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An Autonomous Critical Data Extrapolator for the AGN-201m

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Changing the World's Energy Future

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Idaho National Laboratory

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1 Introduction

Nuclear nonproliferation serves as a key goal, being undertaken by the International Atomic Energy Agency (IAEA) [1]. To recognize proliferation there are two pathways that states, who intend to use nuclear material for malicious purposes can take, diversion can misuse. Diversion is when fissile nuclear material is declared to the IAEA for non-weapon purposes, but then covertly removed. If the source of nuclear material, that is not declared and not fissionable, is placed inside the reactor core to create fissile material used to create weapons then the state is using the second pathway of proliferation, misuse [2]. With the emerging development in areas of simulation and machine learning the creation of virtual models of reactor systems, digital twins, serve as a potential method to identify proliferation through detecting anomalous behavior in the reactor.

A digital twin for a physical nuclear reactor has never been developed, as digital twins serve as an emerging technology. To investigate the process for development and use of a digital twin for a nuclear reactor Idaho State University's AGN-201m serves as the nuclear reactor used for development of this digital twin. A data acquisition system has been installed to the reactor system allowing for the transfer of collected data from a reactor operation to Idaho National Laboratory's Deeplynx data warehouse [3].

When utilizing data to train reactor physics and machine learning models, a significant challenge encountered is the initial state of the data. Nuclear proliferation will have the capacity to be detected when the reactor immediately starts up, nor will it occur after the reactor shuts down. Generally, it will be detected when the reactor is operating at some desired power over a sufficient period for that specific reactor design. For the AGN-201m this will be when the reactor is critical (generally 1 mW or above) for a timespan that is within or less than the range of a regular business day. Datasets sent to Deeplynx have had to be manually cut to when the reactor is critical based on plots of power levels. This method is inefficient and laborious, especially when using multiple datasets at once to train a model. To provide a more streamlined approach an automated critical data extrapolator is developed, with capabilities of recognizing when the reactor operation first reaches criticality, and when the reactor undergoes a SCRAM and is shutdown.

1.1 Previous Research Endeavors

Similar to many recent technological advancements in artificial intelligence, digital twins are an emerging technology with substantial potential for new exploration and applications. Digital twins are virtual models that are capable of sufficiently describing a physical model. In this case, a nuclear reactor. Figure 1 provides an overview of the capabilities of a digital twin, with INL's data warehouse Deeplynx being the hub of this functionality. The benefits of utilization of digital twins are largely still being uncovered in the nuclear industry.

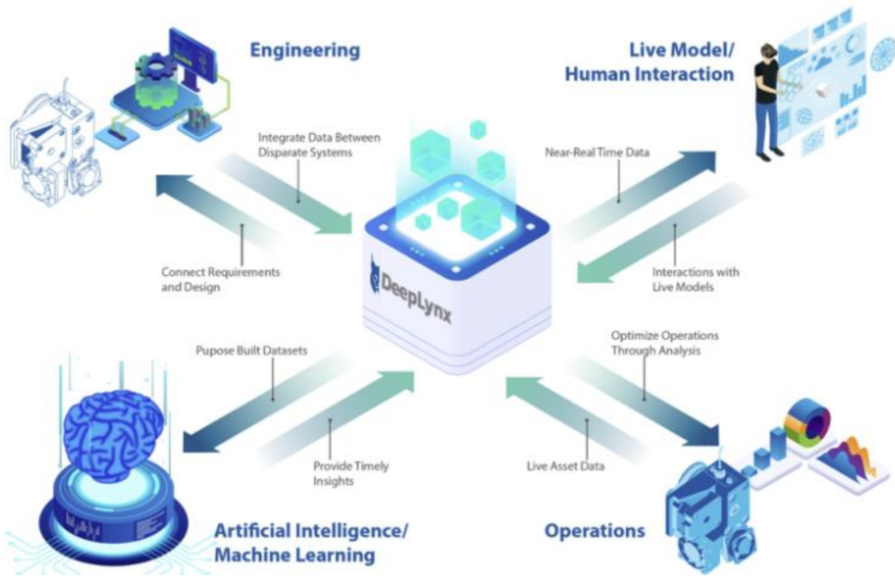

Figure 1: Digital Twin Schematic [4]

Overall, a digital twin is where the premier modeling and simulation programs for a physical system meet. In the case of nuclear energy this includes machine learning and reactor physics models that can then be used to create real-time predictions of the reactor conditions based on the previous conditions fed into the digital twin. Additionally, many digital twins provide adaptability, providing users with a seamless experience no matter their previous knowledge of the system, with capabilities of visualization using augmented and virtual reality.

