseline from “good” data
- If we have sufficiently well-labeled data, this is a classification problem, although you can only “learn” the current decision process.
- For the SNS accelerator an “anomaly” is an errant beam
  - Best results in the 90% accuracy but still not good enough
    - We have more (and new) data now
    - Ideally, the results associate with equipment failure





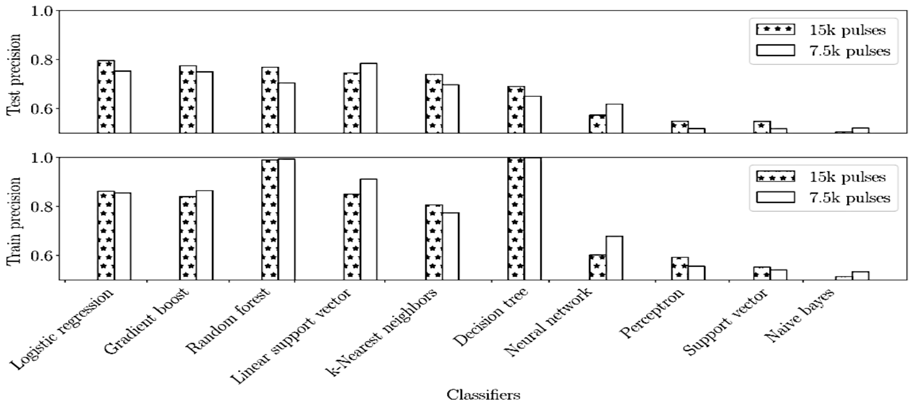
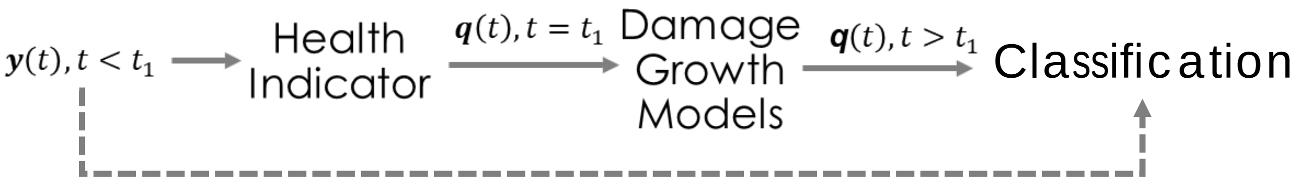


Fig. 3. Classifier test and train performance for the complete dataset and a subset of randomly selected samples.

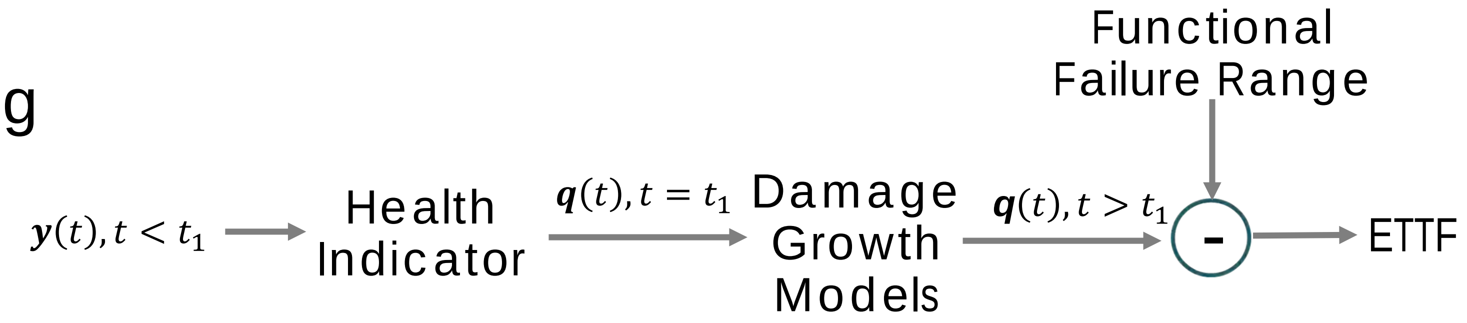
From: M. Rescic, R. Seviour, W. Blokland, “Predicting particle accelerator failures using binary classifiers,” Nuclear Instruments and Methods in Physics Research Section A, Volume 955, 2020, 163240,ISSN 0168-9002, https://doi.org/10.1016/j.nima.2019.163240.

A second step is ETTF

- Anomaly detection: Classify predicted health indicator data into two or more classes

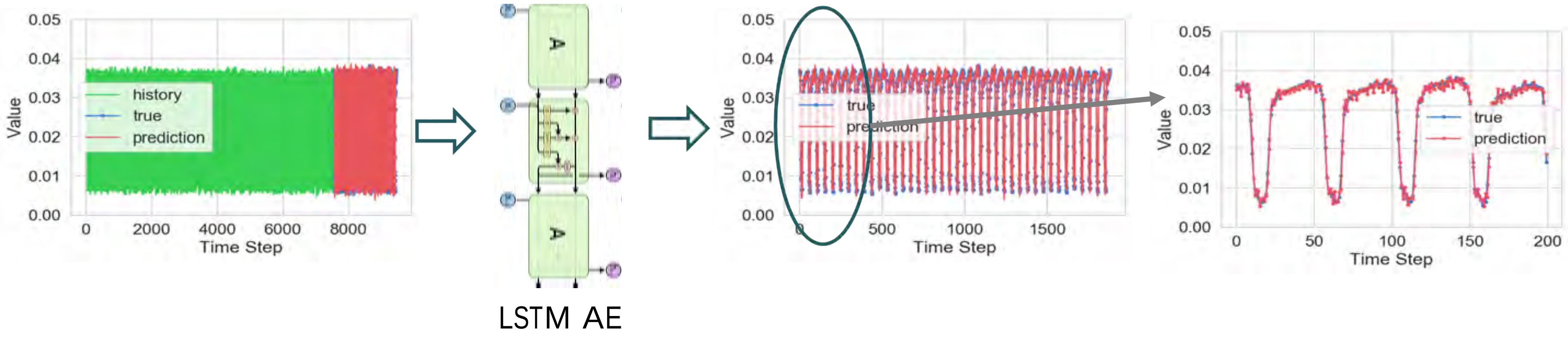


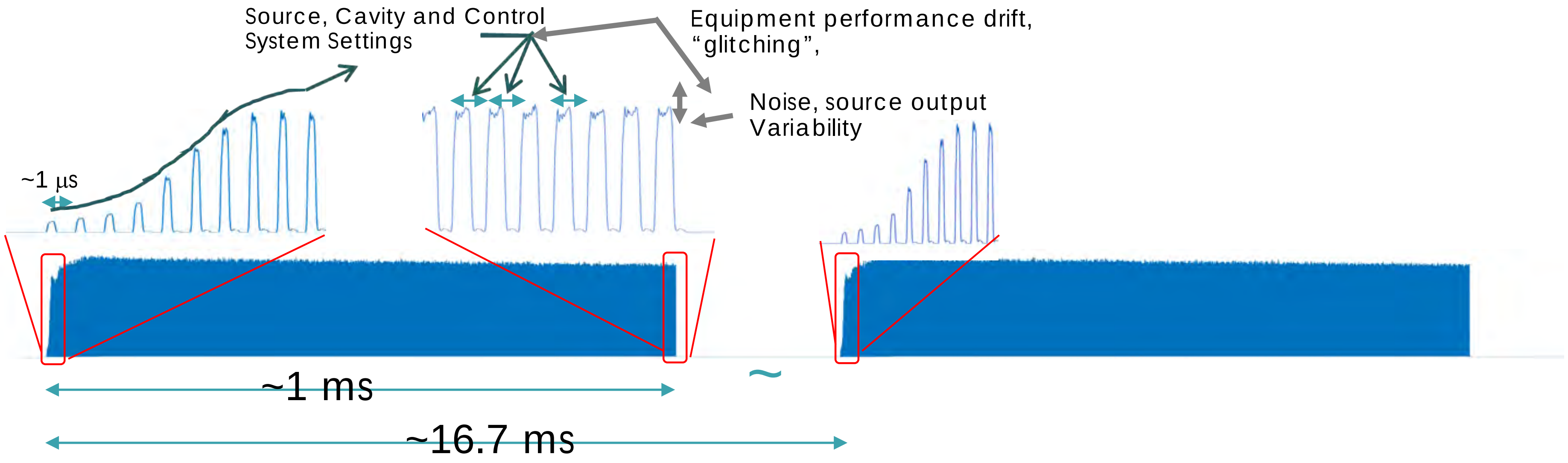
- Identify time-to-failure using damage growth models



- Detect deviations from nominal based on time-series predictions

A predictive model is next, followed by a "causal" model

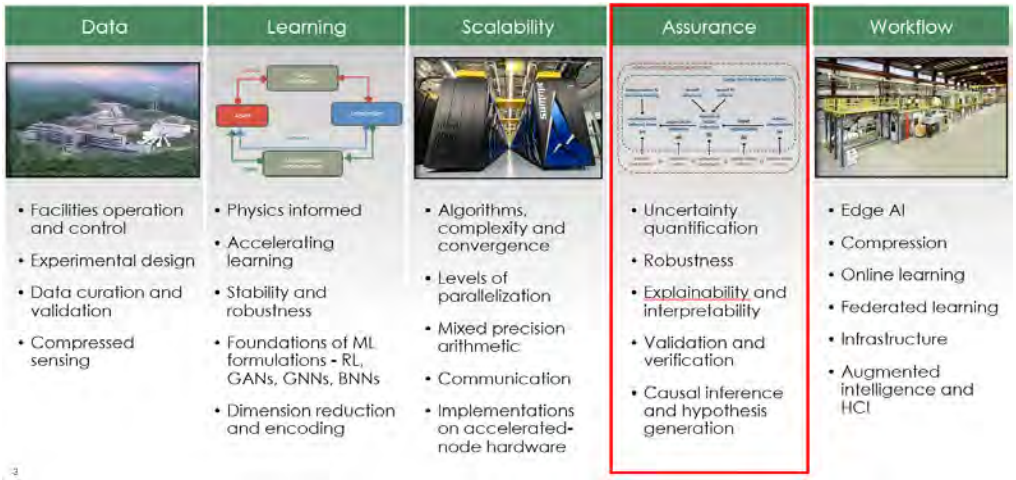




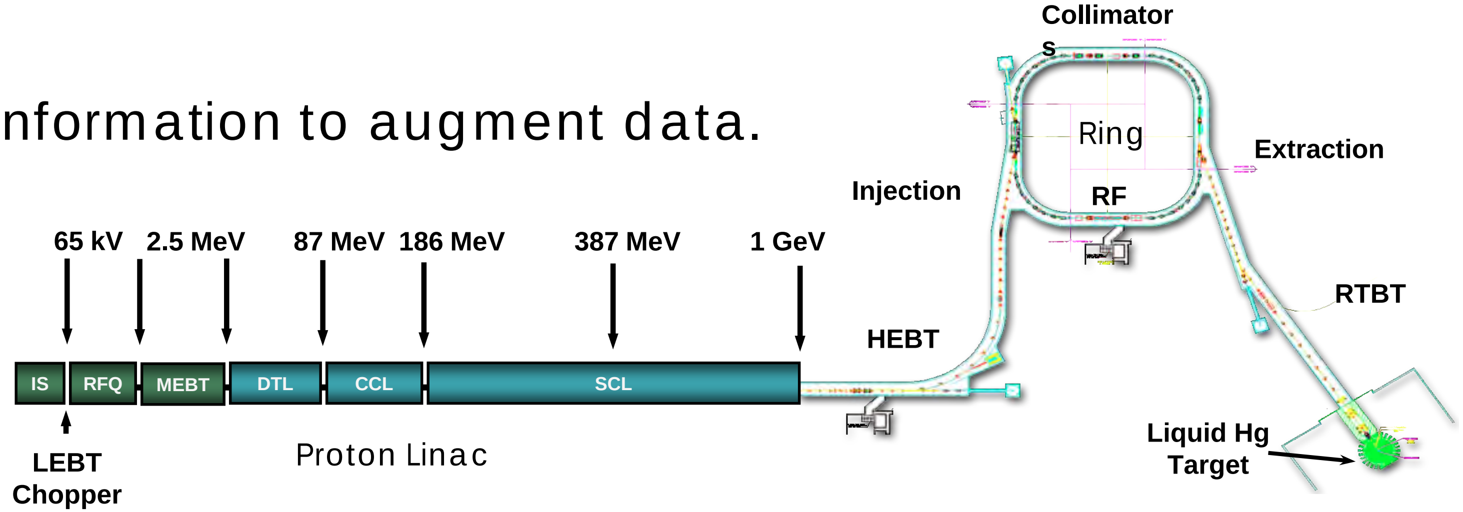
OAK RIDGE
National Laboratory

Summary of challenges

- The single biggest challenge may be assurance. Why should I trust an AI?
  - Includes
    - UQ
    - Validation
    - Reproducibility and Replicability
    - Causal Analysis
  - Includes getting the right data
  - Why should I trust a "digital twin" in a control system?
  - Bias is not just a social issue



- "Informed" learning. Using prior information to augment data.
- Dealing with scales
- Noise and uncertainty



OAK RIDGE National Laboratory

OVERVIEW OF DIGITAL TWIN WORK AT ANL

RICK VILIM
Nuclear Science and Engineering Division
Argonne National Laboratory

Workshop on Digital Twin Applications for Advanced Nuclear Technologies
December 1-4, 2020

OVERVIEW OUTLINE

- Digital Twin – What is it?
- Why the Interest in Digital Twins
- Autonomous Operation
- AI/ML - Enabler of Autonomous Operation
- Digital-Twin Projects at ANL
- Applications
- Challenges

DIGITAL TWIN– WHAT IS IT?

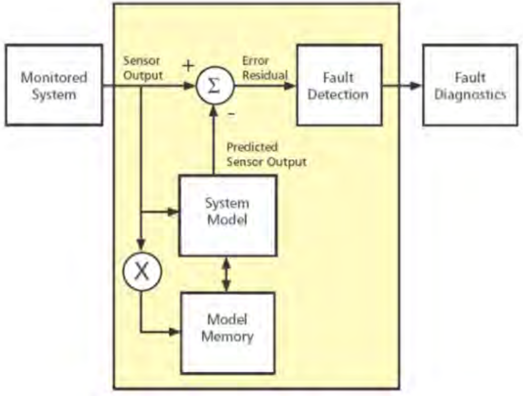
Two variants: Data-driven and physics-based

Digital Twin (DT)

An analytic representation in combination with sensor data provides improved performance for tasks such as diagnosing operational anomalies, understanding system health, and improving system efficiency.

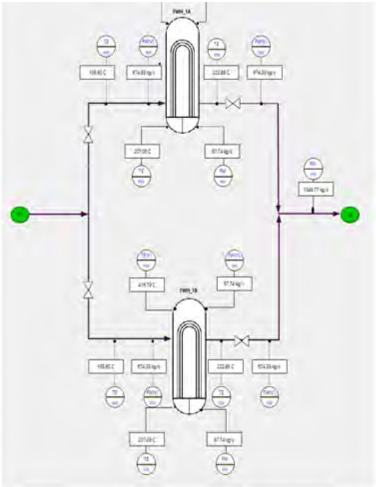
Data-driven (DD)

Constructed using sensor data taken from plant operating history



Physics-based (PB)

Constructed from first principles, which may include conservation balances and constitutive relations

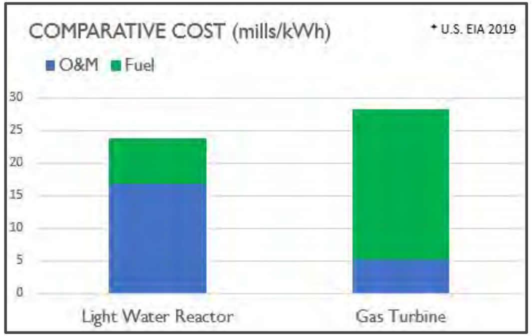


Physical + Virtual Sensor Set

WHY THE INTEREST IN DIGITAL TWINS

Enabler of AI/ML methods for autonomous operation

Increased automation can reduce O&M costs. More efficient allocation of staff and increased plant availability



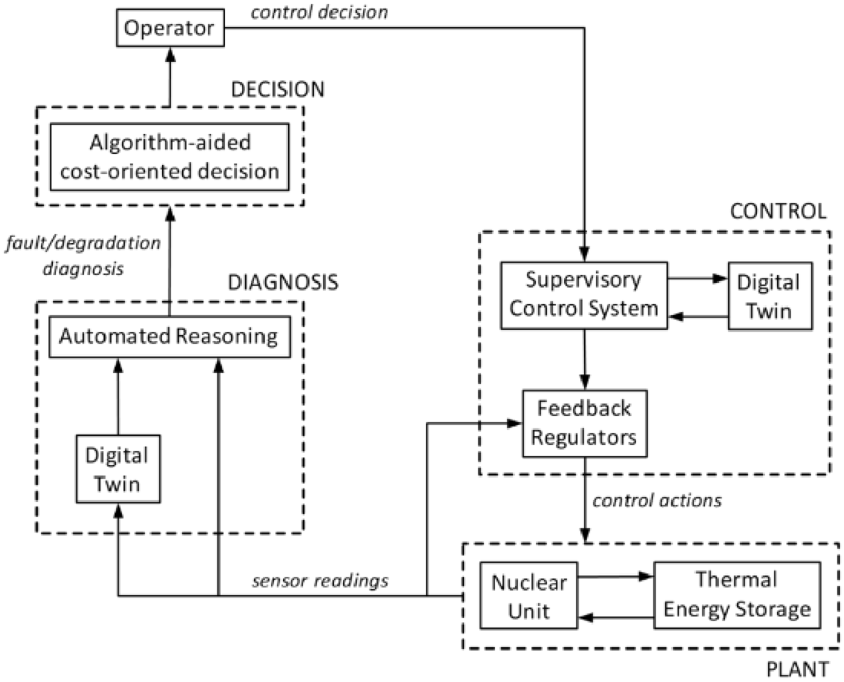
Digital twin models underlie many of the AI/Ml methods that can support autonomous operation

AUTONOMOUS OPERATION

A long-term goal for O&M cost reduction

Elevate human to an oversight role

Routine tasks delegated to the machine

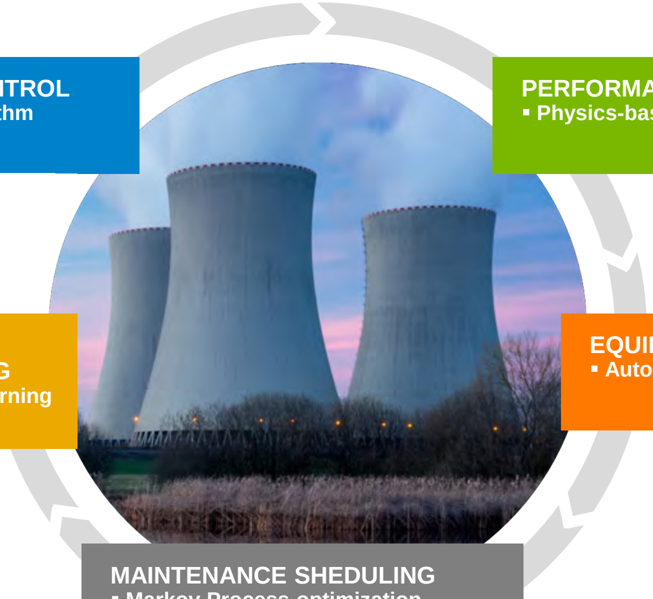


Autonomous Operation

Conceptualize as a set of interconnected tasks and activities

AI/ML - AN ENABLER OF AUTONOMOUS OPERATION

A logical progression is envisioned with successive introduction of AI/ML technologies



AUTOMATED CONTROL
- Supervisory algorithm

PERFORMANCE MONITORING
- Physics-based pattern recognition

OFF-NORMAL DECISION MAKING
- Reinforcement Learning

EQUIPMENT HEALTH MONITORING
- Automated reasoning diagnostics

MAINTENANCE SHEDULING
- Markov Process optimization

A SAMPLING OF ANL DIGITAL-TWIN PROJECTS

All currently underway

PROBLEM	APPLICATION	DIGITAL TWIN	CUSTOMER
1 - Health Monitoring	FW Pump-Motor Set [a]	Physics-based	U.S. Utility
2 - Health Monitoring	HP FW System	Physics-based	U.S. Utility
3 - Maintenance Scheduling	BOP Sensor Selection [a]	Physics-based	U.S. Utility
4 - Performance Optimization	Moisture Carryover [b]	Data-driven	U.S. Utility
5 - Lifetime Extension	Pressure Vessel Nozzle [c]	Combined	DOE NE
6 - O&M	Adv Reactor Automation	Combined	DOE ARPA-E
7 - Design	Adv Reactor Safety [d]	Combined	DOE NE
8 - Manufacturing	Adv Manufacturing	Data-driven	DOE NE
9 - Future Electric Grid	Integrated Energy System	Combined	DOE NE

[a] This presentation [b] R. Vilim presentation, [c] S. Mohanty presentation, [d] R. Hu presentation

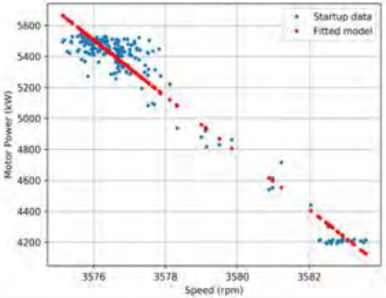
APPLICATIONS (1/2)

Health Monitoring – Equipment diagnostics using physics-based DT

Pump-Motor to be Monitored

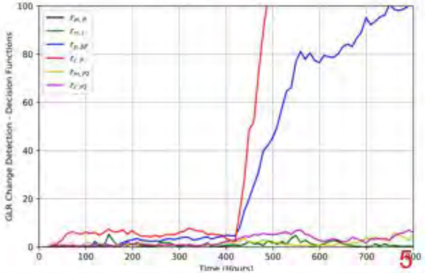
1

Model Calibrated with Plant Data



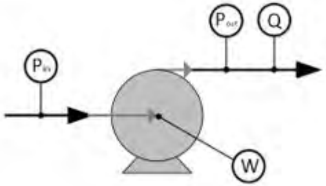
3

Fault Signature Observed for Flowrate Sensor Fault



5

Pump Sensor Set



2

Unique Fault Signatures that Exist for Given Sensor Set

Component Faults			Sensor Faults				
Motor	Bearings	Pump	P_e	I	n	Q	P_{in}/P_{out}
1	0	0	1	0	1	0	0
1	0	0	0	1	1	0	0
0	0	1	0	0	1	1	1
1	1	1	1	0	1	1	0
1	0	0	1	1	0	0	0
1	1	1	1	0	1	0	1

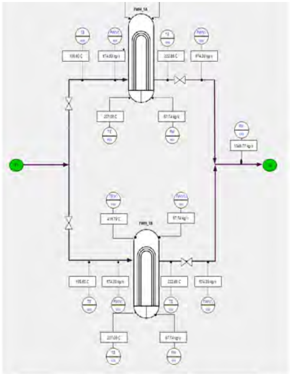
4

Automated Reasoning Correctly Diagnoses Flowrate Sensor Fault

6

APPLICATIONS (2/2)

Maintenance Scheduling – Sensor selection using physics-based DT

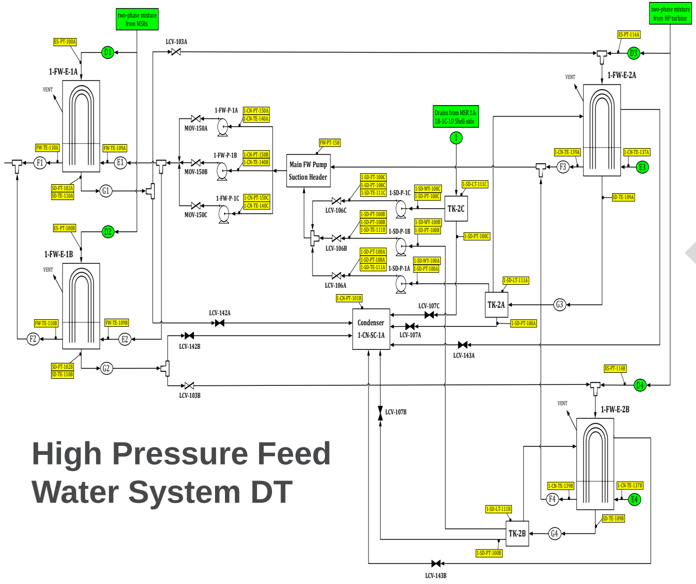


Physical + Virtual Sensor Set

```
//Pseudo code for finding sensor set that yields optimal maintenance
// and asset management scheduling strategy
while      //iterate on sensor set
    spawn sensor_set
    generate virtual_sensors
    generate Current_Likelihood _Component_Faults
    while      //iterate on scheduling of PM procedures
        spawn PM_schedules
        evaluate maintenance_asset_cost_function
    exit_if maintenance_asset_cost_function < epsn
exit_if maintenance_asset_cost_function < epsn
print cost, sensor set, PM schedules
end
```

PRO-AID

	Comp. Label	Comp. Type	Fault		Comp. Label	Comp. Type	Fault
1	1-FW-E-1A	FWH	Fouling	21	PT-100	Press. sensor	Sensor fault
2	1-FW-E-1A	FWH	Tube leak	22	1-FW-P-1A	Feed pump	Pump fault
3	1-FW-E-1A	FWH	Shell leak	23	1-FW-P-1B	Feed pump	Pump fault
4	1-FW-E-1A	FWH	Tube block	24	MOV-150A	Valve	Leakage
5	1-FW-E-1B	FWH	Fouling	25	MOV-150A	Valve	Blockage
6	1-FW-E-1B	FWH	Tube leak	26	MOV-150B	Valve	Leakage
7	1-FW-E-1B	FWH	Shell leak	27	MOV-150B	Valve	Blockage
8	1-FW-E-1B	FWH	Tube block	28	1-SD-P-1A	Drain pump	Pump fault
9	FE-105	Flow sensor	Sensor fault	29	1-SD-PT-100A	Press. sensor	Sensor fault
10	FW-TE-109A	Temp. sensor	Sensor fault	30	1-SD-FT-100A	Flow sensor	Sensor fault
11	FW-TE-110A	Temp. sensor	Sensor fault	31	1-SD-PT-108A	Press. sensor	Sensor fault
12	SD-FT-102A	Flow sensor	Sensor fault	32	1-SD-P-1B	Drain pump	Pump fault
13	SD-TE-110A	Temp. sensor	Sensor fault	33	1-SD-PT-100B	Press. sensor	Sensor fault
14	ES-PT-100A	Press. sensor	Sensor fault	34	1-SD-FT-100B	Flow sensor	Sensor fault
15	FW-TE-109B	Temp. sensor	Sensor fault	35	1-SD-PT-108B	Press. sensor	Sensor fault
16	FW-TE-110B	Temp. sensor	Sensor fault	36	1-SD-P-1C	Drain pump	Pump fault
17	SD-FT-102B	Flow sensor	Sensor fault	37	1-SD-PT-100C	Press. sensor	Sensor fault
18	SD-TE-110B	Temp. sensor	Sensor fault	38	1-SD-FT-100C	Flow sensor	Sensor fault
19	ES-PT-100B	Press. sensor	Sensor fault	39	1-SD-PT-108C	Press. sensor	Sensor fault
20	FW-PT-158	Press. sensor	Sensor fault				



High Pressure Feed Water System DT

Fault ID	Fault	r_2, r_6, r_9
15	Sensor E2.T	25.7%
16	Sensor F2.T	25.7%
17	Sensor G2.w	25.7%
18	Sensor G2.T	25.7%
5	FWH 1B, Fouling	10.1%
7	FWH 1B, Shell leak	5.1%
19	Sensor D2.P	5.0%
	Other faults	< 0.1%

OUTSTANDING CHALLENGES

Need to minimize contributors to risk posed by digital twins

- Sensor Assignment
  - What is the sensor set needed to ensure correct and complete inferencing of plant state and present and future condition?
- Explainable Results/Human Factors
  - Are the results presented in a way that one can understand how they were arrived at?
- Uncertainty Quantification
  - Are the results presented in a way that their reliability is easily understood?
- Validation and Verification
  - Do we have assurance that the results are correct?
- Cyber Security

THANK YOU

MORE INFORMATION @ https://www.anl.gov/nse/artificial-intelligence-and-machine-learning

Christopher Ritter
Director, Idaho National Laboratory
Digital Innovation Center of Excellence

Extending a Digital Engineering Framework through Operations

Idaho National Laboratory

65% of MegaProjects Fail

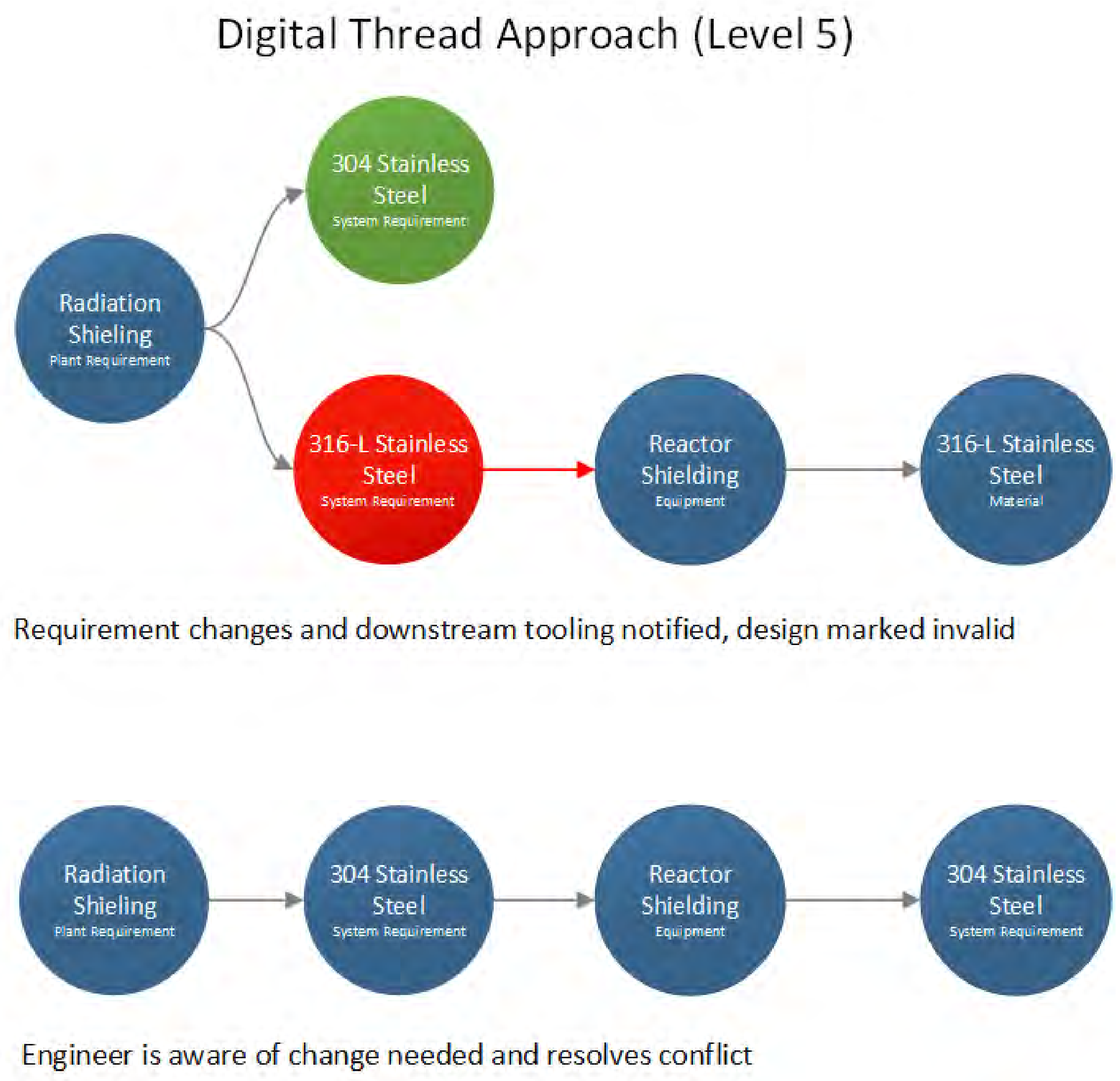
- Failure definition:
  - 25% over budget
  - 25% behind schedule
  - Not able to meet business objectives within one year of the facility start date
- Some factors in failure: Ineffective Interface Management (B5) Inadequate Document Management Plan (B6), Inadequate Integrated Schedule (C7), Ineffective Change Management (C11), Unfit Documents, Procedures, and Processes (C13)

South Carolina VC Summer (Westinghouse/ Post & Courier)

Real World Examples

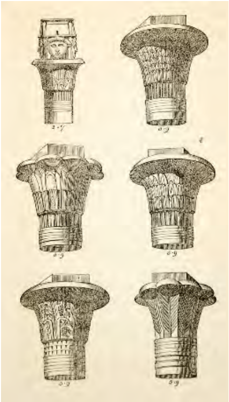
- Kilopower Project KRUSTY Test
  - Design change from 316-L Stainless Steel to 304 Stainless Steel
  - Miss-communication between reactor and mechanical designers occurred for change in materials of shielding
  - Caused schedule delays

- Airbus A380 program
  - Use of CATIA v4 and CATIA v5 in different designer's home countries
  - Data integration issue caused a miscalculation of wiring length
  - Wires were ultimately cut too short, leading to massive schedule delays and a > **$1 billion** cost overrun

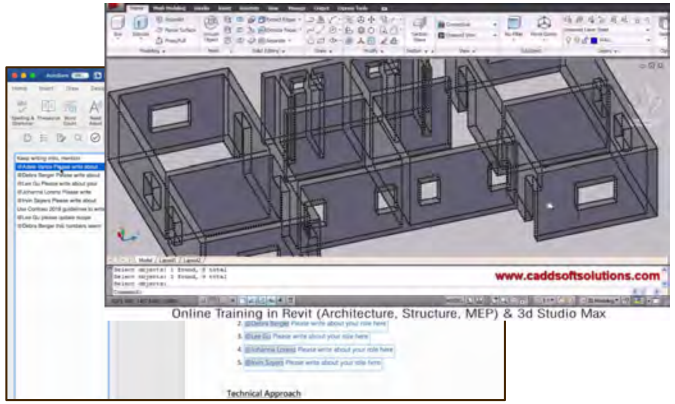


The Vision of Digital Innovation: Digital Engineering & Digital Transformation

Stone Tablet

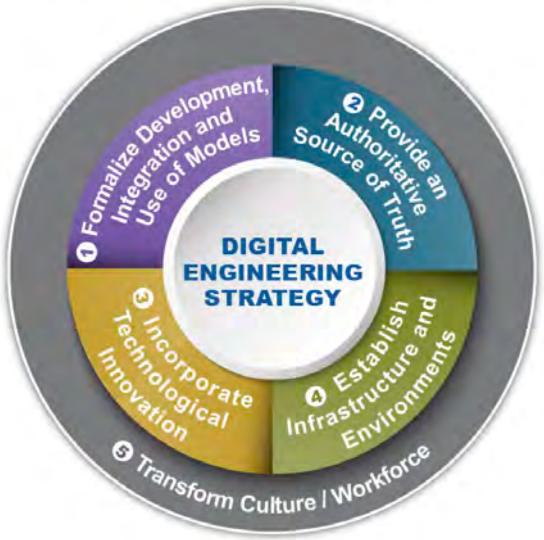


Paper Blueprint



Information Management

1. Use Models
   MBSE & BIM
2. Source Of Truth
   Central Datawarehouse
3. Technological Innovation
   Lab & University Research

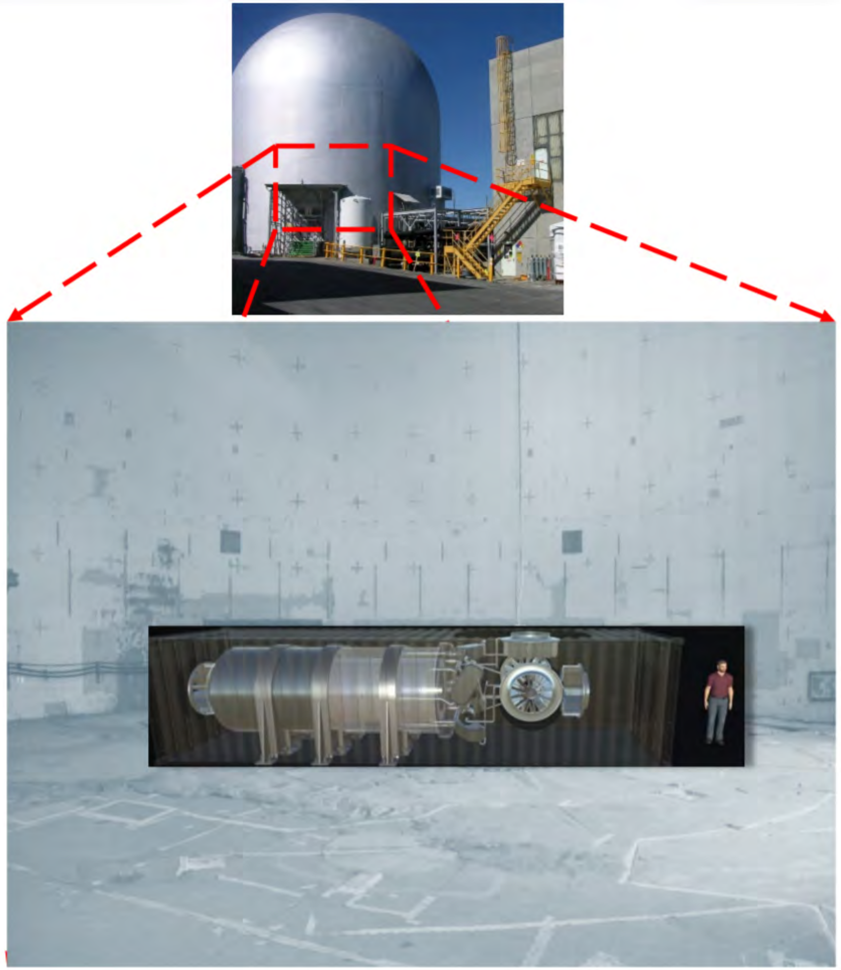


Digital Innovation

4. Infrastructure and Environment
   Cloud Computing & HPC
5. Transform Culture
   Training & Cultural Integration

Digital Engineering in Design - NRIC

- **National Reactor Innovation Center:** The National Reactor Innovation Center (NRIC) at Idaho National Laboratory provides resources for testing, demonstration, and performance assessment to accelerate deployment of new advanced nuclear technology concepts
- **State of the Art**: Document centric exchange of reactor design documents and information
- **Scope**: Transform the traditional engineering design ecosystem from a document-centric paradigm to a digital engineering framework to increase collaboration and efficiency.
- **Opportunity**: Powerful new software allows for the development of new products, services, and capabilities by using digital tools to improve real world outcomes. Industries ranging from construction to aerospace have implemented these techniques to bring down costs and increase productivity. NRIC is leading the way to begin applying these digital tools to advanced nuclear concepts.



Digital Engineering in Design – Versatile Test Reactor

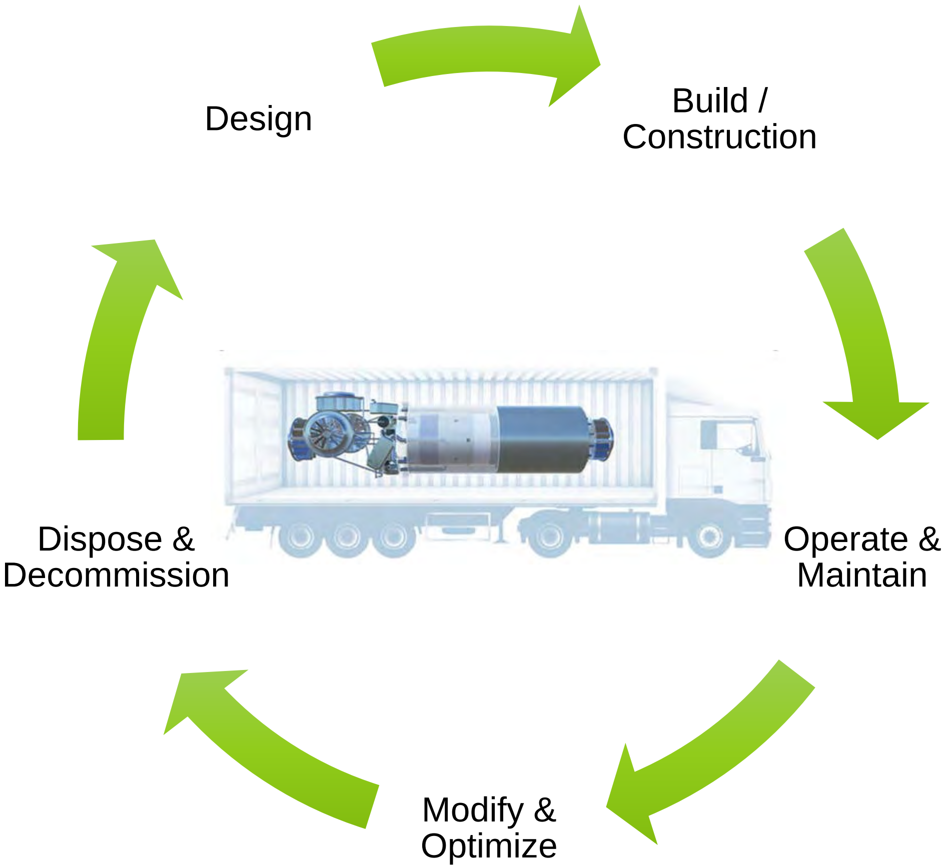
- The VTR will provide support for progress in multiple important science and technology areas including:
  - Testing and qualification of advanced reactor fuels.
  - Testing and qualification of innovative structural materials.
  - Testing of innovative components and instruments.
  - Validation of advanced modeling and simulation tools, and the versatility to support future technical missions.
- Advanced digital engineering ecosystem across design and construction: Connection of requirements management, BIM, pipe stress, seismic, traceability analysis, etc.

Digital Engineering in Operations – NNSA Digital Twin

- **State of the Art**: Safeguards analysis is typically SME based without models; When models exist, they are disconnected, have no AI/ML integration, and no digital twin capabilities
- **Problem**: Development of new advanced reactors (Gen IV) increases importance of new methods to understand diversion and misuse scenarios and determine mitigation pathways
- **Opportunity:** for comprehensive understanding of nuclear fuel cycle facility operations to significantly strengthen nuclear safeguards and nonproliferation regime
- **Future opportunity:** to support diversion/misuse detection for both item (LWR) and bulk (MSR) type advanced reactors. As well as indicators for clandestine reactors

DIAMOND Ontology

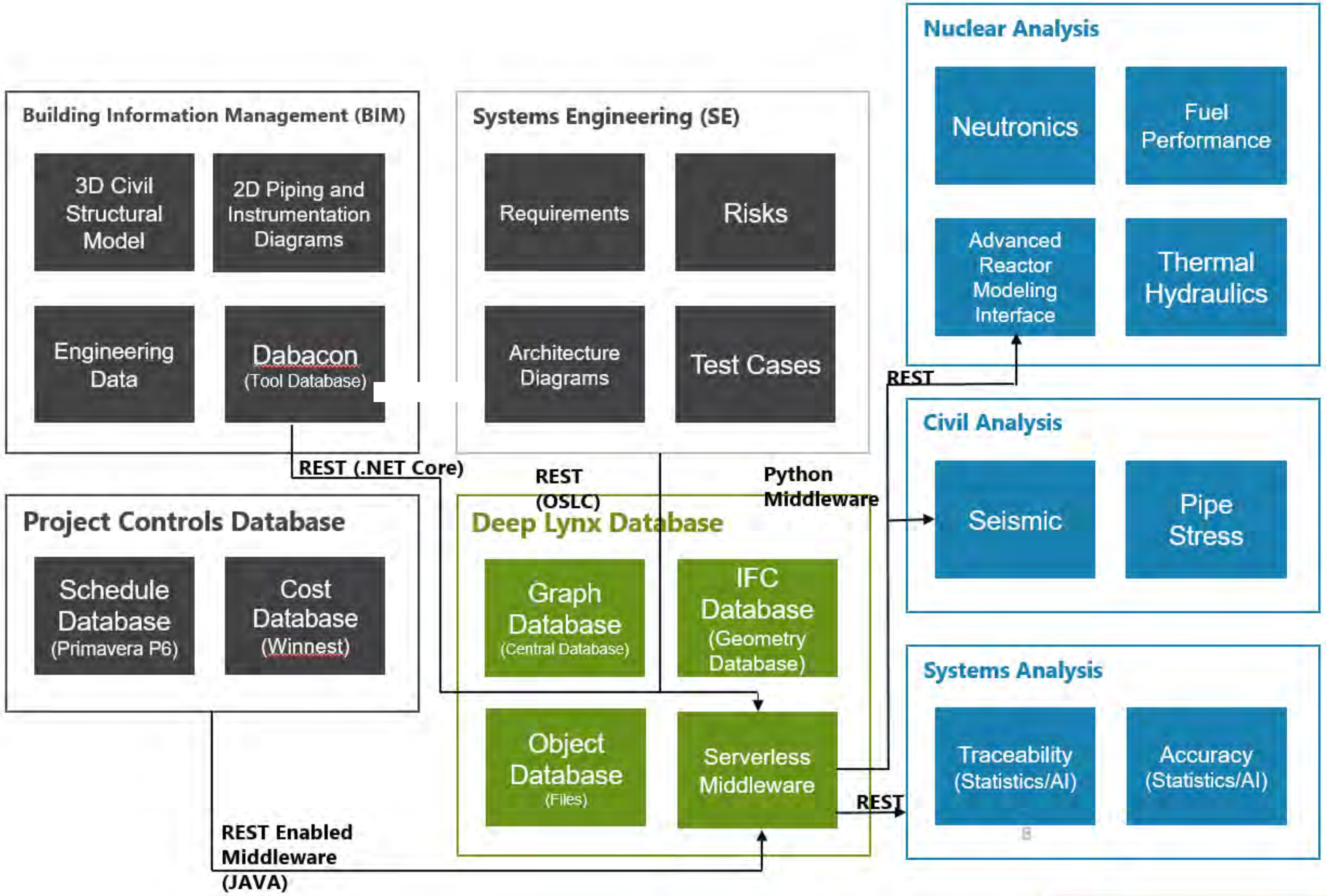
- **Project Objective(s):** This ontology allows for a generic, common framework to enable digital engineering programs. Like previous successful Idaho National Labs initiatives (ex. MOOSE), this data ontology will allow for a common framework to be shared, allowing for more complex energy projects to be undertaken and utilize a plug and play model.
- **Technical Challenges**: (1) Ontological compatibility with other domain ontologies: Mitigated through BFO use (2) Right sized ontology development to ensure the ontology is deep enough to be useful but flexible enough to support multiple designs (3) Verification of the ontology to ensure that functional specifications are executable; this is mitigated by the use of the Monterey Phoenix event trace system
- **Approach**: (1) analysis and selection of top level meta models (BFO/LML) (2) development of lower ontological decompositions for nuclear design using subject matter input to create an easily extendable ontology framework (3) validation and verification of the DIAMOND ontology for nuclear reactor behavior models using Monterey Phoenix (MP)



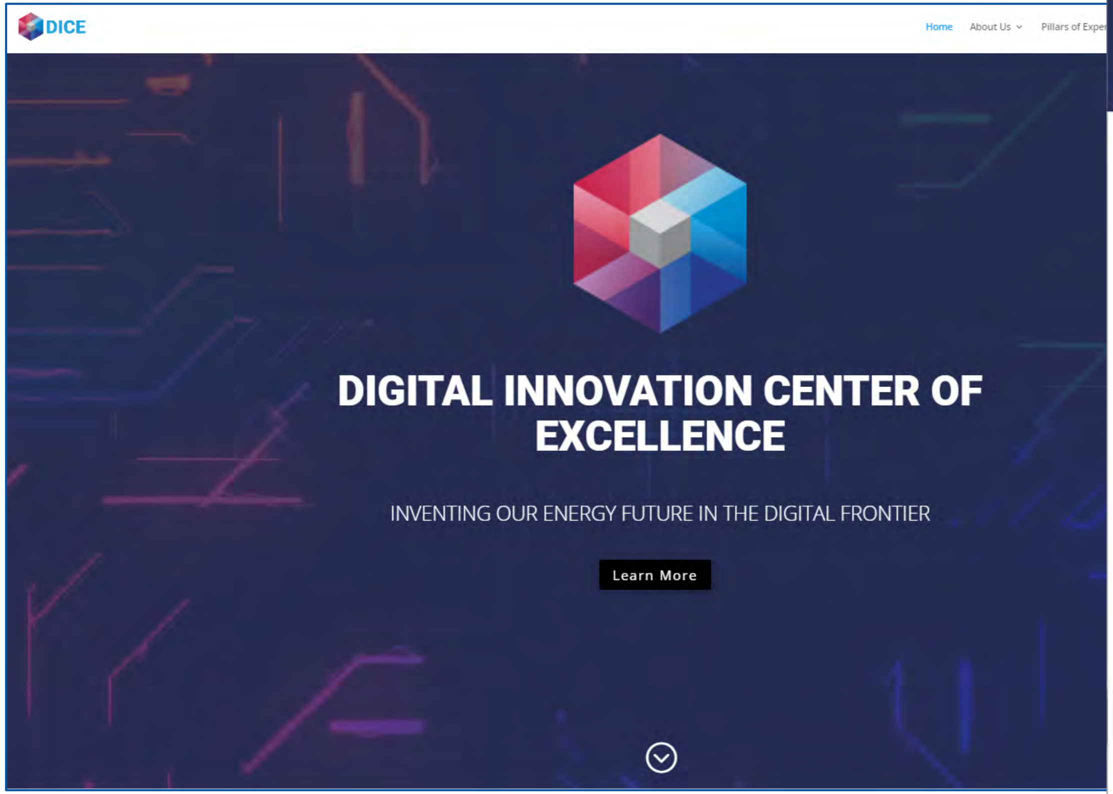
Connection across asset lifecycle

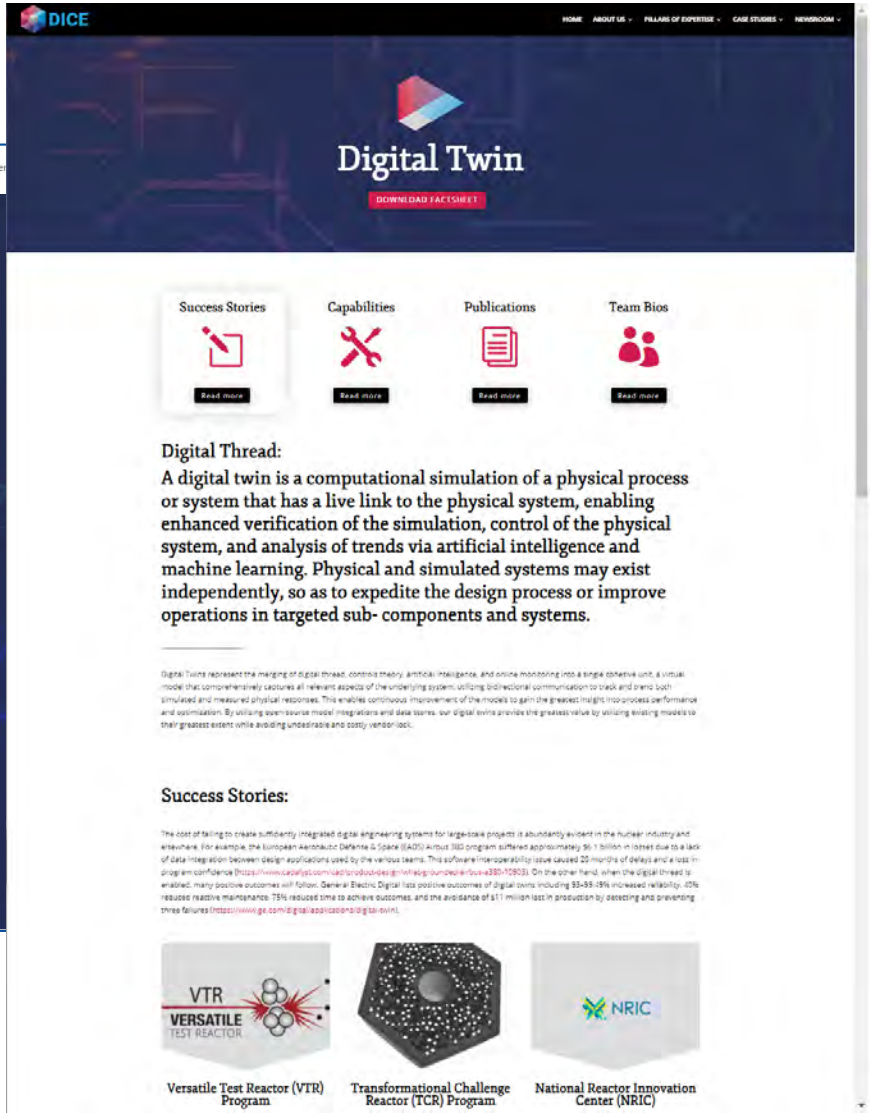
Deep Lynx Datawarehouse

- **Ontology**: Utilizes ontology for a standardized, common data model to enable a generic framework independent of tool/solution
- **Central Software Framework**: This allows for a common software framework to be shared, allowing for code re-use and minimal point-to-point integrations
- **Central Datastore**: This is utilizing the Microsoft Azure Postgres Hyperscale Database which allows a balance between scalability and historical stability



Digital Innovation Center of Excellence (DICE)





dice.inl.gov

Questions

Any Questions?

- **Christopher Ritter**
- Director, Digital Innovation Center of Excellence
- **Email**: Christopher.Ritter@inl.gov
- **Phone**: 208-526-2657 (office) / 301-910-1818 (cell)

Digital Platform for the Transformational Challenge Reactor

Presenters:

Benjamin Betzler – Design Thrust Lead

Vincent Paquit – Digital/Manufacturing/Testing Thrust Lead

Digital Twin Applications for Advanced Nuclear Technologies

ORNL is managed by UT-Battelle, LLC for the US Department of Energy

This work has been authored by UT-Battelle, LLC, under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy

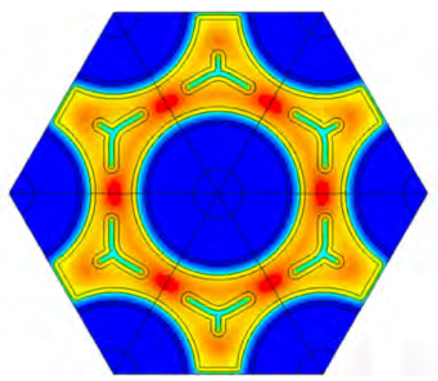
TCR is bringing to bear additive manufacturing (AM) and artificial intelligence (AI) to deliver a new approach

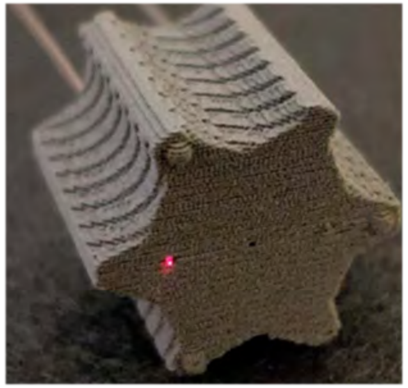
Using AI to navigate an unconstrained design space and realize superior performance

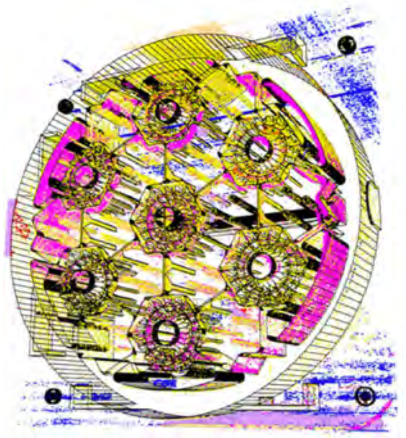
Leveraging AM to arrive at high-performance materials in complex geometries

Exploiting AM to incorporate integrated and distributed sensing in critical locations

Using AI to assess critical component quality using in situ manufacturing signatures

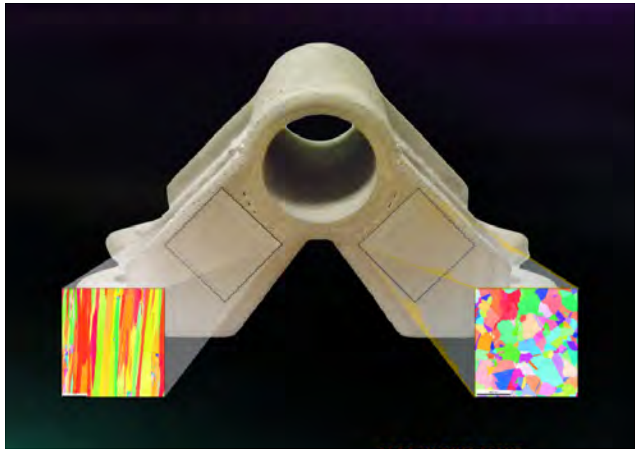


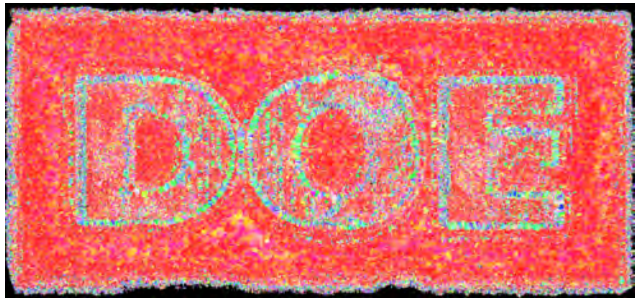




tcr.ornl.gov

Scientific drivers



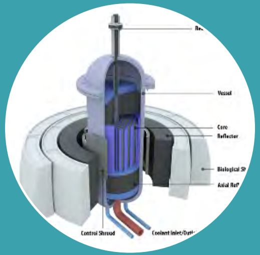


- Certification of AM components by conventional methods eliminates the business case for AM components
- Limited understanding of local and global processing state for additive manufacturing

Develop new certification methodologies for manufacturing technologies

TCR – Digital Platform

Objective: Develop a digital platform and associated processes to couple data analytics with design and manufacturing data for use in rapid prototyping and quality evaluations of manufactured products.

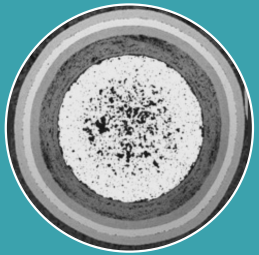


Reactor Design

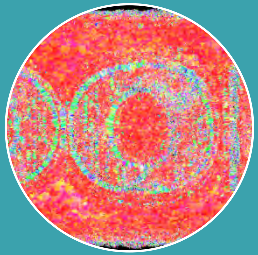
Instrumentation & Control

System and Safety Analysis

Additive Manufacturing



Fuel Production



Material Testing

Digital Platform / Quality Assurance

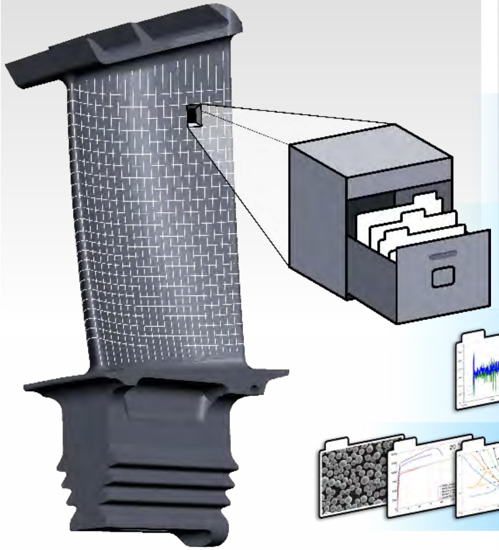
Digital Platform for Manufacturing

Advanced manufacturing technologies produce valuable datasets at every stage of the manufacturing workflow. Collecting, structuring, and analysis such data is paramount to understanding, optimizing and validating the manufacturing process.

IT Infrastructure

- Wired network
- WiFi network
- IoT
- Storage systems
- HPC systems
- Embedded Systems

Voxelized Parts



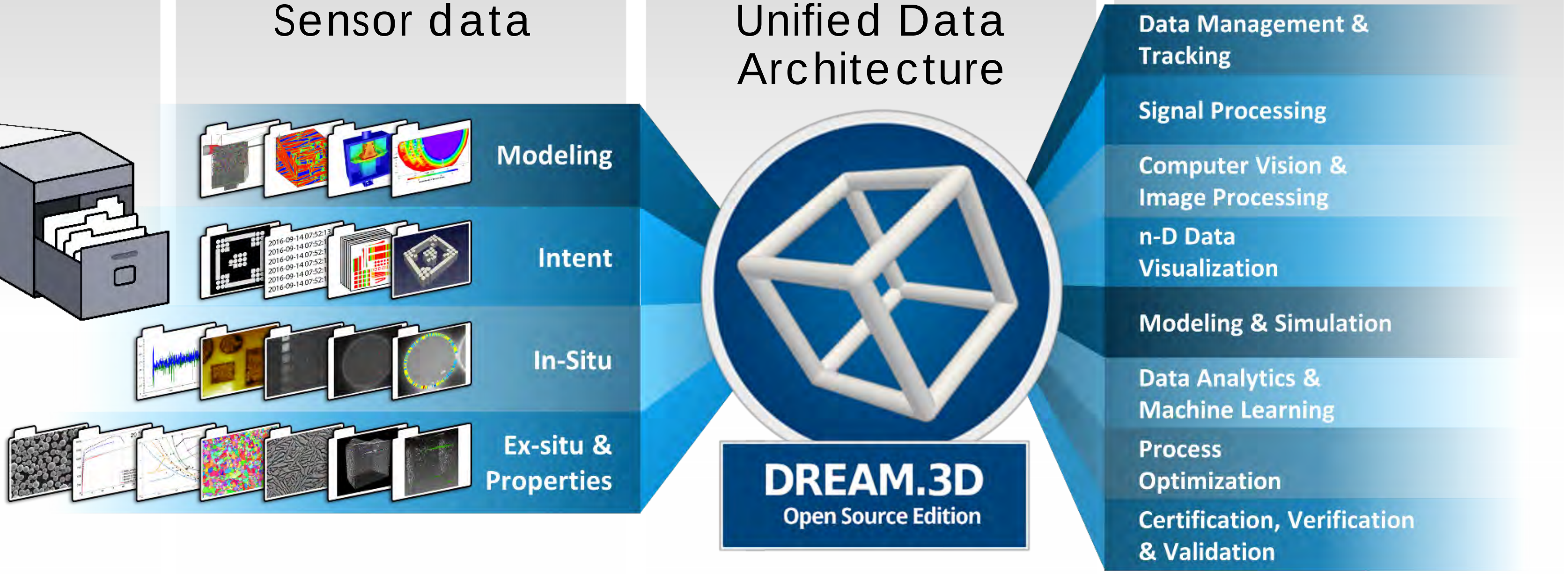
Data Producers

Sensor data

Digital Clone

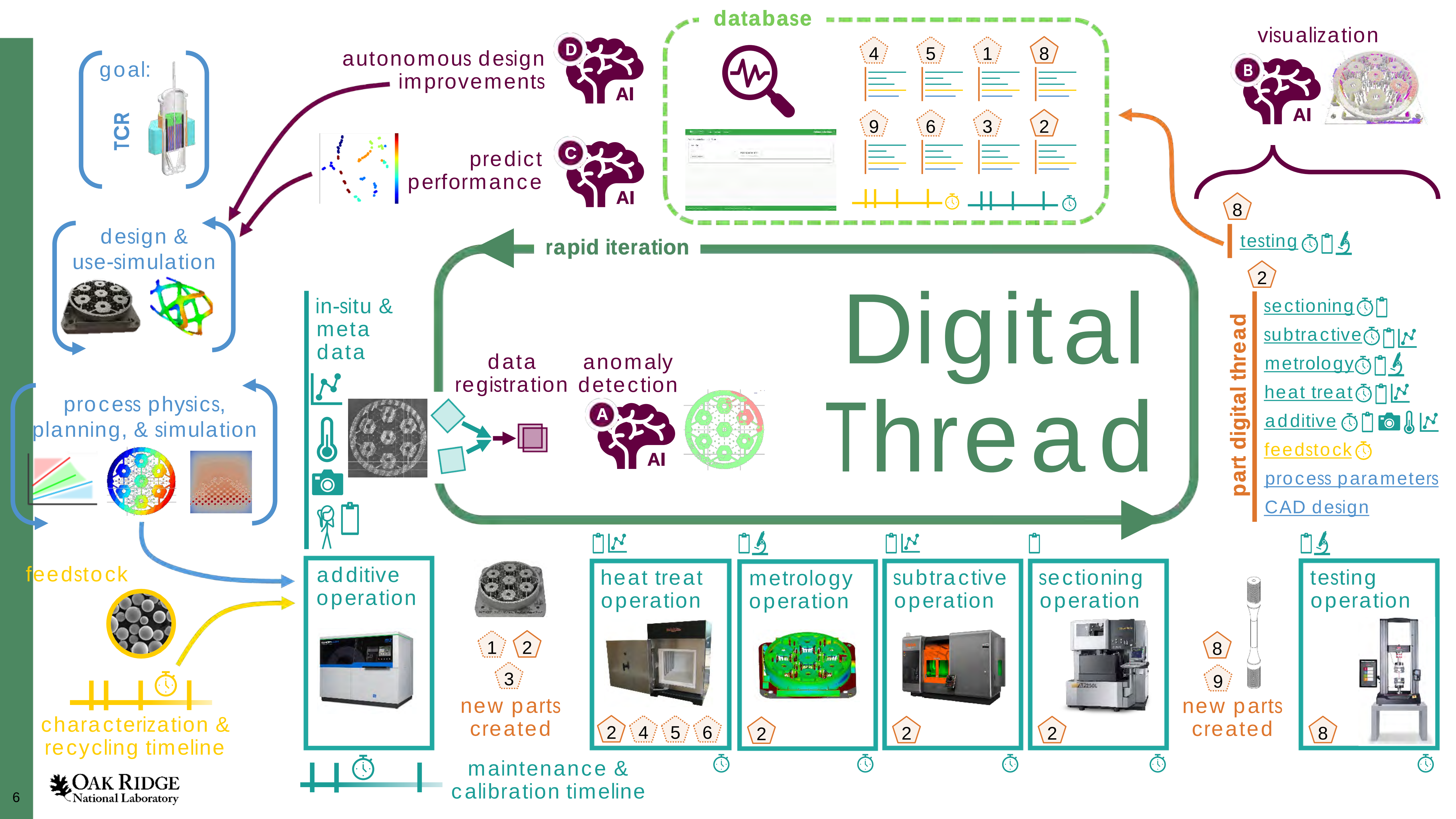
Unified Data Architecture

Data Workflow



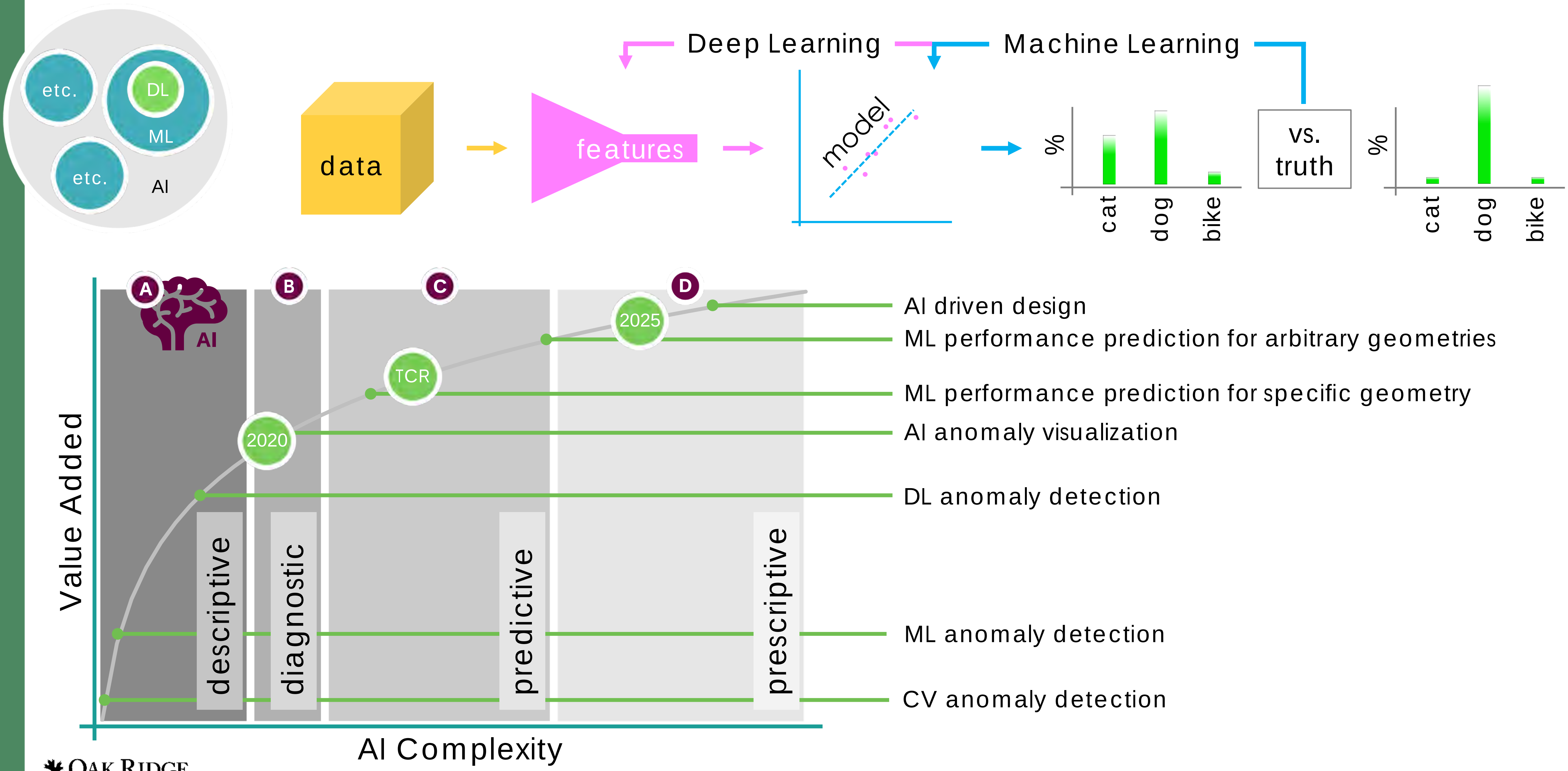
Cybersecurity

Digital Thread



goal:
TCR
autonomous design improvements
D
AI
predict performance
C
AI
database
4
5
1
8
9
6
3
2
visualization
B
AI
design & use-simulation
process physics, planning, & simulation
rapid iteration
Digital Thread
in-situ & meta data
data registration
anomaly detection
A
AI
8
testing
2
part digital thread
sectioning
subtractive
metrology
heat treat
additive
feedstock
process parameters
CAD design
feedstock
characterization & recycling timeline
additive operation
1
2
3
new parts created
heat treat operation
2
4
5
6
metrology operation
2
subtractive operation
2
sectioning operation
2
8
9
new parts created
testing operation
8
maintenance & calibration timeline
Oak Ridge National Laboratory

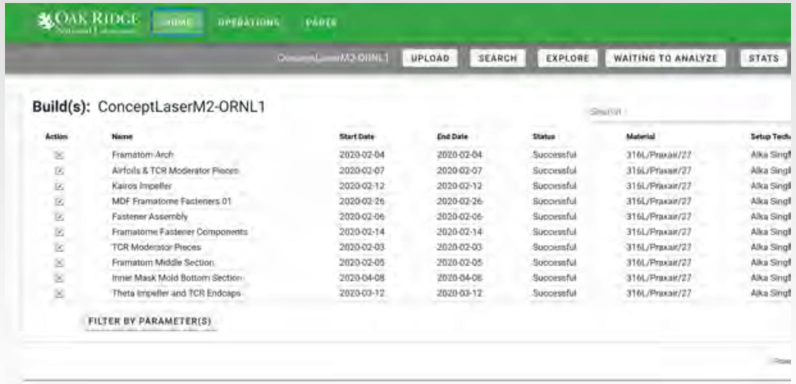
Augmented Intelligence for Advanced Manufacturing



Research Activities

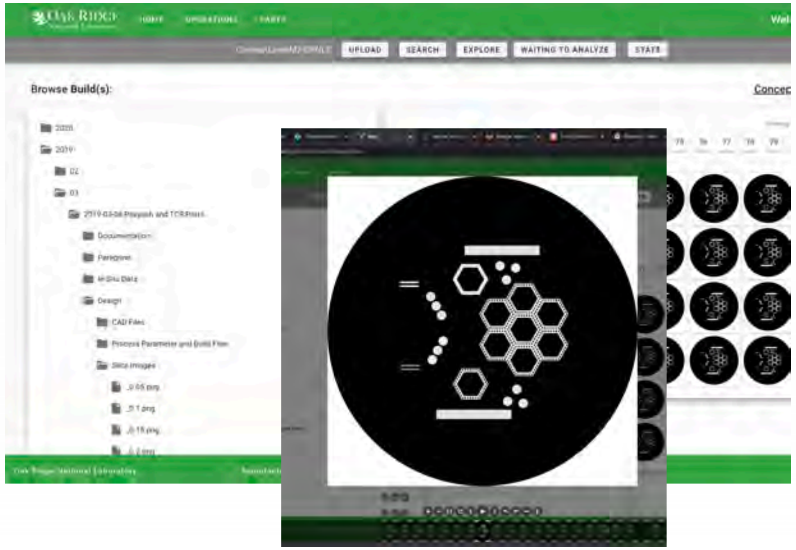
Data management

Metadata search



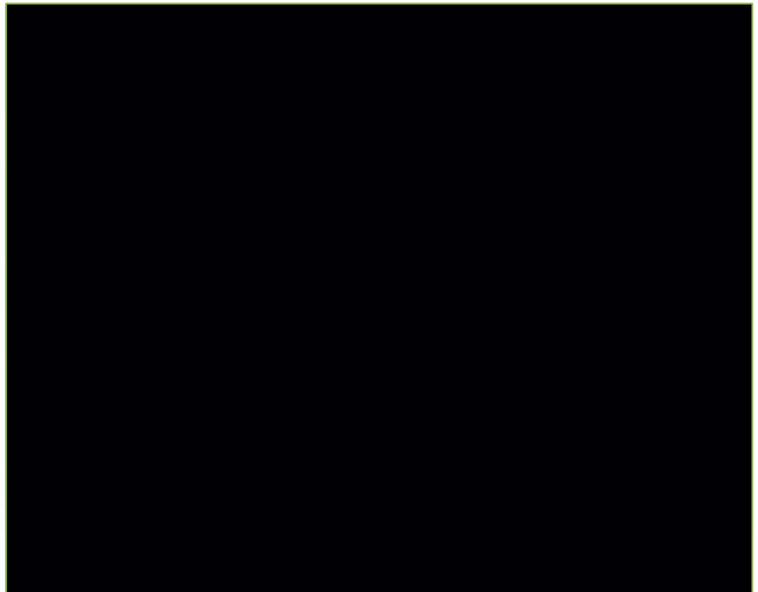
Action	Name	Start Date	End Date	Status	Material	Setup Tech
	Framatom Arch	2020-02-04	2020-02-04	Successful	316L/Praxair/27	Alka Singh
	Airfoils & TCR Moderator Pieces	2020-02-07	2020-02-07	Successful	316L/Praxair/27	Alka Singh
	Kairos Impeller	2020-02-12	2020-02-12	Successful	316L/Praxair/27	Alka Singh
	MDF Framatome Fasteners 01	2020-02-26	2020-02-26	Successful	316L/Praxair/27	Alka Singh
	Fastener Assembly	2020-02-06	2020-02-06	Successful	316L/Praxair/27	Alka Singh
	Framatome Fastener Components	2020-02-14	2020-02-14	Successful	316L/Praxair/27	Alka Singh
	TCR Moderator Pieces	2020-02-03	2020-02-03	Successful	316L/Praxair/27	Alka Singh
	Framatom Middle Section	2020-02-05	2020-02-05	Successful	316L/Praxair/27	Alka Singh
	Inner Mask Mold Bottom Section	2020-04-08	2020-04-08	Successful	316L/Praxair/27	Alka Singh
	Theta Impeller and TCR Endcaps	2020-03-12	2020-03-12	Successful	316L/Praxair/27	Alka Singh

Data viewer

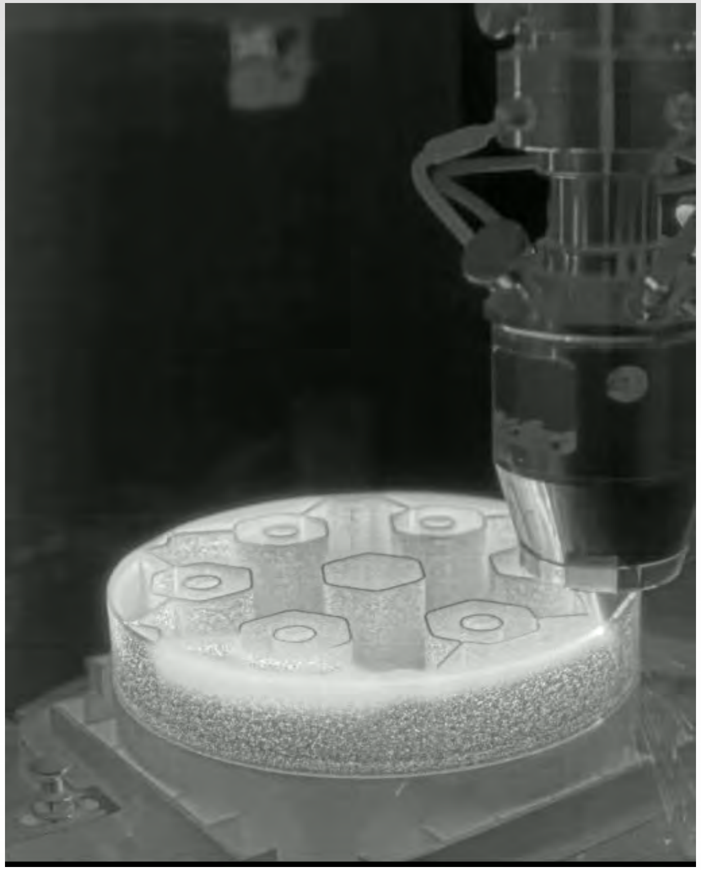


In-situ quality control

printer operator reviewing a *Peregrine* analysis



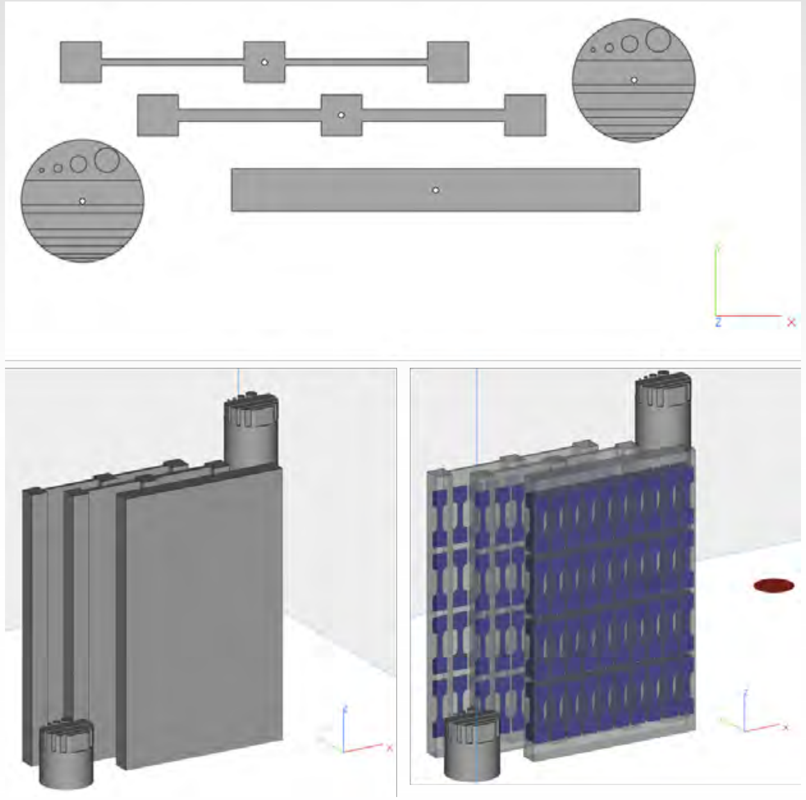
Sensor development



Oak Ridge National Laboratory

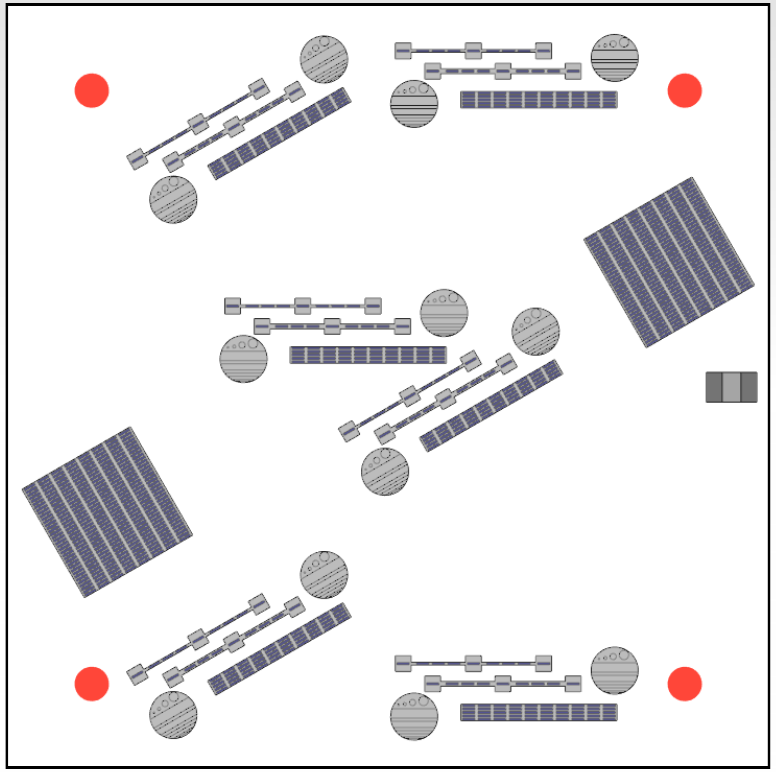
Process Correlation Campaign

Standard Cluster



Location Specific Sample Extraction

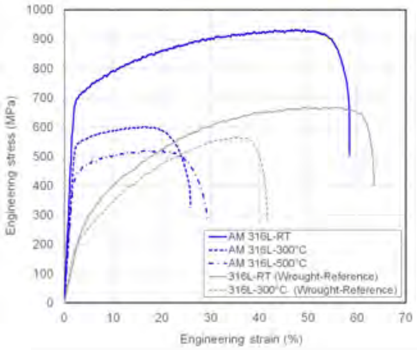
Build 0.1 Layout



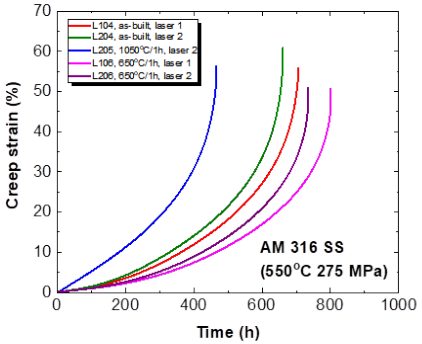
2,784 SS-J3 specimens

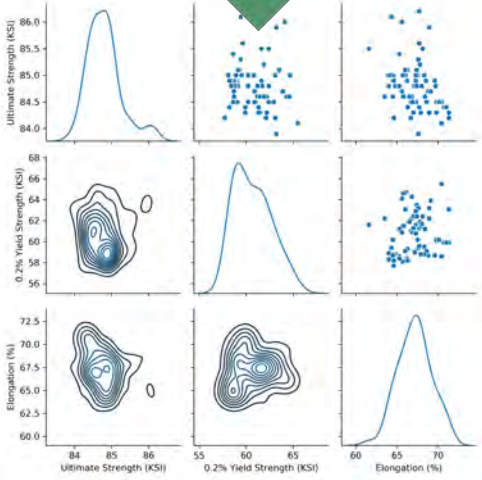
Data Correlation

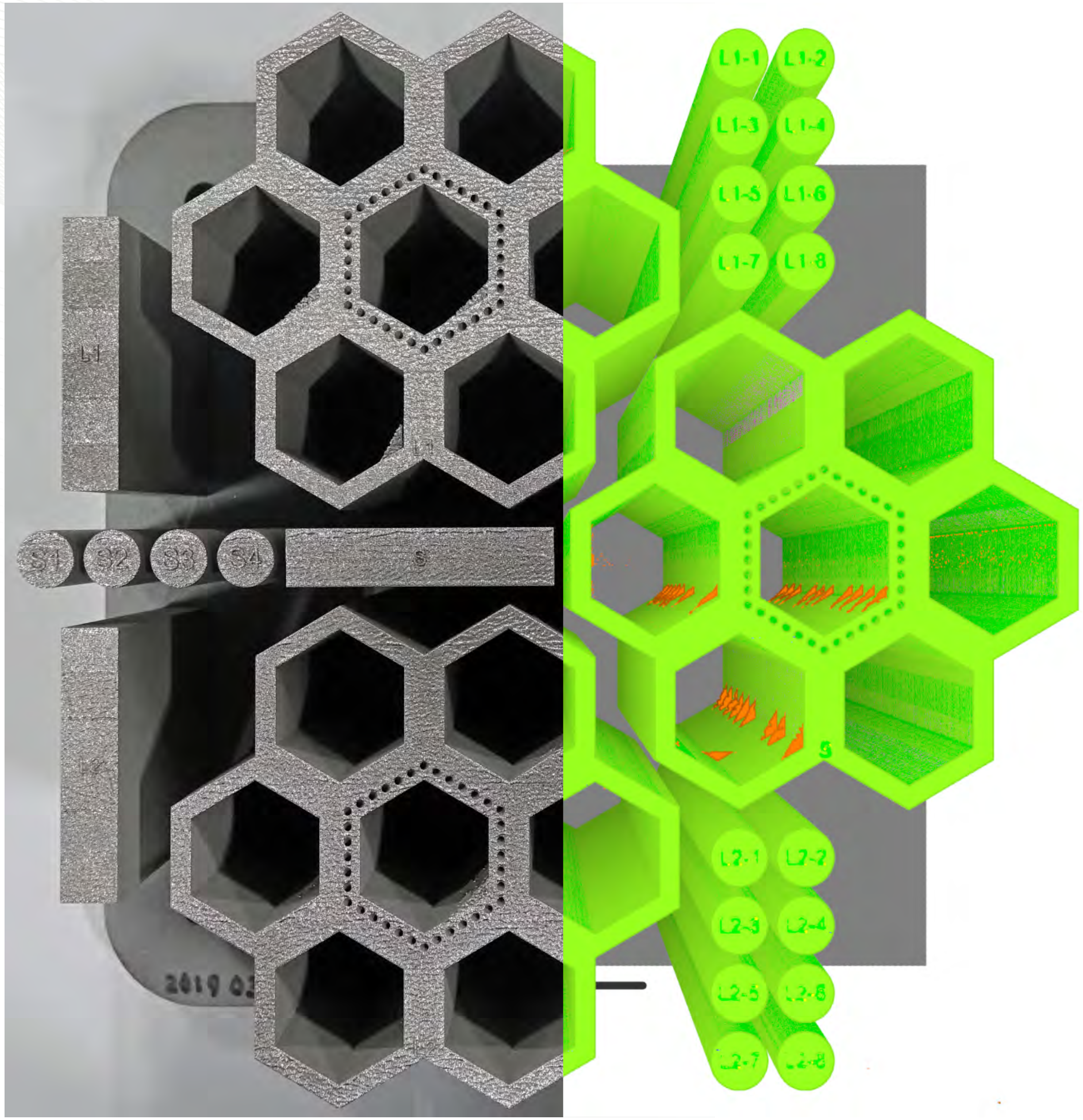
Mechanical properties



Creep properties







Questions?

Contact: paquitvc@ornl.gov
betzlerbr@ornl.gov

Digital Twin-Based Asset Performance and Reliability Diagnosis for the HTGR Reactor Cavity Cooling System Using Metroscope

Eric Helm

12/02/2020

Digital Twin-Based Asset Performance and Reliability Diagnosis for the HTGR Reactor Cavity Cooling System Using Metroscope

Technology Summary

Digital twin-based diagnosis with Metroscope with high reliability for passive and active cooling in SC-HTGR Reactor Cavity Cooling System

Technology Impact

*Close an estimated fixed O&M cost gap of $9.9/MWh to the goal of $2/MWh by a 50% reduction in key plant staff categories for **overall project impact of $3.7/MWh** contribution to the ARPA-E mission for the SC-HTGR design.*

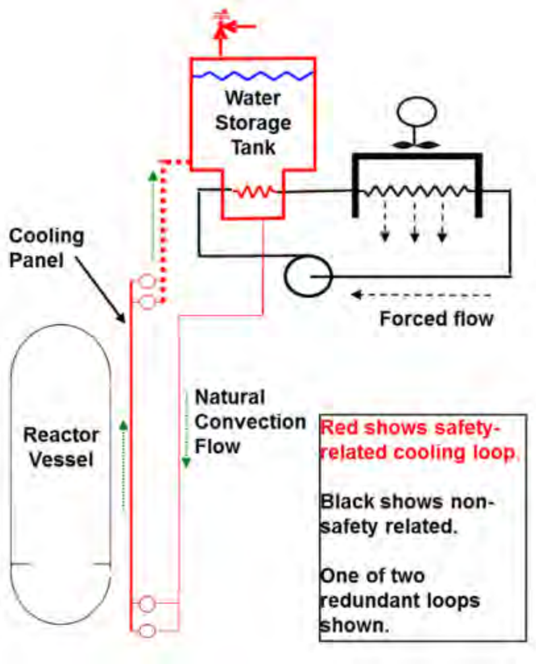
Proposed Targets

Metric	State of the Art	Proposed
Fault detection with minimum sensors	Statistical methods need many sensors and intolerant to drop-outs	Reduce O&M for sensor calibration by 50%
Reliable fault detection	Statistical methods in practice yield majority false positives	Automate diagnosis for aux.systems with >90% reliability
Minimize effort to perform detection	Burden of asset health is on systems engineers	Commercialize software to reduces sys .eng. effort by 50%

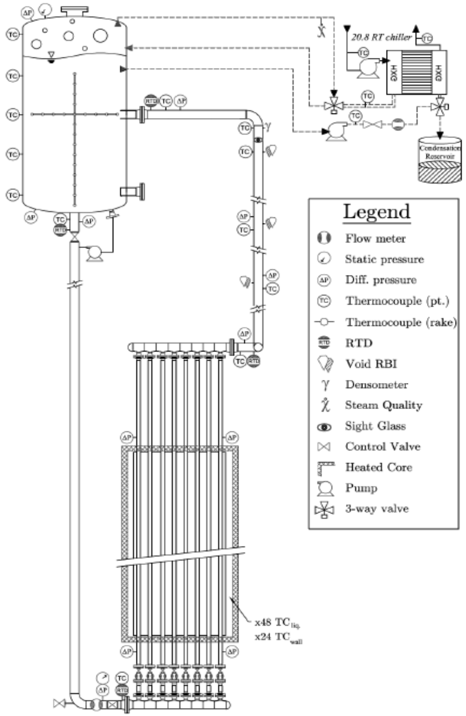
Digital twin-based diagnostics for $3.7/MWh O&M impact with rapid tech-to-market approach

Physical System of Interest and Data Source

SC-HTGR Reactor Cavity Cooling System

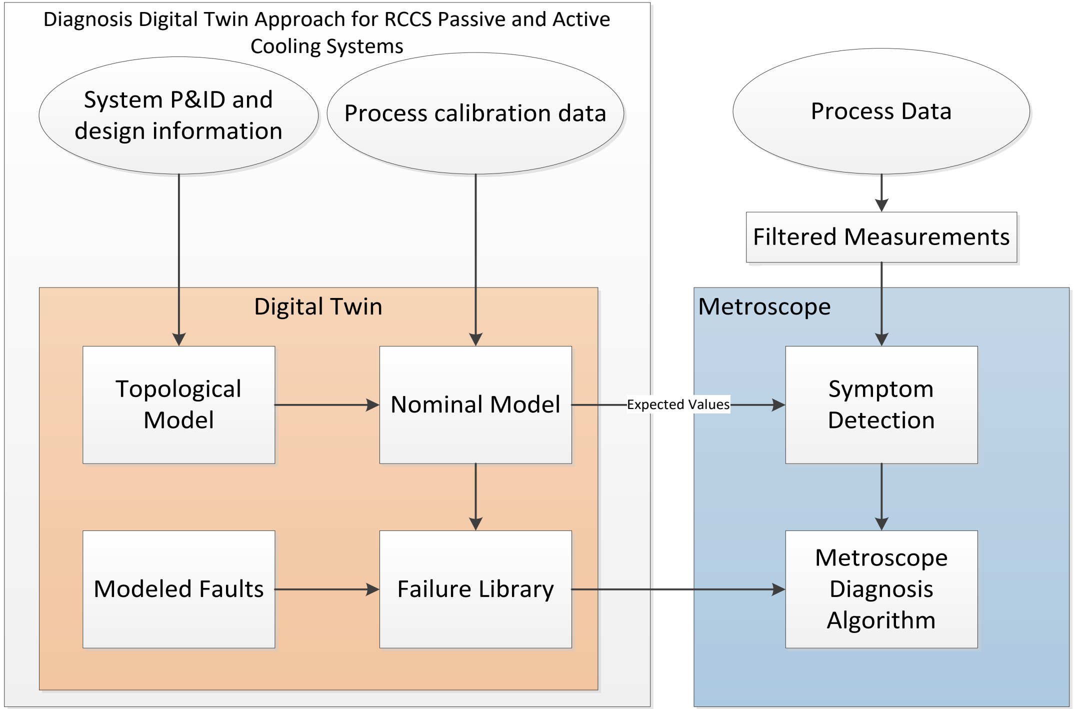


Natural Convection Shutdown Heat Removal Test Facility (ANL)



Technical Project Scope

- Develop the modeling approach
- Model the NSTF (RCCS) digital twins
- Calibrate the digital twins with NTSF data
- Develop the failure library
- Test and validate failure detection performance



Develop the generic capability to determine needed sensors and find faults with no operating fault data

What is Metroscope?

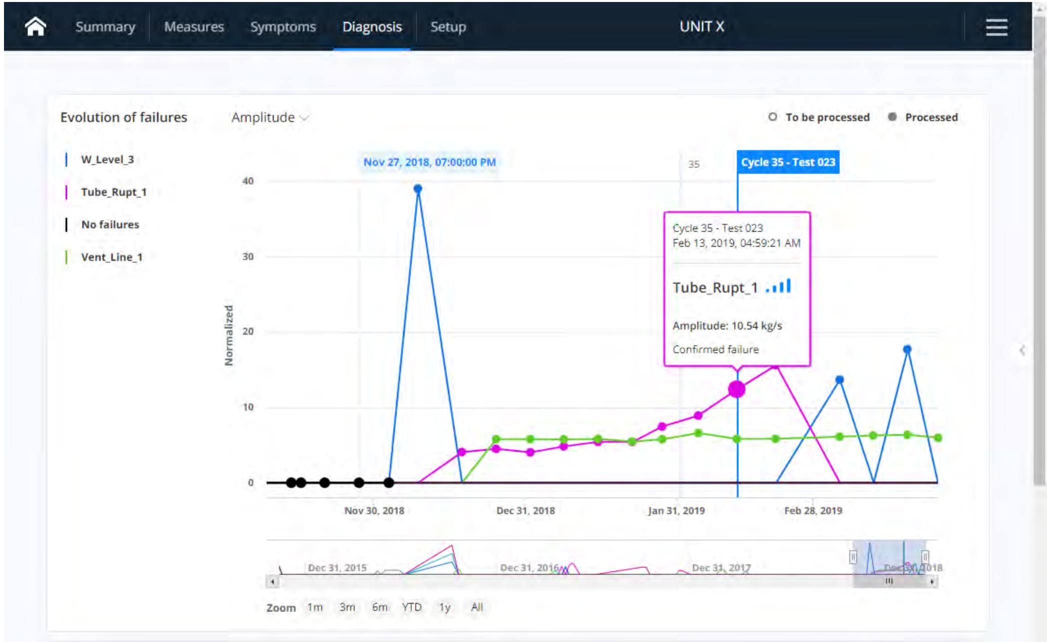
METROSCOPE is Knowledge-Based AI (as opposed to Statistical AI and Machine Learning).

It relies on 2 core features:

- a knowledge base (the Digital Twin) embedding expertise,
- an inference engine (the AI).

