

The AGN-201 Digital Twin: A test bed for remotely monitoring nuclear reactors

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ABSTRACT

Research reactors have historically provided researchers and scientists with a means for testing and understanding the workings of nuclear phenomena. With the lack of new research reactors built in the past decades, it is important now more than ever to utilize and provide evidence for the usefulness of research reactors. This work explores the use of the AGN-201 research reactor at Idaho State University as a test bed for developing a digital twin (named the AGN-201 DT) to realize remote monitoring for nuclear reactors. The goal of the AGN-201 DT is to monitor the AGN-201 reactor and detect when undeclared events take place to provide information for a monitoring agency. The AGN-201 DT was able to detect (without *a priori* knowledge) when multiple undeclared experiments were placed in the core using on-the-fly machine learning and reactor physics analysis. The AGN-201 reactor provided a test bed for developing, deploying, and testing a digital twin for monitoring nuclear reactors.

1. Introduction

Research reactors have been built, operated, and modified to explore various aspects of reactor physics. The Experimental Breeder Reactor I is an example from the United States that provided an understanding of fast neutron systems and fuel breeding (Lichtenberger et al., 1951). This led to the development of the Experimental Breeder Reactor II which pushed the knowledge of fast reactor safety systems, metallic fuel, and the closed fuel cycle (Pope et al., 2022). The boiling water reactor experiments (BORAX) provided insight into how reactors could be used to directly boil water in the core (Rice, 1960; NUCLEAR REACTORS BUILT, BEING BUILT, OR PLANNED IN THE UNITED STATES AS OF JUNE 30, 1970). This paved the way for the development and deployment of boiling water reactors. Few research reactors have been built in recent decades; however, research reactors can still be used to push the boundaries of nuclear sciences.

Research reactors still serve a vital purpose for advancing research and technology development. The 10MWth Missouri Research Reactor (MURR) provides medical isotopes for cancer treatments, and the

University of Missouri is expecting to develop a new reactor (NextGen MURR) to continue this mission (University of Missouri, “NextGen MURR,” University of Missouri, 2024). TRIGA (teaching, research, isotope, general atomics) reactors at universities like Oregon State University and Washington State University provide irradiation facilities for geochronology, radiation hardness testing, radiotracer production, and prompt gamma neutron activation analysis (Oregon State University, “Oregon State TRIGA Reactor,” Oregon State University, 2024; Washington State University, “Washington State University TRIGA Reactor,” Washington State University, 2024). Research reactor across the nation provide a valuable tool to better understand fundamental physics in reactors.

Not only can research reactors be utilized for fundamental science research, but they can also be used to understand how next generation technology can be incorporated with reactors. The Purdue University Reactor One (PUR-1) was the first research reactor to develop an entirely digital instrumentation and control system (Purdue University, 2019). Along with this, they are leading a project to advance cyber-security research for advanced reactors (Purdue University, 2024). Idaho State

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University is utilizing the newly updated AGN-201 reactor to develop a digital twin (DT) for detecting off-normal operations. This work highlights the DT developed (denoted as the AGN-201 DT) and the development process for future researchers to utilize DTs for advance monitoring capabilities.

2. Digital twin technologies

There are multiple definitions for DTs across industries and users and the use cases have varied since their inception in the early 2000 s (Grieves, 2002; Grievew, 2005; Grieves, 2011; Jones et al., 2020; Grieves, 2014). To specify the definition of a DT for this work, the Digital Twin Consortium definition will be adopted: “A digital twin is a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity” (Digital Twin Consortium, “Definition of a Digital Twin,” Digital Twin Consortium, 2024). The ability to synchronize data provides a key differentiator between a DT and traditional modeling and simulation, where the DT system has some input back to the physical world. The virtual representation allows the DT to sufficiently understand the physical state and phenomena to predict future behavior. These predictions can then be used to influence current operation to affect the state of the system (Browning, 2022).

To build situation awareness in a DT, various types of models can be integrated through a digital thread. Digital threads seek to connect information about a system throughout its lifecycle to provide an understanding of the system and its operations. Different types of models and analyses can be integrated depending on DTs intended functionality. Physics-informed models and physics- or data-driven machine learning (ML) models are often employed. Other applications (data pipelines, user interfaces, etc.) or data sources (meta-data, environmental data, etc.) may also be combined as parts of the DT, which can allow for data aggregation, organization, and cohesion.

Given the ability to combine various sensor data to understand complex systems situate DTs as a candidate for advancing new nuclear energy systems. Advanced nuclear reactor vendors are exploring ways to reduce development, operation, and maintenance costs throughout the reactor’s lifecycle. To ensure a robust operational envelope for a first-of-a-kind reactor, these new reactors will likely rely on heavily instrumented systems to provide constant data streams for multiple systems. Heavily instrumented systems provide an avenue to leverage these data to develop one or more DTs. A few options for uses of these DTs include autonomous operations, predictive maintenance scheduling, and remote monitoring (for operations or international safeguards).

While there are multiple use cases for DTs, the focus of this work will seek to understand how DTs can be used to inform international safeguards. DTs could help alleviate concerns that might arise with the expected growth in advanced reactors compared to the limited growth in funding for the IAEA (IAEA, “Energy, Electricity and Nuclear Power Estimates for the Period up to, 2050; IAEA, “The Agency’s Budget Update for, 2023). For a safeguards DT, it would likely be able to incorporate time-dependent reactor operations data, ML models, and reactor physics models to accurately understand the state of the reactor and determine if the reactor is being operated in a nominal manner. Utilizing a DT in safeguards is not meant to replace the inspectors that are currently performing many of these tasks, but the goals would be to provide information in a more succinct manner. Through this, new growth can be achieved in nuclear without compromising international safeguards or placing an undue burden on the inspectors.

3. Digital twin integration

For a DT both a physical and virtual representation are required. The physical asset is represented by the AGN-201 facility, where the data acquisition system (DAS) provides near real-time data for operations. The virtual asset is a series of reactor physics and ML models developed on the Idaho National Laboratory (INL) High Performance Computing

(HPC) clusters and housed on the Azure cloud. The combination of these assets requires the use of a digital thread to ensure that all aspects representing the physical and virtual models align.

Data is obtained from the AGN-201 via the DAS and uploaded into the open-source data warehouse DeepLynx (Idaho National Laboratory, 2024) through the command line tool called Jester (Idaho National Laboratory, 2024). Once data was ingested into DeepLynx, various operations occur on the data and their results are feed back into DeepLynx. Results are available on the DeepLynx web interface or through a beta operator windows program. Additional user interactions are achieved through augmented reality and a real-time model of the reactor and data. A concept of operations for the AGN-201 DT can be found at Ref. (Stewart et al., 2024).

Fig. 1 shows the general structure of the AGN-201 DT, where the processes are spread out across multiple infrastructure including the Azure Cloud, the INL HPC, and the AGN-201 facility. Once all of the components of the DT were developed, the overarching goal of the AGN-201 DT was to detect off-normal operations of the AGN-201. These operations could indicate either an abnormality in the system or a deviation in declared operations. The AGN-201 DT was set to monitor the AGN-201 operations and provide feedback (in the form of a declared anomaly) to an observer.

To verify the operability of the AGN-201 DT, a red-blue team test was performed. A red-blue team test involves splitting the researchers into two teams; the red team’s goal was to perturb the system in some undeclared manner, and the blue team’s goal was to detect the perturbation and discern what caused the perturbation. During this time, there was no communication between the red and blue team to ensure no unfair advantage is given the blue team. Upon completion of the red-blue team test, the two teams would gather, and the blue team would report if deviations in declared operations were found (if any). The remainder of this section highlights the various components of the AGN-201 DT.

3.1. AGN-201 reactor

The AGN-201 (formally an AGN-201M reactor but simplified here as an AGN-201) at Idaho State University (ISU) provides a unique test bed for developing a DT due to its simple design yet similar characteristics to larger power plants. Despite a maximum power of only 5 W, the neutron physics occurring at 5 W are generally applicable to higher power levels: absent potential thermal feedback. The recent installation of a DAS allowed for data streaming both locally and to the cloud.