To address the problems of diversion and misuse of fissionable nuclear material a safe-guards digital twin (SG-DT) has previously been developed to both simulate and train the digital twin to recognize these scenarios [5]. The basis of the digital twin is created from simulations of a 300 Megawatts sodium-cooled fast reactor that is currently under construction and set for startup in 2026. Given that the reactor model is still under development and not in operation a virtual testbed modeling an operation of the reactor was utilized. From the results presented by the machine learning and physics surrogate models digital twins show large potential for shaping the nuclear industry. Apart from virtual and mechanical testbeds theAGN-201m serves as the first-ever nuclear test bed for a digital twin.

2 Data Collection Methods

Understanding the behavior of nuclear reactors and how they can be modeled with live performance predictions serves to be a rather unexplored area of research. The nuclear testbed utilized for the first-ever digital twin of a nuclear reactor is none other than Idaho State University's AGN-201m reactor. The AGN-201m reactor serves as both an educational and research reactor for ISU students and faculty. Given its purposes the reactor is limited to power production of only 5 W [6]. Unlike many commercial power-reactors the fuel for the AGN-201m is found inside of the control rods that are then inserted into the core. Four control rods are employed to power the reactor, two safety control rods which are inserted fully into the reactor, a coarse control rod (CCR), which is the same size as the two safety control rods, and a smaller fine control rod (FCR). Once the reactor undergoes a SCRAM the fueled control rods will drop out of the core using gravity and compressed springs. The insertion heights of the coarse and fine control rods are directly correlated with the power produced. These heights are measured and tabulated as important data for the creation of physics model.

The power output relevant to making predictions to when the reactor is critical is measured by both the Channel 2 and Channel 3 detectors shown by the top-view of the reactor in Figure 2. Channel 2 is used to measure the power produced by the reactor on a logarithmic scale, with capabilities of the inverse period, or change in power of the reactor to be measured as well. Channel 3 is utilized to measure the power of the reactor on a linear scale. Both Channel 2 and Channel 3 will generate a SCRAM when the reactor reaches a power above 6 W (the reactor is still only meant to be operated at a maximum of 5 W, but it will trip a SCRAM at 6 to allow leeway for operations at 5 W).

Apart from the use of control rod heights and Channels 2 and 3's detectors for relevant data, the temperature of the water surrounding the reactor core is also utilized for physics models. To program the Serpent physics model of the reactor it is necessary to have knowledge of what temperature the reactor is at each index to implement it into the algorithm. This occurs on account of how little thermal energy is produced from the AGN-201m reactor core. Generally, the only fluctuation of the water temperature is due to changes in temperature of the surrounding room temperature where the AGN-201m is stationed.

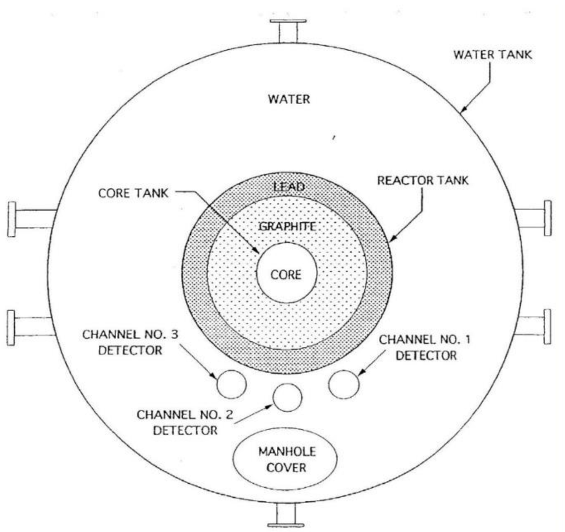

Figure 2: Top-View of the AGN-201m reactor [6]

To define the criticality of the reactor based on data from a previous operation only three main parameters are used to create these automated predictions. To predict startup of the power measured from the Channel 2 detector is utilized. Given that Channel 2 measures power in a logarithmic nature, it provides larger amounts of detail to the behavior of the reactor but is prone to creating noisy data as well. Additionally, the heights of both the coarse and fine control rods are utilized for the detection of shutdown, because will be lowered at the instant of a SCRAM.