It is meant to address problems and decisions where engineers need both expertise and data

METROSCOPE software provides the software tools for automated diagnosis and visualization of fault characteristics.



Metroscope combines digital twin methodology with automation and easy to understand software

Technical Challenges

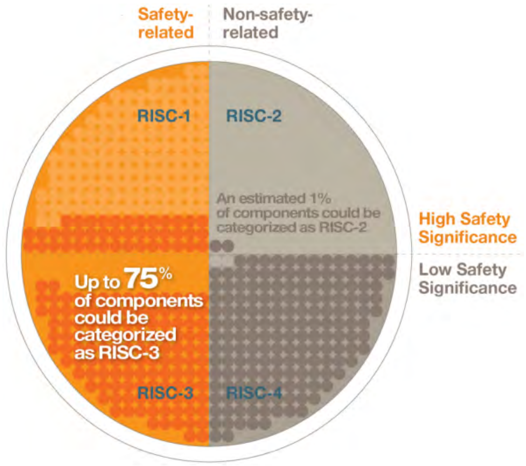
- Address more than one single steady-state system mode
- Determine main failure modes of the RCCS and model in a failure library
- Find or generate meaningful validation data for failure modes
- Determine the best sensor + soft sensor mix

Value and Impact Challenges

- Prove meaningful failure detection impact related to consequential functional failures
- Link to inspection actions that would have formed the regulatory basis for the place
- Demonstrate the cost savings

Technology-to-Market Challenges

- Adapt the Metroscope method quickly
- Join with utility partner to estimate the value-added for a sample PWR or BWR system
- Examine the viability of risk informed approaches (10 CFR 50.69) to leverage this type of monitoring for increased safety assurance and savings
- Follow the HTGR research with a LWR pilot



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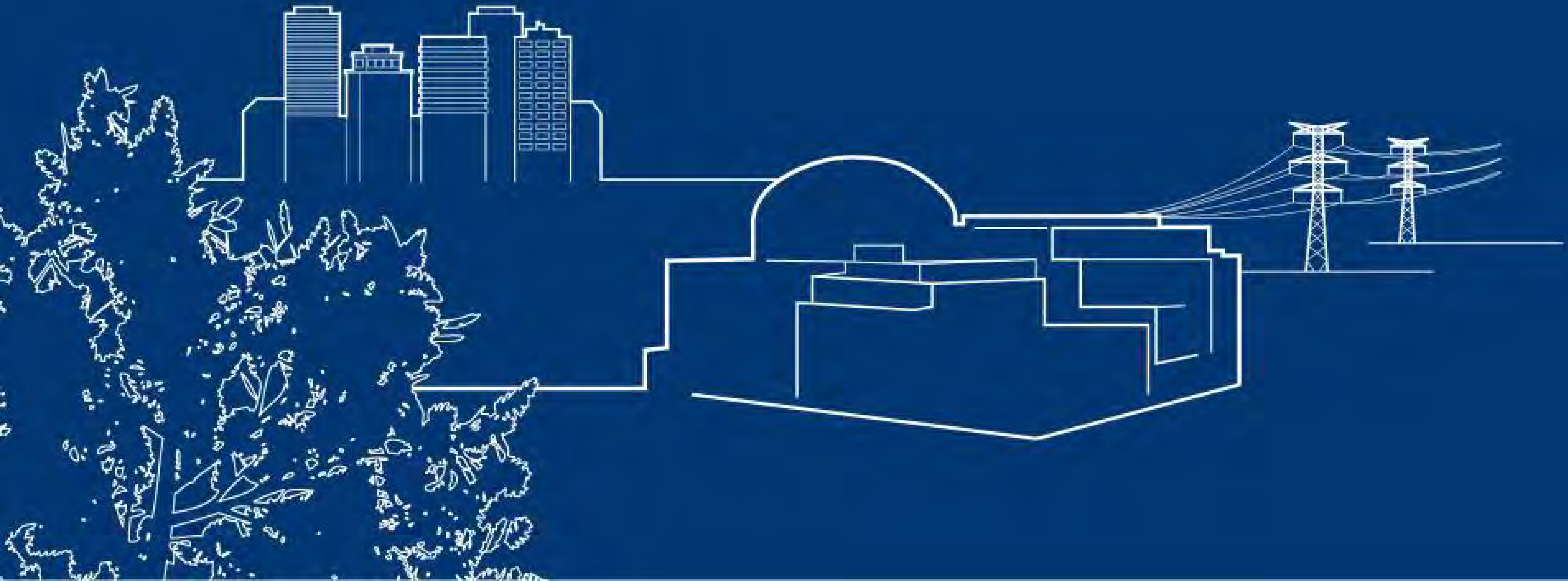

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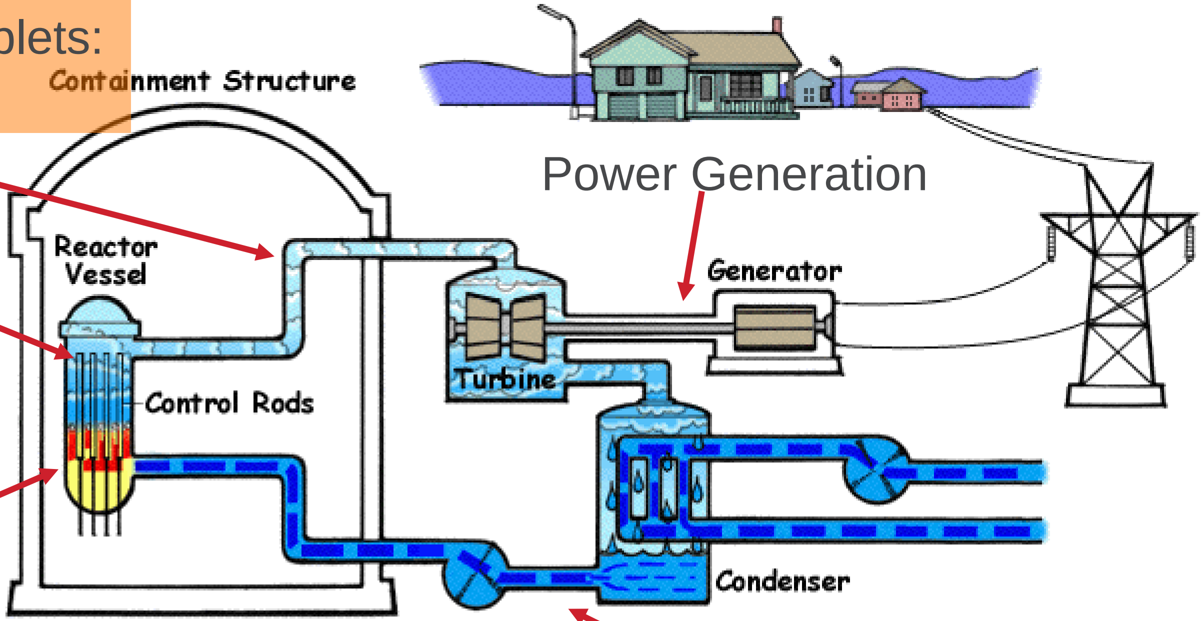
DATA-DRIVEN OPTIMIZATION OF MOISTURE CARRYOVER IN AN OPERATING BWR

RICK VILIM, HAOYU WANG
Nuclear Science and Engineering Division
Argonne National Laboratory

Workshop on Digital Twin Applications for Advanced Nuclear Technologies
December 1-4, 2020

BWR STEAM SUPPLY SYSTEM

Un-separated liquid droplets:
Moisture Carryover



Power Generation

Steam Drying

Coolant Boiling

Coolant Recirculation

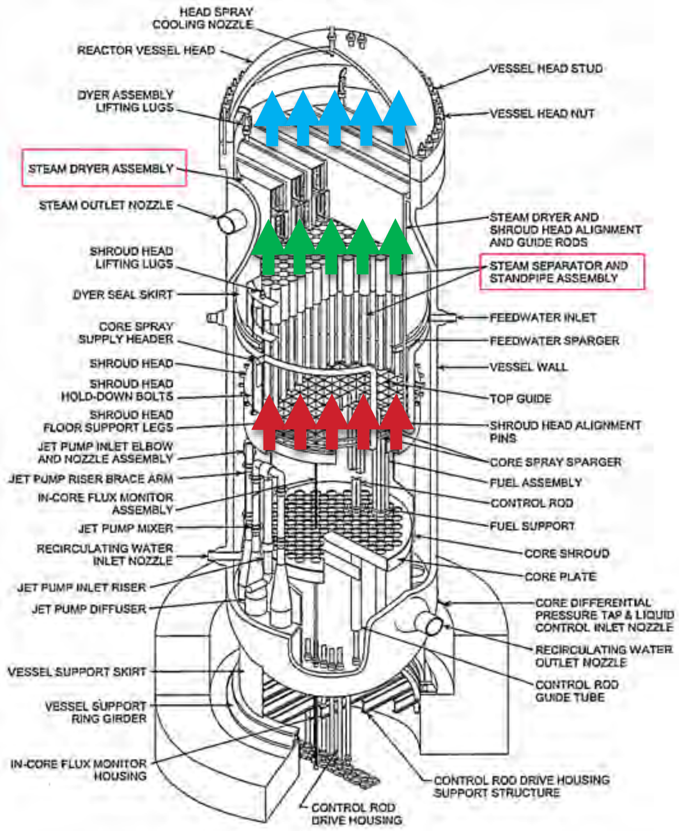
STEAM DRYING PROCESS

Steam drying in GE BWR/4 reactor :

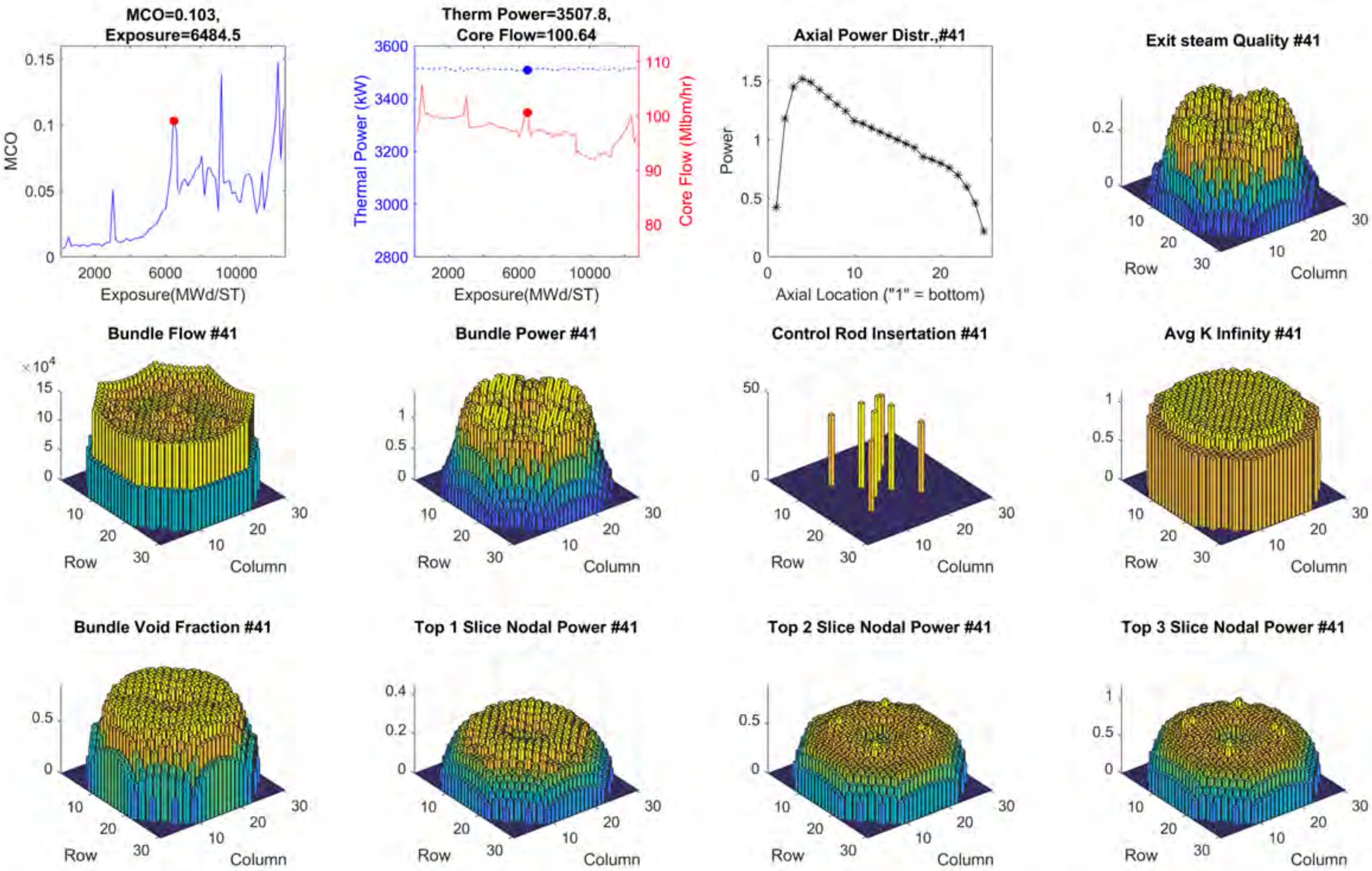
(1) Steam Separator, upgrading the steam quality from ~30% to ~90%;

(2) Steam Dryer, upgrading the steam quality from ~90% to ~99.9%.

Saturated Steam Separators will elevate the Moisture Carryover



MCO DATA



Data:

- *6 completed Cycles;*
- *540 Measurements;*
- *7,000+ variables;*

Task:

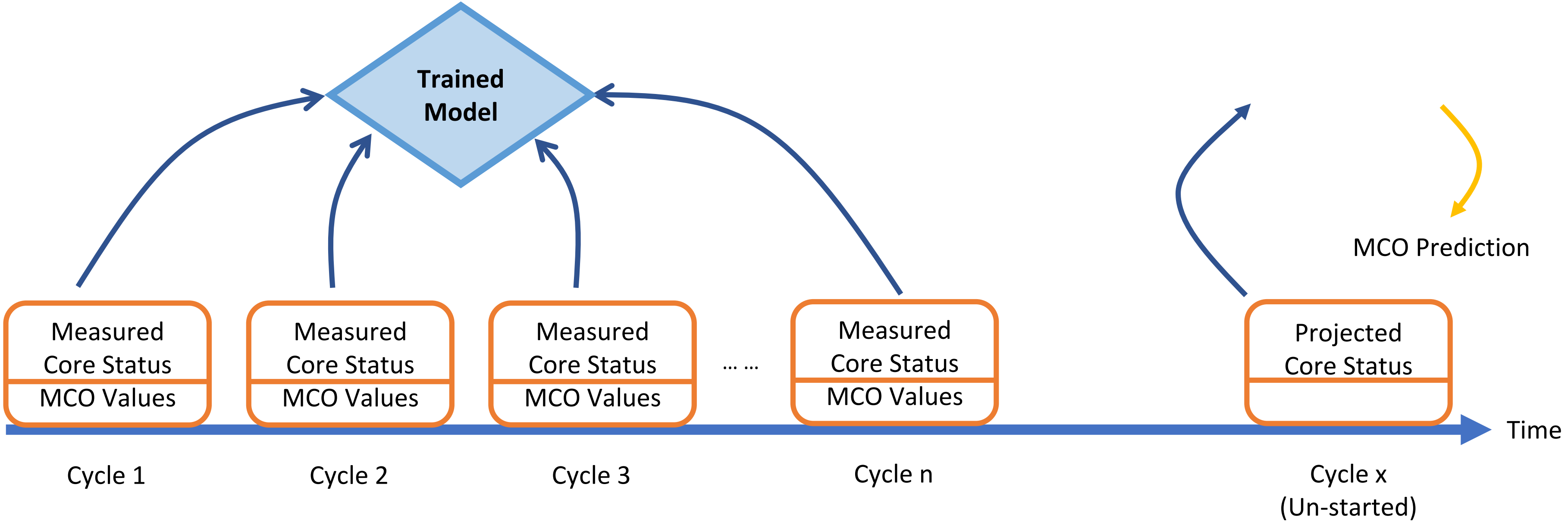
- *Model and Predict MCO*

Keys:

- *Feature Selection*
- *Diversity of training samples*

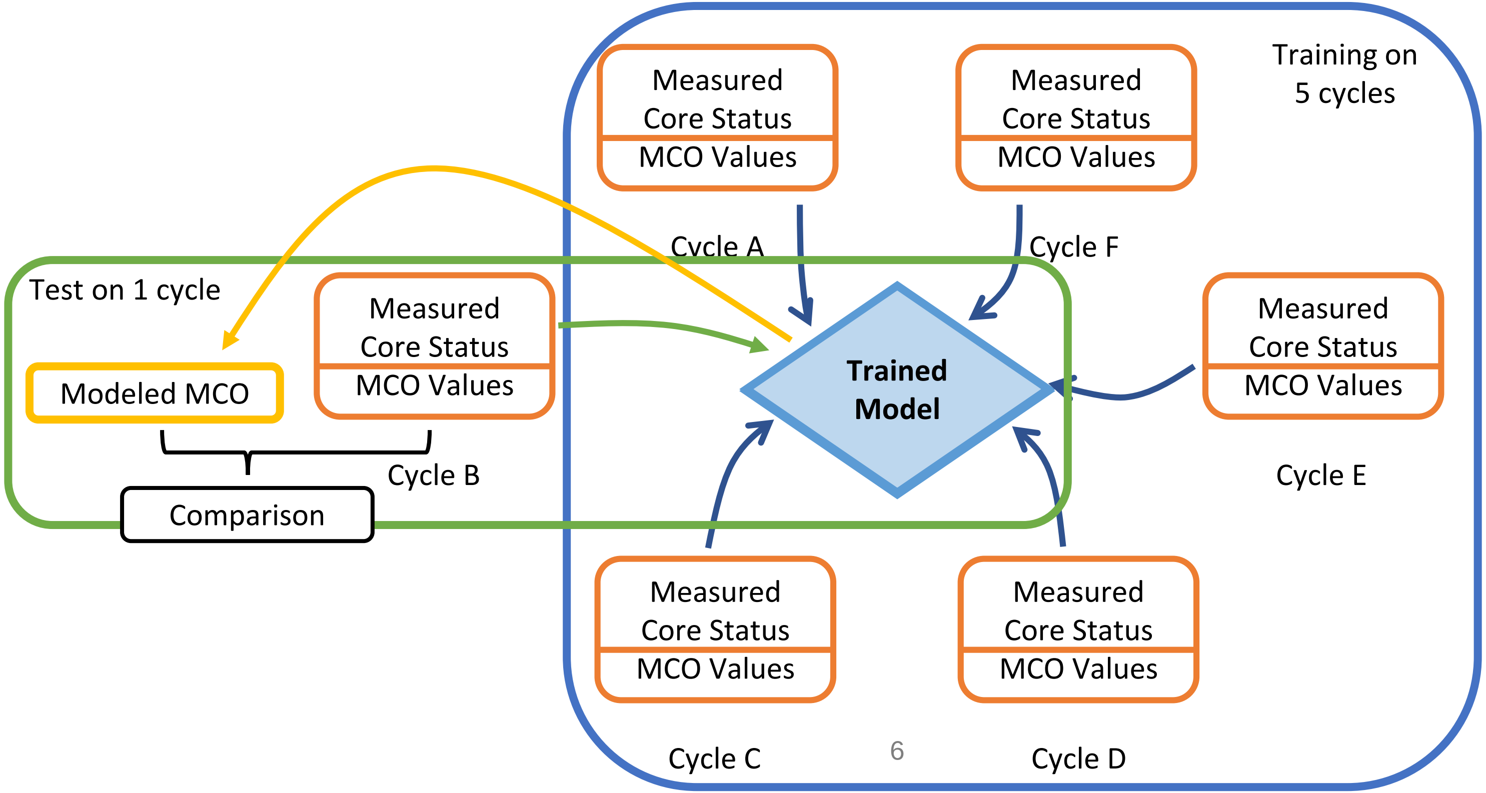
OUT-OF-CYCLE PREDICTION: OBJECTIVE

Accurate prediction of the MCO of an un-started cycle, using the projected core status (operating plan).



OUT-OF-CYCLE PREDICTION: METHODOLOGY

Using 6 cycle data from commercial reactors, train model on 5 cycles, then test on 1 cycle



We assume:

- Both reactors are identical in structure
- All cycles share the identical loading plan.

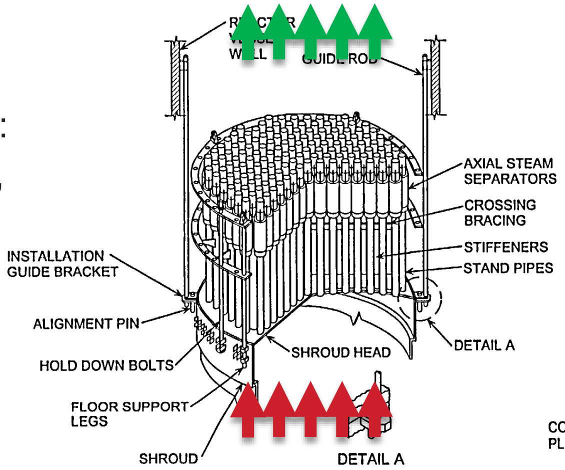
ENGINEERING FEATURE SELECTION

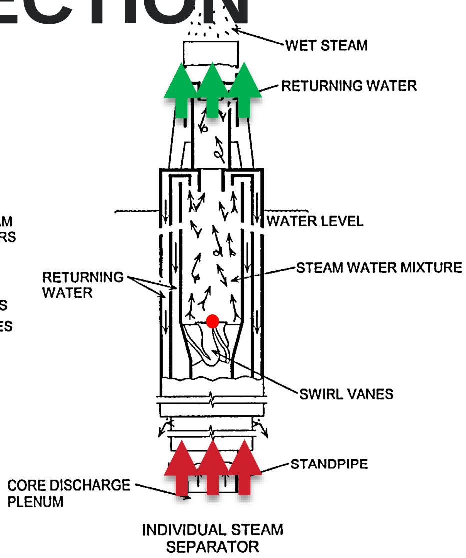
Before Entering the Separator:

Lower initial steam quality (***Q***),

Higher ***MCO*** :

$$MCO \sim \frac{1}{Q^m} \quad (m > 0)$$





In Steam Separator :

Mixture passes swirl vanes, “Centrifuge”;

Liquid Drops hit the wall and get separated.

Lower Liquid Velocity ($\boldsymbol{V_L}$),

Higher ***MCO*** :

$$MCO \sim \frac{1}{V_L^{\,n}} \quad (n > 0)$$

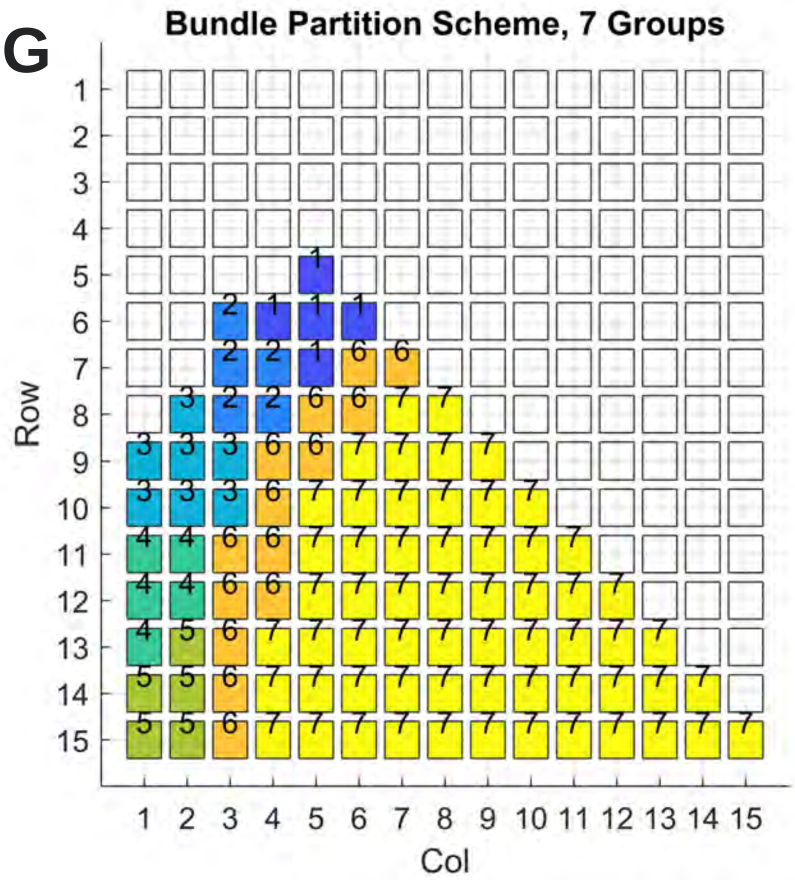
Combining both ***Q*** and $\boldsymbol{V_L}$,

Define a Local Feature ***K*** :

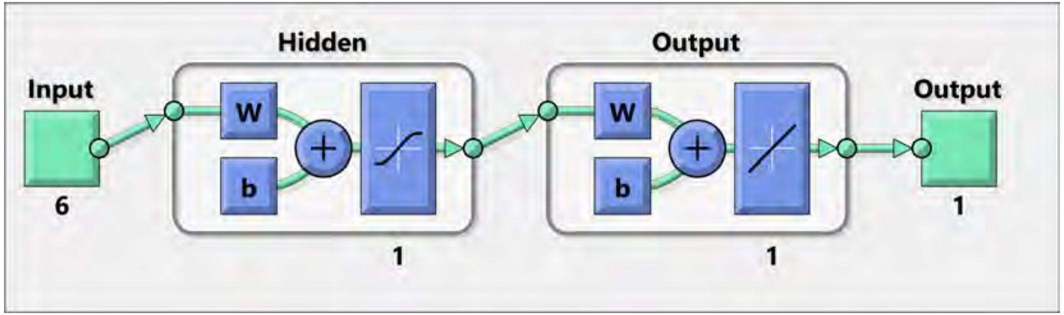
$$K = \frac{1}{Q^m \cdot V_L^{\,n}} \quad (m > 0, n > 0)$$

FUEL LOADING AND GROUPING

- In GE BWR/4 reactor core: 764 bundles;
- In Each 45 degree section: 101 bundles.
- Reducing the input feature space by a factor of 7, which reduces the computation demand while avoids repeated variables;
- Increasing the number of points by a factor of 8.

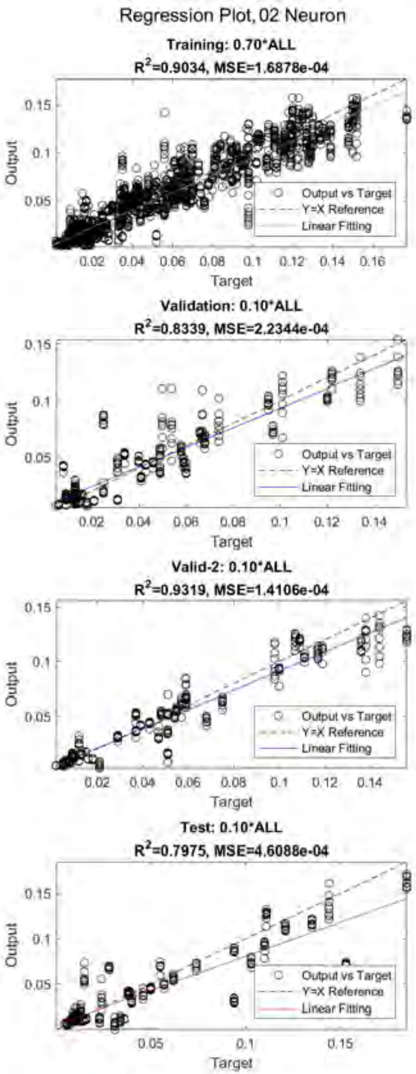


DATA DIVISION FOR VALIDATION

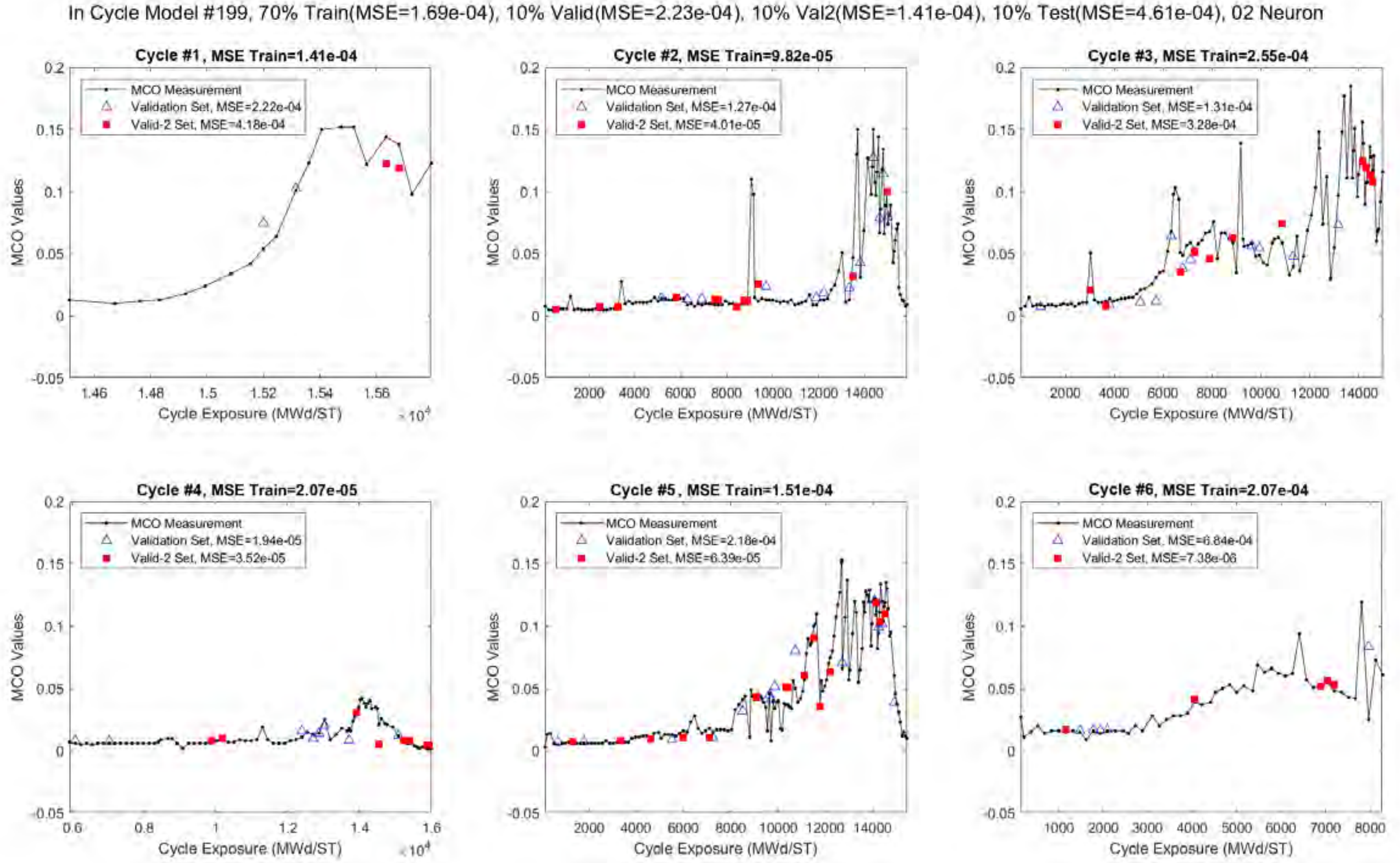


Divide Data into 4 Sets

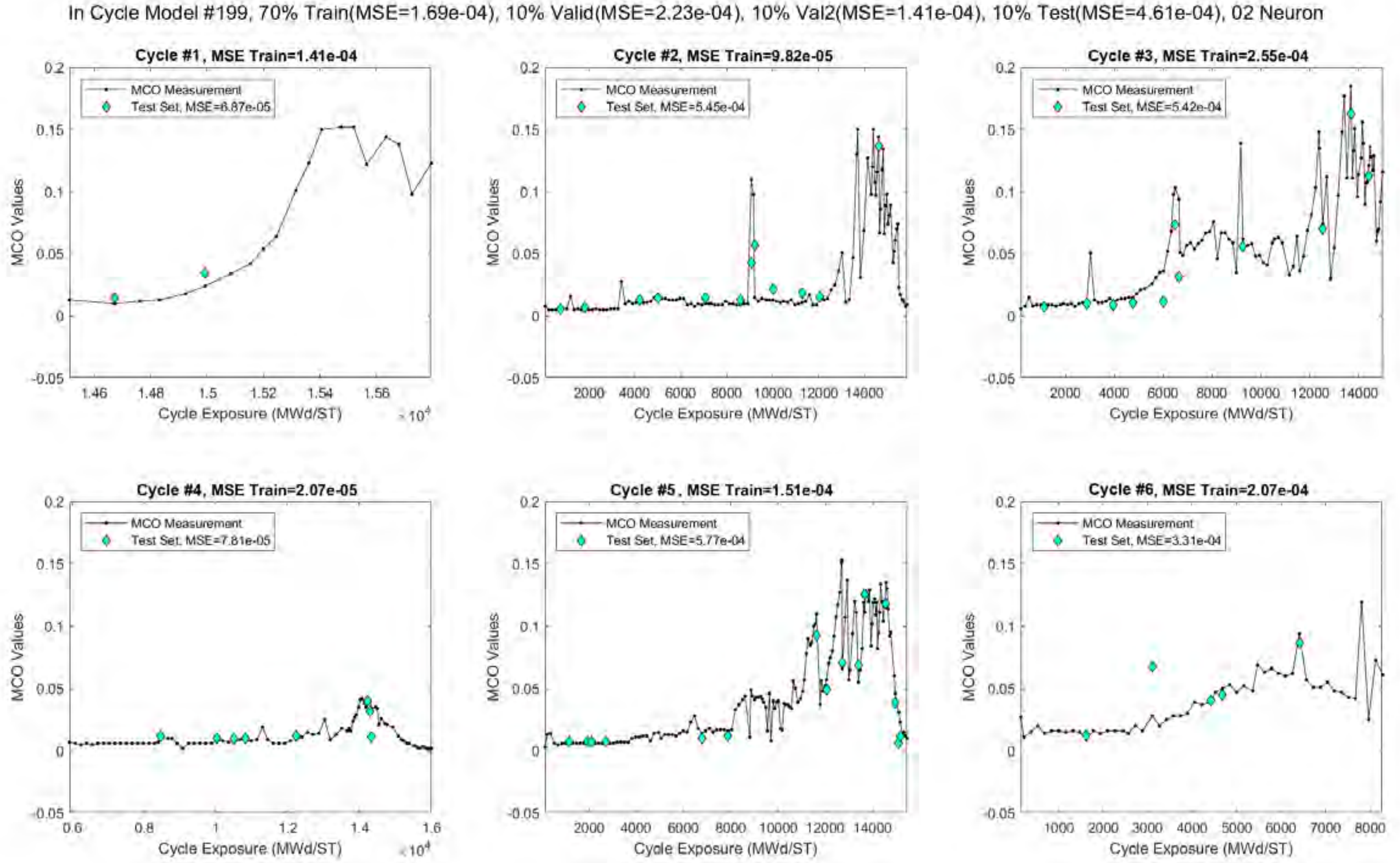
- Training: Optimize neural network parameters, aiming at lowest MSE;
- Valid #1: Stop training when the MSE of Val.#1 stops decreasing, avoid overfit;
- Valid #2: Not used in model training process, for model selection only;
- Test: Independent test, providing a measure of model predictability.



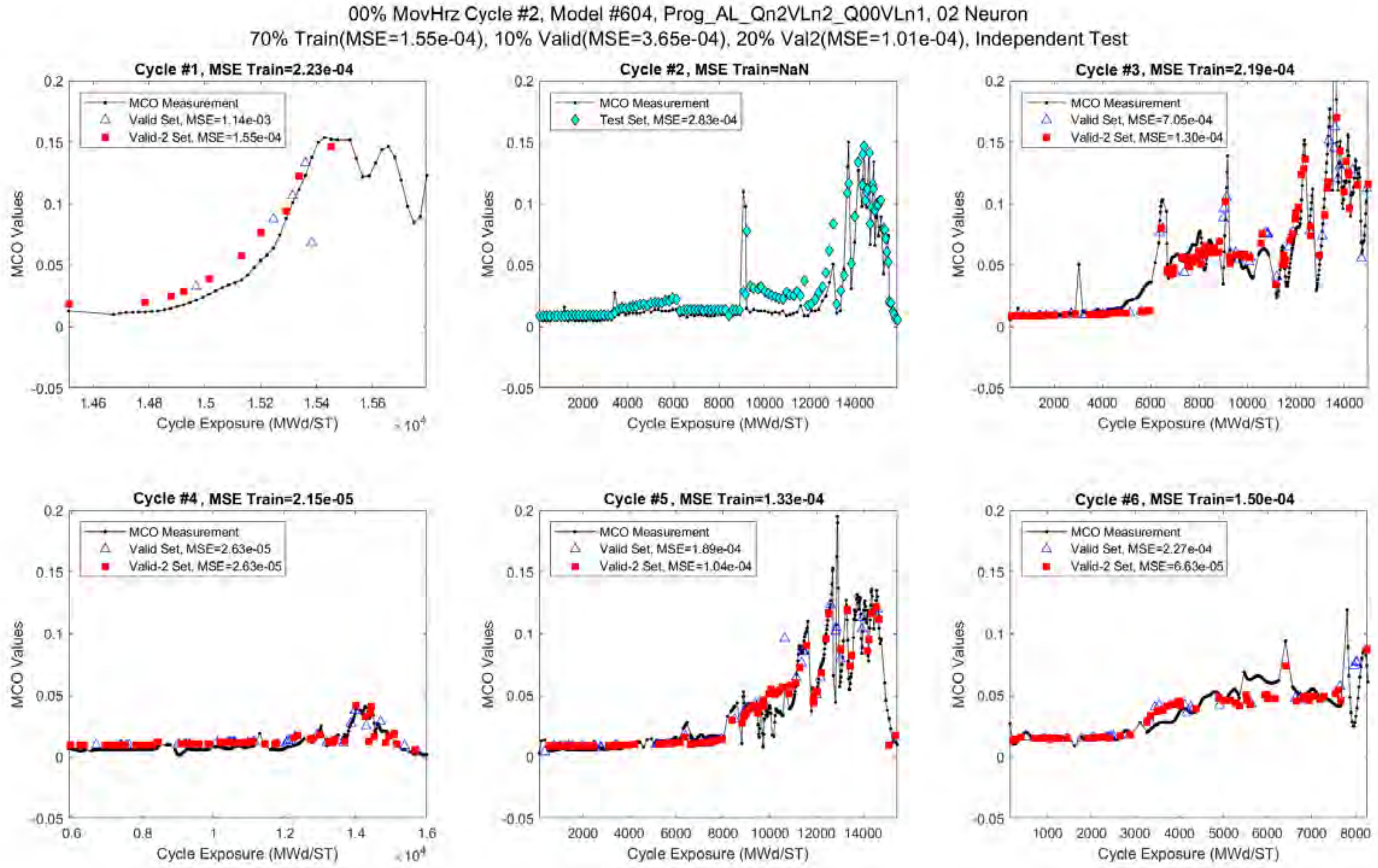
IN-CYCLE MODELING: VALIDATION



IN-CYCLE MODELING: TEST



OUT-CYCLE MODELING: TEST



THANK YOU

Role and Status of VR/AR/MR in Digital Twins in the Nuclear Industry

Rizwan-uddin
Nuclear, Plasma, and Radiological Engg.
University of Illinois

December 1 – 4, 2020
(Virtual) **Workshop on Digital Twin Applications for Advanced Nuclear Technologies (ANL/INL/ORNL/...)**

ILLINOIS | NPRE

Digital Twins

- There are as many (slightly varying) definitions of digital twins as there are people developing and using them.
- "Digital twins," are emulations of real systems that contain simulated communication networks, devices, and other cyber and physical components.
- Live data streamed into the digital twin add additional possibilities

Digital Twins

- Goal is to optimize asset performance and utilization.
- Use it for monitoring, diagnostics and prognostics
- Combine sensory data, with past experience and human expertise to improve performance.
- Use digital twins to find root cause of issues and improve productivity

Digital Twins and VR/AR/MR

- **While most other aspects of "digital twins" can be taken advantage of using just the "digital twin", any desired improvement in design and operational efficiency or in safety assessment that involve *human factors and human machine interface* will benefit from a marriage between digital twin and the VR/AR/MR technology.**

- **VR/AR/MR allow the traditional 2D representations of the digital twin (or of parts of it) to be presented in 3D.**
- **Add interactivity**

Quick overview of VR, AR and MR in the context of digital twins

VR/AR/MR

- Just the way there are many differing definitions of "digital twins," so is the case with AR and MR.
- But, it is getting better; and some sort of consensus is developing.

Virtual Reality (VR)

- Physical world is hidden; and the human being (as opposed to an avatar) is *fully immersed* in a "digital" world; with a strong sense of being present (only) in that "digital world".

- Presence in the digital world can be very "strong", leading to dizziness (roller coaster)

Virtual Reality (VR)

- Immersive
- Interactive

- Typical headsets:
    - Oculus Rift
    - Oculus Go
    - HTC Vive

Images from:
https://www.oculus.com/

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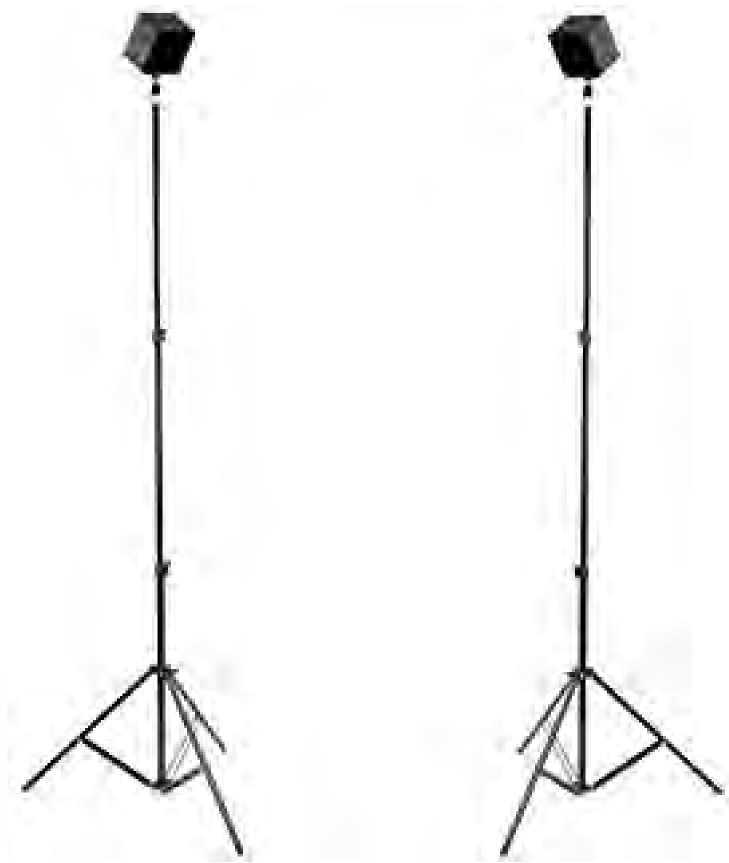
HTC VIVE

www.pbtech.com



www.amazon.com

VR (functionality, and uses)

- User of VR can simply be a stationary “spectator” or can walk around the digital environment.
- In more advanced VR applications, the physical user can interact with her digital surroundings. For example, the user with the help of a hand-held device, can shoot at digital objects, press a “virtual/digital” button to raise or lower a “virtual” control rod, or press a “virtual/digital” button to start a “virtual” pump. It can be used to virtually assemble a set of virtual parts.

VR in Nuclear

- Real locations can be displayed without risking radiation exposure
- Data can be displayed in the context of its environment
- Training using VR – before actual attempt

- Industry involvement:

VR (functionality, and uses)

- Training and Education, and its use in dose reduction for plant workers was considered to be two of the main applications of VR in the nuclear industry
- A VR model of the actual physical plant when complimented with a digital twin is likely to provide an even better environment for increased operational efficiency and safety of NPPs

VR

- The bottom line is that in a VR system, “everything” is digital/virtual.
- There is no interaction with the surrounding “physical” world.

VR Use Case: Lab Training

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VR in a Digital Twin

Augmented Reality (AR)

- One definition of AR:

- *Augment* the information you get when looking at a physica scene through the camera of your cell phone
- So, it is the physical world around you, but the information is augmented *digitally* on your camera screen.

Augmented Reality (AR)

- Example:

- You turn your cell phone camera on, and aim it at a building. A software then adds (overlays) a text that gives you information about the scene (Eifel Tower, Statue of Liberty, Taj Mahal)

- A camera on your car projects the scene in front of you on a screen in your car, and overlays direction or other information (GPS-based info)

Augmented Reality (AR)

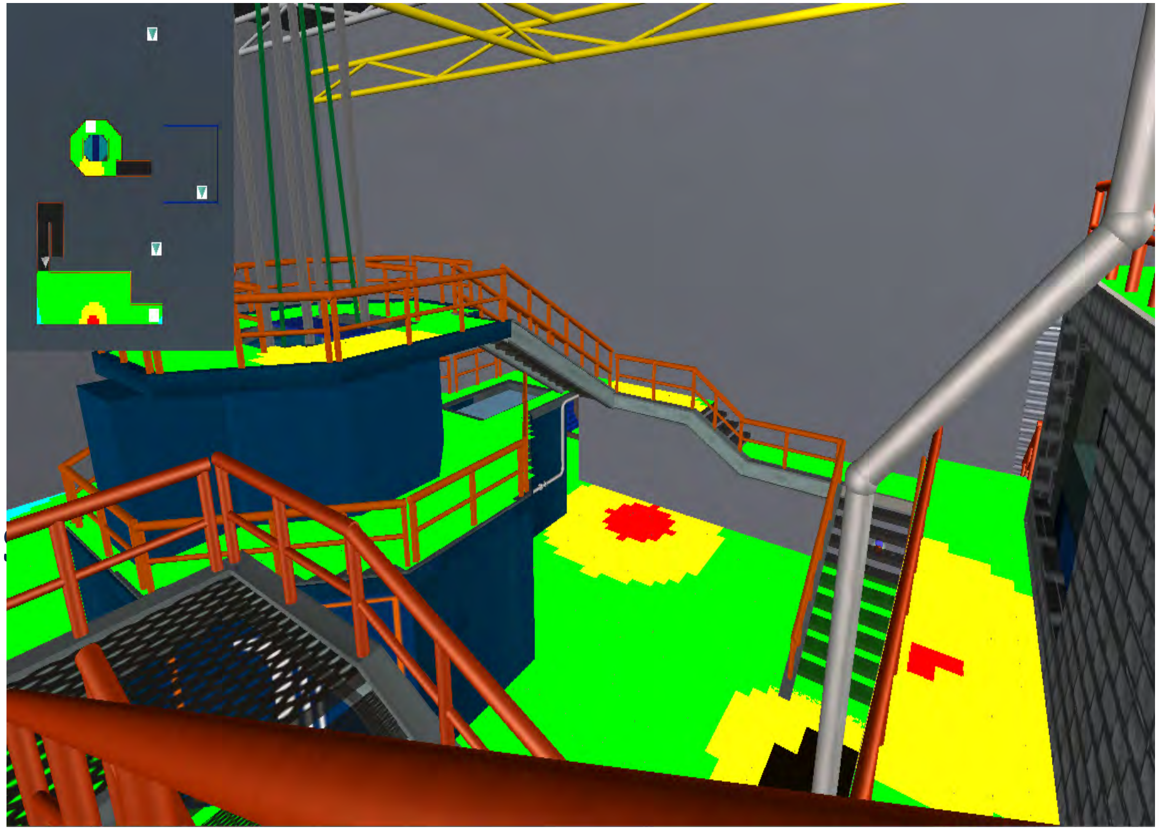
Augmented Reality: functionality and uses

- **Training (overlay information)**

(Using *Unity* and the *Vuforia* Engine, we can scan and detect 3D objects, and place buttons, video players, buttons, and lines to describe components of those 3D objects.)

Augmented Reality: funct and uses

- Dose reduction (Overlay a transparent radiation field on the scene; and show a path of lea dose”)
- Sky is the limit



- Al-Zalloum, MS Thesis, Illinois. APPLICATION OF SHORTEST PATH ALGORITHMS TO FIND PATHS OF MINIMUM RADIATION DOSE, 2009

Mixed Reality

- In mixed reality, one can see the physical world (without a camera), but “digital” objects can be superimposed in the physical world.
- Needs special gadgets such as Microsoft’s Hololens


Turbine 2

Mixed Reality (MR)

- **MR headsets display holograms for the user**

https://www.microsoft.com/en-us/hololens

MR

Holograms are digital objects made of light and sound

They appear in the physical world around us.

Holograms can be controlled by gaze, gestures and voice commands

Mixed Reality

- As long as “digital twin” is that of an existing facility, MR may have limited application

- However, if digital twin is that of a facility that is under design, or under construction, then several applications of MR can be easily imagined

A 2018 paper from Japan

JOURNAL OF NUCLEAR SCIENCE AND TECHNOLOGY
2018, VOL. 55, NO. 9, 965–970
https://doi.org/10.1080/00223131.2018.1473171

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RAPID COMMUNICATION

OPEN ACCESS Check for updates

Radiation imaging using a compact Compton camera inside the Fukushima Daiichi Nuclear Power Station building

Yuki Sato[a], Yuta Tanifuji[a], Yuta Terasaka[a], Hiroshi Usami[a], Masaaki Kaburagi[a], Kuniaki Kawabata[a], Wataru Utsugi[b], Hiroyuki Kikuchi[b], Shiro Takahira[b] and Tatsuo Torii[a]

ABSTRACT

The Fukushima Daiichi Nuclear Power Station (FDNPS), operated by Tokyo Electric Power Company Holdings, Inc., went into meltdown in the aftermath of a large tsunami caused by the Great East Japan Earthquake of 11 March 2011. The measurement of radiation distribution inside the FDNPS buildings is indispensable to execute decommissioning tasks in the reactor buildings. We conducted a radiation imaging experiment inside the turbine building of Unit 3 of the FDNPS by using a compact Compton camera and succeeded in visualizing high-dose contamination (up to 3.5 mSv/h). In addition, we drew a three-dimensional radiation distribution map inside the turbine building by integrating the radiation image resulting from the Compton camera into the point cloud data of the experimental environment acquired using a scanning LRF. The radiation distribution map shows the positions of these contaminations on a real space image of the turbine building. The radiation distribution map helps workers to easily recognize radioactive contamination and to decrease their own exposure to radiation because the contamination cannot be observed with the naked eye.

Recent paper from Japan (2018)

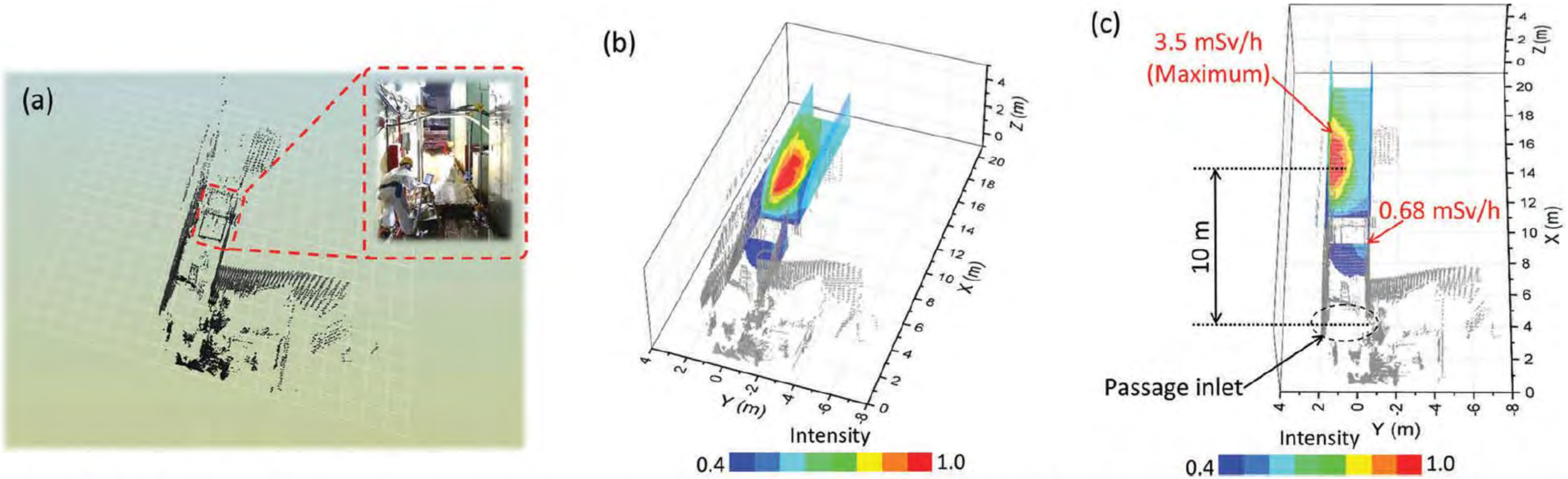
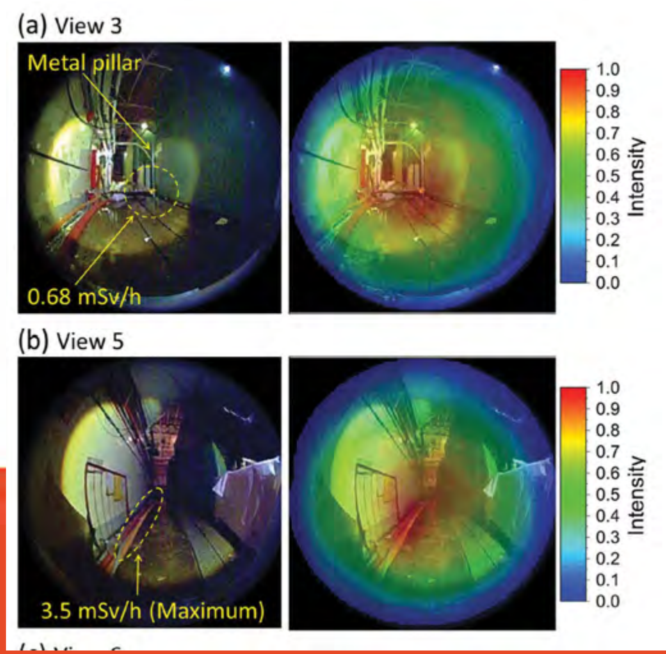


Figure 3. (a) Point cloud data of experimental environment acquired using scanning LRF. Combined metal pipes can be seen. (b,c) Radiation distribution map prepared by superimposing radiation image and point cloud data. In panels (b) and (c), the viewpoints are different.



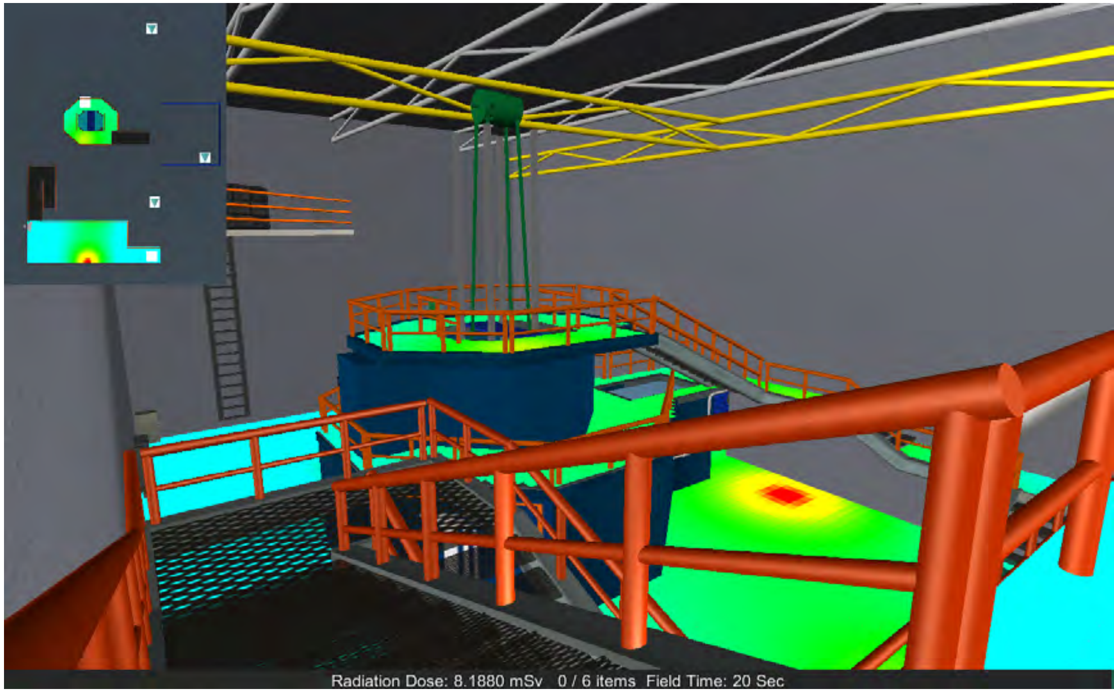
PNNL Student Internship Project

- Model a room and an interactive AR/MR application to collect data at specific locations, and enter data in an online database

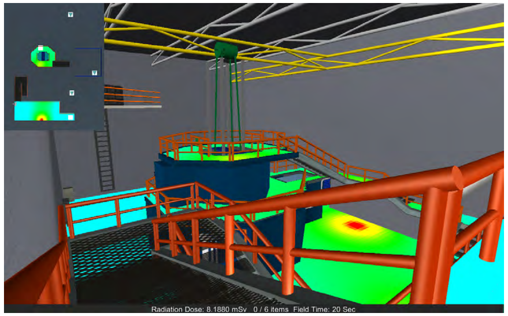
Mixed Reality -- Hololens

Dose Minimization Game

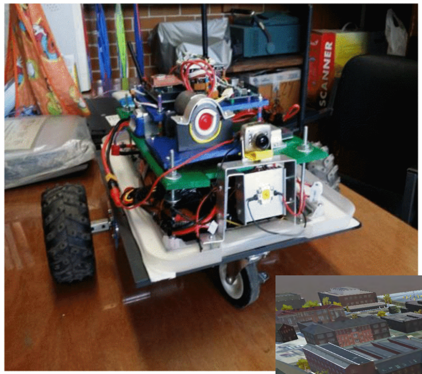
- Goal: Collect six objects in the TRIGA reactor building while minimizing dose

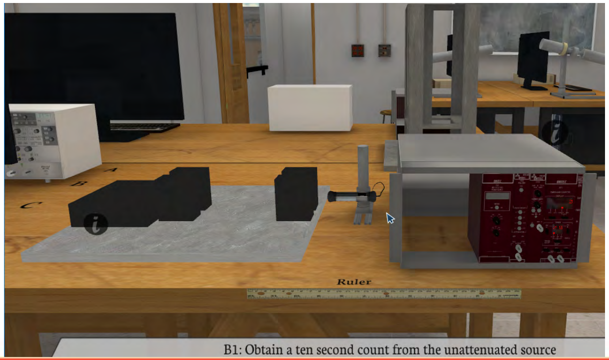


- Display radiation map on demand
- Virtual dosimeter

Where do you want to go?



Thankyou!!

Campus VR Model

MR in Nuclear

- **Headsets can guide a user through collecting radiation measurements**
- **Collected data can be displayed to the user at its location**

Drone Photogrammetry 3D Model Generated in Agisoft Photoscan

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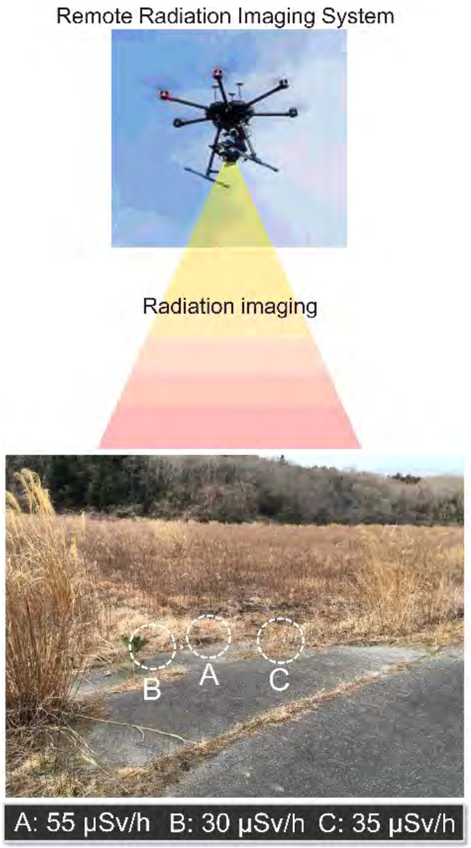
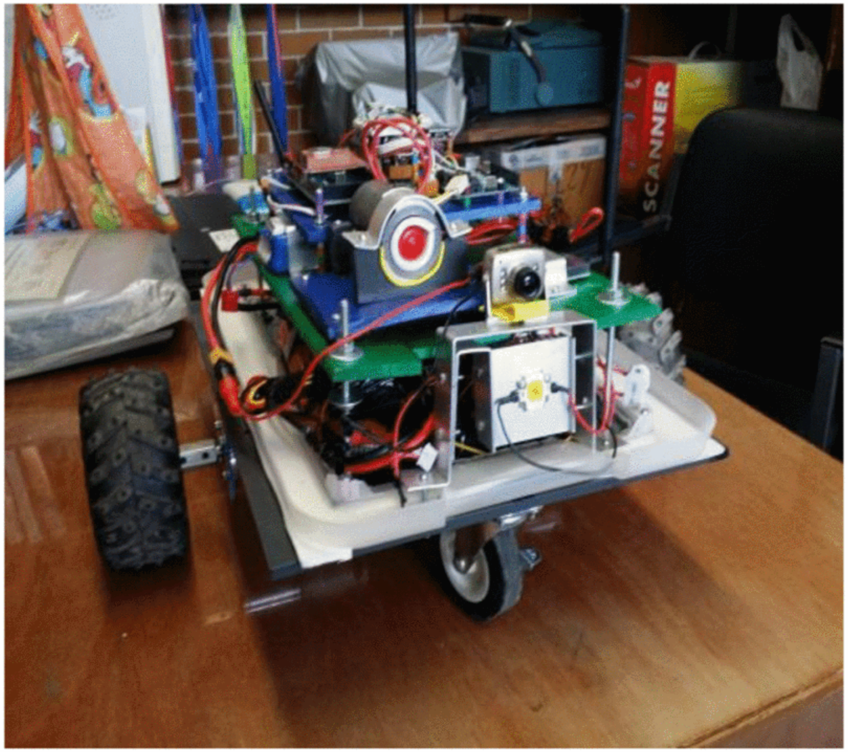
Radiation Measurement Via Drone/Robot



Yuki Sato, Yuta Tanifuji, Yuta Terasaka, Hiroshi Usami, Masaaki Kaburagi, Kuniaki Kawabata, Wataru Utsugi, Hiroyuki Kikuchi, Shiro Takahira, Tatsuo Torii. (2018) Radiation imaging using a compact Compton camera inside the Fukushima Daiichi Nuclear Power Station building. Journal of Nuclear Science and Technology 55:9, pages 965-970.



Vázquez, R. M., & Gutiérrez, E. (2015, November). Mobile robot for gamma radiation detection with long range remote control. In Mechatronics, Electronics and Automotive Engineering (ICMEAE), 2015 International Conference on (pp. 175-180). IEEE.

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Images from:
https://www.oculus.com/

ON-LINE AI/ML & COMPUTATIONAL-MECHANICS BASED PREDICTIVE TOOLS FOR A DIGITAL-TWIN FRAMEWORK

SUBHASISH (SUBH) MOHANTY

Argonne National Laboratory
Nuclear Science and Engineering Division

The results presented are mostly based on research work sponsored through DOE-Light Water Reactor Sustainability Program, US-NRC steam generator tube integrity program and some of the results also based on my PhD thesis work at Arizona State University, sponsored by US Air Force Research Laboratory.

2nd December 2020

Big Picture of a Digital Twin Framework: In context of reactor component structural state & life prediction

Digital-Twin models:

➔ Need to operate in real-time:

To predict the state of structure at a given time.

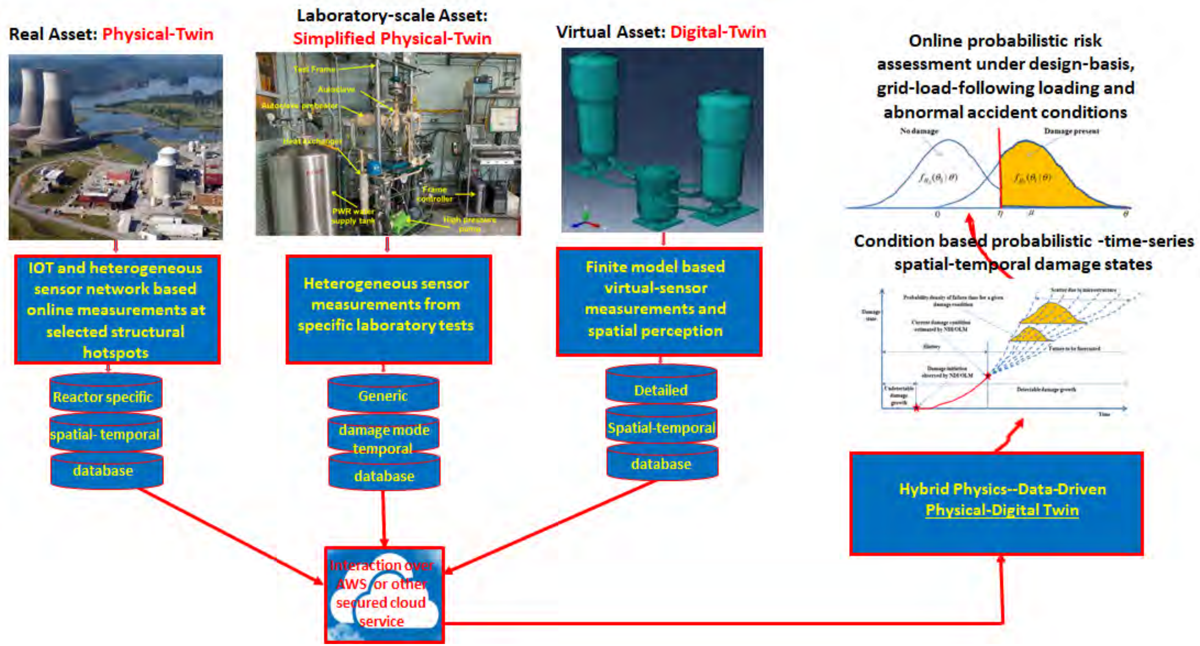
To predict the remaining life of a structure at a given time.

➔ Primarily to be data driven:

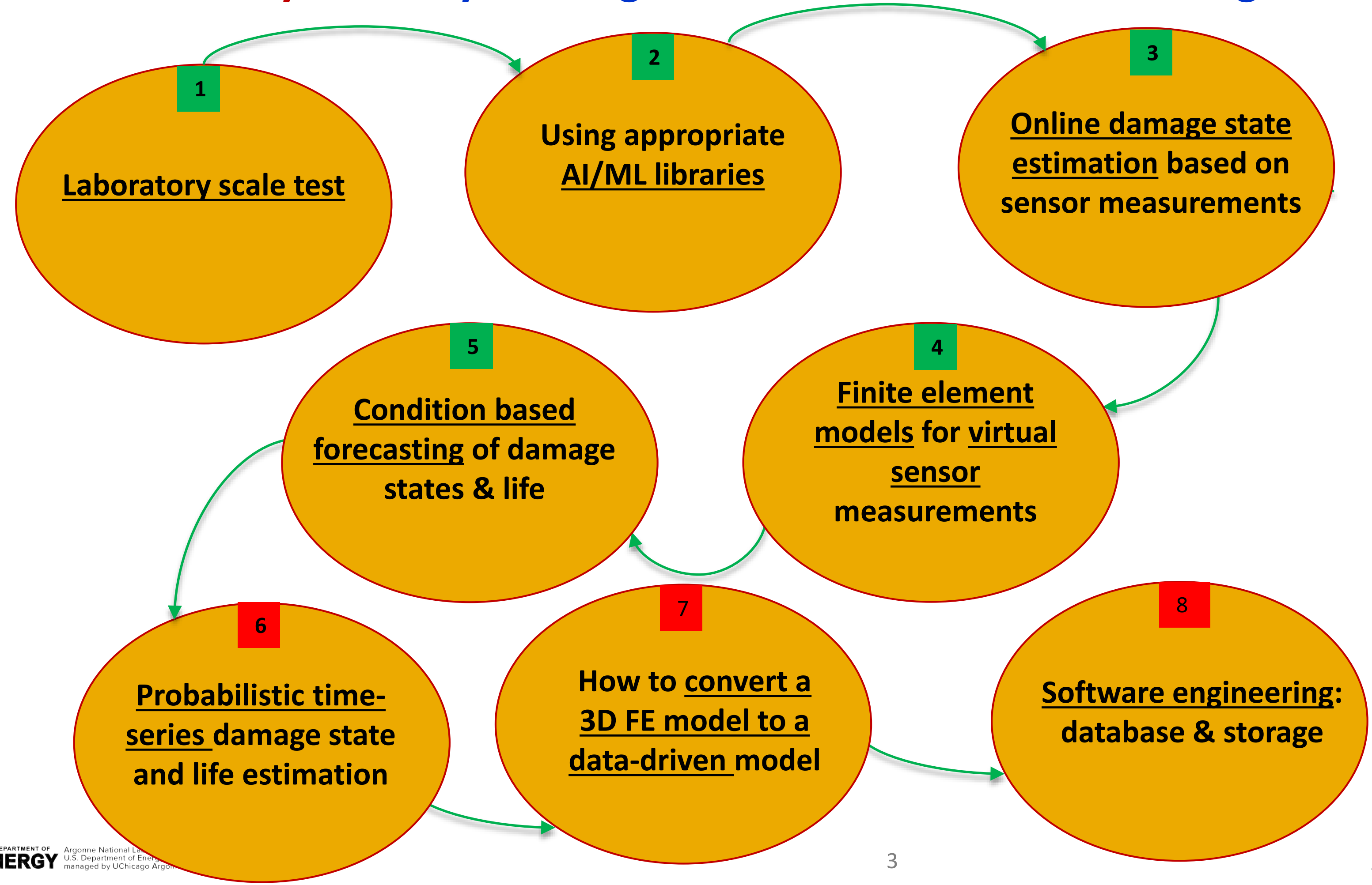
Need historical data.

Either from actual sensor measurements or from virtual sensor measurements (e.g. from physics based finite element model)

What are the source of the data ?



Outline of my talk: Physical-Digital Twin- What are the building blocks?



1

Example results: Laboratory scale test for understanding and modeling the material-damage time evolution over entire fatigue life

Why laboratory scale test important:

➔ Getting data from actual reactor component is not easy due to:

Expensive and inaccessibility
Component currently may not be instrumented
Regulatory hurdles for putting new sensor

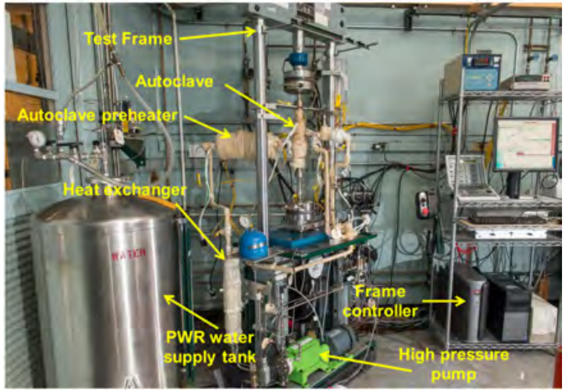
➔ Often getting long duration data is nearly impossible because:

Actual reactor component can have many years of life before failure.

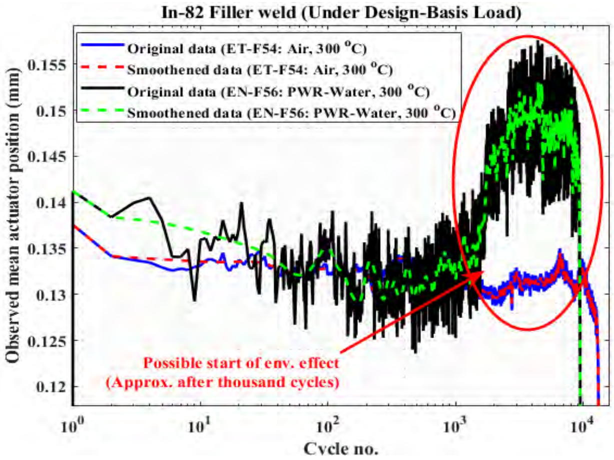
➔ Laboratory scale e.g. fatigue test could generate the required historical data

Inexpensive

Possible to capture different failure modes over entire fatigue life from start to final failure.



🡰 ANL's PWR water test loop



🡰 Comparison of in-air versus PWR-water sensor measurements from fatigue tests (under hundreds of design-basis-loading cycles)

2

Example results: Using appropriate data-driven model & AI/ML libraries

- ➔ Many AI/ML libraries available: such as TensorFlow, Kerras and Scikit-Learn, Apache Spark, Pytorch, Gaussian process, etc.

  # Need exhaustive qualification

- ➔ Many type of model possible with many combinations of input-output mapping

  # Need appropriate selection of input features

  # Need exhaustive qualification of the model

- ➔ Data-driven models are good for modeling unmodellable nonlinear-complex physics, but

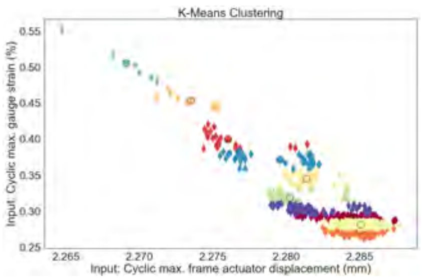
  # Can be sometime disastrous if simply use as a Blackbox

  # Results from model should have some physical sense

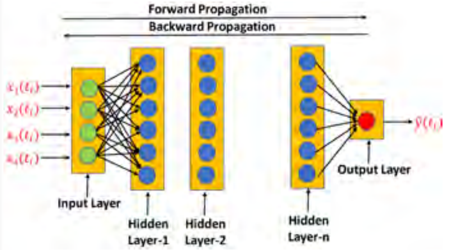
  # Need domain knowledge understanding

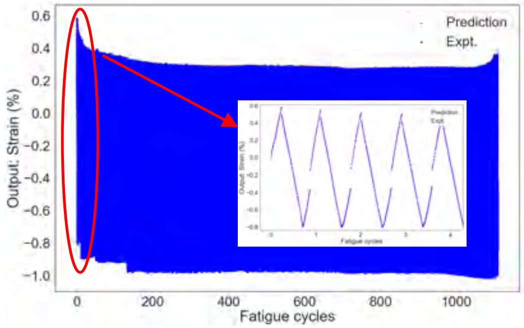
Example of a hybrid Scikit-Learn clustering and Kerras deep-learning based framework for predicting strains from other sensor measurements

Scikit-Learn based K-mean clustering of fatigue test data



Keras based deep learning regression framework



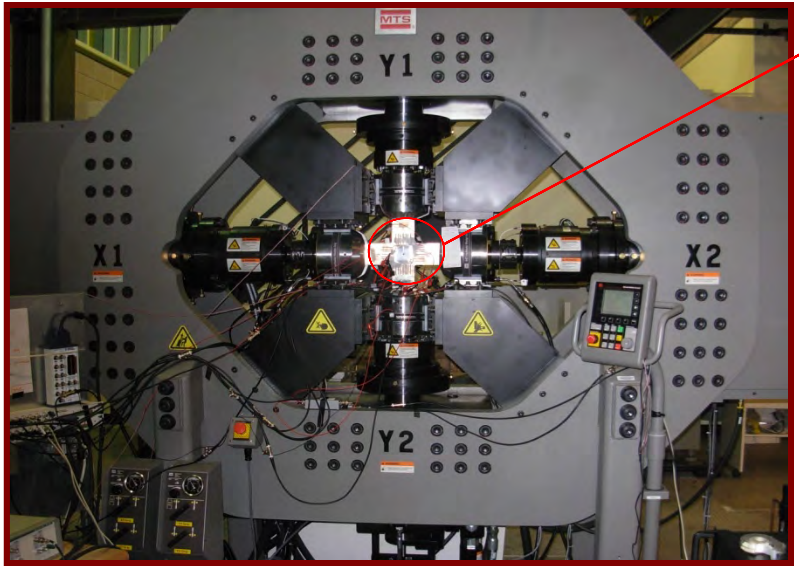


🡐 Prediction of time-series strains subjected to hundreds of fatigue loading cycles.

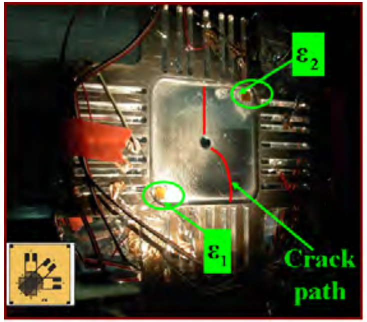
3

Example results: Online damage state estimation based on heterogeneous sensor measurements

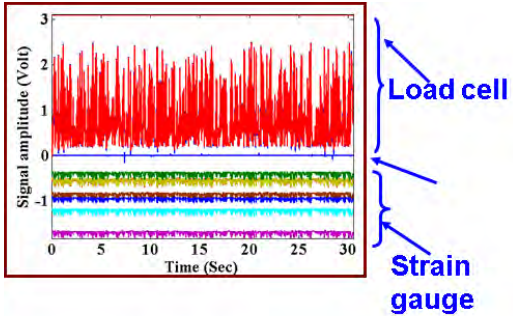
Biaxial test frame (at Arizona state university) with strain-gauge & load-cell measurement based sensor network

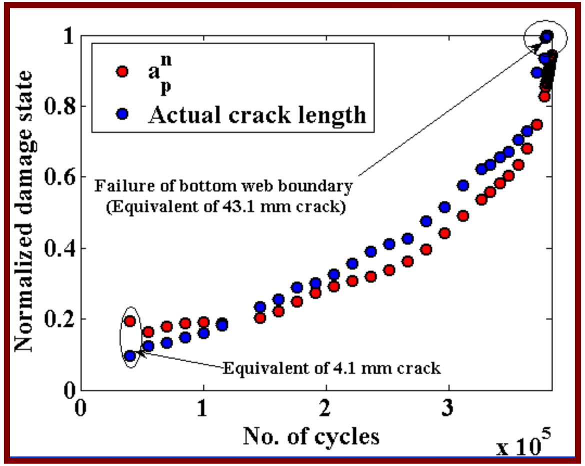


Instrumented cruciform specimen



Heterogeneous sensor measurements from a single loading cycle





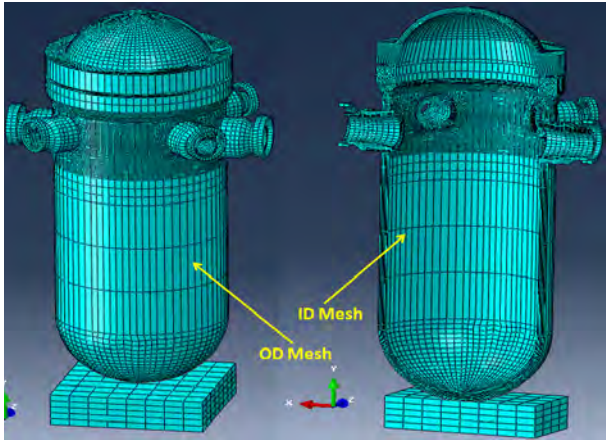
← Online estimated damage states (and their comparison with normalized visually measured crack length) for thousands of fatigue cycle

Note: This slide results are based on my PhD Thesis work at Arizona State University

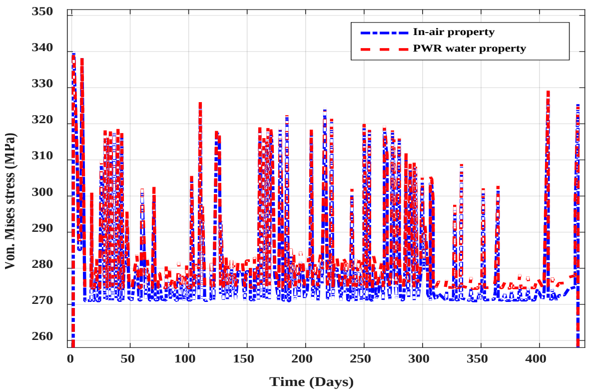
Example results: Physics based finite element model for spatial-temporal virtual sensor measurements

Why physics based model (e.g. 3d FE model)?

- ➔ Structural damage are in general geometry dependent
  - # Need physical measurements at many locations
- ➔ Physical measurements at many locations are not possible
  - # Expensive to put so many sensors
  - # Sometime it is not feasible due to inaccessible locations
- ➔ Developing system level finite element models
  - # not only for predicting the state of the structure at a given time (temporal)
  - # but also for predicting the state of the structure at any given location (spatial)



🡐 Pressure vessel and nozzle assembly finite element model for a two-loop PWR



🡐 Stress states (at a typical ID side location of the hot-leg nozzle) over an entire fuel cycle subjected to grid-following thermal-mechanical loading cycles.

Condition based prognostics of online forecasting of time-series states & life

Why we need condition based prediction ?

➔ Online monitoring and/or NDE

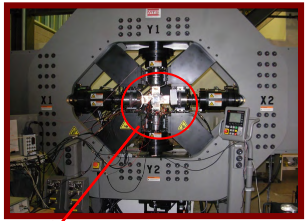
gives the damage state of the structure at a given time.

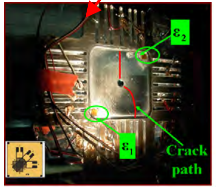
➔ How do we know what is going to happen in future ?

Future structural states at a given time.

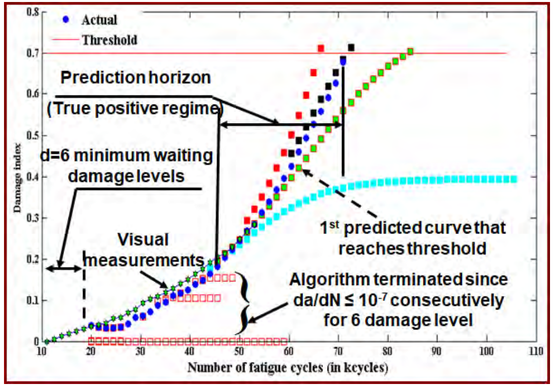
How much life left at a given time.

Strain-gauge instrumented cruciform specimen

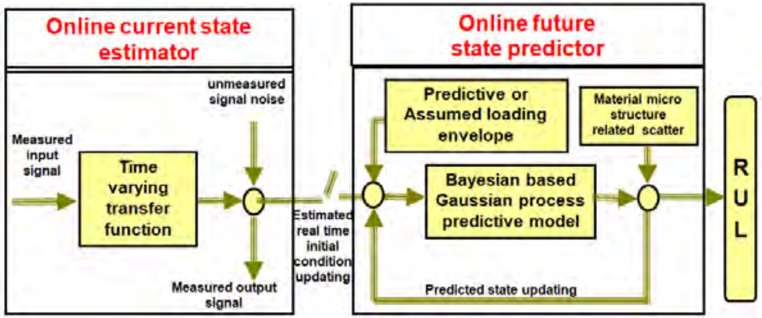




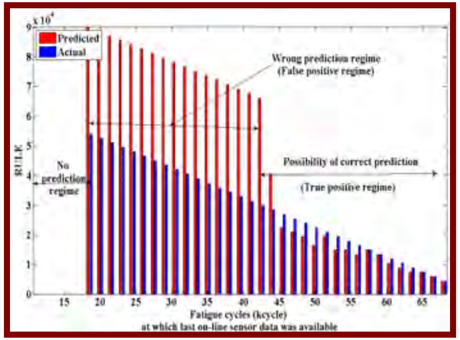
Forecasted states: Correct prediction horizon spans approx. 40% of crack propagation life



Example: Recursive prognostic (physics-guided) model to predict the fatigue damage state of a structure



Forecasted remaining useful life (RUL): Good correlation between prediction and actual RUL in true positive regime



Note: This slide results are based on my PhD Thesis work at Arizona State University

THANK YOU

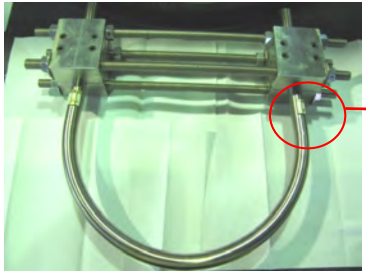
Extra slides

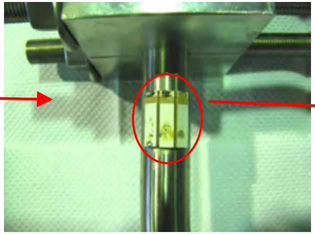
3b

Example results: Types of sensors and sensor network for tracking a particular damage mode (Use of ultrasound sensor for incipient damage tracking)

- ➔ Sensor type selection depends on what type of damage we want to track?
- ➔ How early or severity of the damage to be tracked?
- ➔ Large area damage monitoring and/or few structural hotspots ?

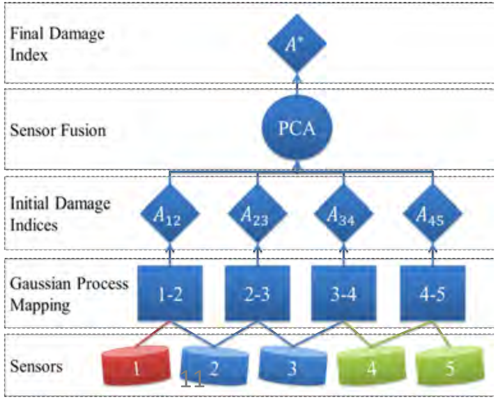
Example online stress-corrosion damage tracking in a steam generator tube using ultrasound sensor network



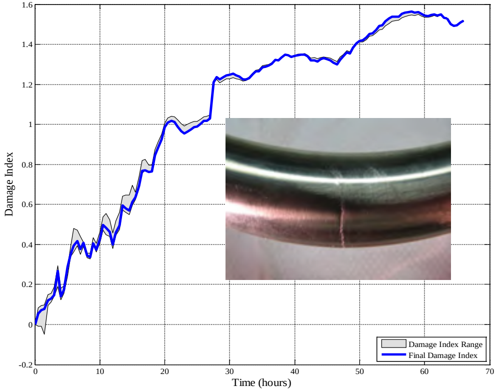


Ultrasound sensor network

Hierarchical sensor network & sensor fusion based damage state estimator



Online estimated damage states and cracked steam generator tube

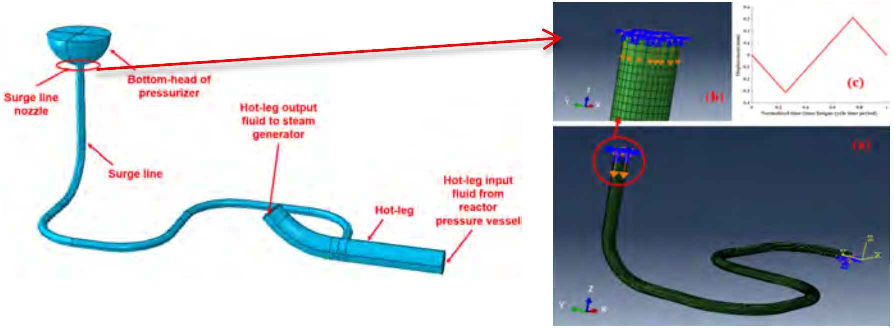


4b

Example results: Physics based component-scale model with time-dependent damage initiation modeling subjected to hundreds of fatigue cycles

- ➔ **Damage evolution in a component is function of:**
  - **# Cyclic hardening/softening**
  - **# Cyclic interaction of loading and environment**
- ➔ **Spatial-temporal time-dependent state of a component can be estimated using cyclic plasticity based finite element model.**
- ➔ **Need HPC based parallel computing for modeling thousands of fatigue cycles.**

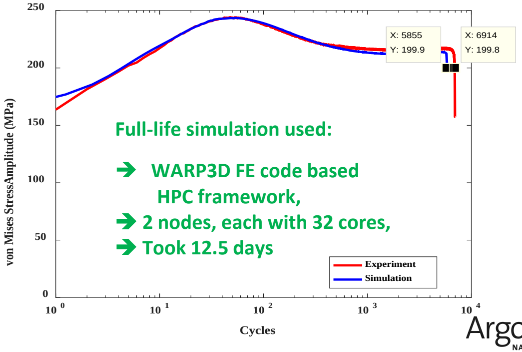
PWR surge-line finite element model



Computation time as a function of CPUs to simulate PWR SL for 10 fatigue cycles using ABAQUS

Number of CPUs	4	8	12	22
Computation time (hr)	25.1	10.3	8.9	3.5

Von Mises stress amplitudes from experiment and simulation.

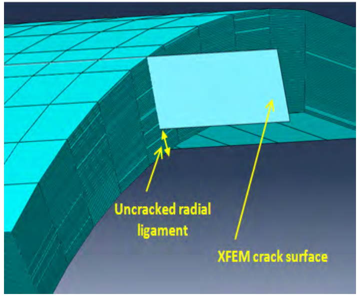


Example results: Physics based component-scale model with time-dependent damage propagation modeling

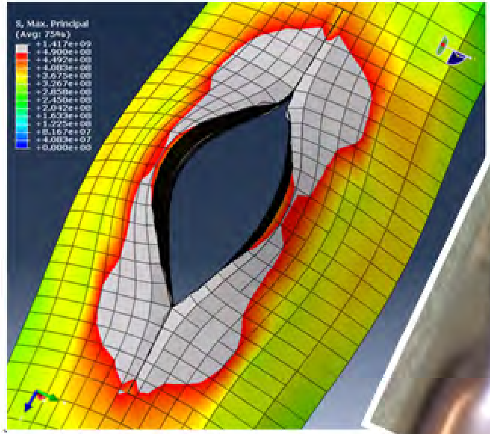
4c

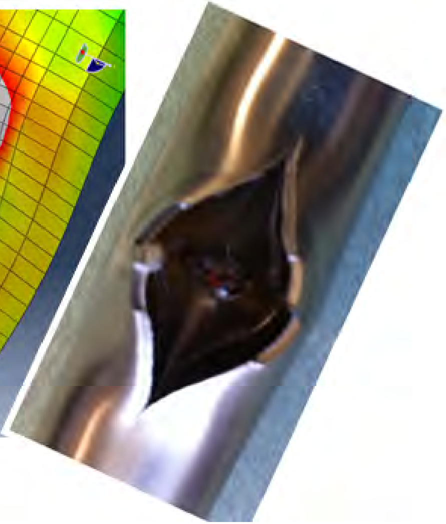
- ➔ Demonstration of time-dependent crack propagation modeling through extended finite element method (XFEM).
- ➔ Steam generator tube (of 1.27mm thick) rupture simulation under severe accident condition.
- ➔ With presence of initial crack:
  - # can be through online measurements
  - # can be from NDE measurements
- ➔ Internal applied pressure : P= 0 to burst.

Initial crack ➔



Extended finite element (XFEM) model simulation vs experiment results of a steam generator tube under severe accident conditions





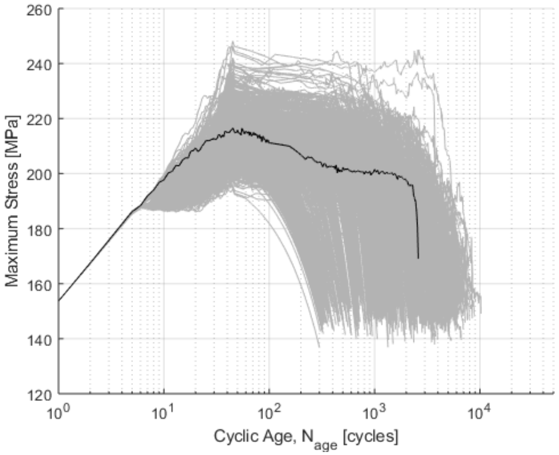
FE → P=40.01 MPa
Expt. → P=41.2 MPa

6

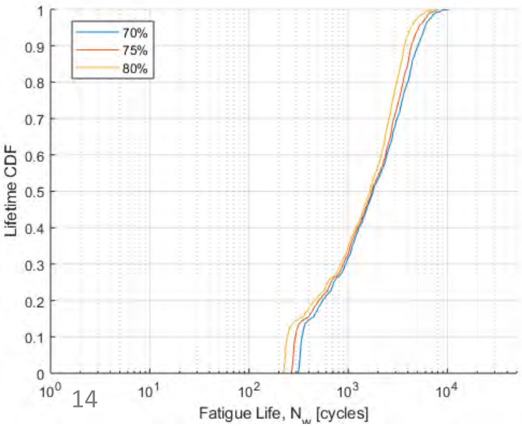
Example results: Probabilistic time-series damage state and life

Why probabilistic model ?

- ➔ **Structural damage are inherently dependent on time-dependent material-damage evolution**
- ➔ **Time-dependent material evaluation are stochastic due to**
  - **# Surface finish of component.**
  - **# Variation in material microstructure.**
  - **# Variation in material interaction with loading and coolant environment.**
- ➔ **Probabilistic models such as Markov-Chain-Monte-Carlo (MCMC) can be used for predicting**
  - **# time-series probabilistic damage states.**
  - **# probabilistic life.**



🡐 Experimentally vs. Markov-Chain-Monte-Carlo (MCMC) simulated maximum stress profiles for a 316 SS test specimen, fatigue tested under PWR-water-coolant environment.



🡐 Corresponding estimated empirical CDF of fatigue lives assuming different failure criterion.

Physics-data-driven model: How to convert a 3D FE model to a data-driven model

Why do we need to convert the FE model to data-driven model ?

➔ For an effective predictive model for a complex 3D geometry, sensor measurements are required from many locations:

Geometry dependency !

➔ Physics-based model e.g. 3D FE model can be a choice for having

Virtual measurements (temporal data) at

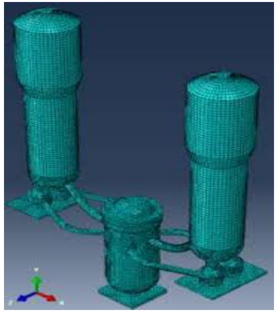
millions of spatial nodal points (spatial data).

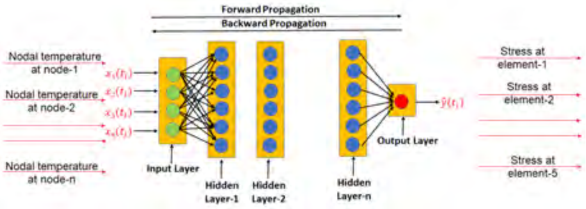
➔ However, FE model are good for offline computation not for online.

Computationally intensive – Software license cost

➔ Then what we do for online model to capture the spatial damage ?

Schematic of AI/ML based FE model data mapping





System-level AI/ML based data-driven model

➔ **Need of parallel AI/ML code/libraries e.g. APACHE Spark to operate with time-series FE data from millions of nodal, elemental and/or integration points**

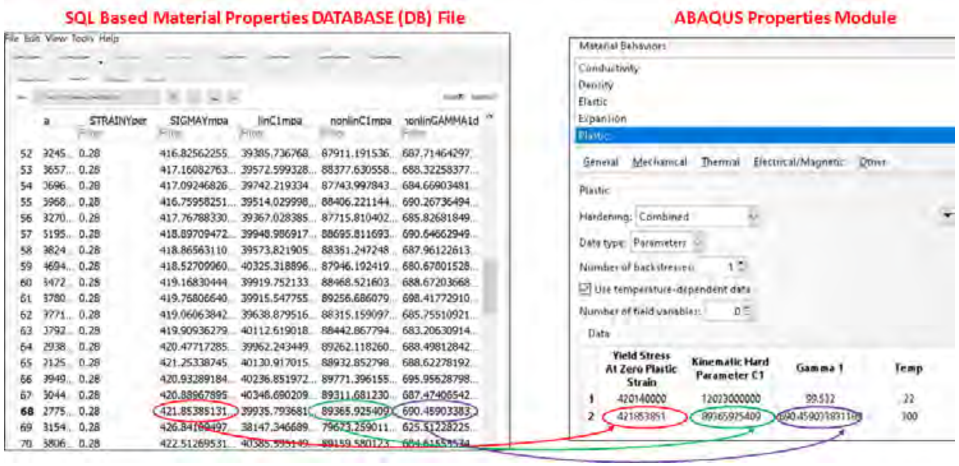
e.g. data = [x1, x2, x3, x4]

distData = sc.parallelize(data)

8 Software engineering: Common database & Interacting over cloud

- ➔ How to store large amount of data from:
  - # Directly from plants: Temporal data
  - # Experiment: Temporal data
  - # FE and/or CFD models: Temporal & spatial data
- ➔ Heterogeneous data source:
  - # Image (Object type database!)
  - # Model parameters and time dependent real/virtual sensor data (Relational database !)
  - # Manual entry data (Unstructured data !)
- ➔ Need commonly used database to explore:
  - # e.g. SQL or NO-SQL
- ➔ Need common place to store the data for largescale multi-organization working on a common goal:
  - # Cloud: AWS, etc.!