The AGN-201 was developed for both research and operational training (Pope et al., 2022). It consists of two major parts: the core region and the ex-core components. The core region contains nine fuel disks of polyethylene homogeneously mixed with uranium dioxide fuel (enriched to 19.9 % U-235). The rough dimensions for the core are 24 cm in height by 25.6 cm in diameter (“Safety Analysis Report Idaho State University AGN-201M Research Reactor,” Idaho State University, Pocatello, 2021; Gorham, 2012). Four fueled control rods are used to manipulate power. A central irradiation facility allows for the insertion of experiments directly into the center of the core. The external region consists of a graphite reflector surrounding the core followed by lead shielding, and finally water shielding. Above the core sits a graphite thermal column that can be removed for experiments; below the core sits the control rod drive mechanisms. The AGN-201 is shown in Fig. 2.

3.2. Data acquisition system

The AGN-201 utilizes a USB National Instruments general purpose DAS. The DAS uses analog voltage inputs using a differential mode for the acquisition. The signals acquired from the DAS include the control rod positions, the count rate from a pulse detector, the power level from a logarithmic ion chamber circuit, the power level from a linear ion chamber circuit, and the reactor period meter signal. The DAS software

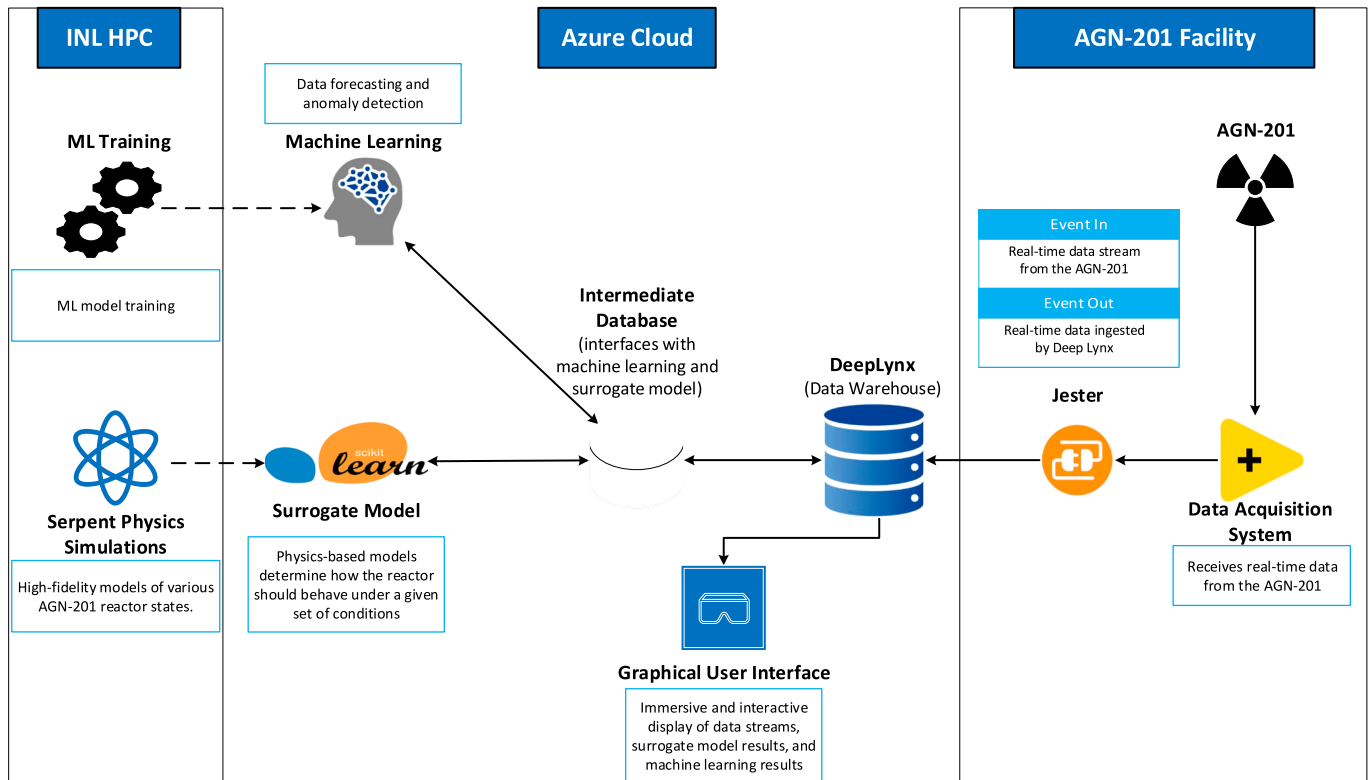


Fig. 1. General structure of the AGN-201 DT. Dotted lines indicate manual transfer of data. Solid lines indicate automated transfer of data.

was written in LabView due to the ease in hardware integration and user interface tools. The user interface can be seen in Fig. 3.

The software scaled the raw signals to the corresponding engineering units seen in Table 1. Derived quantities, such as reactivity, were calculated using both the logarithmic and linear signals. The software saved all the raw data signals, scaled values, and derived signals. The purpose of saving the raw data signals was to keep the most basic form of the data available in case errors or changes were made to the code. All DAS quantities of interest are obtained on a 0.1 s time scale.

The DAS also allowed the operator to indicate when actions were being taken or events had occurred. For instance, the events included inserting and removing the neutron source, declaration of reactor criticality, and inserting or removing an experiment. The software saves a single binary data file for the entire run and text files are created every 10 s. The water temperature does not vary much during operations, instead, the operator records the temperature for the run on the initialization screen.

3.3. Jester

Jester is an open-source tool developed by INL that transfers data from sensor systems to the DeepLynx data lake (Darrington and Conley, 2024). This software was developed and open sourced as part of the ISU DT efforts but with modularity and extensibility in mind. Jester has an extensive plugin system that allows it to work on a myriad of different systems and file types. Both Jester and an ISU-specific plugin were developed as part of this effort. This plugin is responsible for working with Jester to inform how the AGN-201 reactor's DAS outputs the sensor readings and how to input those readings into DeepLynx. The ISU-specific plugin is written in Rust and is designed to tail various CSV files output by LabVIEW and send them on an interval to DeepLynx.

3.4. DeepLynx

DeepLynx (Darrington, 2022) is an open-source data warehouse

focused on enabling complex projects to embrace digital engineering. Unlike other data warehouses, DeepLynx users can use an ontology to define how their data will be represented. DeepLynx enables users to store their data in a graph-like format, ensuring that connections between data can be easily seen and understood.

DeepLynx is hosted on the Microsoft Azure for Government cloud platform, leveraging the Azure Kubernetes system to deploy and manage infrastructure. The Microsoft Azure cloud platform lets DeepLynx connect all other processes and software developed for this DT (see Fig. 4). While fast, this process is not considered “real time” but “near real time” due to the network latency between each process communicating over the web.

DeepLynx is designed to not only store a graphical representation of the AGN-201 reactor but also tabular (or temporal) sensor data. The graph-like format of the AGN-201 can be seen in Fig. 4, which highlights how the physical components from Fig. 2 and Fig. 3 are connect within DeepLynx. All information for the AGN-201 DT passes through the DAS (denoted as DAQ in the figure) into DeepLynx.

Currently, DeepLynx leverages the open-source software Time-scaleDB for storing and querying time-series or tabular data. Data is processed in near real time due to network connectivity via HTTPS. The different components of Fig. 1 are connected via TCP sockets using the HTTPS format. Currently, the system runs in about 30 s loops, including the ML/reactor physics portions of the flow.