Other parameters can be used to define the criticality of the reactor, such as the power measured from the Channel 3 detector, or the Channel 2 inverse-period. Nevertheless, the ones referenced earlier are deemed satisfactory.

3 AGN-201m Reactor Physics Surrogate Models

Apart from machine learning models, the reactor physics surrogate model plays a key role in predictions of operation outcomes and proliferation. From the beginning, a Serpent model is trained based on various characteristics of the AGN-201 reactor. The Serpent model will require three parameters to perform complex mathematical predictions of the state of the reactor. These parameters are the water temperature of the reactor, and the FCR and CCR positions. From this the Serpent model will have the capability of predicting the k-effective (k-eff) of the reactor for each measurement reading provided by the data acquisition system. This interval between the measurements that are taken will be 0.1 seconds.

However, for the Serpent model to create correct reactor predictions it is necessary that the data it is trained on is initially critical (has a k-eff of 1). Therefore, rather than manually recognizing and cutting out non-critical data an automatic method can be put in place, that can work in unison with the existing physics models. This model will allow for the physics models to take in raw data and create accurate predictions as non-critical data will already be cut prior to flowing into the Serpent model. A chart describing the flow of data throughout the training and predictions made by these physics models is illustrated in Figure 3.

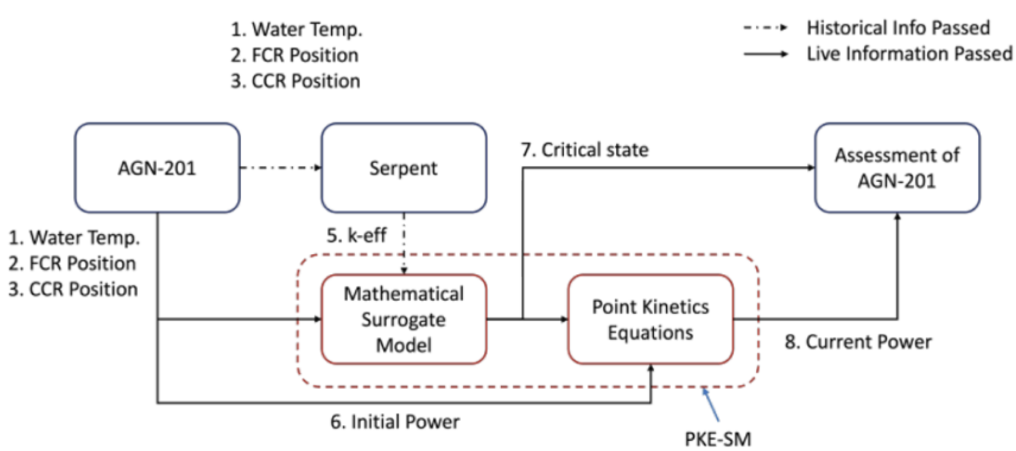

Figure 3: Physics Surrogate Model Flow Chart

4. Autonomous Critical Data Extrapolator

Identifying critical data in an unedited reactor operation dataset must recognize the initiation of two events:

1. When the control rods necessary for criticality are inserted into the reactor (reactor startup).

2. When all the control rods containing the reactor's fuel drop out, and the power drops subsequently (reactor shutdown).

The determination of reactor startup is broken down into two distinct phases. During the time that the reactor is adjusting to its desired power, it is necessary to produce a surplus of neutrons to allow for this power increase. In this phase the reactor is set to be in a "supercritical state", the number of neutrons being produced is larger than the number of neutrons that is being lost. The k-effective is greater than 1 during this period. Once the desired power is reached, there should be an equal number of neutrons being produced and lost in the reactor system; otherwise known as a k-eff equaling 1. Once these conditions are reached the reactor is in a "critical" state. Additionally, apart from noise in the data, the power will approximate to a rather stagnant value. The control rods containing fuel that is inserted into the reactor core will remain stagnant with minor adjustments made to ensure that the power does not drift. Identifying when both periods occur during the operation of a reactor allows for data when K-eff is 1 to be accurately differentiated from the non-critical data that has come before it.