Snapshot of the automatically updated SQL based material model database for reactor Digital-Twin model



Qualification of the Pickering A Test Facility

Workshop on Digital Twin Applications for Advanced Nuclear Technologies

Richard Henry (OPG), John Sladek (CNSC) | 1-4 December 2020

Where a brighter tomorrow begins.

Overview

1 | What is the Pickering A Test Facility (PATF) and how is it used?

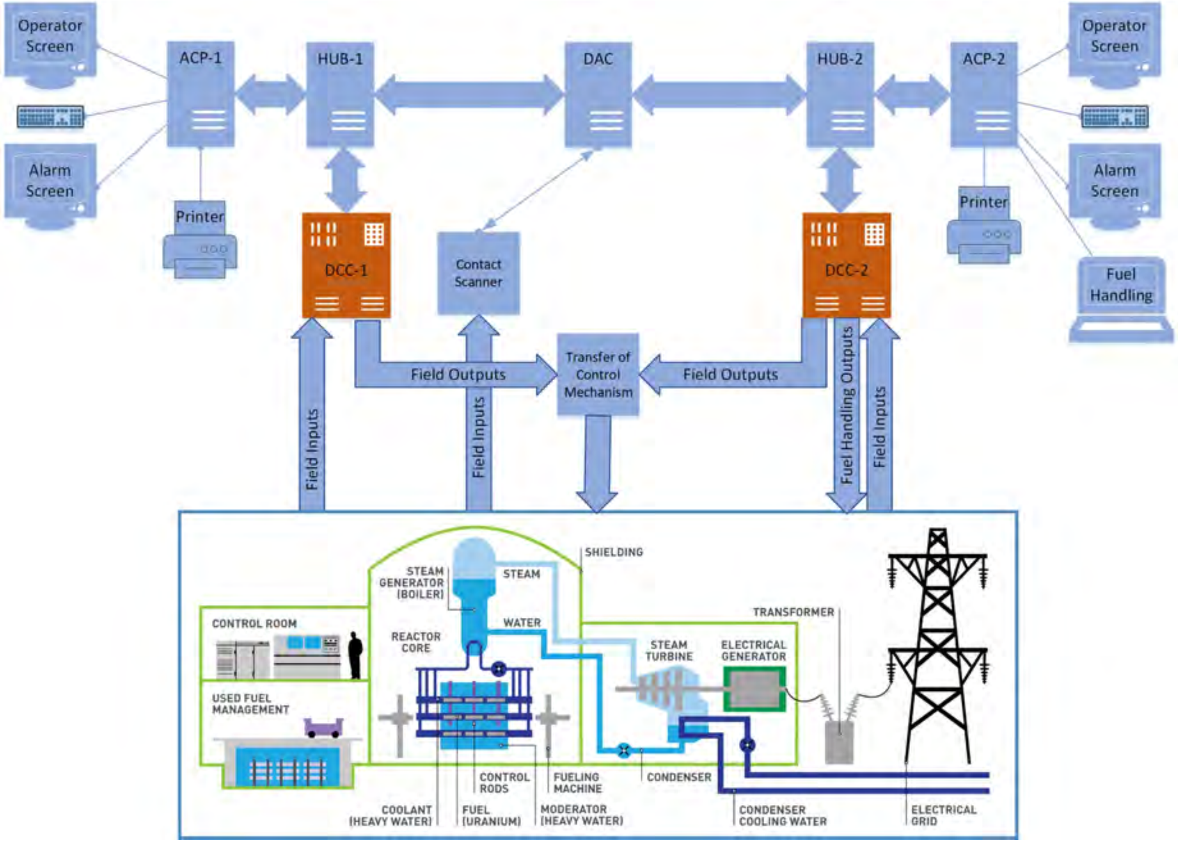
2 | What are the regulatory requirements and process for qualification of Software Tools?

3 | How was the PATF qualified?

Context

- Pickering A 4x540 MW CANDU Pressurized Heavy Water Reactors
  - Placed in service 1971-73. Currently two units in service. Two units in safe store.
- Digital Control Computers (DCC) control major plant processes (Reactor power, Boiler pressure, Online fuel handling)
- Obsolescence issues with legacy test facilities used for software Verification and Validation testing.
- A software-based test facility (digital twin) was developed.
- Qualified September 2011
- Followed existing qualification processes
- No new processes required

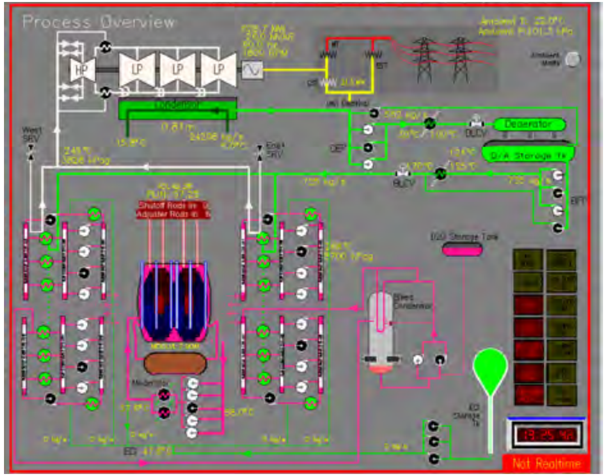
DCC System Context



Pickering A Test Facility Overview

- High-fidelity DCC **Emulation**
  - Function and timing
  - Instructions, peripherals, process input/output, interrupts

- **Simulated** Operator Human Machine Interface
  - Annunciation computer, keyboard and displays
  - Control room panels
- Contact alarm scanner



- Plant **Simulation**
  - Process models
  - Simulated relay logic
  - Simulated stand-alone devices (e.g., PLCs, digital meters)

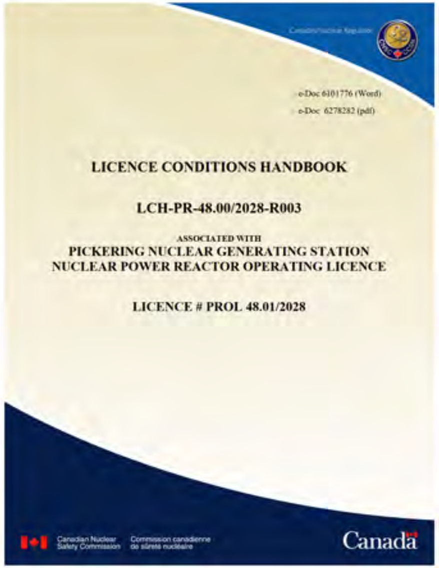
Test Execution for V&V Activities

- **Software engineering tool** used within the development lifecycle
- Test execution controlled by scripting language (Python)
  - Able to control DCC, simulation, etc.
  - Can simulate operator actions (keyboard, panel switches)
  - Can override simulation with substitute values
  - Observe/record process parameters or internal DCC states
- Save and restore "storepoints"
  - Available for all major plant modes of operation (0%-100%FP)
  - Process model state
  - Internal DCC state (memory, disk, registers)
- Allows for development of fully-automated repeatable tests
- Useful for training new staff in DCC fundamentals
- Scenario based analysis of control algorithm changes

```
# Restore 100% full power storepoint
restore('/home/patf/storept/FPSS_ibm1800.stp')
# Set Digital Input 0x41, bit 10 on DCC1 off
# Set Digital Input 0x41, bit 10 on DCC2 off
dcc1.di[0x41].b10=0
dcc2.di[0x41].b10=0
# Print simulated reactor neutron power
print "Starting Power: ", getcdb ('RNTPOW')
# On ACP1, pull up the RRS display and
# decrease reactor power by 10% at rate 3
pace.acp1.keypress("<RRS>")
pace.acp1.keypress("RD3<ENTER><EXECUTE>")
# Run for 30 seconds
run_for (seconds=30.0)
# Print simulated reactor neutron power
print "Ending Power:", getcdb ('RNTPOW')
# Print DCC1 Analog Input @Address /1D01
# in ADC counts and eng. units
print dcc1.ai[0x1D01], dcc1.ai[0x1D01].eng
# Display core location 0x1800
print dcc1.core [0x01800]
# Print dcc registers A, Q and I
print dcc1.a, dcc1.q, dcc1.i
```

Regulatory Requirements for Software QA

- The Pickering Nuclear Generating Station License and Condition Handbook (Effective 17 April 2020):
  - "The licensee shall implement and maintain a **management system**"
    - Licensing basis publication: CSA N286, NPP **QA Program Requirements.**
    - Compliance Verification Criteria include:
      - OPG N-CHAR-AS-002, *Nuclear Management System,*
      - OPG N-PROG-MP-0006, ***Software***
  - "The licensee shall implement and maintain a **design program**."
    - Guidance: N290.14, ***Qualification of Digital Hardware and Software*** *for Use in Instrumentation and Control Applications for Nuclear Power Plants*
  - "The licensee shall implement and maintain a **safety analysis program.**"
    - Guidance: N286.7, *Quality assurance of analytical, scientific and design computer programs for nuclear power plants*



Software Qualification

- N-PROG-MP-0006, *Software*, defines processes for all types of software including,
  - <u>Software Engineering Tools</u> follows OPG N-STI-69000-10002, *Qualification of Software Engineering Tools*
    - This is key to the qualification of PATF for the use case for V&V of software
    - Testing requirements based on categorization of **Target** software (RTPC or SESA)
  - Real Time Process Computing (RTPC). QA Requirements based upon software classification:

Organizations or Countries	Safety Classification of I&C Functions and Systems in nuclear plants			
United States	Systems Important to Safety			(not specified)
	Safety-Related	5		
Canada	Category 1	Category 2	Category 3	Category 4

http://www.world-nuclear.org/uploadedFiles/org/WNA/Publications/Working_Group_Reports/safety-classification-for-iandc-systems-in-npps.pdf

  - Scientific, Engineering and Safety Analysis (SESA) software follow CSA N286.7 QA requirements

N-STI-69000-10002

- Qualification requirements for software engineering tools:

  *Software engineering tools are those used to **support any aspect of the software engineering lifecycle**, including: requirements gathering and specification; design and code production; review and static verification of requirements, design and code; **test case generation, execution, and results analysis**; configuration management and change control; and training.*

- Method

1. Identify target software classification and categorization
2. Select tools
3. **Determine impact severity of tool failure**
4. **Determine mitigating circumstances**
5. **Select a qualification approach**
6. Perform qualification activities
7. Configuration management of software engineering tools
8. Software engineering tool qualification report

Determine Severity of Tool Failure

- Guidance: “Consider the failure modes for **each use** of the **software engineering tool**, and identify the relevant failure effects on the target software. Classify each failure effect based on its potential impact on the safety, functional, reliability, performance or security requirements of the target software.”
- Classification Scheme:

Failure Type	Description
Direct	the tool is incorporated in the target application. Tool is to be considered pre-developed software and qualified to the same degree of rigor as the target software.
Indirect-Causal	Tool failure can introduce errors in the target software which if undetected could result in the target software failing to meet the above requirements.
Indirect-Preventive	A tool failure effect can result in the non-detection of errors in the target software which could result in the failure of the target software to meet the above requirements.
Minimal	A tool failure could have an impact on the target software but no mechanism has been identified that could result in the target software failing to meet the above requirements.
No Impact	A tool failure can have no impact on the target software in meeting the above requirements.

Identify and Classify Mitigations

- Identify any mitigations that eliminate or reduce the impact of the failure effect.
- Classify mitigations as one of the following:

Class	Description
None	
Single	**Single** reliable mitigating activity or procedure which defends against impact. Must be independent of the failure effect (efficacy of mitigation not diminished or nullified by the failure effect). **Examples**: Testing, review, checksum comparison
Multiple	**Multiple** reliable mitigating activities or procedures which defend against impact. Must be independent of the failure effect. Must be independent of each other (having no other common failure mechanism) **Example**: Review of outputs by two independent individuals using different methods.

Determine Qualification Approach

- Qualification grade is determined based upon:
  - **Target** software classification and categorization
  - Impact severity of tool failure
  - Mitigations
  - Result is: **NSR2, NSR3, O**, and **A**
- Qualification method is based on grade
  - **NSR2 / NSR3**: Follow RTPC Category II/III qualification method (e.g., CSA N290.14)
  - **A**: Follow SESA qualification method (e.g., CSA N286.7)
  - **O**: Select qualification method from. For example:
    - Acceptance testing
    - Widespread industry usage (for same purpose)
    - Operating history from third party

Results for PATF

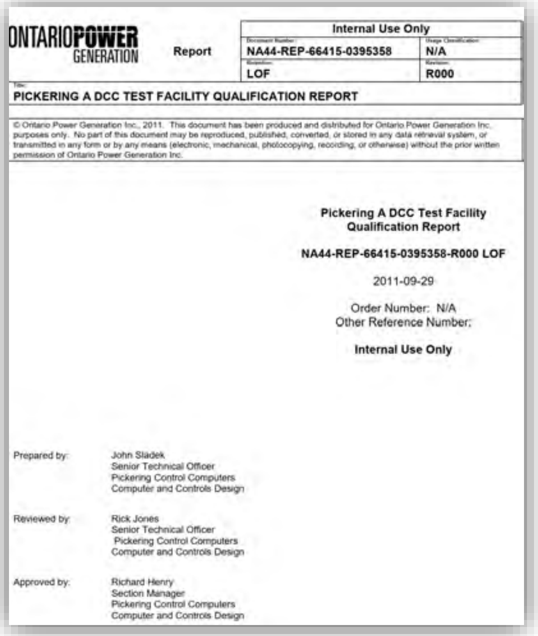
- Target Software Classification and Categorization: System is used for testing of DCC software which is Categorized. → **Category 2.**
- Impact: failure of the software test tool could result in non-detection of errors in the target software. → **Indirect-Preventive**
- Mitigation:
  - Several sets of tests are performed by independent individuals (e.g., unit testing, subsystem testing, integration testing and validation testing)
  - However, some of these tests could all potentially make use of the PATF, so there could be a common failure in the mitigating activities. → **Single**
  - Qualification approach is "**O**" (as per lookup table)
  - Qualification method selected to be "Acceptance Testing"

Table 3.5-1
Qualification Grade

Software Categorization and Classification	Impact of Failure Effect	Mitigating Circumstances		
		None	Single	Multiple
Nuclear Safety Related Category I	Direct	See Note below		
	Indirect-Causal	NSR2	NSR3	O
	Indirect-Preventive	NSR3	O	O
	Minimal	O	O	O
Nuclear Safety Related Category II	Direct	See Note below		
	Indirect-Causal	NSR3	O	O
	Indirect-Preventive	O	O	O
	Minimal	O	O	O
Nuclear Safety Related Category III	Direct	See Note below		
	Indirect-Causal	O	O	O
	Indirect-Preventive	O	O	O
	Minimal	O	O	O
Scientific, Engineering and Safety Analysis	Direct	See Note below		
	Indirect-Causal	A	O	O
	Indirect-Preventive	A	O	O
	Minimal	O	O	O
Common Grade	Direct	See Note below		
	Indirect-Causal	O	O	O
	Indirect-Preventive	O	O	O
	Minimal	O	O	O

Acceptance Testing of PATF

- PATF development team had extensive experience with qualification of DCC hardware and with the software QA processes
  - DCC's previously replaced with hardware emulators (1995-2001)
- Qualification tests focused on:
  - Quality of emulation:
    - Included execution of all OEM diagnostics
    - Test cases for DCC features, based on OEM documentation
  - Test cases to test all features of scripting language
  - Testing of integration of Emulated DCC with plant simulation
  - Testing of transfer of control mechanism
- Qualification tests were implemented using scripting language
  - Simplified qualification testing of a new release of PATF in 2014



ONTARIOPOWER GENERATION

Report

Internal Use Only

Document Number:	NA44-REP-66415-0395358	Usage Classification: N/A
Sheet Number:	LOF	Revision: R000

Title: PICKERING A DCC TEST FACILITY QUALIFICATION REPORT

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Pickering A DCC Test Facility Qualification Report

NA44-REP-66415-0395358-R000 LOF

2011-09-29

Order Number: N/A
Other Reference Number:

Internal Use Only

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ONTARIO POWER GENERATION

Where a brighter tomorrow begins.

Nuclear Virtual Engineering Capability

Dr. Albrecht Kyrieleis

NUCLEAR VIRTUAL ENGINEERING CAPABILITY

Department for Business, Energy & Industrial Strategy

NATIONAL NUCLEAR LABORATORY
Rolls-Royce
Jacobs
VIRTUAL ENGINEERING CENTRE
EDF ENERGY
NUCLEAR AMRC

Jacobs
Challenging today.
Reinventing tomorrow.

Agenda

- Context for NVEC
- NVEC elements
- Case studies
- Future developments

The Nuclear Innovation Programme

NUCLEAR VIRTUAL ENGINEERING CAPABILITY

~£30M (Apr 18 – Apr 20) ~£150M (Apr 20 – Apr 21)

	Research Theme	Apr 18	Apr 19	Apr 20	Apr 21
Advanced Fuels	Accident Tolerant Fuels				
	Coated Particle Fuels				
	Pu containing fast reactor fuels				
	Reactor physics				
	Nuclear Data				
Reactor Design	Thermal hydraulic model development				
	Thermal hydraulic facility development				
	Reactor safety and security				
	Virtual engineering				
	Modelling and simulation				
Spent fuel recycle	Development of proliferation resistant spent fuel recycle technology				
Materials and Manufacturing	Materials testing and development				
	Advanced component manufacturing				
	Large scale manufacturing / assembly				
	Prefabrication module development				
	Codes and standards				
Nuclear facilities and strategic toolkit	Strategic assessments				
	Fast reactor knowledge capture				
	Regulatory engagement				
	Access to irradiation facilities				
Advanced Modular Reactors	Feasibility Study				
	Design Development				

Challenge

- Innovative nuclear power plants needed to meet the UK Government commitment of net zero carbon emissions by 2050
- By 2030 deliver
  - Cost savings of 30% on new build, 20% on decommissioning
  - £2bn domestic and international contract wins

- 'Silo' practices
- Information sharing
- Innovation
- Cost management

The NVEC Partnership

- Jacobs Lead
- Wider partners include: Digital Catapult, University of Bangor, University of Bristol, EvoMetric
- Collaboration includes: UKAEA, Fraser-Nash, Sellafield Ltd, Menai Science Park

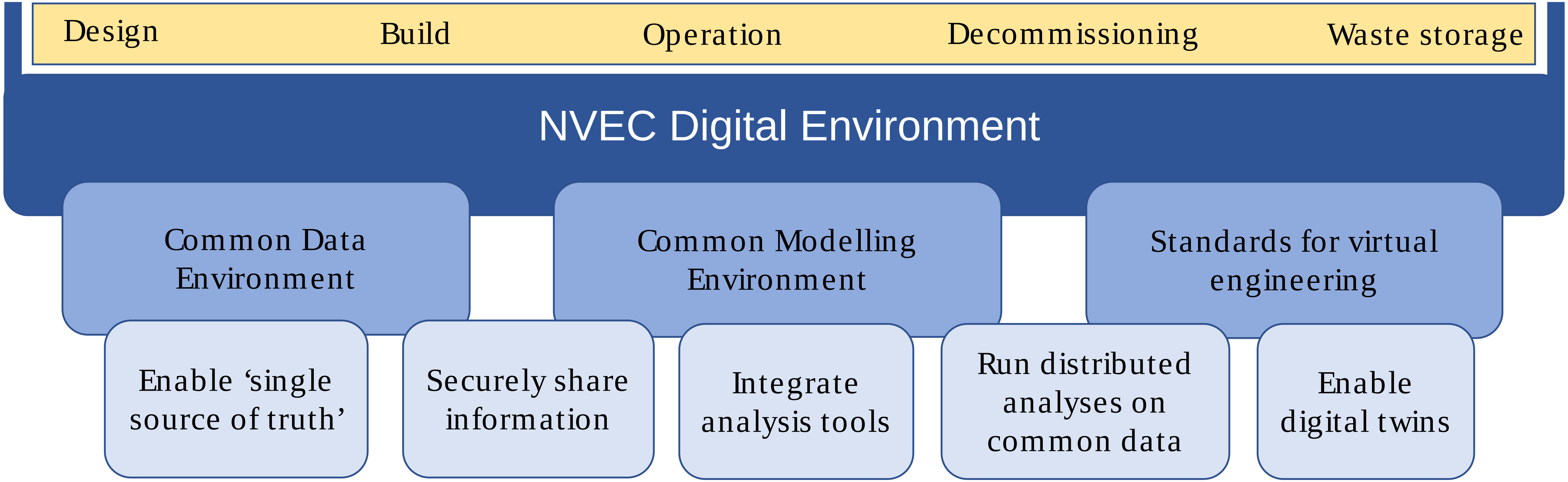
NVEC Elements

- Develop collaborative digital environment to support the nuclear life cycle
  - Use existing technology where possible
  - Open and highly flexible
- Develop operating model, standards and guidance
- Demonstrate benefits of digital environment in various case studies
- Involve stakeholders
- Early adoption

- Develop 'community' which can assume responsibility for
  - issuing **guidance**, maintaining **standards**,
  - discussing and **resolving common technological issues**
  - ensuring a **common approach** across the sector

NVEC Phase 2 Environment

NUCLEAR VIRTUAL ENGINEERING CAPABILITY



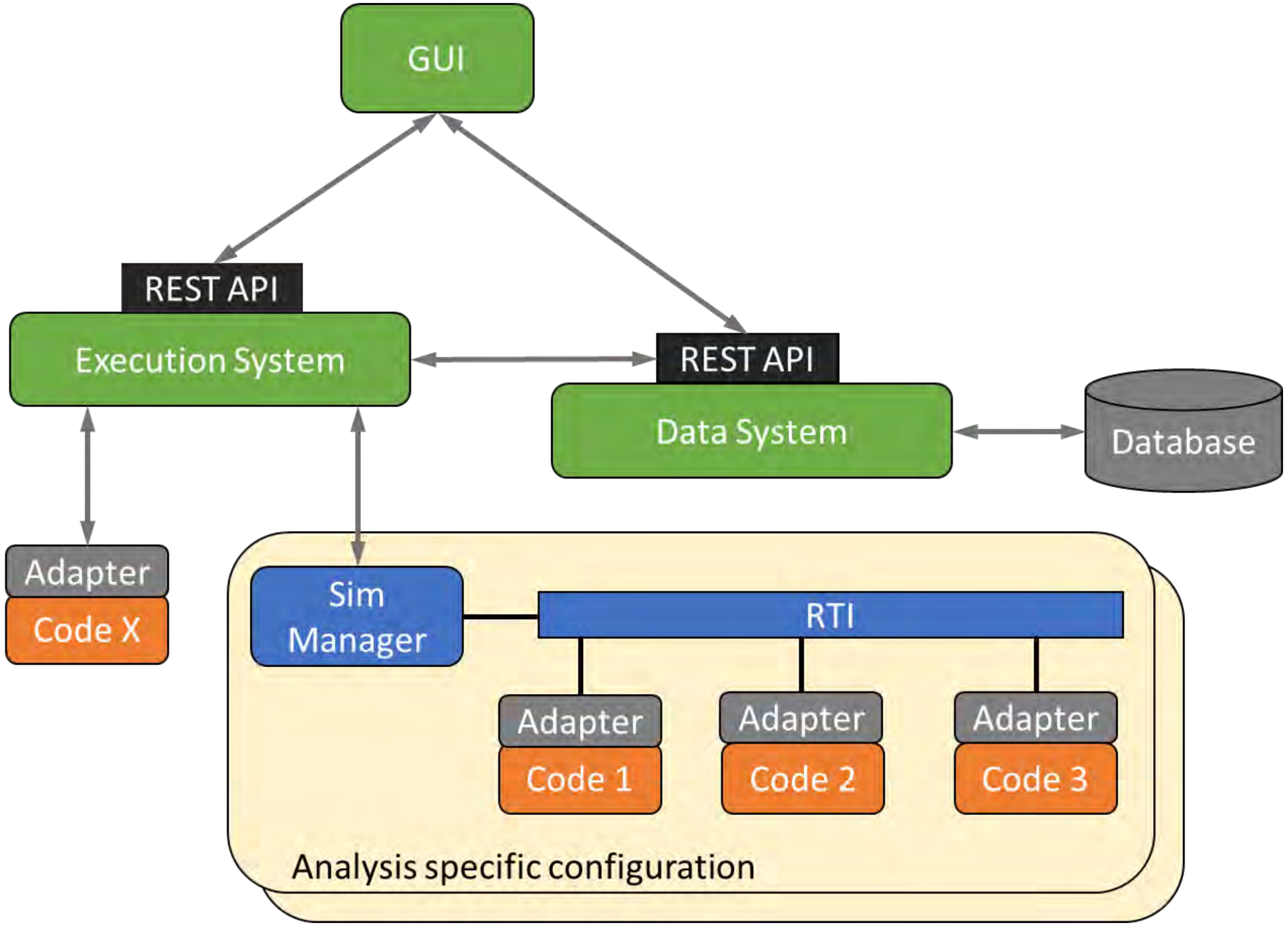
Benefits

NUCLEAR VIRTUAL ENGINEERING CAPABILITY

- Reduced costs
  - Single source of design data; collaborative environment
  - Increased return on investment through efficient operation & maintenance
  - Lower risk leading to reduction in financing costs
- Shortened development times
  - Efficient Design & licensing ; Integrated multi-physics approach
  - More reliable prediction of development times, allowing better synchronisation
- Enhanced credibility, operability, reliability & safety
  - Real time understanding of plant, better planning and predictive maintenance
  - Enhanced training & skills development
  - Reduced risk and perception of risk
- Cross-discipline transfer of expertise; joined-up industry
- Enables innovation and new technology adoption; diverse users

Architecture

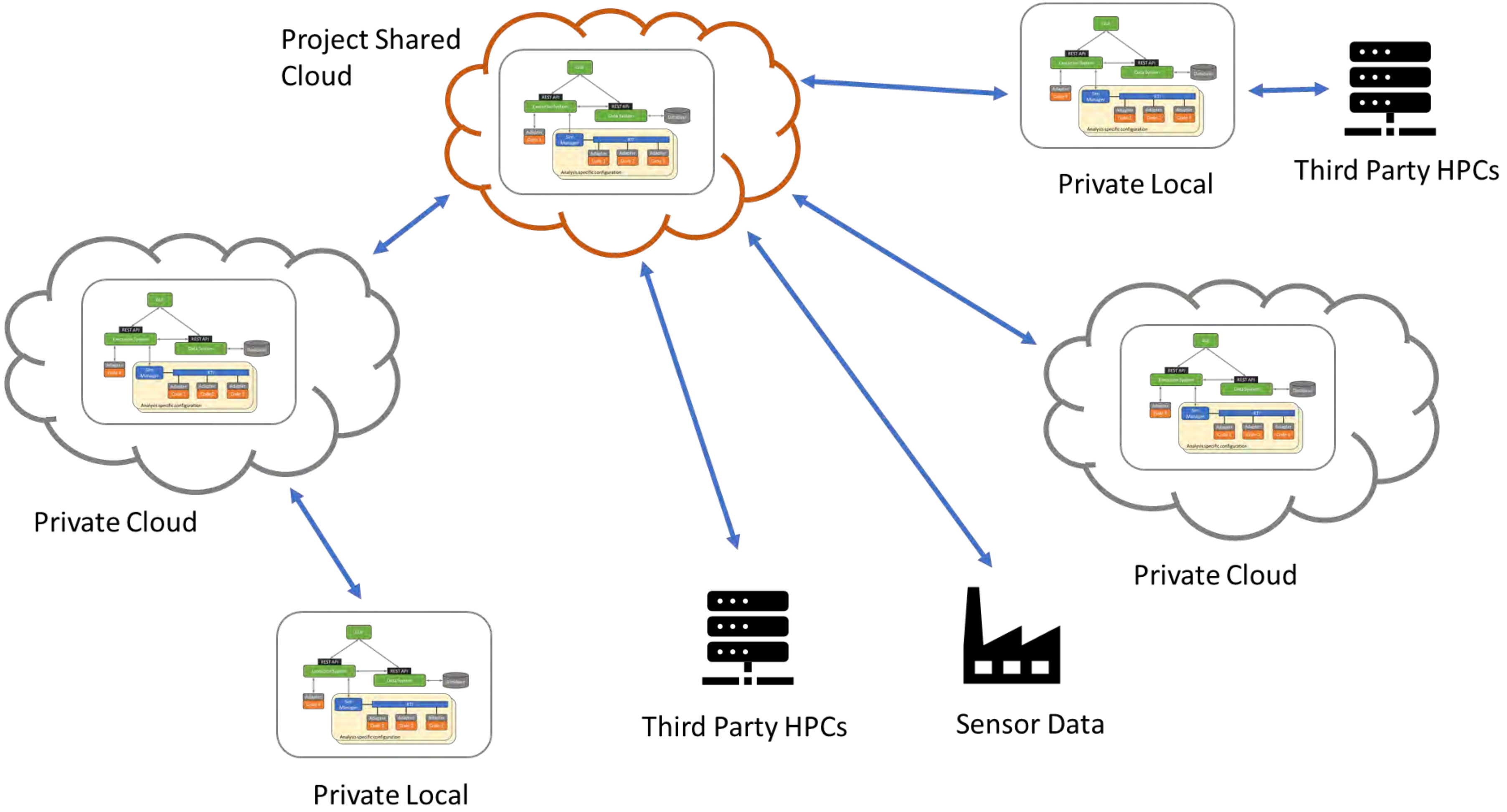
NUCLEAR VIRTUAL ENGINEERING CAPABILITY



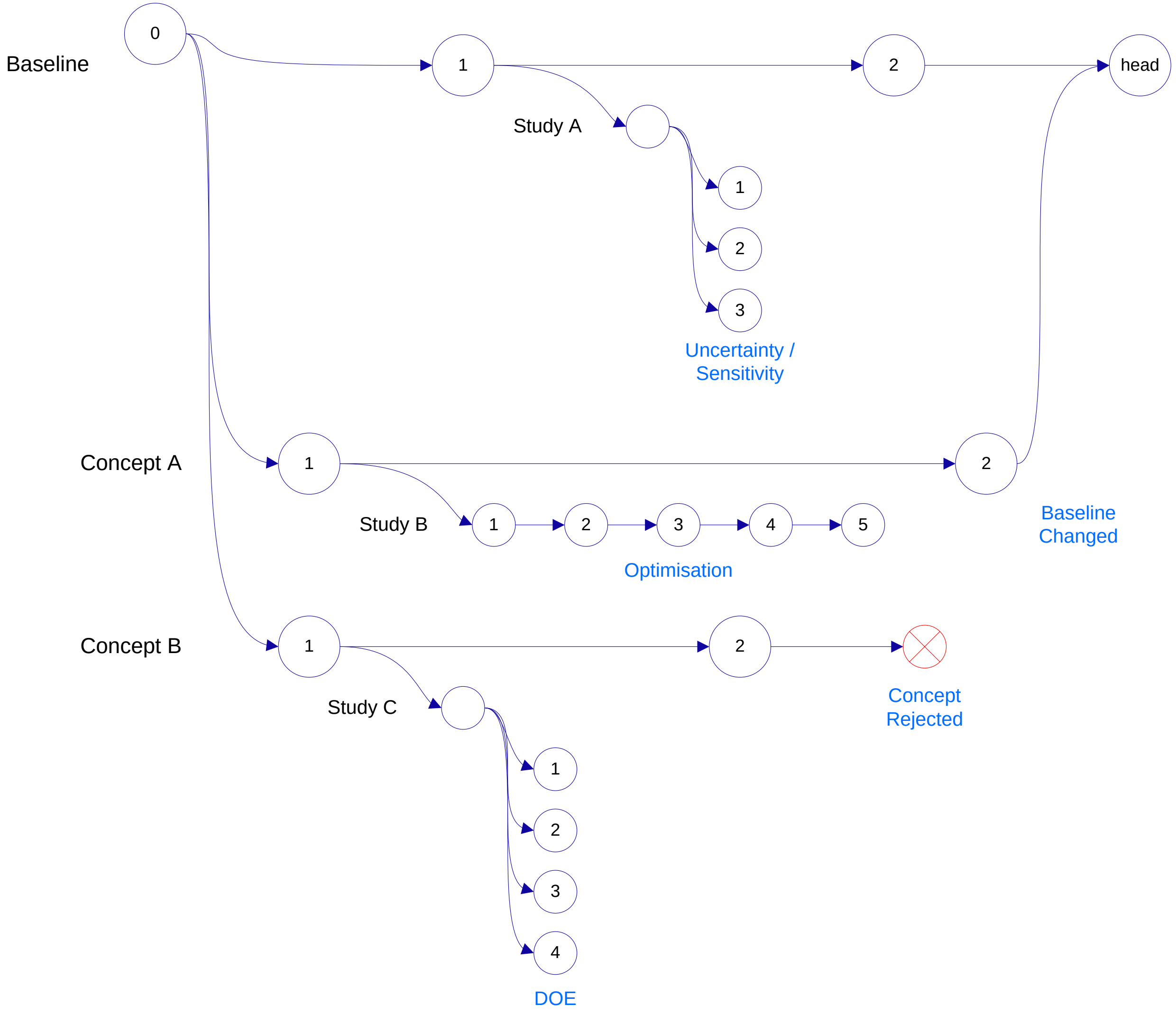
Status

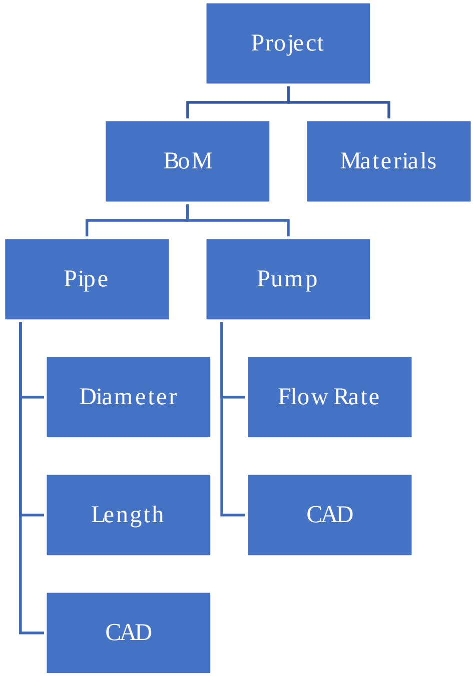
- Initial implementation of all components complete
- Continuous improvement
- Deployed on different systems
- Application to various cases on-going

Networked Architecture



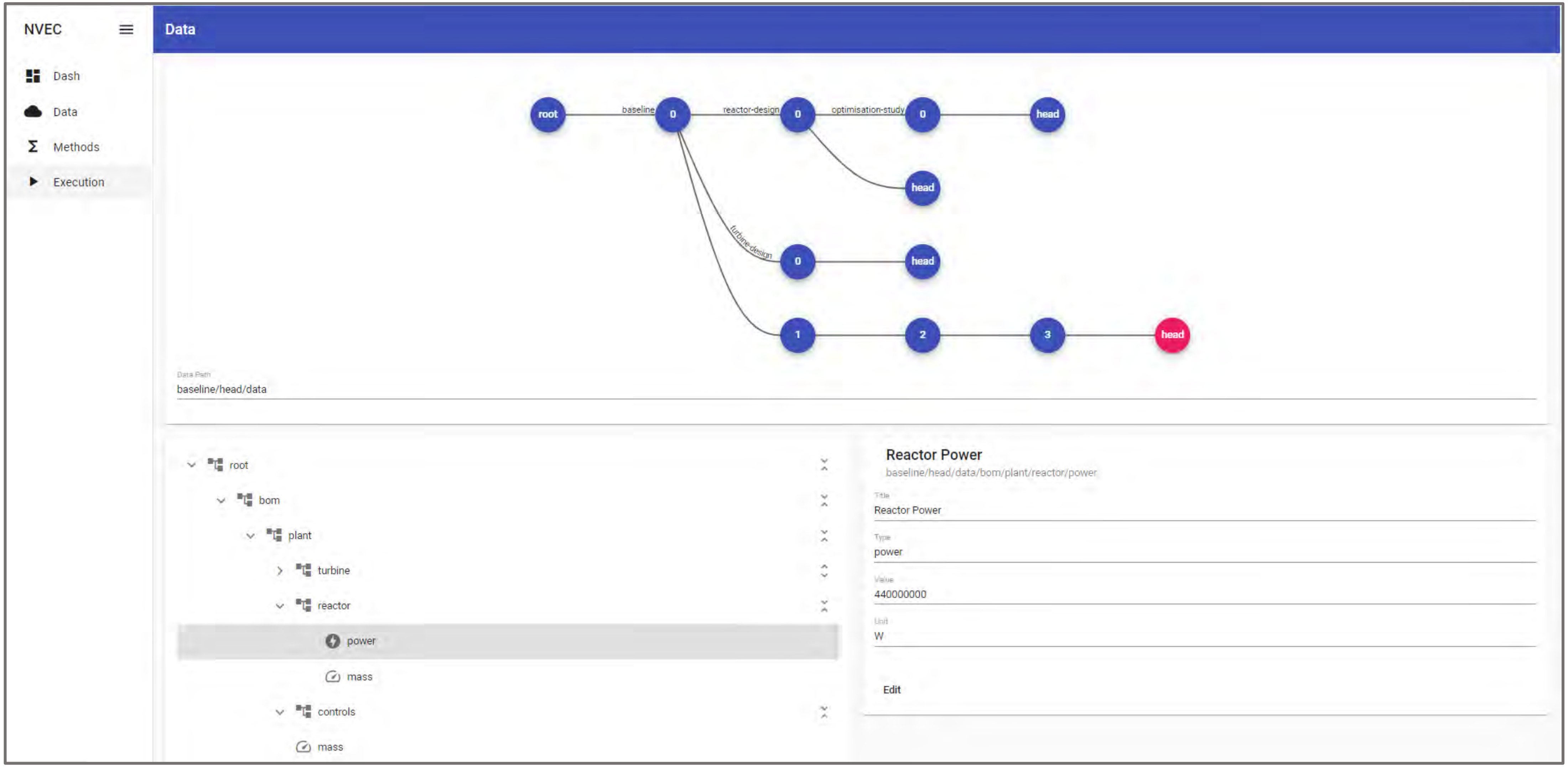
Change Control using the Data System





Graphical User Interface

NUCLEAR VIRTUAL ENGINEERING CAPABILITY



NVEC Multi-Scale Simulation

NUCLEAR
VIRTUAL
ENGINEERING
CAPABILITY

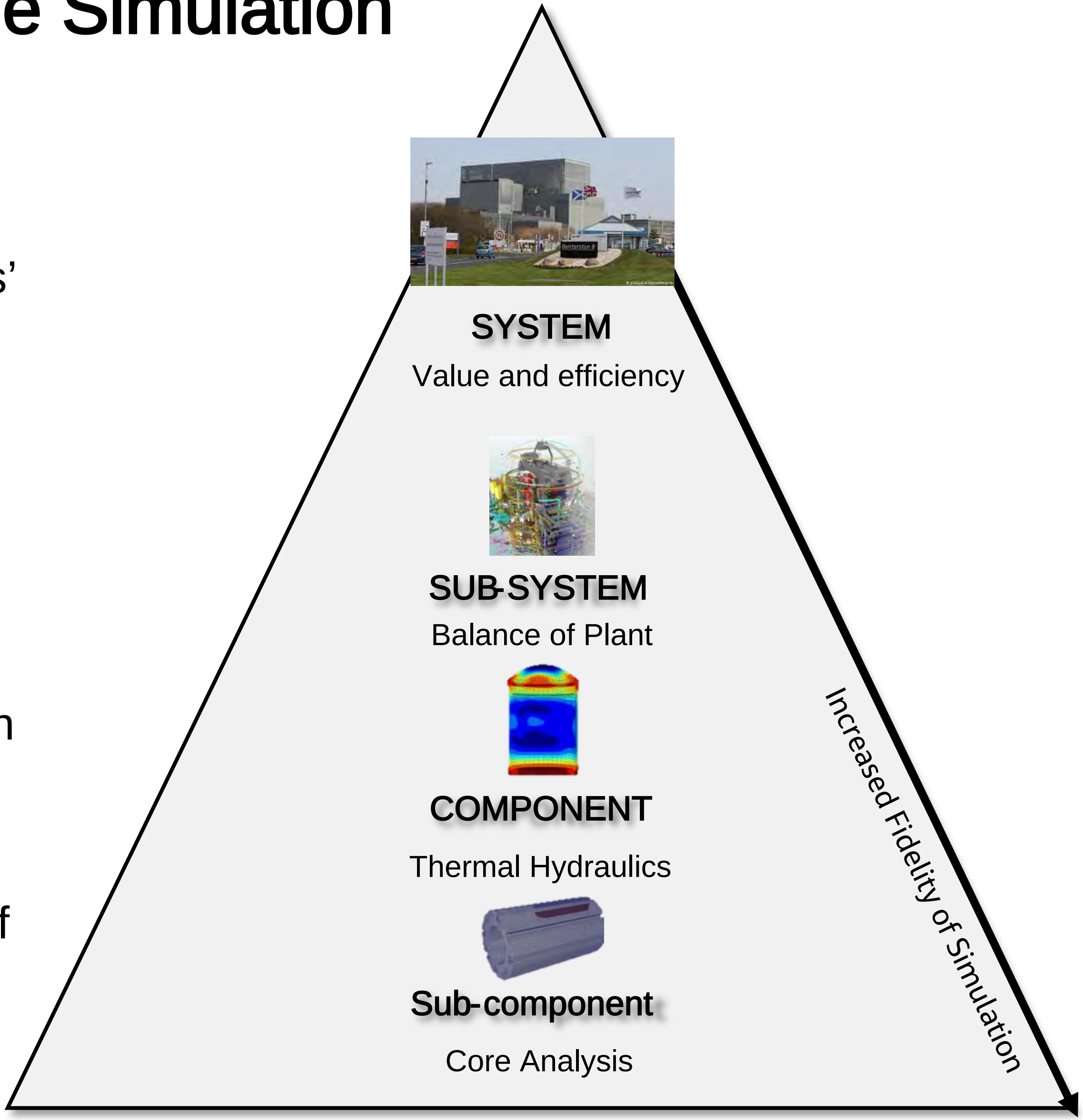
Features

Break down ‘model into hierarchy of components’

‘Equation Orientated’ modelling approach or dedicated code

Code coupling via ‘plug and play’ modular design

Scalable to allow deployment in a range of applications



Benefits

Single tool can analyse many different designs with few changes

Rapid turn-around from concept to outcome from an analysis

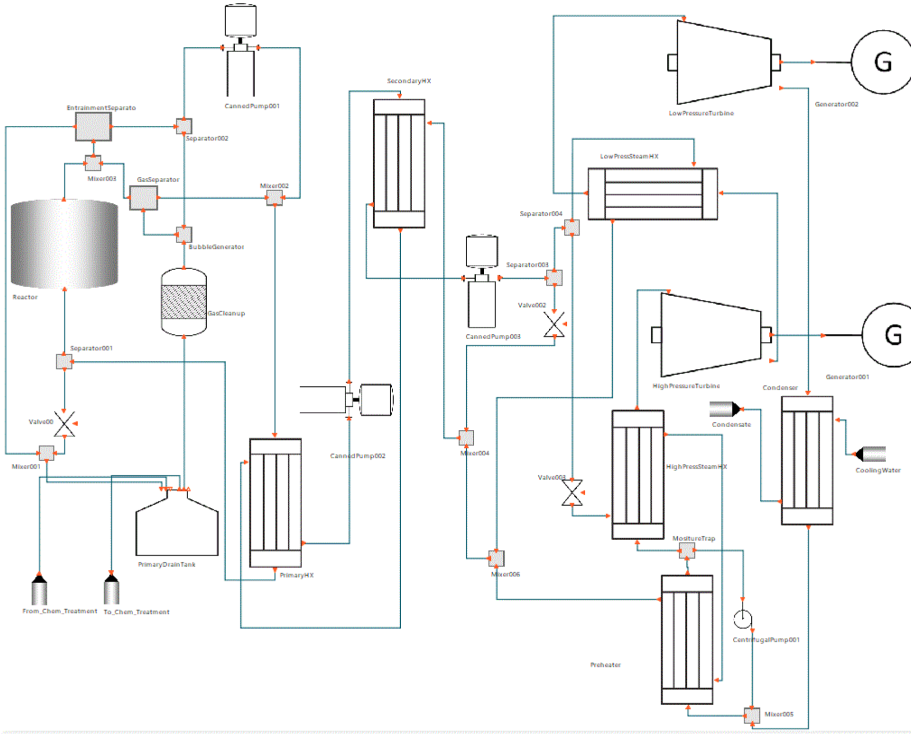
Detailed component analysis via dedicated code where required

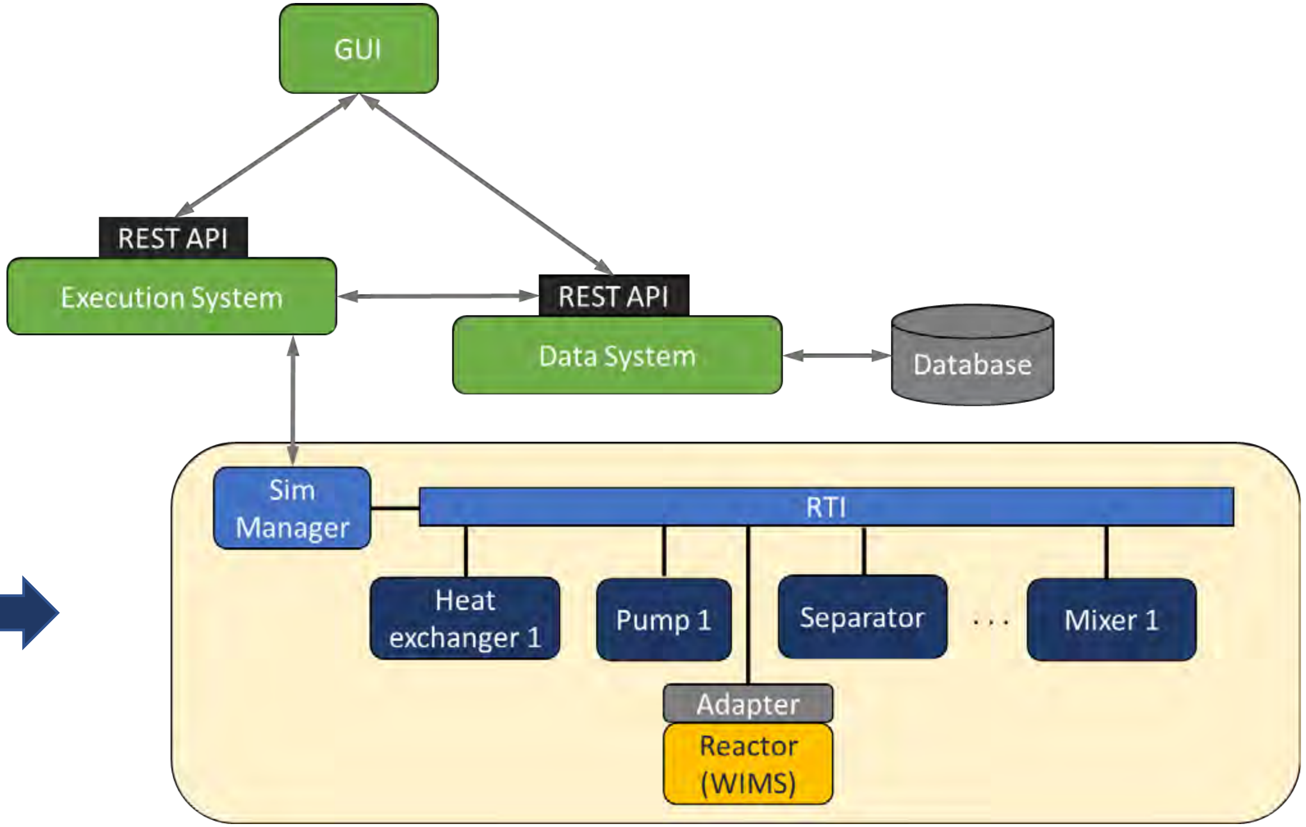
Analyse faults faster as plant simulator and control system can have common features

Case Study: System Level Modelling

- Component libraries can be re-used
- Simulation of operational sequences

- Complex system model of Molten Salt AMR developed and implemented
- Reactor analysis optionally using WIMS code



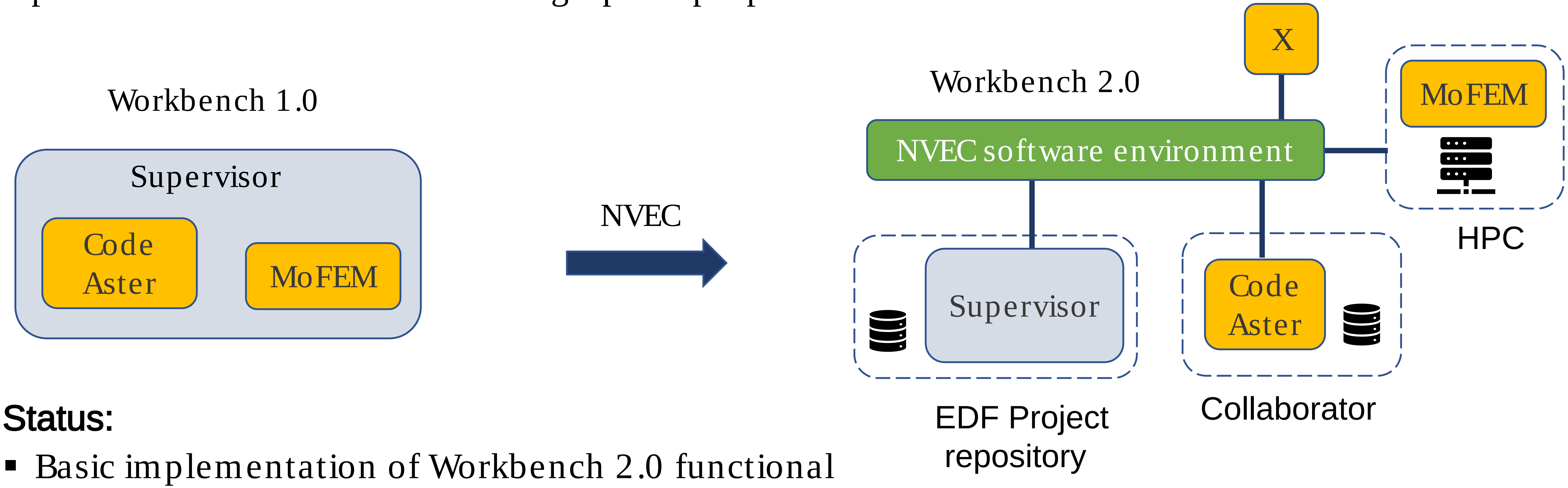


Multi -Scale Simulation GUI

- [Screen shot Sys Lev Sim GUI]

Case Study: AGR Graphite Workbench

Comprehensive simulation of reactor graphite properties over time



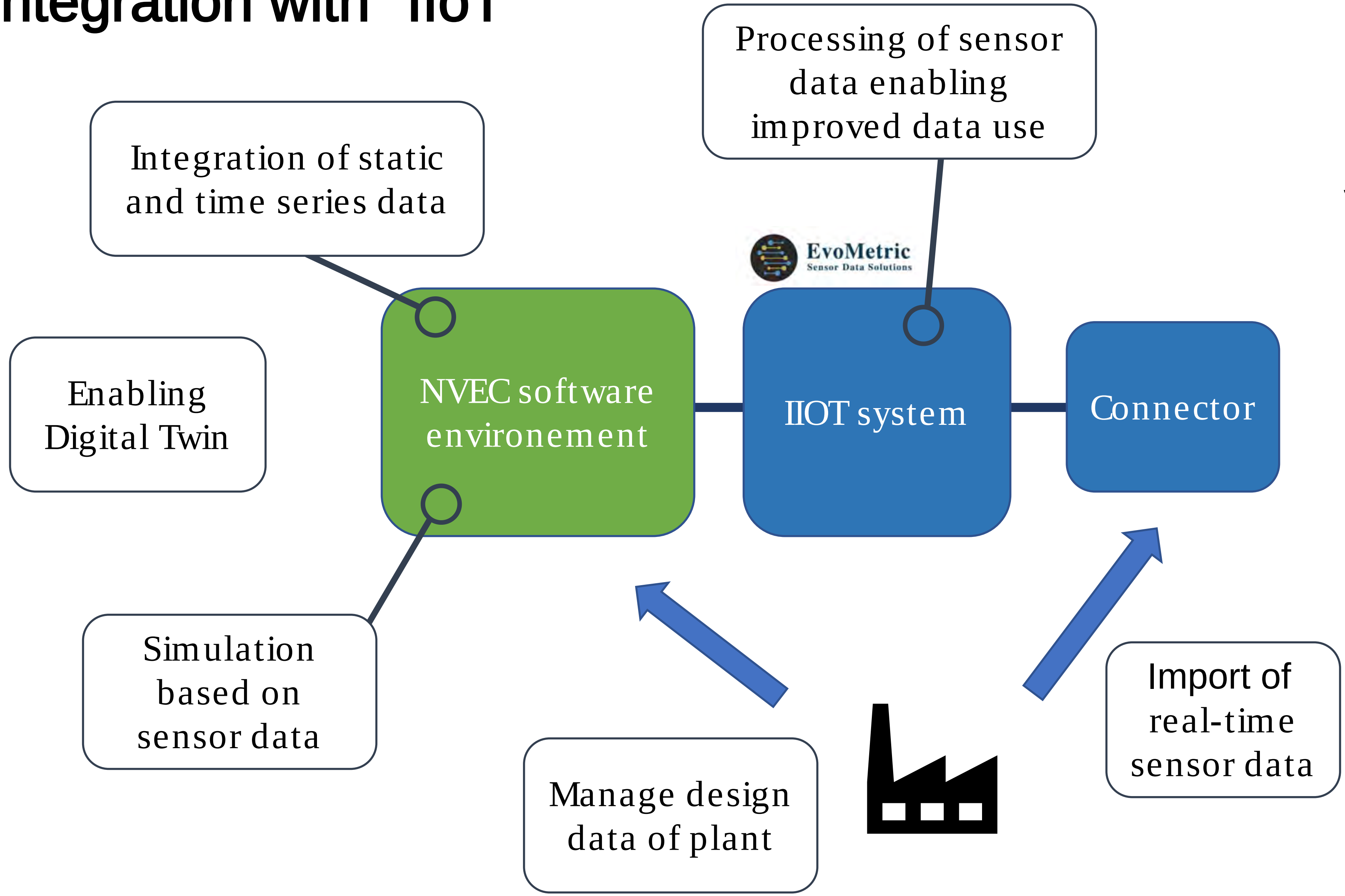
Status:

- Basic implementation of Workbench 2.0 functional

Benefits of integration with NVEC

- Enables sharing of computational infrastructure / increased fidelity / inclusion of future modules
- Improved collaboration between sub-contractors
- Standardisation of analyses: less QA effort and training

Integration with IIoT



Status:

- Design in progress
- Plant at NAMRC setup to export sensor data
- Model of plant sub-system developed (Frazer-Nash)

- Collaboration with Digital Catapult / SMEs on related methods/technologies

Further Applications

- Decommissioning
  - Integration of simulations with point cloud data from innovative decommissioning project (IIND)

- Reactor Physics
  - Completed design of coupling of codes for key workflow (WIMS-ENIGMA) in NVEC

- THOR (Thermal Hydraulic Open-Access Research Facility), University of Bangor
  - Collaboration started aiming at involving NVEC from design stage onwards
  - Data Model for THOR developed

- FAITH
  - Application of NVEC approach and tools on-going

SME Discovery Workshop (held in Sept ’20)

- Exploring opportunities for collaboration
- NVEC enabling innovation through SMEs

Future Developments

- SMR
  - Use NVEC for key requirements: e.g. engineering data management, design, change control
  - Initial NVEC evaluation version in development for Rolls-Royce SMR
- Fusion (STEP, CHIMERA)
  - Develop requirements / information model
- System level digital representations enabling optimisation strategies
  - e.g. AMR, process heat, Hydrogen-Nuclear combinations
- Implementation of operational Digital Twins for existing facilities
- Further development of application for FAITH and THOR/ THUNDER

Future Developments

- Advanced Materials & Manufacturing: more effective structural integrity management
- Increased effectiveness of safety case support
- Social factors study of benefits/obstacles of digitalisation in nuclear
- Develop working practices to support an information management strategy between disciplines
- Develop standards/guidance aiming at a 'NVEC Community'
- Link to the Construction Sector Deal

Summary

- NVEC to help deliver UK Government net zero carbon emissions target by 2050
- Key challenges: 'Silo' practices, information sharing, innovation, cost management
- Development of collaborative digital environment along with standards/guidance
- 'NVEC community': responsible for issuing guidance, maintaining standards, ensuring a common approach across the sector
- Various case studies on-going demonstrating benefits of NVEC
- Broad range of future opportunities

Acknowledgments

- C. Phelps, A. Aslam (Jacobs)
- D. Bowman, K. Vikhorev (University of Liverpool – VEC)
- M. Bankhead (NNL)
- C. Jackson (Rolls-Royce)
- J. Draup, P. Martinuzzi (EDF-Energy)
- S. Marr (NAMRC)

Thank you

Jacobs

Challenging today.
Reinventing tomorrow.

Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

NRC&INL&ORNL 2020 – December 3rd

Susana López (slopez@tecnatom.es)
Pablo Rey (prey@tecnatom.es)

tecnatom

CONTENTS

Who we are

Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

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Who we are

TECHNOLOGICAL CAPABILITIES

- Training
- Simulation
- Control Rooms
- Operation Support
- Emergency Support
- Engineering
- Inspection
- Tests
- NDT Systems
- NDT Products

MARKETS

ENERGY			INDUSTRIAL
REACTORS IN OPERATION	NEW REACTORS	COMBINED CYCLE THERMAL RENEWABLE	AEROSPACE PETROCHEMICAL RAILWAY

Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

Who we are

group tecnatom

tecnatom

tecnatom Mexico

tecnatom Abu Dhabi

tecnatom France

tecnatom brasil

CITEC

tecnatom china – 中国

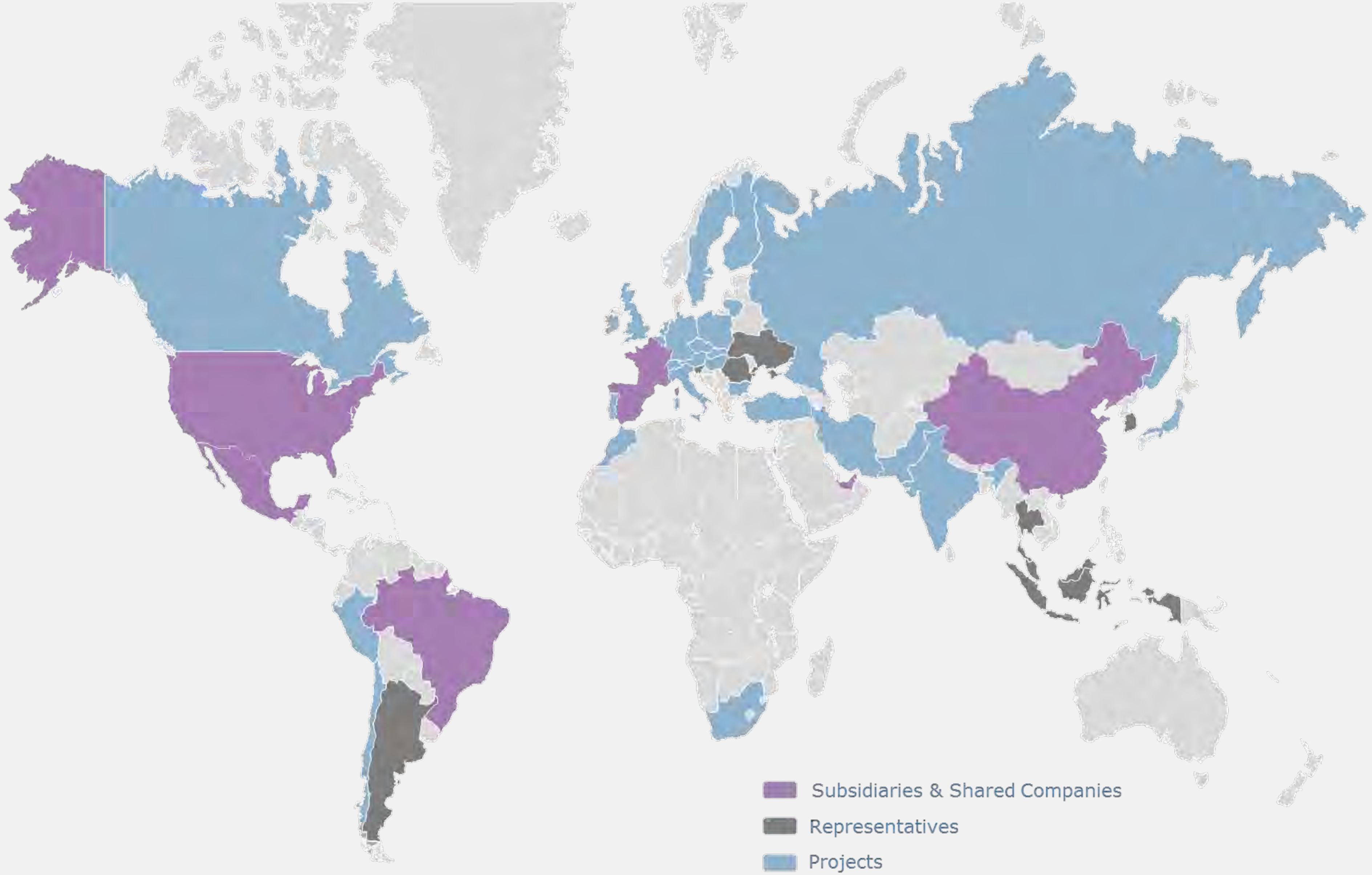
ibercal

sertec

tecnatom USA

FarField

SNGC



The concern

The concern

BWR/6 manufactured by General Electric
Electrical power 1,092.02 MW
Located in Spain

Key facts

- 1st coupling: 14 October 1984
- Commercial operation: 11 March 1985

BOP DCS

- Honeywell TDC 3000 since 1988
- Installed in Full-scope simulator in 2002
- Migrated to Experion in 2005
- Design modifications: control room digitalization

Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

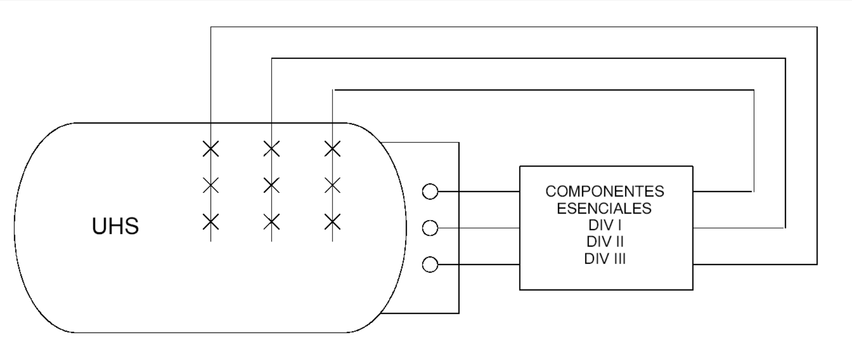
The concern : BWR NPP heat sinks

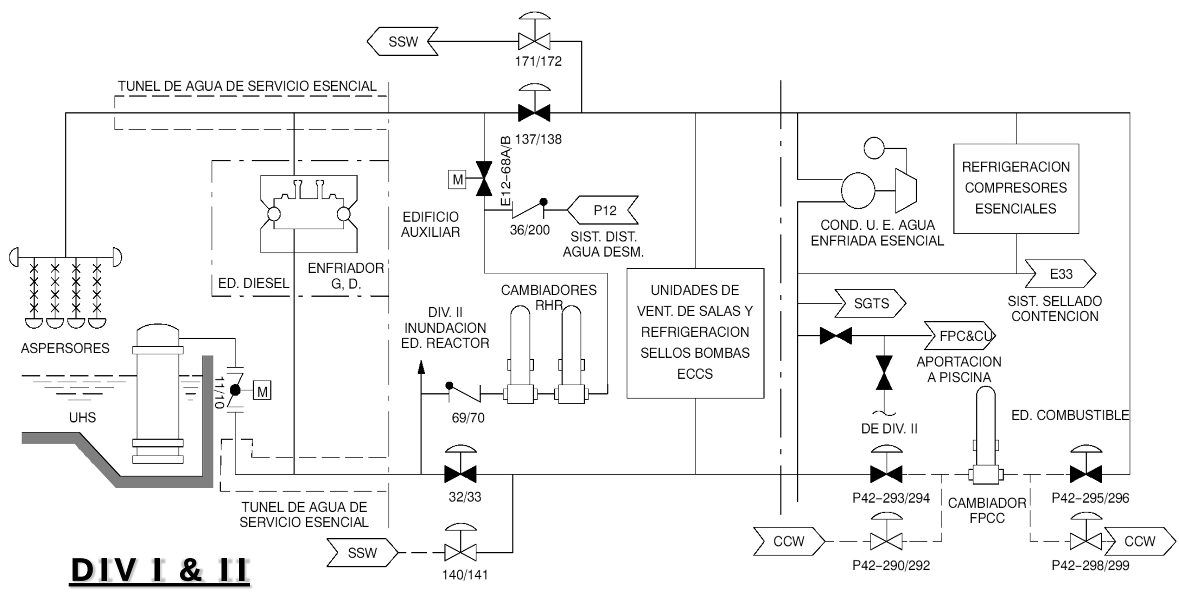
Normal Operation: Main Sink

- 2 natural draught cooling towers (Main condenser)
- Forced draught towers (Auxiliary systems)

Alternative: Ultimate Heat Sink (UHS)

- Pond: 30 days autonomy
- ESW: 3 cooling water pumping and distribution sub-systems
- LOCA or LOOP





The concern: Essential Services Water pipes effective section

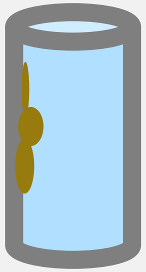
Carbon Steel Pipes

+

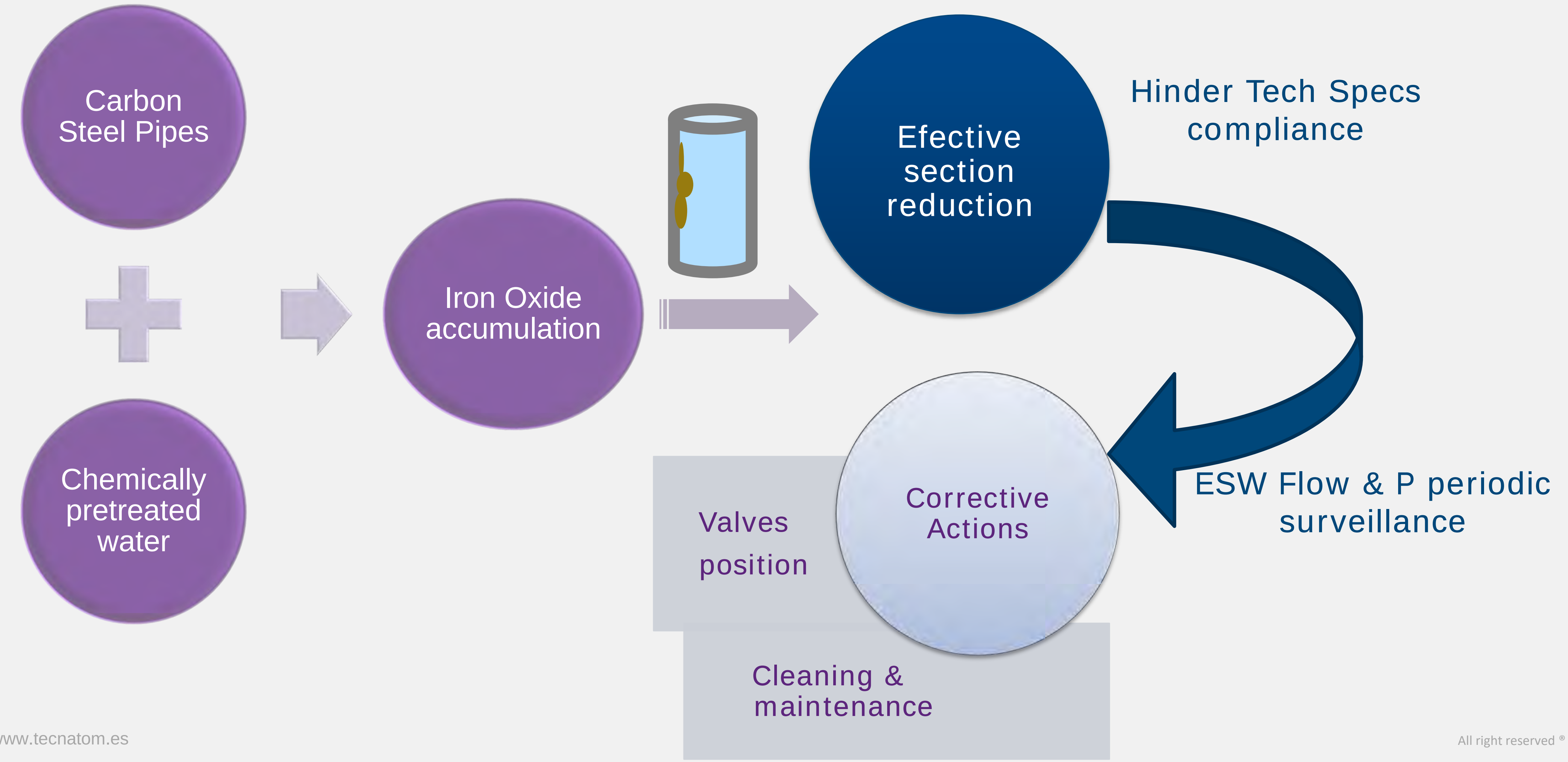
Chemically pretreated water

→

Iron Oxide accumulation



The concern: Essential Services Water pipes effective section



The concern : the solution

Digital Twin to ensure compliance with Technical Specifications

Success story DT P40

Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

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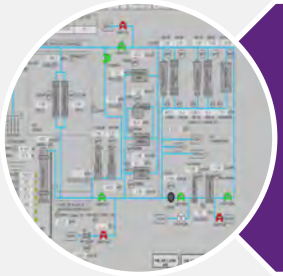
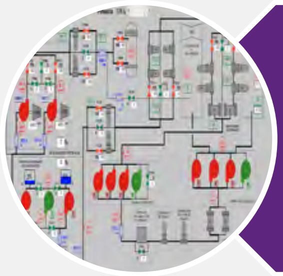
Project DT P40



ESW integration into DCS

Tools for the automated fulfillment of surveillance reports.



Digital Twin

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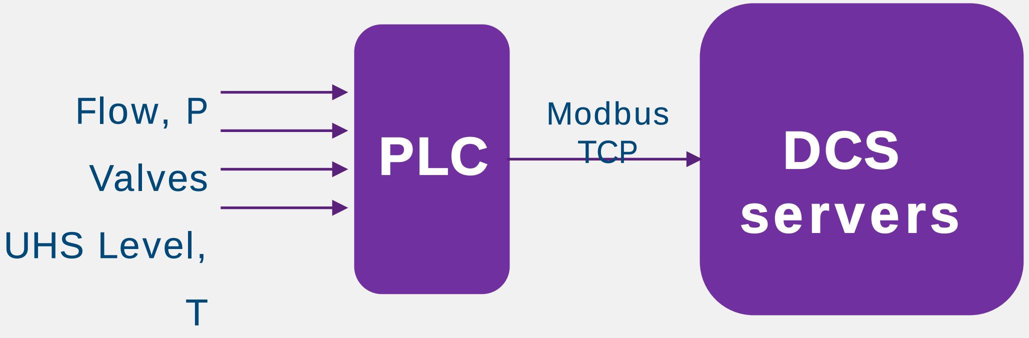
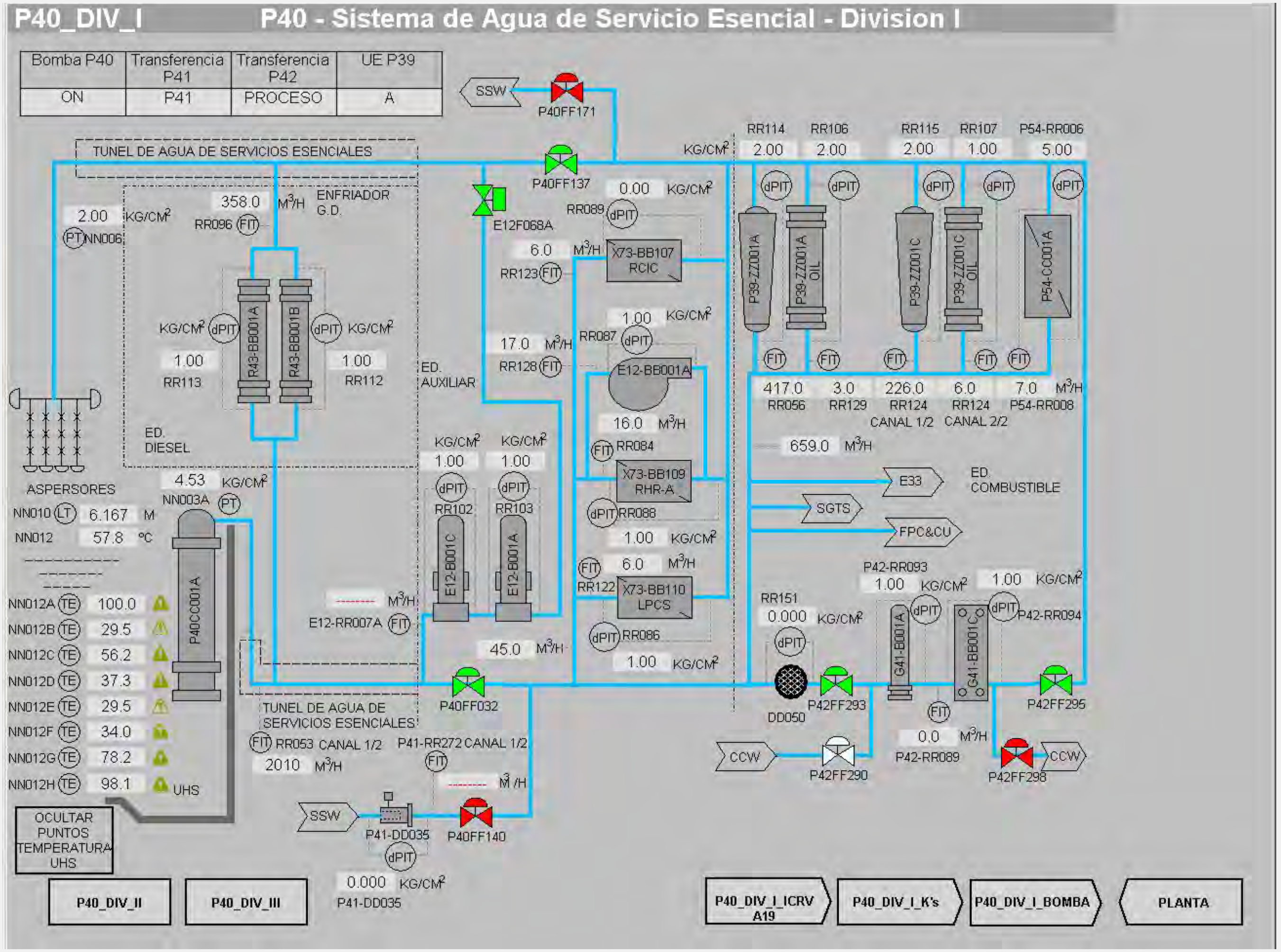
Project DT P40 : ESW integration into DCS

ESW Data Acquisition

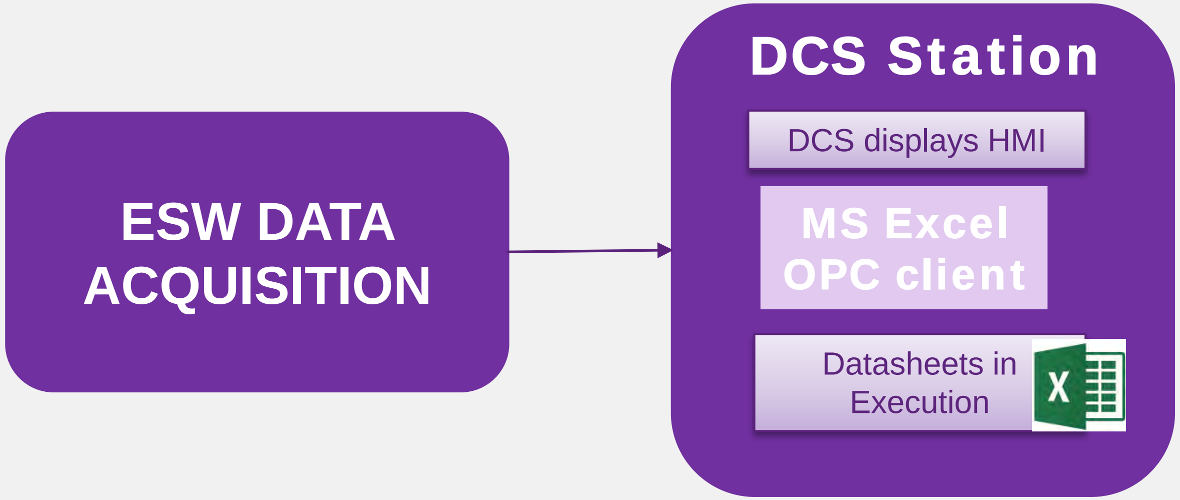


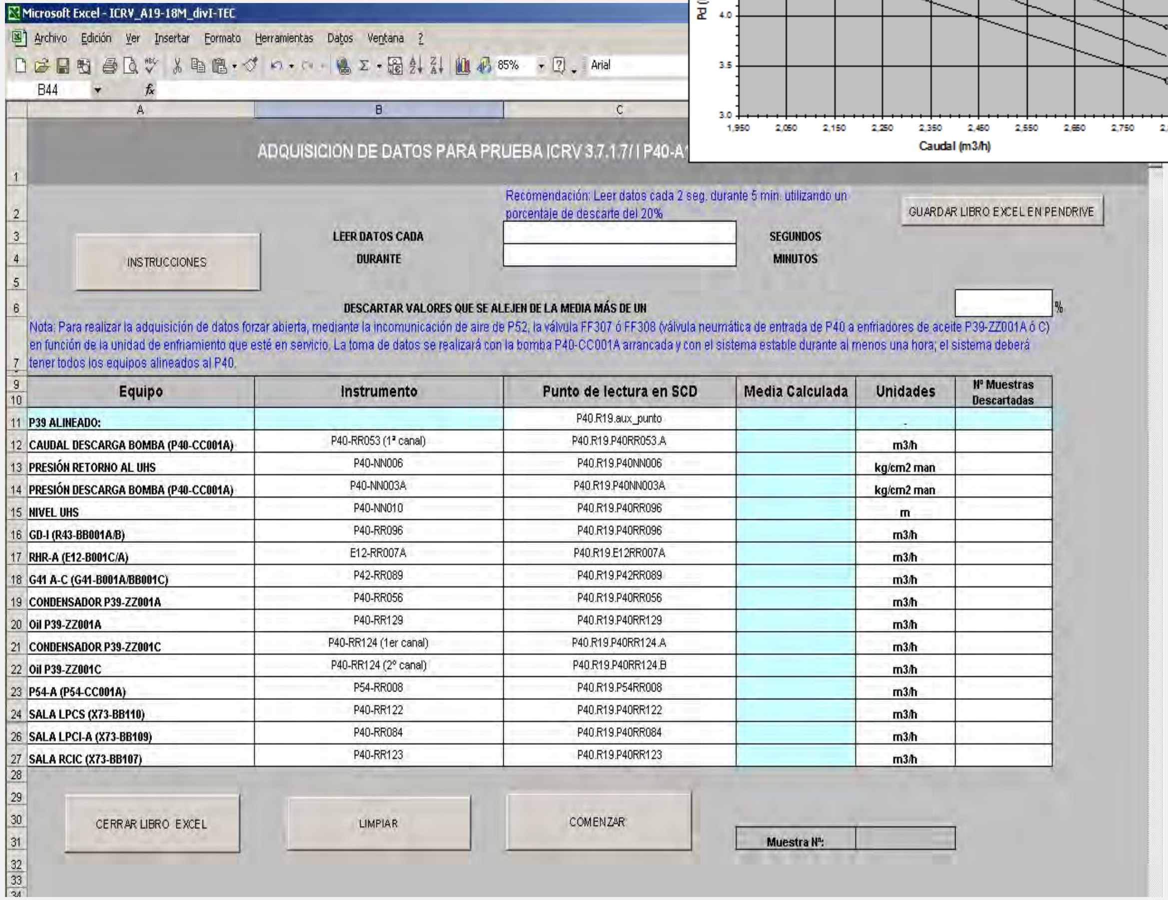
HSI displays:

- Division I, II, III
- Heat exchangers pressure drop (K factor)

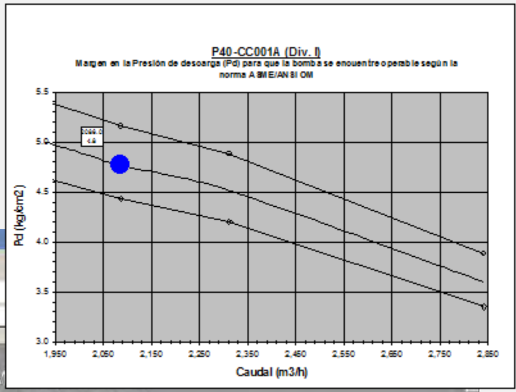


Project DT P40 : Tools for automatization of surveillance reports





Equipo	Instrumento	Punto de lectura en SCD	Media Calculada	Unidades	Nº Muestras Descartadas
P39 ALINEADO:		P40.R19.aux_punto		-	
CAUDAL DESCARGA BOMBA (P40-CC001A)	P40-RR053 (1º canal)	P40.R19.P40RR053.A		m3/h	
PRESIÓN RETORNO AL UHS	P40-NN006	P40.R19.P40NN006		kg/cm2 man	
PRESIÓN DESCARGA BOMBA (P40-CC001A)	P40-NN003A	P40.R19.P40NN003A		kg/cm2 man	
NIVEL UHS	P40-NN010	P40.R19.P40RR096		m	
GD-I (R43-BB001A/B)	P40-RR096	P40.R19.P40RR096		m3/h	
RHR-A (E12-B001C/A)	E12-RR007A	P40.R19.E12RR007A		m3/h	
G41 A-C (G41-B001A/BB001C)	P42-RR089	P40.R19.P42RR089		m3/h	
CONDENSADOR P39-ZZ001A	P40-RR056	P40.R19.P40RR056		m3/h	
Oil P39-ZZ001A	P40-RR129	P40.R19.P40RR129		m3/h	
CONDENSADOR P39-ZZ001C	P40-RR124 (1er canal)	P40.R19.P40RR124.A		m3/h	
Oil P39-ZZ001C	P40-RR124 (2º canal)	P40.R19.P40RR124.B		m3/h	
P54-A (P54-CC001A)	P54-RR008	P40.R19.P54RR008		m3/h	
SALA LPCS (X73-BB110)	P40-RR122	P40.R19.P40RR122		m3/h	
SALA LPCI-A (X73-BB109)	P40-RR084	P40.R19.P40RR084		m3/h	
SALA RCIC (X73-BB107)	P40-RR123	P40.R19.P40RR123		m3/h	



Each division surveillance books:

- **24M: Minimum flow surveillance (all components)**
- **03M: Pumps functional capacity (current and historical working point)**
- **Pressure drop factor (K= dP/Q2)**
  - **Heat exchangers & filters**
  - **Graph over time**

Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

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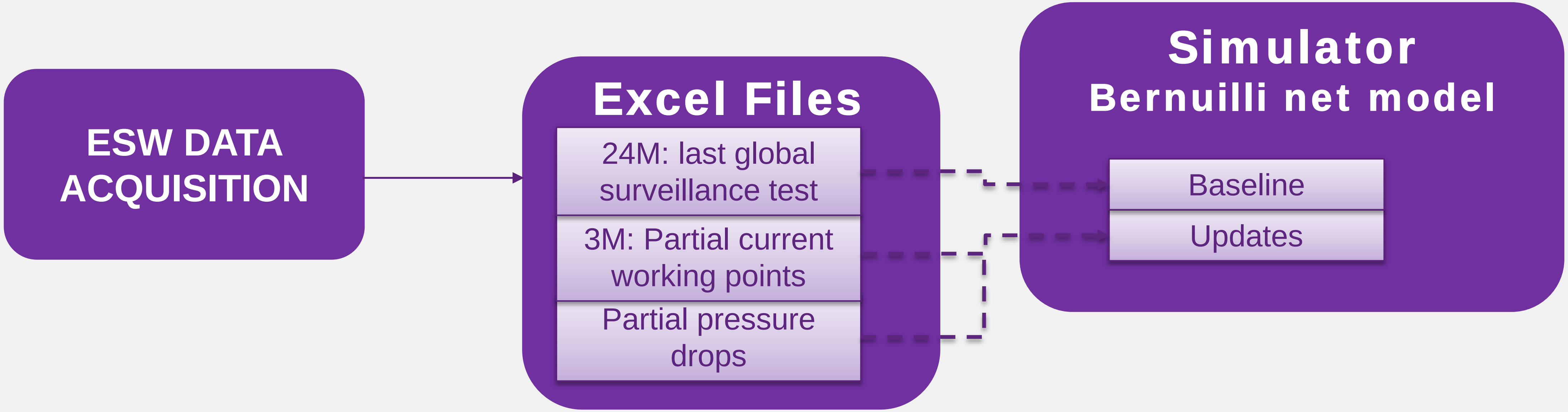
Project DT P40 : Digital Twin



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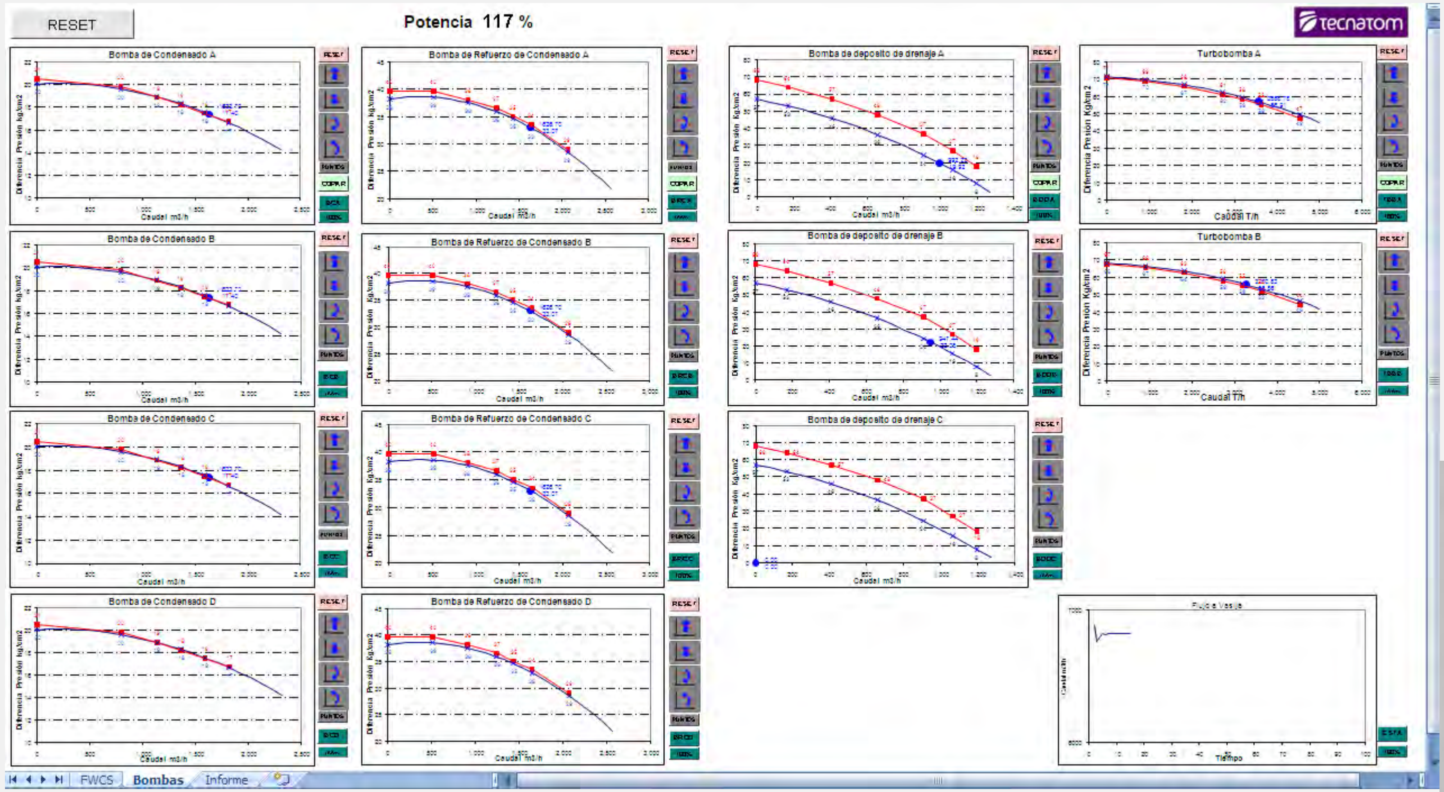
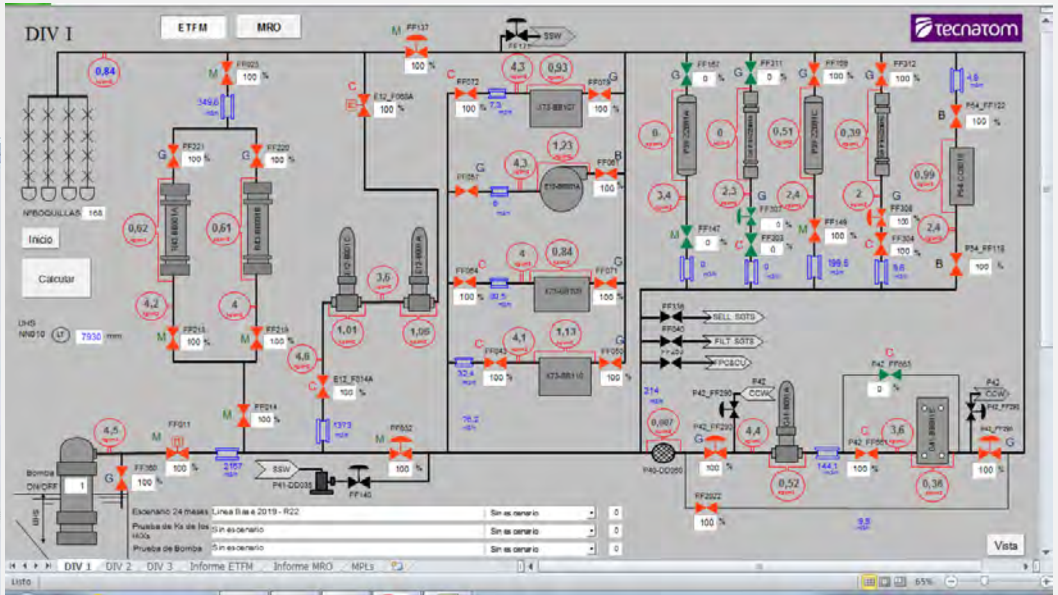
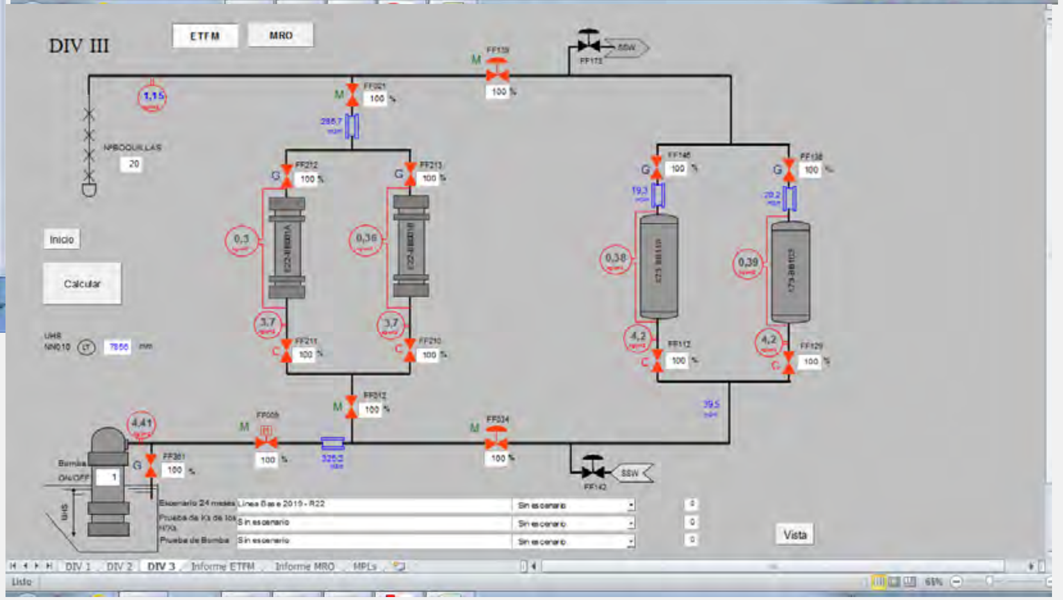
Project DT P40 : Digital Twin







Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

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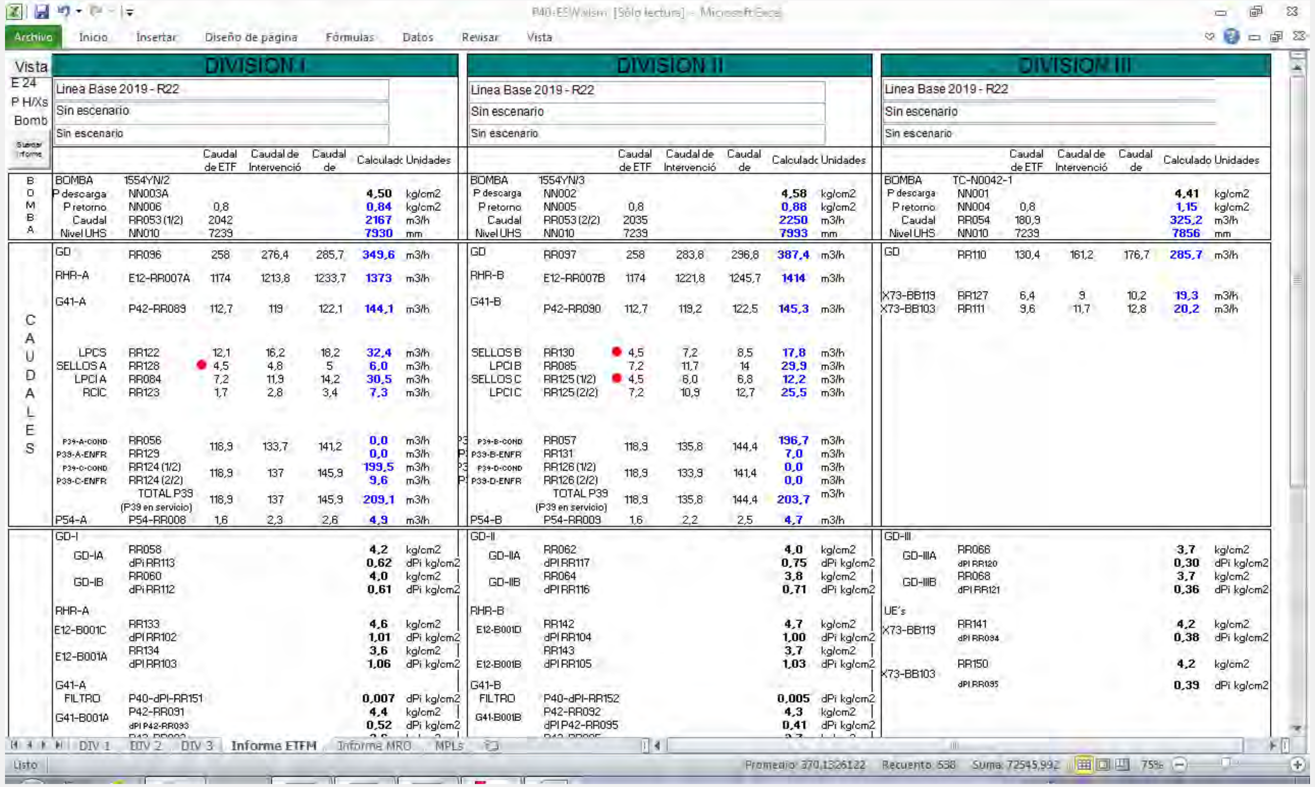
Project DT P40 : Digital Twin

RESULTS



GD	RR110	155	182.2	195.7	291.8	m3/h
UEs	TOTAL	30			41.5	m3/h
X73-BB119	RR127	11	13	13.9	21.8	m3/h
X73-BB103	RR111	18.6	19.4	19.8	19.7	m3/h

GD	RR110	155	182.2	195.7	292.0	m3/h
UEs	TOTAL	30			41.2	m3/h
X73-BB119	RR127	11	13	13.9	22.0	m3/h
X73-BB103	RR111	18.6	19.4	19.8	19.2	m3/h

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Project DT P40 : Digital Twin

ESW DATA ACQUISITION

Excel Files

24M: last global surveillance test

3M: Partial current working points

Partial pressure drops

Simulator

Bernuilli net model

Baseline

Updates

What IF?