3.5. Reactor physics adapter

3.5.1. Initial reactor physics and surrogate models

The neutronics model for the AGN-201 was developed using the Monte Carlo code Serpent (Leppanen, 2015). For the AGN-201 Serpent model, material and geometric characteristics of the core were taken from the Safety Analysis Report, safeguards report, and previous benchmarking performed for various AGN-201 reactors (“Safety Analysis Report Idaho State University AGN-201M Research Reactor,” Idaho State University, Pocatello, 2021; Gorham, 2012). When possible,

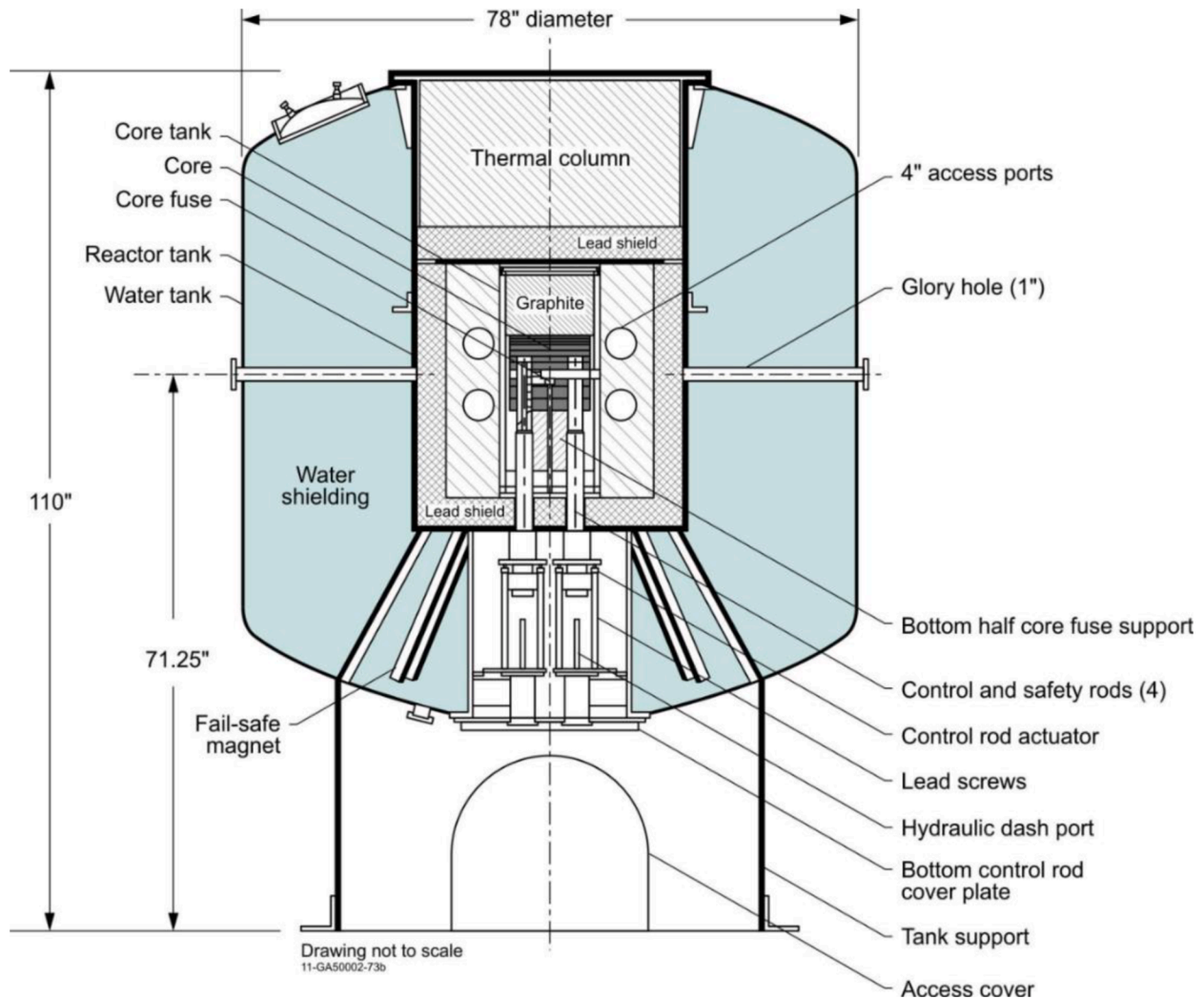


Fig. 2. AGN-201 reactor core and support structures.

geometric information was obtained from the Safety Analysis Report first and supplemented with additional benchmarking data. All material compositions were obtained from (Gorham, 2012). The UO_2 -poly material was obtained by performing mass spectroscopy on two fuel shaving samples in 2012. Most other materials (such as lead, graphite, etc.) were obtained via best estimates based on historical data (Wetzel et al., 2019). Utilizing data from characterized sources such as the SAR and mass spectroscopy provided the most realistic representation of the AGN-201 for the DT. Fig. 5 shows a plane slice of the Serpent model at the midpoint highlighting the two safety control rods and the central irradiation facility.

The Serpent models were used to create a high-fidelity neutronics model of the core. Using this model, core reactivity (i.e. k_{eff}) could be determined via the fine control rod (FCR) height, coarse control rod (CCR) height, and temperature. Examining 23 startups from historical operations, the average k_{eff} for a critical core was 1.00165 (± 0.0004); the statistical 3-sigma uncertainty was less than 10 pcm. Based on historical data there is a 165 pcm bias in predicting a critical core, with an approximately 40 pcm (\$0.053) uncertainty in estimating k_{eff} . For a 3-sigma uncertainty this yields a 120 pcm (\$0.16) uncertainty.

Serpent provided a detailed physics analysis of the AGN-201, but it was too slow to be utilized during operations. Each simulation took approximately one hour to complete using 12 nodes with 48 processors each on INL's high-performance computing cluster. To overcome this, a series of 196 Serpent models, with varying temperatures, CCR heights,

and FCR heights, were executed to create a data set from which a surrogate model (SM) could be generated. The SM was a Gaussian process regression (GPR) model, using the scikit-learn Python module, that calculated k_{eff} based on the FCR insertion depth, CCR insertion depth, and temperature (Pedregosa, 2011).

Results for both the Serpent and GPR models were consistent, where the GPR model had an R^2 value of 0.9997 and a mean absolute error of 1.04 %. The largest error occurs when the CCR and FCR rods are nearly full out. Table 2 shows the modeled and experimental neutronics parameters of interest. The bias of the Serpent and GPR for a critical core is approximately 165 pcm based on known critical core configurations. The Serpent and GPR models tend to overestimate the CCR and FCR worths by approximately 11 % and 24 %, respectively. This difference is likely a combination of slight material differences, and the experimental methodology for obtaining the FCR and CCR worths. The larger difference in the Doppler coefficient is due to the small range of temperatures the AGN-201 operates within resulting in limited cross-sectional variance among these temperatures (Loveland, 2015). Experimentally the difference is due to the temperature readout only being accurate to the tenth of a degree and the temperature readout being in the water tank, not the core region. Temperature is not expected to vary much during operations, but the location and accuracy lead to larger uncertainties given the small temperature ranges. Despite this, with the uncertainties captured the Serpent and SM provide a realistic representation of the physical system which can be used to monitor the system.



Fig. 3. AGN-201 DAS graphical user interface.

Table 1

DAS quantities of interest generated from raw signals.

DAS Quantities of Interest [unit]
Channel 1 Power [counts/second]
Channel 2 Logarithmic Power [watts]
Channel 3 Linear Power [watts]
Temperature [Celsius]
Coarse Control Rod Height [cm]
Fine Control Rod Height [cm]
Inverse Period [1/second]

The GPR SM is used to detect anomalies based on deviations from the initial k_{eff} value. A Python script is used to determine when the reactor is critical at the start of each operation. The SM examines the current k_{eff} from the reactor data, compares this against the expected k_{eff} , and determines if it is within the expected standard deviation. Table 3 shows the condition declared for reactivity changes between the initial and instantaneous k_{eff} .

Capturing k_{eff} allows for an understanding of the state of the reactor. When the reactor is critical (i.e. not changing in power), k_{eff} should be within the expected uncertainty. If an experiment (i.e. a neutron poison or neutron moderator) were to be placed in the core this would perturb the state, resulting in k_{eff} being outside the expected range. For example, if a piece of cadmium were to be placed in the central irradiation facility, the control rods would have to be inserted further into the core to compensate for the negative reactivity added by the cadmium. During operations, this would manifest in k_{eff} appearing larger than expected and outside the range of normal operations.

3.5.2. MOOSE models

Additional work was undertaken on a deterministic AGN-201 model using the Multiphysics Object-Oriented Simulation Environment (MOOSE) framework (Lindsay, 2022). Within the MOOSE framework are a number of multiphysics modules, including Griffin (for reactor physics) (Prince et al., 2024), which can model various reactor designs. The development of a MOOSE-based model provided a code-to-code

comparison with Serpent. It is envisioned that different reactor concepts could require multi-physics modeling; this work provides a framework for how to create and integrate a MOOSE-based model.