Alongside identification of reactor startup, it is key to separate data after the reactor is SCRAMmed. The data acquisition will still observe data after the initial dropping out of control rods and subsequent rapid drop in reactor power. Training machine learning (ML) models and reactor physics for the digital twin on this data may lead to large decreases in accuracy on the models' predictions. ML models for the AGN-201m digital twin are programmed to predict live data once the reactor is operating. It would be useless to detect nuclear proliferation when the reactor is shutdown. Data after shutdown is cut to allow data that is solely critical to be used for training of models.

It must be noted that transient data after the reactor is initially critical for some time is allowed to be included in the final critical dataset. The beginning of the operation dataset must be critical to obtain a K-eff of 1. Upon obtaining the initial K-eff of 1, additional data involving further supercritical modes of operation can be incorporated to precisely depict an average AGN-201m operation. This allows for the consideration of the reactor's ability to function at multiple power levels within a single operational cycle.

4.1 Startup Recognition

The detection of reactor startup to a reasonable power is necessary for having an initial K-eff value that is based on critical data, to accurately train point kinetics models to make predictions on the AGN-201. During the beginning of data acquisition, control rods used to adjust reactor power may still not be inserted into the core until later in the recorded reactor operation. It is necessary to recognize when the reactor is operating at a considerable power with the coarse and/or the fine control rods inserted at a significant depth in the reactor core.

To detect the beginning of critical data the rate of change in power measured from the Channel 2 sensor utilized. This recognition method is based on the premise of two empirical observations:

1. When the reactor is increasing in power (super-critical state) the rate of change, or slope, of the power will be larger than its original stagnant, but not yet critical initial power.

2. Once the reactor reaches a critical state the power that the reactor is operating will stay stagnant around that desired power. Although, data seen during criticality may be noisy, the rate of change of that data will be largely minimized compared to the slope experienced during the transient power increase.

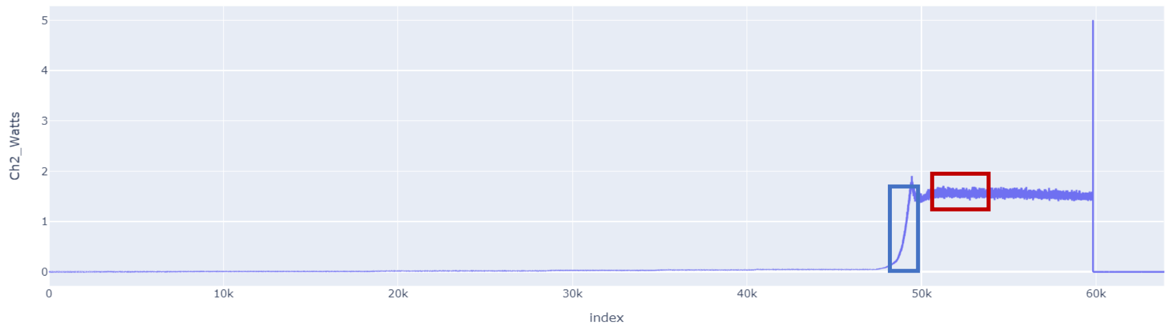

Figure 4: Unedited Reactor Operation Power

Figure 4, shown below, displays the power measured from the Channel 2 sensor from a reactor operation against the index of each datapoint. The plot created based on the reactor power is time-depended on each index representing 0.1 seconds worth of power. Highlighted inside of the blue circle is an example of a transient power increase to reach a desired power level. Across a range of indexes, the slope seen from this power increase is much larger than any rate of change of power experienced previously in this operation. The power will then stabilize at its desired value in the region highlighted by the red square. Although the data is noisy, the average rate of change across an interval of time will stabilize to a significantly reduced gradient. Both regions specified previously serve as an excellent first pass to the creation of a model that can detect the beginning of critical data.

Unless specific experimental/operational procedures are specified for a specific operation the AGN-201m will normally operate a ~10 mW of power. In the case of the dataset plotted in Figure 4, the reactor will reach a critical state much earlier than what is identified above. Through close observations it is seen that a small increase of power results in a stabilization at a considerable power directly before the 20,000th index. Figure 5, shown below, displays a magnified version of this region of data where criticality is initially reached.