Prediction

- Quantitative result of eventual system use or complete test

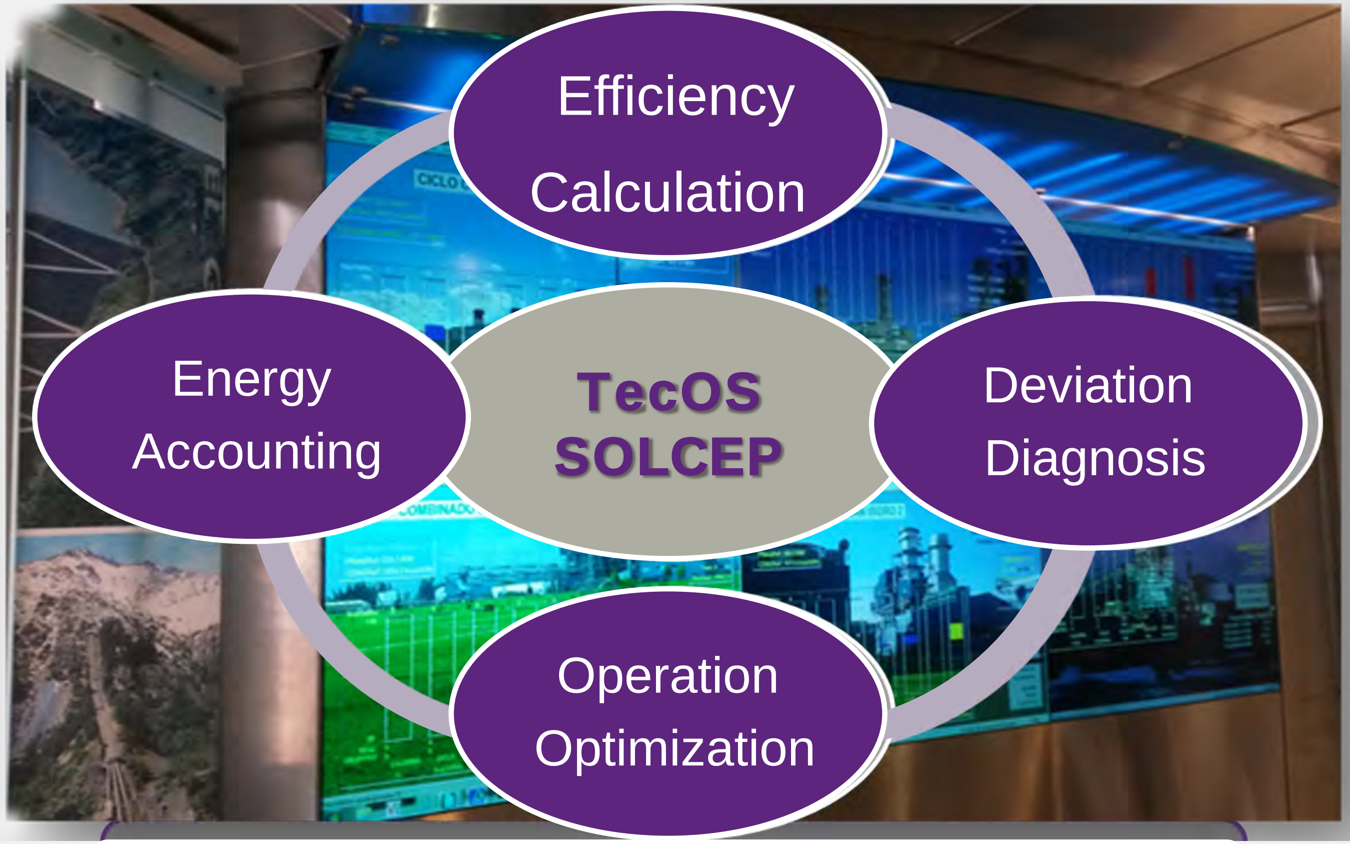
Best system configuration

- Simulate valves and pumps operation

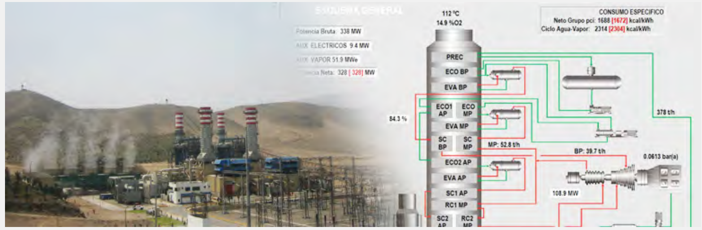
Other success stories

Project DT TecOS SOLCEP

ASME PTC PM 1993(2010). Performance Monitoring Guidelines for Power Plants

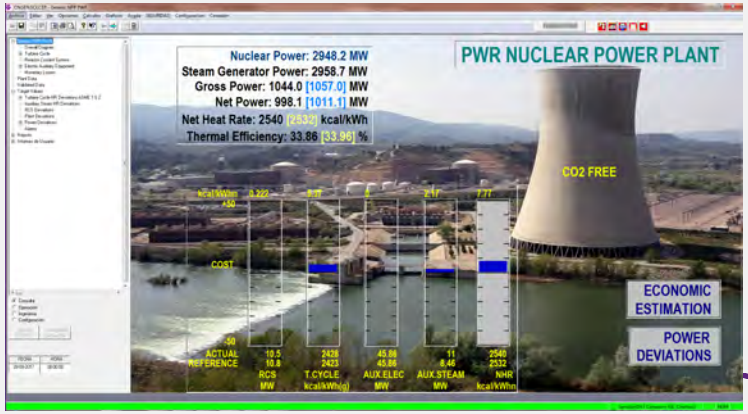


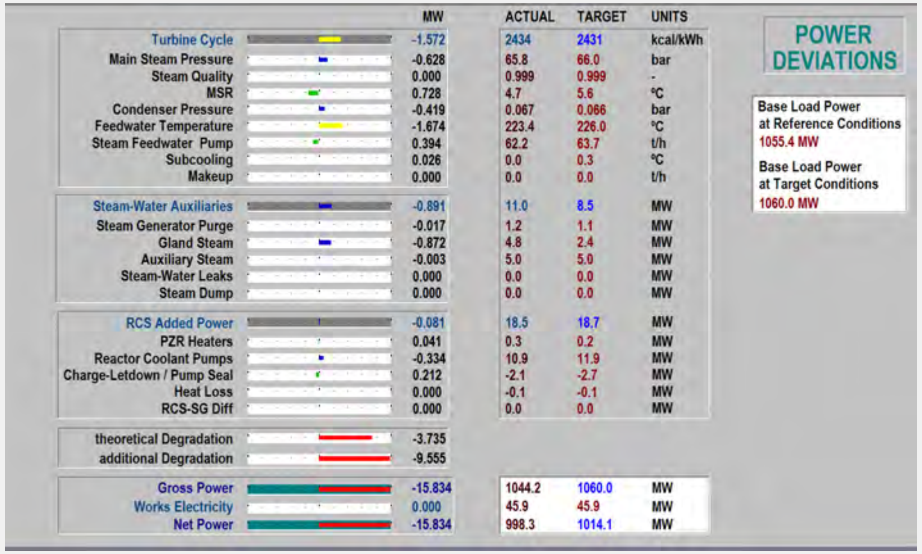
Assisted Diagnostic (Tecnatom Engineers)

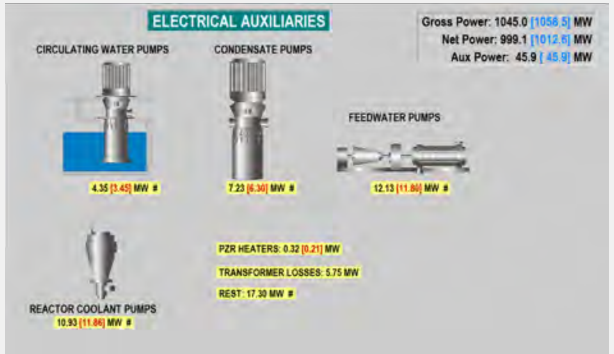


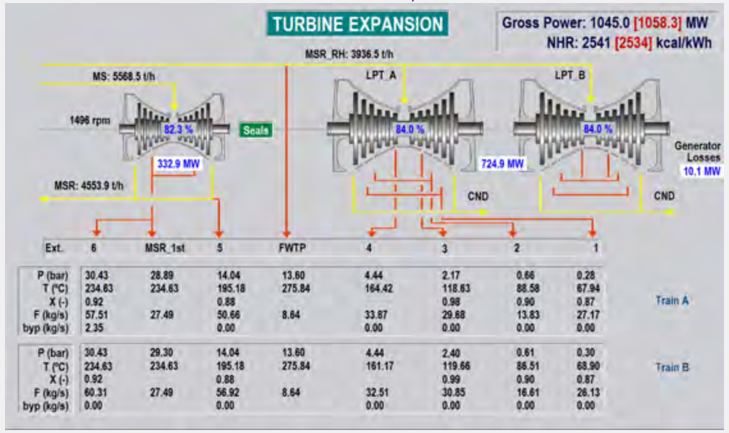
Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

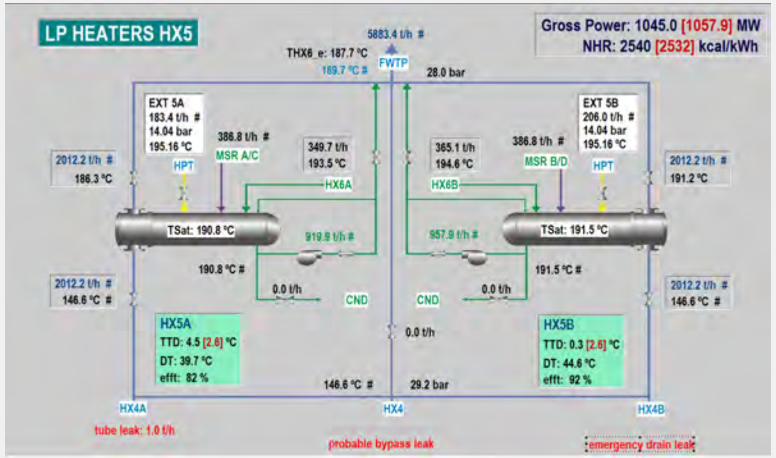
Project DT TecOS SOLCEP







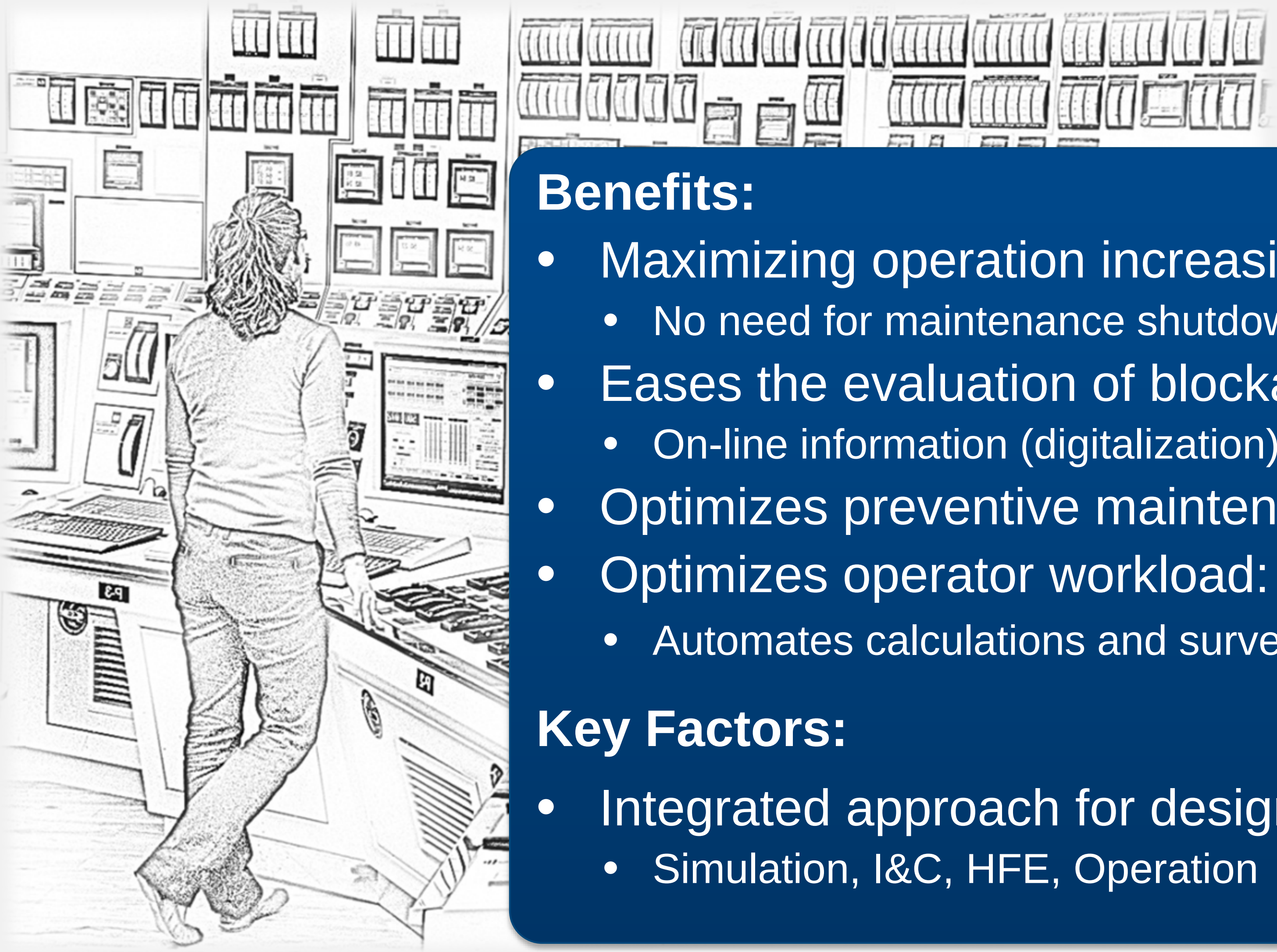




Conclusions

Benefits of Digitalizing and Employing Simulation to Increase Plant System Performance and Ensure Compliance with Technical Specifications

Conclusions



Benefits:

- Maximizing operation increasing safety margins
  - No need for maintenance shutdown
- Eases the evaluation of blockages and soiling
  - On-line information (digitalization)
- Optimizes preventive maintenance tasks (cleaning)
- Optimizes operator workload:
  - Automates calculations and surveillance and test requirements reports

Key Factors:

- Integrated approach for design modifications
  - Simulation, I&C, HFE, Operation

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European Commission

THE EU FRAMEWORK PROGRAMME
FOR RESEARCH AND INNOVATION

EURATOM RESEARCH AND TRAINING PROGRAMME
FISSION RESEARCH

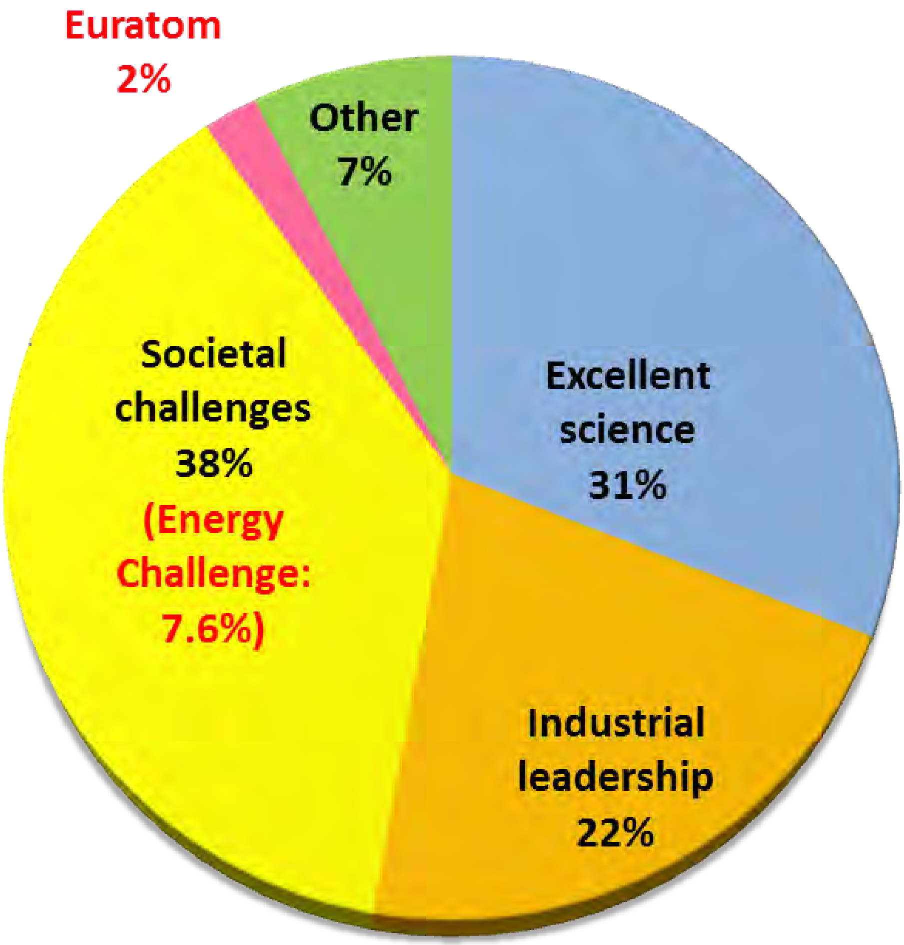
Panagiotis MANOLATOS
DG RTD
Clean Planet
panagiotis.manolatos@ec.europa.eu

DIGITAL TWIN

4-5 December 2020

HORIZON 2020

Challenges – Overall budgets



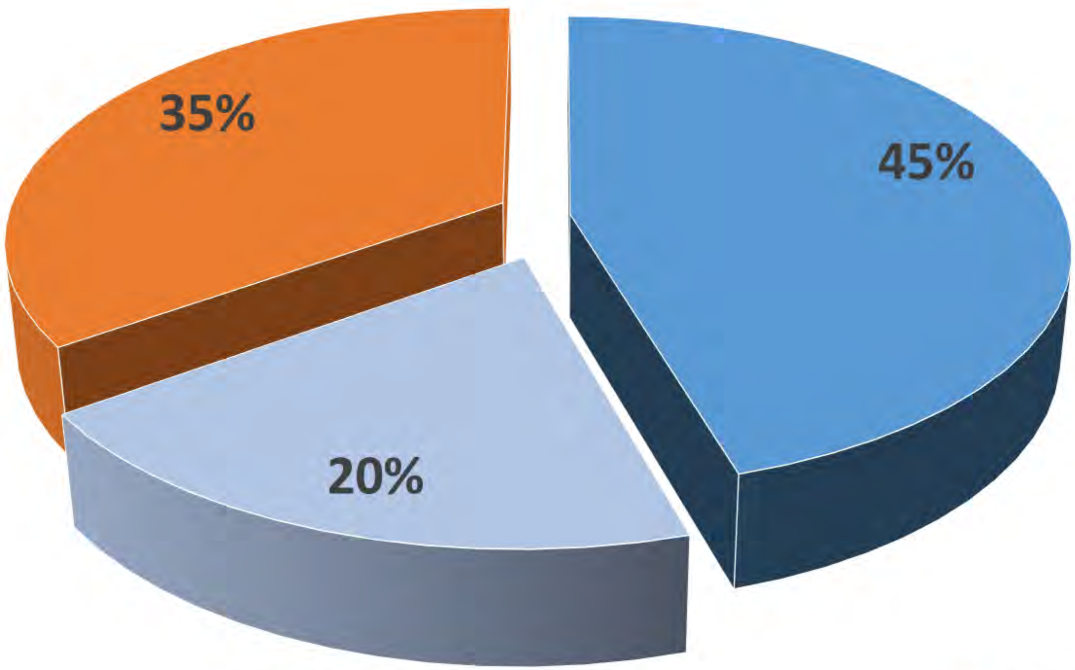
Total budget H2020:
EUR 74,83 billion

Budget of the
Energy Challenge:
EUR 5,69 billion

European Commission

Euratom Research & Training Programme 2019 - 2020

Total Budget: € 770 million



- DG RTD
  Indirect actions
  Fusion R&D Programme
  € 350 million
- DG RTD
  Indirect actions
  Nuclear Fission, Safety & Radiation Protection
  € 152 million
- DG JRC
  Direct Actions
  Nuclear Safety & Security
  € 269 million

Council Regulation

Euratom indirect actions specific objectives:

(a) supporting **safety** of nuclear systems;

(b) contributing to the development of safe, longer term solutions for the management of ultimate **nuclear waste**, including final geological disposal as well as partitioning and transmutation;

(c) supporting the development and sustainability of **nuclear expertise** and excellence in the Union;

(d) supporting **radiation protection** and development of medical applications of radiation, including, inter alia, the secure and safe supply and use of radioisotopes;

Council Regulation

Euratom indirect actions specific objectives:

(e) moving towards **demonstration of feasibility of fusion** as a power source by exploiting existing and future fusion facilities;

(f) laying the **foundations for future fusion** power plants by developing materials, technologies and conceptual design;

(g) promoting **innovation** and industrial competitiveness;

(h) ensuring availability and use of **research infrastructures** of pan-European relevance.

Current Euratom Nuclear Fission and Radiation Protection budget share

~ 40%	**Reactor systems** • Safety of existing nuclear installation (Gen-II-III) • Safety of Advanced nuclear systems (Gen-IV) • Partitioning, Transmutation and closing the fuel cycle • Cross-cutting aspects (e.g. fuels, materials, simulation, nuclear data) • Other applications (e.g. cogeneration, support to Research Reactors)
~ 20%	**Radiation protection**
~ 20%	**Geological disposal**
~ 20%	**Research infrastructures; Training and mobility; Cross-cutting**

Source: EC

Types of Actions – Research / Innovation

Research and Innovation Actions

They are actions with Research and Development activities as the core of the project intending to establish new scientific and technical knowledge and/or explore the feasibility of a new or improved technology, product, process, service or solution

- may include basic and applied research, technology development and integration, testing and validation on a small-scale prototype in a laboratory or simulated environment

- may contain closely connected but limited demonstration or pilot activities aiming to show technical feasibility in a near to operational environment

- 100% funding rate

"Pure" Innovation Actions

*"'Innovation action' means an action primarily consisting of activities **directly aiming** at producing plans and arrangements or designs for new, altered or improved products, processes or services. For this purpose they may include prototyping, testing, demonstrating, piloting, large-scale product validation and market replication"*

- 70% funding rate (100% for non-profit legal entities)

Types of Actions – Coordination and Support

Coordination and Support Action

Actions consisting primarily of accompanying measures such as standardisation, dissemination, awareness-raising and communication, networking, coordination or support services, policy dialogues and mutual learning exercises and studies, including design studies for new infrastructure and may also include complementary activities of strategic planning, networking and coordination between programmes in different countries.

Nuclear Fission & Radiation Protection Research (NRFP)

Call 2019-2020 Calendar

WP Adoption: *14 December 2018*

Call Open: *15 May 2019*

Submission deadline: *25 September 2019*

Evaluation: *November 2019*

62 proposals received

EC requested : EUR 265 million

EC budget : EUR 134 million

Signature of GAs: ***May 2020***

Research and Innovation Actions (RIA)

Topic	Budgets (EUR million)
Nuclear safety - NFRP-01: Ageing phenomena of components and structures and operational issues	16
Nuclear safety - NFRP-02: Safety assessments for LTO upgrades of Generation II and III reactors	12
Nuclear safety - NFRP-03: Safety margins determination for design basis-exceeding external hazards	8
Nuclear safety - NFRP-05: Support for safety research of Small Modular Reactors	8
Nuclear safety - NFRP-06: Safety Research and Innovation for advanced nuclear systems	7.6
Nuclear safety - NFRP-07: Safety Research and Innovation for Partitioning and/or Transmutation	6

Coordination and Support Actions (CSA)

Topic	Budgets (EUR million)
Nuclear safety - NFRP-08: Towards joint European effort in area of nuclear materials	1.1
Education and Training - NFRP-11: Advancing nuclear education	5
Research Infrastructure - NFRP-16: Roadmap for use of Euratom access rights to JHR experimental capacity	1.1
Research Infrastructure - NFRP 17: Optimised use of European research reactors	1.1

Innovation Action (IA)

Nuclear safety - NFRP-04: Innovation for Generation II and III reactors	12

Nuclear safety

Topics NRFP - 1, 2

Topic	Acronym	Title	Duration (Months)	Max EC contribution (M€)	Total cost (M€)
NFRP-01	ACES	Towards improved assessment of safety performance for long-term operation of nuclear civil engineering structures	48	4	5,5
	ENTENTE	European database for multiscale modelling of radiation damage	48	4	5
	INCEFA-SCALE	Increasing safety in npps by covering gaps in environmental fatigue assessment - focusing on gaps between laboratory data and component SCALE	60	4	6,8
	STRUMAT-LTO	Structural materials research for safe long term operation of LWR npps	48	4	4,8
NFRP-02	AMHYCO	Towards an enhanced accident management of the hydrogen/co combustion risk	48	4	4
	APAL	Advanced PTS analysis for LTO	48	4	4,6
	CAMIVVER	Codes and methods improvements for VVER comprehensive safety assessment	36	4	4

Abstracts, coordinator, and further info is published as soon as the Grant Agreements are signed and can be found at :

https://cordis.europa.eu/projects/en

International Cooperation

- **Multilateral**
  - **International Energy Agency (IEA)**
  - **Nuclear Energy Agency (OECD-NEA)**
  - **International Atomic Energy Agency (IAEA)**

- **Bilateral**
  - **Association Agreements with Switzerland and Ukraine**
  - **Cooperation with Japan, Canada, US, China, Korea, Brazil, Argentina…**

International Cooperation

Participation

Open for all legal entities established in third countries and for international organisations.

Restrictions only possible if introduced in the work programme.

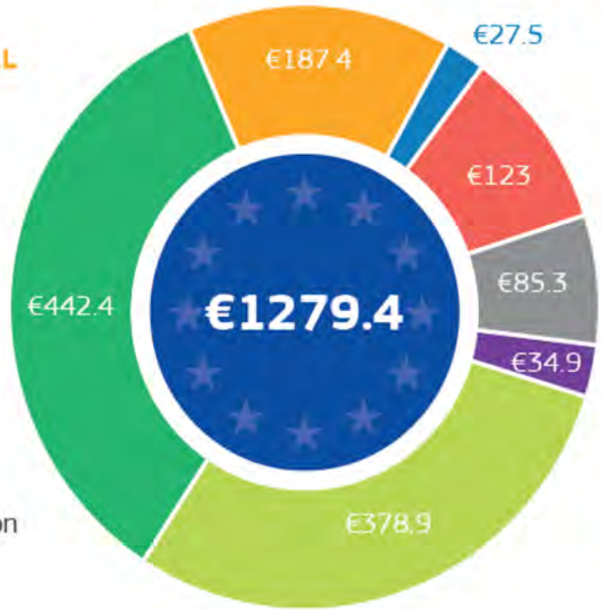
- ✓ **For reciprocity reasons**
- ✓ **For security reasons**

Funding

- ✓ **Third country identified in the Work Programme**
  or
- ✓ **participation deemed by the Commission essential in the action**
  or
- ✓ **when provided under a bilateral scientific and technological agreement**

EU priorities: 2021-2027 MFF proposal

In billion euro, current prices



I. SINGLE MARKET, INNOVATION AND DIGITAL
€187.4

1 Research and Innovation
2 European Strategic Investments
3 Single Market
4 Space

II. COHESION AND VALUES
€442.4

5 Regional Development and Cohesion
6 Economic and Monetary Union
7 Investing in People, Social Cohesion and Values

III. NATURAL RESOURCES AND ENVIRONMENT
€378.9

8 Agriculture and Maritime Policy
9 Environment and Climate Action

IV. MIGRATION AND BORDER MANAGEMENT
€34.9

10 Migration
11 Border Management

V. SECURITY AND DEFENCE
€27.5

12 Security
13 Defence
14 Crisis Response

VI. NEIGHBOURHOOD AND THE WORLD
€123

15 External Action
16 Pre-Accession Assistance

VII. EUROPEAN PUBLIC ADMINISTRATION
€85.3

17 European Public Administration

Source: EC

European Commission

Commission proposal for

Horizon Europe

THE NEXT EU RESEARCH & INNOVATION PROGRAMME (2021 – 2027)

Research and Innovation

Horizon Europe budget proposal (2021-2027)

€ 100 B including € 3.5 from InvestEU

Source: EC

Thank you!

#HorizonEU

http://ec.europa.eu/horizon-europe

Research and Innovation

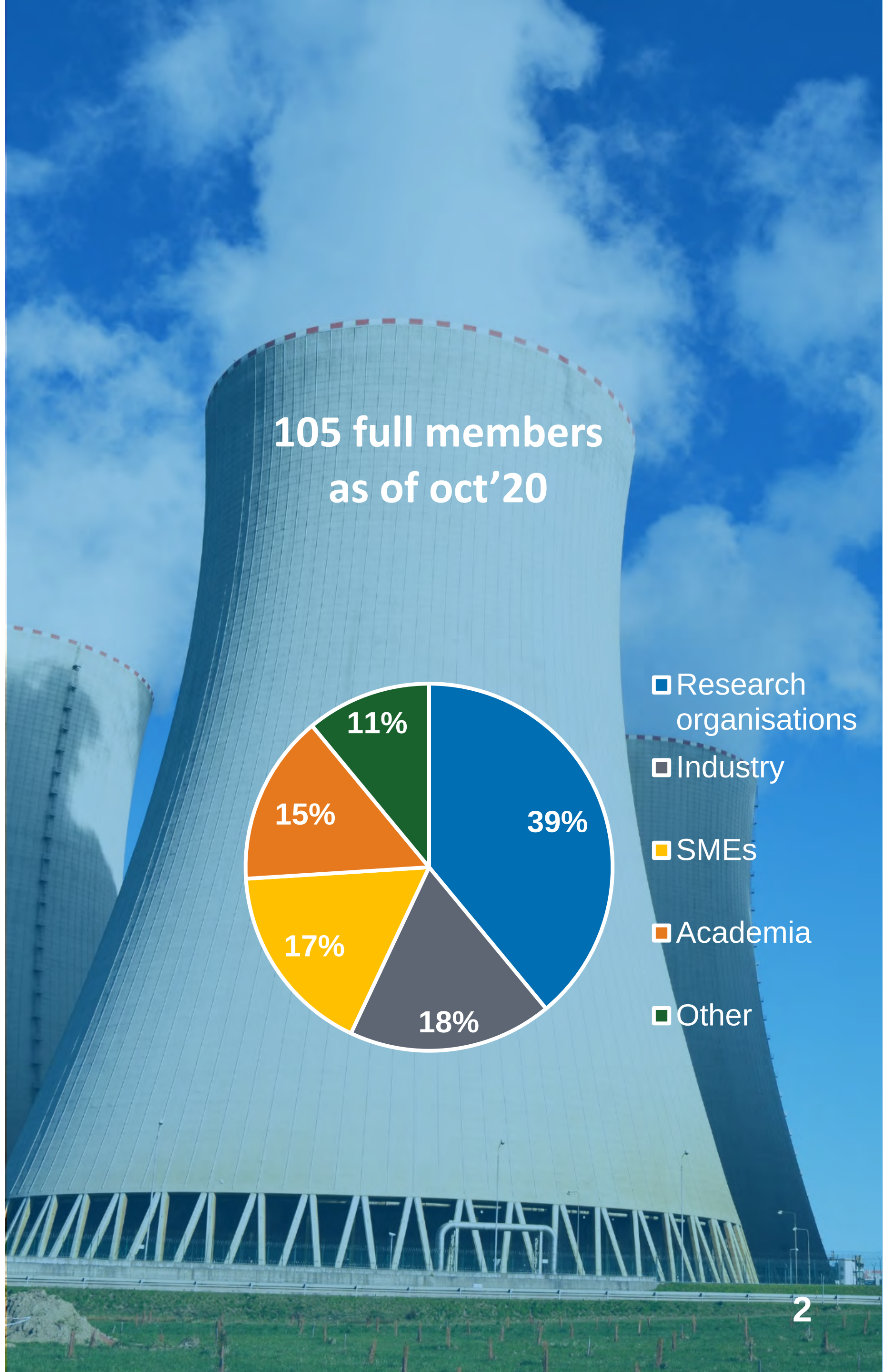
SNETP
Sustainable Nuclear Energy Technology Platform

European R&D&I towards Digital Twins

A. Al Mazouzi (General Secretariat)

SNETP in a nutshell

- SNETP was set up in 2007 under the auspices of the European Commission with the goal to **support technological development for enhancing safe and competitive nuclear fission in a climate-neutral and sustainable energy mix**.
- In line with the objectives of the SET-Plan, SNETP aims to contribute to:
  - ➢ Lowering European greenhouse gas emissions
  - ➢ Assuring security of energy supply for Europe
  - ➢ Stabilizing electricity prices in Europe
- The association gathers various types of stakeholders: industry, research centres, safety organisations, universities, non-governmental organisations, SMEs, etc.



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Objectives

Promoting Scientific Excellence

Agree on, implement and promote common R&I priorities within the SNETP community representing the three pillars

Boosting Innovation

Facilitate industrial-driven and intersectoral innovation (digital, robotics, materials, etc.) in nuclear for current and new applications (non-power, hydrogen, etc.)

Representing nuclear fission R&D in European Affairs

Promote SNETP expertise and research priorities towards European institutions

Strenghtening International Relations

Promote SNETP expertise and research priorities towards international nuclear institutions (IAEA, OECD/NEA, GIF, etc.)

Providing solutions to Industry

Foster industrial-driven research addressing the needs of SNETP industrial members in particular regarding safety, supply chain, licensing and cost-competitiveness

Cooperating closely with Regulators

Reinforce cooperation between SNETP and the different regulatory and standardization bodies.

Supporting R&D infrastructures

Support projects and initiatives aiming at maintaining/refurbishing/building the needed infrastructure to perform R&D&I in the nuclear field.

Sharing Experience with European Associations

Fostering and coordinating interactions with European associations in the field of nuclear, and any other sector with potential mutual interests with nuclear.

Engaging with Civil Society

Engage with civil society and non-nuclear stakeholders to rationalize the debate on the European energy mix and enhance the acceptability of nuclear.

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SNETP-Strategic Research and Innovation agenda

- Establishes long-term research priorities for its members
- Provides a clear research plan for industry, policy makers and research centers
- Provides state of the art analysis on nuclear research & innovation topics in line with European foreseen electricity mix in 2050 and the Green deal
- Prioritizes the topics of added value to the end users
- Create a synergy between various industrial sectors: cross-sectorial innovation (digital, material, space, ocean, robotics, etc.)
- Establish win-win relationship with national/European and international stakeholders
- Initiate and disseminate innovation within the nuclear sector

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Wo is SNETP?

AFRY · ANSALDO NUCLEARE · ARTTIC · axpo · BEL V · Nuclear Research Centre University of Bristol, University of Oxford · BECKER TECHNOLOGIES · bay · cea · CEIDEN · CHALMERS UNIVERSITY OF TECHNOLOGY · Ciemat

CIRTEN · Canadian Nuclear Laboratories / Laboratoires Nucléaires Canadiens · cnrs · Canadian Nuclear Safety Commission / Commission canadienne de sûreté nucléaire · CANDU Owners Group Inc. COG "Strength Through Co-operation" · CRIEPI Central Research Institute of Electric Power Industry · CENTRO TECNOLÓGICO CTC · CVŘ Centrum výzkumu Řež · CENTRUM PRE VEDU A VÝSKUM · DOOSAN · Università di Pisa · EMPRESARIOS AGRUPADOS · European Commission

EDF · EDF ENERGY · ELEXIM · ÉMI ÉPÍTÉSÜGYI MINŐSÉGELLENŐRZŐ INNOVÁCIÓS NKFT. · ENEA · enen · ENERGORISK · ENGIE · ENS European Nuclear Society · EPRI ELECTRIC POWER RESEARCH INSTITUTE

FINNUCLEAR · FORATOM THE VOICE OF THE EUROPEAN NUCLEAR INDUSTRY · fortum · framatome · Fraunhofer IZFP · JÜLICH Forschungszentrum · GRS · HZDR HELMHOLTZ ZENTRUM DRESDEN ROSSENDORF · IBERDROLA · IDOM

IFE · Universität Stuttgart · INAIL ISTITUTO NAZIONALE PER L'ASSICURAZIONE CONTRO GLI INFORTUNI SUL LAVORO · ichtj · Inesco ingenieros · INNOMERICS · INRNE · kiwa · IPP CENTRE · IRSN INSTITUT DE RADIOPROTECTION ET DE SÛRETÉ NUCLÉAIRE · ISSPMT

ivs · Jacobs · JAEA · Jožef Stefan Institute · KAERI · Kebco · KIT Karlsruher Institut für Technologie · KKL Kernkraftwerk Leibstadt · KTH · LABORELEC GDF SUEZ · LEI · LGI sustainable innovation · LUT University

N.IN.E. NUCLEAR AND INDUSTRIAL ENGINEERING · NATIONAL CENTRE FOR NUCLEAR RESEARCH · NATIONAL NUCLEAR LABORATORY · NRG · nuccon · NUCLEAR AMRC · orano · The Open University · Preussen Elektra · POLITECNICO MILANO 1863 · PAUL SCHERRER INSTITUT PSI

RATEN REGIA AUTONOMA TEHNOLOGII pentru ENERGIA NUCLEARA · RISK ENGINEERING LTD. · Rolls-Royce · sck cen · SLOVENSKÉ ELEKTRÁRNE · NUCLEARELETTRICA · S.R.S. Servizi di Ricerche e Sviluppo S.r.l. · SSTC NRS STATE ENTERPRISE STATE SCIENTIFIC AND TECHNICAL CENTER FOR NUCLEAR AND RADIATION SAFETY · STU FEI · SVTI ASIT

SWERIM · tecnatom · TRUEFLAW · TUM Technische Universität München · TVO · UC UNIVERSIDAD DE CANTABRIA · ÚJV · ktu · MANCHESTER 1824 The University of Manchester · UPC · UNIVERSITAT POLITÈCNICA DE VALÈNCIA · VATTENFALL

VTT · vuje · VZÚ PLZEŇ · Westinghouse · WORLD NUCLEAR ASSOCIATION · Wölfel · ZAG

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Current state of Digital Reactor

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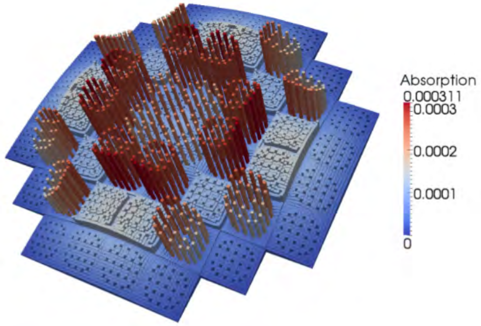
Different uses in Reactor Simulations

Higher representativity

Simulators

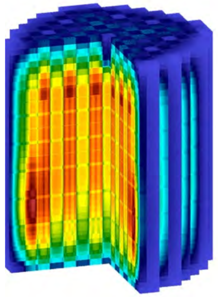
- Operators training
- Driver assistance systems
- Operations studies

Best estimate



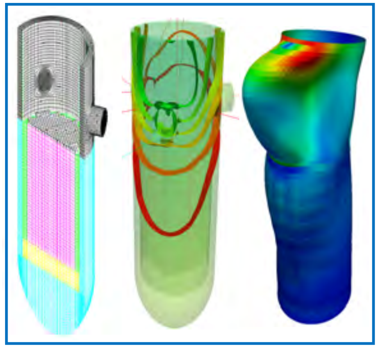
- Design Studies
- Reactor Design
- Accidents and safety studies

Best efforts



- Quantification of simulation biases
- Reference for safety studies

High Fidelity



- Reference calculations
- Studies in extreme situations (accidents…)
- Substitute for experiments where no data are available

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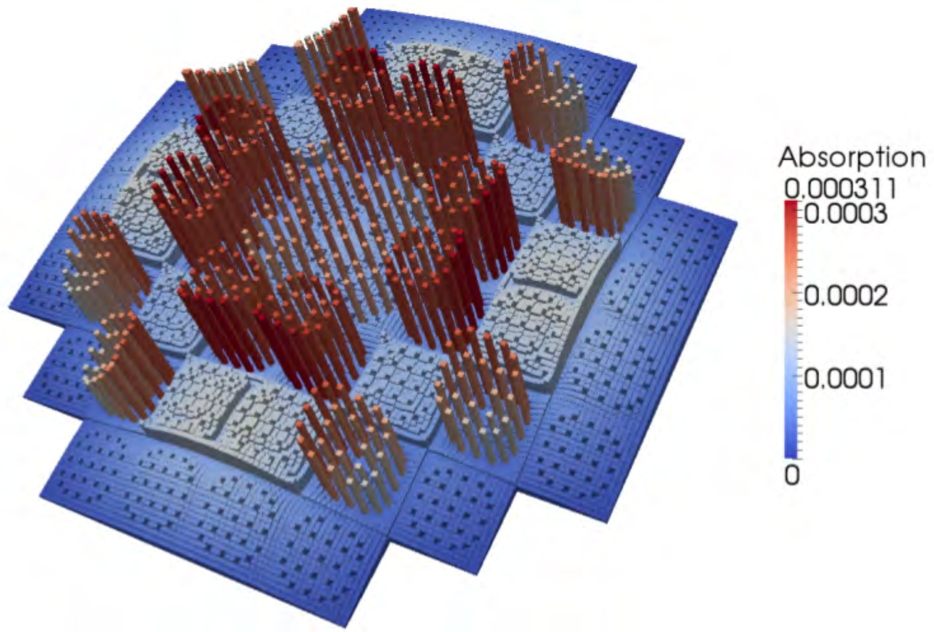
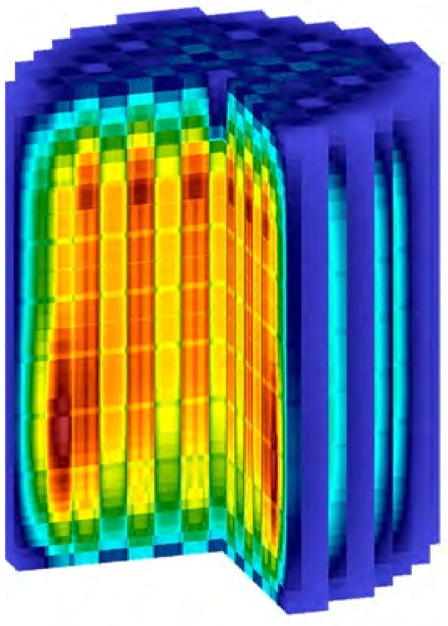
The European Nuclear sector has a long standing experience in developing a lot of physics codes including state of the art thanks to the EURATOM support and international collaboration

Emphasis on codes – Neutronics



neutronics code

- Both lattice and core calculations
- Transport solvers on unstructured meshes
- Parallelization on thousands of nodes
- Depletion chain with more than a thousand isotopes
- Allows advanced calculation such as direct calculation (on going work)



H2020 projects:
- ARIEL (2019-2023)
- SANDA (2020-2024)

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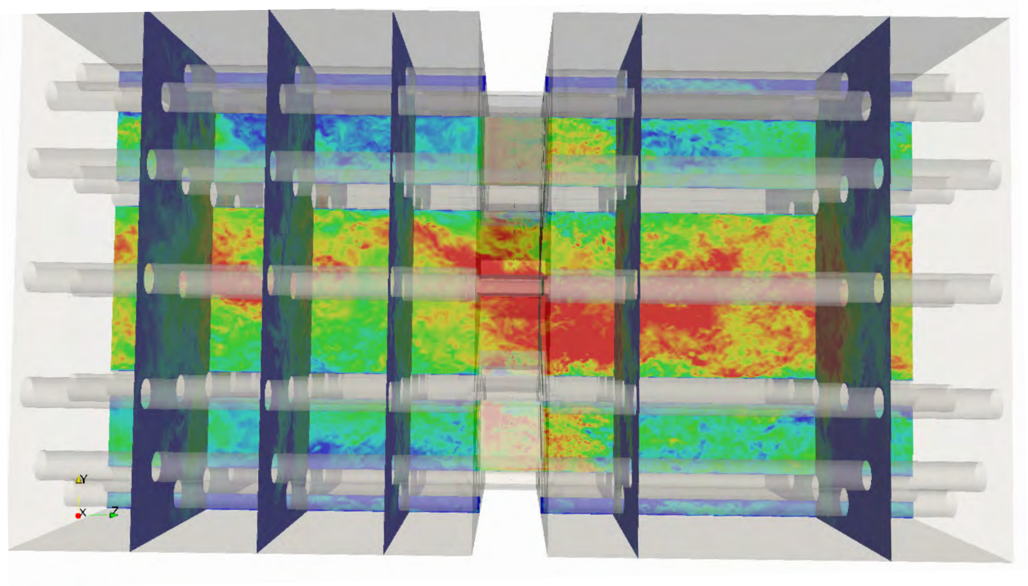
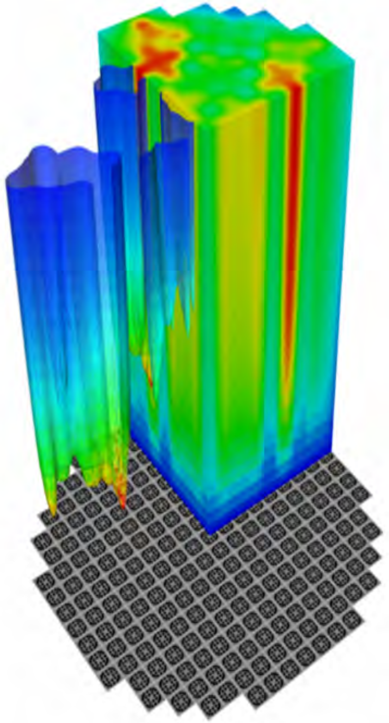
Emphasis on codes – Thermalhydraulics



CFD code

- Single and multiphase flows
- RANS and LES turbulent models
- Unstructured meshes and parallelization on tens of thousands of nodes
- Multiphysics: Fire, Severe Accidents, turbomachinery, ground water flows, …



- Single and multiphase flows
- Based on the porous media assumption
- Used for Cores, Steam Generators, Heat exchangers
- used for Safety analysis, Core refueling operations ad R&D studies

H2020 projects (exemples):

- McSafe (2017-2020); McSafer (2020-2024)
- Cortex (2017_2021)
- PIACE (2020-2024)
- CAMVVER (2020-2024)

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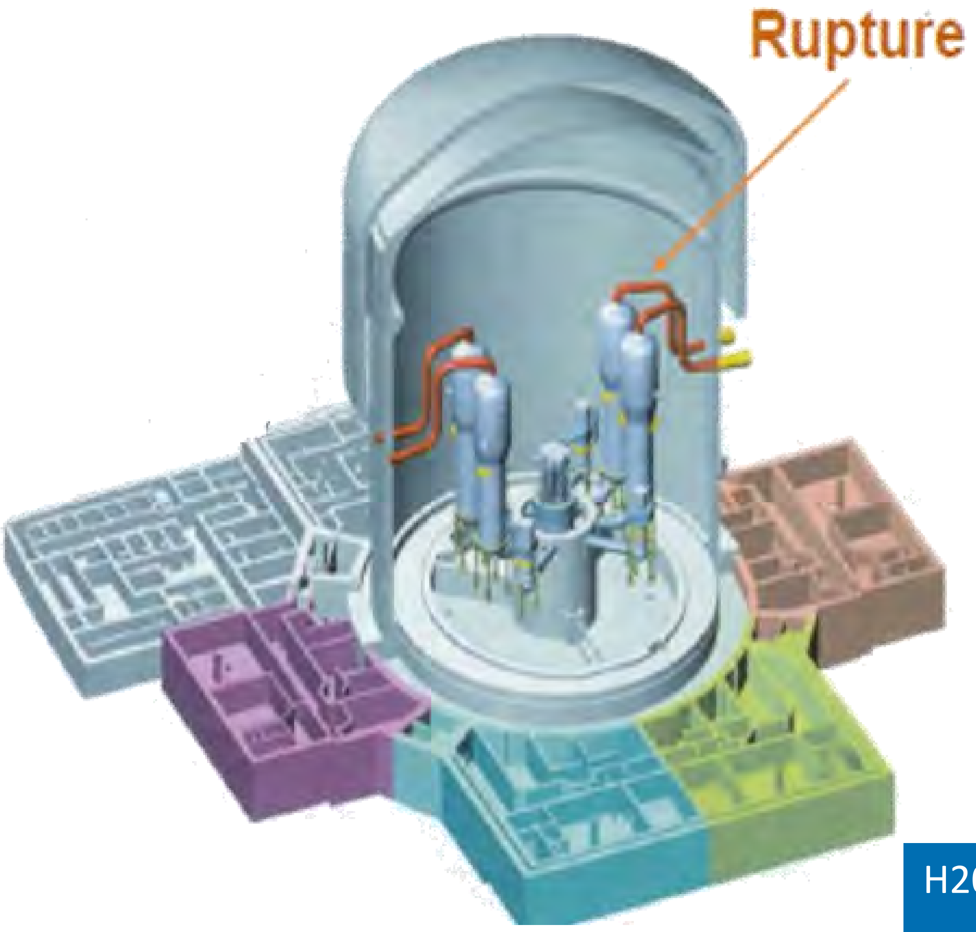
Advanced Modeling Applications

Typical use case : Steam-line break accident (SLB)



- This transient has been studied for decades by with different simulation tools.
- Very complex situation with strong physics coupling and 3D effects : good candidate for advanced simulation codes (CFD, neutronics transport with unstructured meshes…)
- Allows benchmarking between legacy and new generation of codes (test for code interchangeability)
- Possibility benchmarking with other international software (VERA from CASL,…)
- Good candidate for advanced visualization techniques to help understand the physics.

H2020 projects (examples):

- INCEFA+ & INCEFA-SCALE (2015-2025)
- MEACTOS (2017-2021)
- MUSA (2020-2024)
- APAL (2020-2024)

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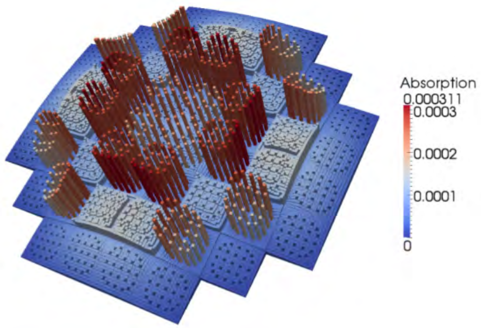
Improvements in Reactor Simulations

Representativity/quality

Simulators

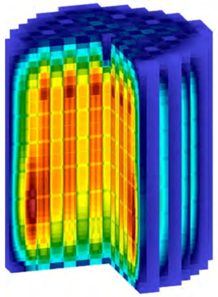
- Operators training
- Driver assistance systems
- Operations studies

Best estimate



- Design Studies
- Reactor Design
- Accidents and safety studies

Best efforts



- Quantification of simulation biases
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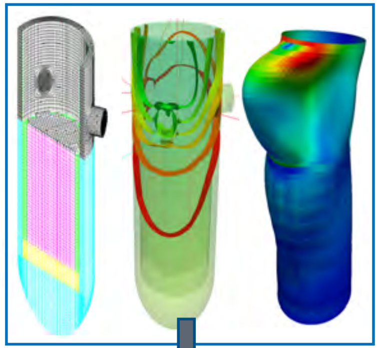

- Reference calculations
- Studies in extreme situations (accidents…)
- Substitute for experiments where no data are available

Interoperability / Interchangeability

Exploitation

R&D / Expertise

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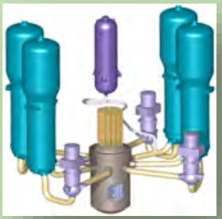
Codes and Data integration

DATA



CAD and Geometries calculation

Operating point

Physical tests and database validation

Validation of ϕ modelling

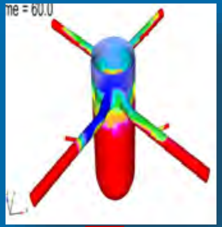
Users Needs

SOFTWARE INTEROPERABILITY & MODULARITY

Data acquisition from physical tests and exploitation

Minimization of experiments tests → **Validation of the Digital Reactor**

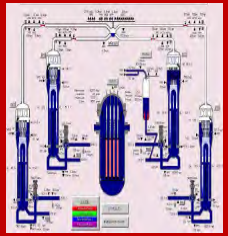
Advanced Modeling of the whole core



Optimization of the number of calculations → **Physics coupling including Uncertainties Quantification**

Models reduction

Real time modeling of the power plant



Improving physics representativity + Automation of the validation → **Visualization of complex physics phenomena**

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Some Scientific and technical challenges

- Goals / Challenges

  - Building a multi-physics (interoperability) and multi-scale (interchangeability) platform where all relevant physics codes should be able to plug in seamlessly.
  - Being able to come together with a common standard (API, data model exchange) for both new and legacy codes.
  - Building bridges to allow *advanced* codes to be used in simulators as well.
  - Using reduction models techniques for *at least* real-time simulation .
  - Taking into account, from the ground up, the possibility to quantify uncertainties.
  - Developing the right methodology for propagating uncertainties when doing multi-physics.
  - Being able to understand the physics involved as complexity increases dramatically.
  - Using advanced, ergonomic, visualization techniques (metaphors, AR, VR…) as a helping tool.
  - V&V of the whole platform when using strongly coupled physics.

Need of collaboration (European and international)

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Sustainable Nuclear Energy
Technology Platform

SNETP added value

- **SNETP is the only European wide association dedicated to collaborative nuclear research.**
  - All major European R&D organisations involved in nuclear are members of the association.
  - Various events are organised and online tools are deployed to facilitate collaboration of the community on new projects proposals. Since its creation in 2007, SNETP has supported discussions on approximately 300 project ideas.
- **The specific European Technology & Innovation Platform (ETIP) status provides an important visibility to SNETP and its members**, with privileged access to relevant high-level managers within EU institutions, international organisations, and member states.
- **SNETP and its members contribute to the shaping of European energy policies**, by exchanging with peers on research priority topics, by producing reference documents (e.g. SRIA) on the state of R&D&I in Europe, by publishing position papers, etc.

Contact us

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SNETP
Sustainable Nuclear Energy
Technology Platform

October 18, 2020

Chris Spirito
Nuclear Cybersecurity Specialist

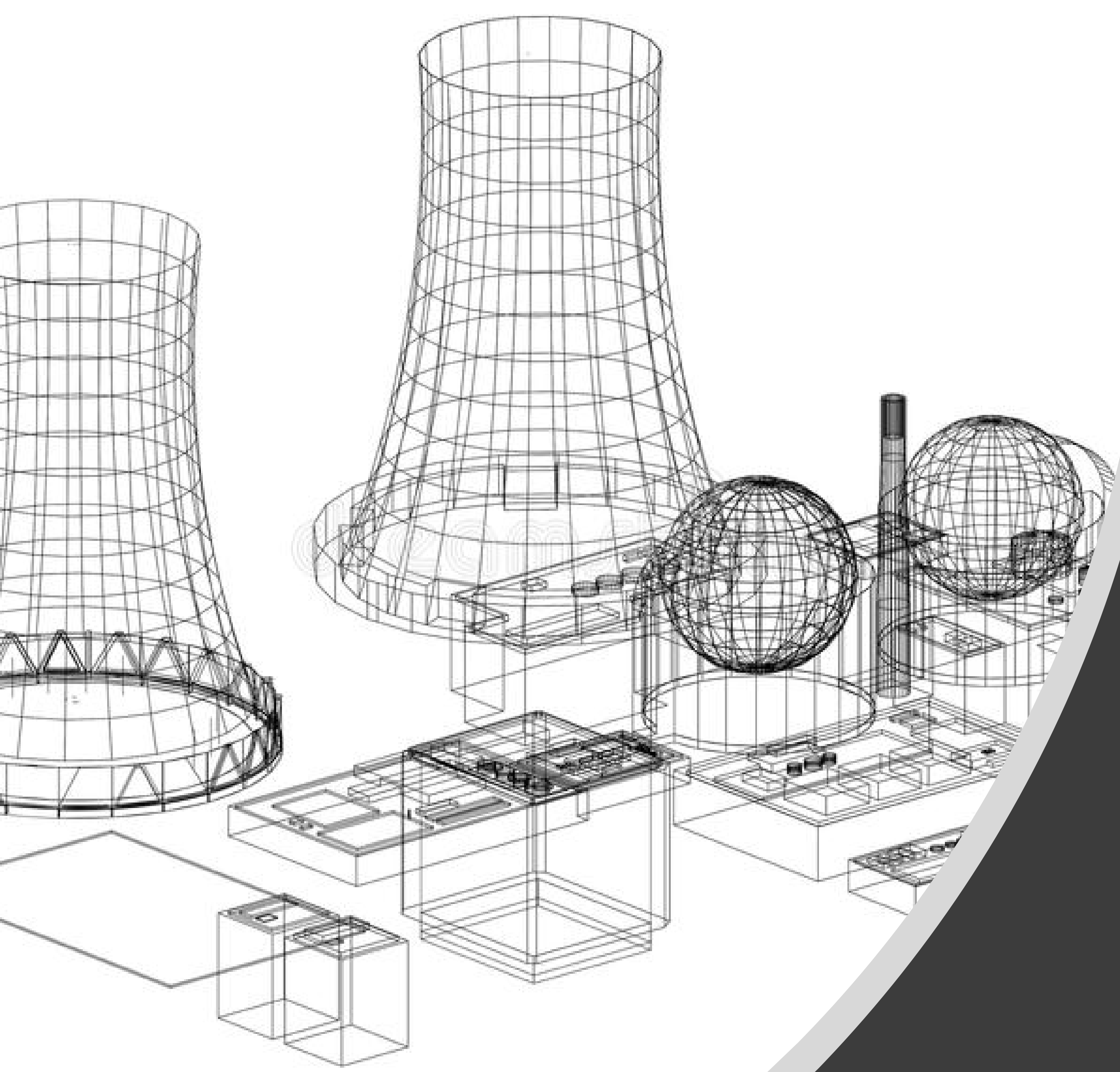
Digital Twins and Cyber Capability Development

Idaho National Laboratory

War Operations Plan Response WOPR (circa 1983)

Simulation Software / AI:
- Joshua

Simulation Models:
- Basic Strategy (Tic-Tac-Toe)
- Complex Strategy (Chess)
- Basic Warfare
  (Air-to-Ground Actions)
- Tactical Warfare
  (Theaterwide Biotoxic and Chem)
- Digital Twin
  (Global Thermonuclear War)



Cyber Capability Development (Digital Twins // Systems)

Reactor Simulators:
- IAEA Asherah, GSE GPWR, …

Digital Twin Targets:
- Systems
  (Pressurizer, Condenser, …)
- Components
  (PLCs, FPGAs, …)
- Comm Mediums
  (Analog, Digital, …)
- Functional Targets
  (Diodes, Proto. Converters)

Cyber Capability Development (Digital Twins / Humans)

Personality Characteristics:
- Curiosity & Relentlessness
- Novelty & Creativity,

Motivation and Ethics:
- Mercenary & Ideology

Strategies
- Weakness Exploitation
- Denial & Deception

Enumerate Interaction Pathways

Cyber Capability Development (Digital Twins / APTs)

Interactive Test Ranges:
- Integrated AI
- Infrastructure Modeling

Attack Library:
- Validation of Capabilities
- Validation of Processes
- Theoretical Testbed

Idaho National Laboratory

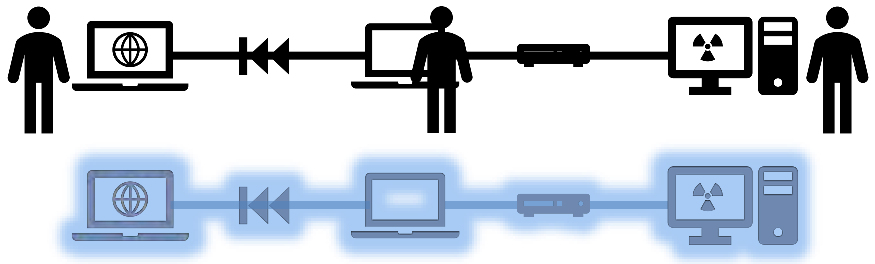
Cyber Security for Digital Twins

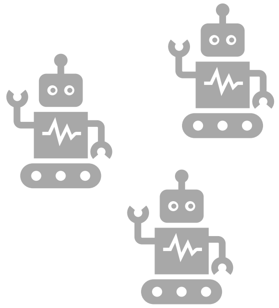
Cynthia DeBisschop and Alan (Al) Konkal
Senior Cyber Security Analysts
NRC Contractors, Cyber Security Branch (CSB)
Division of Physical and Cyber Security Policy (DPCP)
Office of Nuclear Security and Incident Response (NSIR)

U.S.NRC
United States Nuclear Regulatory Commission
Protecting People and the Environment

Overview

- Background
- Motivation
- Considerations for Entire Life Cycle of Digital Assets
- Cyber Security Vulnerabilities and Protective Strategies
- Summary





ICON LEGEND

→ **Real World**
→ **Virtual Model**
→ **Technology Gap**

Collaborative Review

INL DICE Glossary[1] of Terms: What Does Cyber Analyst Hear?

- **Digital Twin.** The computational simulation of a physical process or system that has a live link to the physical system, enabling enhanced verification of the simulation, control of the physical system, and analysis of trends via artificial intelligence and machine learning.
- **Artificial Intelligence (AI).** The simulation of human intelligence in computers or computer-controlled robots, allowing them to perform tasks commonly associated with intelligent beings.
- **Machine Learning.** The application of AI that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.
- **Operational AI.** The application of artificial intelligence (AI) in energy systems to automate expensive and manual human activities and improve the efficiency of asset operations.
- **Next Gen AI.** The simulation of human intelligence in computers or computer-controlled robots, allowing them to perform tasks commonly associated with intelligent beings.

[1] Source: Idaho National Laboratory (INL) Digital Innovation Center of Excellence (DICE) at https://dice.inl.gov/glossary-of-terms

Technology Gap Must Close Safely, If at All

INL DICE Operational Artificial Intelligence[2] Description

The use of artificial intelligence (AI) in energy applications has a game-changing potential in automating expensive and manual human activities in various types of industries. In the energy industry, power plants (especially nuclear) rely on staff performing several types of manual activities on a regular basis. Future energy plants, including advanced nuclear reactors, are designed to reduce the dependence on people for the operations, maintenance, and support activities of a plant. A light water nuclear power plant is typically full of analog gauges and manual actuators. By comparing a nuclear power plant control room to a modern airplane cockpit where the plane can fly itself and the pilot's role can be reduced to simply monitoring the airplane, it is obvious that a significant technology gap exists that needs to be closed. Human intelligence needs to be replaced by machine intelligence in various forms of AI if this vision is to be realized.

- **Comparison of nuclear power plant (NPP) control room to modern self-flying-airplane cockpit**
- **Mention of need to close significant technology gap if this Vision is to be realized for NPPs**
- **Cyber Security Analyst: Technology gap must close safely, if at all**

[2] Source: Idaho National Laboratory (INL) Digital Innovation Center of Excellence (DICE) at https://dice.inl.gov/operational-artificial-intelligence

Motivation

Pop Quiz[3] from October 2019 Forbes Article "How to Protect Your Digital Twin"

Q. "Which of the following is more valuable: a Boeing 777 or the digital twin of a Boeing 777?"

A. "The first option, the physical plane, is an expensive item – buying a new one will cost you around $344 million. Yet, the digital twin of a 777 is far more valuable. It's the digital simulation of the plane that constantly collects situational awareness data and is used to understand and improve the ongoing performance of various parts and systems. If you control the digital twin, you control every 777 on (and above) the planet."

BONUS. Fill in the Blank.

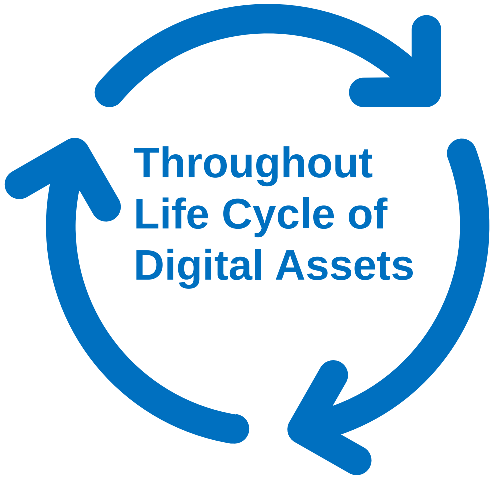
Cyber Security Analyst: To effectively _protect_, think carefully throughout the evolution. Keep the vision in mind. Evaluate protections with every step along the road!

[3] Source: Kawalec, Andrzej, ''How to Protect Your Digital Twin,'' Forbes Technology Councill Post, October 21, 2019, at https://www.forbes.com/sites/forbestechcouncil/2019/10/21/how-to-protect-your-digital-twin

Need to Understand/Consider

(Now, Throughout Evolution, and Before Procurement or Use)

- Technology Itself
- Security Gaps
- Threat You Are Designing Against
- Changes to Environment of Digital Assets
- Attack Surfaces of Digital Assets
- Cyber Risk
- Consequences of Cyber Attacks
- Defense-in-Depth Protective Strategies



Cyber Security Vulnerabilities

- **Data Exfiltration.** Plant sensors and data streams need to be connected to virtual model to realize concept. Digital twin is intended to be near-perfect blueprint of its real twin. Potential exists for monitoring and exfiltration of information about types of systems and sensors used by plant.
- **Man in the Middle Attack.** Early component failures may result due to alternated maintenance cycles based on faulty data after a compromise, if data is used for predictive maintenance. Scenarios that involved predictive component failure were used in the now famous Stuxnet attack. Untimely failure of a key component could be used as an element of a kinetic attack.
- **Supply Chain Attack.** Digital twins can be used to model new components, testing how they will perform under real-world conditions. Data obtained from components of digital twin models can be used in manufacturing. Compromised components data could lead to manufacturing faulty components.

Protective Strategies

Fully Implement a Sound Cyber Security Framework

- NEI 08-09, RG 5.71, NIST 800-53, and NIST 800-82
- Implement security patches and remediate vulnerabilities quickly
- Harden digital twin platforms
  - Utilize hash code-based allowlisting
  - Remove all unnecessary files and services
  - Implement Anti-Virus and Host Intrusion Detection Systems
- Identify security and remediate gaps between the twin and the physical hardware

Protective Strategies

Secure Software Development Environments

- Develop in secure isolated environment
- Verify all Third Party and Open Source Code
- Test for language conformance, known vulnerabilities and flaws
- Conduct peer code reviews
- Use a secure repository control
- Utilize security testing techniques, fuzzing and penetration testing

Protective Strategies

Implement Software Hardening

- Harden software to make the binary resistant to hacking
- Use coded cyclic redundancy checks (CRC) or embedded hash codes checks, binary runtime encryption
- Utilize inline coding and merge functions to minimize modular code, and altered code flow to make reverse engineering difficult
- Implement glass box techniques
  (Binary code can only run on designated hardware)

Protective Strategies

Supply Chain and Intellectual Property

- Supply Chain Protection
  - Audit vendors for compliance with cyber security best practices
  - Test and verify third-party code releases prior to introducing them into your environment
  - Purchase hardware and software from trusted sources
- Protection of All Intellectual Property
  - Secure all digital twin artifacts, documents, schematics, etc.
  - Protect all information flow to and from the digital twin platform
  - Minimize access to source code and critical design elements

Summary

- This presentation offers considerations from a regulatory perspective while digital twin technology is in development.
- Before procurement or use of technology and throughout its evolution, there is a need to understand the attack surfaces and environments associated with digital assets.
- Nuclear power plant operators maintain the following throughout the life cycle of digital assets: a security defensive architecture to address the attack surfaces and environments, and multiple layers of cyber security protections to establish sufficient defense-in depth. Defense-in-depth protective strategies are maintained to ensure the capability to detect, respond, and recover from cyber attacks.
- Such an objective depends on understanding and careful consideration of technology before procurement or use.

IAEA
International Atomic Energy Agency
Atoms for Peace and Development

Asherah NPP Simulator Cybersecurity in a Digital Closed-Loop Environment

The 2020 Workshop on Digital Twin Applications in the Nuclear Industry

Rodney Busquim e Silva
December 3, 2020

Nuclear Power Plants Rely on Digital-based Systems

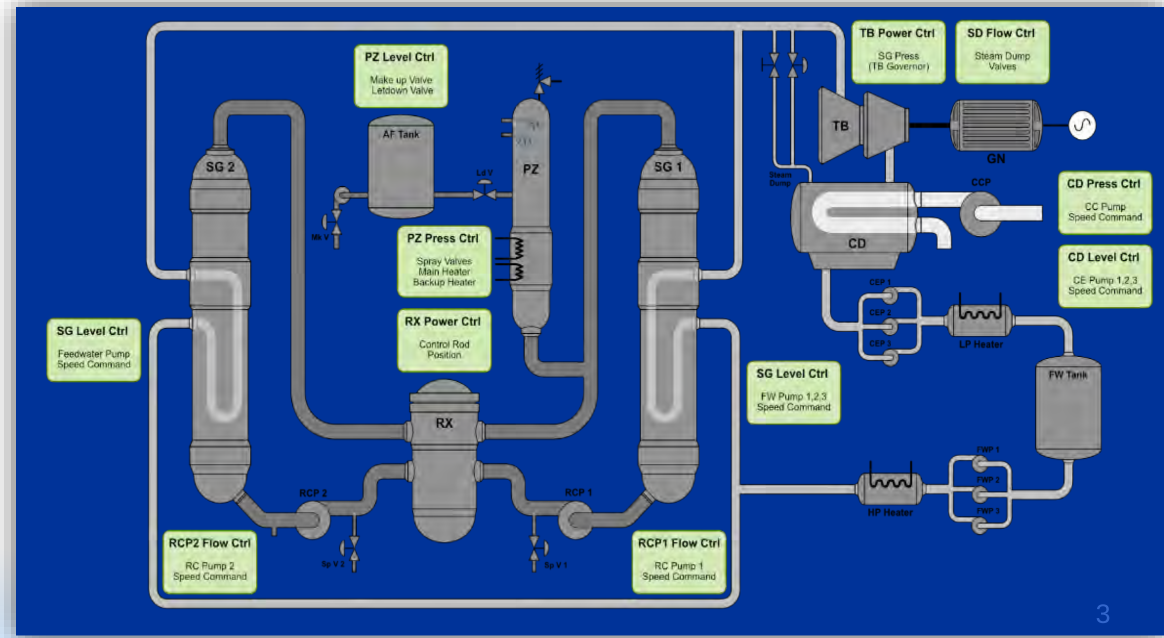
IAEA

- NPPs are among the most complex energy systems ever built.
- NPP functions and processes rely on a myriad of digital IT and I&C systems.

- NPPs’ capital cost and the radioactive nature of nuclear fuel demand computational tools for licensing, operation and accident analysis.
- NPPs are among the most emblematic examples of critical infrastructure cyber-targets.

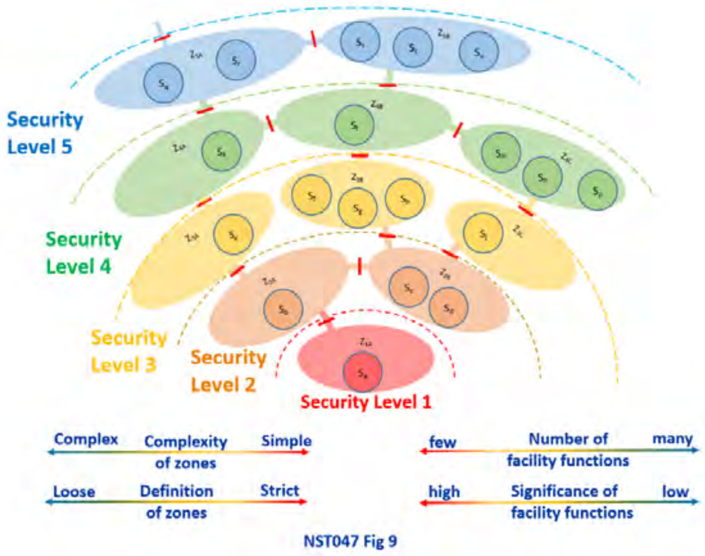
The Challenge

How can we improve cybersecurity capabilities, conduct IT and I&C research, increase awareness, and perform training and hands-on exercises in an integrated nuclear power plant environment?



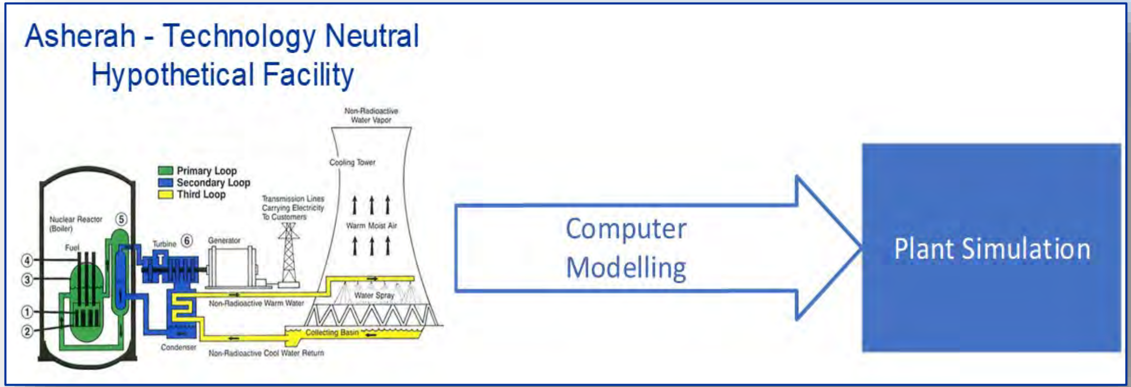
In a NPP environment, how do we:

- assess the facility impact of a system being compromised?
- evaluate the effectiveness of segregating facility functions?
- assess computer security (CS) vulnerabilities in the systems that perform functions?
- evaluate the use of de-coupling mechanisms?
- test the effectiveness of firewall rules?
- … and assess many other CS related issues?



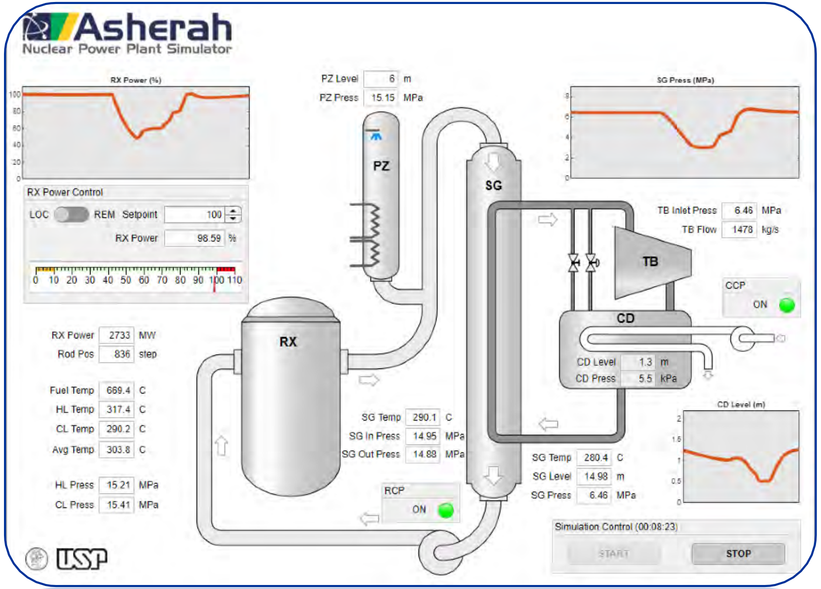
IAEA CRP: Asherah NPP Simulator (ANS)

A hypothetical/neutral PWR named "Asherah" was defined based upon several NPP existing designs.



- The results were combined to produce a technological neutral facility.
- USP developed ANS model to be the heart of a cyber security assessment test bed.
- The simulator was designed specifically for the simulation of cyber-attacks.

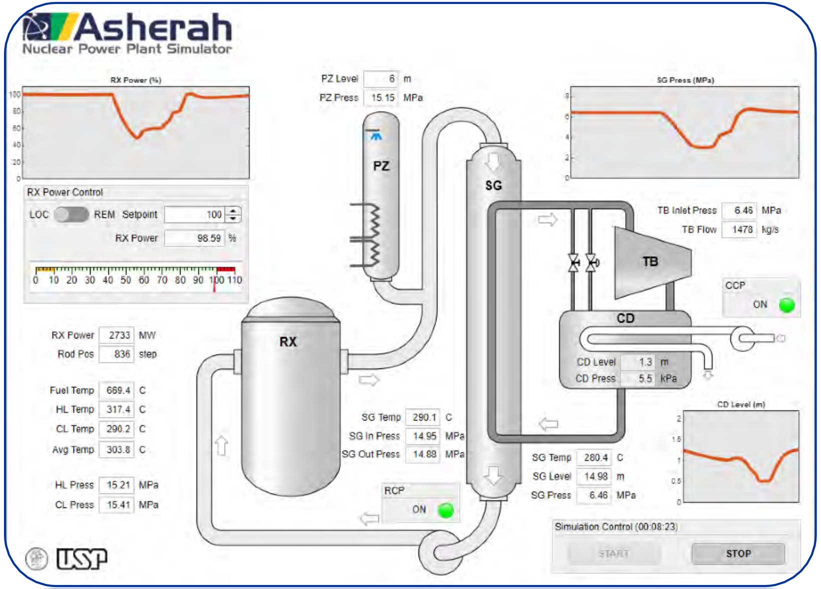
IAEA CRP: Asherah NPP Simulator (ANS)

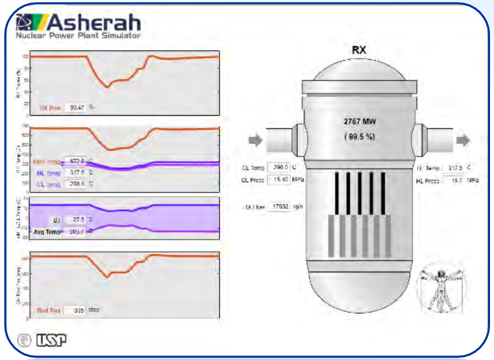


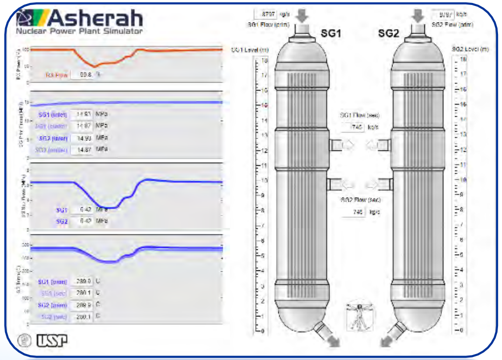
Local HMI & Simulation Control

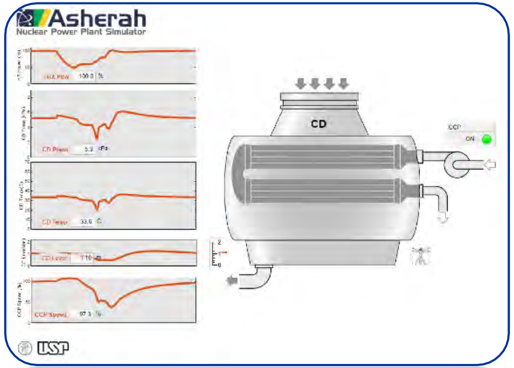
- ANS reproduces the Asherah NPP behavior using dynamic models.
- It is based on:
  - The TMI core.
  - Typical industry systems and equipment.
  - Standard control logic.
- It has been implemented using the Matlab/Simulink environment.
- It has the capability to interface with IT/OT equipment for cyber security assessment.

IAEA CRP: Asherah NPP Simulator (ANS)









Local HMI & Simulation Control

WATCH THE VIDEOS

ANS Interfaces

- ANS has been connected to physical and virtual controllers - and other equipment.
- USP developed I/O interfaces for Modbus and OPC-UA & DA communication.
- USP has also developed a light OPC UA Server & client, i4BrSrv, for ANS communication.

ANS Deployment Modes

Abstract & Portable

Standalone — ANS (plant processes & controllers) running in one VM

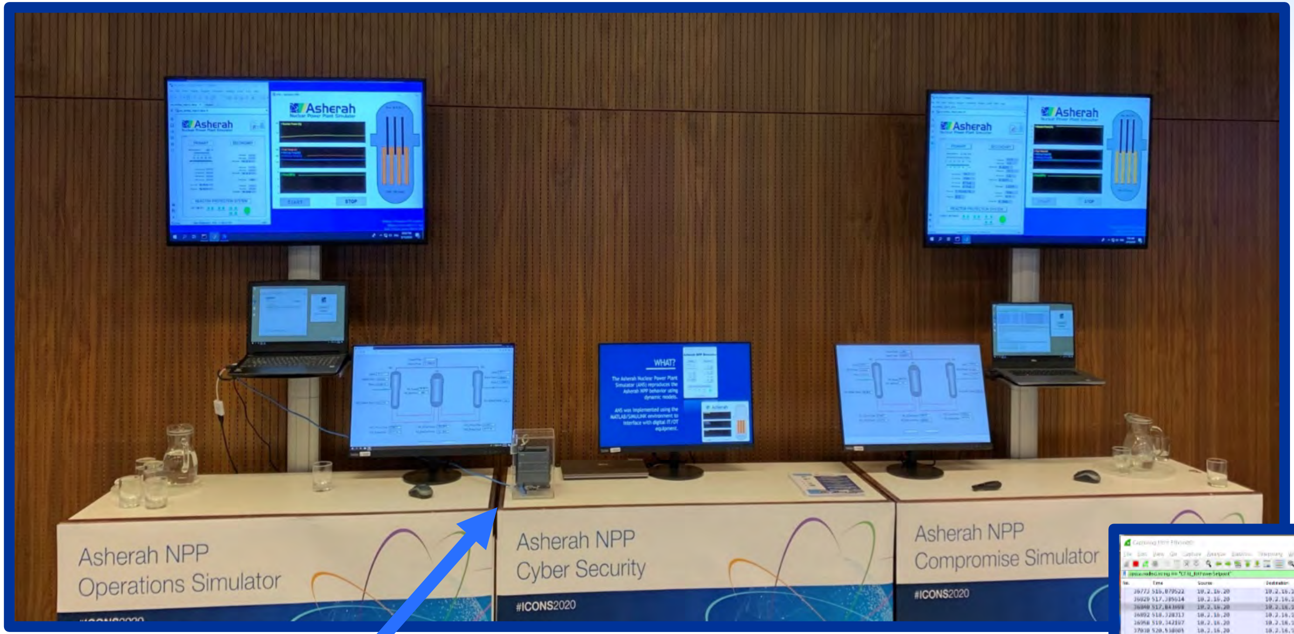
Model-Based — ANS plant processes & controllers running in many VMs

CLDT-Based — ANS plant processes & controllers running in a Closed-Loop Digital Twin (CLDT) test bed

HIL-Based — ANS plant processes & controllers running in a Hardware-In-the-Loop (HIL) test bed

Concrete & Complex

IAEA ICONS 2020 DEMO: HIL and Model-based Run

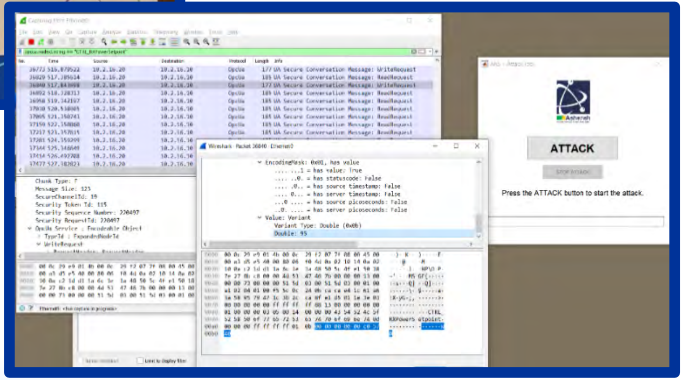


Easy to run by any user

Model & HIL based setups

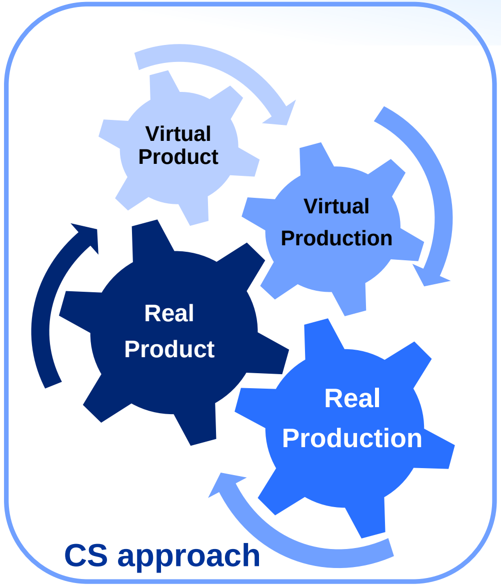
4 Virtual machines per setup

Easy to analyze the network



Closed-Loop Digital Twin (CLDT)

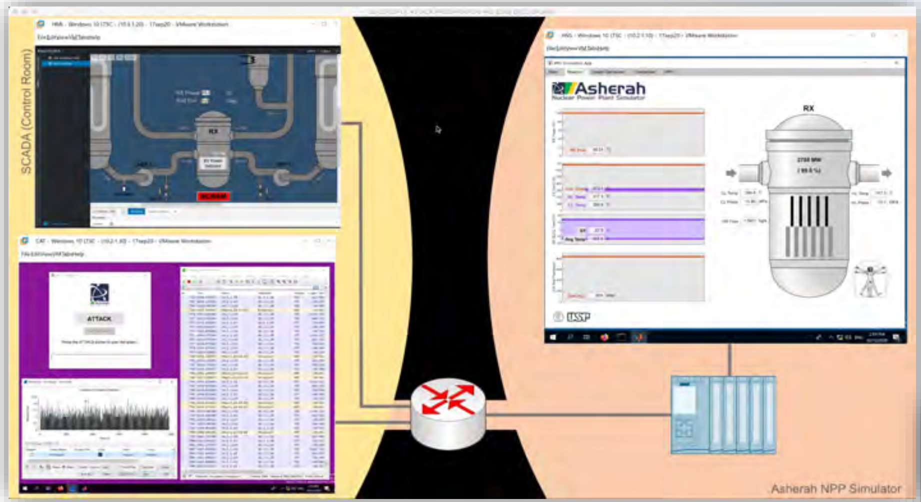
- A DT is a simulated/emulated device/system that replicates in detail their physical counterparts on the logic and network layer.



- A DT may be leveraged for CS purposes in two ways:
  - Simulation mode
  - Replication mode

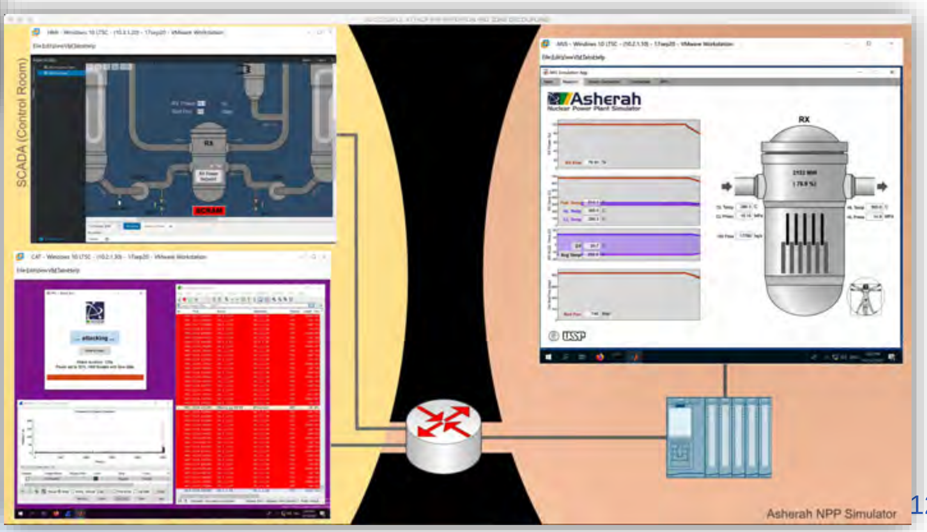
- CS can be introduced during the **product design** and production phases.
- CS can be seamlessly integrated in the entire digital-based systems **lifecycle**.

ANS PLC CLDT: Successful Attack Example



- Attack scenario where a PLC is compromised from outside the I&C controllers network.
- A PLC DT integrated with the ANS CLDT test bed allows for assessment of the network indicator of compromise and of the facility impact.

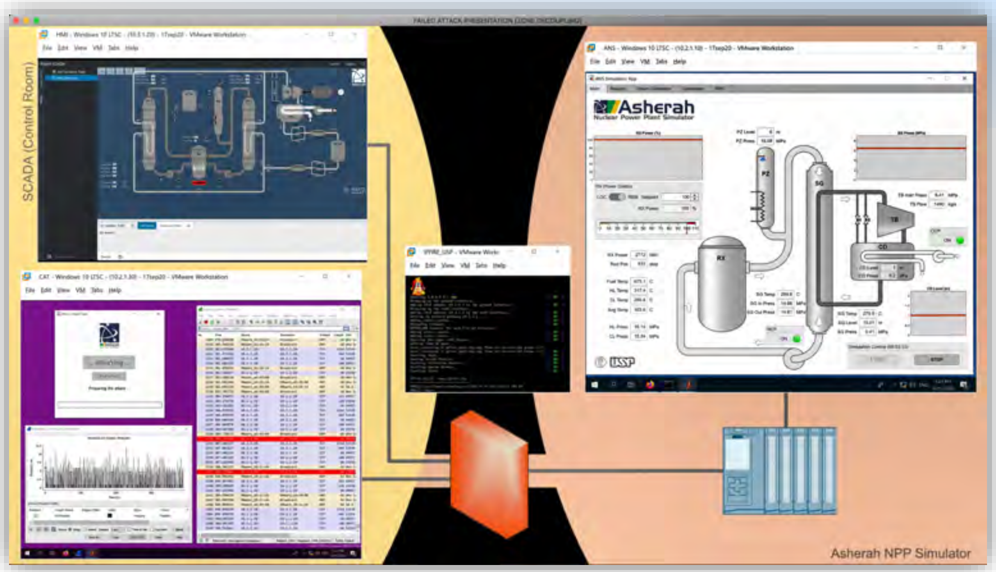
WATCH THE VIDEOS



ANS PLC CLDT: Unsuccessful Attack Example

The ANS PLC CLDT Simulation mode test bed allowed for:

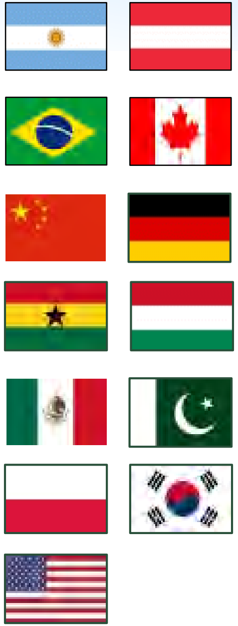
- Monitoring of NPP facility functions.
- Assessment of the effectiveness of a computer security strategy.
- Monitoring I/O tags at the PLC (process).
- Checking integrity and availability of PLC I/O tags and HMI tags (network).
- Introduction of CS from the design phase.



WATCH THE VIDEOS

Final Remarks

- DTs create new possibilities for monitoring, simulating, estimating and assessing states of real systems.
- ANS was developed for an IAEA CRP (17 teams of 13 MS) for computer security research and it has been supporting graduate and postdoctoral studies.
- ANS has been integrated in test beds, applied in CS exercises and demonstration in Austria, Brazil, Canada, China, Germany, ROK and USA.
- DTs can be leveraged for computer security purposes when integrated with nuclear simulators like the ANS.



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Thank you!

Advanced Modeling and Simulation and its Future Role in Nuclear Systems Digital Twin Technology

Dave Kropaczek
Oak Ridge National Laboratory

Technical Session: Multiphysics Modeling
Digital Twin Applications for Advanced Nuclear Technologies
December 1-4, 2020

ORNL is managed by UT-Battelle, LLC for the US Department of Energy

Digital Twin – Role of Modeling and Simulation

"The digital twin is the virtual representation of a physical object or system across its life-cycle. It uses real-time data and other sources to enable learning, reasoning, and dynamically recalibrating for improved decision making." *

In Nuclear Systems, the digital twin may be characterized by:

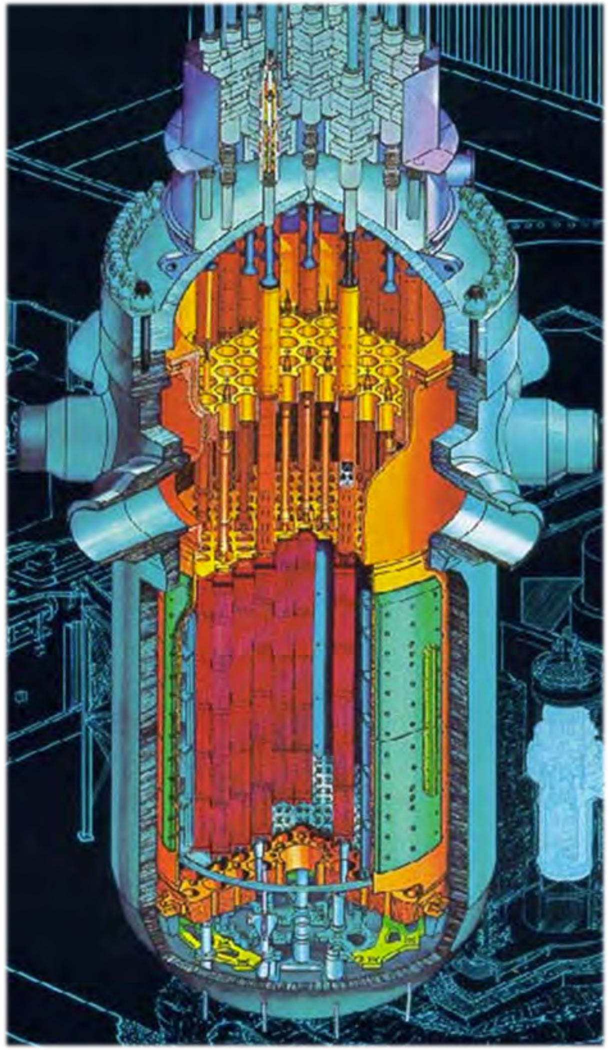
- Virtual simulator for the plant systems and subsystems, including the reactor core and fuel
- Use of a wide-range of sensors (in-core/ex-core detectors, thermocouples, pressure, flow, etc.)
- Mapping of sensor data onto the virtual model through update of the simulator model parameters
- Recalibration of the virtual simulator based on real-time data
- Use of the virtual simulator to monitor operational limits (e.g. core, fuel)
- Use of the virtual simulator to make future projections regarding reactor behavior under "what if" scenarios
- Use of the virtual simulator as part of the reactor control system (human or autonomous)

By these definitions, the digital twin for nuclear systems has existed for decades in the form of on-line core monitoring systems. What has changed are the advances in modeling, sensors, calibration techniques, and predictive analytics to enable a step change in decision-making capabilities for reactor operation.