Additionally, MOOSE has the Stochastic Tools Module (STM) (Slaughter, 2023), which can be used to create SMs directly from full model evaluations within the framework. The ultimate goal of creating a DT whose virtual model component can be dynamically updated and operated at near real-time speeds necessitates an innovative approach to cut computation costs and increase flexibility. Given a cost of 5,210 core-hours per Serpent model simulation, compared to roughly 332 core-hours per Griffin simulation, utilizing the MOOSE framework to create virtual models for a DT could be favorable.

Griffin models require two main components, a geometric mesh and nuclear cross-section data. The mesh, shown in Fig. 6, was generated using Siemens NX (Siemens Digital Industries Software, 2021) to create the solid geometry and then meshed using Cubit (Coreform and Cubit, 2023). Cross-section data was generated directly from a Serpent simulations at various state-points, which Griffin linearly interpolates between to cover the range of operating conditions. The Griffin model achieves a significant reduction in computation time while largely maintaining important reactor characteristics like FCR and CCR worths (\$0.50 and \$1.88, respectively). Though a marked improvement, computation costs are still not on the desired scale for a successful DT, an issue solved by the STM.

SM generation has two important considerations, sampling size and type and surrogate type. The STM offers many options for each, and each surrogate is affected differently by each sampling method. Preliminary exploration of three surrogate types and three sampling types with various sizes is underway. Nearest point (NP), polynomial chaos (PC), and Gaussian process surrogates were chosen along with Latin-hypercube sampling, quadrature-based sampling, and Cartesian product sampling. These encompass a diverse array of sampling methods and surrogate types and are assessed on training costs and preservation of reactor characteristics when compared to the Griffin model.

NP surrogates produced step-function-like results, demonstrating a severe lack of accuracy throughout the continuum of operating



Fig. 4. DeepLynx graphical representation of the AGN-201 DT.

conditions. Gaussian process surrogates, though a significant improvement upon the NP models, were generally less accurate with smaller training sets when compared to PC models. Preliminary results suggest that the PC surrogates best balance computation cost and modeling accuracy. A 7th-order PC surrogate trained on a Latin-hypercube training sample containing 512 points was ultimately chosen as it best characterizes rod worths and can be trained with relatively few resources. Fig. 7 shows the resulting coarse control rod curve with full Serpent model and the associated SM values overlaid.

When compared to the Serpent model coarse rod worth, the general trends are similar, notably the somewhat flat region in the first 20 % of rod insertion, though the percent error in that region is significant. The remainder of the region maintains a low percent error with an average of 2 % rather than 9 % for the entire region. This results in a root mean

square error of \$0.02. The surrogate also maintains an overall rod worth of \$1.90, nearly identical to the Griffin model they were trained with only a \$0.04 difference from the full Serpent model.

3.6. Machine learning adapter

3.6.1. Anomaly detection

The Isolation Forest (IF) algorithm, an unsupervised ML technique, was specifically tailored for the AGN-201 DT to autonomously identify anomalies based on the AGN-201 operational data. Utilizing unsupervised learning algorithms allows the algorithm to learn the representational feature space unique to a dataset without labeled data. IF operates on the principle of isolating anomalies instead of profiling normal data points (Liu et al., 2008). This approach assumes that anomalies are few

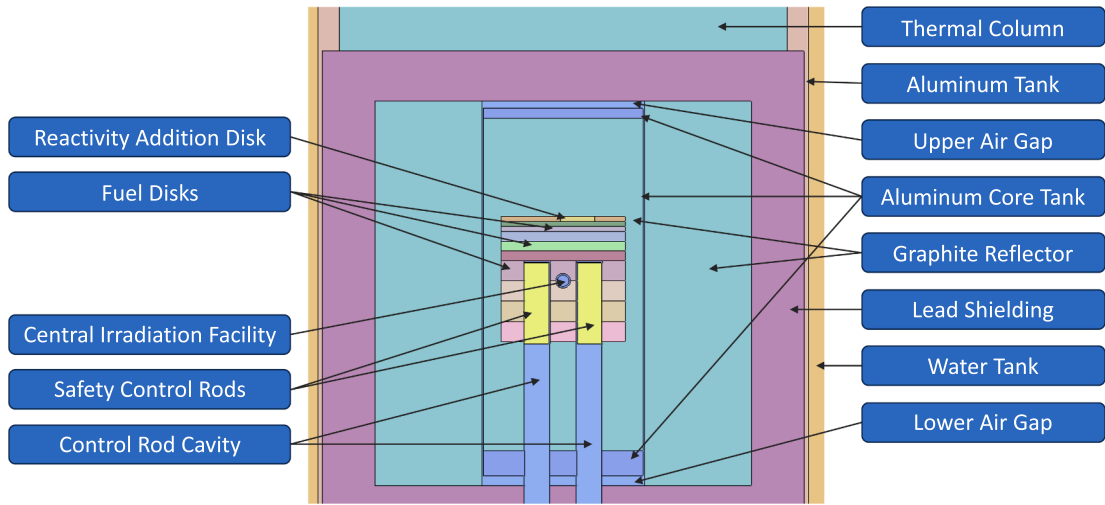


Fig. 5. Plane view of the Serpent AGN-201 model with various aspects labeled for clarity.

Table 2
Modeled and operational experimental quantities of interest for the AGN-201.

	Modeled Value	Experiment Value	Difference
Coarse Control Rod (\$)	1.86 (± 0.07)	1.68 (± 0.06)	-0.18 (0.09)
Fine Control Rod (\$)	0.52 (± 0.07)	0.42 (± 0.04)	-0.10 (0.08)
k_{eff}	1.00165 (± 0.0004)	1.00000	165 pcm (± 40 pcm)
Doppler Coefficient (pcm/K)	-17.9 (± 10)	-26.3 (± 11)	-8.4 (14.9)

Table 3
SM condition ranges for normal and off-normal operations.

Condition	Range
Normal	<40 pcm
Possible off-normal	40 pcm – 80 pcm
Likely off-normal	80 pcm – 120 pcm
Off-normal	>120 pcm

and different in their feature spaces, making them easier to isolate. To illustrate how the algorithm transforms data to isolate anomalies, Fig. 8 shows a three-feature space visualization that demonstrates the concept behind IF’s ability to isolate anomalies.

The algorithm works by constructing a forest of isolation trees, where each tree isolates observations by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of the selected feature. Anomalies are expected to have shorter paths in these trees, as they have attribute values that are considerably different from the normal cases. This characteristic path length, from the root node to the terminating node, serves as a measure of normalcy or anomaly. Shorter paths suggest an anomaly, as they indicate an observation that is easier to isolate from the rest of the dataset. In Fig. 9, dashed lines indicate the hypothetical splits by an isolation tree, and the two rectangles represent the isolation areas. The annotations explain the shorter path for anomalies and longer paths for normal data demonstrating the process of isolating points.

The application of IF within the AGN-201 DT facilitates a nonintrusive method for nonproliferation monitoring by detecting significant deviations from normal operational patterns, which may suggest

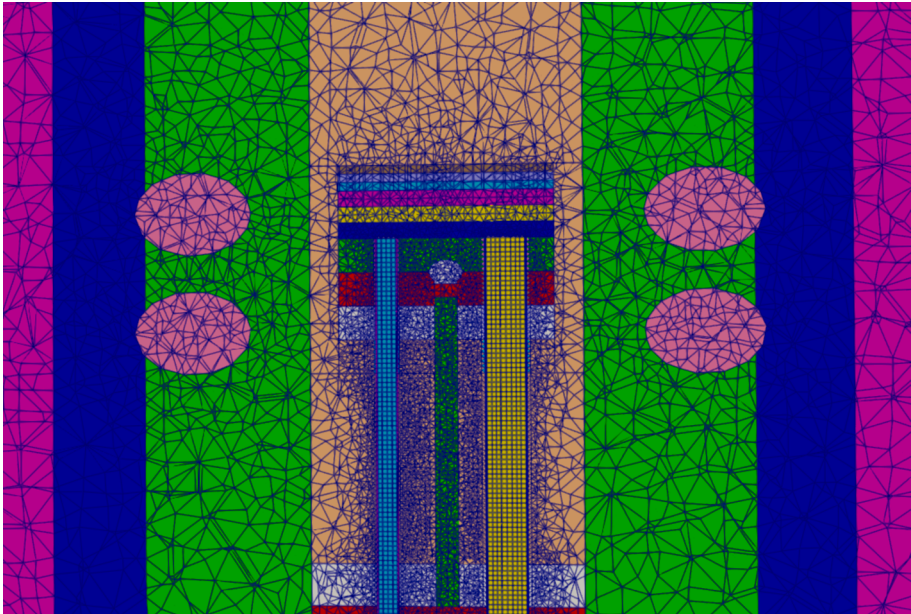


Fig. 6. AGN-201 core three dimensional (3D) mesh cutaway.