Figure 5: Initial Criticality in Data

Similar methods used to determine criticality in the regions larger power/power gradient can still be applied to the determining criticality of a much smaller scale like that shown above. To enable the program to detect criticality accurately on this lesser scale, two influential factors are modified. First is the range of indexes through which the gradient of the power is measured. If the slope occurs on a smaller scale, then the time-period that the slope is analyzed must also be diminished to allow for the slope only in the transient region to be evaluated without any contamination from the slope of critical data. Likewise, the slope in the supercritical region will have a smaller incline, and the noise in the critical data that follows will be reduced as well leading to a smaller of the average rate of change. New slope thresholds are therefore found for both the supercritical and critical regions. Once the threshold is reached in the data for supercritical and critical reactor behavior the data comes before both regions are respectively partitioned off the main dataset. This leaves a dataset with immediate conditions beginning at criticality, allowing for modeling software to be trained on data with a starting K-eff of approximately 1. Data that promptly begins at critical conditions is shown in Figure 6 below.

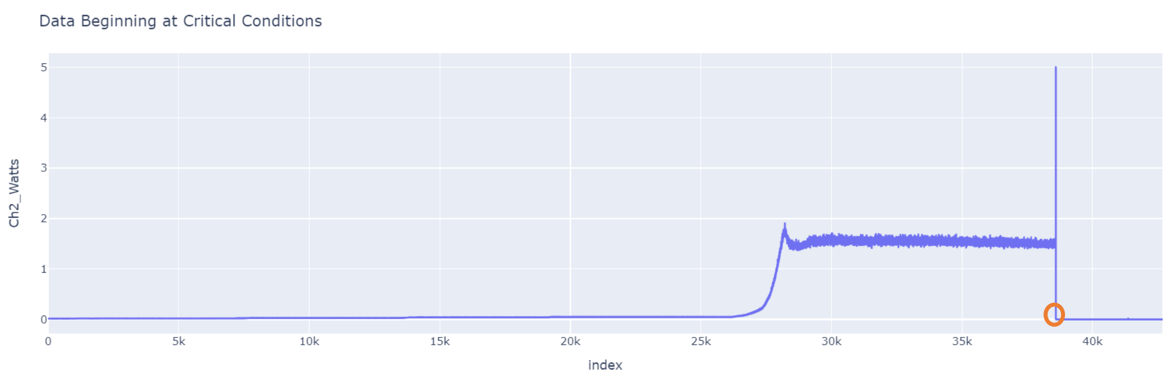

Figure 6: Data Beginning at Critical Conditions

The power at the point where the data is cut is found to be at approximately 17.1 mW. At this point the incoming power data stabilizes to a nearly constant power level.

4.2 Shutdown Recognition

Overall, the data acquisition system and the reactor operation system for ISU's AGN-201m still remain to be two distinct systems. Taking this into account, even after the reactor undergoes a SCRAM and the fuel is ejected from the reactor core data will still be collected. To create a final dataset to be utilized by reactor physics and machine learning models alike, data after the shutdown period must be partitioned off to ensure that the digital twin makes predictions with the highest possible accuracy.

There are many characteristics of the operation data after shutdown that can be used to classify the shutdown of the reactor. These features include, but are not limited to:

- A large negative reactor period, signifying how the reactor power has dropped fast over a small timeframe.

- The power output of the reactor dropping into a small range (microwatt – picowatt range) as the fuel is no longer in the reactor core.
- An instantaneous lowering of the coarse and fine control rod positions inside the core. At the time of a SCRAM both control rods will drop out of the reactor core.

When programming the functionality to autonomously detect the shutdown of the AGN-201m it is not necessary to include all the parameters into the application, as some features may be harder to recognize compared to others. The reactor period signifies the change in power over time; therefore, a similar method that is used to detect initial criticality may also be employed to detect shutdown. However, it is significantly more difficult to find rate of change thresholds that can detect shutdown in all operation datasets. The gradients may vary from instantaneous shutdowns, shown by the 90-degree drop in the power curve on Figure , to drops that where the power is slowly let down before the reactor is SCRAMmed. This same difficulty arises when detecting a specific value that the power drops to when a SCRAM is undergone. The AGN-201m can still operate at very low power, even in the micro-watt range, which may be the power after shutdown for a different dataset. Both approaches fail to offer a cohesive method for identifying reactor shutdown and its precise moment.