* *https://www.ibm.com/blogs/internet-of-things/iot-cheat-sheet-digital-twin/*
with credit to Josh Kaizer, NRC

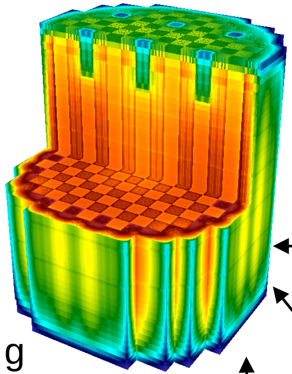
Digital Twin - Virtual Simulator

- High fidelity predictive simulation for quantities of interest
  - Safety parameters (temperatures, power deposition)
  - Operational parameters (power response, energy output)
  - Component behavior (lifetime analysis)
- Physics-based modeling for key phenomena
  - First-principles based (elimination of correlations)
  - Multi-physics response for coupled physics
  - Includes neutronics, thermal-hydraulics, chemistry, and materials modeling
- High geometrical resolution
  - Sufficient resolution to make use of real-time sensor data
  - Modeling across length scales – atomistic to engineering scale
- Comprehensive, usable and extensible software system
  - Verified software – code and solution verification
  - Validated software – single and integral effects tests
  - Quantified uncertainties for model parameters and input data



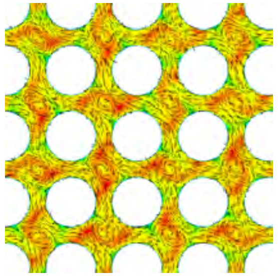
Multi-Physics Coupled Simulation

Reactor Physics



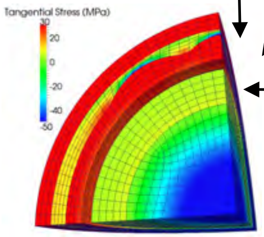
- $(n + \gamma)$ Transport
- Nuclear XS Feedback
- On-the-fly XS Processing
- Isotopic Transmutation

Thermal Hydraulics



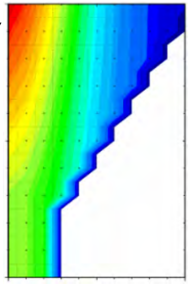
- Mass, Momentum, and Energy Transport
- Whole-core flow field resolution
- Multi-phase flow

Fuel Performance

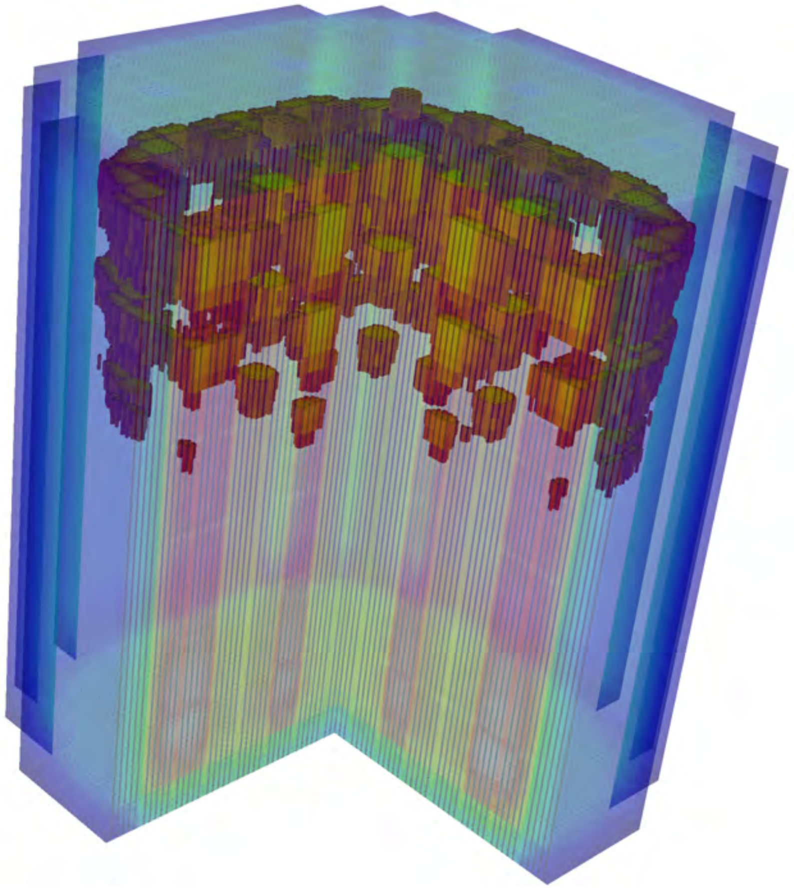


- Thermal Transport
- Fuel Evolution (relocation, swelling)
- Clad Evolution (creep)
- Mechanical Contact

Coolant Chemistry



- Crud source term
- Surface deposition and growth
- Equilibrium thermodynamics
- Chemical Kinetics



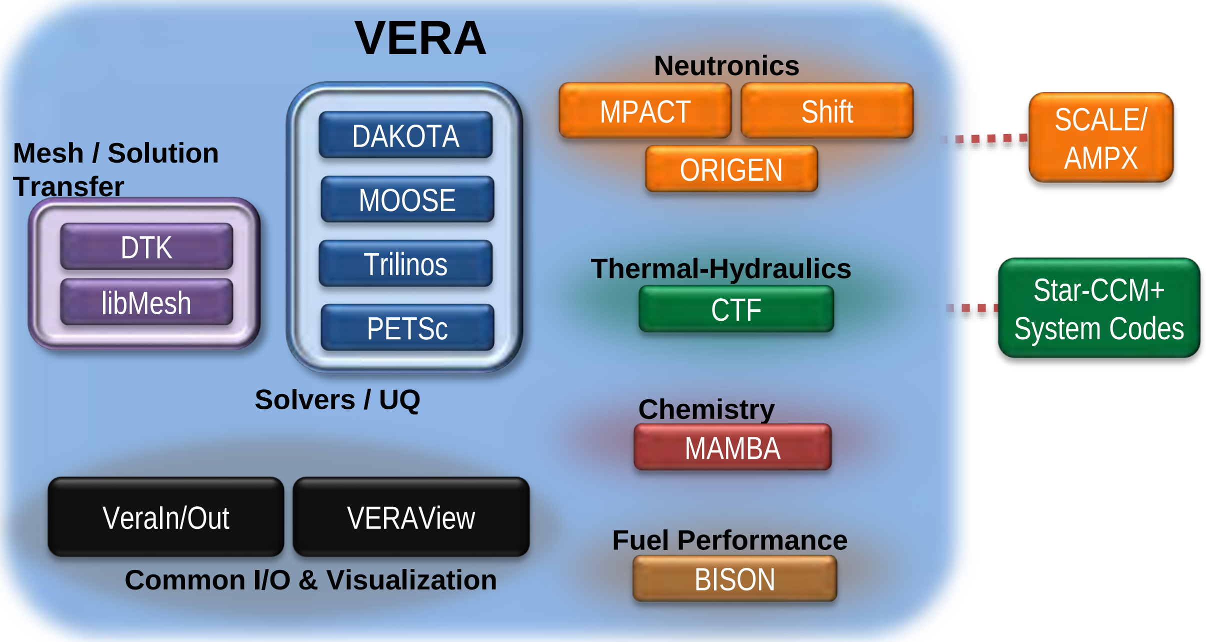
Crud distribution in a PWR

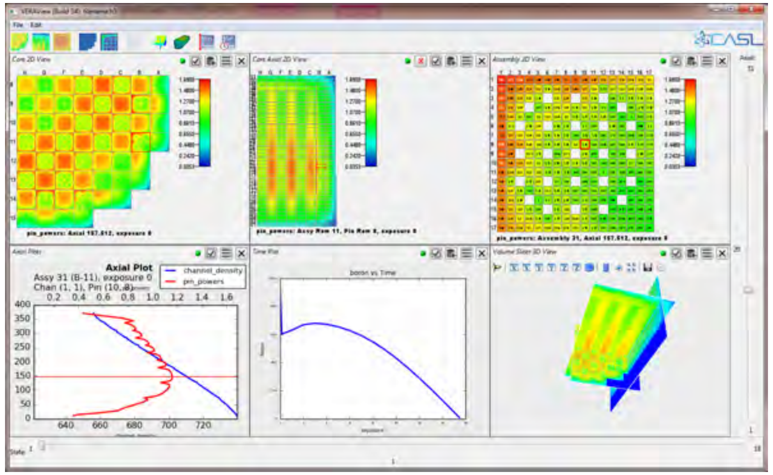
Physics Phenomena of Interest are Common to All Reactor Types

VERA – A Fully Integrated Capability for Reactor Analysis

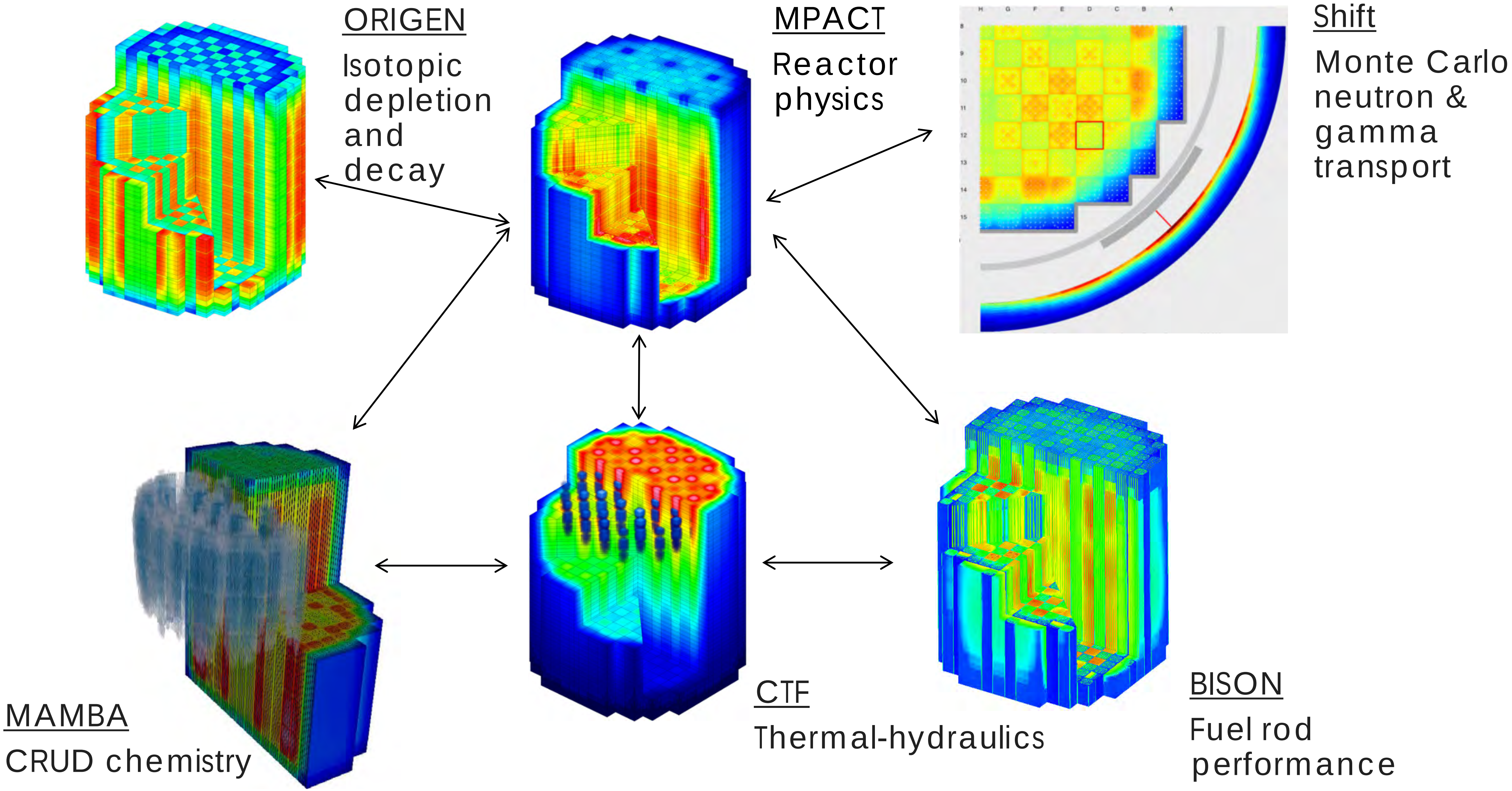
Virtual Environment for Reactor Applications

- High Resolution:
  - Fully coupled and pin-resolved neutronic, T/H, and crud growth physics
  - Detailed rod-wise fuel performance analyses
- Integrated Applications:
  - Modeling in-core and ex-core detector prediction of axial offset (AO) due to CRUD deposition
  - Identification of PCI failure risk during load follow operation with accident tolerance fuel and cladding
  - Accumulation of radiation damage in the reactor vessel due to neutron fluence
  - Prediction of cladding integrity during reactivity-initiated transient using coupled neutronics and T/H with offline fuels analysis
- Performance & Usability:
  - User-friendly I/O (e.g. automated mesh generation and data transfers)
  - Integrated visualization tools



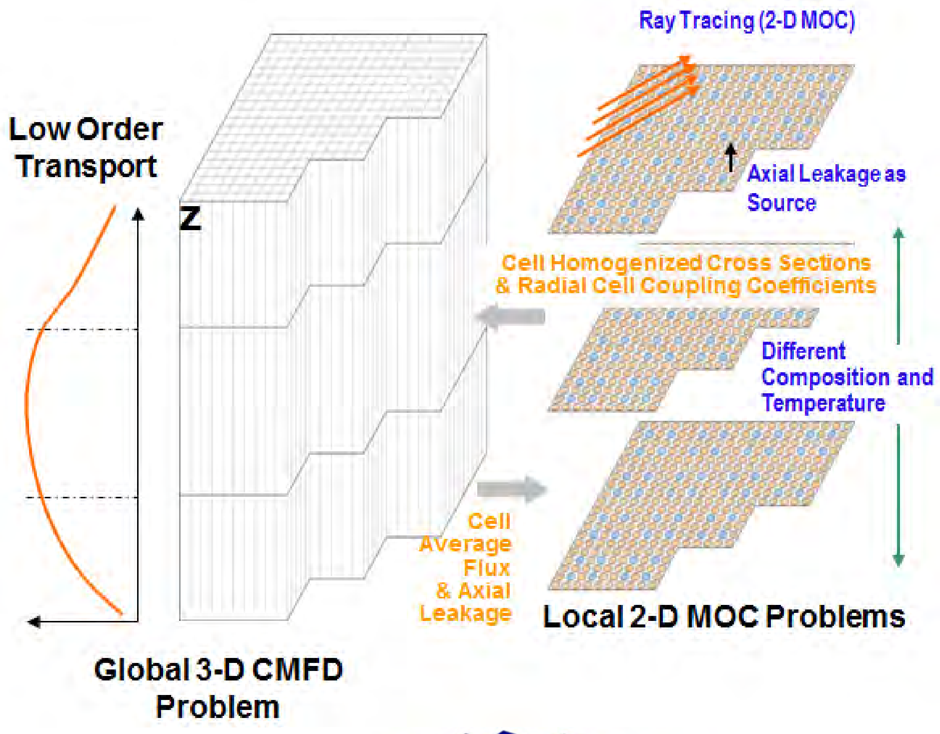


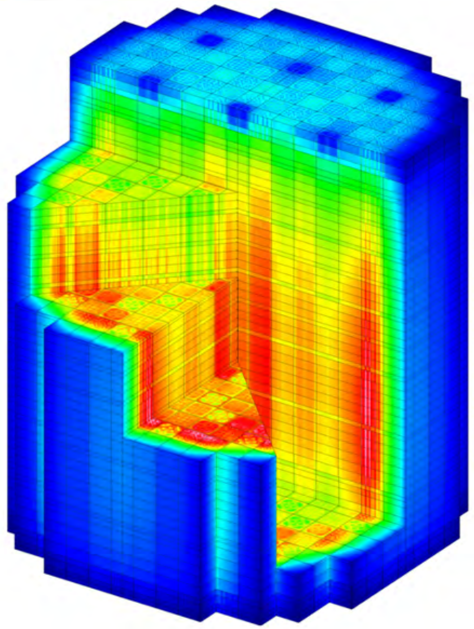
VERA Key Physics Codes



MPACT

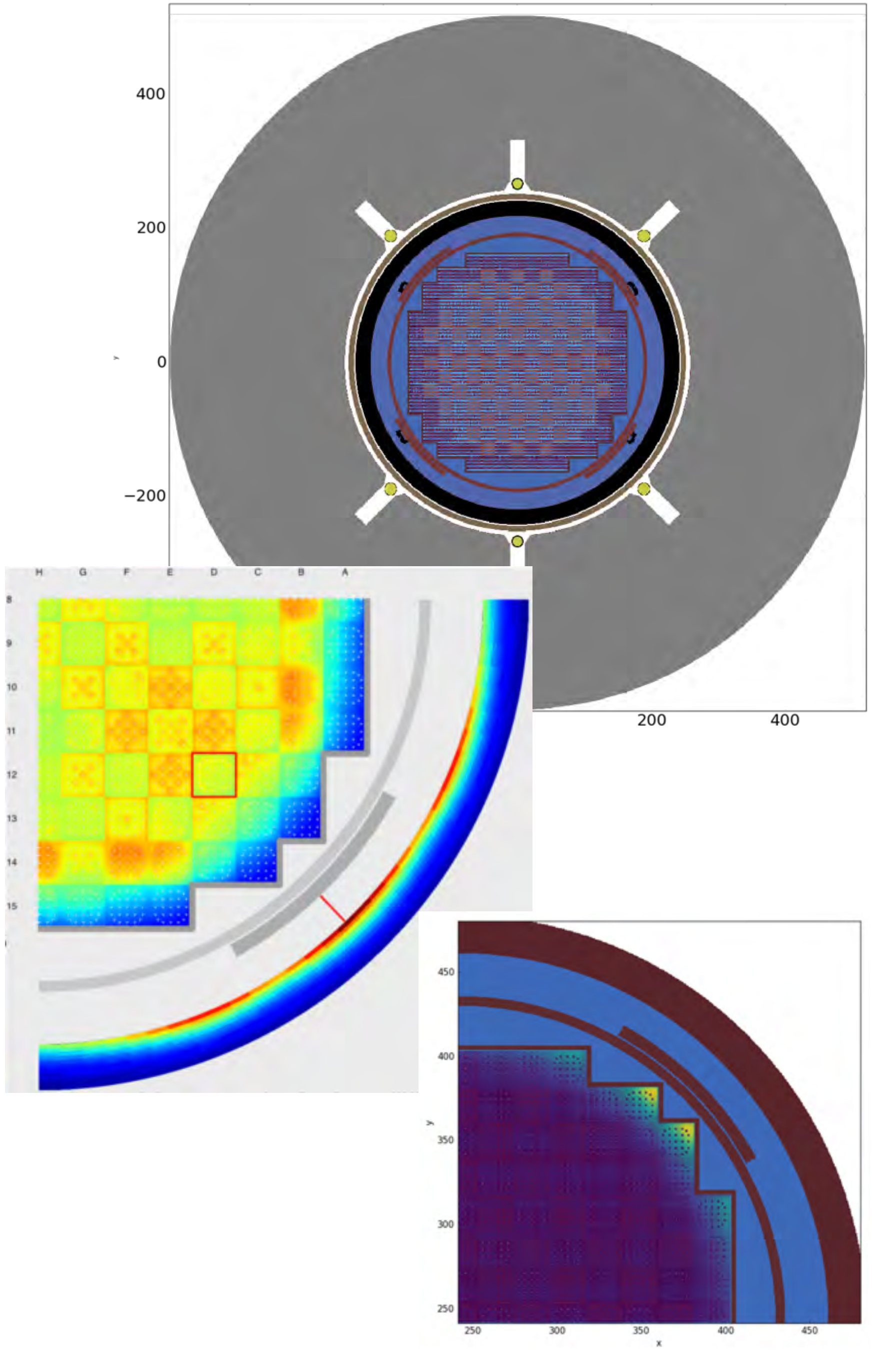
- Advanced 3D Neutronics
  - Method-of-Characteristics
  - 51 energy group nuclear data library
  - Whole pin-wise resolution, including intra-pellet power and isotopic distributions
- Steady-state and transient capability
- Integrated explicit isotopic depletion and decay with ORIGEN
- 3D accuracy comparable to continuous-energy Monte Carlo methods, including Shift and MCNP
- Core shuffling and control rod movement
- In-core detector responses
- Validated against critical experiments and over 150 fuel cycles





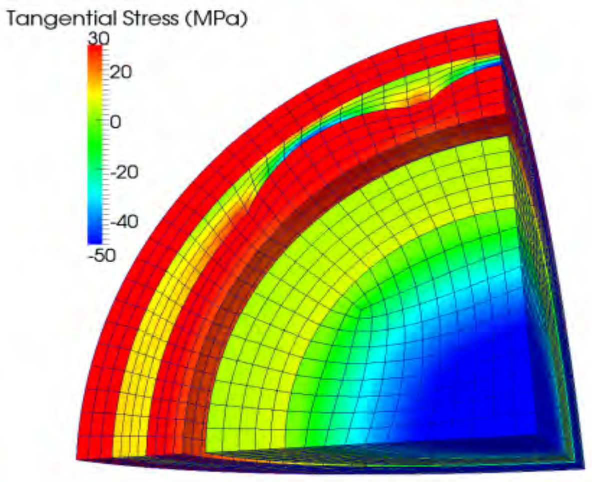
Shift

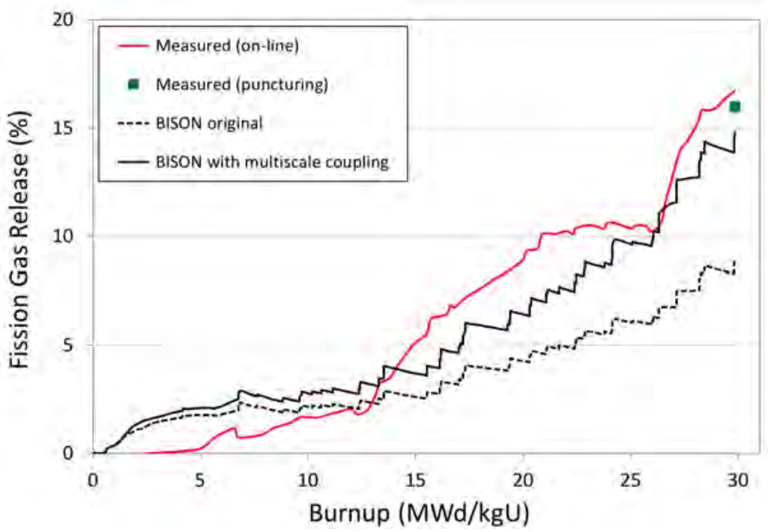
- Accurate and efficient neutron and gamma transport
  - Continuous-energy Monte Carlo neutron & gamma transport to any region outside of the reactor core
  - State-of-the-art hybrid methods focus particles toward the regions of interest
- General geometry capability for ex-vessel region
- MPACT provides accurate 3D fission source & isotopics
- Enables best-estimate vessel fluence analysis and coupon irradiation
- Ex-core detector response calculations and weighting factor generation
- Coupling with materials models allows for calculation of concrete degradation and core structure embrittlement



BISON

- VERA can be used to perform detailed fuel rod performance analysis with BISON
  - Finite element-based engineering scale fuel performance code
  - Solves the fully-coupled thermo-mechanics and species diffusion equations in 1D symmetric, 1.5D, 2D axisymmetric or generalized plane strain, or 3D
- Lower length scale and mechanistic models for key physics phenomenon (e.g. fission gas release, thermal conductivity) applicable to existing and future ATF fuel forms and clad
- Fuel rod geometry and power histories used to automatically create BISON inputs for any or all fuel rods in a reactor core
- BISON results are collected into VERAOut format for whole-core fuel rod performance analysis or screening



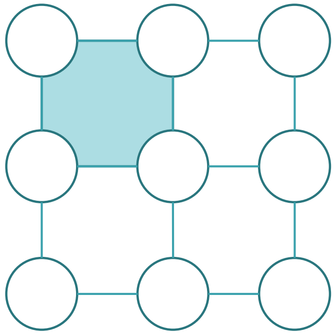


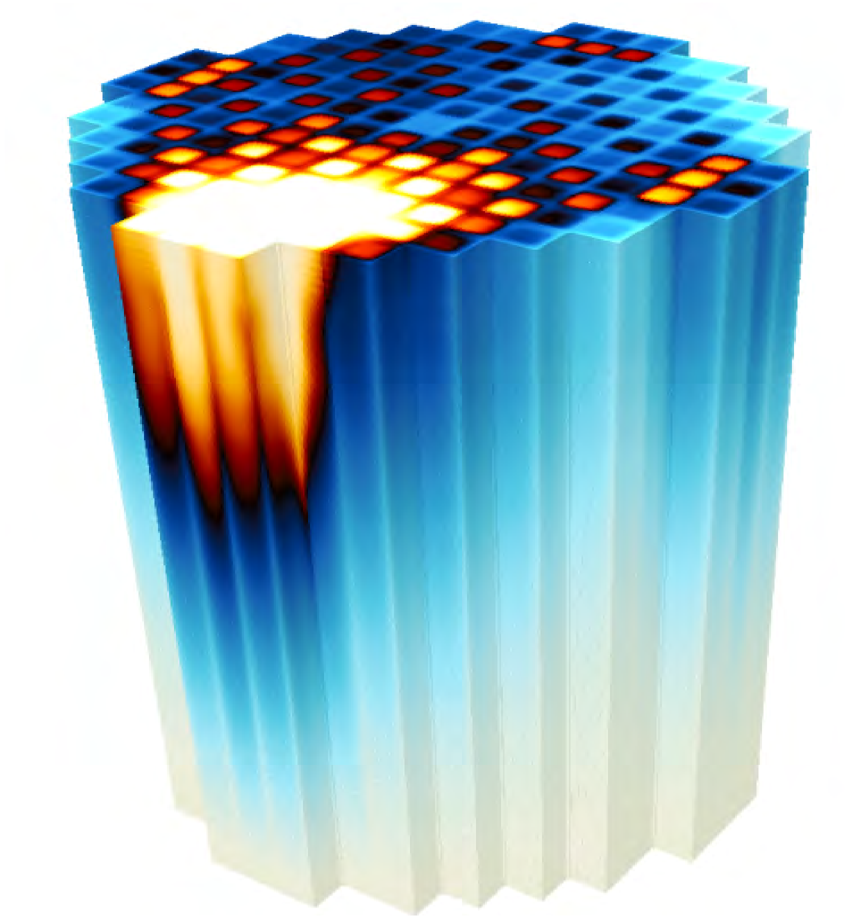
Ref. K. Gamble, G. Pastore, M. Cooper, D. Andersson, ATF material model development and validation for priority fuel concepts, CASL-U-2019-1870-000, July 2019.

CTF

- Whole-Core Two-Phase Subchannel Thermal-Hydraulics
  - Three-field representation of two-phase flow
  - Continuous vapor (mass, momentum and energy)
  - Continuous liquid (mass, momentum and energy)
  - Entrained liquid drops (mass and momentum)
  - Non-condensable gas mixture (mass)
  - Native, transient fuel temperature model
- Cross flow between channels
- Coupling with Systems Codes (TRACE, RELAP) via inlet and exit boundary conditions
- Spacer grid pressure loses and blockages and intra-grid form losses
- Use of higher resolution computational fluid dynamics (CFD) simulation to improve the subchannel modeling

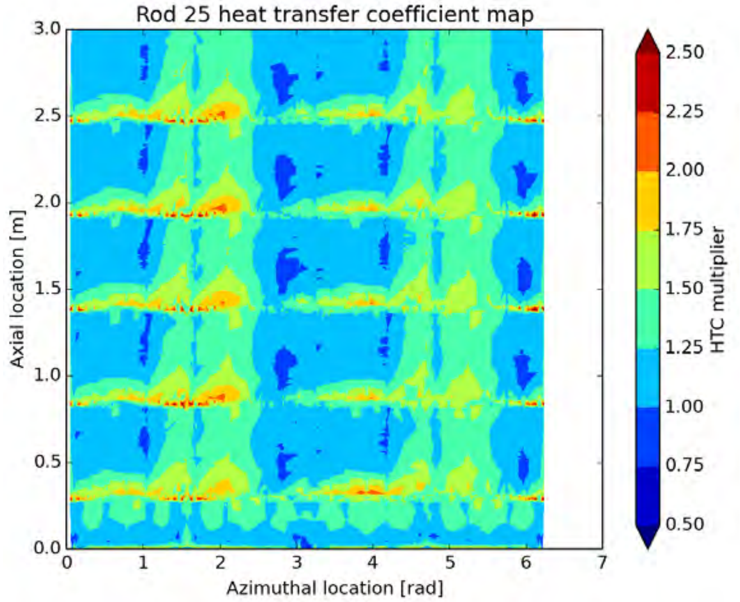
Sub-Channel Discretization for the entire core



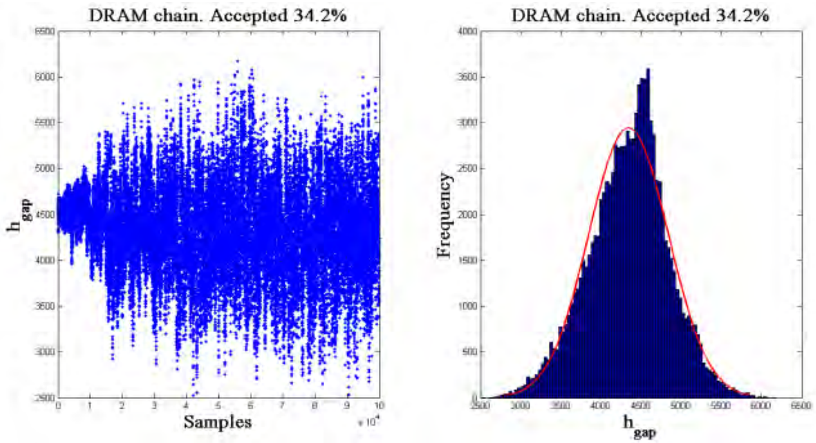


Addressing Modeling Gaps

- Use of high resolution, high fidelity methods to improve lower resolution model for key System Response Quantities (SRQs)
  - STAR-CCM+ informs CTF
  - SRQs include azimuthal heat flux and TKE
- Use of integral experiments and system level data to calibrate fundamental model parameters where Single Effects Tests (SETs) data does not exist
  - Bayesian calibration allows for establishment of uncertainty bounds on calibrated parameters



Ref. Salko, R., S. Slattery, T. Lange, M. Delchini, W. Gurecky, E. Tatli, and B. Collins, Development of Preliminary VERA-CS Crud-Induced Localized Corrosion Modeling Capability, CASL-U- 2018-1617-000, June 2018.



Ref. B. Kuwaileh and P. Turinsky, Data Assimilation and Uncertainty Quantification Using VERA-CS for a Core Wide LWR Problem with Depletion, CASL-U-2016-1054-000, April 2016.

Watts Bar Unit 2 Power Ascension

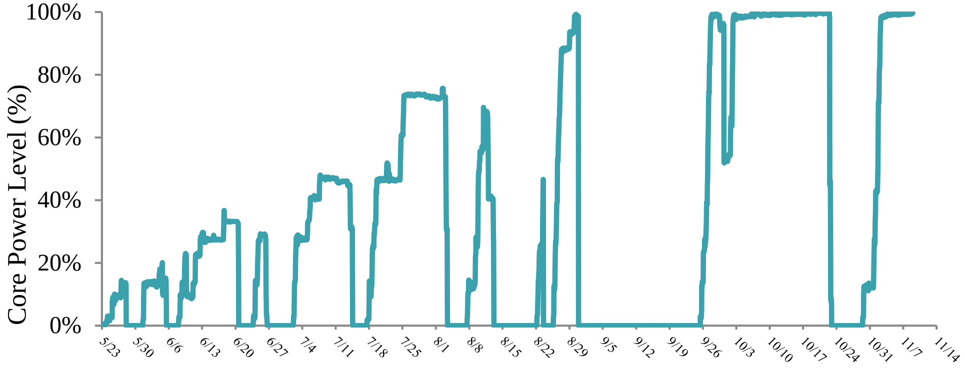
First US reactor startup in over two decades modeled in near real time as a ‘blind prediction’

- 4,130 hourly state-points
- 13.5 days of runtime on 2,784 cores
- 892,837 core-hours
- 16,605 fully-coupled neutronics/TH iterations

Accurate comparison to measurement, including a new Vanadium-wire, in-core flux map system (± 2.4%)

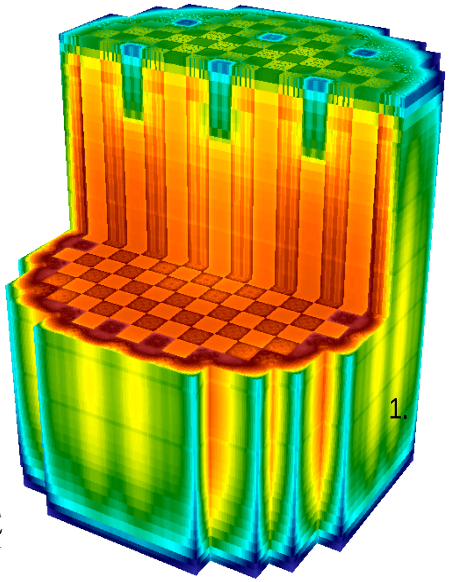
Pin-by-pin spatial detail of ‘non-measurable’ quantities of interest (e.g. Xe-135)

Watts Bar Unit 2 Power Ascension



Measured Power Distribution (M/P)
(Full Power, 5.6 GWD/T Exposure)

	R	P	N	M	L	K	J	H	G	F	E	D	C	B	A
1							1.03			1.03					
2			1.03			0.99		0.99							
3								1.01		1.02		1.02		1.01	
4		1.03	1.01					0.99							
5					0.99				0.98		0.99		0.98		
6	1.03		1.02			0.98		0.96						0.97	
7				1.02			0.97			1.00			0.97		
8	1.04		1.02		1.00		1.00			0.97		0.98	1.00	0.98	
9		1.04							0.98		0.98				1.00
10					1.01		1.01					0.97			
11	1.02				0.99			1.01			0.98				1.00
12						0.99			1.02			0.98			
13			1.05		0.99			1.02						1.01	
14			1.03				1.04			0.98		1.02			
15					1.00			1.03							



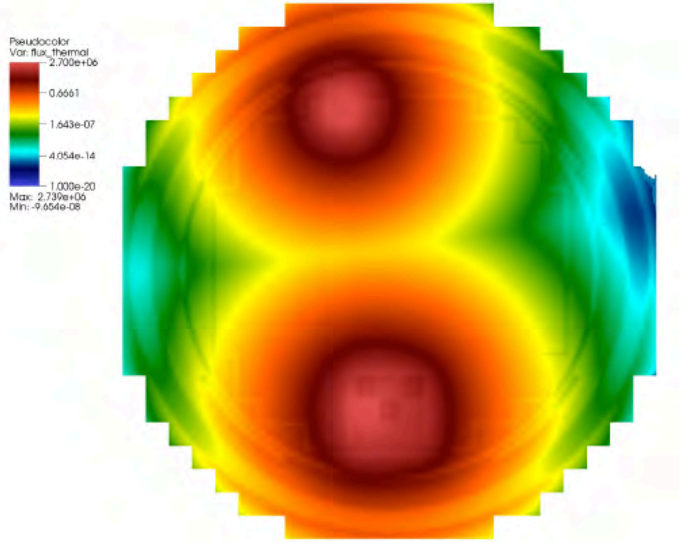
Watts Bar 2 predicted, transient Xenon-135 distribution at 28% power level

1. Ref. A. Godfrey, B. Collins, C. Gentry, S. Stimpson, J. Ritchie, Watts Bar Unit 2 Startup Results with VERA, CASL-U-2017-1306-000, March 2017.

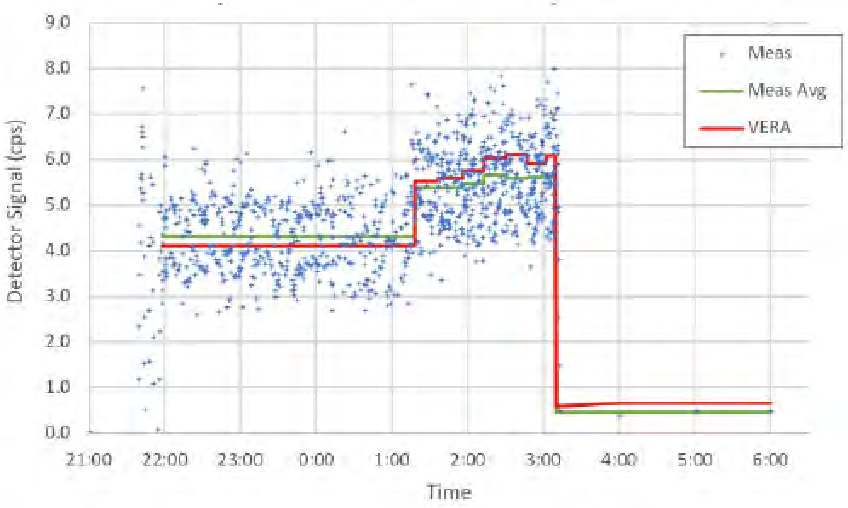
OAK RIDGE National Laboratory

VERA Simulation of Signal Response

- First-of-a-kind capability demonstrated for VERA-Shift applied to coupled in-core/ex-core calculations
- Addresses a concern over secondary source signal strength as seen by the source range detectors (SRD) during refueling
- In this application, virtual detector signals were generated for the refueling shuffle sequence with direct comparison against measured count rates
- Excellent agreement between measured and predicted signal



WBN1 C8 Thermal Flux with 9 Assemblies Loaded for Southern SRD



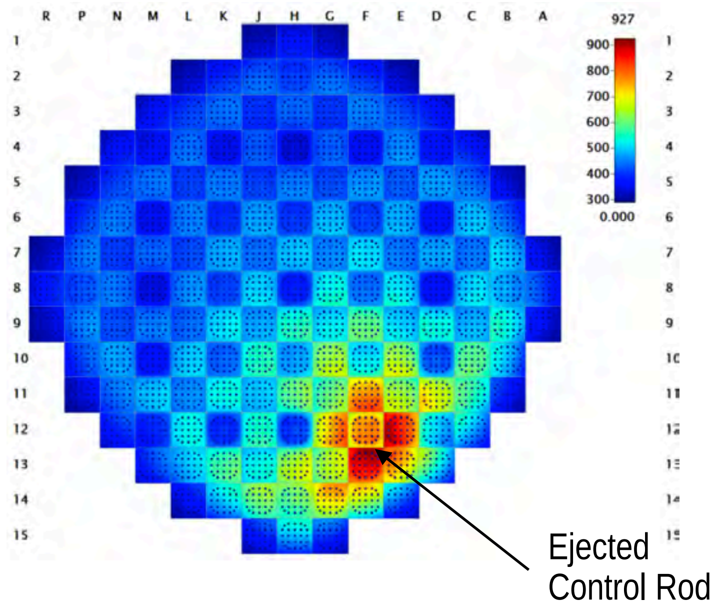
Ref. Godfrey, E. Davidson, G. Wolfram, B. Collins, C. Gentry, G. Ilas, S. Palmtag, T. Pandya, K. Royston, Watts Bar Unit 1 Source Range Detector Response Validation During Refueling, CASL-U-2018-1561-000, December 2018.

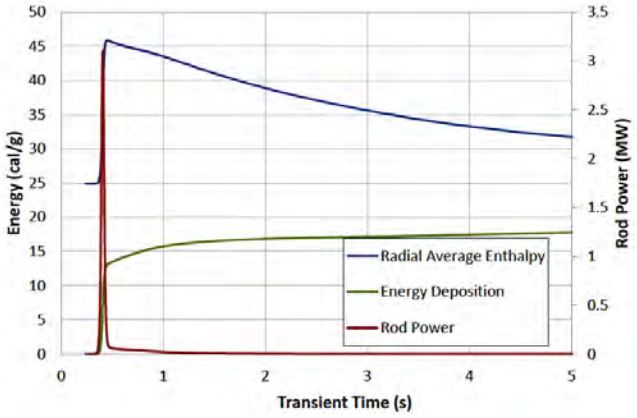
DOE-NE Advanced Modeling Simulation

Light Water Reactors - Near-term focus

- Provide support for advanced LWR nuclear technologies and target areas for which current LWR modeling and simulation capabilities cannot be used

- Areas include:
  - Accident tolerant fuels
  - High burnup, high enrichment fuel
  - Materials fabrication and performance, including advanced manufacturing
  - Two-phase fluid flow, including flow regime transitions
  - Reactor operational performance
  - Reactor safety performance





AP1000® RIA fuel rod enthalpy and energy deposition evolution (ATF fuel form)

Ref. S. Ray, V. Kucukboyaci, Y. Sung, P. Kersting, R. Brewster, Industry Use of CASL Tools, CASL-U-2019-1739-000, September 2018.

OAK RIDGE National Laboratory

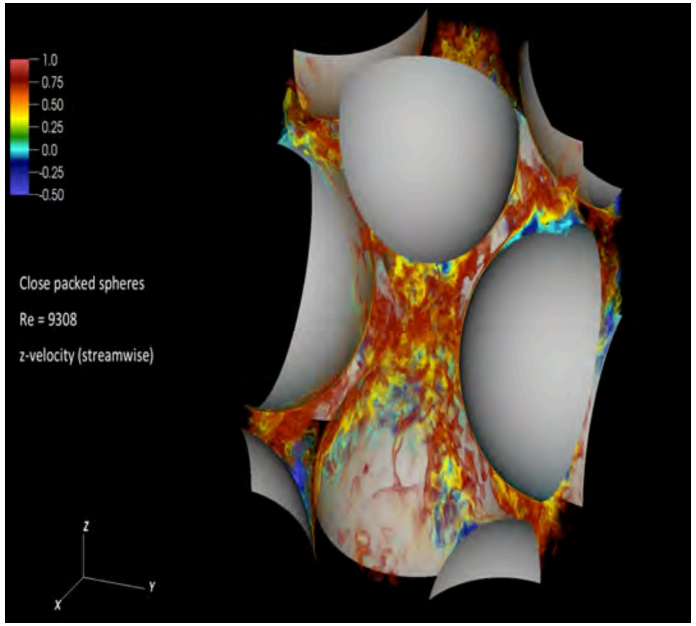
DOE-NE Advanced Modeling Simulation

Advanced Non-Light Water Reactors - Near-term focus

- Target areas identified by industry, GAIN Technical Working Groups, and the US NRC to support their activities including molten salt, HTGR, and fast reactor technologies

- Support industry and the NRC for the rapid development and demonstration of microreactors in the 3-5 years time frame

- Areas include:
  - Fuels
  - Materials fabrication and performance, including advanced manufacturing
  - Chemistry
  - Reactor systems

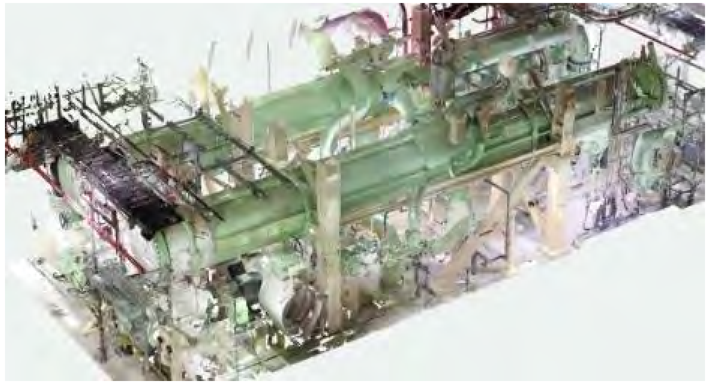


Turbulent Heat Flux – Nek5000/BISON

Summary

- The virtual reactor simulator is one aspect of the Digital Twin for Nuclear Systems
- High fidelity, high resolution virtual simulator technology has rapidly evolved to the level of high predictability for reactor quantities of interest based on coupled, multi-physics modeling
  - First principles combined with multi-scale approach can capture the relevant physics phenomena
- Uncertainties in input parameters and closure relations may nevertheless be an issue for a particular reactor configuration (fuel form, coolant).
  - Model gaps can be addressed through use of formal calibration methods
  - Such methods benefit from availability of measured data required for calibration
- Integration of high fidelity, high resolution simulation with advanced sensors result in unprecedent detailed of reactor behavior

Modeling and Simulation to Support Digital Twins



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Digital Twin Applications for Advanced Nuclear Technologies
Online Workshop
December 1-4, 2020

INTRODUCTION

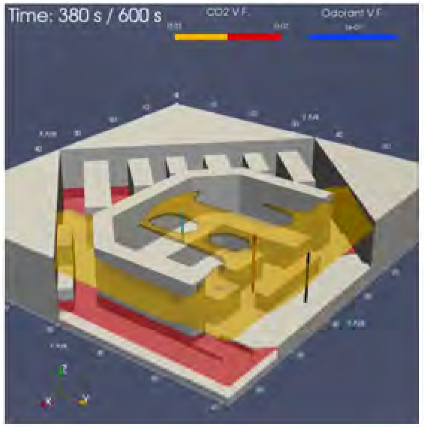
Digital Twin is a virtual replica of a physical asset

- Can be a plant, system or specific component
- Enhanced understanding of physical asset integrating data + simulation
- Can use Machine Learning (ML) & Artificial Intelligence (AI) to identify causal relationships and produce reduced-order models (ROM)
- Predict performance and expected response of the asset
- Identify vulnerabilities

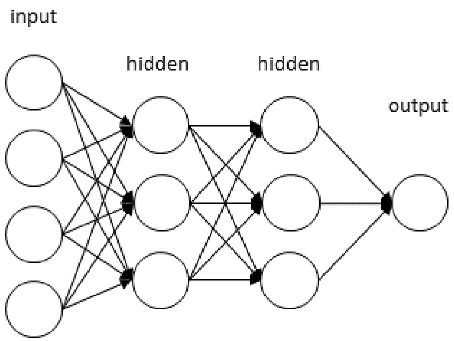
Types of Digital Twins

- Design – identify issues before construction and optimize system
- Construction – support scheduling and evaluate as-built deviations
- Operations – monitor performance degradation and maintenance
- Others

Physics-Driven Modeling



Data-Driven Modeling



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EXAMPLE - DESIGN DIGITAL TWIN

Design by simulation

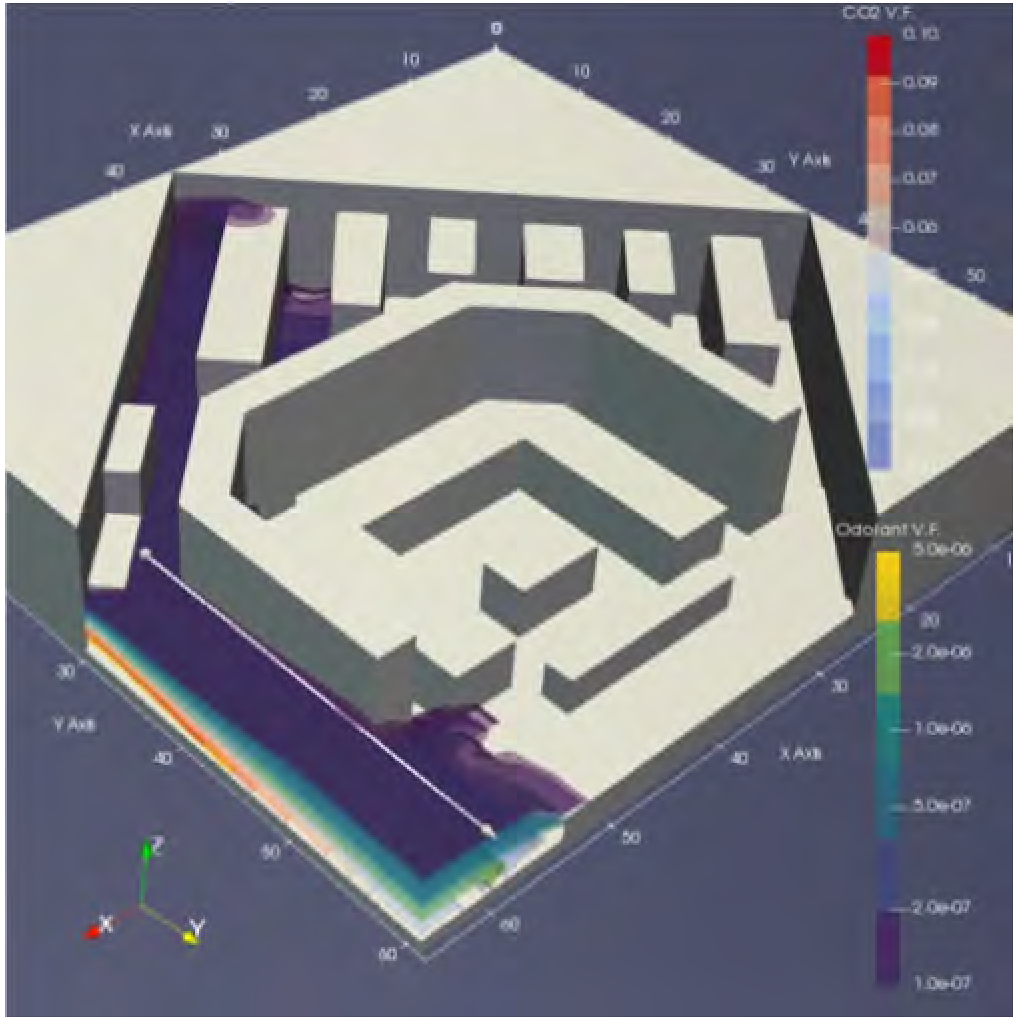
- Physics based modeling provides access to a wealth of data, including unmeasurable quantities
- Can be more cost effective than testing

Attributes:

- Identify system faults before the system is built
- System optimization

Example – Ventilation System

- Toxic gas and room habitability assessments
- Location and sizing of HVAC and filtration
- Complex geometry and recirculation patterns
- Simulation identified local pockets of higher concentration for original design



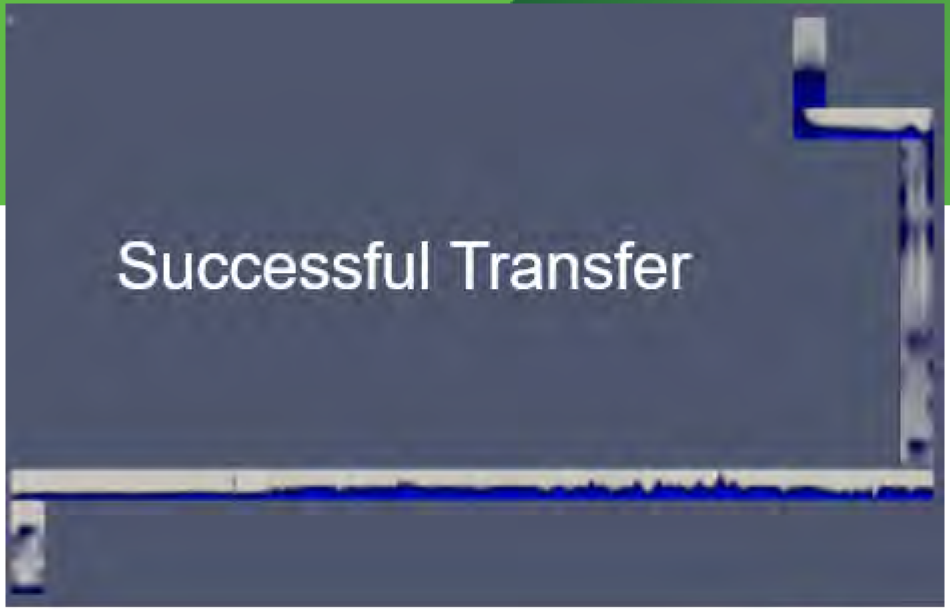
EXAMPLE - OPERATIONS DIGITAL TWIN

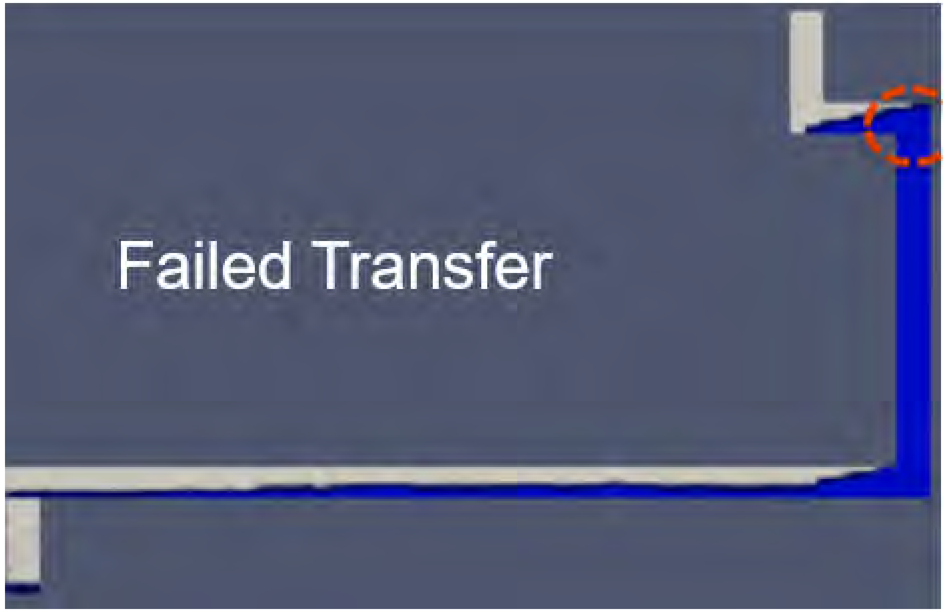
Attributes:

- Connected to the physical asset by continuously monitoring and collecting information
- Continuously learning and dynamically updating
- Simulation used to fill in knowledge gaps (e.g., non-existent data for fault scenarios)

Example - Vacuum transfer system

- Time critical transfer of fluid
- Performance degradation of seals and vacuum system
- Elongate time between maintenance and minimize downtime
- Pre-emptively schedule maintenance before failure





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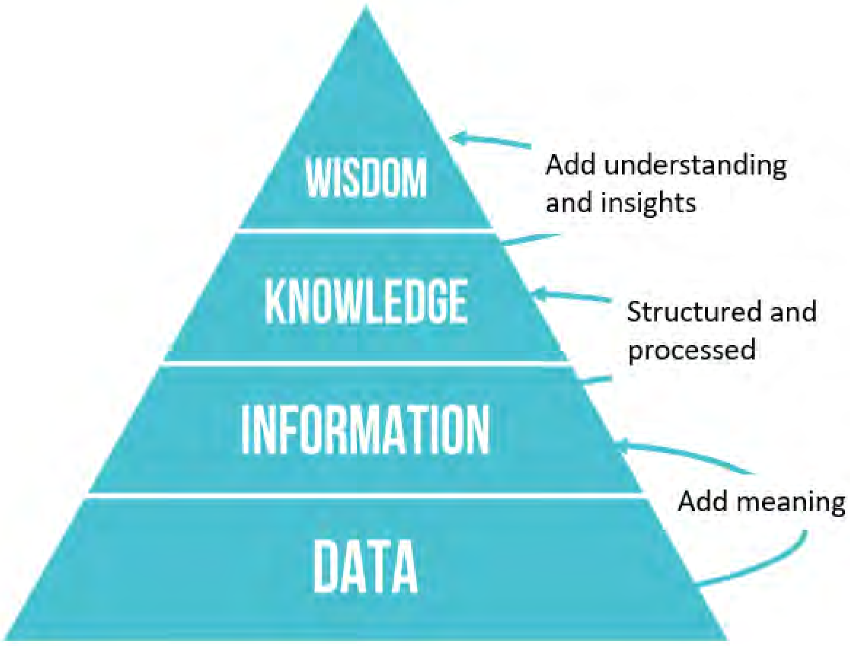
REQUIREMENTS

- Modeling & Simulation (M&S) plays an important role in digital twins to:
  - Fill in knowledge gaps or lack of available data
  - Provide access to unmeasurable quantities
- However, the M&S results must be **obtainable** and **meaningful**
  - Design by simulation requires VVUQ of M&S tool
  - Will need to assimilate M&S results with information obtained directly from the asset (I&C signals) and resolve discrepancies
- The following must be considered with respect to applying M&S for digital twins
  - Establish Applicability
  - Data Assessment
  - Software Requirements
  - Computational Requirements



From - J. Rowley, "The Wisdom Hierarchy: Representations of the DIKW hierarchy", Journal of information Science, pp. 163-180, 2006

APPLICABILITY OF M&S TOOLS

- Just like any other application of M&S, one must establish the credibility and applicability of the evaluation model (code + inputs) for the intended application
  - Provides confidence that the simulation includes the **necessary physics** and **produces accurate results** throughout the application domain
  - Establish the **uncertainty** and **trustworthiness** of the results

- Established methods for assessment
  - US NRC Code Scaling, Applicability and Uncertainty (CSAU) using Phenomena Identification and Ranking Table (PIRT)
  - Evaluation Model Development and Assessment Process (EMDAP) from Reg. Guide 1.203

- *Provide good frameworks for evaluating the adequacy and sufficiency of a result; however, in practice many applications of these methods tend to rely heavily on engineering judgement.*

APPLICABILITY OF M&S TOOLS

- Need quantitative approaches to assess
  - Accuracy of results, including uncertainty and effects of scale
  - Domain coverage – where are the holes?
  - Adequacy – what level of agreement is sufficient?

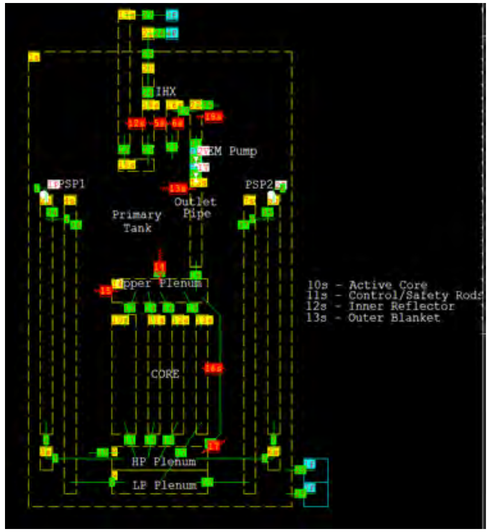
- Quantitative approaches
  - Reduce reliance on engineering judgement
  - Rank and prioritize areas for improvement both in the simulation and experimental needs

- Example:
  - Predictive Capability Maturity Quantification (PCMQ)

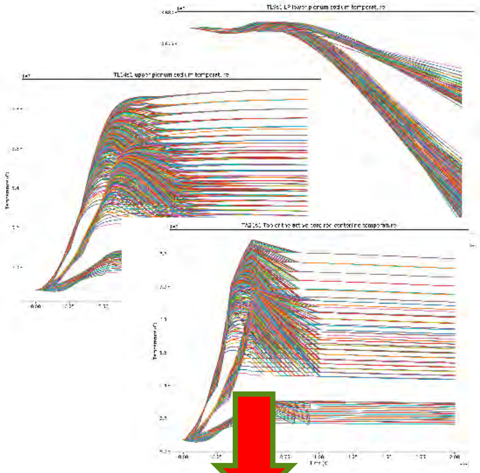
DATA ASSESSMENT

- Must assess the quality and trustworthiness of M&S data prior to training ML algorithms.
  - Establish confidence or identify unexpected results
- Automated tool to parse results
  - Search against multiple criteria and types
  - Limits (>,<), logical (AND/OR), inflection points, etc.
- Scanning tool and criteria developed to identify unexpected or anomalous behavior in simulation results
  - Reinforces that samples and training data cannot be treated as a “black-box”

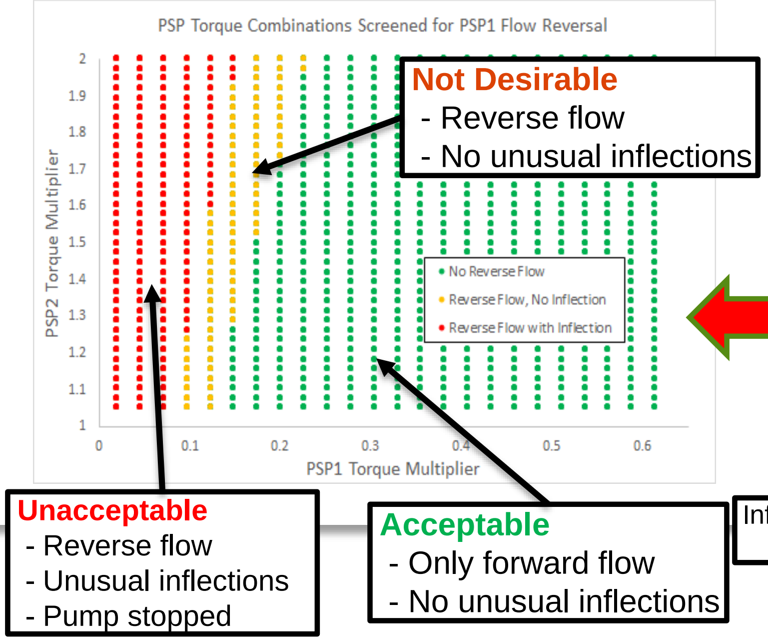
Model of EBR-II

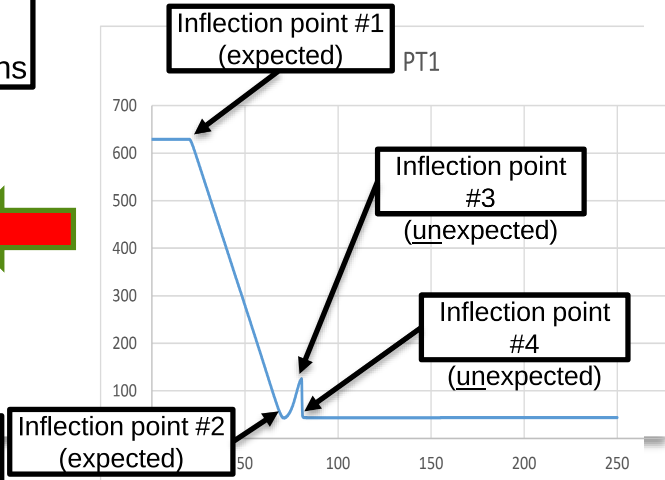


Simulation results from range of transients

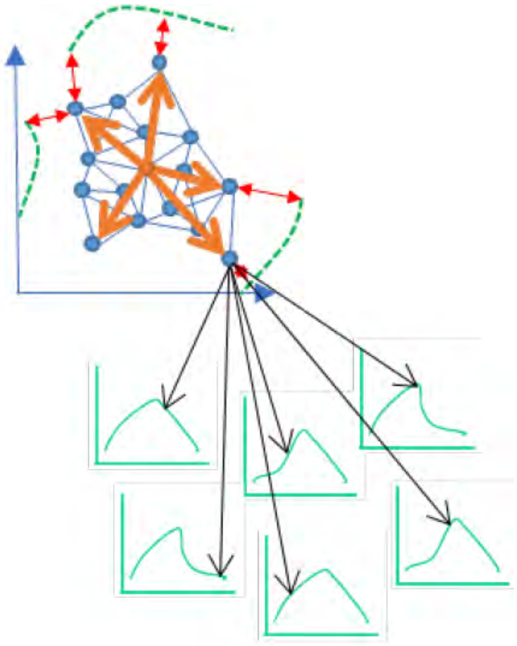


Unexpected behavior in simulation results?





DIGITAL TWINS AS SOFTWARE



- Digital twin functionality is similar to M&S
  - Stores prototypical conditions, physics, and closures to make inferences and predictions for real systems
  - But, generally able to provide results much faster than M&S
- Digital twins include different types of software
  - Computational Engine or simulator
  - Training of ML/AI algorithms
  - Digital twin itself
- ML/AI are new paradigms relative to existing nuclear SQA standards (e.g., 10 CFR 50 Appendix B, ASME NQA-1)
  - Not static and continuously learning, but must be able to verify results
  - Must provide transparency & traceability to gain confidence in these technologies
- Depending on functionality or role of the digital twin, may also need to consider software reliability, hazard analysis and cybersecurity.

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COMPUTATIONAL REQUIREMENTS

- Several different considerations for "computational performance"
  - Effectiveness of process for generating training data
    - Adaptive sampling and coverage assessment
    - Assisted using other available knowledge bases
  - Digital Twin Training Process
    - Balance accuracy with potential for overfitting
    - Hyperparameters represent an additional sensitivity/uncertainty
  - Execution time for Digital Twin
    - Depends on the time scale for the event, but initial response must be real-time
    - Potential for recommendations to change during processing time

- Need a general purpose, validated and robust simulation engine to generate training data
  - Can involve $O(10^4\text{-}10^6)$ or more simulations, so even a small fraction of simulations that fail to run to completion can be problematic.
  - Requires a 3-D, coarse-grid CFD code that can model all facets of the plant (reactor vessel, piping systems and containment) using a variable mesh and is applicable to both LWR and non-LWRs
  - GOTHIC is an industry trusted multi-physics, multi-scale M&S tool that supports digital twin development

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CONCLUSIONS

Digital twin solutions support decision making and provide a variety of benefits.

Modeling & simulation plays an important role in digital twins

- Must establish the credibility of M&S results as it directly impacts the credibility of digital twins
- Therefore, this is a critical element to the adoption, and regulatory approval, of ML based technologies for nuclear applications

- Cost Savings
- Increased Safety
- Equipment Reliability & Loss Avoidance
- Operations Flexibility
- Reduced Reactive Maintenance
- Higher Efficiency
- Optimized Design/Construction

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WORKSHOP ON DIGITAL TWIN APPLICATIONS FOR ADVANCED NUCLEAR TECHNOLOGIES

December 1–4, 2020

Argonne NATIONAL LABORATORY

MULTI-PHYSICS MODELING FOR ADVANCED REACTOR SAFETY

RUI HU
Nuclear Science and Engineering Division
Argonne National Laboratory

U.S. DEPARTMENT OF ENERGY
Argonne National Laboratory is a U.S. Department of Energy laboratory managed by UChicago Argonne, LLC.

Safety Characteristics of Advanced Reactors

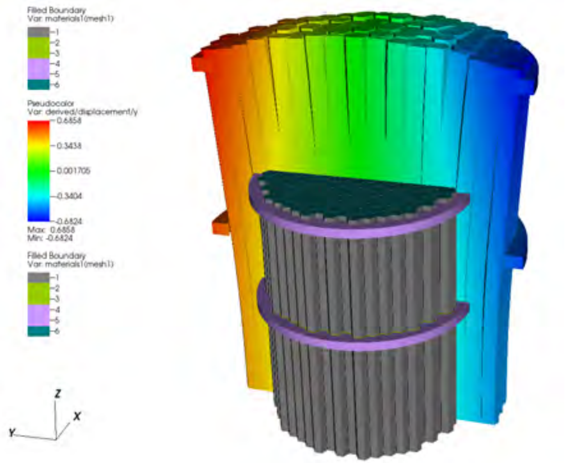
Pursuing high levels of inherent (walk-away) safety

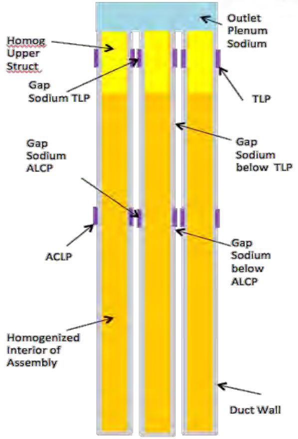
- Inherent reactivity feedback
- Passive decay heat removal
- Ultimate heat sink (ambient air)
- Advanced fuel
  - TRISO, metallic, liquid
- SMR and Micro-Reactor
  - Small nuclear fuel inventories
  - Large surface to volume ratio

- Multi-physics calculation for unprotected transients?
- Accurate modeling of in-vessel heat transport (from the core to vessel wall)
- Detailed simulation vs. lumped parameter approach
- Integrated modeling of reactor cavity cooling system or vessel cooling system

Needs for Multi-scale Multi-physics Capability (1)

- Analysis of the transient behavior of a nuclear reactor requires coupled simulation of reactor kinetics and thermal-hydraulics of the reactor core
- In advanced nuclear reactors, e.g. Sodium-cooled fast reactor, the reactivity feedback due to core radial and axial thermal expansion are important
- The coupled simulation of thermal-hydraulics and thermal-mechanics is important for the multi-physics simulations of advance reactors for accurate prediction of thermal reactivity feedbacks



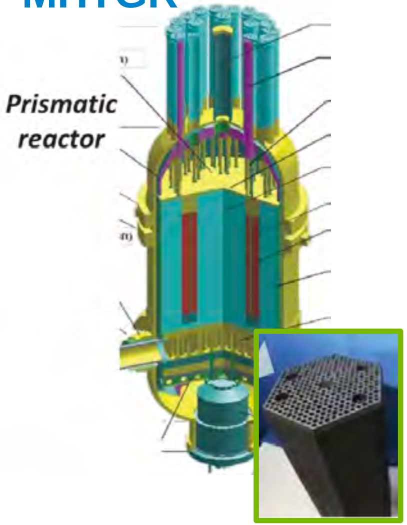


Needs for Multi-scale Multi-physics Capability (2)

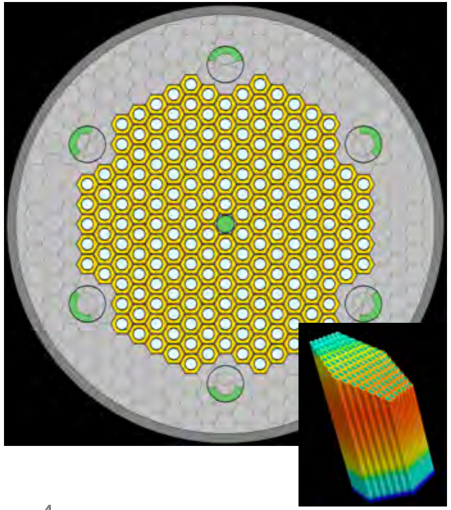
- Decay heat removal
  - Most advanced reactor designs rely on passive safety system, such as RCCS
  - Decay heat must be conducted from core to surface: fuels/structures are strongly thermally-coupled, and requires multi-dimensional modeling and simulation capabilities

PB HTGR

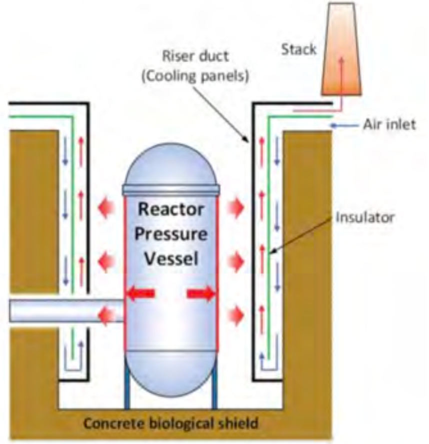
MHTGR



Heat-pipe Reactor



RCCS

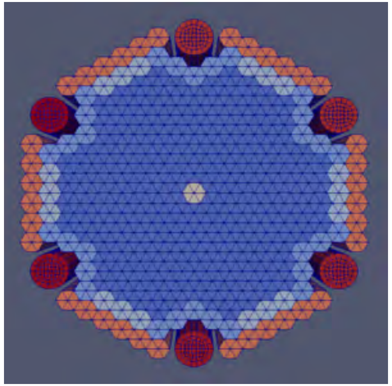
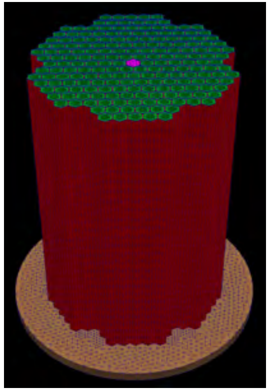
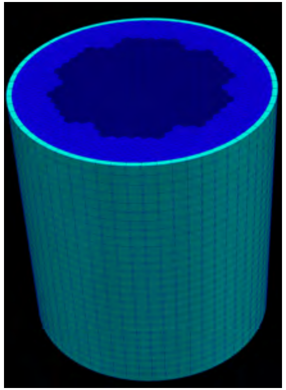
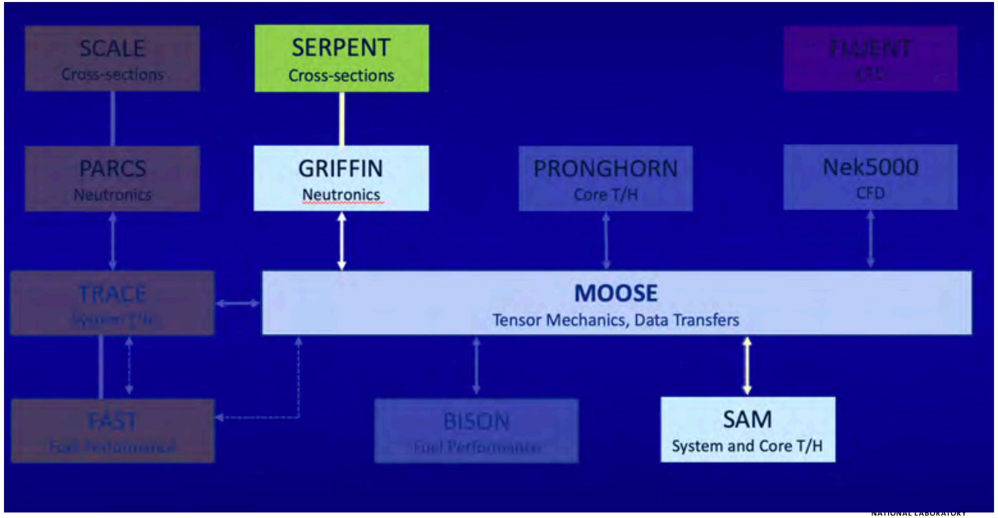


Sources: High Temperature Gas-cooled Reactor Technology Training Curriculum; ANL/NSE-19/25; UCBTH-14-009

MULTI-PHYSICS SIMULATION OF HEAT PIPE MICRO-REACTOR

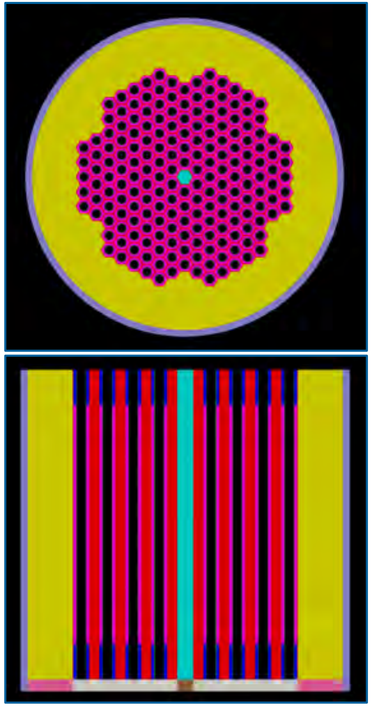
COUPLED CODE SIMULATIONS

- Joint Argonne-INL-NRC efforts using BlueCRAB
- Coupled codes in reference heat pipe microreactor model
  - Reactor Kinetics (MAMMOTH/Rattlesnake)
  - Thermomechanics (MOOSE Tensor Mechanics)
  - 3D Heat Transfer (SAM)
  - Heat Pipe Heat Exchanger (SAM)
  - Reactor Cavity Cooling System (SAM)
- MOOSE: multi-physics framework
- MAMMOTH: INL neutronics code
- SAM: ANL system code

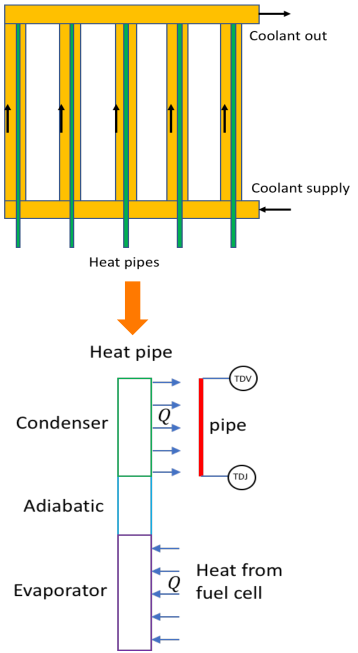





SAM MODELS

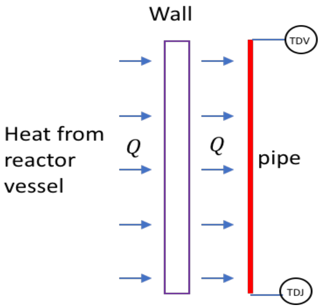
Reactor core

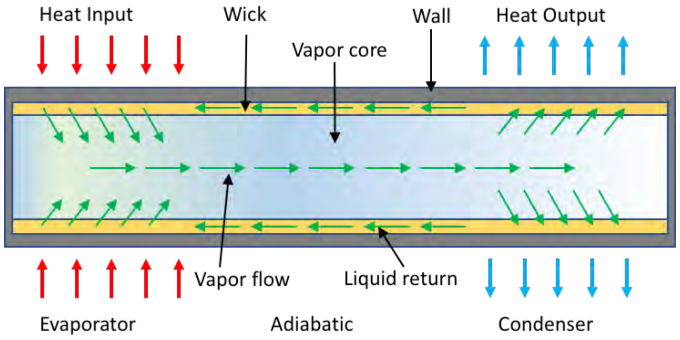


Heat pipe heat exchanger



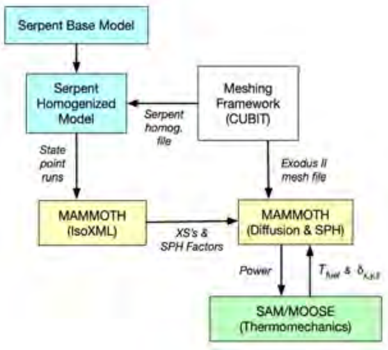
RCCS

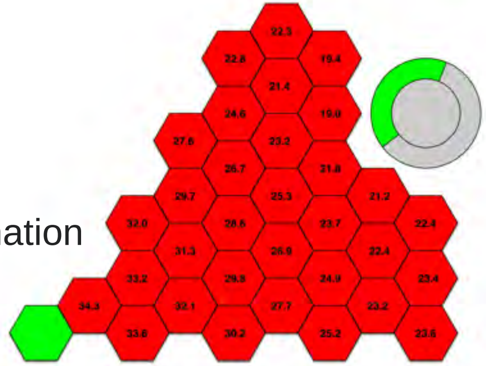


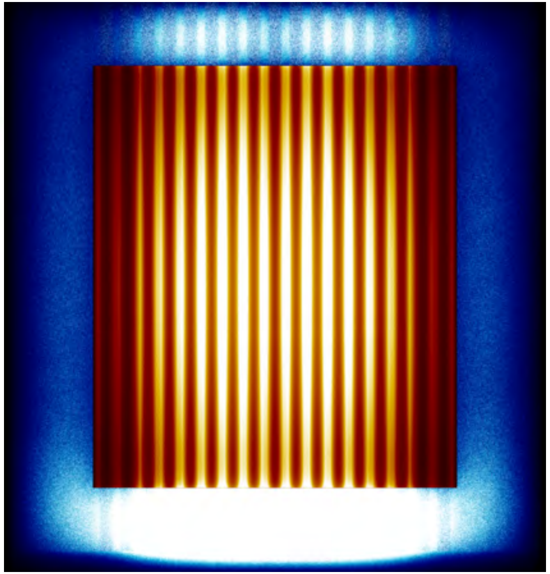


MAMMOTH REACTOR PHYSICS MODEL

- Beginning-of-life (BOL) conditions
- Multi-group diffusion solver with MAMMOTH/Rattlesnake
- Correction with the super-homogenization (SPH) equivalence scheme
- Cross-section preparation with SERPENT Monte Carlo code
- Reactivity feedback effects
  - Doppler effect: fuel temperature
  - Radial expansion: radial core mesh deformation
  - Axial expansion: fuel axial mesh deformation



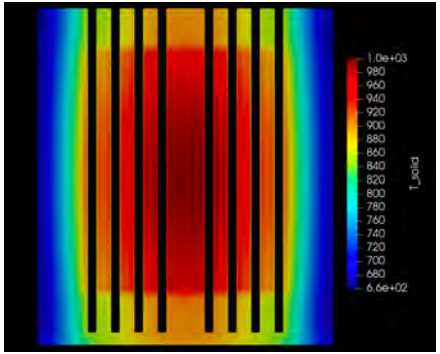




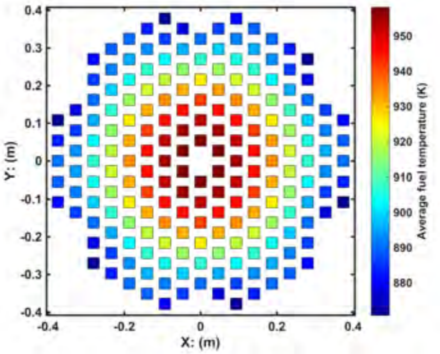
STEADY STATE

- The model works very well for the steady state operation analysis
- Average fuel temperature keeps very well the symmetry of the reactor core
- Heat pipe near the center removes roughly 1.5 times heat compared with heat pipe near the periphery of the core (average 26 kW)

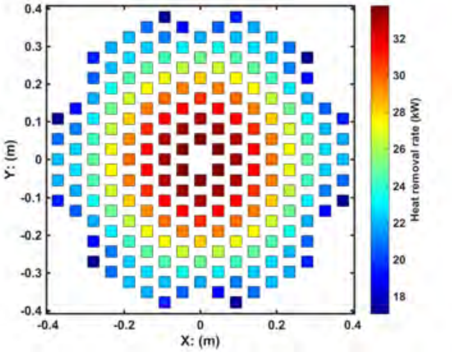
Parameters	Value
Eigenvalue	0.99990492
Total power	5.0 MW
Power to heat pipes	4.8942 MW
Power to RCCS	0.05291 MW
Average fuel temperature	914.7 K
Average hex can temperature	912.8 K
Average bottom/top reflector temperature	866.9 K
Average side reflector temperature	765.6 K
Average plate temperature	803.6 K
Average vessel wall temperature	674.5 K



Reactor core temperature



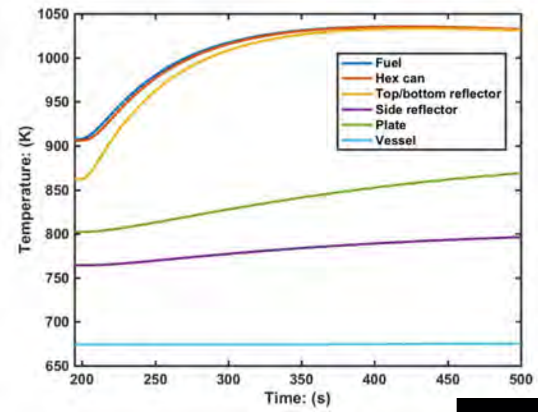
Average fuel temperature



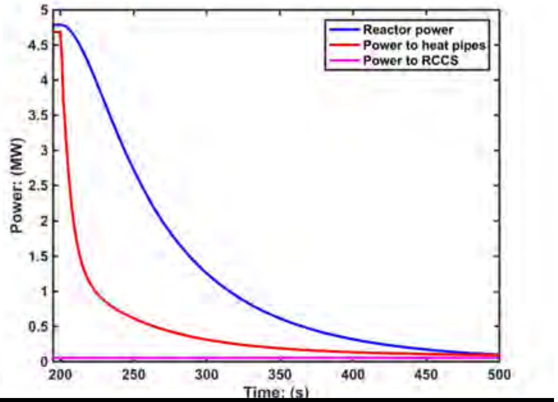
Heat pipe heat removal rate

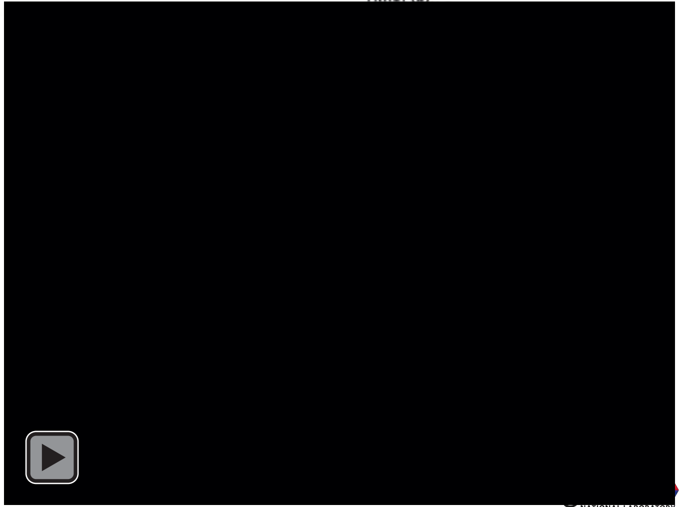
LOSS OF HEAT SINK

- Heat pipe heat removal rate drops quickly to a lower level
  - Flow rate drops to 0.1% of steady-state value
  - Slow decrease due to the thermal inertial of the heat pipes
- Reactor power drops quickly due to the strong negative reactivity feedback
- Decay power was not considered yet in the reactor physics model



Average solid temperature





Fuel average temperature

MULTI-PHYSICS MODELING FOR DIGITAL TWIN DEVELOPMENT

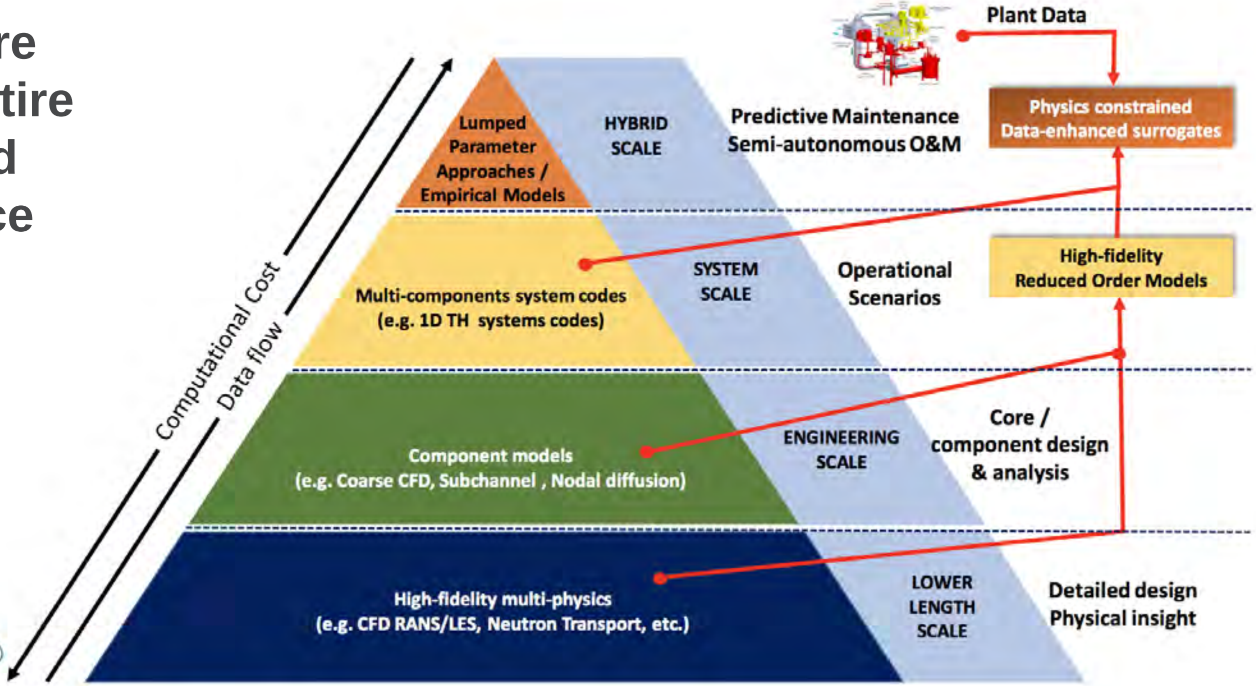
U.S. DEPARTMENT OF ENERGY
Argonne National Laboratory is a U.S. Department of Energy laboratory managed by UChicago Argonne, LLC.

Argonne NATIONAL LABORATORY

SCALABLE DIGITAL TWIN IN SAFARI PROJECT

Physics-based to ensure robustness over the entire range of operations and data-enabled to enhance predictive capabilities.

SAFARI: Secure Automation for Advanced Reactor Innovation, ARPA-E GEMINA Award

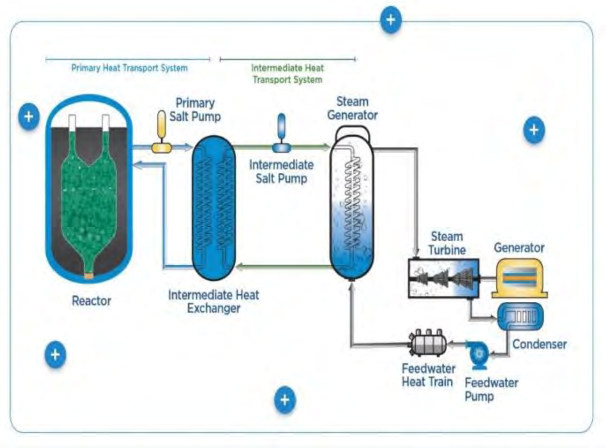


(Courtesy of A. Manera, UM)

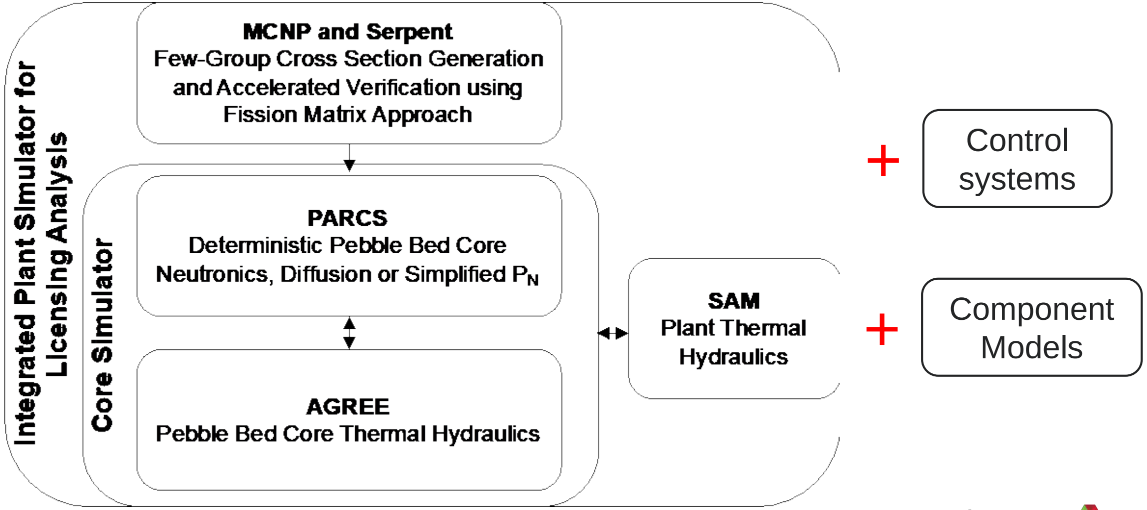
University of Michigan, Argonne National Laboratory, INL, Kairos Power, Curtiss-Wright

MULTI-PHYSICS MODELING FOR DIGITAL TWIN DEVELOPMENT

- Multi-physics simulations including plant control and protection systems
- To build the ML-augmented, physics-based reduced order models of the FHR
- To demonstrate the accuracy of the digital twin and the commercial benefit



https: //kairospower.com



MULTI-SCALE MULTI-PHYSICS MODELING CAPABILITY NEEDED FOR ADVANCED REACTOR SAFETY AND SCALABLE DIGITAL TWIN DEVELOPMENT


Argonne
NATIONAL LABORATORY

Mechanical and
Aerospace Engineering

UNIVERSITY OF CENTRAL FLORIDA

Hybrid Physics-Informed Neural Networks, Cumulative Damage Models, and Digital Twins

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Prognosis and digital twins

Maintenance costs

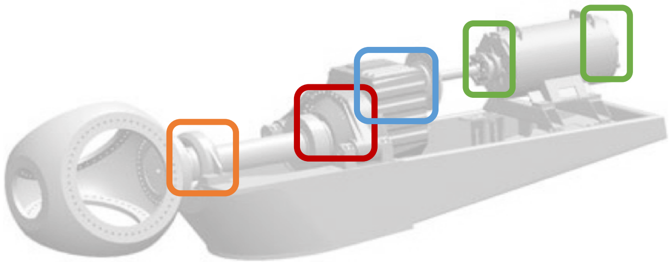
- Production lost
- Component
- Equipment rent, labor, etc.

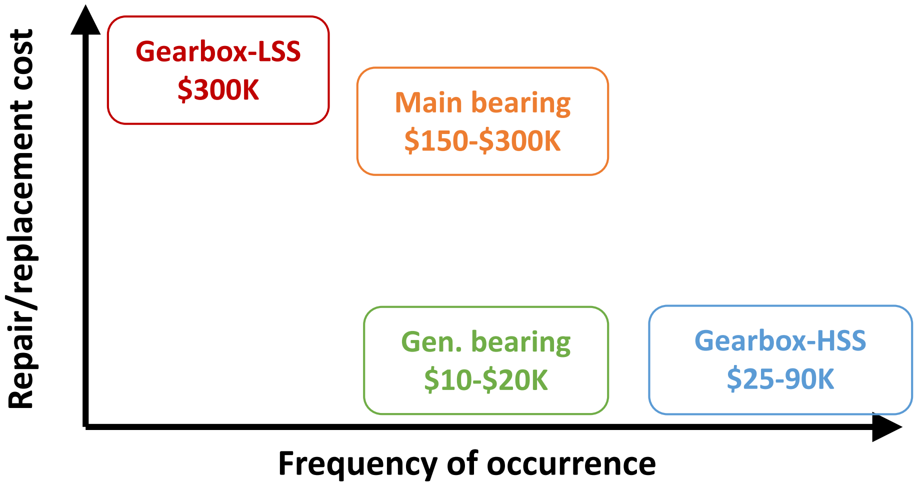
Prognosis and digital twin challenges:

- Physics not fully understood
- Data is highly unstructured
  - Operation/controls vastly available (?)
  - Poor inspection and failure data

1. Digital twins must bridge the gap between model predictions (understanding) and observations (reality)
2. <u>Hybrid models can be really helpful</u>

(a) Onshore wind turbine example





Sethuraman, L., Guo, Y., & Sheng, S. (2015). Main bearing dynamics in three-point suspension drivetrains for wind turbines. American Wind Energy Association Conference & Exhibition, May 18–21, Orlando, FL.

Physics-informed neural networks are not new…

JOURNAL OF COMPUTATIONAL PHYSICS 91, 110–131 (1990)

Neural Algorithm for Solving Differential Equations

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AND

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Received August 17, 1988; revised October 6, 1989

Finite difference equations are considered to solve differential equations numerically by utilizing minimization algorithms. Neural minimization algorithms for solving the finite difference equations are presented. Results of numerical simulation are described to demonstrate the method. Methods of implementing the algorithms are discussed. General features of the neural algorithms are discussed.

2018 Advances in Neural Information Processing Systems

(NeurIPS 2018 – Best paper)

Neural Ordinary Differential Equations

Ricky T. Q. Chen*, Yulia Rubanova*, Jesse Bettencourt*, David Duvenaud
University of Toronto, Vector Institute
{rtqichen, rubanova, jessebett, duvenaud}@cs.toronto.edu

Abstract

We introduce a new family of deep neural network models. Instead of specifying a discrete sequence of hidden layers, we parameterize the derivative of the hidden state using a neural network. The output of the network is computed using a black-box differential equation solver. These continuous-depth models have constant memory cost, adapt their evaluation strategy to each input, and can explicitly trade numerical precision for speed. We demonstrate these properties in continuous-depth residual networks and continuous-time latent variable models. We also construct continuous normalizing flows, a generative model that can train by maximum likelihood, without partitioning or ordering the data dimensions. For training, we show how to scalably backpropagate through any ODE solver, without access to its internal operations. This allows end-to-end training of ODEs within larger models.

How can we leverage this concept to build digital twins?

Cumulative damage models and uncertainty quantification

Fatigue crack growth

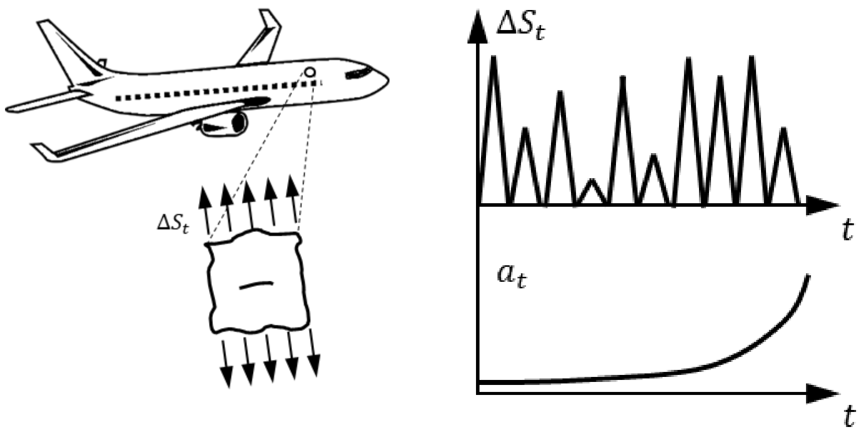
$$\frac{da}{dN} = C\Delta K^m$$

where:
- N: number of cycles
- C and m: material properties (coupon tests)
- $\Delta K = F\Delta S\sqrt{\pi a}$
- ΔS: engineering analysis (e.g., FEM)

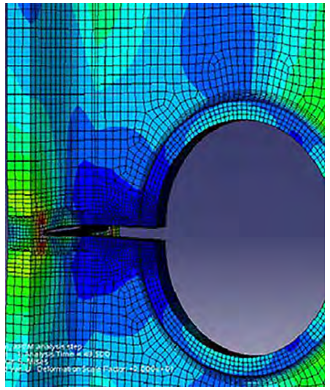
What if ΔK or ΔS are not accurate?