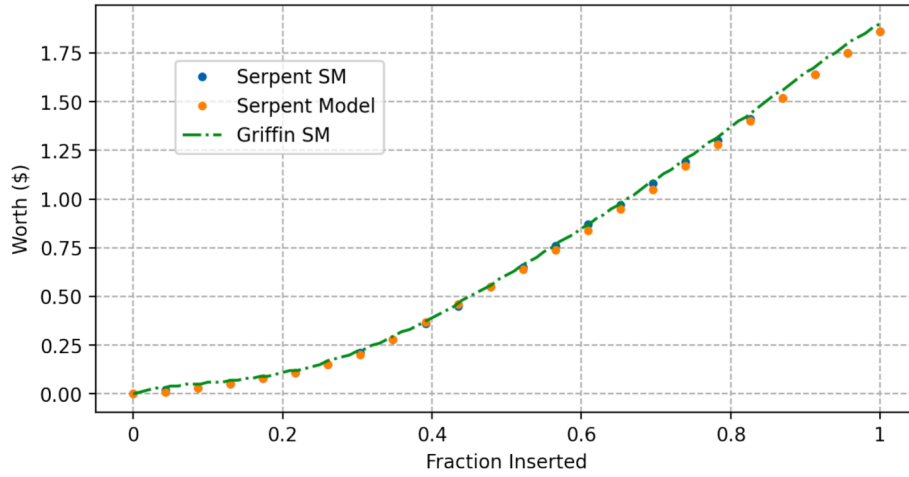


Fig. 7. Coarse rod worth comparison between a Serpent model, Serpent surrogate model, and Griffin surrogate model.

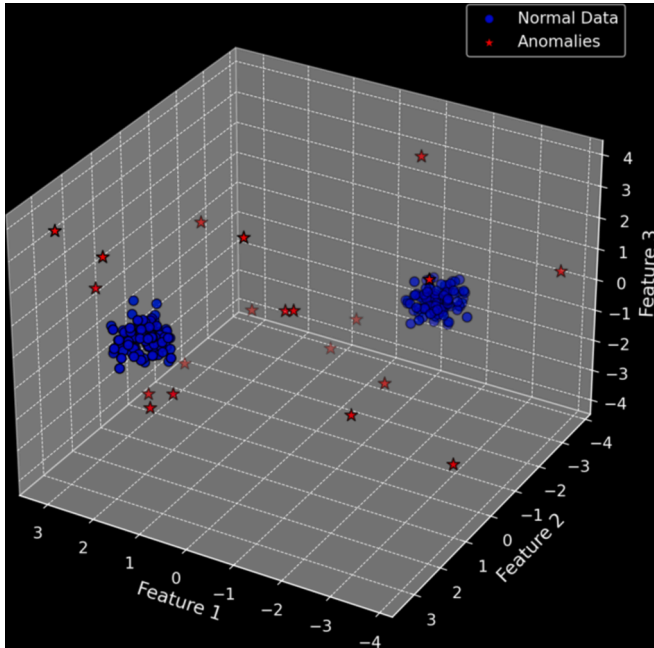


Fig. 8. Demonstration of IF's isolation of anomalies in multivariable feature space.

proliferation activities. By leveraging the IF algorithm, the AGN-201 DT can suggest anomalistic behavior without extensive preprocessing or manual intervention. This methodological choice not only reduces computational burden, extensive labeling, or customization across reactor designs but also minimizes the risk of overlooking deviations in operational data, making it a great additional tool of the DT's anomaly detection framework.

The IF model was assessed using data collected from the AGN-201 reactor over a three-month period. The model utilized all available operational features found in Table 1. No explicit labeling of anomalies was required, as the IF is an unsupervised learning algorithm designed to detect deviations from normal operational patterns.

To align the model's sensitivity to anomalies, hyperparameter tuning was performed by adjusting the number of trees in the forest and the sub-sampling size. The final model used 100 trees with a sub-sampling size of 256, which provided a good balance between detection capability and computational efficiency. The model's performance was validated by injecting synthetic anomalies into the dataset and

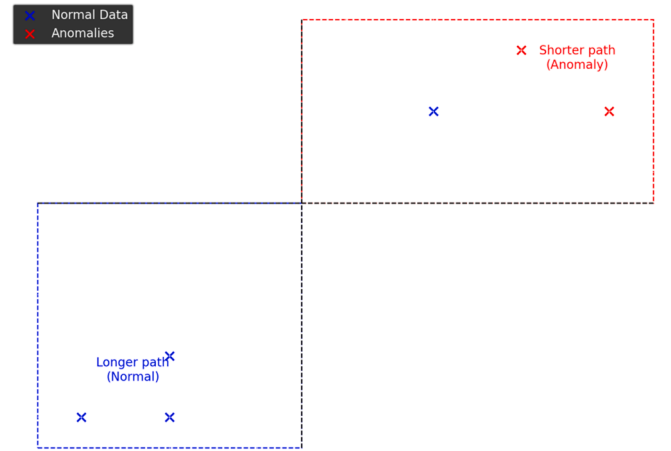


Fig. 9. Demonstration of IF's decision function in forest trees.

confirming that these were successfully detected without raising excessive false positives.

3.7. Graphical user interface

The visualization of the ISU AGN-201 DT was created using Unity, a real-time development platform for 3D and extended reality applications, which provided a rich suite of tools and a variety of build platforms. The Microsoft HoloLens 2 was the mixed reality (MR) device selected, allowing the user to view a virtual representation of the reactor and facility overlaid on their physical surroundings and interact with that environment through the use of device-provided hand tracking. Mixed reality was selected to allow a versatility in viewing the model, both offsite in a remote setting and onsite in the facility, overlaying the virtual environment on its physical counterpart, while still allowing the user to see their physical surroundings, aiding in safe operation.

A model of the facility where the ISU AGN-201 resides was created to be able to give remote users familiarity with the surroundings of the reactor (see Fig. 10). The reactor model was supplied from ISU and imported into Unity. The scale of the reactor model was not 1:1 with the ISU AGN-201, so the model was viewed in MR at the facility and then scale was adjusted to fit the physical asset. Several features were included to enable the user to toggle visibility of the structure surrounding the reactor and another to toggle the transparency of the reactor to be able to see inside it to view the core and control rods.

4. Assessment of the AGN-201 DT

4.1. Red-Blue team test

The red-blue team test involved the ISU reactor supervisor (red team) modifying the operational parameters of the AGN-201 reactor. The perturbations were within regulatory limits but in ways the DT had not previously seen, to simulate a potential bad actor nefariously using to the reactor. The DT analysts (blue team) then analyzed the resulting outputs from the AGN-201 DT and determined if and when anomalous actions were taken.

The first test was conducted in July 2023 and consisted of three separate alterations to the reactor with different amounts of reactivity change. From the highest to lowest reactivity change, the list of alterations to the reactor is:

- Experiment 1: Insertion of a polyethylene rod into the central irradiation facility (between 38 and 60 minutes)
- Experiment 2: Insertion of a cadmium foil into the central irradiation facility (between 83 and 100 minutes)
- Experiment 3: Removal of two graphite blocks from the thermal column (between 110 and 112 minutes)

Fig. 11 shows the response of the channel 3 power, FCR, and k_{eff} to the three experiments along with the ability of the SM and IF algorithms to detect the experiment. The first twenty minutes of the operations were removed, as this period was before the reactor was critical. For the polyethylene rod insertion, the FCR was withdrawn to compensate for the added reactivity; during this time SM shows a k_{eff} value which is statistically lower than expected during normal operations. The opposite was true for the cadmium foil. The FCR had to be inserted, resulting in a larger k_{eff} value than normal. The last event was not caught by the SM, as the reactivity change due to the removal of two graphite blocks was within the uncertainty. The ML adapter on the other hand was able to capture this event as the change in the FCR height was counter to the

change in the reactor power shown. For the ML adapter, there were two other areas flagged as anomalous (not shown) near the beginning and end of the operation. These are the startup and shutdown of the reactor; while these were flagged, a user investigating these would likely be able to distinguish them from anomalies. Both anomaly detection methods were able to capture the first two events, where only the IF method caught the third event.