To ensure maximum accuracy in the data that is used, utilizing the positions of the fine and coarse control rods has been proven to provide an instantaneous recognition of shutdown of the AGN-201m. Once the reactor operator shuts the reactor down, both the coarse and fine control rods will be measured to be at or near zero centimeters, meaning that they are fully removed from the core. The exact moment of reactor shutdown for the example dataset is signified by the orange circle displayed in Figure 6. Once the control rods are measured to have dropped the power measured from the Channel 2 detector will experience a similar instantaneous drop, as each measurement is taken at each $1/10^{th}$ of a second. Based on testing parameters on various datasets shutdown it is found that shutdown will result in both the CCR and FCR heights reaching below 1 cm or the CCR reaching below 0.3 cm. As data iteratively passes through the critical data extrapolator model, if any point of the data reaches this point shutdown is recognized and the remaining non-critical data is partitioned off. The result, after data before startup and after shutdown is separated is displayed by Figure 7.

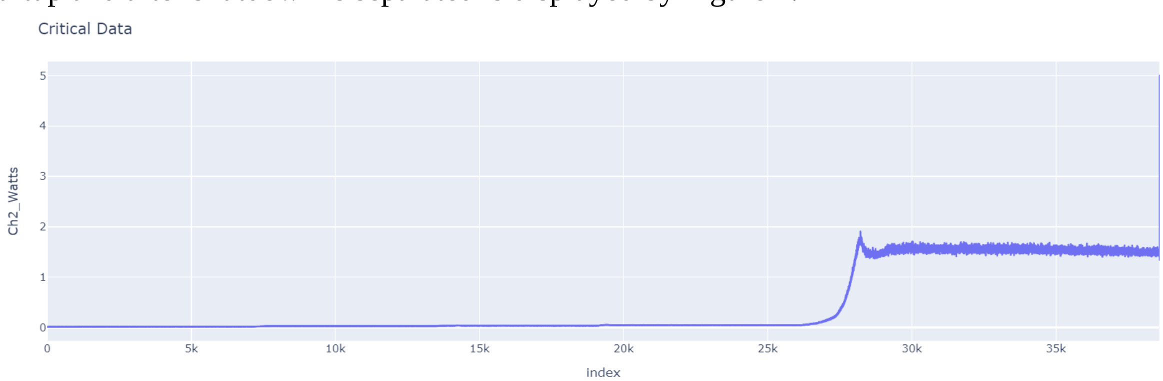

Figure 7: Final Critical Dataset

Future Initiatives

Following all the final tests to validate the accuracy of the critical data extrapolator the process will begin to include this model into the Digital Twin of the AGN-201. Altercations to the architecture of the extrapolator may be necessary to allow for the model to perform live, but the main methods to determining startup and shutdown will remain the same. As the physics surrogate model requires an initial k-eff of 1 to perform properly the critical data extrapolator will serve as the gatekeeper, allowing the reactor physics and machine learning models to operate only when criticality is reached.

The criticality extrapolator will also function as a component of a broader project. The project will entail the training of a deep learning neural network based on data created by the virtual digital twin. Data will first pass through the critical data extrapolator and then be employed for data generation from a physics surrogate model. The predicted data will then be utilized to train a recurrent neural network (RNN), where, based on its architecture and the data it is trained on will make predictions of its own. Overall, these predictions will be compared to actual AGN-201m data to verify the accuracy of the RNN. This larger project will serve as the first machine learning model to have ever been trained on data that is predicted from the digital twin of a nuclear reactor.

Conclusion

Digital twins represent an evolving technological advancement in the digital engineering field. Idaho State University's AGN-201m serves as the first nuclear test bed to ever be used to investigate the potential digital twins have in the detection of nuclear proliferation. It has been recognized that raw data transfer from operational data, generated by sensors in the AGN-201m cannot be immediately used to train reactor physics or machine learning models. To overcome this obstacle an automated critical data extrapolator has been developed with the capabilities of autonomously detecting and cutting out non-critical data out of a reactor operation.

Methods used to detect non-critical data that occurs prior to reactor startup and shutdown includes the use of power measured by the Channel 2 detector, and the CCR and FCR positions. Gradients in power are utilized to determine startup. When a larger gradient threshold is met in a 1 second interval of data then the operation is seen to be in a supercritical stage. Once the slope following this supercritical stage dissipates to a lower threshold then the reactor is detected to be critical. Finally, measurements of control rods dropping out of the reactor core are employed to detect shutdown at the end. These methods can be conducted in an iterative manner, for operations when shutdown criteria are met, but the reactor is never SCRAMmed. Overall, this method provides a streamlined approach of transferring raw data into usable with the possibility of the program working in unison with models of the AGN-201 to allow for accurate digital twin predictions.

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