We propose using hybrid models for uncertainty quantification

(a) Fatigue crack growth at fuselage panel



(b) Finite element modeling



Physics-informed neural networks are perfect for prognosis digital twin

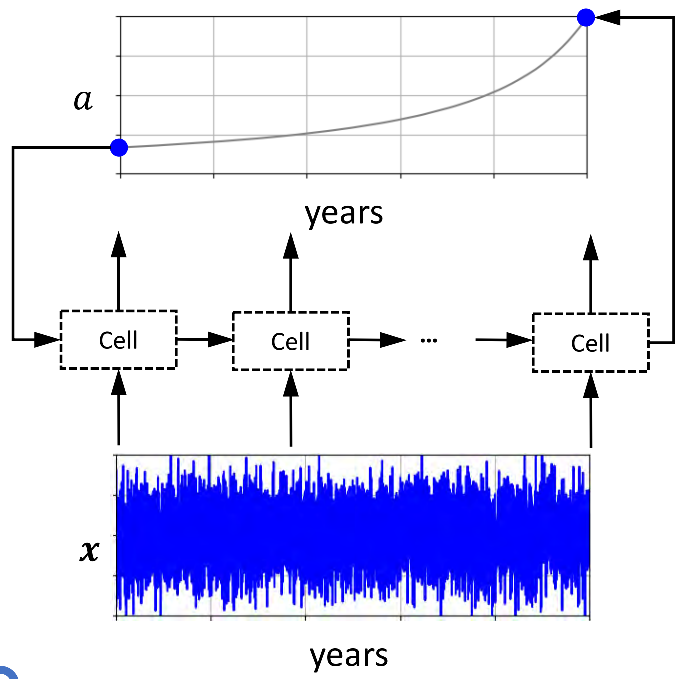
Use case:

- Very few output observations
- Inputs observed throughout
- Sequences are VERY long
- Cell models transition never observed

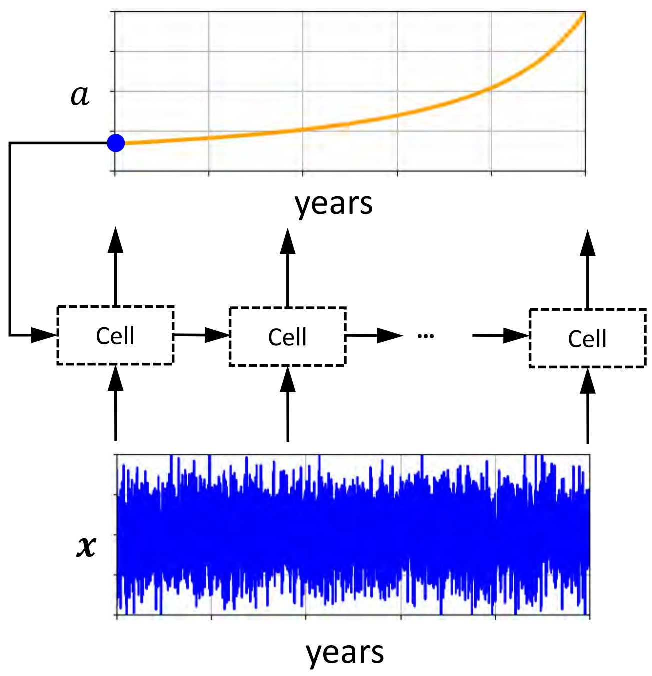
If output is observed throughout, data-driven **recurrent neural networks** (LSTM, GRU, etc.) might be useful, otherwise…

Very hard (impossible) without physics

(a) Typical training



(b) Typical prediction

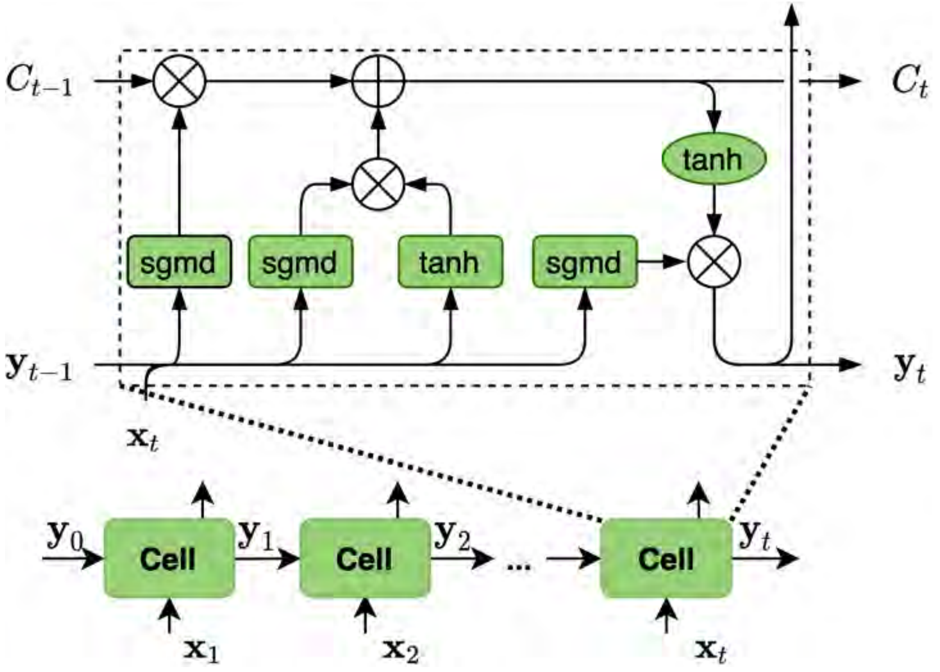


Blue: observed data
Gray: desired output (never fully observed)
Orange: Recurrent neural network prediction

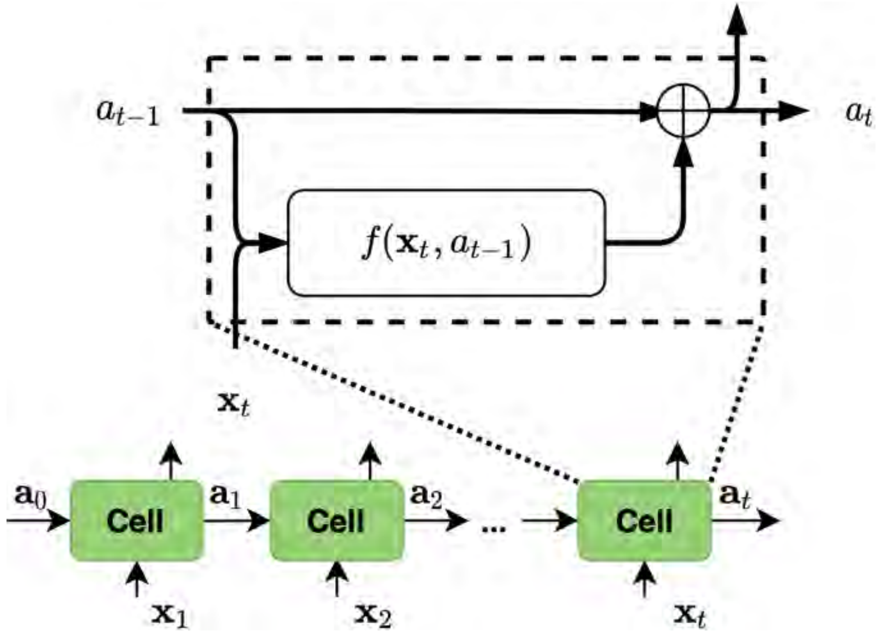
R. G. Nascimento and F. A. C. Viana, "Cumulative damage modeling with recurrent neural networks," AIAA Journal, Online First, 13 pages, 2020, DOI: 10.2514/1.J059250.

Cumulative damage model with recurrent neural networks

(a) Long short-term memory (LSTM) cell



(b) Euler integrator cell (cumulative damage)



$$\frac{da}{dN} = C\Delta K^m \quad \Longrightarrow \quad f(\boldsymbol{x}_t, a_{t-1}) = C\Delta K^m$$

- **RNNs are perfect fit for damage accumulation,**
- $f(x_t, a_{t-1})$ **can be customized.**

R. G. Nascimento, K. Fricke, and F. A. C. Viana, “A tutorial on solving ordinary differential equations using Python and hybrid physics-informed neural network,” Engineering Applications of Artificial Intelligence, Vol. 96, 2020, 103996, DOI: 10.1016/j.engappai.2020.103996.

Wind turbine main bearing fatigue

Model-form uncertainty:

- Bearing fatigue: relatively well-understood
- Grease degradation: difficult to model with physics

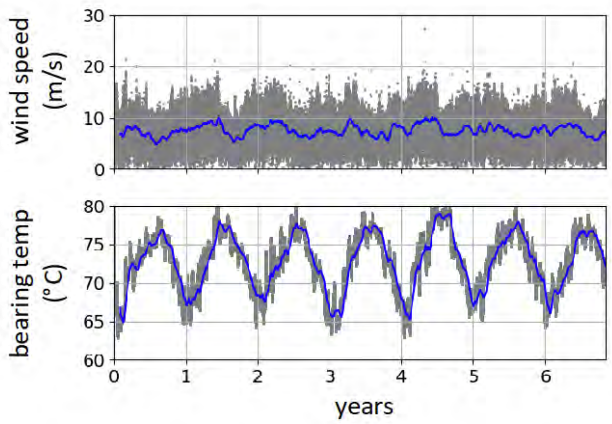
Damage inspection:

- Bearing: not always measurable
- Grease:
  - Laboratory: accurate but expensive
  - Visual: large uncertainty but affordable

Unbalanced data:

- Supervisory control and data acquisition (SCADA) system (per 10 mins)
- Inspection depends on operator inspection policy

(a) SCADA data



(b) Visual grease inspection ranking (high variability)

Example of ranking

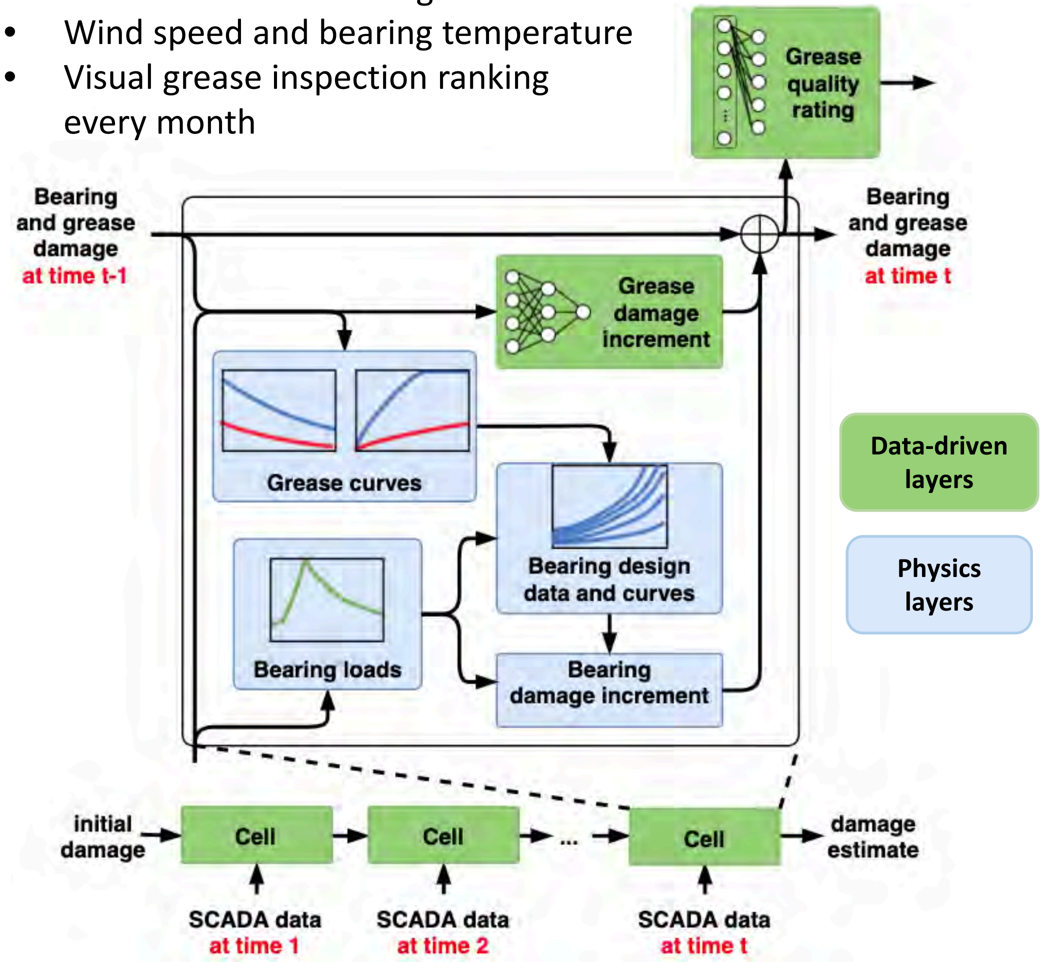
Y. A. Yucesan and F. A. C. Viana, "A physics-informed neural network for wind turbine main bearing fatigue," International Journal of Prognostics and Health Management, Vol. 11 (1), 2020.

Y. A. Yucesan and F. A. C. Viana, "Hybrid physics-informed neural networks for main bearing fatigue prognosis with visual grease inspection," Computers in Industry, Accepted.

Hybrid physics-informed neural network

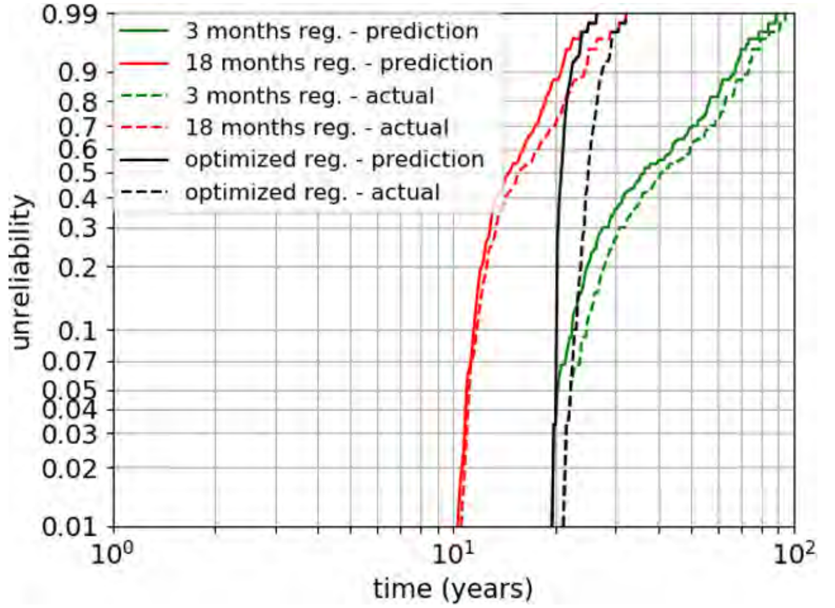
(a) Hybrid model

10 turbines used for training
- Wind speed and bearing temperature
- Visual grease inspection ranking every month



(b) Turbine-level service optimization

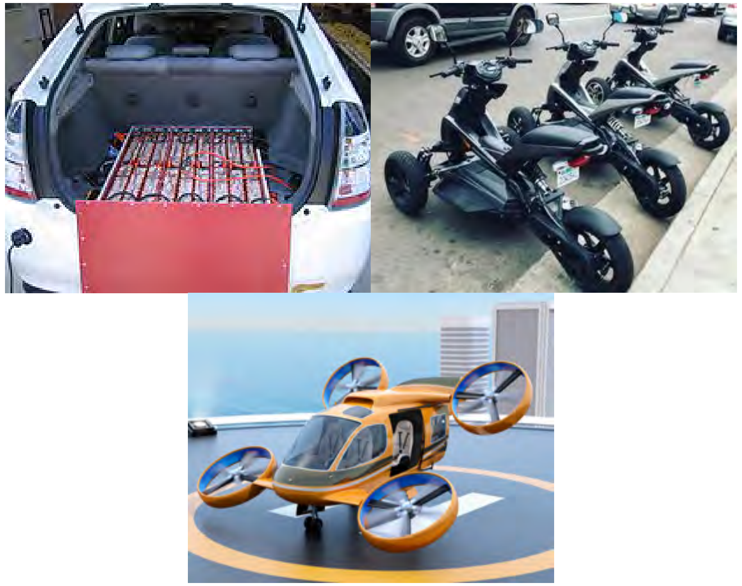
Regreasing optimization @ 120 turbines
- Wind speed and bearing temperature



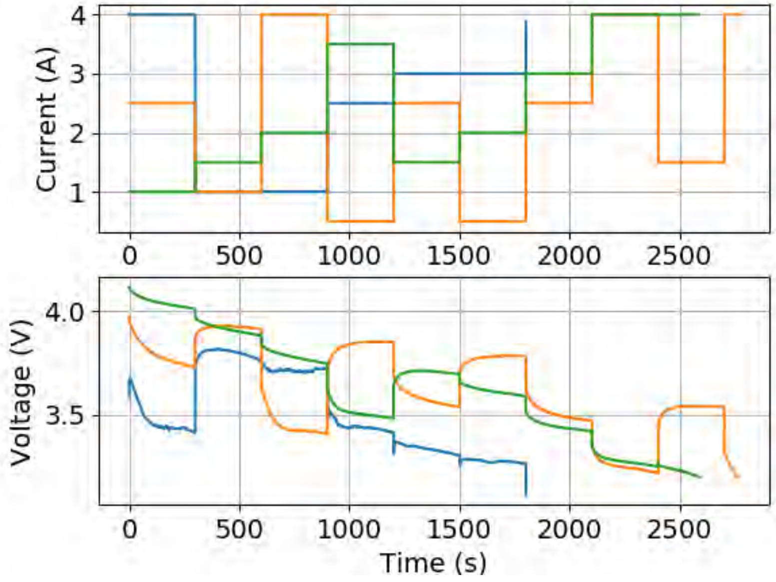
We optimized service intervals on a turbine-by-turbine basis

Lithium-ion battery aging modeling

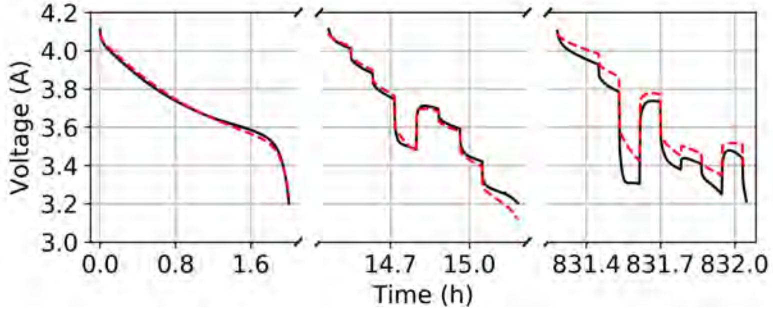
Key technology for electric vehicles



(a) Example of random loading conditions



(b) Aging can cause models to diverge from observations



Challenges:

- Prognosis models depend on a number of empirically adjusted factors
- Hard to account for aging

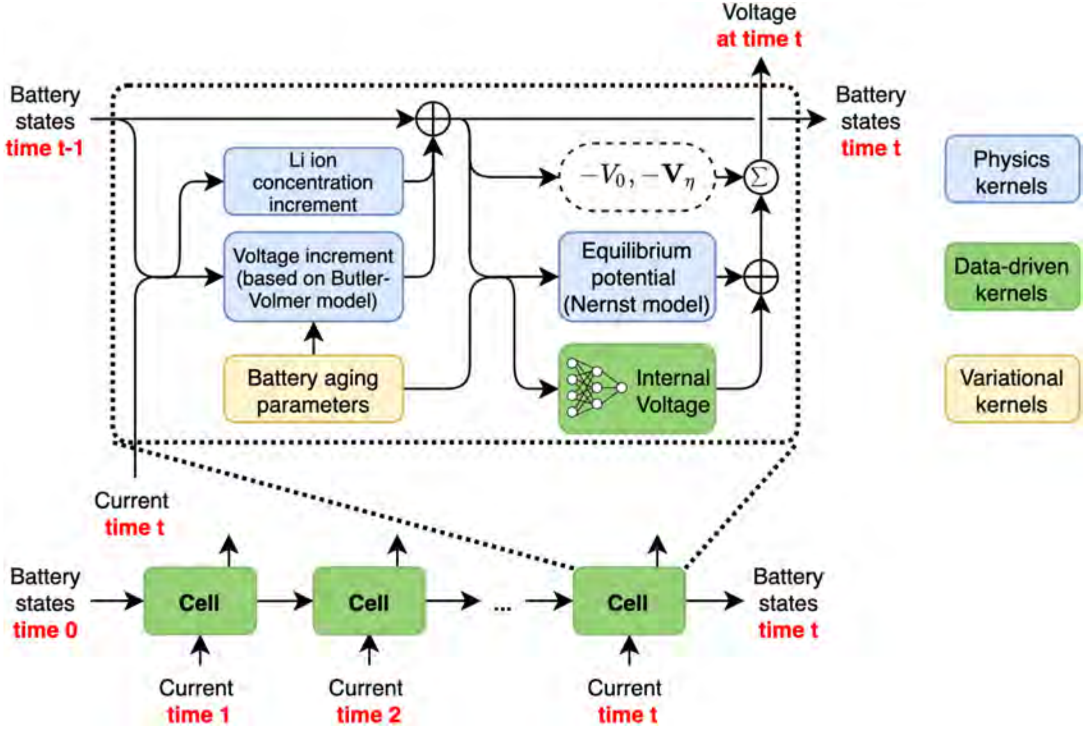
R. G. Nascimento, M. Corbetta, C. S. Kulkarni, and F. A. C. Viana, "Hybrid Physics-Informed Neural Networks for Lithium-Ion Battery Modeling and Prognosis," Applied Energy, submitted.

Hybrid physics-informed neural network

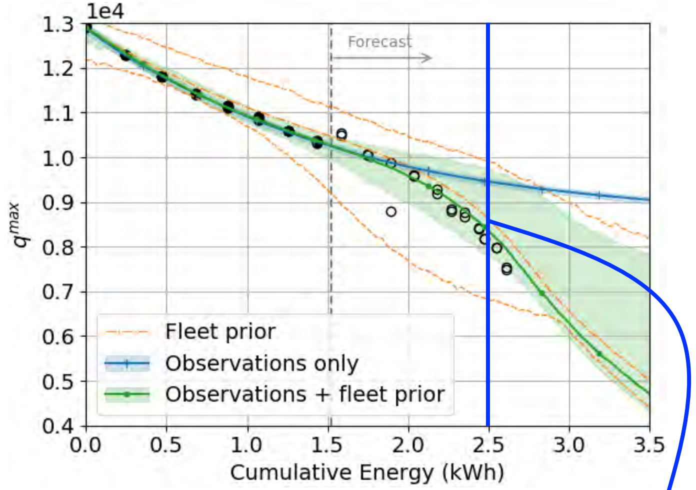
(a) Hybrid model

8 batteries used for training

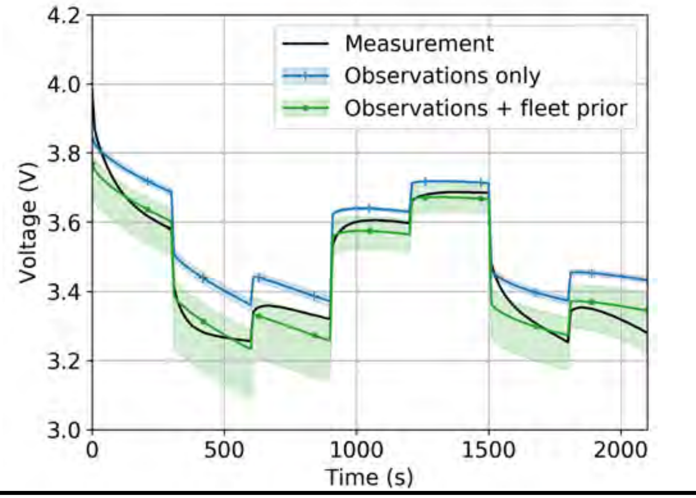
- Current and voltage time histories
- Internal voltage adjusted with constant discharge
- Battery aging is a probabilistic model adjusted using hundreds of hours worth of data



(b) Aging model

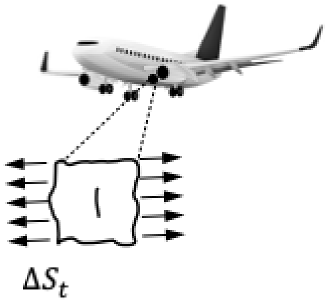


(c) Probabilistic forecast data



Model-form uncertainty in corrosion fatigue

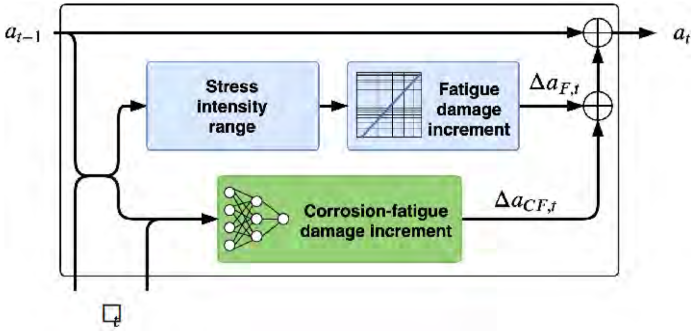
Challenge
- Assumed: pure mechanical fatigue
- After 5 years: corrosion-fatigue



Data
- Load history of 5 years: 150 aircraft
- Crack length: 15 aircraft at end of 5th year.

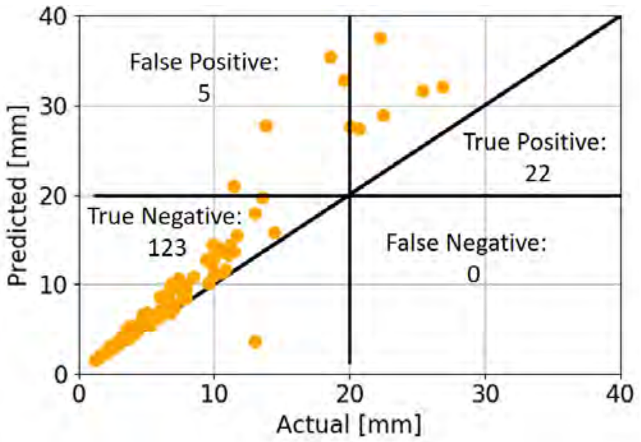
Damage accumulation grossly underestimated!!!

(a) Hybrid physics-informed neural network cell

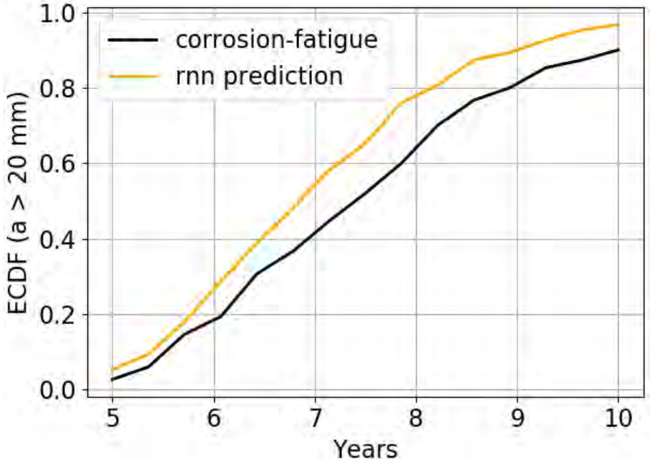


A. Dourado and F. A. C. Viana, "Physics-informed neural networks for missing physics estimation in cumulative damage models: a case study in corrosion fatigue," ASME Journal of Computing and Information Science in Engineering, Vol. 20 (6), 10 pages, 2020.

(b) Fleet prediction at the end of 5th year.



(c) Probability of failure forecast



Probabilistic Mechanics Laboratory

Publications:

pml-ucf.github.io/publications

GitHub

Physics-informed neural networks package
github.com/PML-UCF/pinn

Ordinary differential equation solver:
https://github.com/PML-UCF/pinn_ode_tutorial

Wind turbine main bearing fatigue
github.com/PML-UCF/pinn_wind_bearing

Corrosion-fatigue prognosis
github.com/PML-UCF/pinn_corrosion_fatigue

Credit really goes to my PhD students

Andre Von Zuben

Arinan Dourado

Kajetan Fricke

Renato Nascimento

Yigit Yucesan

Sponsors and Collaborators

Baker Hughes

NASA

NREL
NATIONAL RENEWABLE ENERGY LABORATORY

INSA
INSTITUT NATIONAL
DES SCIENCES
APPLIQUÉES
LYON

Probabilistic Mechanics Laboratory

A Quantitative Framework to Assess Tradeoffs in Alternative Models and Algorithms for Prognostics and Health Management

Saikath Bhattacharya and Lance Fiondella

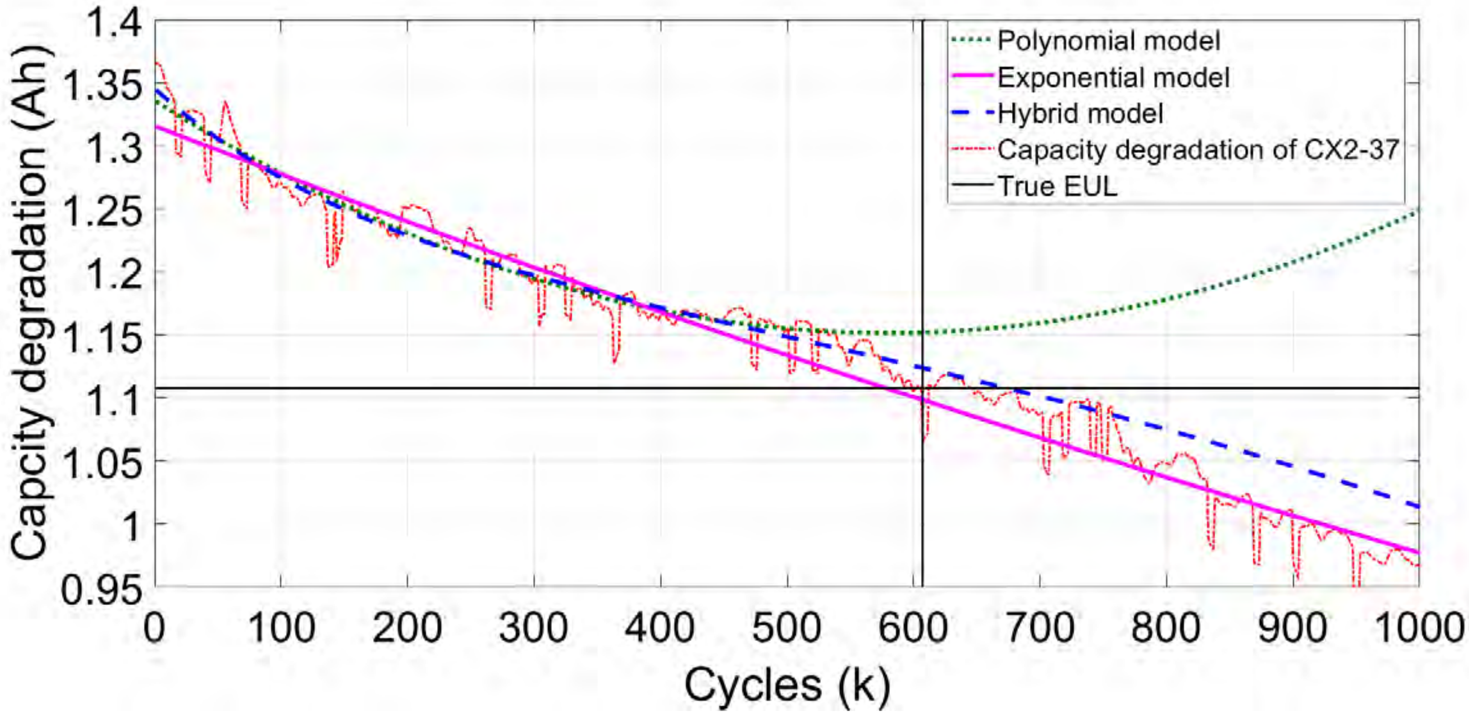
Introduction

- Prognostics and health management
  - Modernizing system reliability engineering with sensing, models, and algorithms to accurately estimate remaining useful life
  - Promotes nonfunctional RAM+C (reliability, availability, maintainability, and cost) requirements

Motivation

- Previous studies
  - Emphasize development of
    - Degradation models
    - Algorithms to estimate model parameters
  - Typically
    - Restricted to single maintenance cycle and focused on enhancing prediction
    - Do not assess long term performance of competing methods

Limitations of Academic Modeling Studies



Number of cycles used to fit models (500)
Often hand-picked to make a proposed model appear favorable

Motivation (2)

- Fewer studies
  - Assess impact of PHM decisions on cost and other derived reliability measures
  - Restricted to simulation and analytical techniques (not data-driven)

Proposed Approach

- Objective framework to assess
  - Performance decisions made by alternative combinations of models and algorithms
  - Adapts analytical methods from maintenance theory to data-driven approach
    - Average cost per unit time
    - Utilization
    - Safety
    - Availability

Capacity (Battery) Degradation Models

Some parametric models

- Polynomial model
  - $y_k = x_1 k^2 + x_2 k + x_3$ (1)
- Exponential model
  - $y_k = x_1 e^{x_2 k} + x_3 e^{x_4 k}$ (2)
- Hybrid model
  - $y_k = x_1 e^{x_2 k} + x_3 k^2 + x_4$ (3)

Filtering for Battery Degradation Models

- Unscented Kalman filter
  - Recursively updates degradation model parameters ($\mathbf{x}$) based on capacity in past and present cycles (y_k) to estimate RUL
- Particle Filtering
  - Based on Bayesian Monte Carlo simulation with importance sampling to update parameters

Preventive Maintenance

- Based on present model parameter estimates
- Recommends maintenance
  - If remaining useful life (RUL) prediction less than prognostic distance
- Continues operation otherwise

Reliability, Availability, and Maintainability Measures

- Given unit lifetime τ and maintenance interval T, inter-renewal time $Z = \min(\tau, T)$ such that

$$E[Z] = \int_0^T (1 - F(t))dt$$

  - $R(t) = 1 - F(t)$ - Unit reliability (complement of CDF)

Age Replacement Maintenance Model

- Average cost per unit time

$$\eta_{age}(T) = \frac{F(T)C_{ER} + \big(1 - F(T)\big)C_{PM}}{\int_0^T \big(1 - F(t)\big)dt}$$

  - $F(T)$ - Probability of failure before maintenance
  - C_{ER} - Cost of emergency repair
  - C_{PM} - Cost of preventive maintenance

Age Replacement Maintenance Model (2)

- Average cost per cycle

$$C(\theta) = \frac{\sum_{i=1}^{l}\{C_{PM} I(k_i) + C_{ER}[1 - I(k_i)]\}}{\sum_{i=1}^{l}\{k_i^{\theta} I(k_i) + EUL_i[1 - I(k_i)]\}}$$

  - θ – Prognostic distance
  - l – Number of units
  - $I(k_i)$ - Indicator function of i^{th} unit
  - k_i^{θ} - Cycle at which preventive maintenance performed on i^{th} unit with prognostic distance θ

ILLUSTRATIONS

Data and Methodology

- Utilized Li-ion battery data set ($n = 4$)
  - Performed least squares estimation on battery exhibiting most cycles prior to failure and used as initial estimates for UKF and PF (also considered battery with fewest cycles)

Data and Methodology (2)

- Ratio of emergency and preventive repair costs

$$\frac{C_{ER}}{C_{PM}} = 1{,}000$$

- Mean times to repair

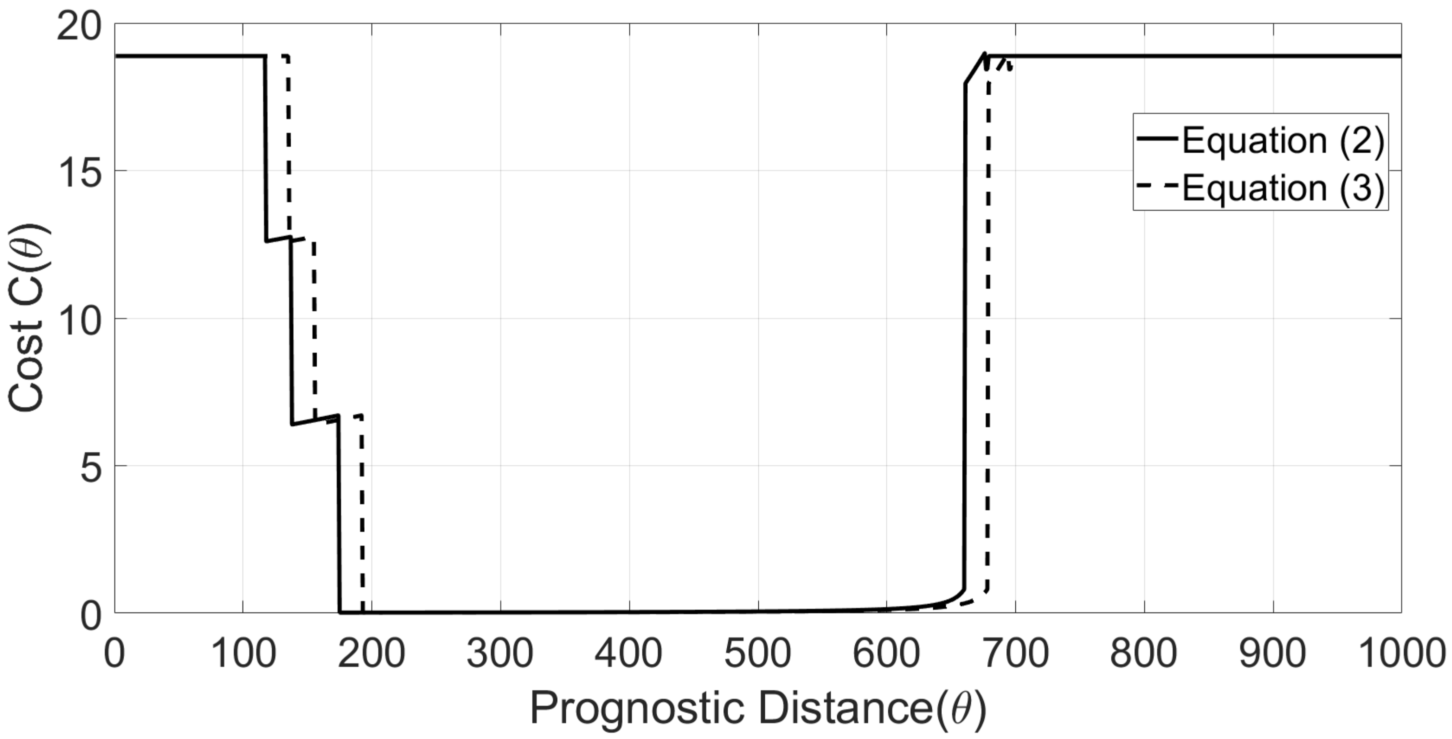
$$MTTR_{PM} = 3 \text{ and } MTTR_{ER} = 8$$

Point Example: Equation (2) under UKF with $\theta = 150$

Measure	CX2-34	CX2-36	CX2-38
True EUL (cycles)	505	560	524
Maintenance $\left(k_i^\theta\right)$	505	527	511
Predicted EUL (cycles)	679	677	661
Unused life (cycles)	0	33	13
Cost $C(\theta)$	10,000	10	10
Safety $S(\theta)$	0	1	1
Time to repair (cycles)	8	3	3

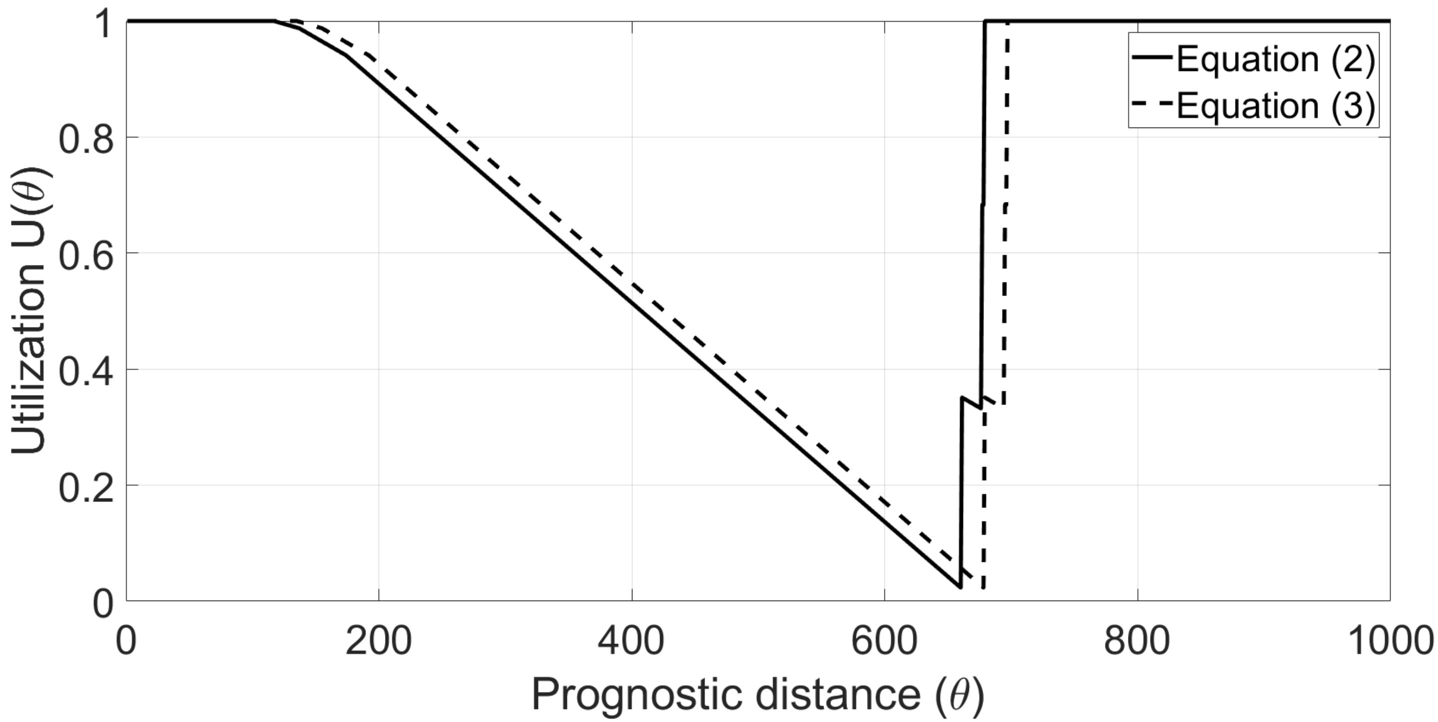
$C(150) = \frac{10{,}020}{1{,}543} = 6.494,\quad U(150) = \frac{1{,}543}{1{,}589} = 97.11\%,\quad S(150) = \frac{2}{3},\quad A(150) = 99.1\%$

Average Cost per Cycle (UKF)



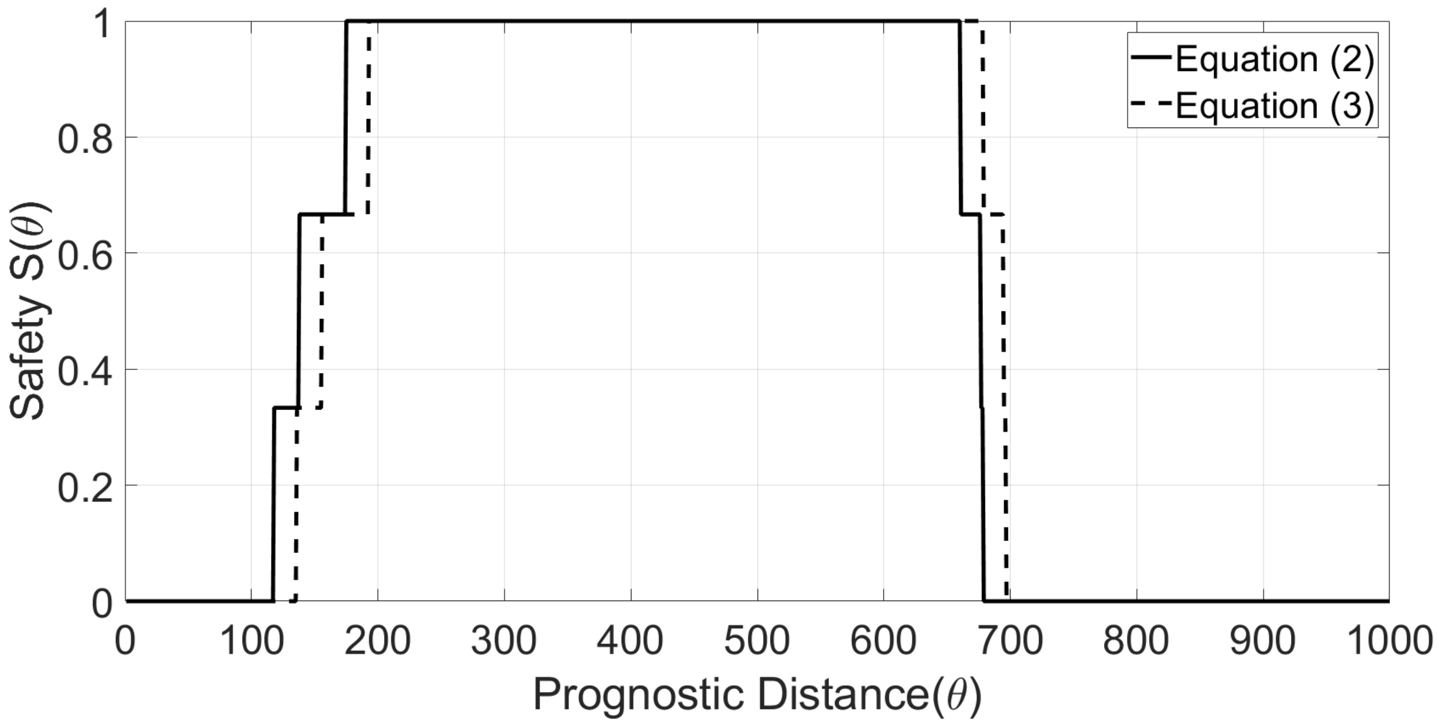
Prognostic distance $\theta \in (175,678)$ minimizes cost

Utilization (UKF)



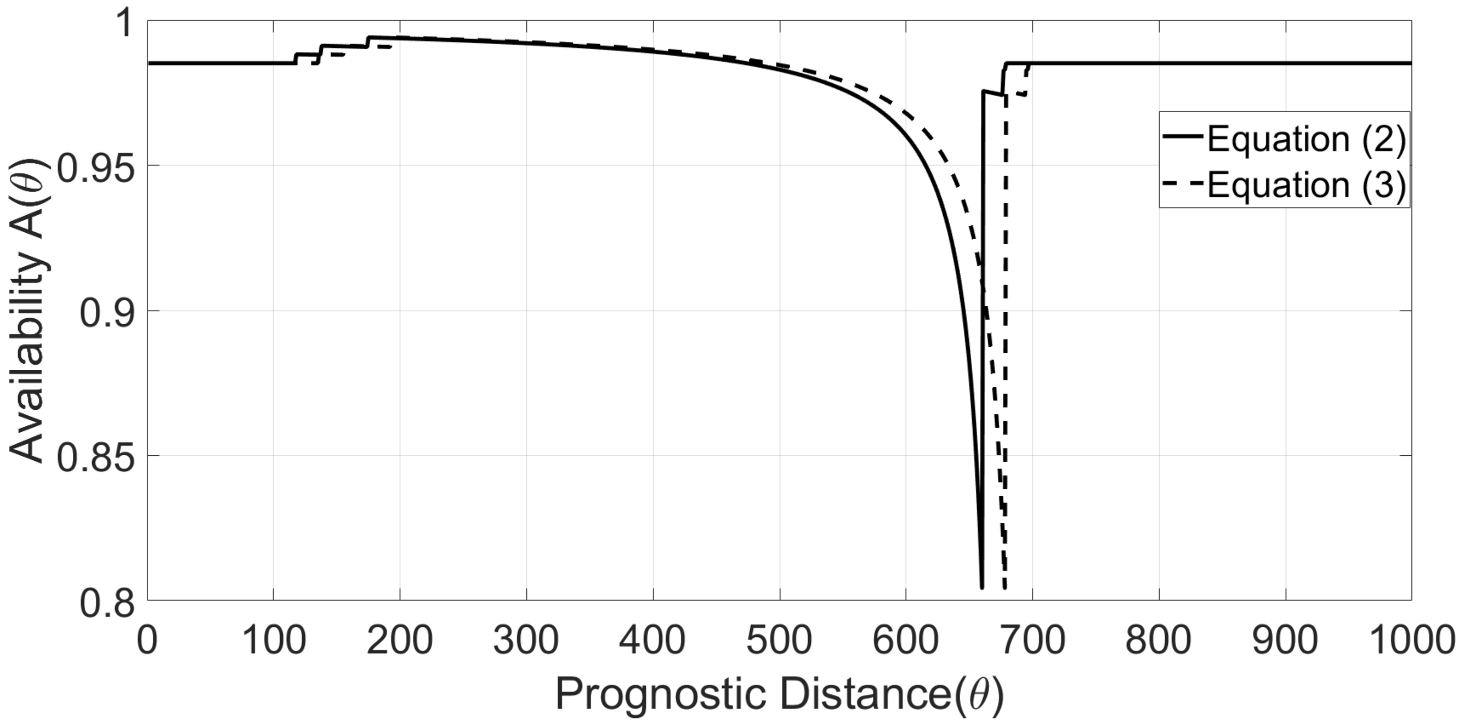
Utilization decreases monotonically as larger prognostic distance initiates earlier maintenance

Safety (UKF)



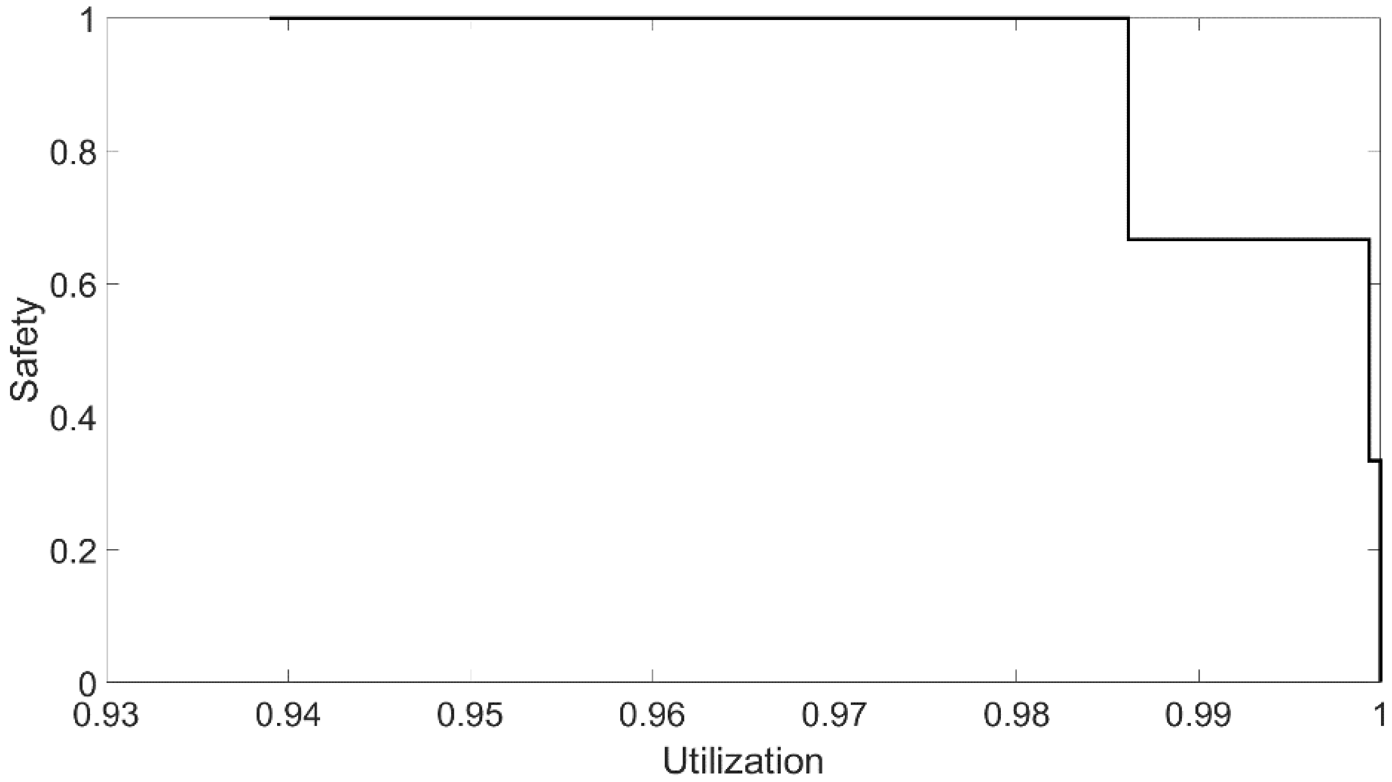
Safety and average cost per cycle exhibit inverse trends

Availability (UKF)



Low utilization corresponds to low availability

Example tradeoff (UKF)



Safety and utilization competing constraints

Summary and Conclusions

- Proposed framework to assess
  - Quantitative performance of PHM decisions made by alternative combinations of models and algorithms
- Developed RAM+C measures for PHM
  - Average cost per unit time, utilization, safety, and availability

Summary and Conclusions (2)

- Applied to combinations of three degradation models and two filtering methods with Li-ion data set
- Proposed approach
  - Offers method to select prognostic distance to balance stakeholder needs
  - Can be applied to other domains, degradation models (physics of failure), and algorithms (deep learning)

Future work

- Open source framework
  - Crowdsource contribution of
    - Models
    - Algorithm
    - Datasets/Challenges
  - Raise academic standards for comparison
  - Promote collaboration between academic, industry, and government stakeholders

- Formulation of additional quantitative measures
- Performance of particle filtering on quantitative measures
- Comparison of quantitative measures in window minimizing cost

BACK UP SLIDES

Additional Measures

- Utilization

$$U(\theta) = \frac{\sum_{i=1}^{l}\left(k_i^{\theta} I(k_i) + EUL_i\big(1 - I(k_i)\big)\right)}{\sum_{i=1}^{l} EUL_i}$$

  - EUL_i - End of useful life of i^{th} unit

- Can take values in interval $(0,1)$

- Poses competing objective with cost and safety

Additional Measures (2)

- Safety

$$S(\theta) = \frac{\sum_{i=1}^{l} I(k_i)}{l}$$

  - Fraction of units that undergo preventive maintenance

- Minimizing cost corresponds to maximizing safety

Additional Measures (3)

- Availability

$$A(\theta) = \frac{MTTF}{MTTF + MTTR}$$

- Mean time to failure (MTTF)

$$MTTF = \frac{1}{l}\sum_{i=1}^{l}\left(k_i^{\theta} I(k_i) + EUL_i(1 - I(k_i))\right)$$

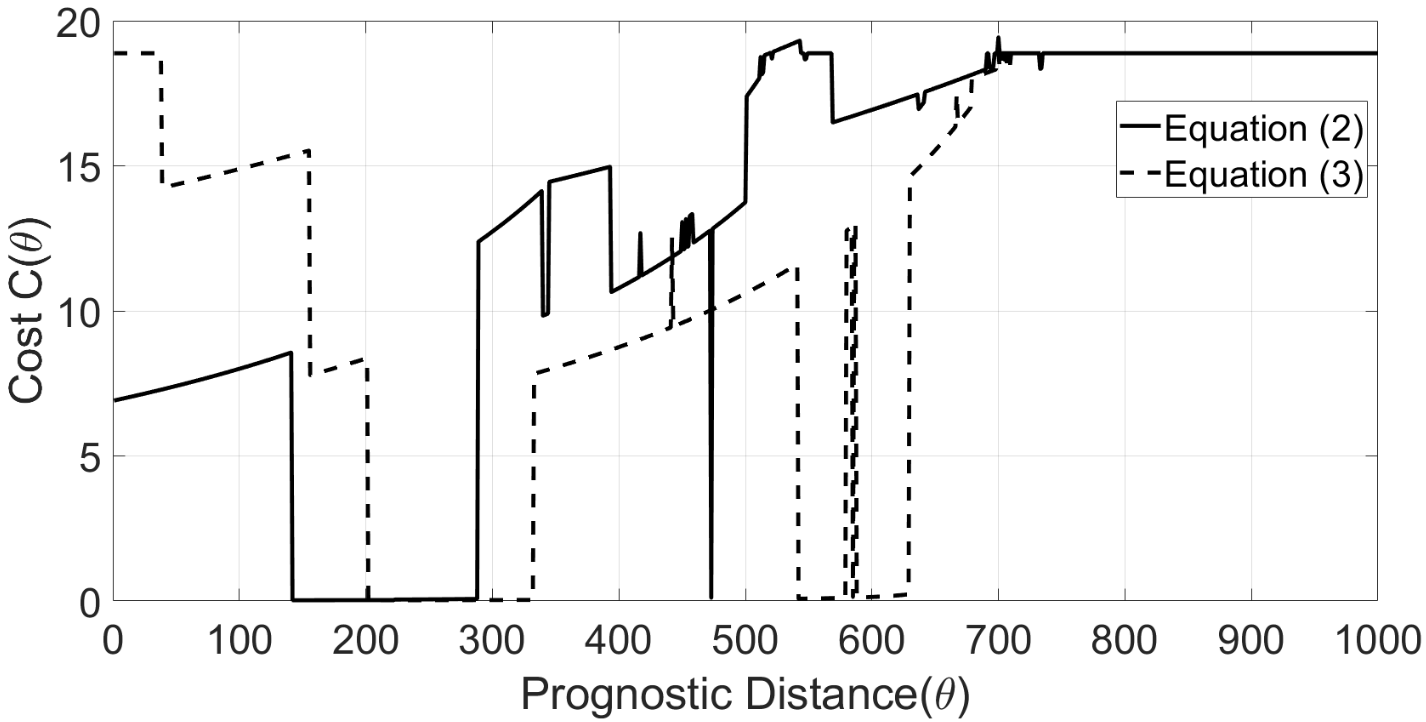
Additional Measures (4)

- Mean time to repair (MTTR)

$$MTTR = \frac{1}{l}(l_{PM}MTTR_{PM} + l_{ER}MTTR_{ER})$$

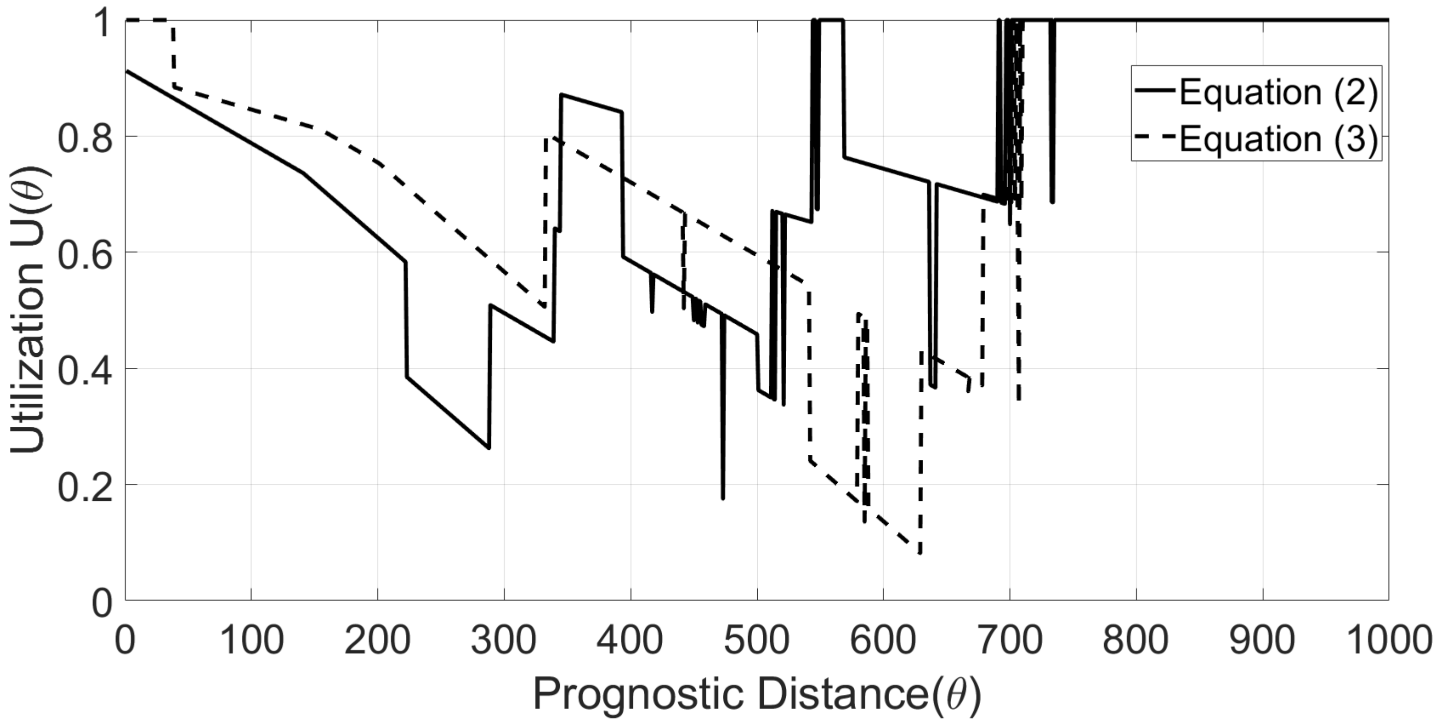
  - l_x - Number of units subject to $x \in (PM, ER)$
  - $MTTR_x$ - Mean time to repair given that unit underwent $x \in (PM, ER)$

Average Cost per Cycle (PF)



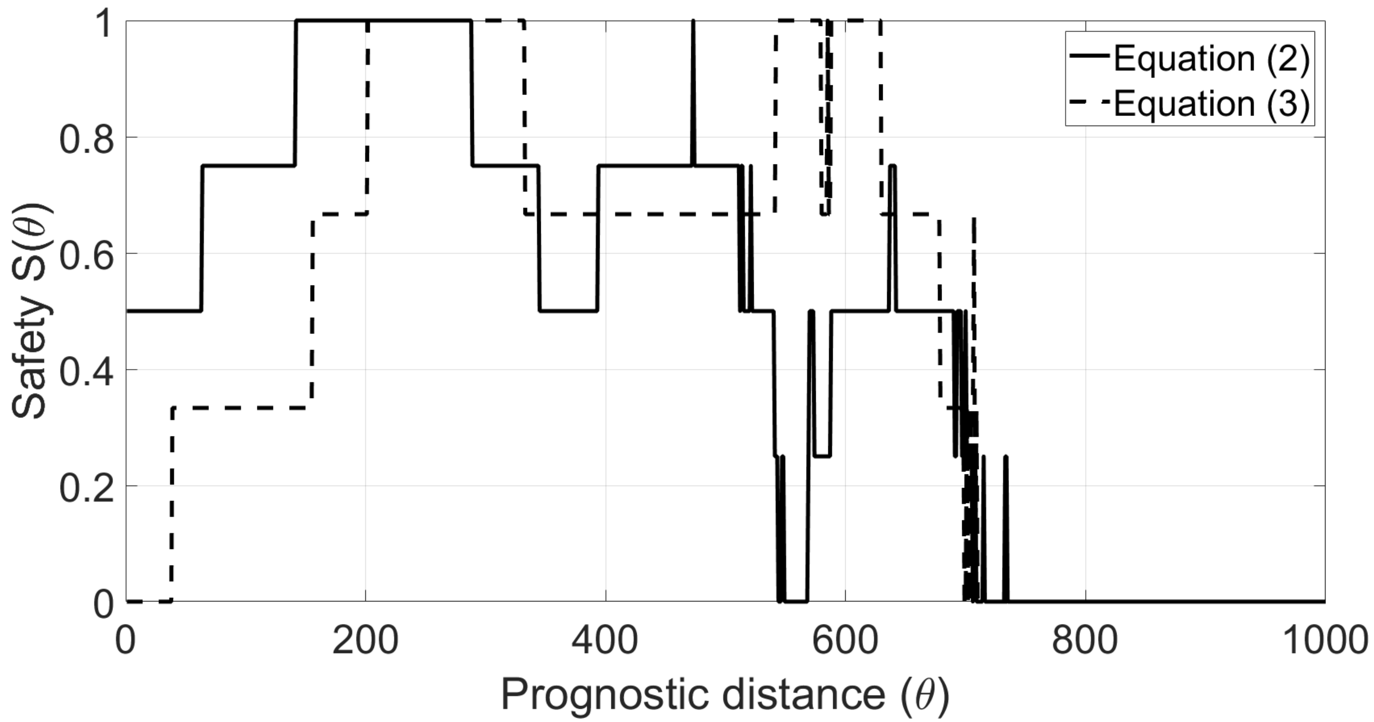
Prognostic distance $\theta \in (202{,}288)$ minimizes cost

Utilization (PF)



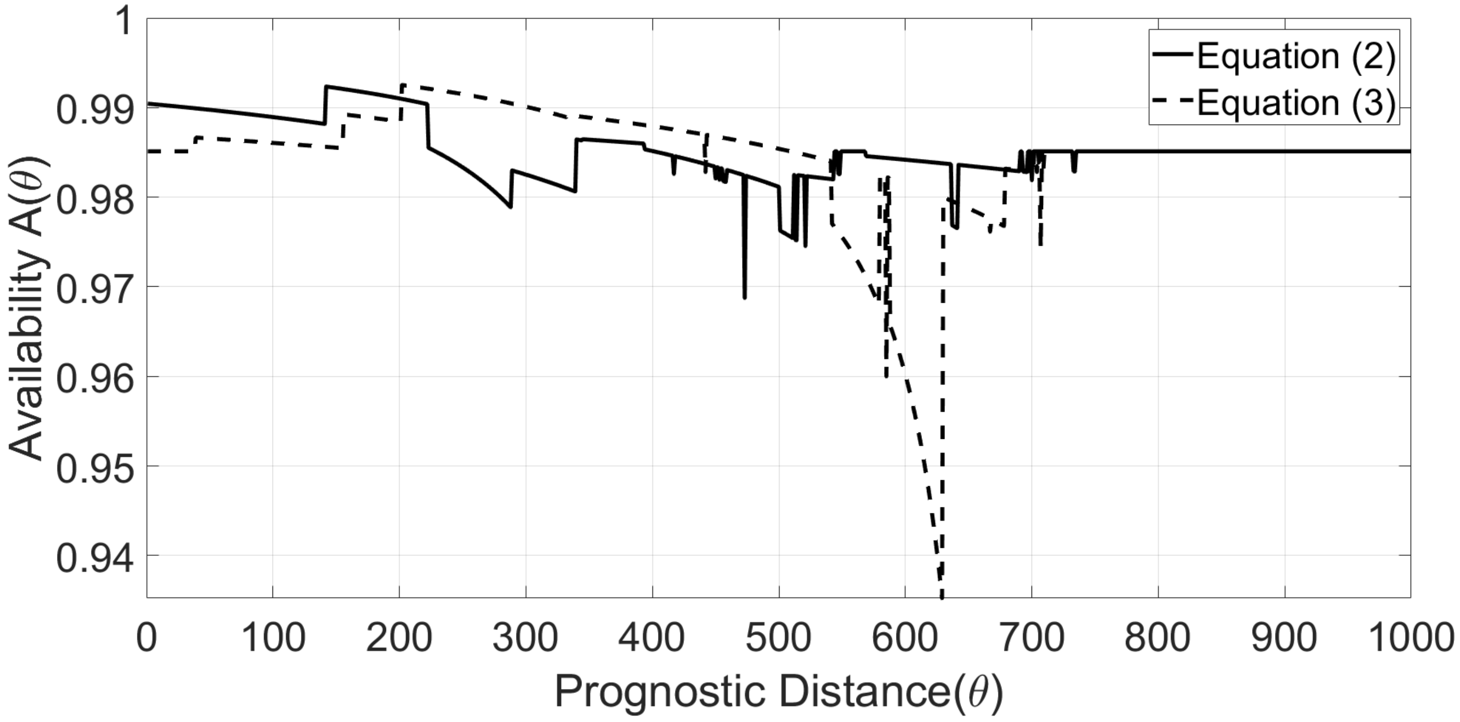
Prognostic distances that produce low utilization correspond to low cost

Safety (PF)



Safety and average cost per cycle exhibit inverse trends

Availability (PF)



Low utilization corresponds to low availability

Measures in Prognostic Window with Cx2-37 (most cycles to failure)

	Unscented Kalman Filter			**Particle Filter**		
θ	**Left**	**Mid**	**Right**	**Left**	**Mid**	**Right**
Eq (2)	175	412	660	142	215	288
$C(\theta)$	0.020	0.039	0.810	0.025	0.031	0.071
$U(\theta)$	0.939	0.482	0.023	0.734	0.596	0.262
$A(\theta)$	0.994	0.988	0.804	0.992	0.990	0.978
Eq (3)	193	435	678	202	267	332
$C(\theta)$	0.020	0.039	0.810	0.025	0.030	0.037
$U(\theta)$	0.939	0.482	0.023	0.751	0.628	0.500
$A(\theta)$	0.994	0.988	0.804	0.992	0.991	0.988

Conservative strategy selects θ at midpoint

Measures in Prognostic Window with Cx2-34 (most cycles to failure)

	Unscented Kalman Filter			Particle Filter		
θ	**Left**	**Mid**	**Right**	**Left**	**Mid**	**Right**
Eq (1)	101	343	586	330	361	392
$C(\theta)$	0.019	0.035	0.267	0.035	0.039	0.044
$U(\theta)$	0.937	0.503	0.067	0.512	0.456	0.4013
$A(\theta)$	0.994	0.989	0.925	0.989	0.988	0.986

Eq (3)	136	374	613	160	261	362
$C(\theta)$	0.020	0.039	0.576	0.022	0.028	0.044
$U(\theta)$	0.887	0.459	0.031	0.815	0.634	0.401
$A(\theta)$	0.994	0.988	0.852	0.993	0.991	0.986

Equation (3) with UKF stable in both scenarios

Digital Twins in a Nearly Autonomous Management and Control System for Advanced Reactors

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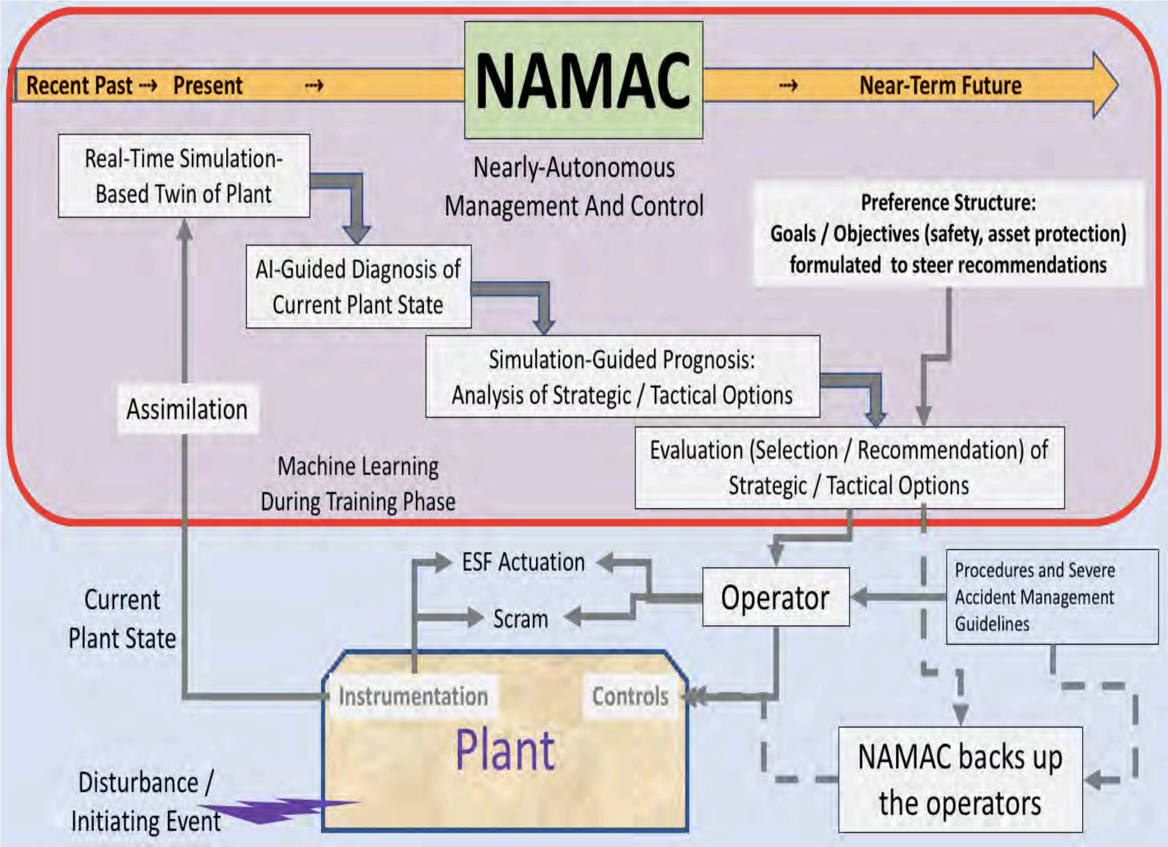
North Carolina State University

12/08/2020

Nearly Autonomous Management and Control (NAMAC)

- A comprehensive control system to assist plant operations
  - Knowledge integration
    - Scenario-based model of plant (systems, success paths)
    - plant operating procedures, tech. specs., etc.
    - Real-time measurements
  - Digital twin technology
    - Power of AI/ML
- NAMAC
  - Diagnoses the plant state
  - Searches for all available mitigation strategies
  - Projects the effects of actions and uncertainties into the future behavior
  - Determines the best strategy considering plant safety, performance, and cost.



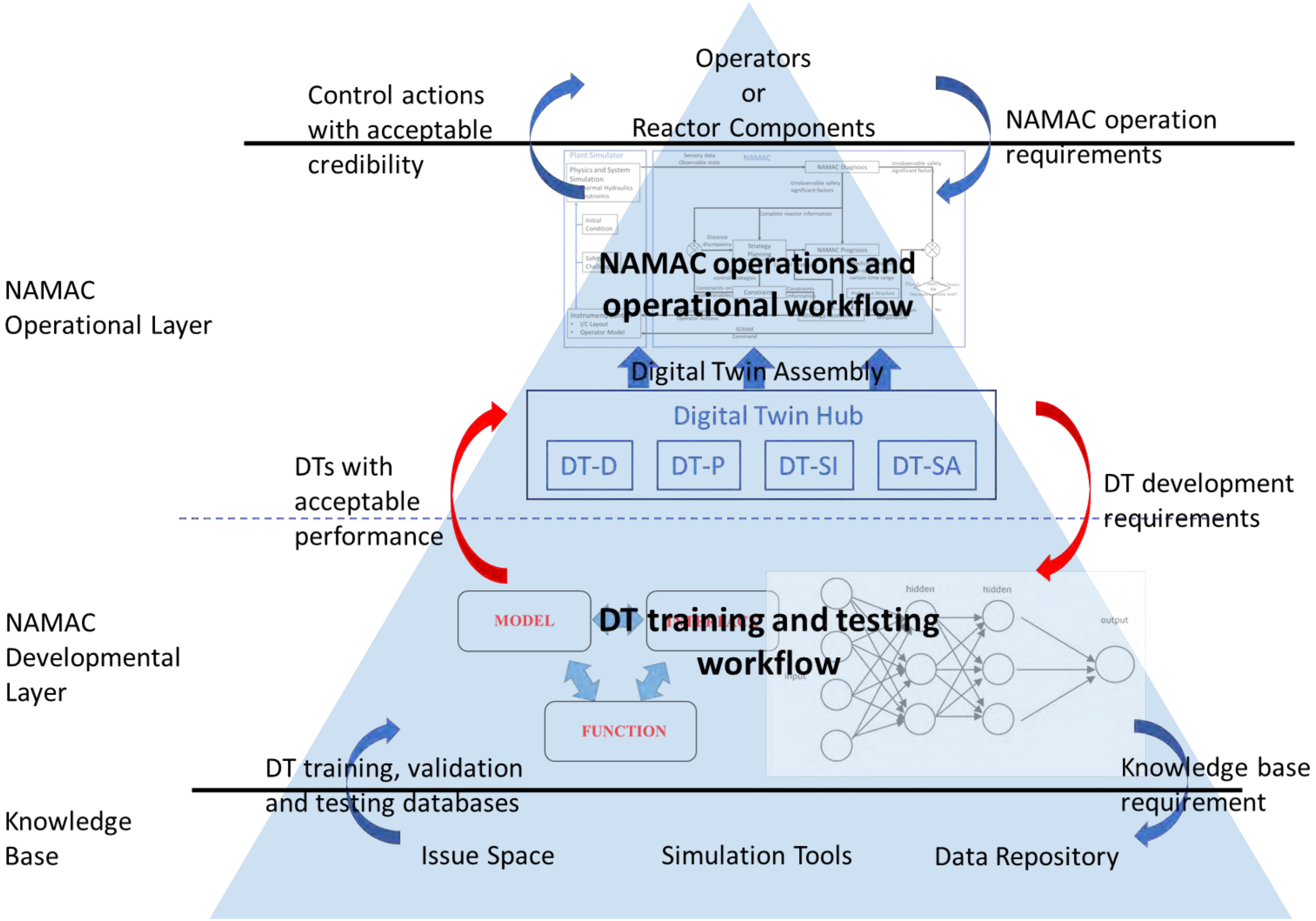
Guiding Principles and Development Philosophy

- High-level requirements
  - Technology neutral
  - Accurate representation (twin) of the plant
  - Dynamic and real-time: diagnosis, prognosis, and evaluation during operations
  - Adaptive (or continuously learning)
  - Explainable: outputs are traceable and justifiable

- Design principles for an intelligent autonomous control system
  - Three-Level Architecture
  - Knowledge Base
  - Digital Twin
  - Digital Twin Development and Assessment Process
  - Trustworthiness Assessment

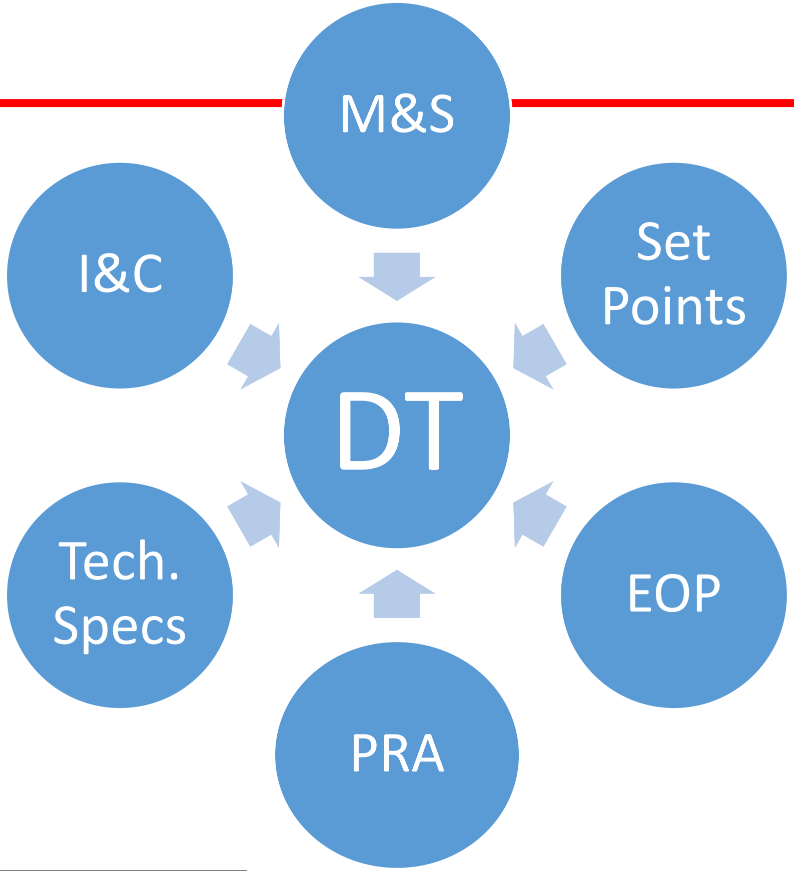
Three-Layer Architecture

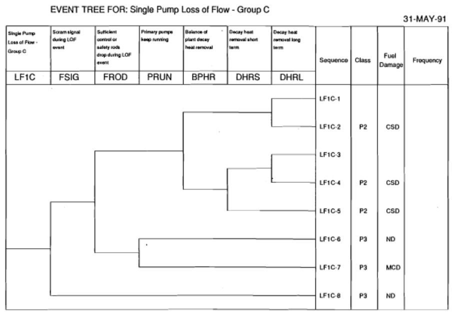
- Individual Digital Twins (DT) are assembled into a DT-Hub to support decisions in operation, maintenance, safety management, etc. in the Operational Layer
- Each Digital Twin (DT) is a knowledge acquisition system to support specific functions
  - Digital Twin for Diagnosis (DT-D)
  - Digital Twin for Strategy Inventory (DT-SI)
  - Digital Twin for Prognosis (DT-P)
  - Digital Twin for Strategy Assessment (DT-SA)
- Developmental Layer extracts useful information from the knowledge base and creates Digital Twins (DT)
- Knowledge base stores data from simulations, operations, documents, procedures, etc.



Knowledge Base

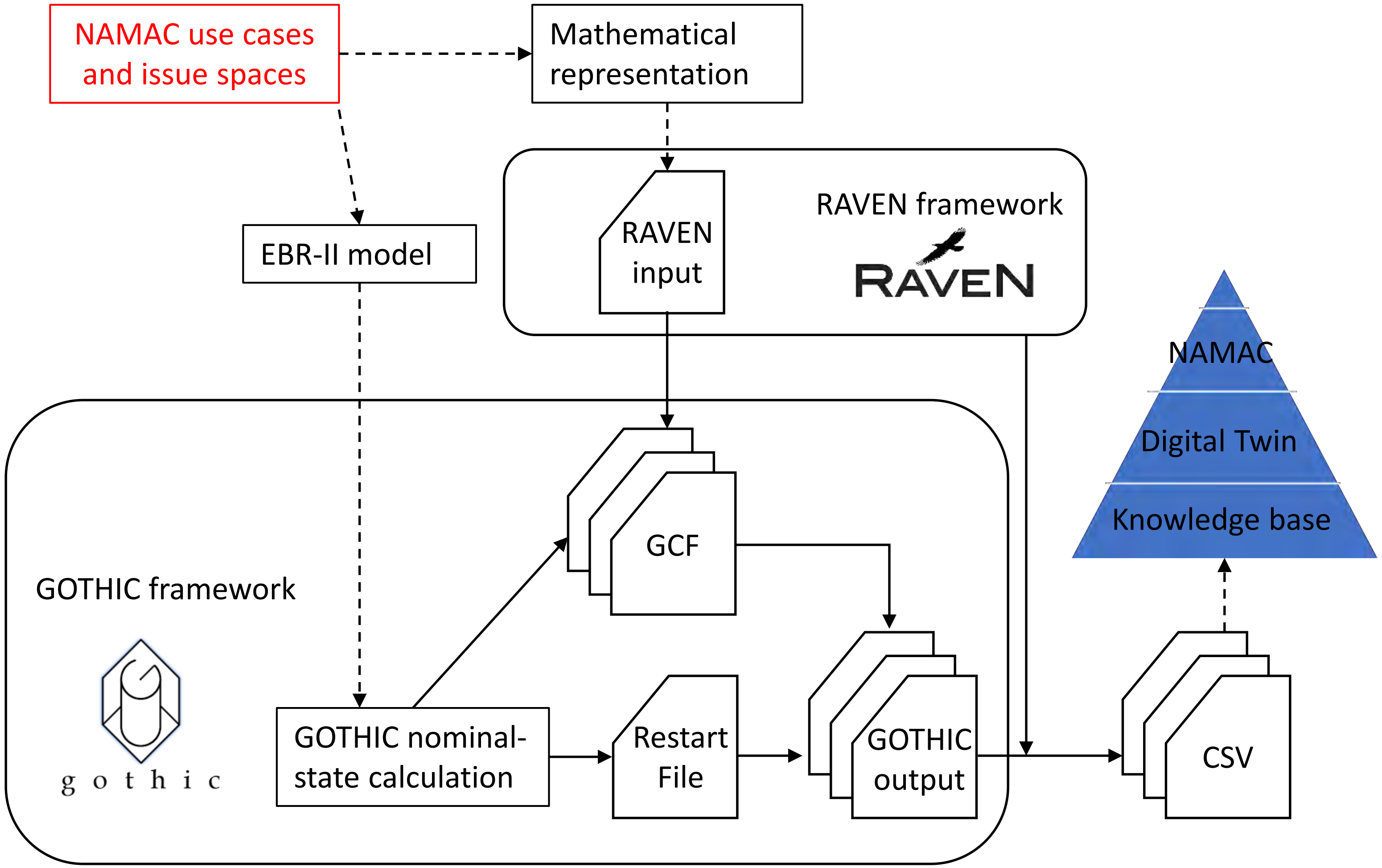
- Knowledge base is the foundation of DTs and NAMAC
- Integrate knowledge from a variety of sources
  - Plant monitoring systems
  - Scenario based modeling & simulation (M&S)
  - Operating limits and control procedures
  - Probabilistic assessment of the risk
  - Emergency Operating Procedures (EOP)
- Knowledge base will transit from simulation-based data to assimilating sensor data as a new plant comes on-line and operating history becomes available
  - M&S will always be a key contributor to the knowledge base, particularly for accidents and other low frequency events where actual plant data may not be available.
- Not just "raw" data signals, but these sources are vital knowledge bases
  - Leverage existing information
  - Minimize propensity to treat ML and DTs as "black-box"





Database Generation in Knowledge Base

- NAMAC Database generation:
  - Training databases are generated by sampling scenarios to populate information in the application domain
  - The Digital Twin are constructed according to the databases for supporting diagnosis, prognosis, etc.



Digital Twin

- Digital Twin technology - construct a digital replica (twin) for the real reactors and transients
- DTs must provide insights equivalent to Modeling and Simulation (M&S), but need to learn and provide those insights much faster than the development and uses of M&S
- But DTs are tightly coupled with operation
  - Assimilating and adapting to real-time information from the operating environment
  - Interacting with user for specific objectives

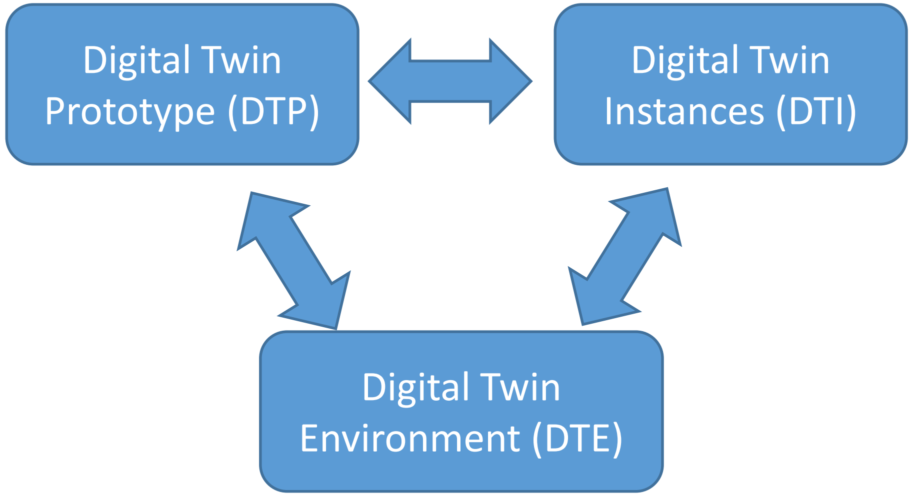
Definitions for DTs [1]

MODEL

- Data-driven model
- Mechanistic model
- Reasoning-based model

INTERFACE

- API
- I/O
- User Interface



FUNCTION

- Use cases
- Objectives
- Output types

[1] F. Kahlen, et al., "Transdisciplinary perspectives on complex systems - new findings and approaches", Springer, 2017

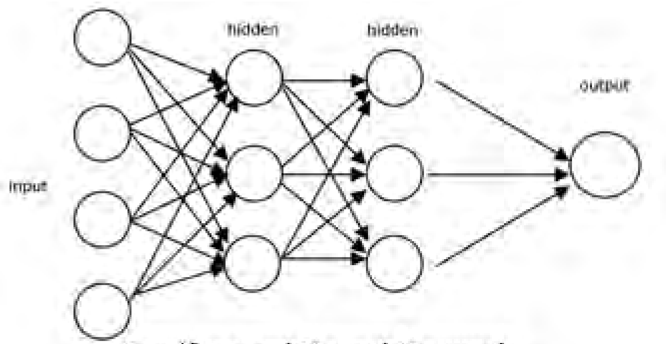
Digital Twin Training and Algorithms

- Artificial Neural Network (ANNs) is currently the major technology in constructing Digital Twins and NAMAC system.

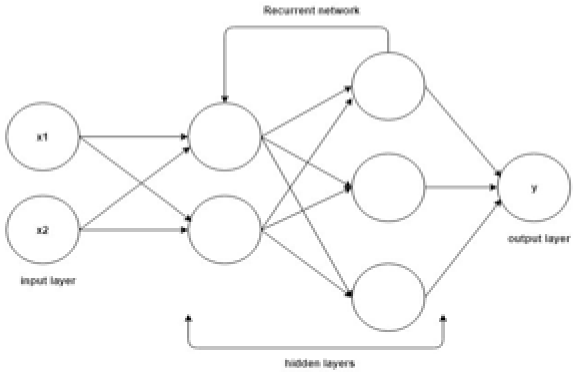
- As complexity of NAMAC case studies increases, advanced algorithms are required to support DTs
  - Modular framework allows for multi-tiered implementation
  - Do not need a single, monolithic solution to cover all conditions

- Two classes of advanced algorithms are being investigated:
  1. *Knowledge/reasoning-based methods*
     - Provide **explainability** and **transparency**
  2. *Model free methods*
     - Deep learning capability that is needed for **diversity** and **complexity**

- Need both types for NAMAC



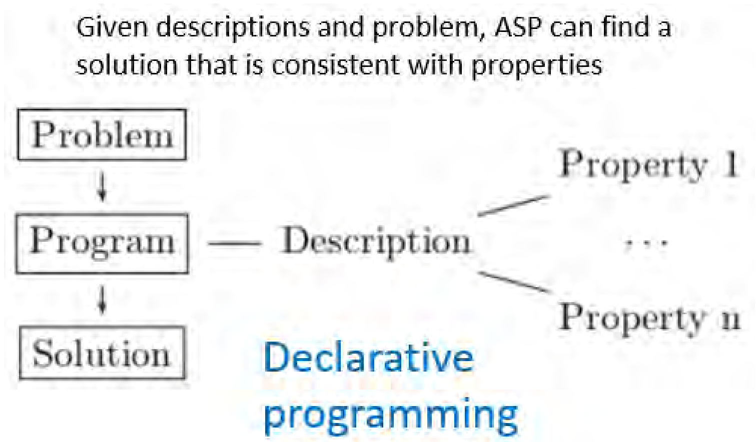
Feedforward Neural Network

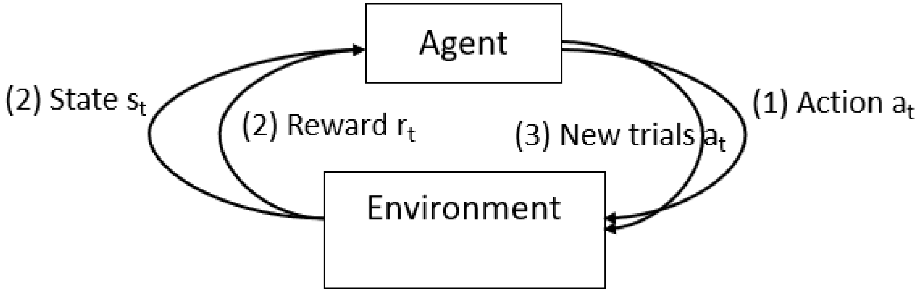


Recurrent Neural Network

Digital Twin Training and Algorithms

- Advanced Algorithms
  - **Answer Set Programming (ASP)** is a form of declarative programming oriented towards difficult search problems
    - Discrepancy Checker (DC)
  - **Ensemble modeling** employs a voting technique to aggregate/select predictions from a set of base models
    - Digital twin for diagnosis (DT-D)
  - **Reinforcement Learning (RL)** interacts with the environment and is time aware
    - Wholistic NAMAC for furnishing recommendations
  - **Adaptive sampling** techniques for data generation
    - Efficient process to support Strategy Inventory (DT-SI)
  - **Meta-Learning** to accelerate and optimize development

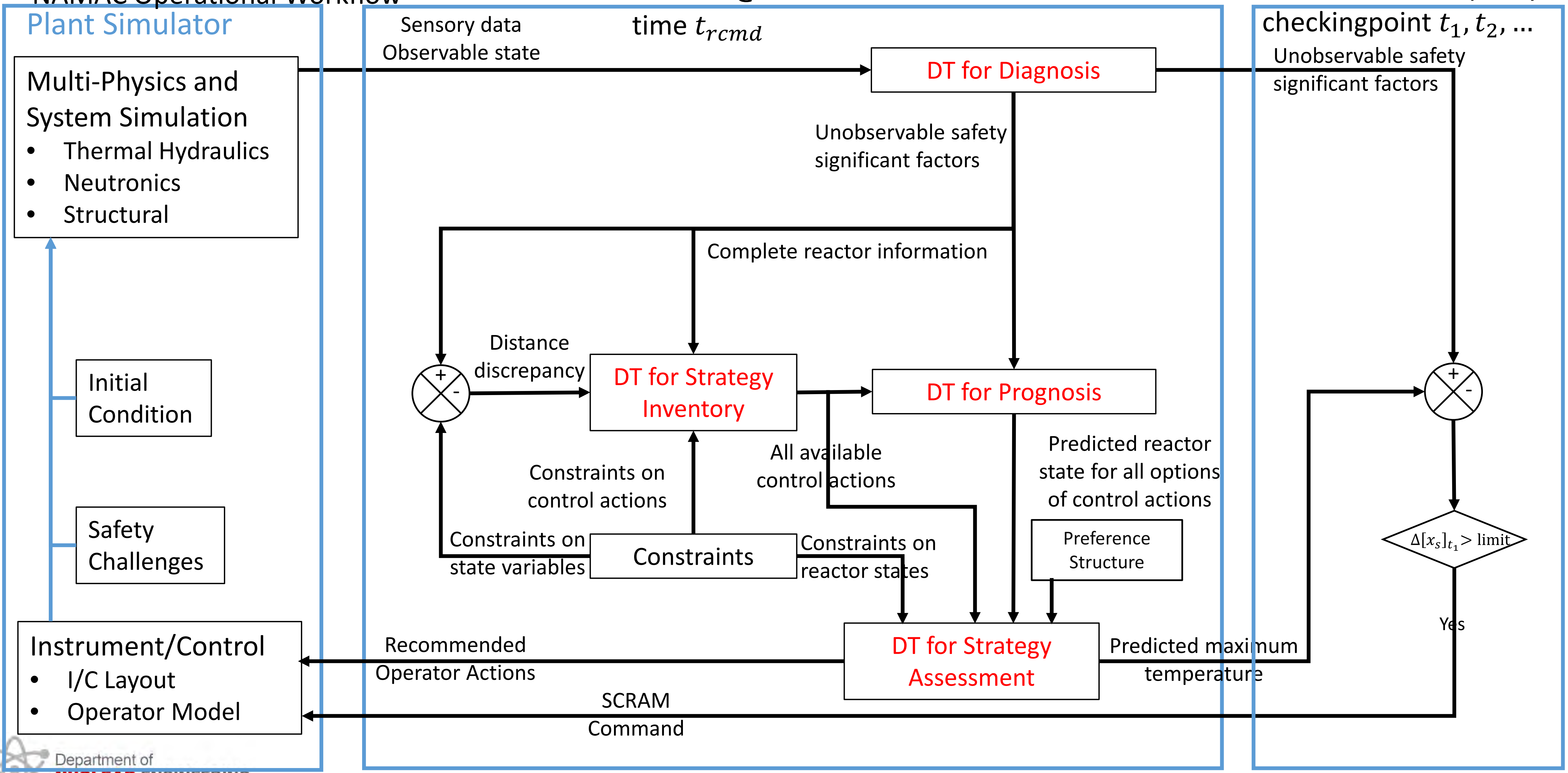




Modular Framework

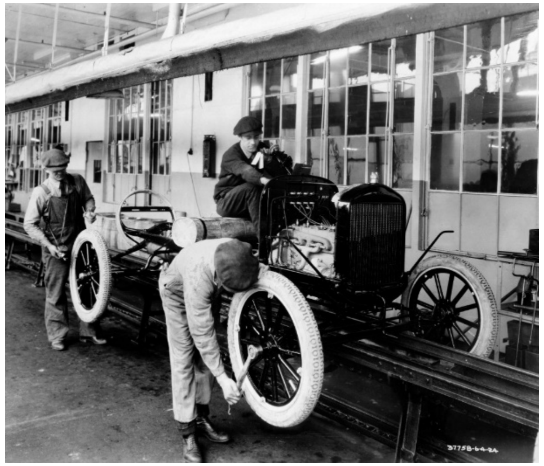
	Function	Modeling
Diagnosis	Recover full reactor states by assimilating plant sensor data with the knowledge base	Neural nets (feedforward & recurrent); Logic programming (Answer Set Programming)
Strategy Inventory	Find all available control/mitigation strategies	Uniform sampling Reinforcement Learning
Prognosis	Predict the transients of state variables over a time range	Neural nets (feedforward & recurrent)
Strategy Assessment	Rank possible mitigations strategies and make recommendations considering preference structure	Safety margin/limiting surface; Expected utility;
Discrepancy Checker	Detect unexpected transient during operations considering DT trustworthiness for current conditions	Distance metrics; Logic programming (Answer Set Programming)

- NAMAC Operational Workflow



The Development and Assessment Process (DAP)

- Instead of claiming to have a perfect autonomous system for a specific reactor during a specific scenario, our objective is to have a "smart" Development and Assessment Process (DAP) that produces NAMAC systems for generic types of reactors based on requirements from all stakeholders.