The red-blue team test provided a verification test for how a DT could be used for detecting off-normal operations. Once the operation was complete, the monitors at INL (blue team) assessed the raw data, ML results, and reactor physics results to assess what occurred in the time. During periods where k_{eff} dropped significantly, it was hypothesized that either a neutron producer or neutron moderator was placed in the core. When k_{eff} increased significantly, the hypothesis was that a neutron poison was placed in the core. For the first two events, both reactor physics and ML models predicted an anomaly. For the last case, only ML picked up an anomaly. Despite this, the reactor physics did show a minor deviation (within the uncertainty), which could have indicated some type of neutron poison (or in this case neutron leakage) present.

Once these assessments were made, a memo was drafted and sent to the AGN operations staff (red team). The red and blue team then met (virtually) to discuss the actual experiments performed and the ability to discern experiments. This provided a set of feedback for both the operations and monitoring staff. This level of feedback was minimal and not automated. It is envisioned that future work would encourage an automatic detection and notification of the monitoring team. The DT could then be used to interrogate and understand what types of events may have caused the off-normal condition.

The application of IF proved effective for anomaly detection, particularly highlighted by its success in differentiating all simulated significant anomalous events within the AGN-201 DT. This success, however, was reliant on several critical factors. IF particularly struggles to detect small deviations during its tree partition predictions if proper hyper parameterization is not carefully developed and tested. The high



Fig. 10. AGN-201 facility depicted through MR.

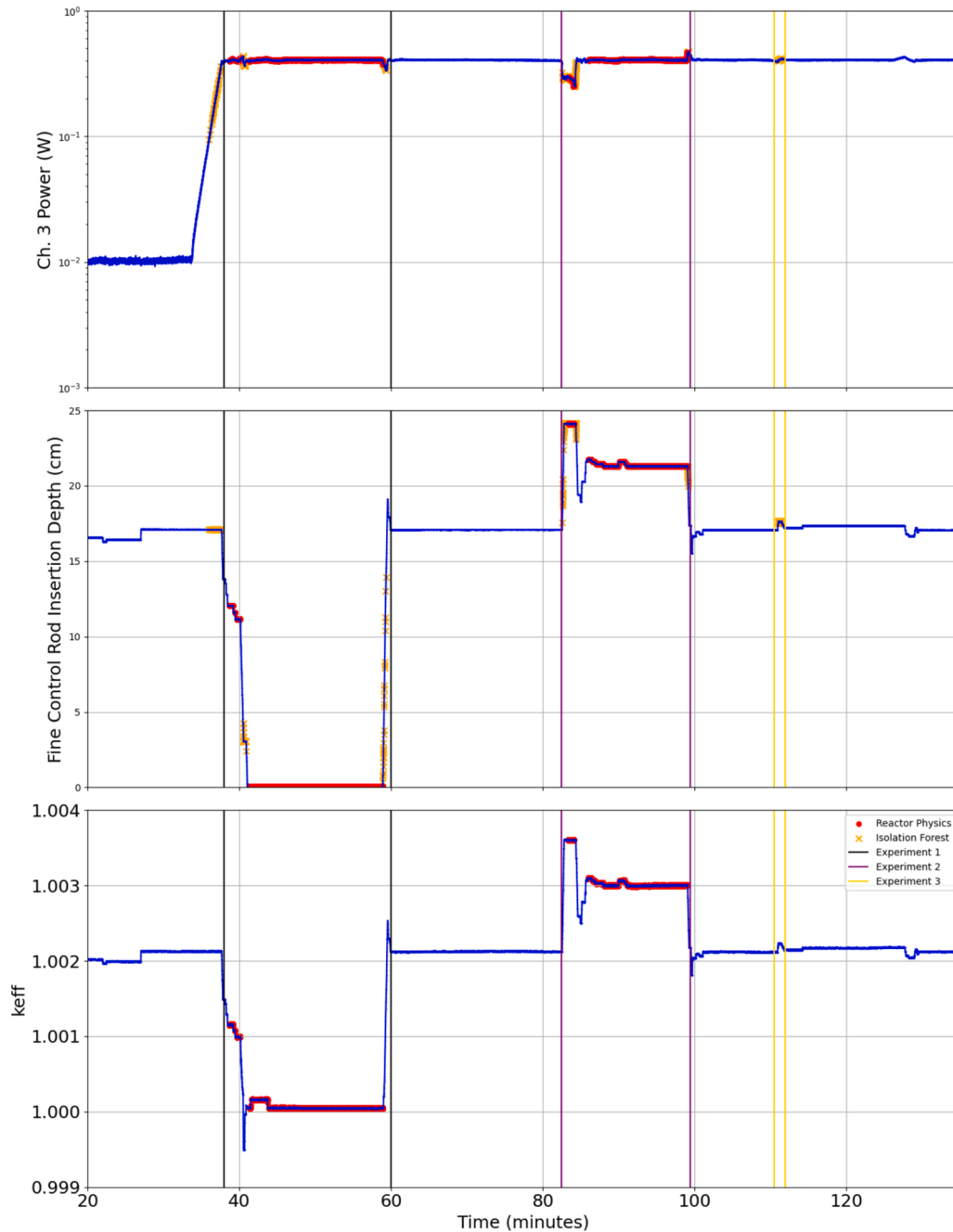


Fig. 11. Anomaly detection using the ML and SM adapters for the red-blue team exercise.

fidelity of anomaly detection necessitated by the AGN-201 DT environment was met through the careful tuning of the IF's hyperparameters. The algorithm's precision was achieved through an empirical approach of parameter selection, validation with subject matter expert analysts, and cross-referencing with physics-based anomaly detection techniques, all of which help validate and optimize the model's performance for the specific operational data of the AGN-201 reactor. Additionally, the reliance on multivariable analysis and sensor stability was critical; sensor data variability and instability could affect the algorithm's performance. Notably, some sensors became less informative post-startup, and anomalies detected in early stages of data streaming required careful interpretation to avoid false positives. This careful development requires a balance between detection sensitivity and computational efficiency for effective anomaly detection, as larger tree partition predictions will lead to increased computation.

The AGN-201 DT is a prototype for investigating international nuclear safeguards. In this regard, the importance of the DT is the ability to automatically detect anomalies and report this to monitors. For real-world operations, a safeguards DT would be utilized by a monitoring agency (such as the IAEA). For this type of DT, an immediate response to the operating facility is not desired, but instead immediate response to monitoring agency would be used to assess if the off-normal conditions were indicative of a real anomaly, material diversion, or reactor misuse. Using DTs could reduce the burden of international safeguards (i.e. in-person inspections) and allow for the growth of nuclear energy without the deterioration of nuclear safeguards.

There are multiple ways that a reactor could be monitored. For the AGN-201, the simplest approach was preferred for monitoring. For this work, a pure neutronics model was used to evaluate k_{eff} and discern difference between normal and off-normal conditions. Given the

simplicity, certain experimental anomalies were not able to be detected, as sufficient physics were not monitored. Future work could envision using other quantities such as reactor power (i.e. time-dependent physics assessment), power distribution (i.e. assembly power), reactor period, etc. Utilizing additional physics would likely provide a more robust reactor physics modeling approach for detecting off-normal operations.

4.2. Visualization

Data was gathered from previous experiments and used to develop interactions with the reactor, and this historical data was stored on the headset and replayed in the standalone visualization. Fig. 12 shows an MR rendering of the AGN-201 core along with the various types of data that can be streamed to the headset. The ability to stream data from DeepLynx to the headsets was developed to be able to view the state of the reactor in near real time, but because of some issues that caused downtime on the reactor, live streaming of data was not tested. If headset data had been streamed the data would have been read, and both the current state and results from the ML/reactor physics algorithms would be displayed on a panel that the user could summon. They could then select some data of interest, and a time-series graph would appear, showing graphs for both results and predicted data. The reactor state would also be reflected in the control rods position moving up and down, which could be seen in the transparency mode.