1924 – Ford assembly line

1965 – Ford assembly line

2019 – Tesla smart factory

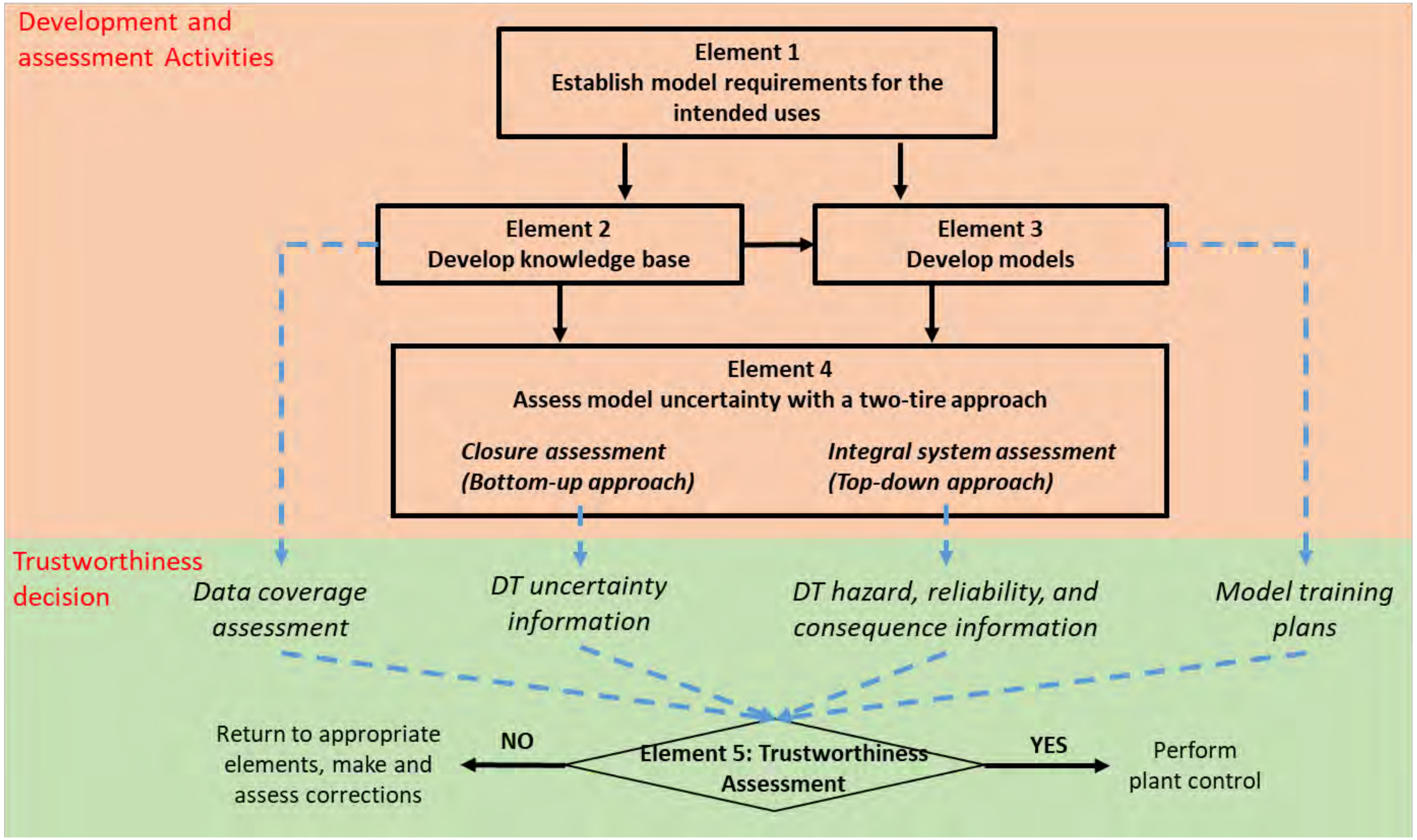
Evolution of "Development and Assessment Process (DAP)" for Automobile

[1] [2] Picture by Ford, "The evolution of assembly lines: A brief history", https://robohub.org/the-evolution-of-assembly-lines-a-brief-history/, 2014
[3] Picture from "Popular Mechanics", https://ottomotors.com/blog/what-is-the-smart-factory-manufacturing, 2019

Digital Twin Development and Assessment Process

- DT-DAP for a scalable and robust application of digital twins and NAMAC concept to generic types of use cases and advanced reactors.

- The DAP is conducted iteratively to deliver a reliable NAMAC with a set of credible DTs
  - *Element 1*: Refined requirements
  - *Element 2*: More complex and realistic knowledge base
  - *Element 3*: Different machine-learning algorithms
  - *Element 4*: ML uncertainty quantification, software reliability analysis
  - *Element 5*: Digital twin trustworthiness assessment



Adopted from U.S. NRC RG 1.203 “Transient and Accident Analysis Methods”

Digital Twin Trustworthiness

- In fundamental, the NAMAC make recommendations by **extracting** knowledge from knowledge base and **assimilating** them with **real-time** sensor signals – Digital Twin
  - Considering the complexity and heterogeneity of knowledge base, we investigate **data-driven models** and **machine-learning algorithms** for

- However, for complex systems and difficult tasks, the uncertainty of the DTs in NAMAC, if being overlooked, could introduce additional risks and degrade the trustworthiness of NAMAC recommendations, especially when the DT itself is complicated and black-box

- As a result, we need a trustworthiness assessment framework for DTs in NAMAC (ongoing)

  (1) monitor uncertainty that could complicate the determination of mitigation strategies

  (2) make uses of information from the DT development and assessment process

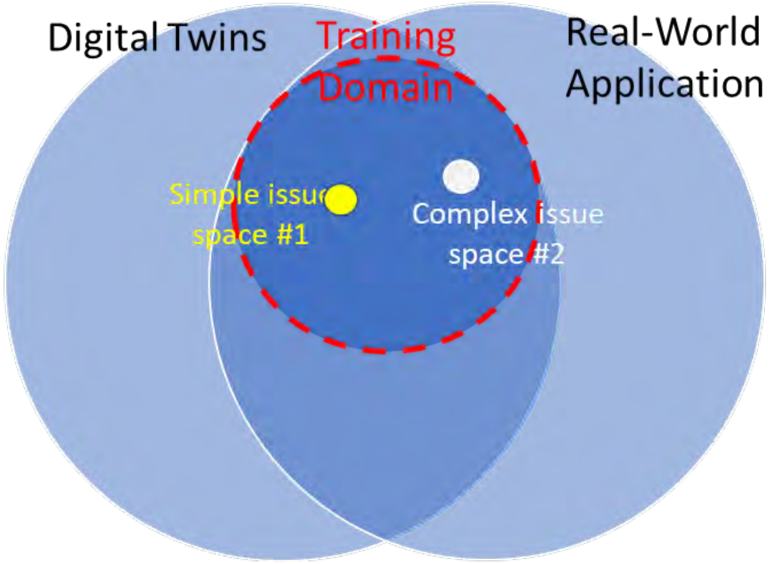
  (3) do this in real time

A gap between

the development & assessment of a digital twin

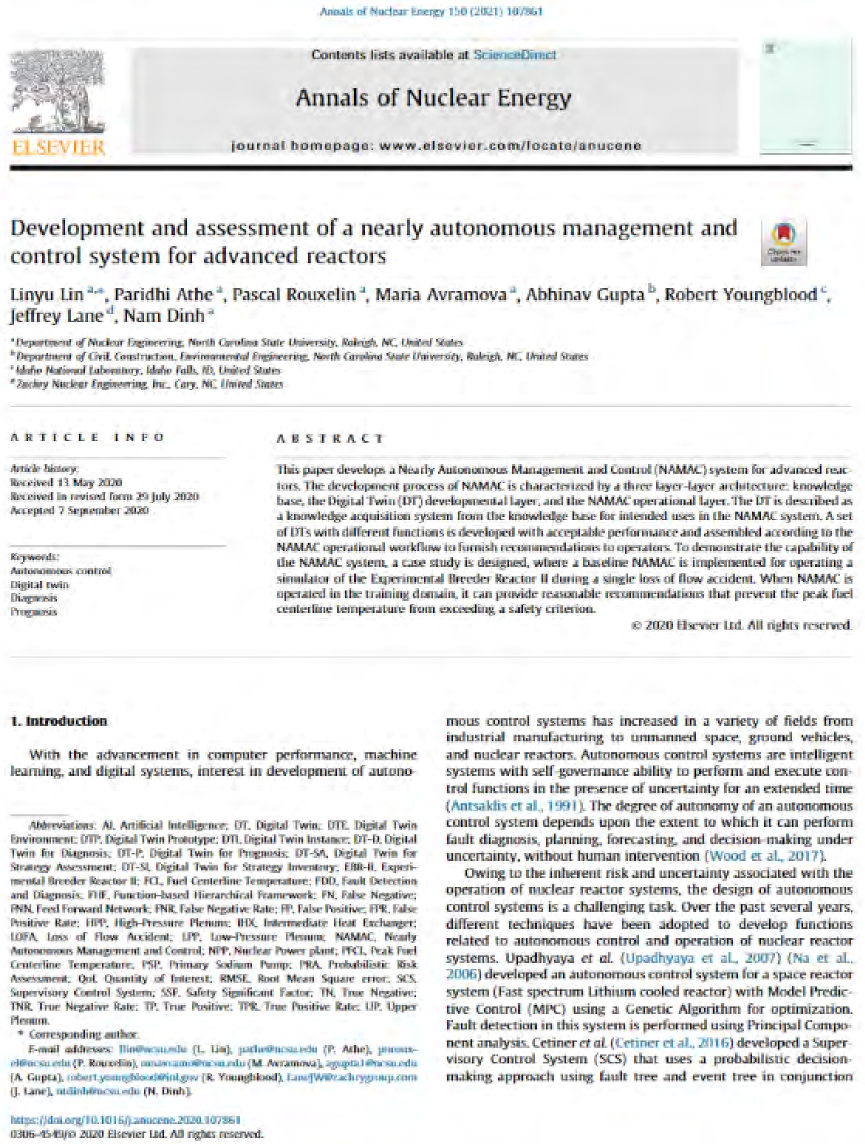
and

the use & regulation of a digital twin



Summary

- Implementation of digital twins for extracting and assimilating the knowledge base with real-time information
- Proof-of-concept of NAMAC for one class of transients
  - Pump malfunction ranging from flow anomaly to complete loss of flow accident
  - NAMAC provides recommendations during the event consistent to human operator norm
- The design of a digital twin development and assessment process (DT-DAP) for implementing, improving, and collecting evidence of a generic types of digital twins in autonomous systems
  - DT-DAP at scoping stage that is driven by user experiences and sensitivity analysis
  - Informed by EMDAP, but necessarily seeks to provide quantitative basis to support NAMAC decision making
  - *Next steps – the trustworthiness and robustness of DTs based on both intrinsic (i.e., uncertainty quantification, reliability) and contextual properties (i.e., confidence, safety-related vs. non-safety related).*



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Development and assessment of a nearly autonomous management and control system for advanced reactors

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ABSTRACT

This paper develops a Nearly Autonomous Management and Control (NAMAC) system for advanced reactors. The development process of NAMAC is characterized by a three layer-layer architecture: knowledge base, the Digital Twin (DT) developmental layer, and the NAMAC operational layer. The DT is described as a knowledge acquisition system from the knowledge base for intended uses in the NAMAC system. A set of DTs with different functions is developed with acceptable performance and assembled according to the NAMAC operational workflow to furnish recommendations to operators. To demonstrate the capability of the NAMAC system, a case study is designed, where a baseline NAMAC is implemented for operating a simulator of the Experimental Breeder Reactor II during a single loss of flow accident. When NAMAC is operated in the training domain, it can provide reasonable recommendations that prevent the peak fuel centerline temperature from exceeding a safety criterion.

1. Introduction

With the advancement in computer performance, machine learning, and digital systems, interest in development of autonomous control systems has increased in a variety of fields from industrial manufacturing to unmanned space, ground vehicles, and nuclear reactors. Autonomous control systems are intelligent systems with self-governance ability to perform and execute control functions in the presence of uncertainty for an extended time (Antsaklis et al., 1991). The degree of autonomy of an autonomous control system depends upon the extent to which it can perform fault diagnosis, planning, forecasting, and decision-making under uncertainty, without human intervention (Wood et al., 2017).

Owing to the inherent risk and uncertainty associated with the operation of nuclear reactor systems, the design of autonomous control systems is a challenging task. Over the past several years, different techniques have been adopted to develop functions related to autonomous control and operation of nuclear reactor systems. Upadhyaya *et al.* (Upadhyaya et al., 2007) (Na et al., 2006) developed an autonomous control system for a space reactor system (Fast spectrum Lithium cooled reactor) with Model Predictive Control (MPC) using a Genetic Algorithm for optimization. Fault detection in this system is performed using Principal Component analysis. Cetiner *et al.* (Cetiner et al., 2016) developed a Supervisory Control System (SCS) that uses a probabilistic decision-making approach using fault tree and event tree in conjunction

Abbreviations: AI, Artificial Intelligence; DT, Digital Twin; DTE, Digital Twin Environment; DTP, Digital Twin Prototype; DTI, Digital Twin Instance; DT-D, Digital Twin for Diagnosis; DT-P, Digital Twin for Prognosis; DT-SA, Digital Twin for Strategy Assessment; DT-SI, Digital Twin for Strategy Inventory; EBR-II, Experimental Breeder Reactor II; FCT, Fuel Centerline Temperature; FDD, Fault Detection and Diagnosis; FHF, Function-based Hierarchical Framework; FN, False Negative; FNN, Feed Forward Network; FNR, False Negative Rate; FP, False Positive; FPR, False Positive Rate; HPP, High-Pressure Plenum; IHX, Intermediate Heat Exchanger; LOFA, Loss of Flow Accident; LPP, Low-Pressure Plenum; NAMAC, Nearly Autonomous Management and Control; NPP, Nuclear Power plant; PFCT, Peak Fuel Centerline Temperature; PSP, Primary Sodium Pump; PRA, Probabilistic Risk Assessment; QoI, Quantity of Interest; RMSE, Root Mean Square error; SCS, Supervisory Control System; SSF, Safety Significant Factor; TN, True Negative; TNR, True Negative Rate; TP, True Positive; TPR, True Positive Rate; UP, Upper Plenum.

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- GOTHIC license is provided by Zachry Nuclear Engineering, Inc. GOTHIC incorporates technology developed for the electric power industry under the sponsorship of EPRI, the Electric Power Research Institute.

Structural Condition Monitoring with a Digital Twin: Explorations on a Nuclear Containment Vessel Model

Presenter: Dr. Timothy Kernicky, EPIC Research Assistant Professor of Civil Engineering, University of North Carolina Charlotte

Contributors: Dr. Matthew Whelan

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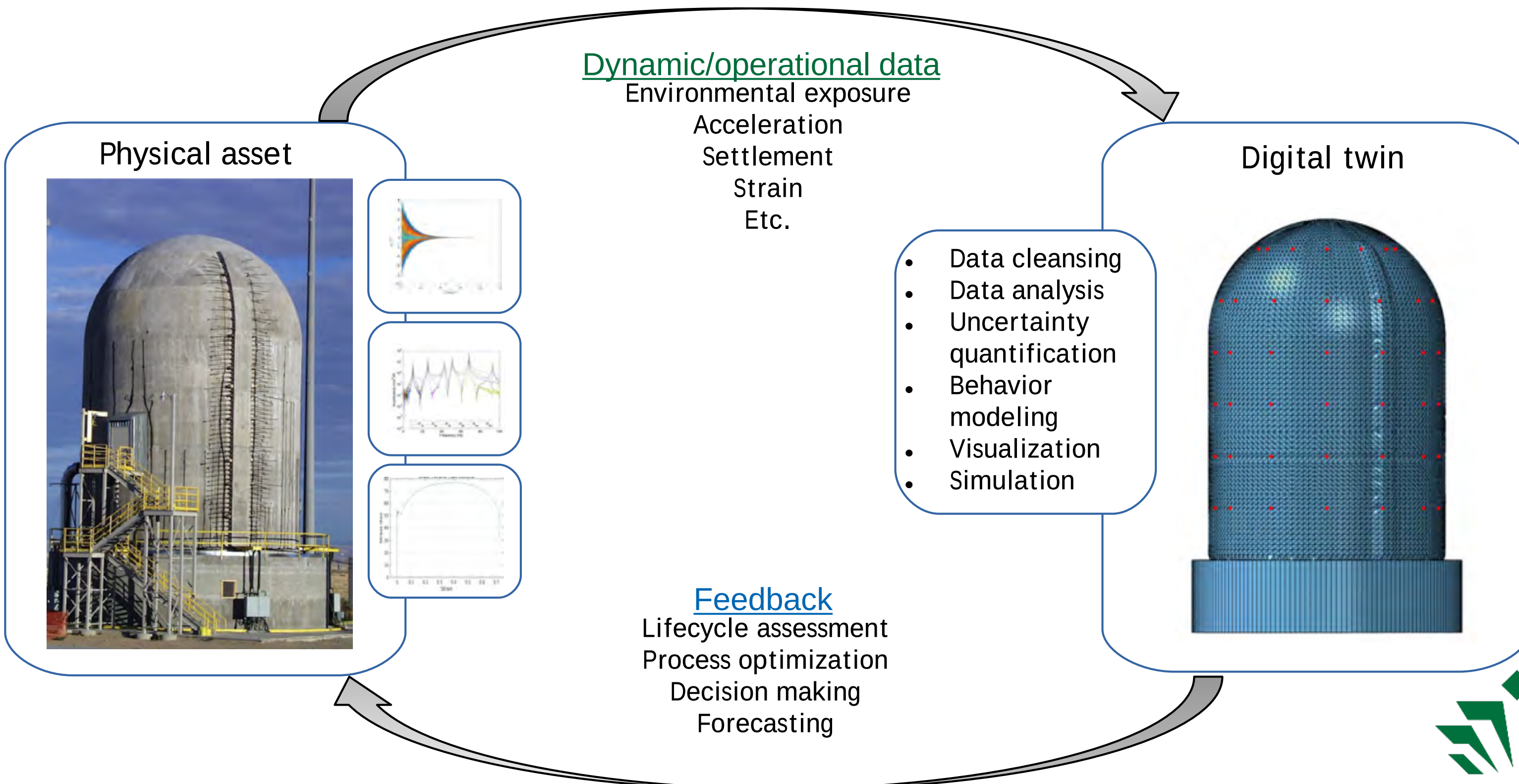
Digital Twin

- A digital twin is more than a digital model that faithfully represents physical assets and processes
- The primary distinguishing feature of a digital twin is its connection to the real-world asset with the ability to inform the state of the physical asset



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First Step: Structural Identification

- The first step towards successful digital twin deployment is the development of a “trusted” model, which faithfully replicates the performance of the physical asset

- This simple study leverages vibration-based structural identification to calibrate a set of uncertain material parameters of the digital twin using synthetic measurement data

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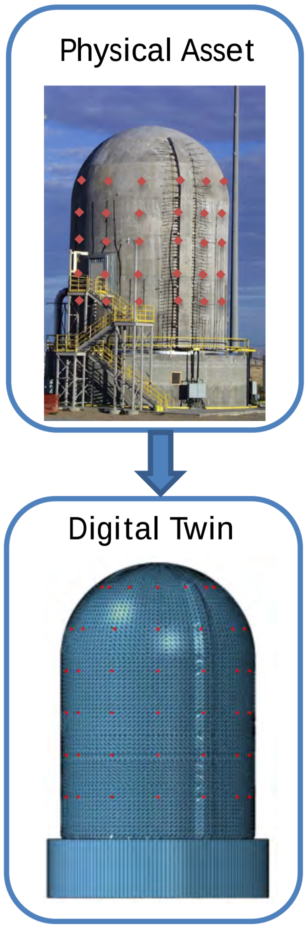
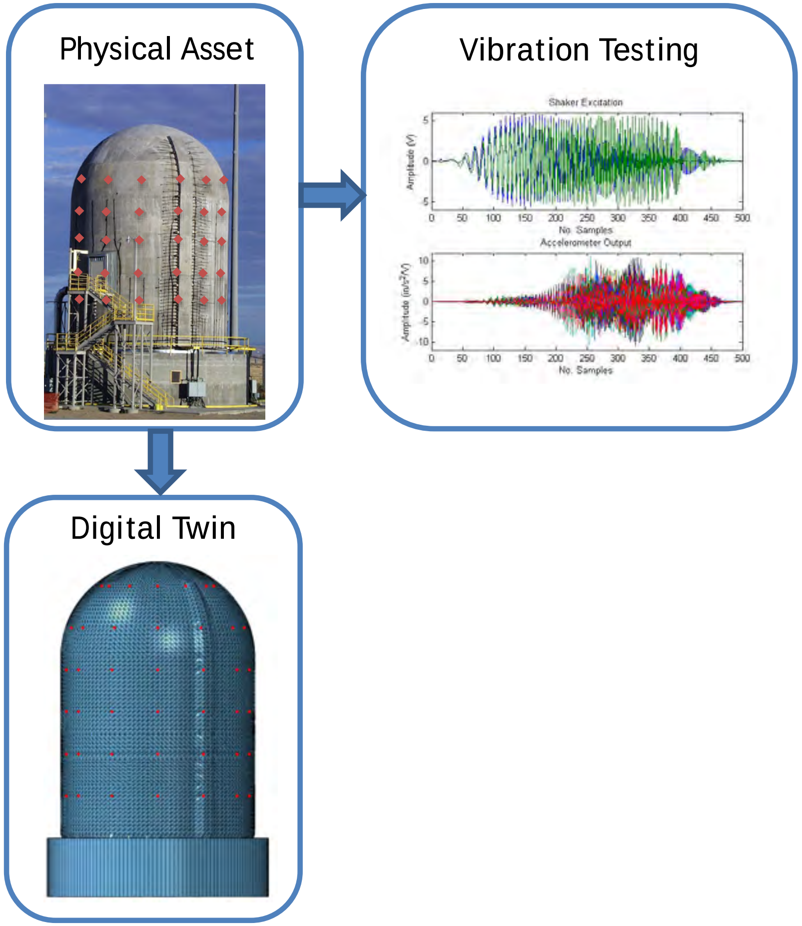
Vibration-Based Structural Identification



- Finite element (FE) model of physical asset created
- Initial model suffers from
  - Parameter uncertainties
    - Geometries
    - Material properties
  - Idealization errors
  - Discretization errors
- FE model may be leveraged to develop appropriate sensor array for physical structure

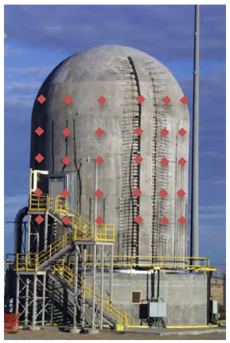
Vibration-Based Structural Identification



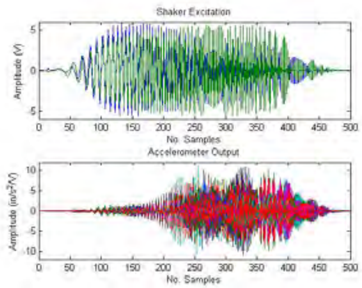
- Vibration data is acquired from sensor array on the physical structure
- Structure excitation can be ambient (operational) or forced

Vibration-Based Structural Identification

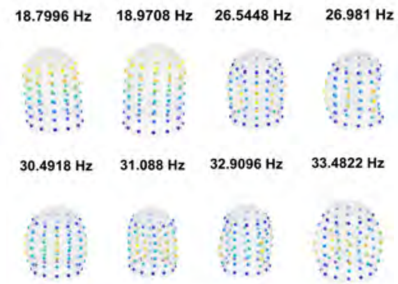
Physical Asset



Vibration Testing

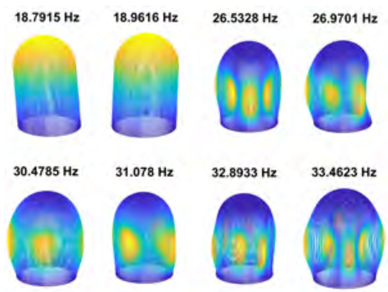


Modal Properties Estimates



Digital Twin

Analytical Modal Analysis



- Modal properties of the physical asset are identified
- Modal properties of the digital twin are extracted from the system matrices, [K] & [M]

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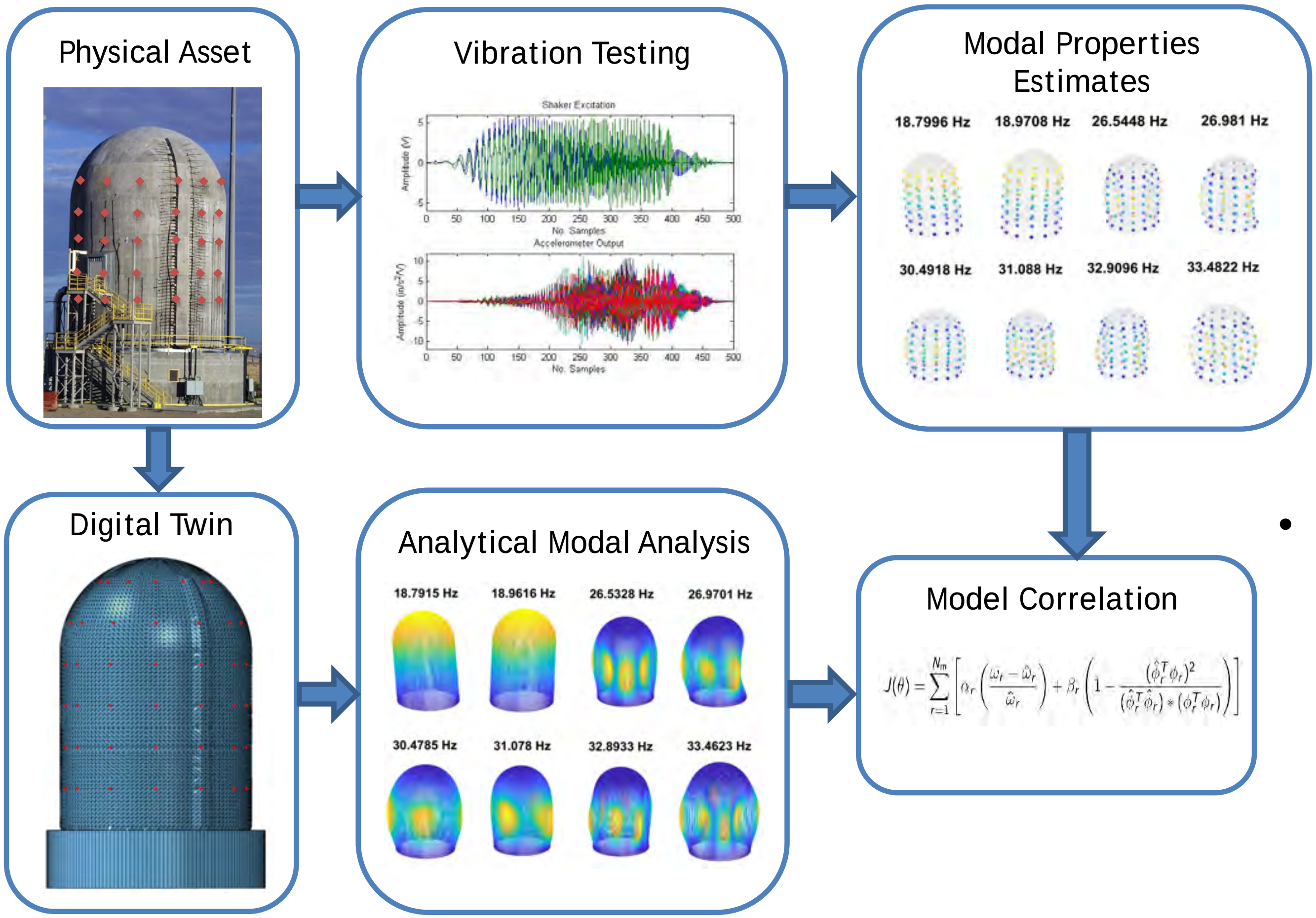
Vibration-Based Structural Identification



- Correlation between the physical and FE modal properties is determined by a modal measure of fit, which accepts natural frequencies and mode shapes as input.

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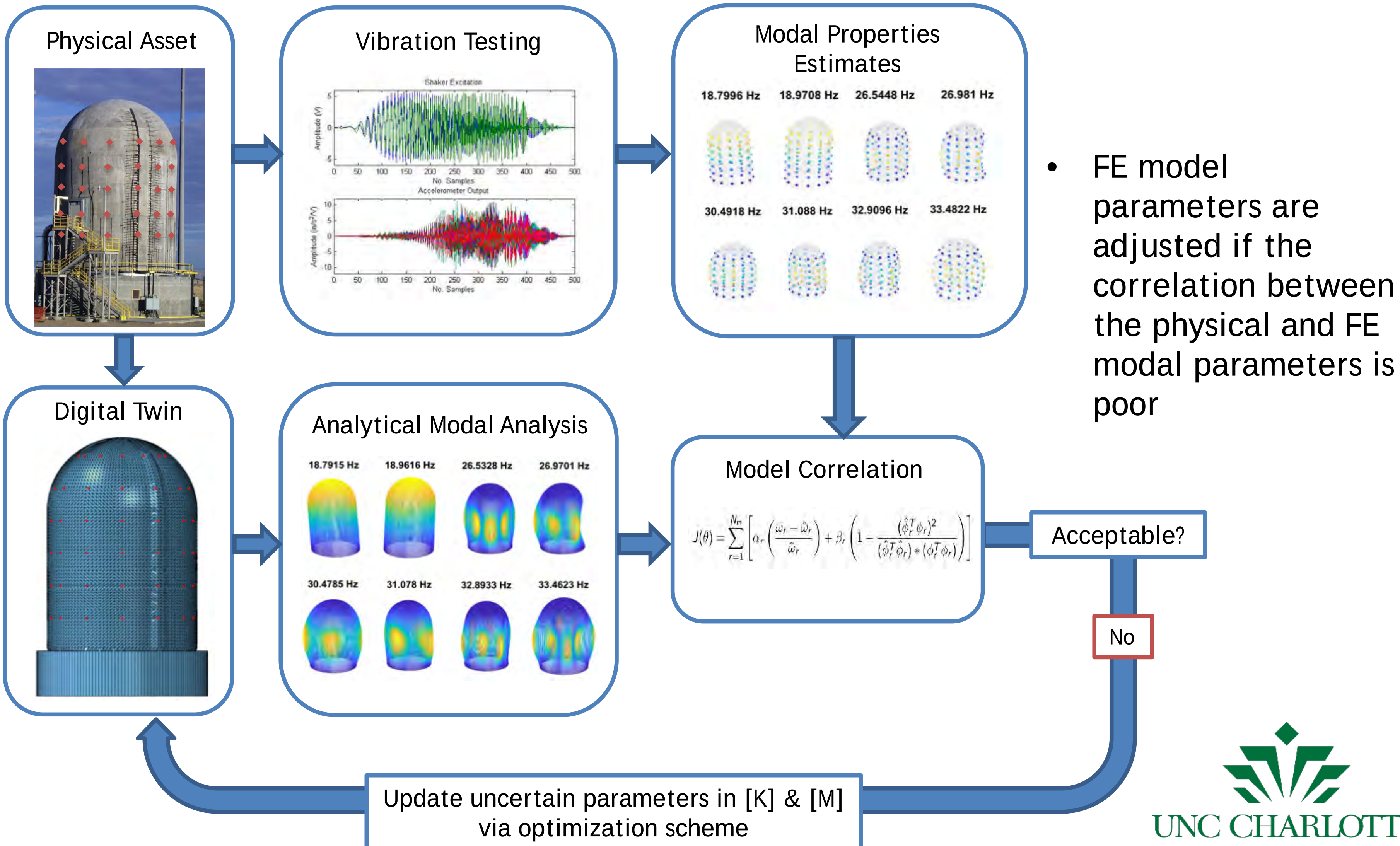
Vibration-Based Structural Identification



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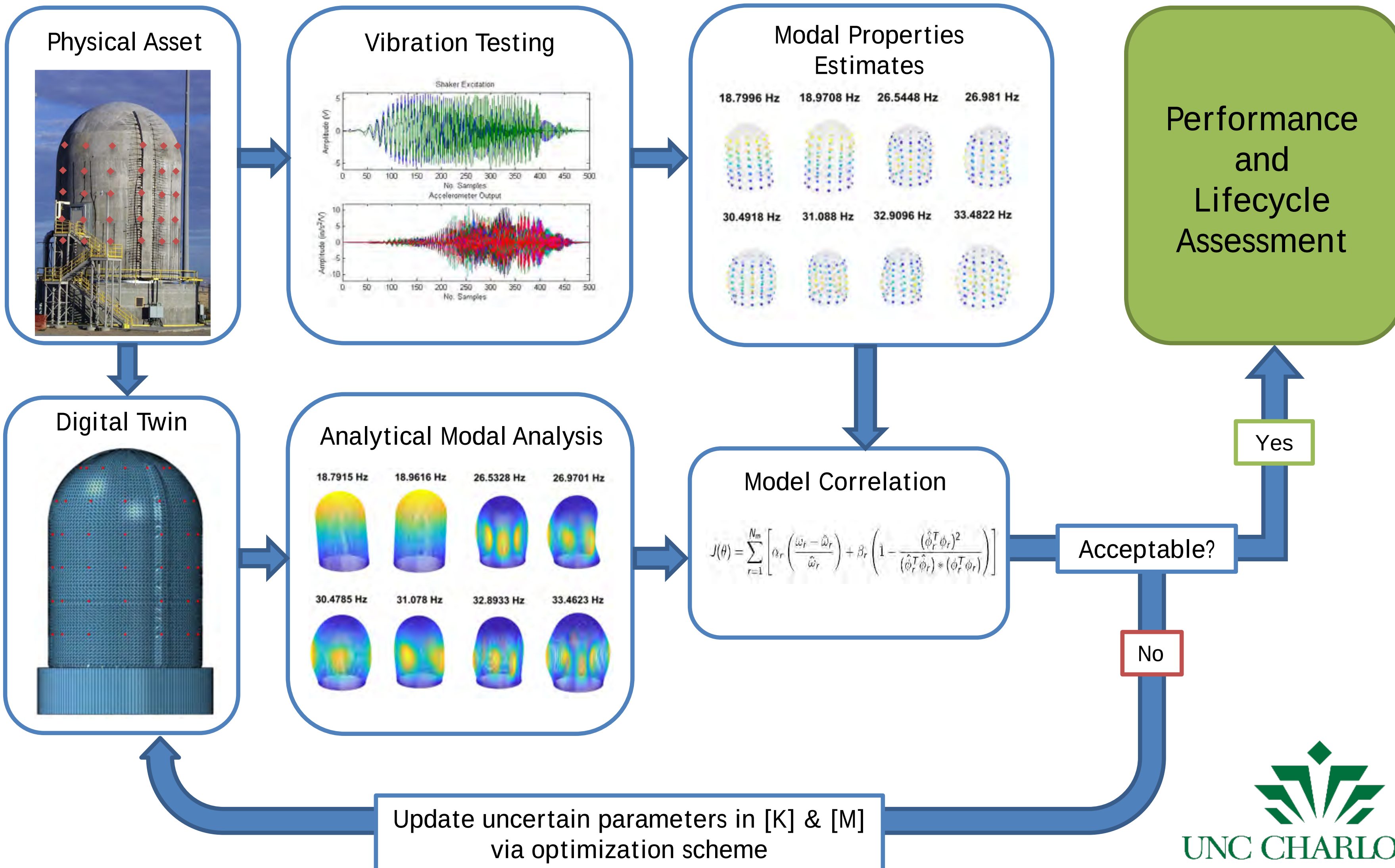
Vibration-Based Structural Identification



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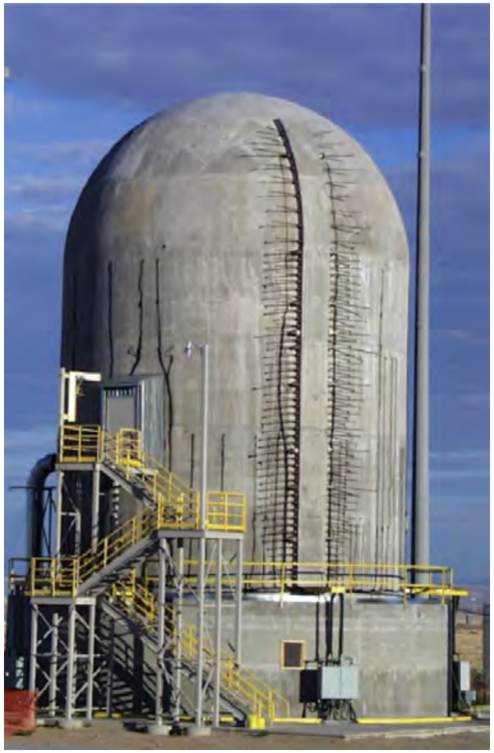
Digital Twin Study of a Containment Vessel

- This study will demonstrate a potential capability to track changes/deterioration in a concrete containment vessel
- The structure explored is based on the 1:4 scale model of the Ohi-3 containment vessel in Japan, which was funded by NUPEC and the NRC and tested by SNL [NUREG/CR-6810, SAND2003-0840P]
- Two FE models will be utilized in this study.
  - One represents the physical asset from which "in-service", synthetic measurements are obtained
  - The second will serve as the digital twin to be updated
- Measurements of dynamic properties (modal parameters) will be used by the digital twin to inform changes in the structural condition, while synthetic response measurements obtained from the "physical" structure will be used to correct the digital twin



[NUREG/CR-6810, SAND2003-0840P]

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Concrete Containment Model

- A simplified finite element model was created using ABAQUS
- Four locations of interest where penetrations exist in the vessel were chosen as uncertain parameters to identify
  - main steam penetration (M/S)
  - feed water penetration (F/W)
  - equipment hatch (E/H)
  - air lock (A/L)
- The modulus of elasticity of each section of elements was used as the uncertain parameter to be updated
- Four deterioration scenarios were examined to demonstrate the ability of the methodology to identify material degradation

Case	Parameter	Stiffness Change (%)
1	$E_{M/S}$	0
2	$E_{M/S}$	-5
3	$E_{M/S}$	-15
4	$E_{M/S}$	-25

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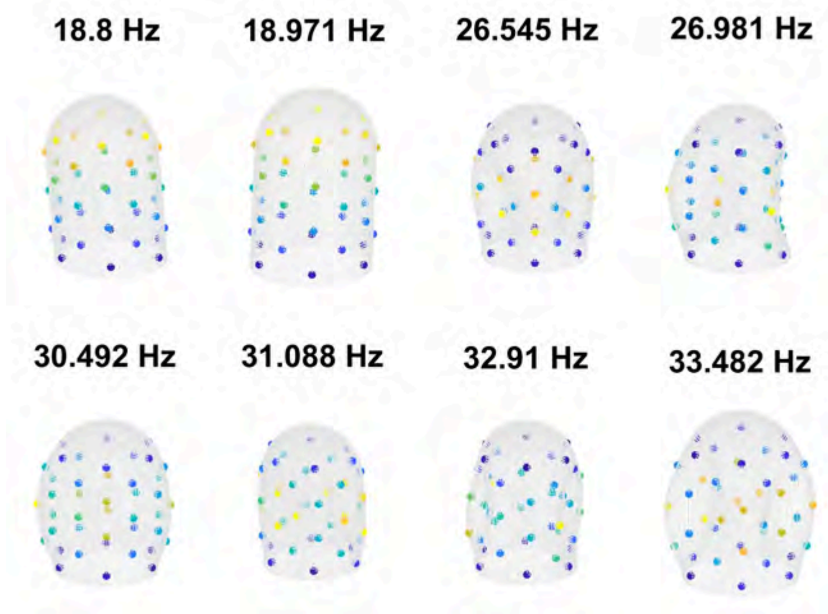
Development of Synthetic Dataset

- Synthetic measurement data was extracted from the finite element model in the form of natural frequencies and mode shapes from 42 biaxial sensors
- Noise was added to the synthetic measurements by adding 0.5% Gaussian noise to generate 10 sets of data



Synthetic natural frequencies and mode shapes for Case 1

	Case 1	Case 2		Case 3		Case 4	
Mode	f_n	$\Delta f(\%)$	MAC	$\Delta f(\%)$	MAC	$\Delta f(\%)$	MAC
1	18.800	-0.033	1.000	-0.108	1.000	-0.200	1.000
2	18.971	-0.041	1.000	-0.135	0.999	-0.250	0.999
3	26.545	-0.038	1.000	-0.122	0.999	-0.218	0.999
4	26.981	-0.031	1.000	-0.100	0.999	-0.183	0.999
5	30.492	-0.035	1.000	-0.115	0.999	-0.212	0.999
6	31.088	-0.025	1.000	-0.080	0.999	-0.148	0.999
7	32.910	-0.045	1.000	-0.141	0.999	-0.248	0.999
8	33.482	-0.048	1.000	-0.149	0.999	-0.258	0.999

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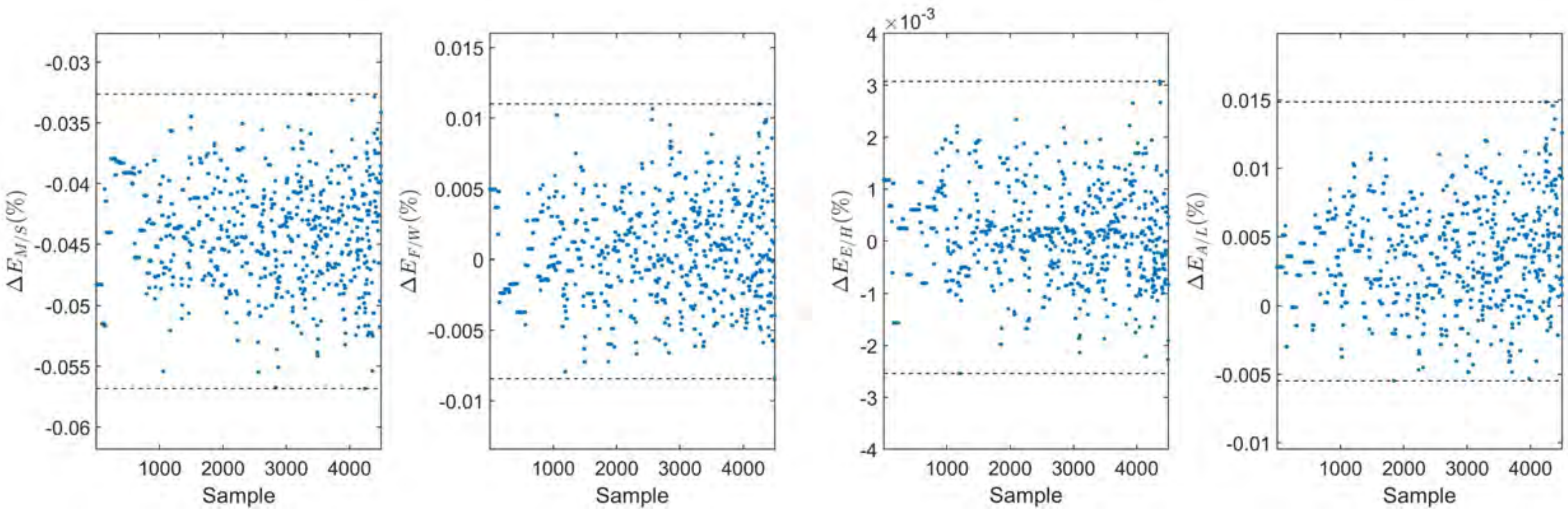
Bayesian Model Updating

- Probabilistic updating was utilized as the model updating method, which accounts for measurement and modeling uncertainties
- Each uncertain parameter was assigned lower and upper bounds to which an adaptive Markov Chain Monte Carlo sampling method was used to generate 5000 posterior probability distributions



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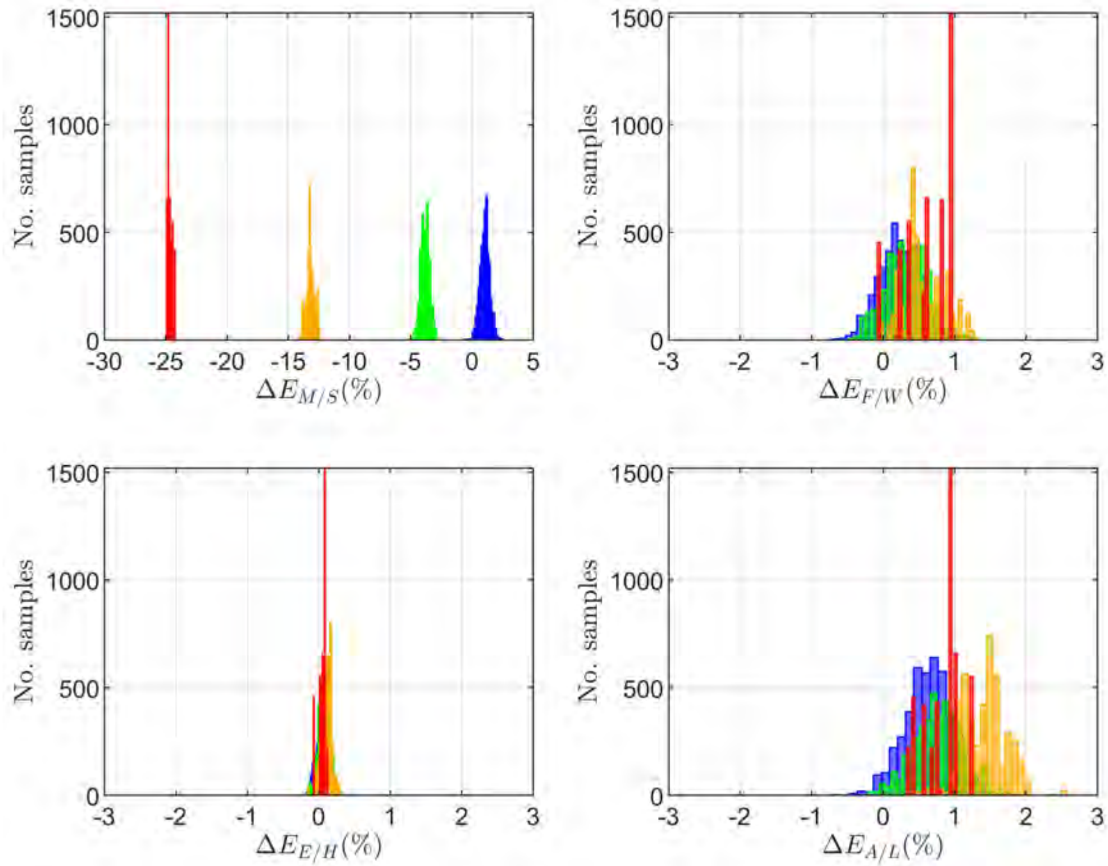
Bayesian Model Updating

- The discrete distributions of the points samples clearly indicate a successful identification of deterioration in the modulus of elasticity of the M/S elements, with negligible changes identified in the other parameters



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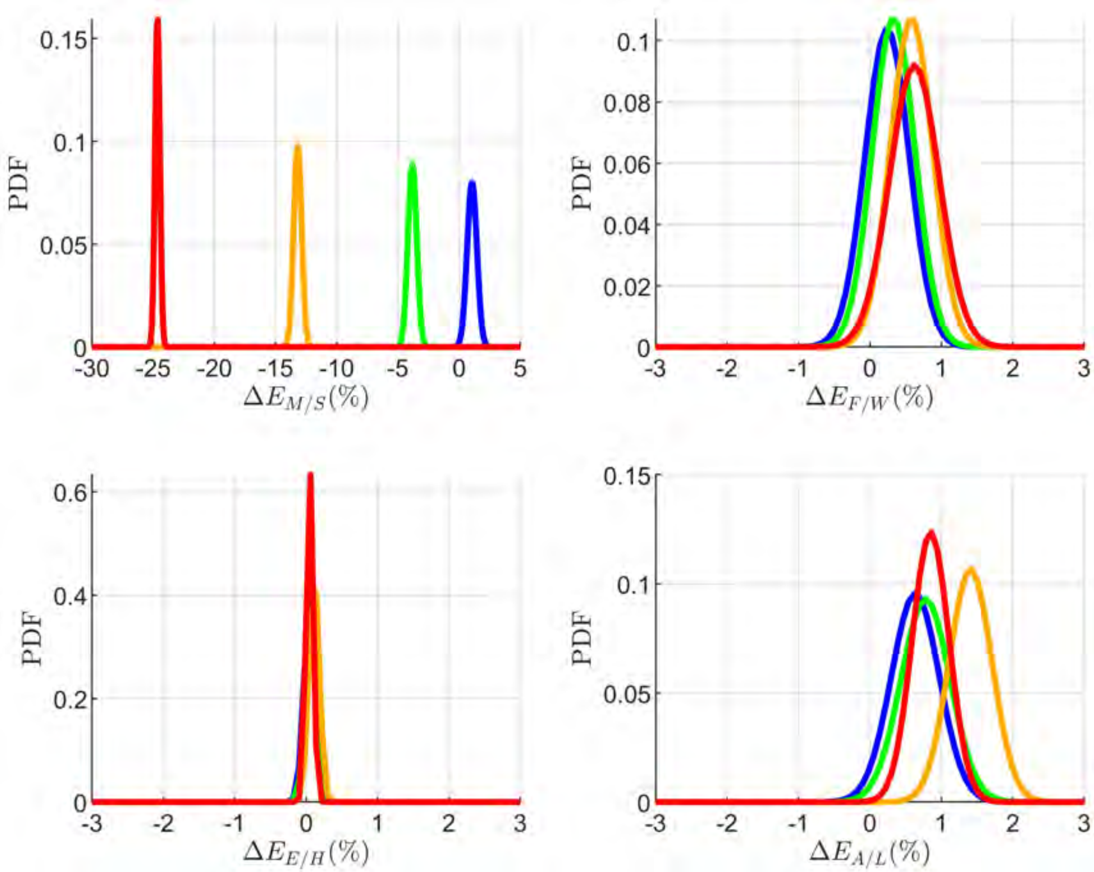
Bayesian Model Updating

- Posterior probability density functions may be analyzed from which confidence bounds may be placed on the parameter identification



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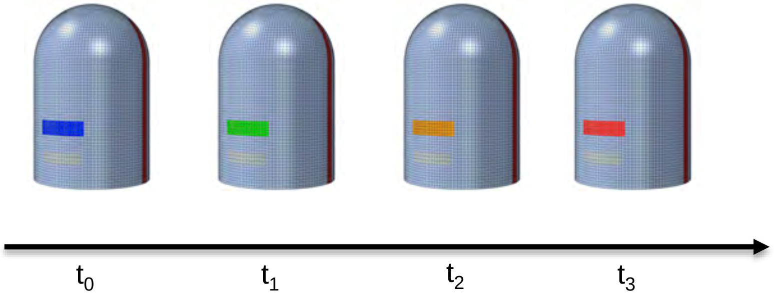
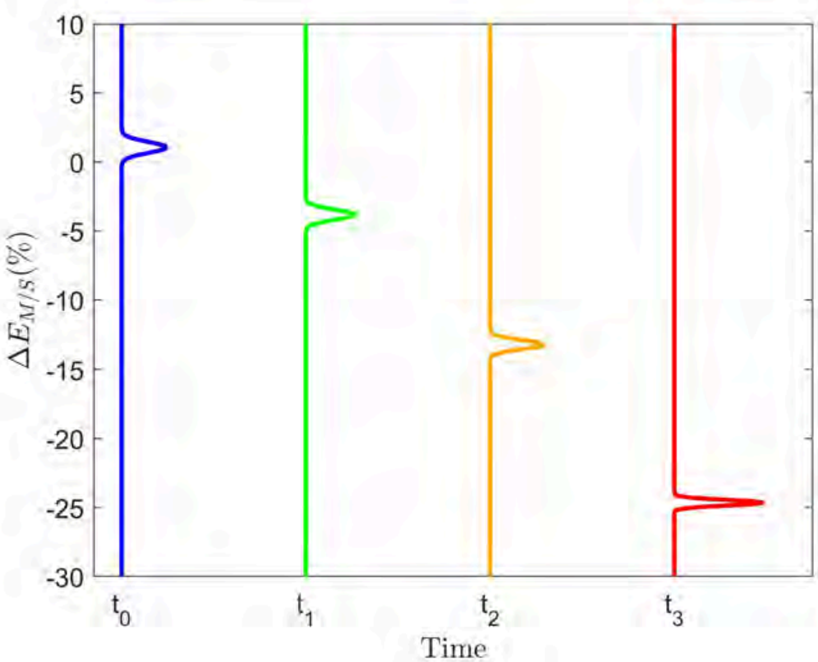
Trusted Model…Now What?

- Once a faithful digital representation of a physical structure has been realized:
    - Performance of the structure may be monitored by using historical and present-day data streams
    - Critical limit states may be evaluated in a digital environment
    - Lifecycle analyses may be performed to inform maintenance outside of routinely scheduled programs





Trusted Model…Now What?

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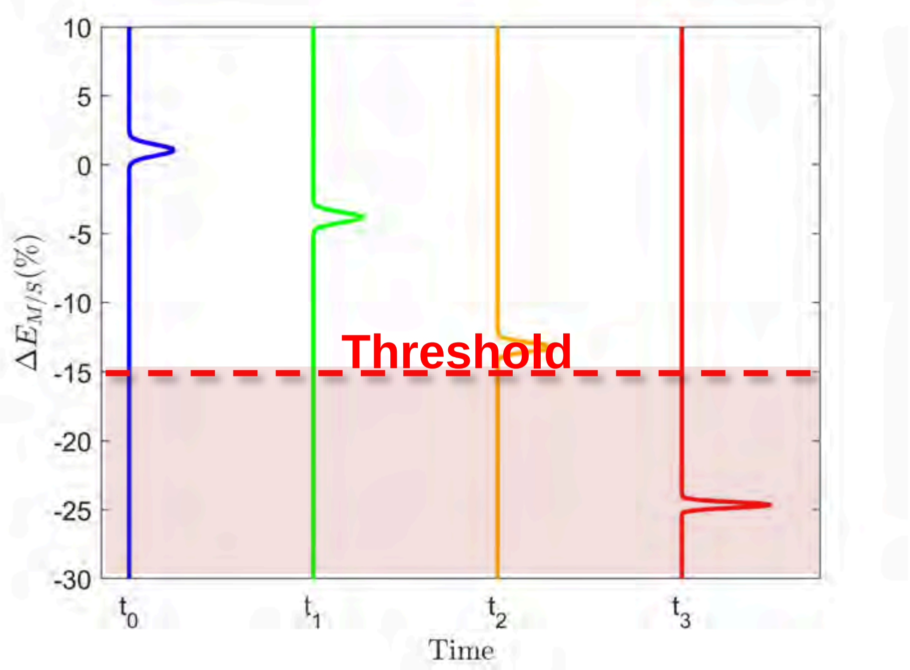

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Challenges

- Physical Asset
  - Development of appropriate performance metrics
  - Deployment of suitable sensor net to capture relevant physical phenomena
- Digital Twin
  - Development of data pipeline to connect physical sensors to digital twin
  - Creation of routines to process and interpret operational data

- Development of end-user application of methodology
- Instruction of end-user knowledge-base

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Advantages of Methodology

- May provide near real-time assessment
- Not inhibited by outages as other periodic inspections
- Can incorporate data from periodic inspections
- Capable of identifying hidden/local deterioration
- Identifies potential areas of preventative maintenance

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Digital Twins for Prognostic Health Management (PHM) in Nuclear Energy: Opportunities and Challenges

Pradeep Ramuhalli
Distinguished Scientist

Virtual Workshop on Digital Twin Applications for Advanced Nuclear Technologies

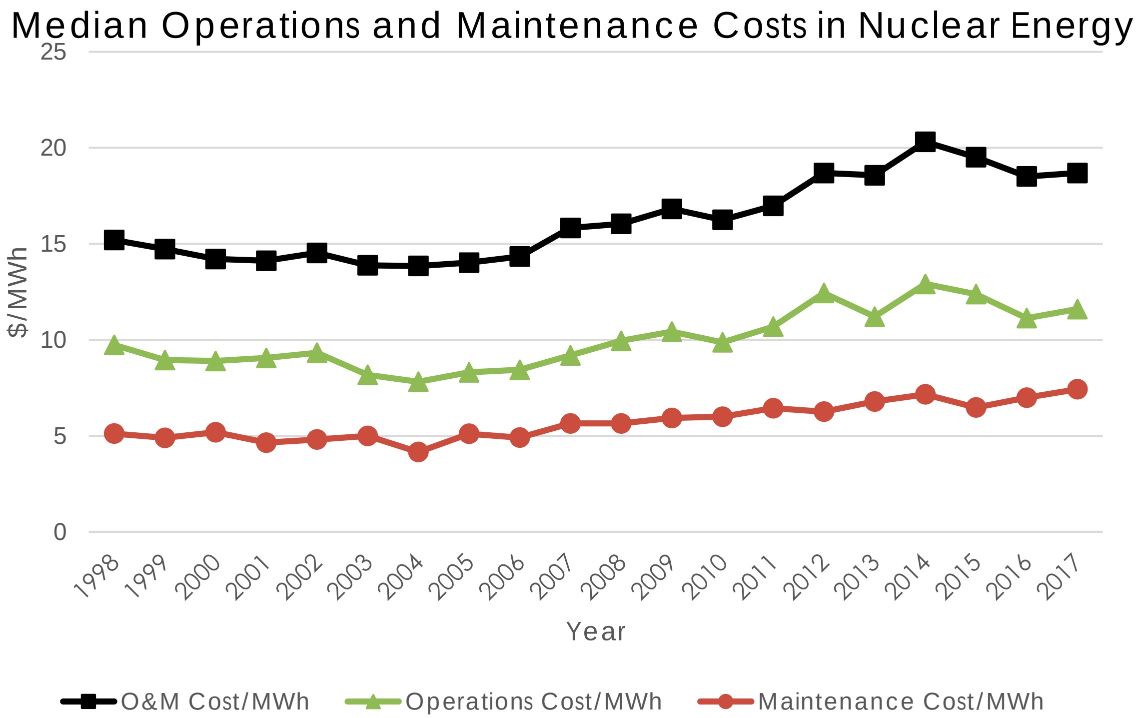
December 3, 2020

U.S. DEPARTMENT OF ENERGY

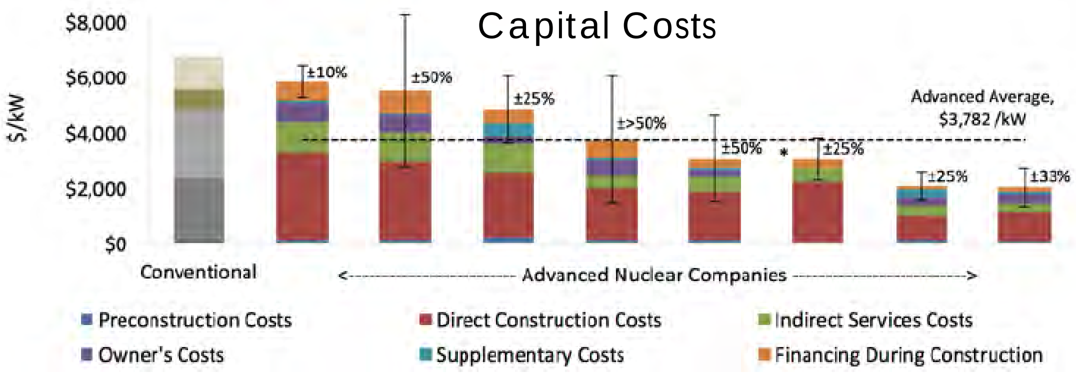
Outline

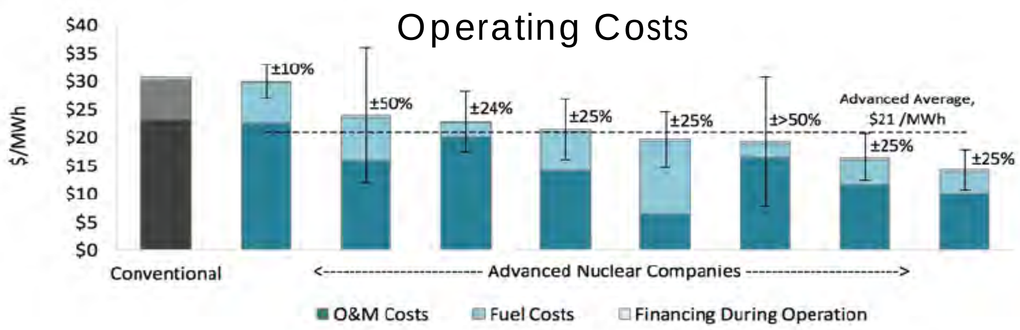
- Background – drivers for prognostics health management in nuclear power
- Diagnostics, prognostics and decision making - An integrated solution using intelligent digital twins
- Examples
- Research Needs and Summary

The Big Picture



Data from: " Broken: Costs to Operate, Maintain Electricity Generation Have Soared Over Two Decades" (uptake.com/energy)





Energy Options Network Report (2019) " What Will Advanced Nuclear Power Plants Cost? A Standardized Cost Analysis of Advanced Nuclear Technologies in Commercial Development"

Operating Plants

Advanced Reactors

Need: Information-driven Asset Management Technologies and best practices to lower operating and maintenance costs while maintaining safety and reliability

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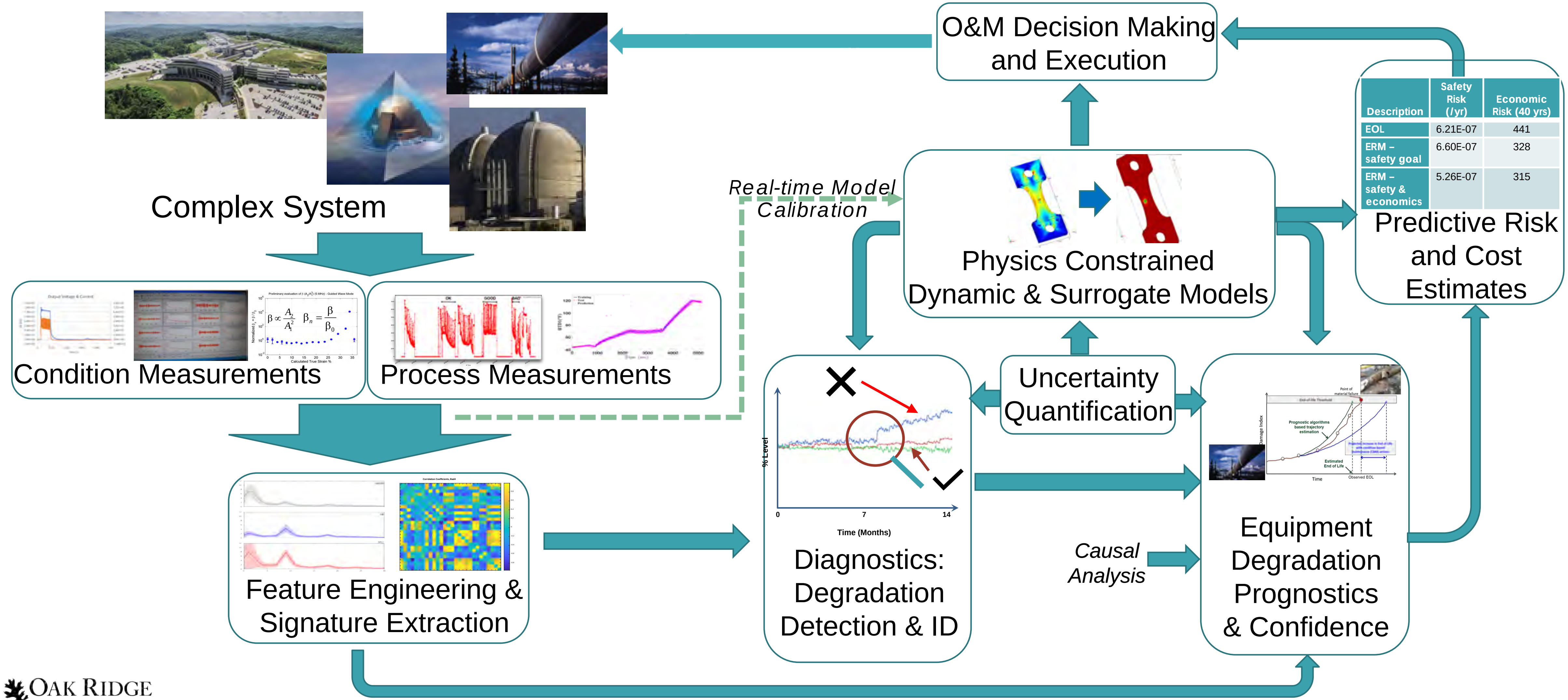
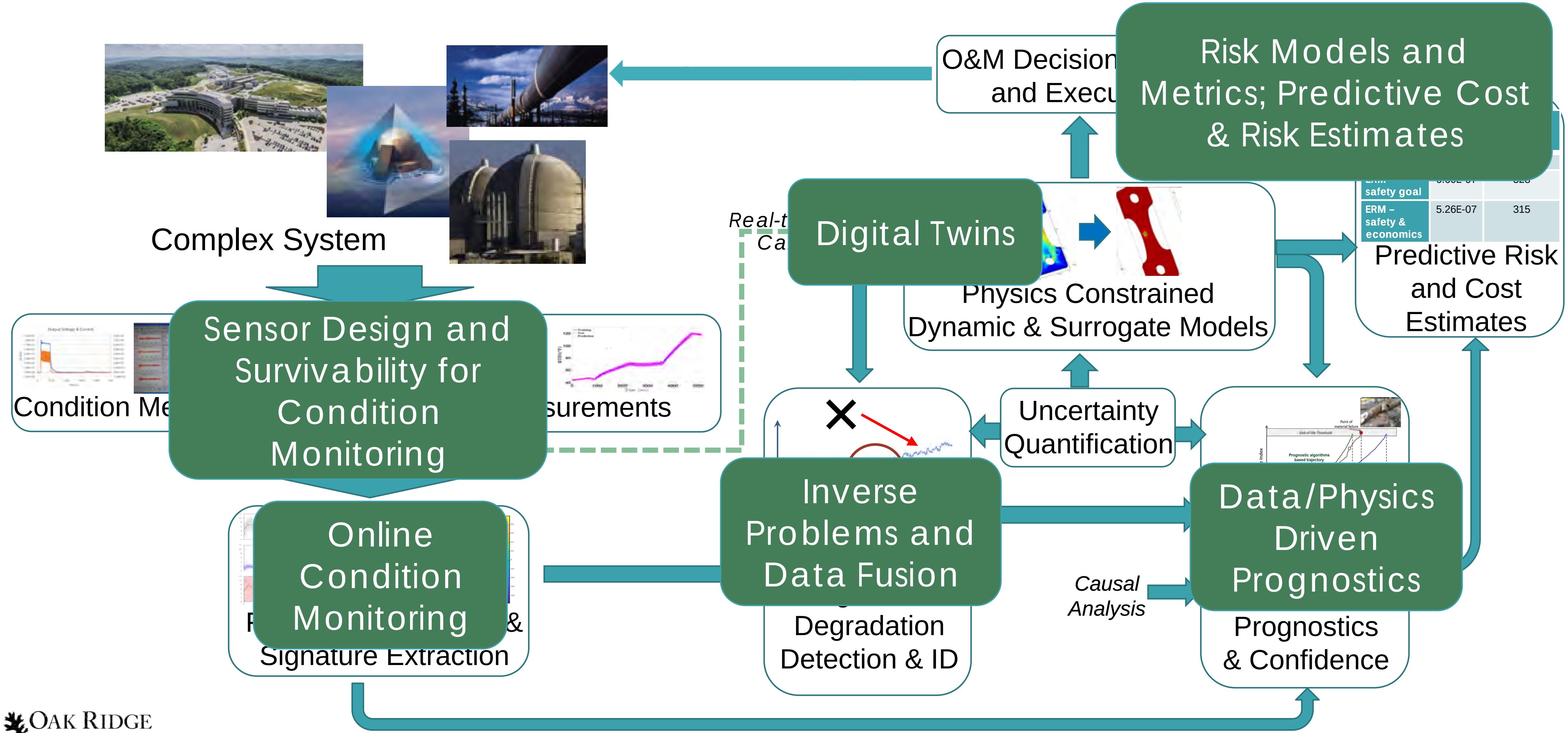
Diagnostics and Prognostics Enable Information-Driven Asset Management



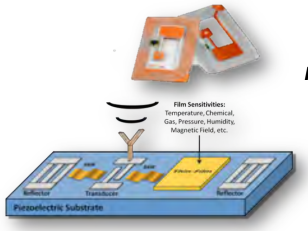
Description	Safety Risk (/yr)	Economic Risk (40 yrs)
EOL	6.21E-07	441
ERM – safety goal	6.60E-07	328
ERM – safety & economics	5.26E-07	315

Intelligent Digital Twins Enable PHM



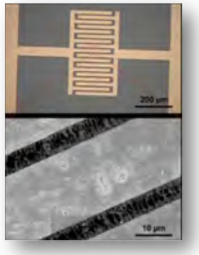
Together with Advances in...

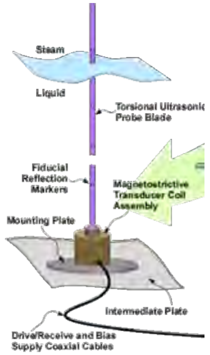
- Sensors and instrumentation
- Modeling and simulation methods and high performance computing
- Data analytics, especially domain-aware data analytics
- Communication technologies
- Advanced manufacturing



SAW Chemical Sensors


>2Mrad JFET-based Sensor Interface Electronics (DOE NEET)

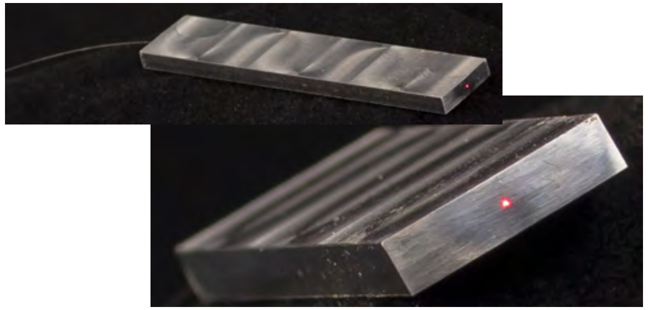


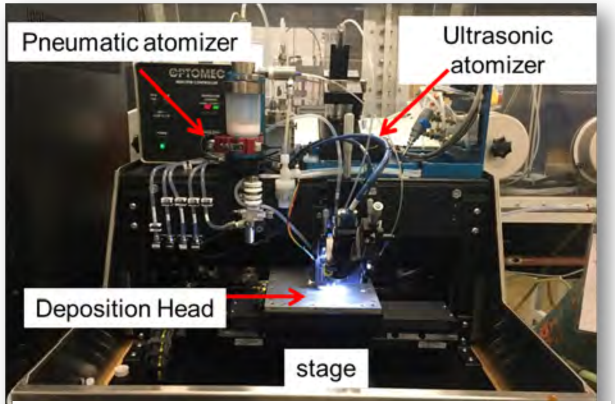


Temperature, Pressure and Level Sensors

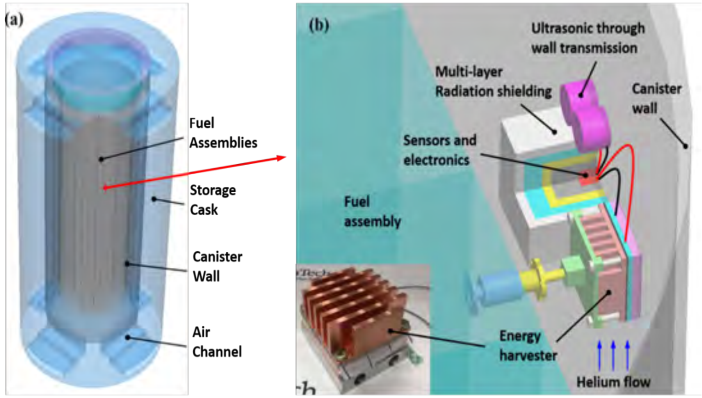

316L sheathed sensor in AM 316L build

Novel Ex-Vessel, In-Vessel, and In-Core Sensors and Electronics


High Temperature Compatible and Embedded Sensors for Nuclear Process and Component Health Monitoring



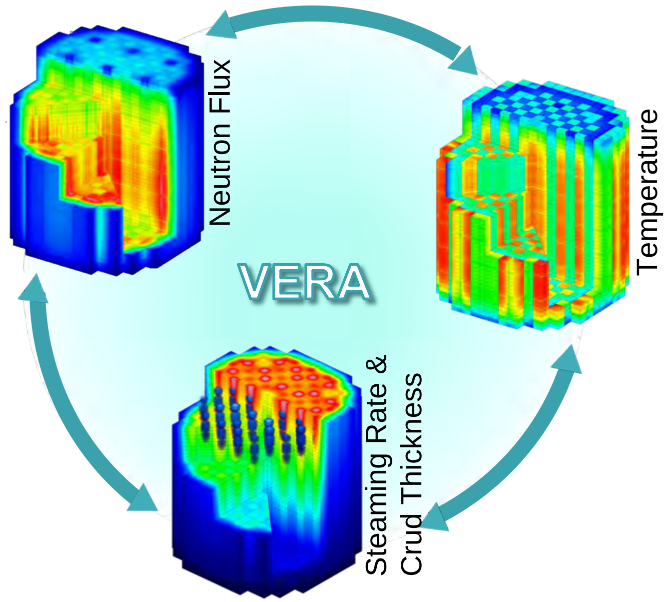
3D Printing Passive Wireless Sensors

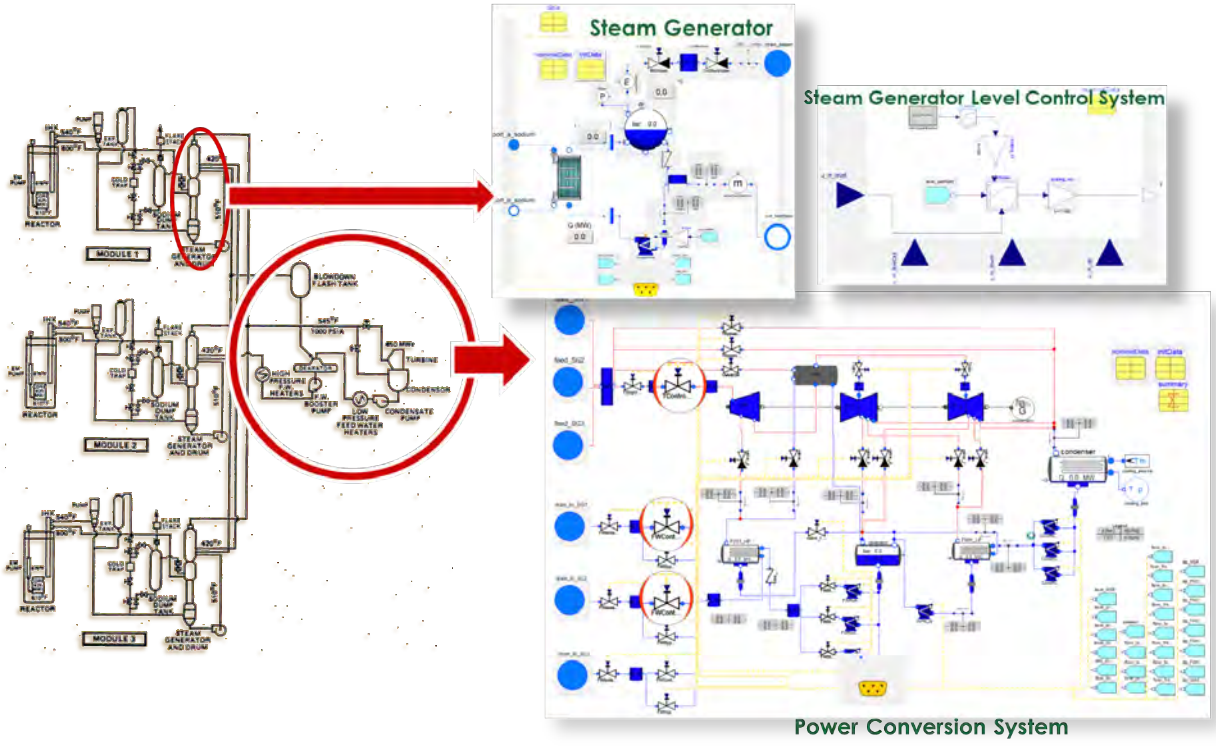


Self-powered Through-Wall Communication

Digital Twin

- A software design pattern that represents a physical object with the objective of understanding the asset's state, responding to changes, improving business operations and adding value (Gartner)
- Potential for different levels of fidelity and for different uses, and spanning the range from fully data-driven to physics-based
  - What is "good enough" for the problem?

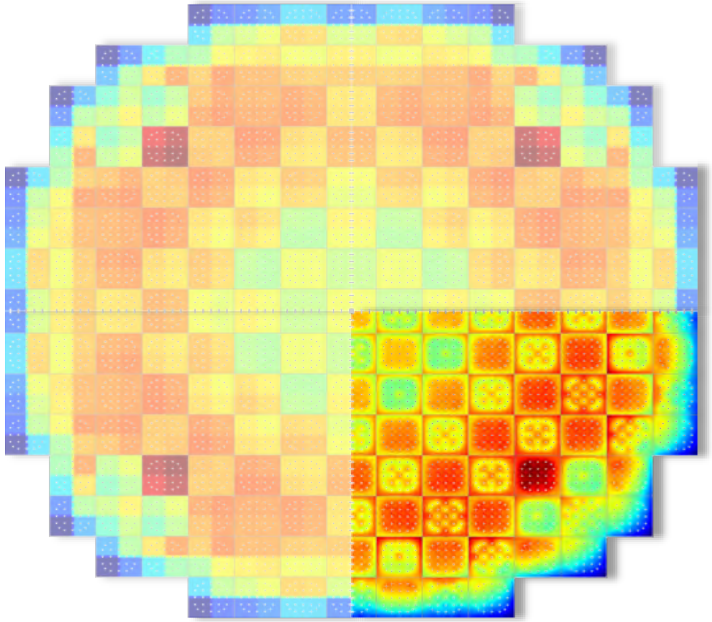




ALMR PRISM Power Block

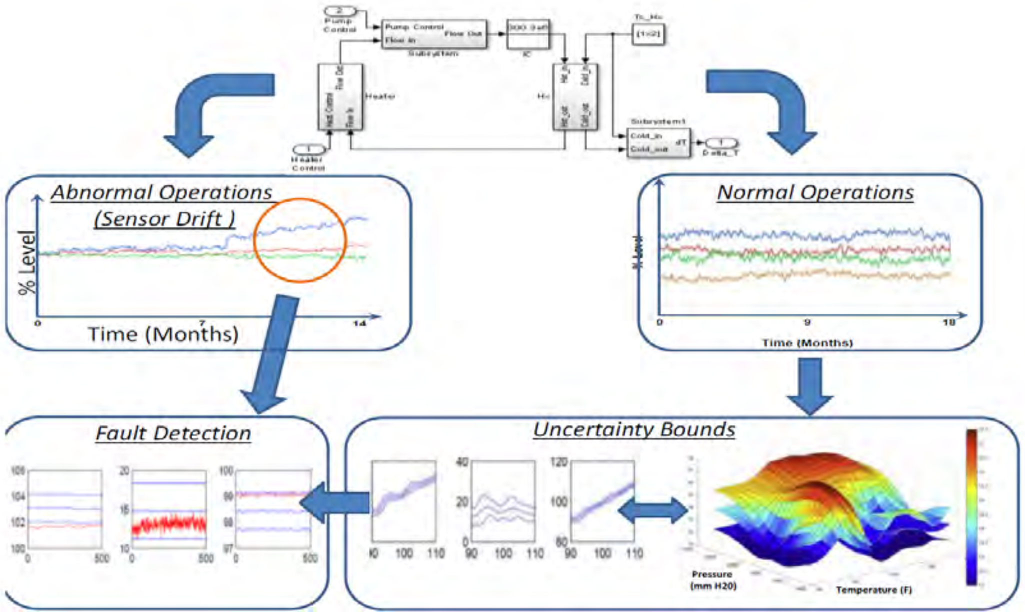
Intelligent Digital Twins for Diagnostics and Prognostics

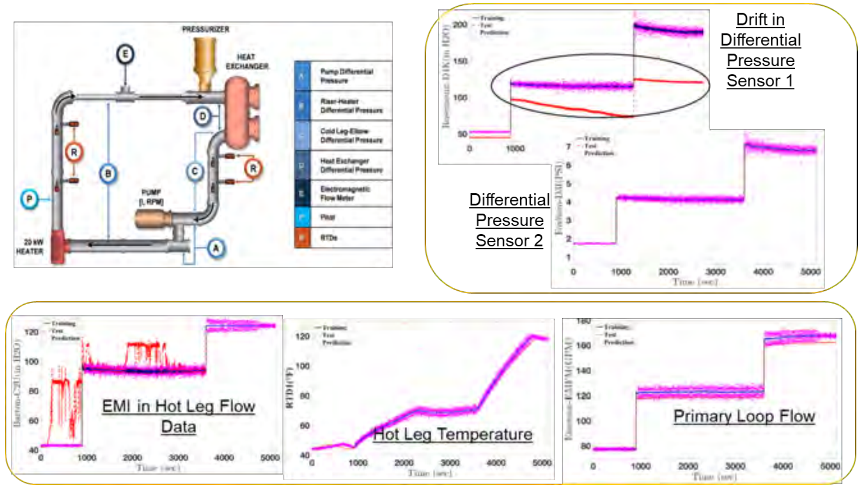
- Hybrid (Data-driven, with domain information) can serve as digital twins for diagnostics and prognostics
- Reliability assessment and prediction
  - Sensors
  - Active components (pumps, valves, etc.)
  - Passive components (piping, vessel, etc.)
  - Sub-system (power conversion unit, etc.)
- Risk-informed operational decision making for autonomous operations
- Risk-informed maintenance decision making for cost reduction



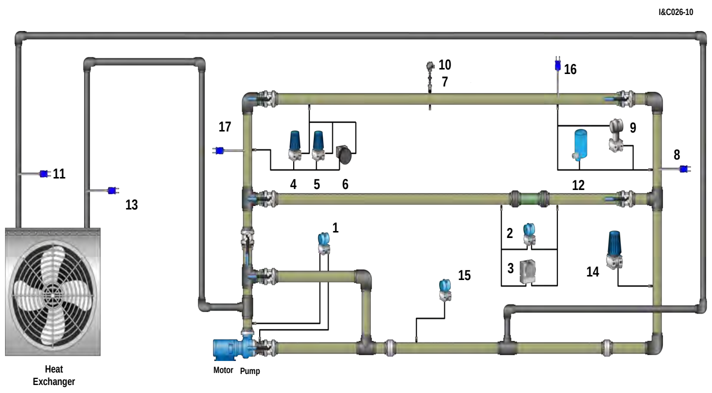
Physics Informed Machine Learning Reduced Order Model

Robust Virtual Sensor Models Can Improve Sensor Drift Detection and Compensation Performance

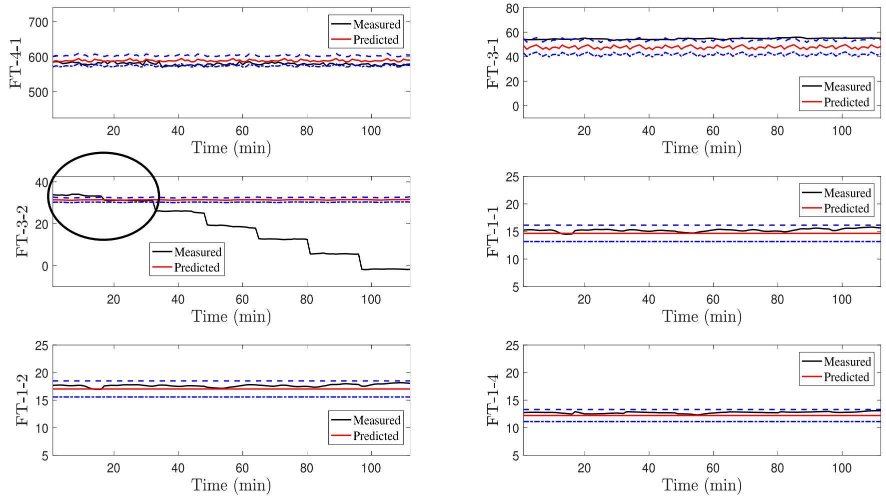




Example of Sensor Calibration Drift Detection and Compensation



ITEM	ID	SENSOR TYPE	MANUFACTURER
1	FT-4-1	DIFFERENTIAL PRESSURE	ROSEMOUNT
2	FT-3-1	DIFFERENTIAL PRESSURE (SMART)	ROSEMOUNT
3	FT-3-2	DIFFERENTIAL PRESSURE	BARTON
4	FT-1-1	DIFFERENTIAL PRESSURE	FOXBORO
5	FT-1-2	DIFFERENTIAL PRESSURE	FOXBORO
6	FT-1-4	DIFFERENTIAL PRESSURE (SMART)	BARTON
7	TE-1-2	RTD (SMART)	ROSEMOUNT
8	TC-2-1	THERMOCOUPLE TYPE-J (SMART)	ROSEMOUNT
9	FT-2-1	DIFFERENTIAL PRESSURE	SCHLUMBERGER
10	CTRL-TEMP	RTD (SMART)	ROSEMOUNT
11	TC-HX-OUT	THERMOCOUPLE TYPE-J	OMEGA
12	FT-2-3	DIFFERENTIAL PRESSURE	HONEYWELL
13	TC-HX-IN	THERMOCOUPLE TYPE-J	OMEGA
14	CTRL-PSR	GAUGE PRESSURE	FOXBORO
15	PT-2	GAUGE PRESSURE	ROSEMOUNT
16	TC-LOOP-FAR	THERMOCOUPLE TYPE-E	OMEGA
17	TC-PUMP-OUT	THERMOCOUPLE TYPE-K	OMEGA



Tipireddy, Ramuhalli et al, ANS NPIC-HMIT 2017

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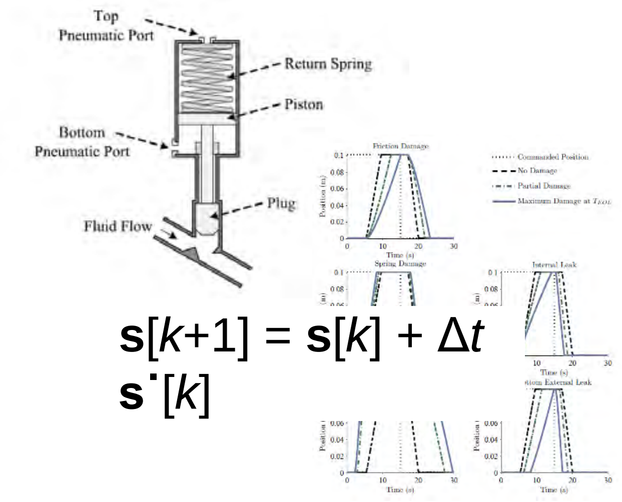
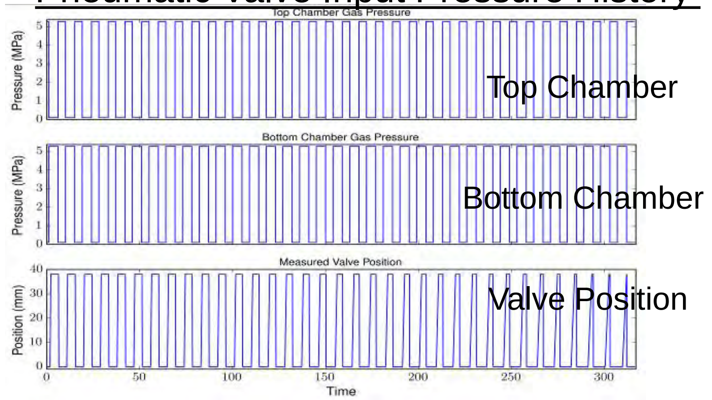
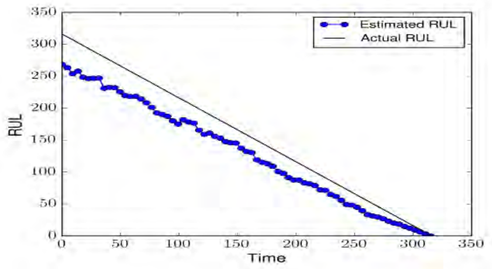
Data-driven, Physics-Inspired Models for Diagnostics and Predictive Maintenance



$$\mathbf{s}[k+1] = \mathbf{s}[k] + \Delta t\, \dot{\mathbf{s}}[k]$$

Pneumatic Valve Input Pressure History

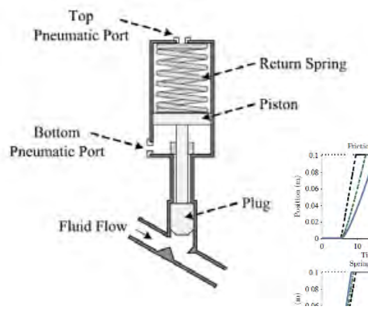




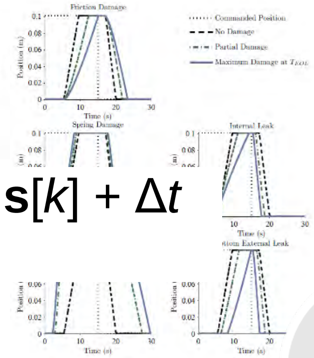
Prognostic Result: RUL

Data shown from Daigle and Goebel, IJPHM, 2008
Roy, Ramuhalli et al, ANS NPIC-HMIT 2015
Dib, Roy, et al, ANS NPIC-HMIT 2017

Data-driven, Physics-Inspired Models for Diagnostics and Predictive Maintenance



$\mathbf{s}[k+1] = \mathbf{s}[k] + \Delta t\ \dot{\mathbf{s}}[k]$



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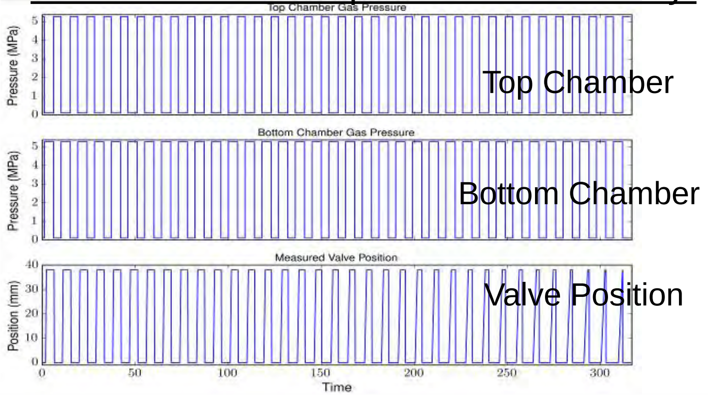

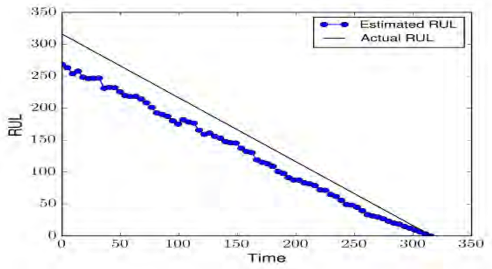

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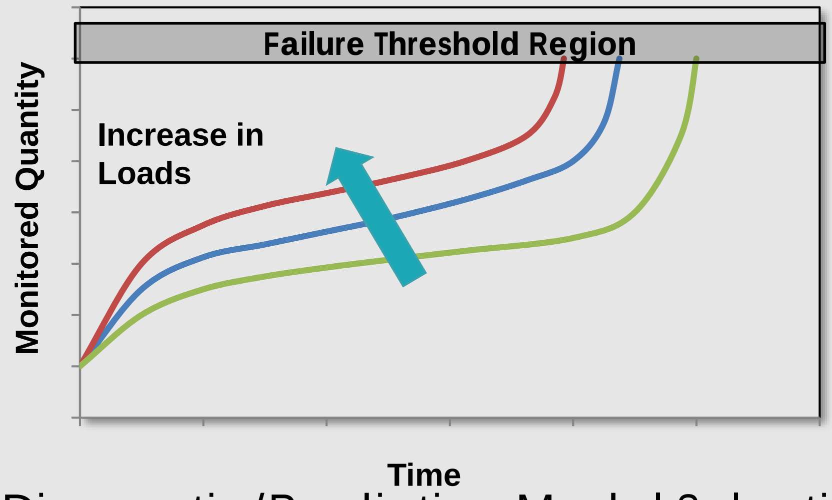
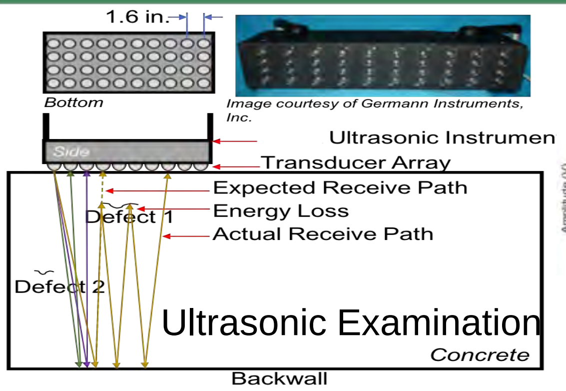


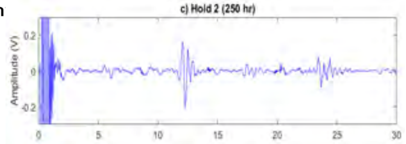
Diagnostic/Predictive Model Selection

Data shown from Daigle and Goebel, IJPHM, 2008
Roy, Ramuhalli et al, ANS NPIC-HMIT 2015
Dib, Roy, et al, ANS NPIC-HMIT 2017

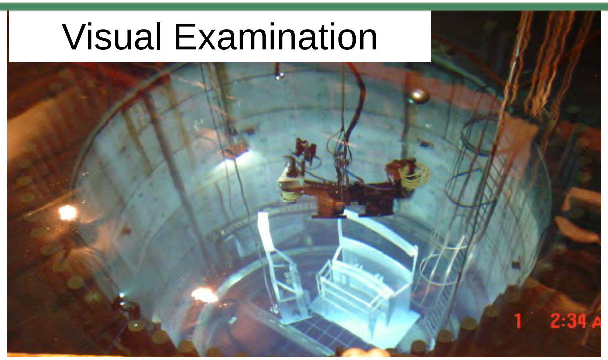
Complex Multi-scale Physics of Failure Models Challenge PHM for Materials Failure; Data-driven Models Show Promise

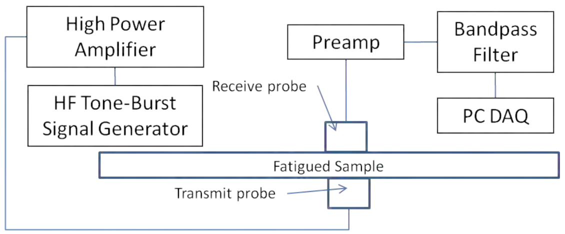


Ultrasonic Examination

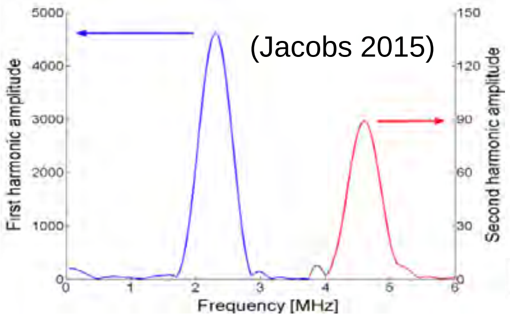


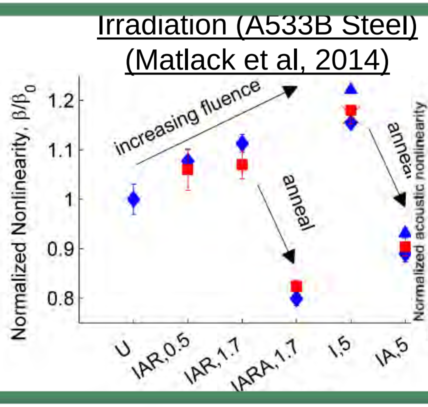
Visual Examination

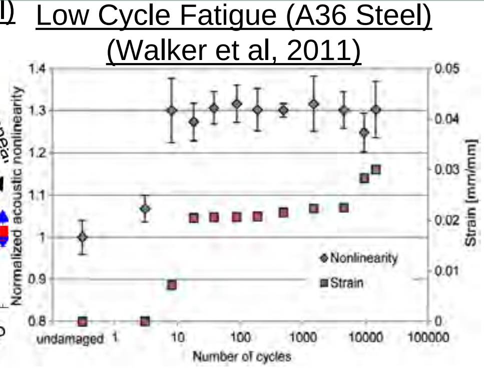


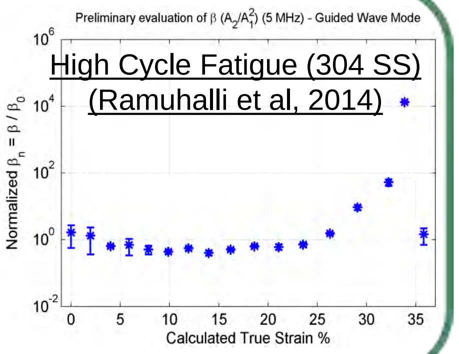


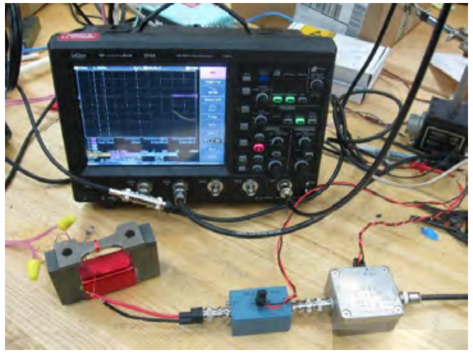
Nonlinear Ultrasonics

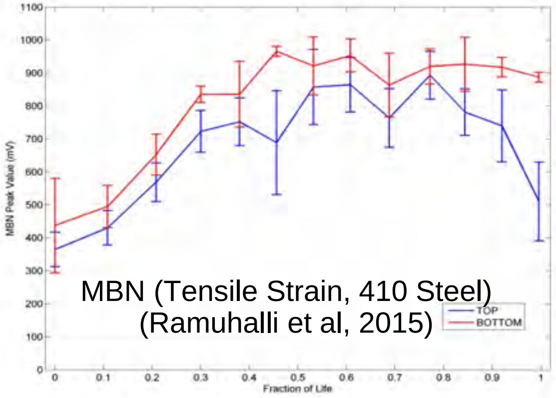


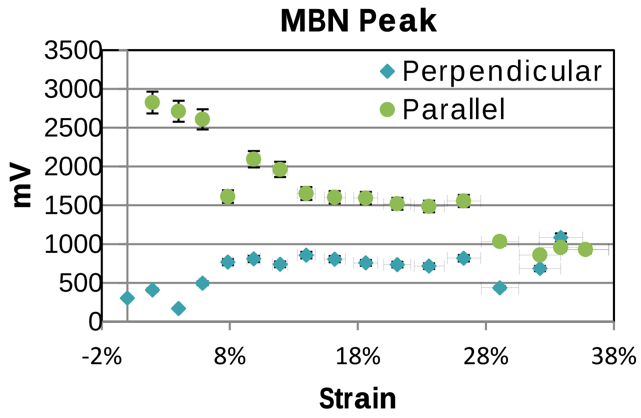








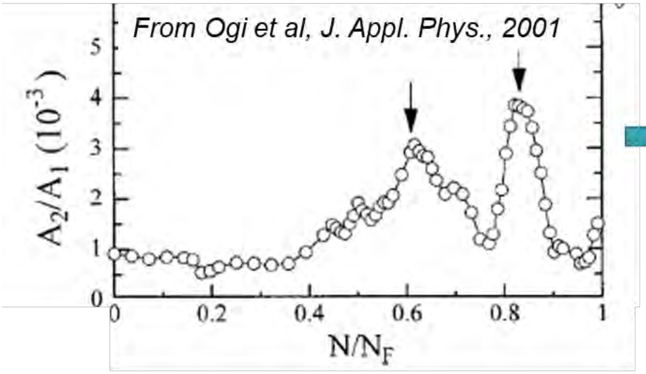


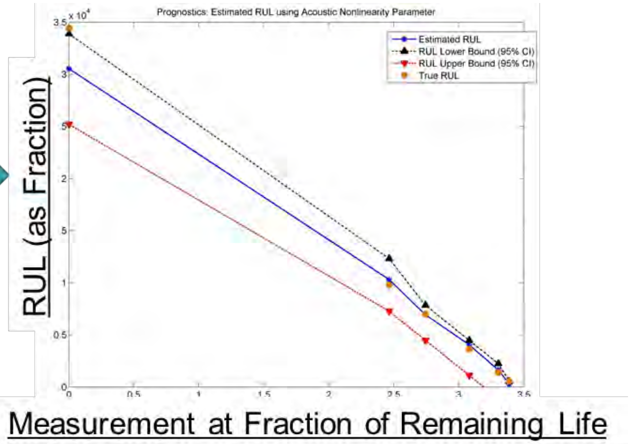


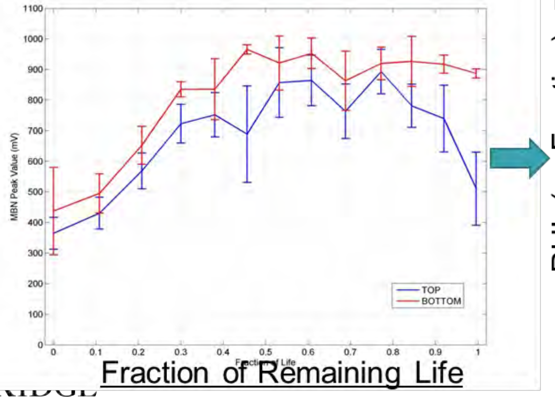
Magnetic Barkhausen Noise

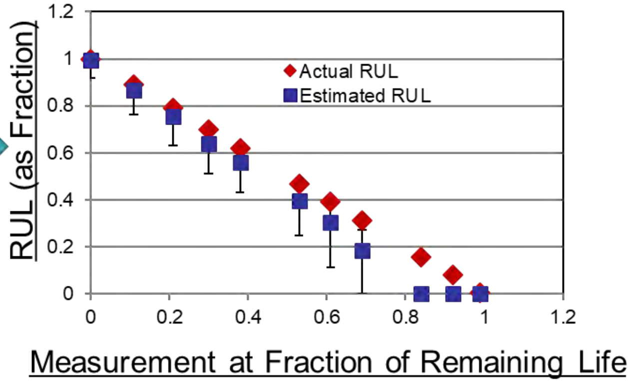
Bayesian Methods Allow Integration of Failure Physics Information, Condition Data, and enable Uncertainty Quantification

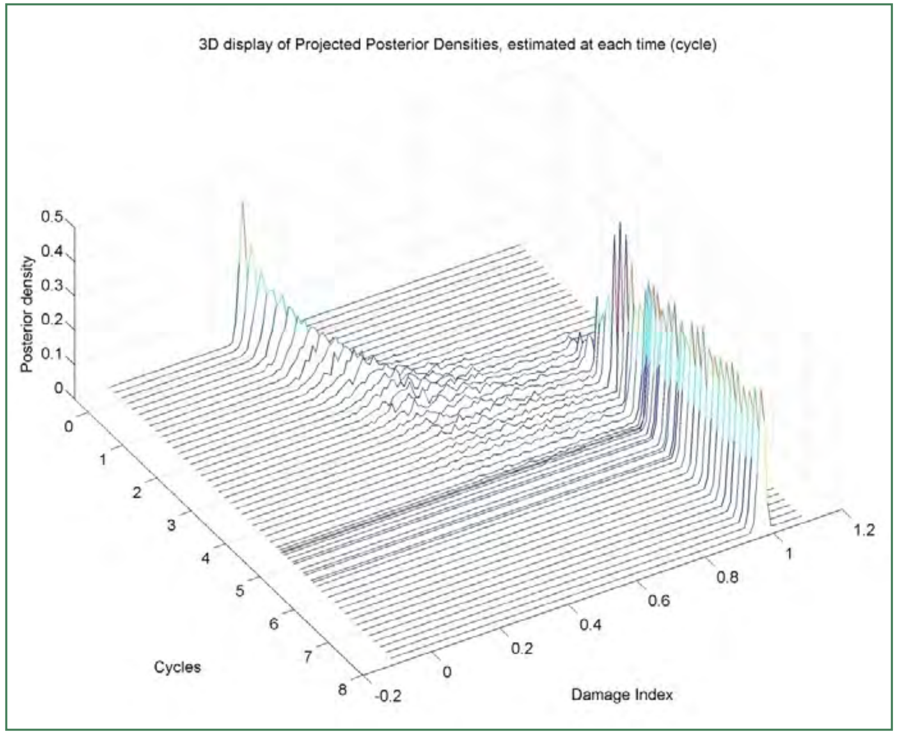
- Underlying models can be at desired level of fidelity
- Prediction updates with new measurements
- Model updates over time also possible to reflect reality







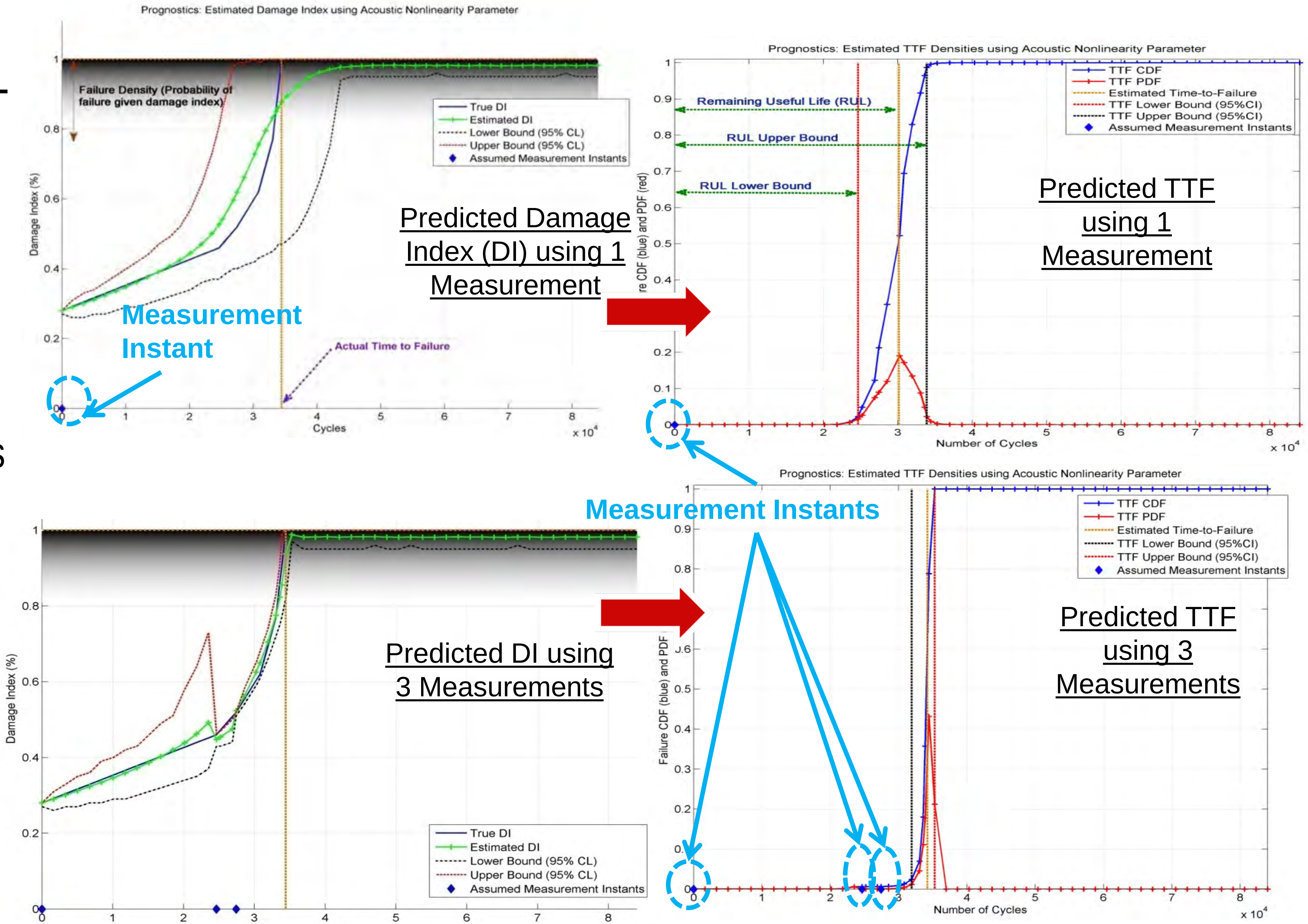




Evolution of Posterior Probability Density with Time

Example: Predicted Time-to-Failure (TTF) for Fatigue Crack Initiation

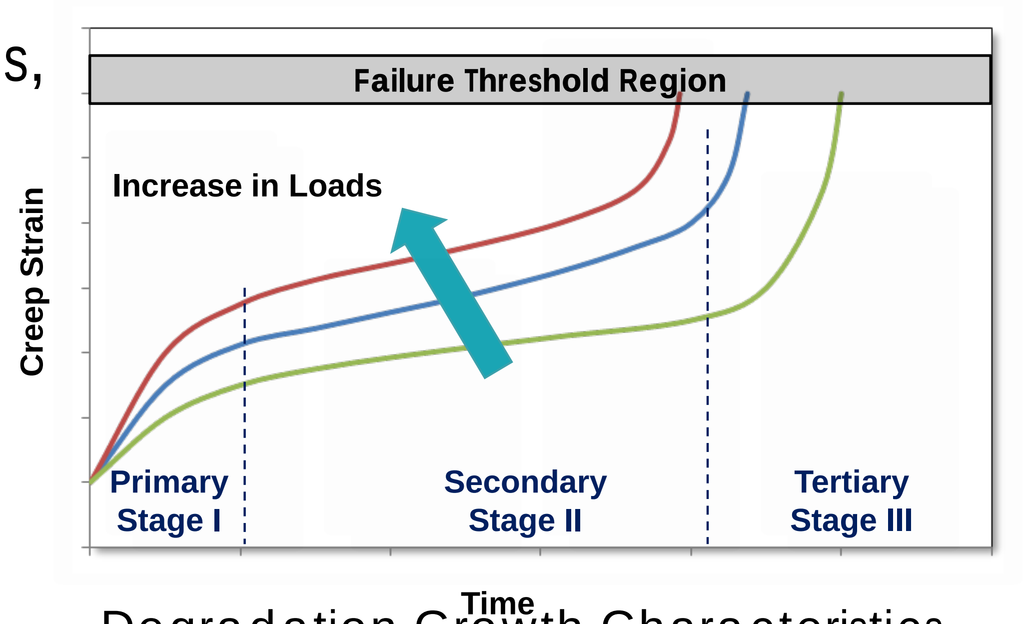
- Diagnostics and prognostics using data-driven models of
  - Damage growth
  - Measurement
- Necessary data may be difficult to acquire
- Physics-inspired models (damage growth and measurement) have been used in other instances with good accuracy



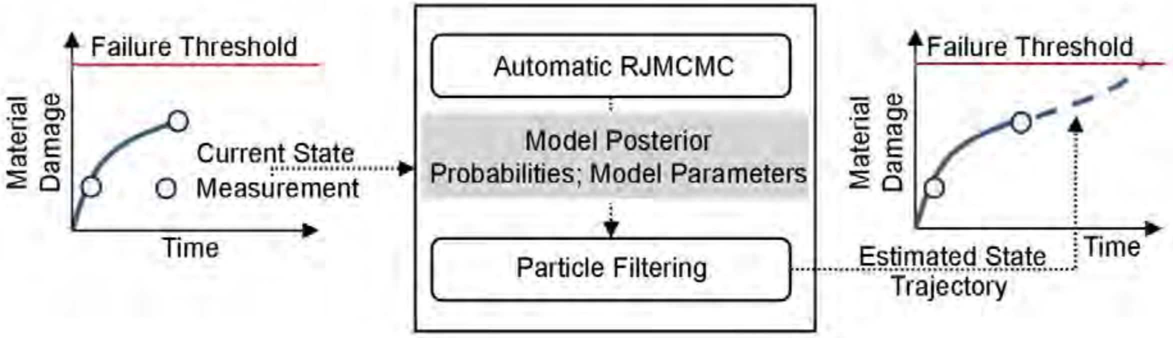
Ramuhalli et al, ANS NPIC-HMIT 2012

Digital Twin Model Updates are Essential for Many Applications

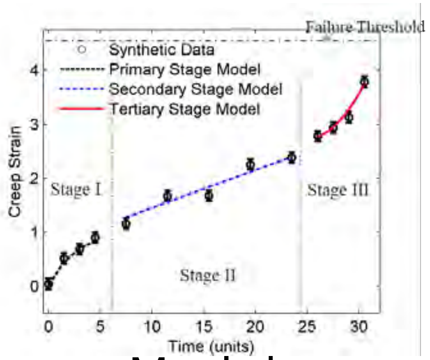
- Limited examples for certain fault conditions, and limited data
- Operational conditions may vary over time
- System or component condition may vary, requiring different models
- New failure modes with longer term operation
- Continuous learning, with model selection, will be necessary



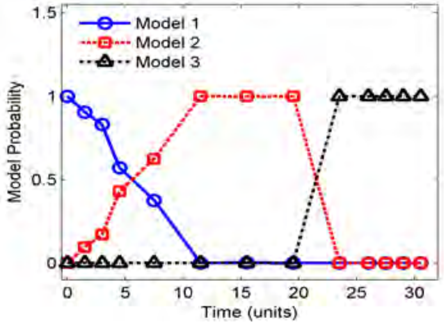
Degradation Growth Characteristics – Function of Time and Load



RJMCMC for Model Selection



Models



Model Likelihood

Roy, Ramuhalli et al, ANS NPIC-HMIT 2015

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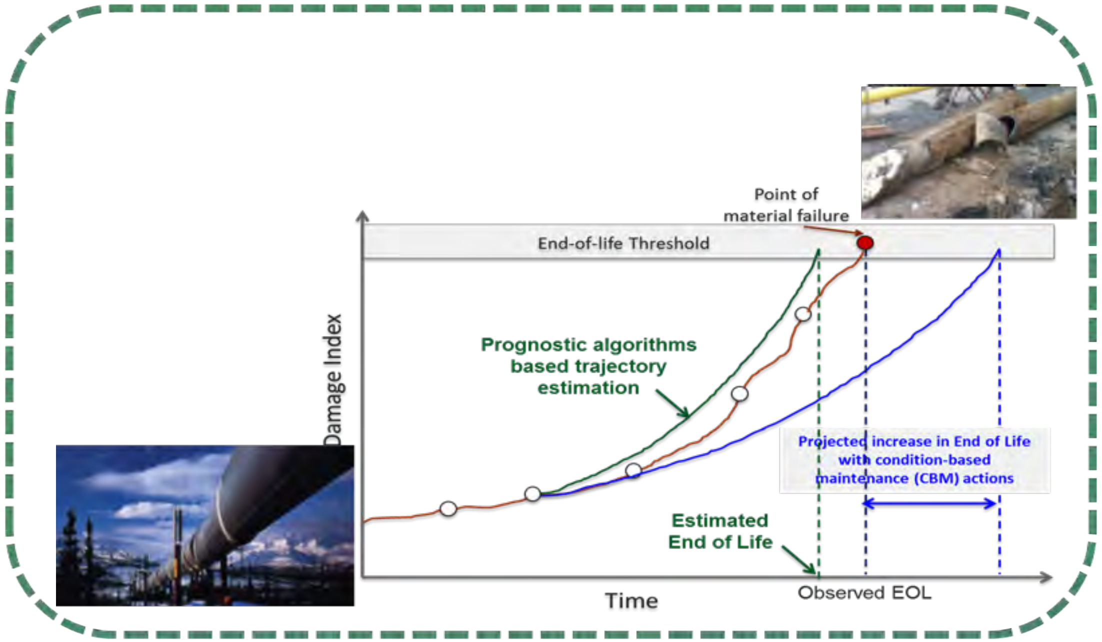
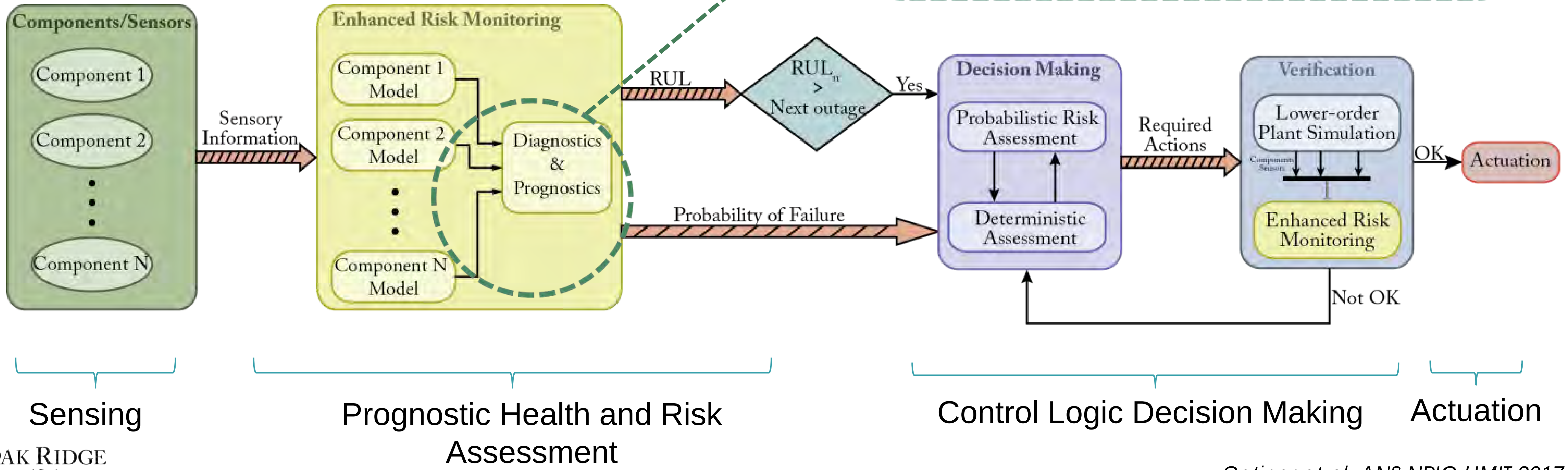
Integrating Prognostic Results with Risk-Informed Operational Decision Making





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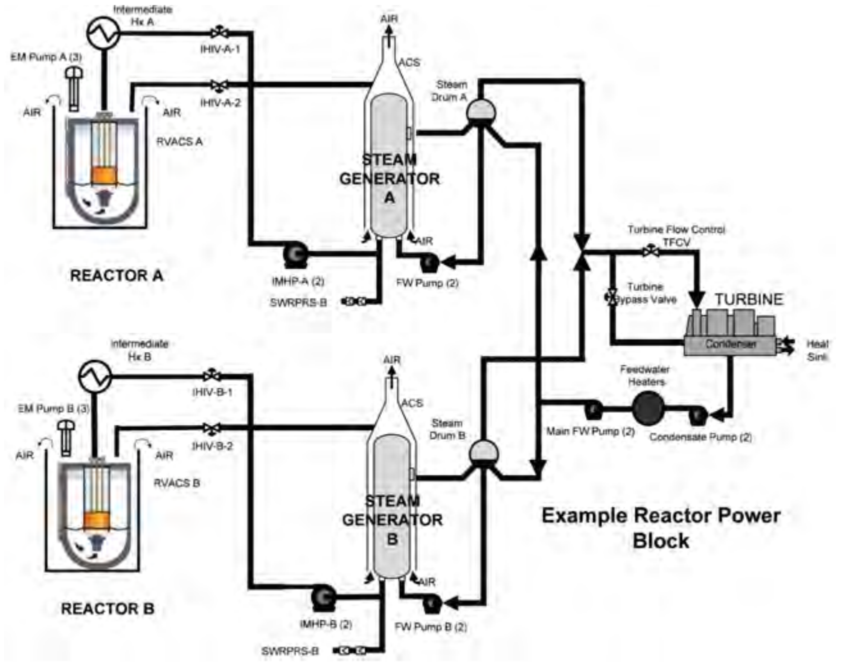
Cetiner et al, ANS NPIC-HMIT 2017

Integrating PHM and Risk Monitors with Plant Control Logic

- Risk: Measure of probability of some undesirable consequence
  - Core damage frequency, large early release frequency, health consequences to the public

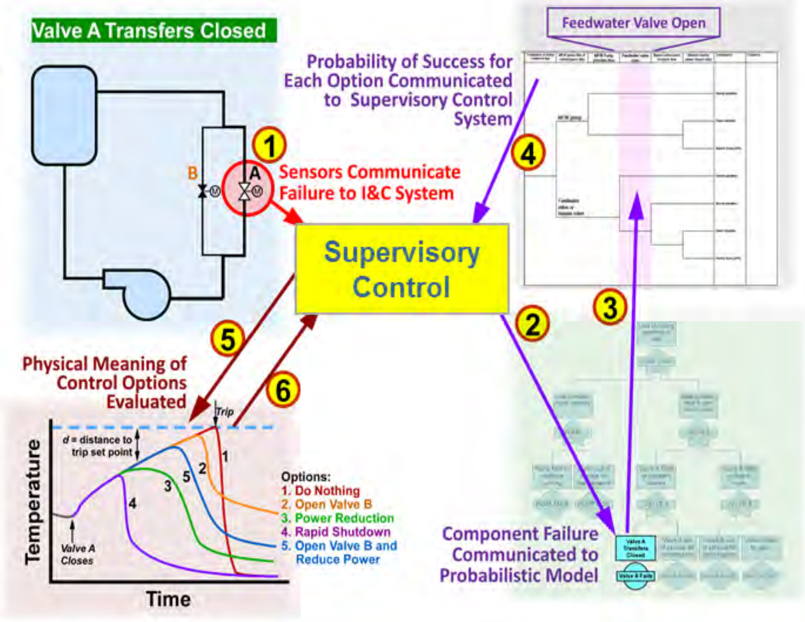
EE	SGL	RVACS	SEQUENCE OUTCOM	SEQ. PROB	SEQ NAM
External Event - Plug/Failure of RVAC	Steam Generator Louver	Reactor Vessel Auxiliary Cooling			
EE			no CD	0.00E+00	
	SGLV		no CD	0.00E+00	
		OP-RVACS	CD	0.00E+00	10

Simplified Reactor PRA Event Tree



Simplified Diagram of Multimodule Reactor

- Elements of PHM integration with risk monitors
  - Equipment condition assessment (ECA) and prognostics for predictive health assessment
  - Predictive risk assessment (safety and economic)
  - Uncertainty quantification



Cetiner, Muhlheim et al, Nuclear News 2015

Risk-informed Decisions: Economics and Safety

- Methodology for using cost metrics for component replacement scheduling
- *Hypothetical cost and failure rates used in analysis*
- Assessment computes safety related risk metric (CDF) and normalized cost over 40 years for three cases
  - Case A: Run to end-of-service-life; replace during scheduled outage.
  - Case B: Use diagnostics/prognostics; replace equipment just prior to plant exceeding safety limit.
  - Case C: Use diagnostics/prognostics; replace equipment if risk of unplanned outage at a future time. Schedule based on optimizing cost metric.

Case #	Description	Expected CDF (/yr)	Reduction in Economic Risk Over 40 yrs (Relative to Case A)
A	Expected end-of-life replacement	6.21E-07	-
B	ERM – safety goal based maintenance	6.60E-07	25.6%
C	ERM – safety and economics based maintenance	5.26E-07	28.6%

Ramuhalli, Veeramany et al, ICONE25, 2016

Summary

- Digital twin solutions for intelligent asset management and autonomous operations
  - Enabled by technology advances in sensing, data analysis, modeling and simulation, and machine learning
- Technical challenges still exist and are targets for ongoing research
  - Research leveraging advances in machine learning
- Resulting technologies enable sustainable nuclear power by improving the reliability and economics of nuclear plants

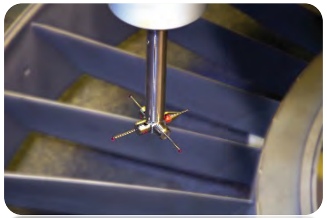
Looking Forward: Some Challenges

- Data
  - Data access and data quality
  - Optimal sensor type and placement
  - Testbeds for data generation and verification and validation (V&V)
- Technology Development
  - Robust digital twin development
  - Model selection and model updates
  - Robust diagnostics and prognostics in the presence of concurrent mechanisms, influencing factors, interacting subsystems, and measurement drift
  - Methods for semi-autonomous decision making
- Deployment
  - V&V approaches
  - Uncertainty quantification
  - Cybersecurity

Acknowledgments

- A number of collaborators have contributed to the work presented here, and include staff from National Laboratories (ORNL, PNNL, ANL, Bettis, INL), Universities (UT-Knoxville, PSU, WSU, ISU, CSU-LB, WUSTL, Ajou University), and Industry (AMS Corp.)
- A portion of the research presented here was supported by the USDOE Office of Nuclear Energy through the Advanced Reactor Technologies (ART), Nuclear Energy Enabling Technologies (NEET), and the National Scientific User Facility (ATR-NSUF) programs. A portion of the research was supported by the NNSA Office of Defense Nuclear Nonproliferation (NA22). Parts of this work were supported by Ajou University (S. Korea).
- Oak Ridge National Laboratory is operated by UT-Battelle for the US Department of Energy.

Questions?

Managing Regulated Change: An Enterprise-Level Digital Twin for the Nuclear Industry

Michael Mazzola, Robert Cox, Jeffrey Hawkins
Energy Production and Infrastructure Center (EPIC)
UNC Charlotte, NC, USA
mmazzola@uncc.edu EPIC.UNCC.EDU

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Energy Production and Infrastructure Center

Outline

- Introduction to EPIC
- Consensus on Nuclear Energy has Changed
- Construction Best Practice has Yet to Change (Enough)
- Translating Enterprise Digital Twin Culture to Construction
- Leveraging the Single Source of Truth for JIT Regulation

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EPIC

EPIC's Mission

- Education for Engineers in Energy
- Research and Development
- Economic Development

www.epic.uncc.edu

Albert and Freeman
Energy Production and Infrastructure Center

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Practical Nuclear Experience through Partnerships with SMR Developers

- EPIC expertise is being applied to inspection techniques and construction sequencing for SMR’s
- EPIC is supporting the development of a construction-related LTR for the NRC
- Digital Twin Pilot Projects include
  - Structural health monitoring (Dr. Tim Kernicky presented on Thursday)
  - Adapting Enterprise DT’s from Advanced Manufacturing to Construction (partnership with Siemens)
- “Single Source of Truth” for structural and geotechnical models during construction (partnership with EPRI and Purdue)
- EPIC nuclear industry advisor is Mr. Jeff Hawkins, retired Vice President – Project Director Fluor Nuclear Power

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Consensus on Nuclear Energy has Changed

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The message is we need new nuclear…

A carbon-free future is a nuclear future
by Rep Michael Burgess & Bud Albright

> "Contrary to what Hollywood might have you believe, nuclear power is one of the safest and most reliable sources of energy in the world, producing approximately 20% of our nation's electrical power, and more than half of our nation's carbon-free energy."

- **The environmental emergency of the second decade is climate change.**
- **Zero emission sources that work 24 hours a day are important again.**

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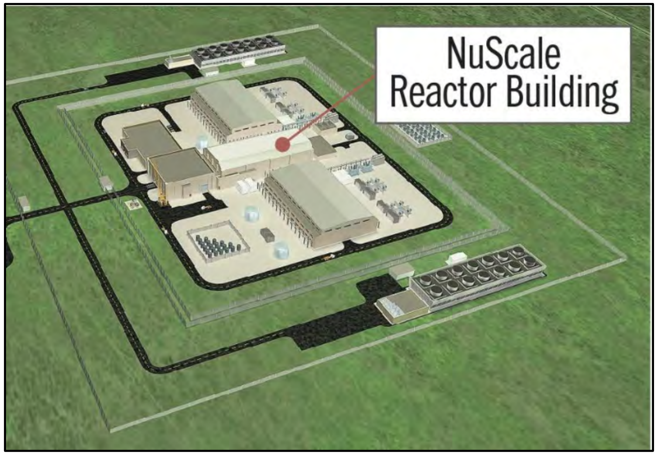
If it is affordable and in time…



Is next generation nuclear technology destined to serve Utah?
by Amy Joi O'Donoghue, DeseretNews, Nov. 11, 2020

"UAMPS spokesman LaVarr Webb said the power association will not move forward with the project unless costs per megawatt hour remains at $55 or lower and the current timeline for licensing and permitting is preserved."

- **Acceptance for new nuclear energy depends on cost and schedule.**
- **"More than 50% of costs are civil works."**

  Tim Schmitt, Engineering Supervisor for Civil Analysis,
  and Carl Fisher, VP for Products and Engineering,
  Framatome, meeting at EPIC, Nov. 1, 2018

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Construction Best Practice has Yet to Change “Enough”

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What do experienced nuclear construction professionals say?

January 28, 2019 Workshop on Large Energy Plant Construction hosted by EPIC. Industry contributors: EPRI, Framatome, Atkins SNC Lavalin and Duke Energy

- Planning, scheduling, and sourcing optimized by and connected to the design.
- Fully 3D digital representation of complete design that remains trusted.
- Avoid "over the wall" design strategy – artificial separation between designer and construction—Reduce the cascade of ECO's!
- Consider how the regulator will interpret as-built construction—Is it to license or not?

What does the Construction Industry Institute say?

CII analyzed the performance of 975 light and heavy industrial projects.*

- Only 5.4% met "best in class" predictability in cost and schedule.
- Owners and contractors constructing large capital projects have resisted full-scale adoption of integrated digital tools and platforms to drive project performance.
- Nuclear plant construction is the most expensive example.

*www.pwc.com/us/en/industries/capital-projects-infrastructure/library/digital-twin-platform-capital-projects.html

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NEI | TECHNICAL REPORT

NEI 20-08

Strategic Project Management Lessons Learned & Best Practices for New Nuclear Power Construction

Prepared by the Nuclear Energy Institute
April 2020 Rev 0

nei.org

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Translating Enterprise Digital Twin Culture to Construction

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Aerospace and Nuclear – Both regulated for safety and economics

Commercial Aerospace Regulatory Hierarchy

- Accountable entity for the Type Design Certificate: Aircraft manufacturer (e.g., Boeing)
- Safety Regulator: Civil Aviation Authority (e.g., Federal Aviation Administration)
- Economic Regulator: Owner/operator (e.g., Airlines)

Nuclear Energy Regulatory Hierarchy

- Accountable entity for the License: Owner/operator (e.g., Utility)[†]
- Safety Regulator: Nuclear Safety Authority (e.g., Nuclear Regulatory Commission)
- Economic Regulator: Rate Setting Authority (e.g., Public Utility Commissions)

- In the Commercial Aerospace Industry, airliner OEM leads the integrated product team for the entire life cycle of the product (airliner).
- In the Nuclear Energy Industry, the owner of the plant should lead the integrated project team during the construction project[†] (planning, construction, handoff) and thence for the life cycle of the plant (operation, maintenance, and decommissioning).

[†] NEI Technical Report 20-08 *Strategic Project Management Lessons Learned & Best Practices for New Nuclear Power Construction*, pp. 15-16.

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Build the airplane, not the airport.

Characterized by:
- All digital design
- Automated component production by supply chain
- Repeatable component dimensions
- Reliable assembly by OEM
- Cost competitive
- High production rates
- Achieved in a regulated environment designed for safety

Characterized by:
- Single design (no two airports alike)
- Local fabrication
- No complete digital design
- Diminishing supply chain

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Methods to improve the work culture to one of “finish on-time and within budget”

Digital Twin for New Nuclear Construction

- Includes **enterprise** level program management support throughout construction.
    - A programmatic approach to cost saving with clear leadership, responsibility, and organization for project management.
    - Information technology and data analytics leveraged to simplify workflow, to make shared information current and consistent, and to automate administrative tasks.
    - IT based actionable spend analytics for improved decision-making strategies.
    - IT based actionable data analytics for improved procurement.
- Trusted model of what is built or modified for the life of the project.
- Design for construction and assembly. (Similar to DFMA)
- Incorporate details about fabrication processes so components can be produced by any vendor in the supply chain.

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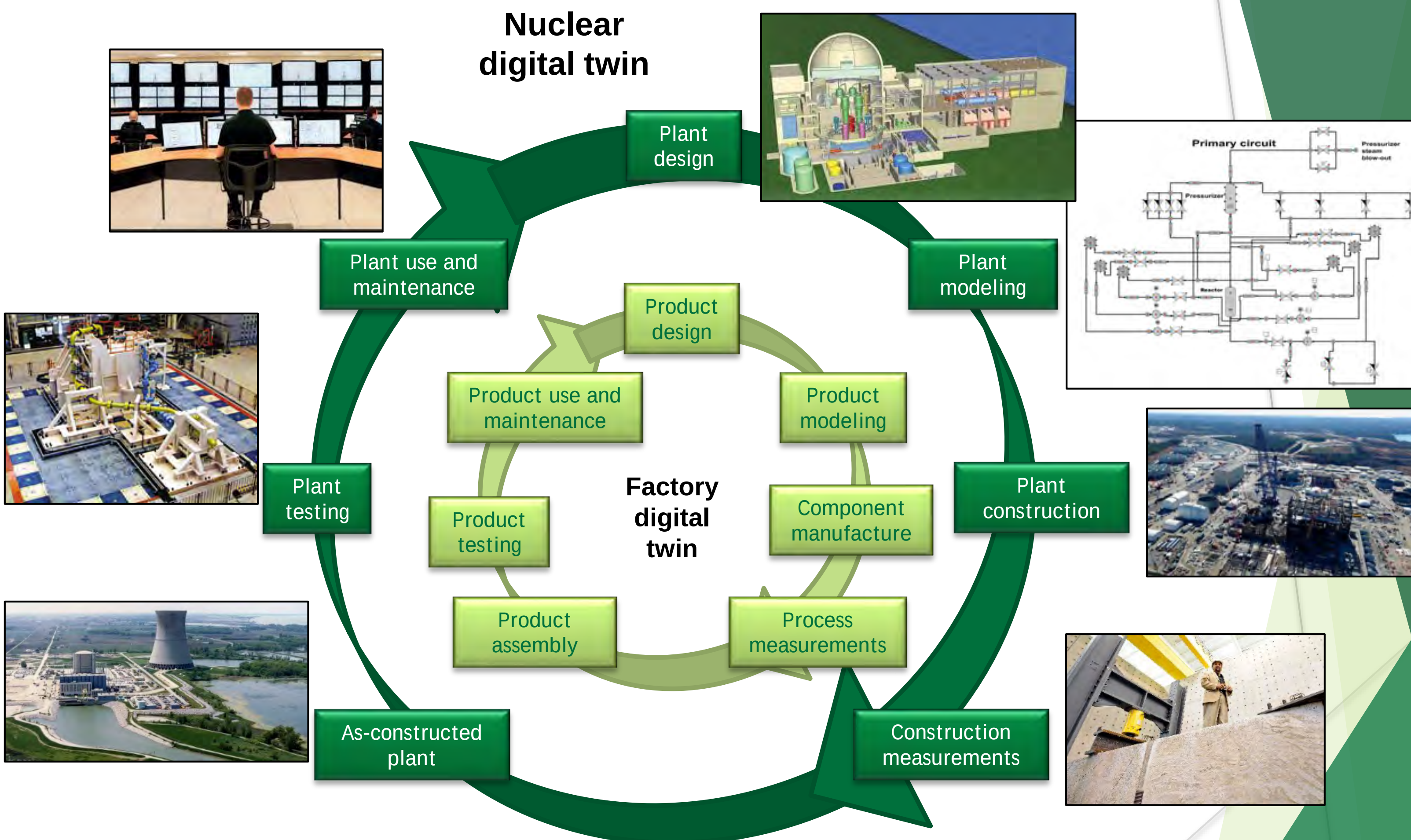
Analogy to Advanced Manufacturing



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Leveraging the Single Source of Truth for Just In Time Regulation

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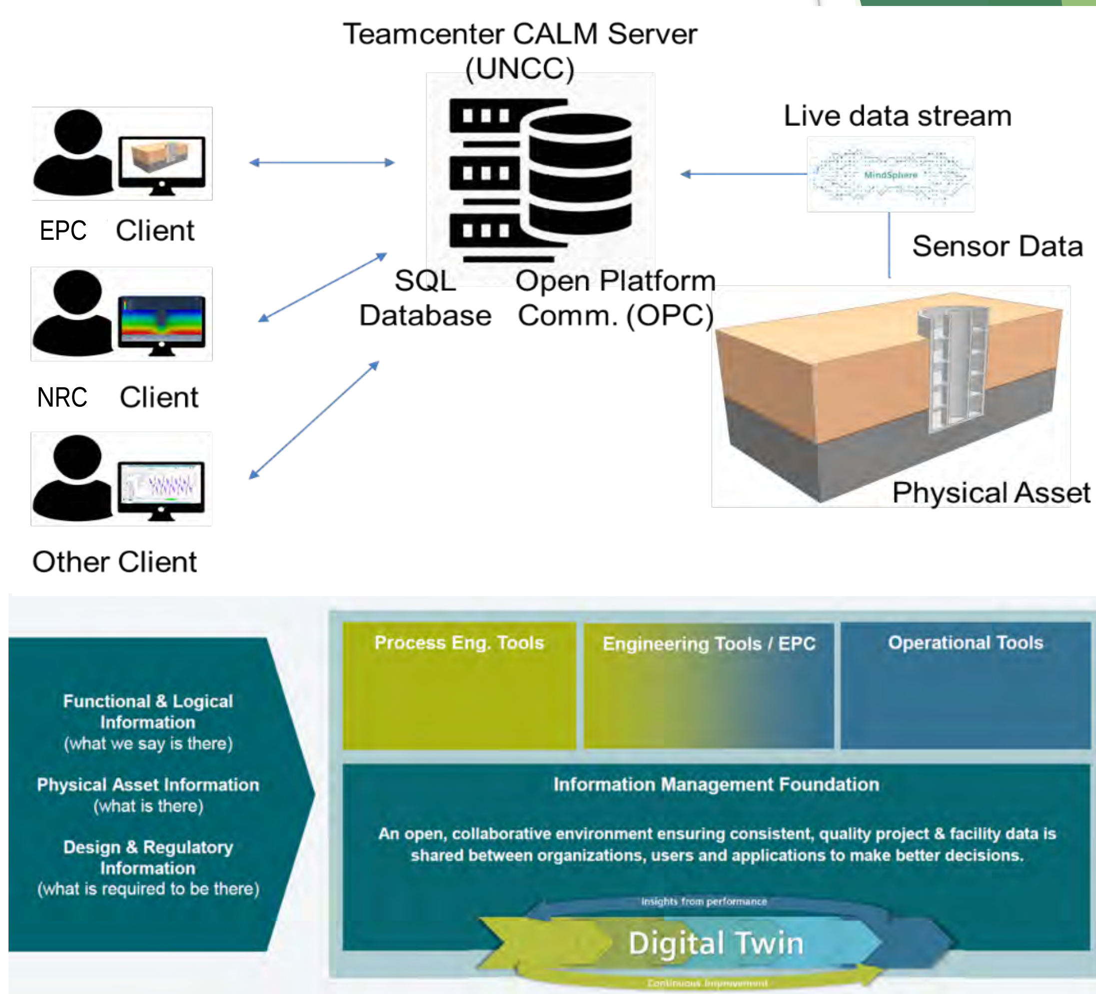
Part 52 Current Rules

- Part 52 licensees may proceed with construction departing from licensing basis only after:
- 1) the licensee, with collaboration from the NRC, determines that a License Amendment Request (LAR) is not required; or
- 2) the licensee submits a LAR and the NRC reviews and approves it; or
- 3) the licensee receives Preliminary Amendment Request (PAR) "no objection" letter from NRC.
- The PAR "no objection" letter is provided only after the associated LAR is developed, submitted and accepted for review by the NRC.

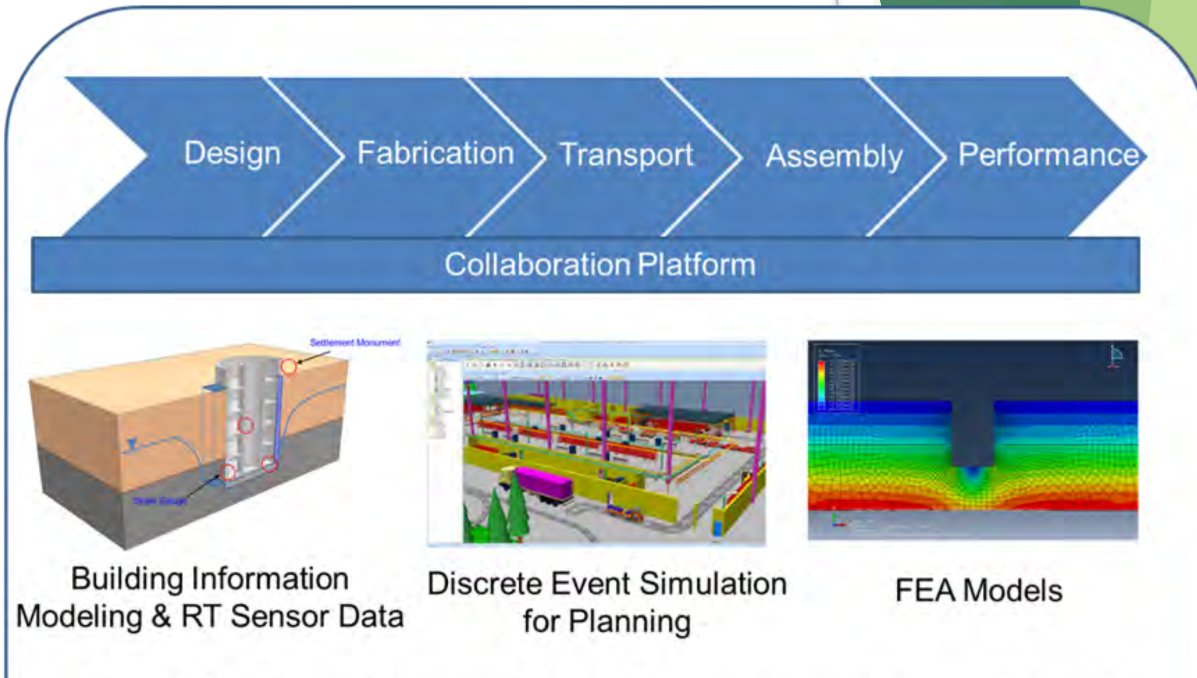
Project Management and Regulator Have Access to the Same Single Source of Truth

- Interfaces to different clients and project, technical, or regulatory software systems available in Teamcenter.
- Consideration of phases of the project and how the Part 52 restrictions should be applied.
- Projects could be allowed to advance specified phases prior to the final COL being issued.
- The phased approach allows parallel project execution to occur.
- Risk should be well defined and understood by management and regulator.



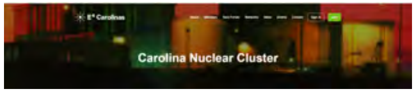
Maintaining Single Source of Truth during Construction - Example

- Structures constructed using innovative technologies
- Structures tracked through design, fabrication, transport, assembly, and in-service life
- E.g., Finite-element structural and geotechnical models can be integrated application domains



The Digital Twin: End-to-end solution to acquire and stream data and augment it using simulation models

2020 External Partnerships



advanced energy

CCOG Centralina Council of Governments

CHARLOTTE

CLEMSON UNIVERSITY

Dominion Energy

DUKE ENERGY

EPRI ELECTRIC POWER RESEARCH INSTITUTE

EnergyUnited YOUR LOCAL CONNECTION A Touchstone Energy Cooperative

framatome

GE

HITACHI

INL Idaho National Laboratory

Joules Accelerator

KIT Karlsruhe Institute of Technology

LS Energy Solutions

NREL NATIONAL RENEWABLE ENERGY LABORATORY

NC Environmental Quality

STATE OF NORTH CAROLINA DEPARTMENT OF TRANSPORTATION

NC Electric Cooperatives Your Touchstone Energy Cooperatives

NC STATE UNIVERSITY

NC SUSTAINABLE ENERGY ASSOCIATION

NEI NUCLEAR ENERGY INSTITUTE

OAK RIDGE National Laboratory

Piedmont Natural Gas

pillsbury

POWER ENGINEERS

RESEARCH TRIANGLE CLEANTECH CLUSTER™ » Transformation Through Collaboration

Sandia National Laboratories

sas

SRNL SAVANNAH RIVER NATIONAL LABORATORY OPERATED BY SAVANNAH RIVER NUCLEAR SOLUTIONS

SIEMENS energy

SDS Reliability Matters

TVA

TERRESTRIAL ENERGY

DEPARTMENT OF DEFENSE UNITED STATES OF AMERICA

DEPARTMENT OF ENERGY UNITED STATES OF AMERICA

DEPARTMENT OF TRANSPORTATION UNITED STATES OF AMERICA

United States NIC Nuclear Industry Council

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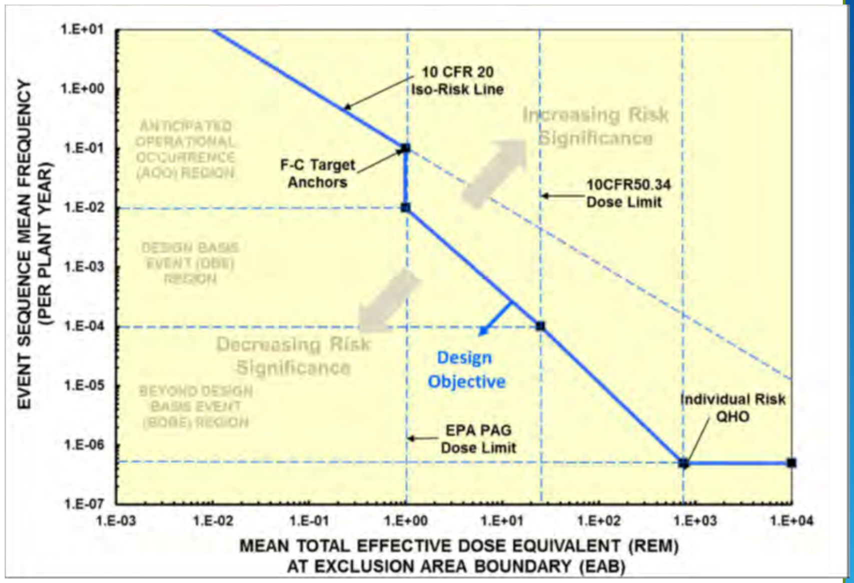


EMRALD

SAPHIRE

DIAMOND

December 4, 2020

Mike Calley

Department Manager, Regulatory Support

Including Risk in Digital Twins

Idaho National Laboratory

Nuclear Safety and Regulatory Research Division

Let’s start with the punchlines

- Many next generation reactors will use digital twin technology (DT) for design and operation
- “Risk” in terms of performance shortfalls is a powerful way to characterize and understand complex systems
- Risk, in terms of a “public health” frequency-consequence idea, is a key part of the next-gen risk-informed approach (e.g., in NRC’s SECY-19-0117)
- For completeness in design and operation, we must consider uncertainties
- When we put these together, we can realize a major efficiency if we design, operate, and license advanced reactors using a digital twin approach that includes a risk element

Outline

- **Risk**
  - What does it mean to use the word “risk” in the context of a DT?
- **Context**
  - Why is context important for operation of a reactor?
- **Framework**
  - How would we include risk when using a DT?

“Risk” tends to be used to describe one of two contexts

Risk represents a measured impact to safety

Risk Analysis → science-driven way to make things *safer*

PRA or PSA

Uncertainty Quant. or Risk Analysis

Risk represents a performance shortfall

Risk Analysis → science-driven way to make things *better*

For a DT, risk can be addressed for different metrics

Risk represents a measured impact to safety

Risk Analysis → science-driven way to make things *safer*

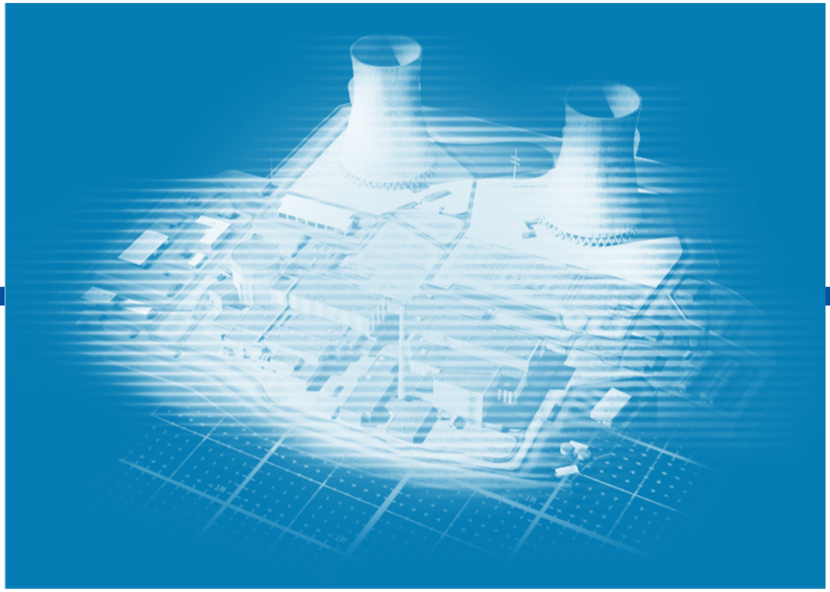
PRA or PSA

Uncertainty Quant. or Risk Analysis

Risk represents a performance shortfall

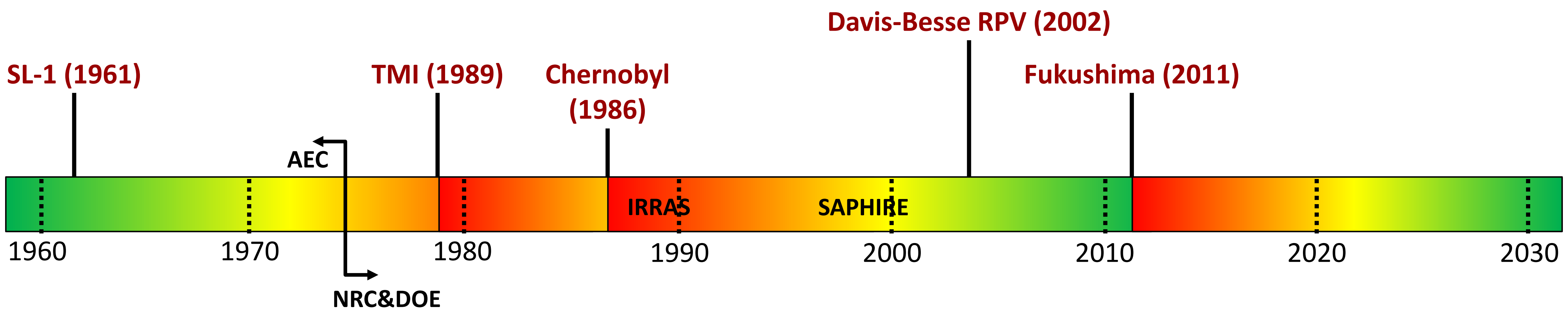
Risk Analysis → science-driven way to make things *better*

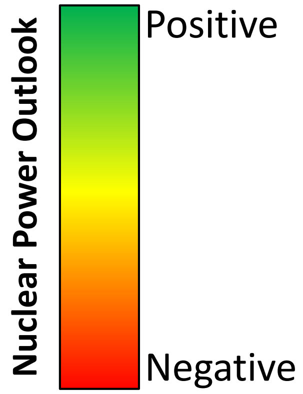
Core Damage
Fuel Damage
Material Release
Public Dose
Etc.



Costs
Availability
Reliability
Etc.

Context is important to understand off-normal events

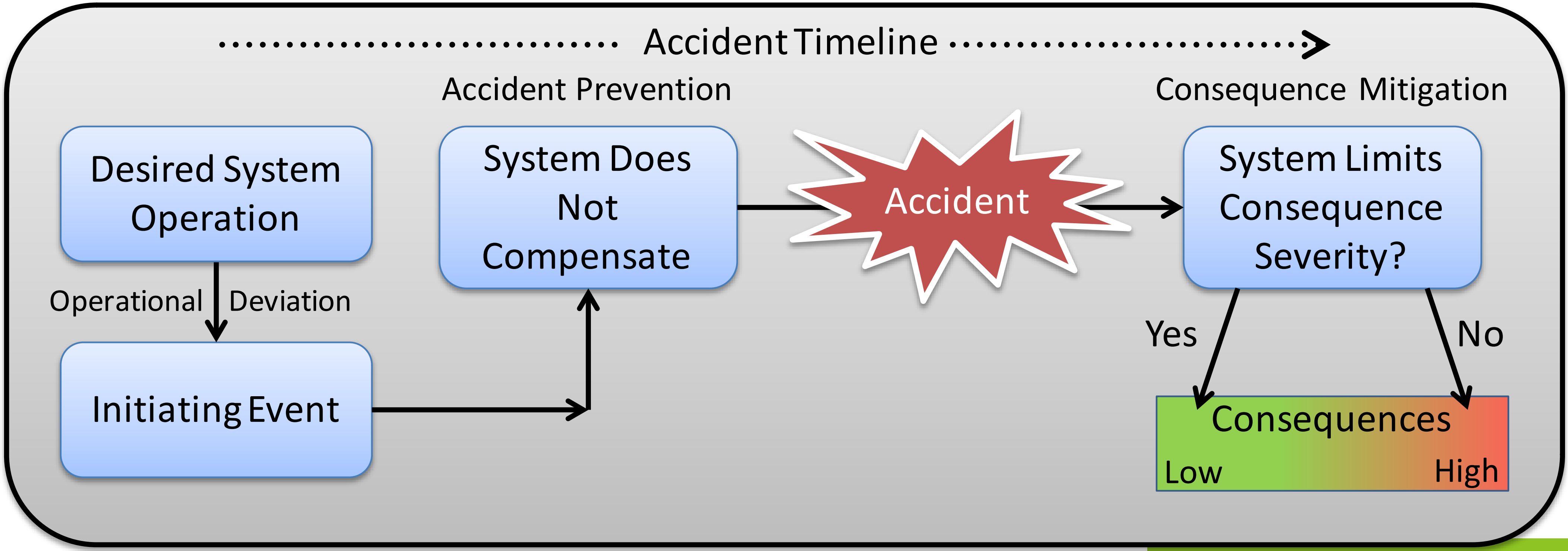




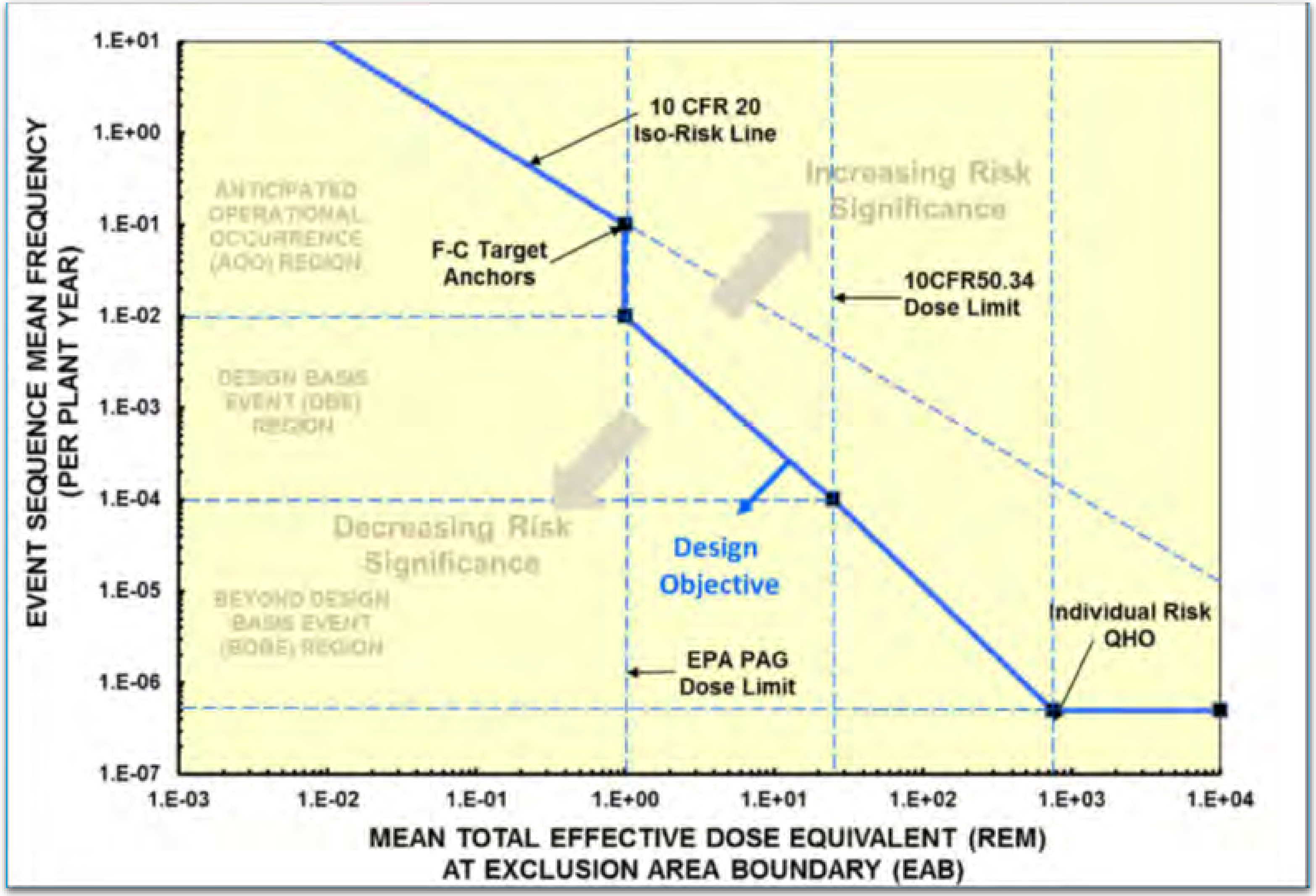
- **Understanding what is going on with, and around, a nuclear reactor is vital to capturing possible off-normal scenarios**
  - Off-normal events can be triggered by human actions, plant degradations, external events, or …
- **Having a model of the reactor physics (e.g., thermal-hydraulics, neutronics, materials) only captures part of the scenario story**

A scenario depicts off-normal behavior

- **Context for a facility includes and understanding of possible hazards**
- **For hazards that may impact a DT, context sets the scenario**
  - Scenario = initiating event + enabling conditions + undesired events/actions



From risk concepts & models comes risk-informed decisions



Frequency-consequence target (derived from NEI 18-04)

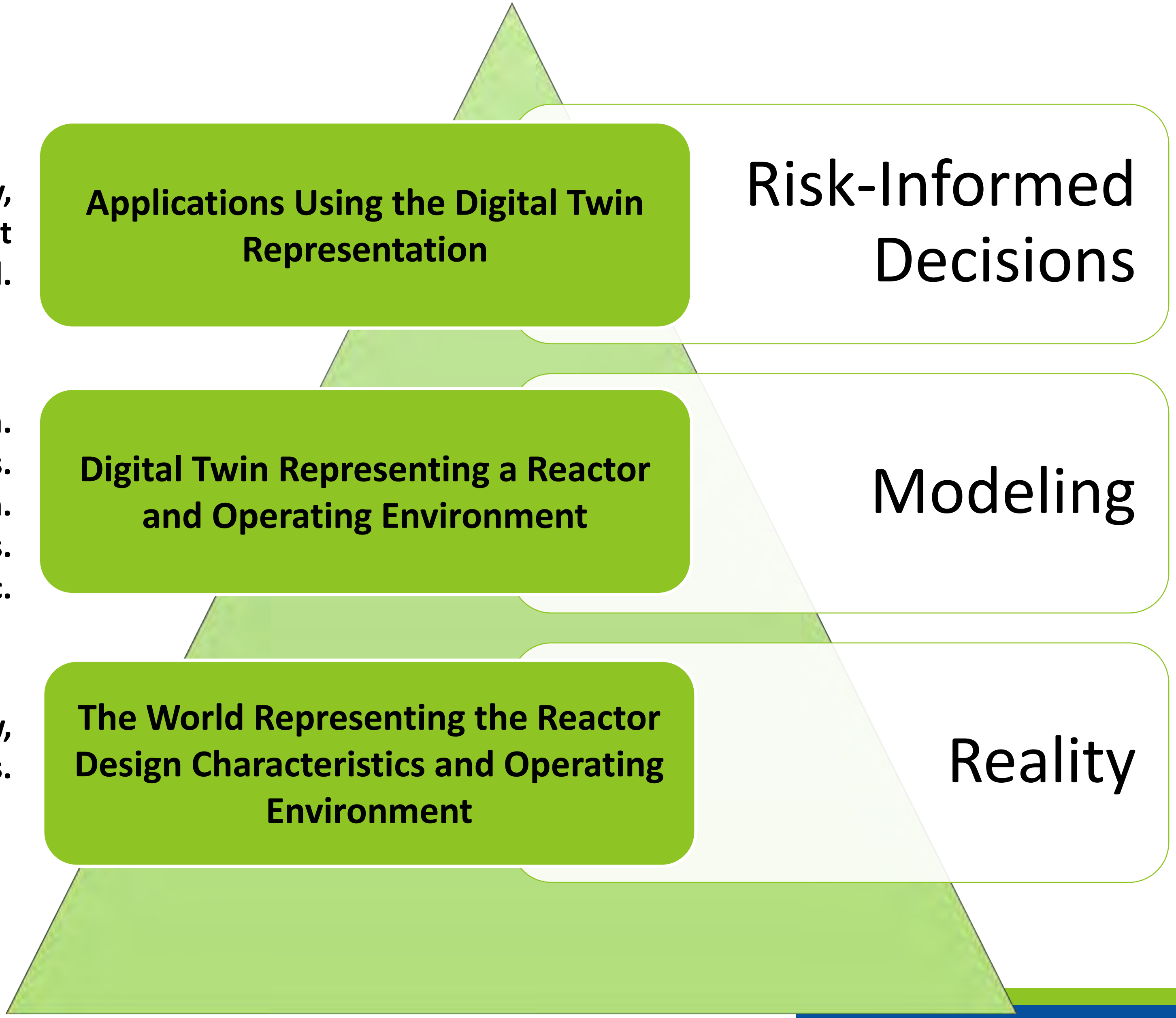
DT framework

Design, operation, safety, reliability, economics, and regulatory questions that are answered via the digital twin model.

Models for physical phenomena.
Models for probabilistic outcomes.
Models for reactor operation.
Models for reactor physical properties.
Etc.

The actual reactor including how, when, and where it operates.

Uncertainty



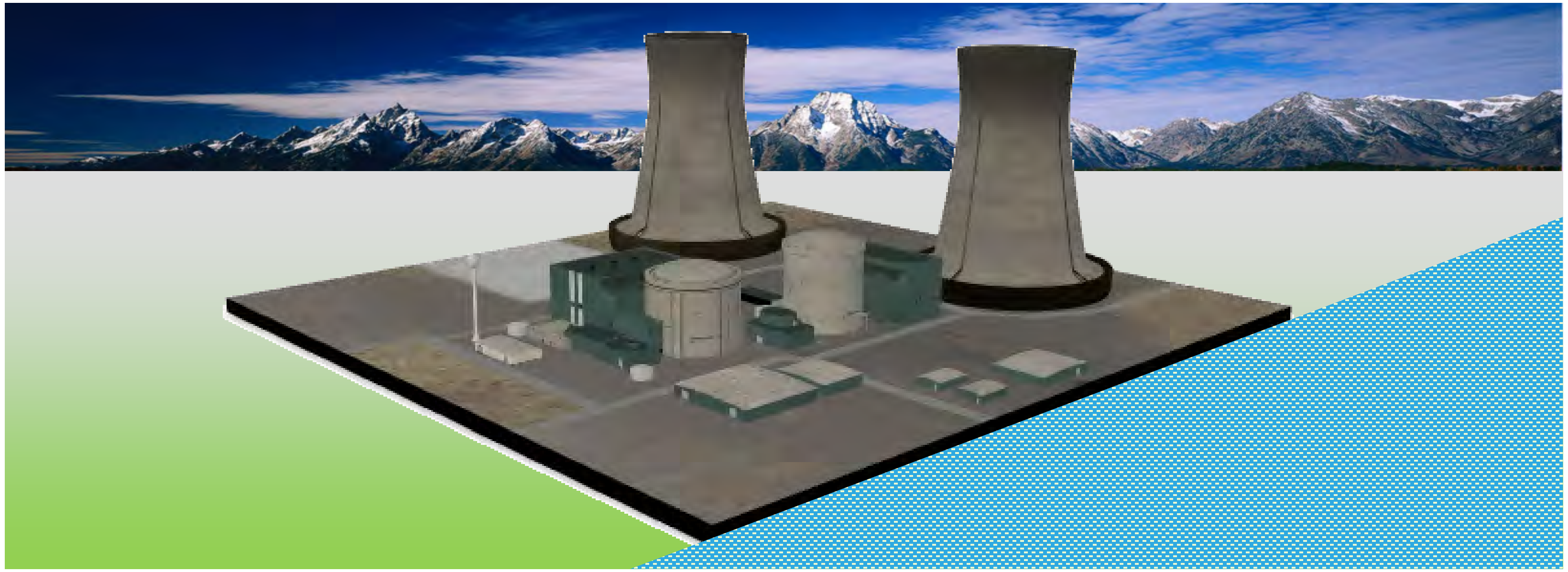
DT modeling, including risk, implies usage of computational risk assessment

- **Computational Risk Assessment integrates risk and physics models**
- **CRA is a combination of**
  - Probabilistic scenario creation where scenarios unfold (in the computer) and are not defined a priori
  - Mechanistic analysis representing physics of the unfolding scenarios
- **CRA is not simply solving traditional PRA models faster or with higher precision**
  - It is a different way of approaching a safety analysis or a performance-shortfall evaluation

Integrating the worlds of physics and probability leads us to predictions based upon an approach called "computational risk assessment"

CRA Steps for Scenario Generation	Enabling Conditions	Initiating Event	Plant SSC Response to Initiator	SSC Failures & Successes	Scenario Simulation

3D Models for the DT including Systems, Structures, & Components (SSC)



Computational Layers Used for the Analysis

- Probabilistic events — **These tend to be stochastic models (but could be load/capacity)**
- Seismic
- Flooding
- . . .
- Thermal-hydraulics

These tend to be physics models

In summary

- **DT for design and operation**
  - Helps us understand the facility, and how it will operate, before and during actual operation
- **Performance shortfall to characterize and understand complex systems**
  - Helps us to focus on the strengths and weakness of these systems
- **Public health risk is a part of the next-gen licensing**
  - Helps us license advanced reactors in an efficient manner
- **We must consider uncertainties**
  - Helps us characterize our knowledge about the operation- and safety-cases
- **These points imply we should include risk for our advanced reactor DTs**

Michael.Calley@inl.gov

Thank you!

Defense Nuclear Nonproliferation Research & Development

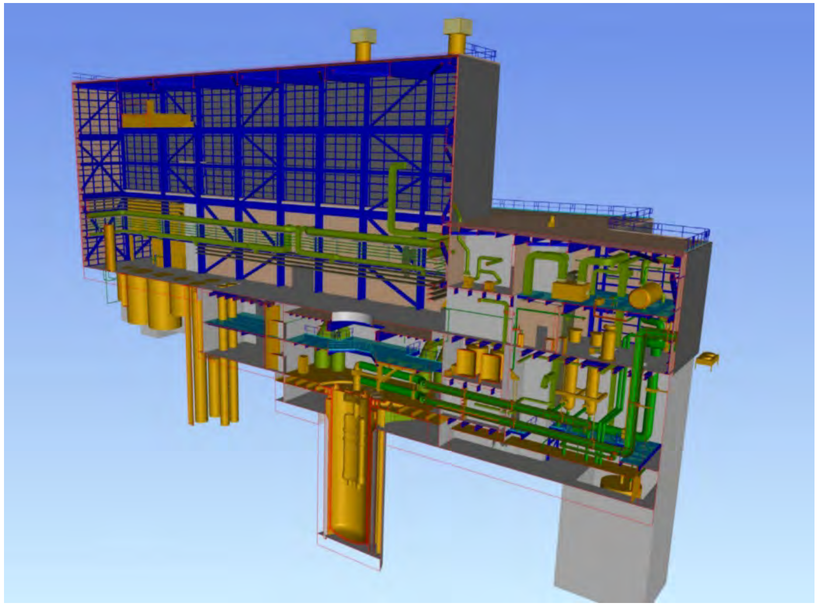
Towards a Digital Twin to Detect Nuclear Proliferation Activities

NA-22 Office of Data Science

Christopher Ritter (PI), Sam Bays, Eric Bohney, Ross Hays, John Koudelka, Ross Kunz, Gustavo Reyes, Mark Schanfein

Current Limits of Practice

- State of the Art:
  - Safeguards analysis is typically SME based without models
  - When models exist, they are disconnected, have no AI/ML integration, and no digital twin capabilities
- Problem: Development of new advanced reactors (Gen IV) increases importance of new methods to understand diversion and misuse scenarios and determine mitigation pathways



Versatile Test Reactor: Gen IV Sodium Cooled Fast Reactor (scheduled for operation in 2026)

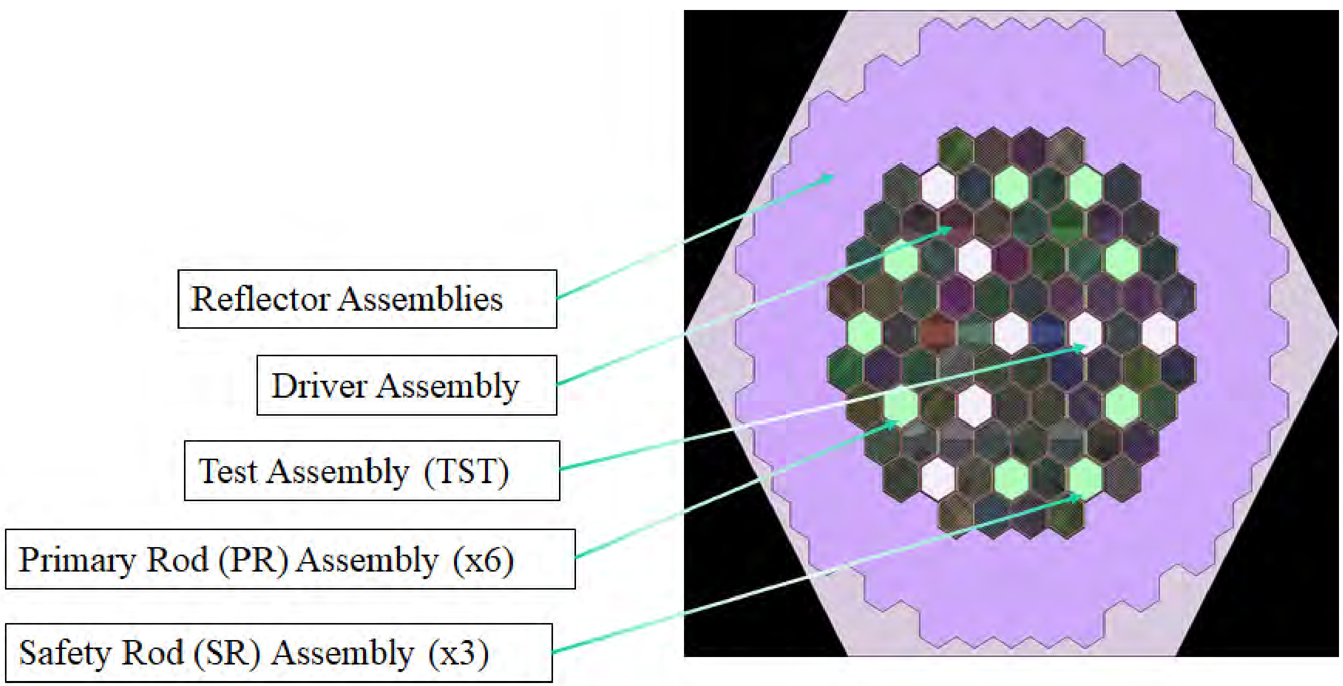
Diversion / Misuse Definitions

National Nuclear Security Administration
Defense Nuclear Nonproliferation

- **Diversion**: The special fissionable nuclear material (Pu239, U233, U enriched in U233/235) that has been declared to the International Atomic Energy Agency is removed surreptitiously either by taking small amounts of nuclear material over a long time (known as protracted diversion) or large amounts in a short time (known as abrupt diversion)
- **Misuse**: The undeclared source material (material that can be transmuted into special fissionable nuclear material: depleted uranium, natural uranium, and thorium) is placed in the core uses the neutron flux for the transmutation

Nuclear Physics Overview

- **Thermal Output: 300 MWth**
- **Cycle Length: 400 days**
- **Outage Length: 20 days**
- **Three batches of fuel in the core**
  - **(Fresh, 1st burned, 2nd burned)**



Diversion / Misuse Scenarios

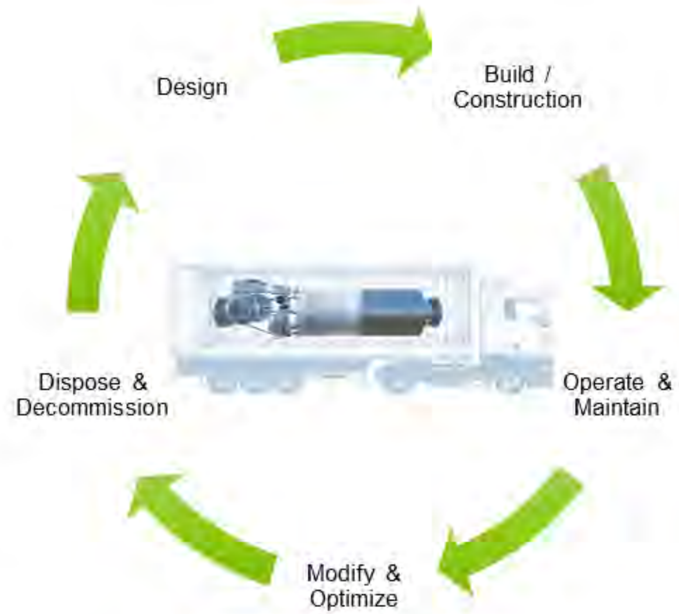
National Nuclear Security Administration
Defense Nuclear Nonproliferation

- **Target**: *Obtain 1 Significant Quantity (SQ) of Plutonium (Pu = 8 kg) for a clandestine weapons program, ideally in 1 year*
- Diversion - diverting 1, 2, 4, 8, or 12 fuel pins per 217 pin *declared* assembly and substituting with either lead (Pb), stainless steel (SS), or natural uranium pins. Thereby immediately obtaining the fissionable Pu intended for the fresh fuel.
- Misuse - placement of a whole *undeclared* assembly(s) (referred to as a target) of fertile natural uranium in an experiment test location(s) within the reactor. Thereby transmuting the NU to Pu over time.

Key Technologies

DIAMOND Ontology

- **Project Objective(s):** This ontology allows for a generic, common framework to enable digital engineering programs. Like previous successful Idaho National Labs initiatives (ex. MOOSE), this data ontology will allow for a common framework to be shared, allowing for more complex energy projects to be undertaken and utilize a plug and play model.
- **Technical Challenges**: (1) Ontological compatibility with other domain ontologies: Mitigated through BFO use (2) Right sized ontology development to ensure the ontology is deep enough to be useful but flexible enough to support multiple designs (3) Verification of the ontology to ensure that functional specifications are executable; this is mitigated by the use of the Monterey Phoenix event trace system
- **Approach**: (1) analysis and selection of top level meta models (BFO/LML) (2) development of lower ontological decompositions for nuclear design using subject matter input to create an easily extendable ontology framework (3) validation and verification of the DIAMOND ontology for nuclear reactor behavior models using Monterey Phoenix (MP)



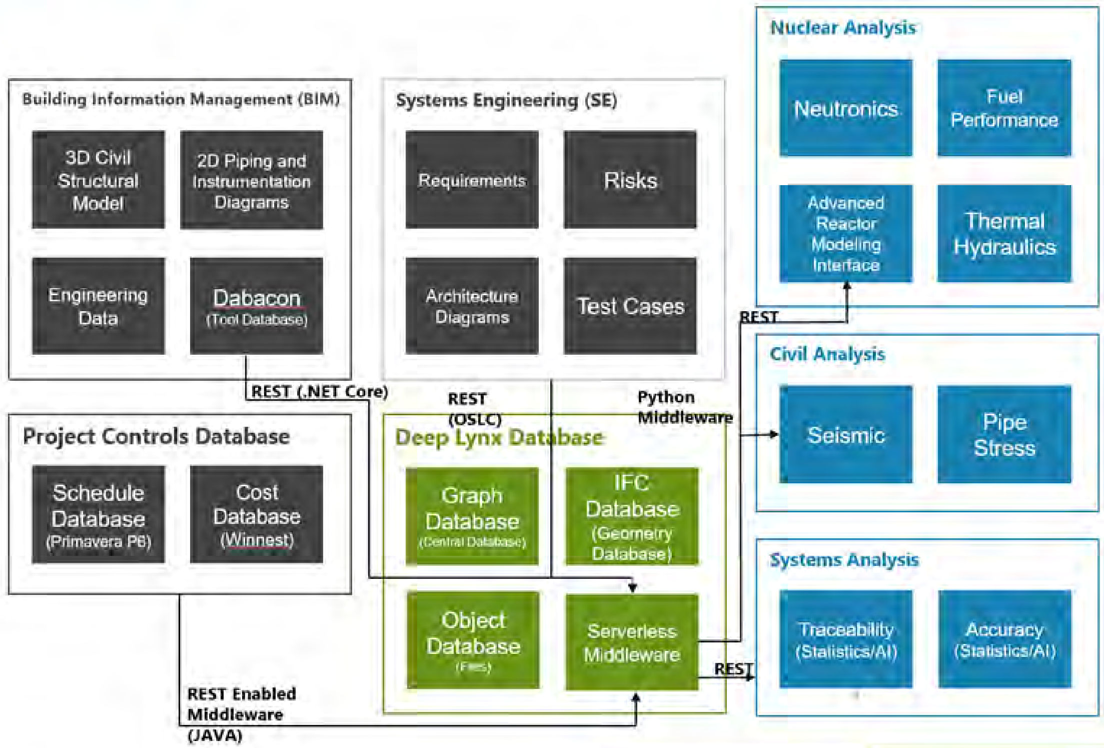
Connection across asset lifecycle

IDAHO NATIONAL LABORATORY

Key Technologies

Deep Lynx Datawarehouse

- **Ontology**: Utilizes ontology for a standardized, common data model to enable a generic framework independent of tool/solution
- **Central Software Framework**: This allows for a common software framework to be shared, allowing for code re-use and minimal point-to-point integrations
- **Central Datastore**: This is utilizing the Microsoft Azure Postgres Hyperscale Database which allows a balance between scalability and historical stability



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Digital Twin Data Model

- **Model Input:**
  - List of selected parameters (fuel design, location, operations, etc.)
  - SERPENT input generating scripts (utilize above parameters)
  - SERPENT version, installation, runtime data
  - Output data extraction script
- **Model Output:**
  - SERPENT data is passed through extraction script to yield selected parameters
  - Parameters stored in HDF5 archive, passed to DeepLynx.
  - DeepLynx extracts archive, converts to DIAMOND type

Digital Twin Data Model

- **Current Status**
  - Defining and converting input parameters within generation scripts
  - Defining output parameters of current and future interest, creating DIAMOND type classes and relationships
  - Establishing automated linkages, authentication methods between cloud data host, local SERPENT installation
- **Future Work**
  - Expand DIAMOND type mappings
  - Automate creation, execution of SERPENT inputs
  - Automate extraction, ingestion of data to DeepLynx.

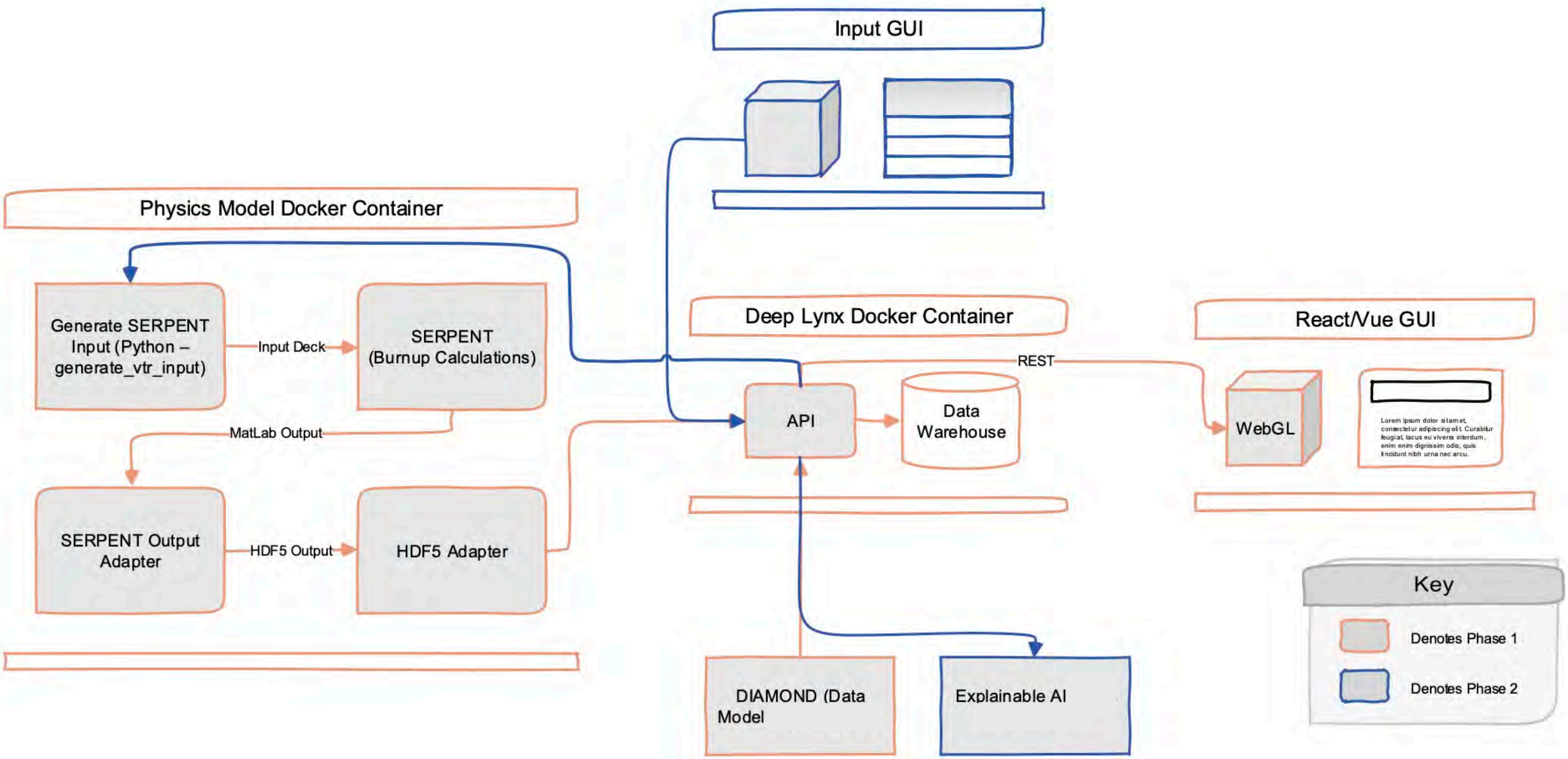
Questions

Digital Twin Software Overview

- **INL HPC (High Performance Computing) hosting:**
  - Serpent: burnup calculations
  - Serpent output adapter and HDF5 to JSON converter (python) for ingestion to Deep Lynx
- **Deep Lynx data warehouse**
  - NodeJS
  - PostgreSQL
  - DIAMOND data model
- **Input and Output GUIs**
  - Input[2]: Visual selection to create input to Serpent
  - Output: WebGL app that provides 3D model of reactor

2: Phase 2

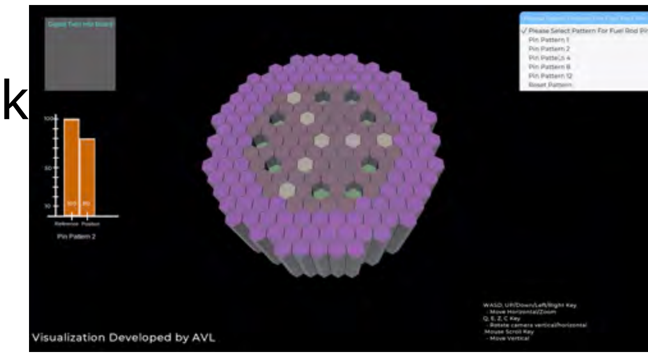
Digital Twin Data Pipeline

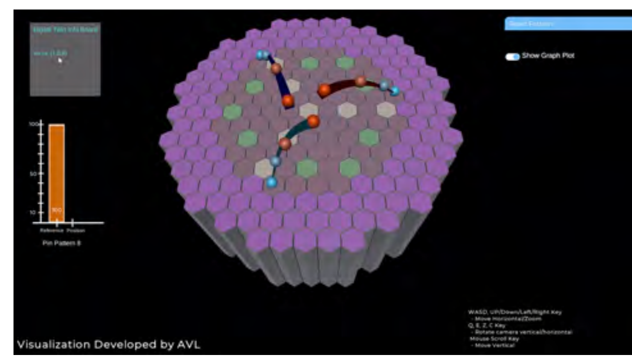


Questions

Digital Twin Visualization Technology

- **Web-based, Virtual Reality environment**
  - Reactor model developed in Autodesk Inventor and 3DS Max
  - WebGL 3D environment
    - Visual Analytics
    - Integration of 2D & 3D
    - RESTful API calls for data
    - Scalable (desktop, laptop, tablet)
  - Dynamic Interaction
- **Data Connection**
  - Calls to Deep Lynx for data
  - Digital Twin is controlled by the result

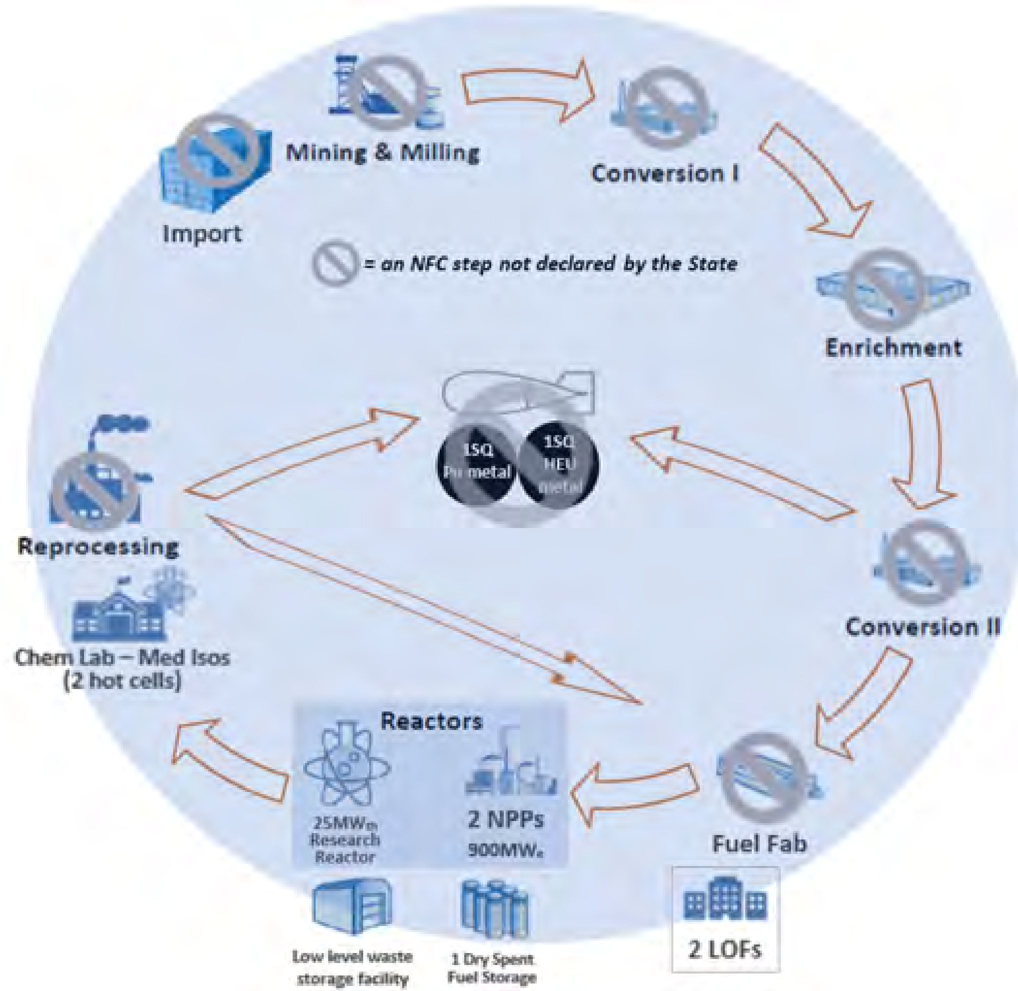




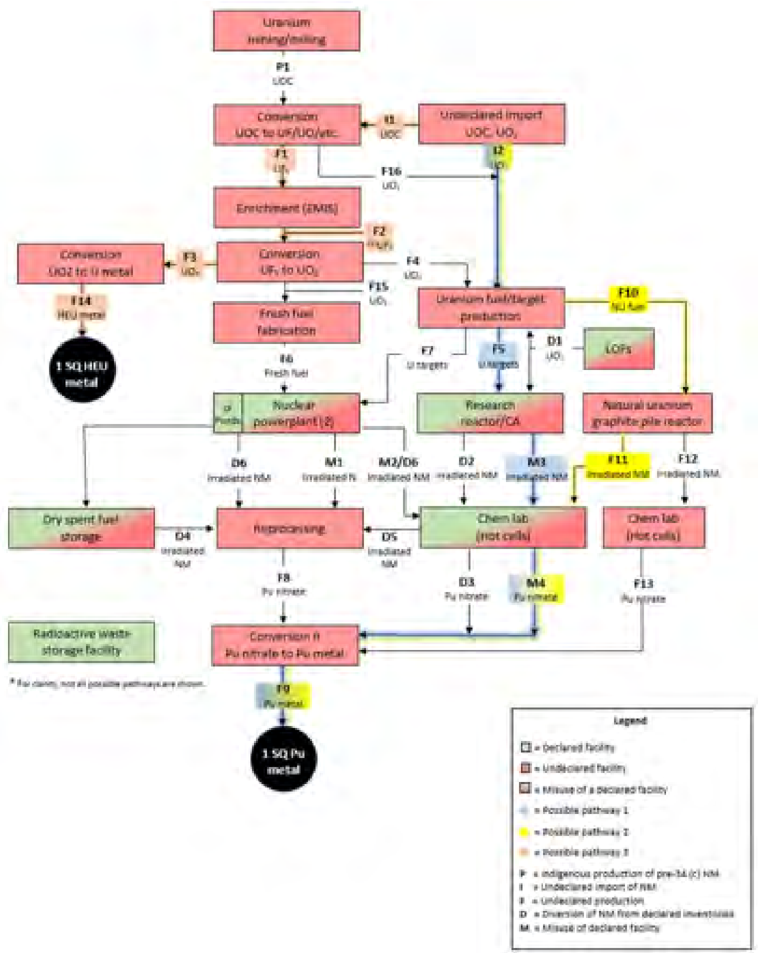
Questions

Realizing DT's Full Potential

- *Diversion* & *Misuse* at <u>declared</u> facilities may indicate <u>undeclared</u> facilities & activities
- NPP a great place to start…
- The value of DT applies to the entire NFC



Using DT in IAEA's Maturing State Level Concept



Questions

- SLC is applied holistically in a State based on its declared NFC, technical capabilities, etc.
- Safeguards activities driven by acquisition path analysis (APA)
- DT can point to misuse/diversion at other NFC steps in the State
- DT informs IAEA's AP Complementary Access activities
- This can lead to a more effective International Safeguards program

Expected Results

- Complete and demonstrated digital twin framework for safeguards by design
- Opportunity for comprehensive understanding of nuclear fuel cycle facility operations to significantly strengthen nuclear safeguards and nonproliferation regime
- Future opportunity to support diversion/misuse detection for both item (LWR) and bulk (MSR) type advanced reactors. As well as indicators for clandestine reactors