The ability to view the time-series data in a graph needed to be developed in-house. Viewing large amounts of data in 3D space as normal Unity game objects is prohibitive to performance in MR, so the particle system from Unity was adapted to render large amounts of objects on the GPU.

4.3. Implications

The AGN-201 DT was developed to provide anomaly detection through remote monitoring of a nuclear reactor by combining live operational data with reactor physics simulations and ML interpretations of how the reactor was operating. For this work, we developed the physics and ML models to determine if the AGN-201 was being operated in a manner that was not declared. A physics-informed SM was used to determine the k_{eff} during operations based on the control rod heights and temperature of the reactor. This level of fidelity was sufficient to distinguish large changes that occurred in the core. For remote monitoring, distinguishing large changes in reactivity was sufficient; however, this will not be the case for all DT technologies.

Expanding the DT concept to other nuclear facilities would likely require additional analytical capabilities; in the form of ML, statistical analysis, or multiphysics models. The first would focus on real-time predictions of core operations to determine in a short time frame if the reactor is operating normally. The second would provide a more static-approach and examine deviations in global core parameters that might indicate off-normal operations occurred during a given time. Multiphysics models would provide a more in depth understand of the underlying physics of the core, especially when thermal feedback is present. Finally, the continued inclusion of real-time anomaly detection to help flag potential anomalies that a user would be able to sort through.

Further assessment of the AGN-210 DT for international safeguards requires some additional discussion to highlight strengths and weaknesses. DTs designed for international nuclear safeguards would likely come in two forms: a DT developed by a reactor vendor, and a DT developed by the IAEA. The DT from the developer could be used as an interface between the vendor and the IAEA. Through the DT, the vendor could highlight how safeguards have been implemented into the design before it is built. This process should help ensure compliance with

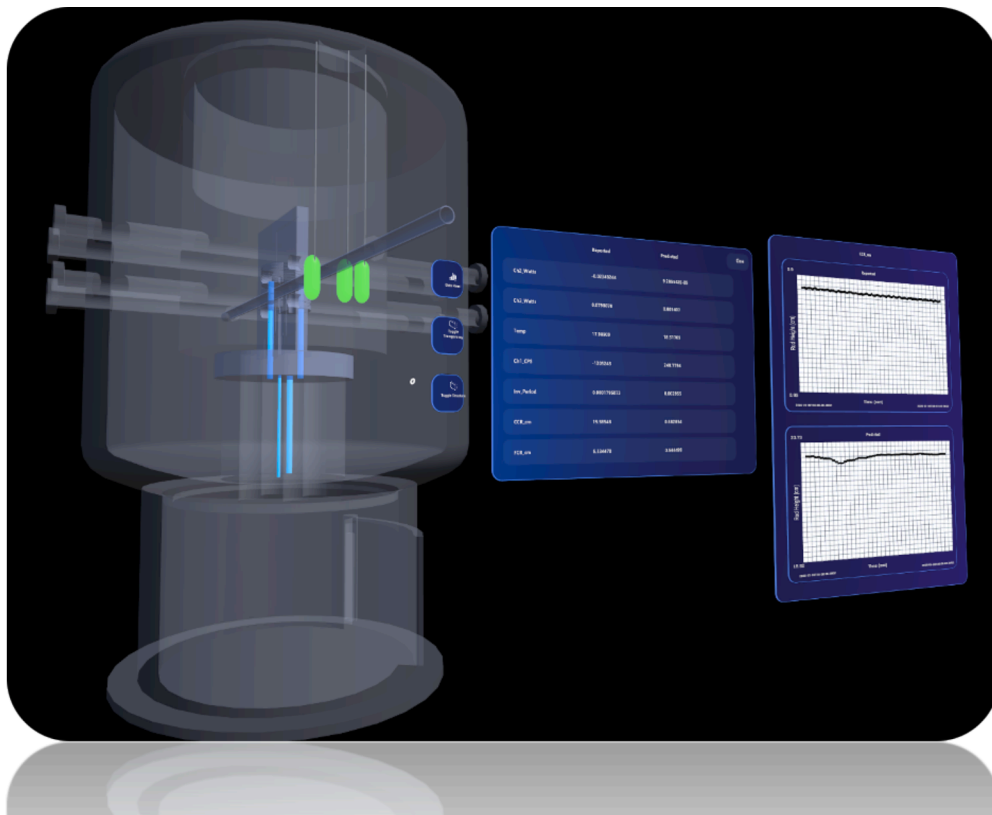


Fig. 12. AGN-201 MR showing the core, detector placement (in green), and operational data being streamed to the HoloLens.

international safeguards regulations for the states that the reactor would be built. Along with this, interfacing with the IAEA in this fashion would likely reduce costly retrofits that to incorporate safeguards (IAEA, 2016). However, these DTs would likely not be utilized by the IAEA to perform safeguards assessments in the field.

For the IAEA, a separate DT would be required; this DT would likely be developed and implemented by the IAEA for an individual reactor. For international safeguards, a DT could be envisioned to monitor various capabilities depending on the need. Near-real time monitoring of a facility, similar to what is presented here, could provide vast quantities of data which might reduce the number of in-person visits for an IAEA inspector. Similarly, data could be obtained on a less frequent basis (days, months, etc.) where the DT could be used as validation of normal operations.

Along with safeguards, remote monitoring would ideally be the first step in developing a more interactive DT which could incorporate feedback into the reactor. Providing feedback would allow for remote facility shutdowns, but more importantly, it could allow for autonomous operations. Autonomous operations have the potential to push the next generation of nuclear energy to allow flexible plant operations and expanded deployment, therefore reaching new and emerging energy and resource markets. Breakthroughs such as the AGN-201 DT, autonomous control of a non-nuclear asset (Wilsdon, 2023), and predictive reactor control (Oncken, et al., 2023; Lin, 2021; Lin, 2023) provide an avenue for realizing and demonstrating autonomous operations.

Despite the many potential advantages DTs provide the nuclear industry, there are several challenges and key considerations that should be resolved to properly create DTs that can fulfill these roles (Yadav, 2021; Yadav, et al., 2021). The high velocity, volume, and variety of data that need to be processed, integrated, and assessed can provide challenges for developing and implementing DTs effectively. DT will likely work jointly with existing monitoring and control systems which may include human machine interfaces which will need to be thoroughly tested and demonstrated to ensure safe and effective operations. Finally, to operate within a nuclear environment, the DT system must meet certain regulations and security requirements (Smidts et al., 2023). Despite these challenges, DTs could be the difference between success and failure in deploying and adopting new nuclear technologies.

5. Conclusions

The AGN-201 DT was the first DT of an operating research reactor which could detect and flag anomalous operations in near real time based on ML and reactor physics. To accomplish this, the AGN-201 DT combined near real time operational data streamed from the AGN-201 and combined these data with ML and reactor physics SMs. Along with this, the AGN-201 DT helps provide a visual understanding of the AGN-201 and its operations. The AGN-201 provides a steppingstone to potentially deploy DT technologies to agencies, such as the IAEA, to allow for remote monitoring of facilities.

Overall, the AGN-201 DT was able to monitor the AGN-201 reactor during operations and, during two separate red-blue team tests, detect when the reactor was not being operated in a declared manner. Despite this, the reactor physics SM was only able to capture large changes in reactivity, due to the inherent uncertainty in describing k_{eff} . These large changes were corroborated by the anomaly detection methods, where ML was able to detect even smaller perturbations. The combination of both ML and physics-informed anomaly detection help provide a deeper understanding and explanation of what is occurring during operations.

Using the AGN-201 research reactor a new technology was developed and deployed to showcase how research reactors can provide new and novel technologies with a testbed for deployment. Through the process of building the AGN-201 DT, several success stories and setbacks were encountered. This article has documented many of these encounters in the hopes that they will provide a foundation for future researchers to continue developing advanced DT technologies to push

nuclear reactor operations.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

References

- "NUCLEAR REACTORS BUILT, BEING BUILT, OR PLANNED IN THE UNITED STATES AS OF JUNE 30, 1970.," Argonne National Laboratory, 1970.
- "Safety Analysis Report Idaho State University AGN-201M Research Reactor," Idaho State University, Pocatello, 2021.
- J. Browning, S. A., R. Kunz, J. Hansel, B. Rolston, K. Wilsdon, A. Pluth and D. McCardell, "Foundations for a fission battery digital twin," *Nuclear Technology*, vol. 208, no. 7, pp. 1089-1101, 2022.
- C. Pope and W. Phoenix, "Idaho State University AGN-201 Lower Power Teaching Reactor - An Overlooked Gem," in *Nuclear Reactors Spacecraft Propulsion, Research Reactors, and Reactor Analysis Topics*, London, IntechOpen, 2022, pp. 67-81.
- Coreform LLC., *Cubit*, Coreform LLC., 2023.
- J. Darrington and T. Conley, "Jester: Time Series and Tabular Data Packaging for DeepLynx," INL, 2024. [Online]. Available: <https://inlsoftware.inl.gov/product/jester>.
- J. Darrington, "The DeepLynx Data Warehouse," Idaho National Laboratory, INL/MIS-22-69294, Idaho Falls, 2022.
- Digital Twin Consortium, "Definition of a Digital Twin," Digital Twin Consortium, 2024. [Online]. Available: <https://www.digitaltwinconsortium.org/initiatives/the-definition-of-a-digital-twin/>. [Accessed 1 October 2024].
- Gorham, M., 2012. Experimental Parameterization of the Idaho State University AGN-201 Research and Training Reactor. Idaho State University, Pocatello.
- Grieves, M., 2002. PLM Initiatives. University of Michigan Lurie Engineering Center, Ann Arbor, MI, Paper presented at the Product Lifecycle Management Special Meeting.
- Grieves, M., 2011. Virtually Perfect: Driving Innovative and Lean Products through Product Lifecycle Management, New York. McGraw-Hill, NY.
- M. Grieves, "Digital twin: Manufacturing excellence through virtual factory replication," White Paper, 2014.
- Grieve, M., 2005. Product lifecycle management: The new paradigm for enterprises. *International Journal of Product Development* 2 (1/2), 71–84.
- IAEA, "Energy, Electricity and Nuclear Power Estimates for the Period up to 2050,," IAEA, Vienna, 2021.
- IAEA, "The Agency's Budget Update for 2023,," IAEA, Vienna, 2003.
- IAEA, Safety of Nuclear Power Plants: Design, Vols. Nuclear Energy Series, SSR-2/1 (Rev. 1), Vienna: IAEA, 2016.
- Idaho National Laboratory, "DeepLynx," Idaho National Laboratory, [Online]. Available: <https://github.com/idaholab/Deep-Lynx>. [Accessed 2024 October 1].
- Idaho National Laboratory, "Jester," Idaho National Laboratory, [Online]. Available: <https://github.com/idaholab/Jester>. [Accessed 2024 October 1].
- Jones, D., Snider, C., Nassehi, A., 2020. Characterizing the digital twin: A systematic literature review. *CIRP Journal of Manufacturing Science and Technology* 29, 36–52.
- J. Leppanen, "Serpent - a continuous-energy monte carlo reactor physics burnup calculation code (user's manual)," VTT Technical Research Centre of Finland, 2015.
- H. V. Lichtenberger, M. Novick, B. C. Cerutti, R. A. Cameron, D. F. McGinnis, E. N. Pettitt, G. K. Whitham, R. A. Haroldsen and L. J. Koch, "Experimental Breeder Reactor (Progress Report, April 1, 1951 Through January 31, 1953)," Argonne National Laboratory, 1953.
- Lin, L., et al., 2021. Development and assessment of a nearly autonomous management and control system for advanced reactors. *Annals of Nuclear Energy* 150, 107861.
- Lin, L., et al., 2023. Development and assessment of a model predictive controller enabling anticipatory control strategies for a heat-pipe system. *Progress in Nuclear Energy* 156, 104527.
- Lindsay, A., et al., 2022. 2.0 - MOOSE: Enabling massively parallel multiphysics simulation. *SoftwareX* 20, 101202.

- F. Liu, K. Ting and Z. -H. Zhou, "Isolation Forest," in *2008 Eighth IEEE International Conference on Data Mining*, Pisa, Italy, 2008.
- R. Loveland, "Temperature Effects on the ISU-AGN-201 Reactor," Idaho State University, Master's Thesis, Pocatello, 2015.
- J. Oncken et al., "Adaptive Model Predictive Control for Heat-Pipe-Cooled Microreactors Under Normal and Heat Pipe Failure Conditions," in *13th Nuclear Plant Instrumentation, Control & Human-Machine Interface Technologies (NPIC&HMIT 2023)*, Knoxville, TN, 2023.
- Oregon State University, "Oregon State TRIGA Reactor," Oregon State University, 2024. [Online]. Available: <https://radiationcenter.oregonstate.edu/oregon-state-triga-reactor-0>. [Accessed 1 October 2024].
- Pedregosa, F., et al., 2011. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research* 12, 2825–2830.
- C. Pope, R. Stewart and E. Lum, "Experimental Breeder Reactor II," in *Nuclear Reactors - Spacecraft Propulsion, Research Reactors, and Reactor Analysis Topics*, Intech Open, 2022.
- Prince, Z., Hanophy, J., Laboure, V., Wang, Y., Harbour, L., Choi, N., 2024. Neutron transport methods for multiphysics heterogeneous reactor core simulation in Griffin. *Annals of Nuclear Energy* 200, 110365.
- Purdue University, "First all-digital nuclear reactor system in the U.S. installed at Purdue University," Purdue University, 8 July 2019. [Online]. Available: https://www.purdue.edu/newsroom/archive/releases/2019/Q3/first-all-digital-nuclear-reactor-control-system-in-the-u.s.-installed-at-purdue-university.html?utm_source=cerkl&utm_medium=[Accessed 1 October 2024].
- Purdue University, "Purdue leading \$6M DOE-sponsored research for small modular reactor and advanced reactor technologies," Purdue University, 26 June 2024. [Online]. Available: <https://www.purdue.edu/research/features/stories/purdue-leading-6m-doe-sponsored-research-for-small-modular-reactor-and-advanced-reactor-technologies/>. [Accessed 1 October 2024].
- R. Rice, "Preliminary design and hazards of report. Boiling Reactor Experiment V (BORAX V).," Argonne National Laboratory, 1960.
- Siemens Digital Industries Software, *Siemens NX*, Siemens, 2021.
- Slaughter, A., et al., 2023. MOOSE Stochastic Tools: A module for performing parallel, memory-efficient in situ stochastic simulations. *SoftwareX* 22, 101345.
- Smids, C., Reyes, G., Endres de Oliveria, C., Cao, L., 2023. The research challenges in security and safeguards for nuclear fission batteries. *Progress in Nuclear Energy* 159, 104627.
- R. Stewart, E. Ryan and A. Shields, "AGN-201 Digital Twin Concept of Operations," Idaho National Laboratory, INL/RPT-24-80534, Idaho Falls, 2024.
- University of Missouri, "NextGen MURR," University of Missouri, 2024. [Online]. Available: <https://nextgenmurr.missouri.edu>. [Accessed 1 October 2024].
- Washington State University, "Washington State University TRIGA Reactor," Washington State University, 2024. [Online]. Available: <https://nsc.wsu.edu/reactor/>. [Accessed 1 October 2024].
- Wetzel, L., Busch, R., Carpenter, K., Bpowen, D., 2019. Nondestructive and Supplemental Measurements of the University of New Mexico, ORNL-TM-2019/1410. Oak Ridge National Laboratory, Oak Ridge.
- Wilsdon, K., et al., 2023. Autonomous control of heat pipes through digital twins: Application to fission batteries. *Progress in Nuclear Energy* 163, 104813.
- Yadav, V., et al., 2021. The state of technology of application of digital twins. U.S., Nuclear Regulatory Commission.
- V. Yadav et al, "TECHNICAL CHALLENGES AND GAPS IN DIGITAL-TWIN-ENABLING TECHNOLOGIES FOR NUCLEAR REACTOR APPLICATIONS," US Nuclear Regulator Comission, 2021.