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Integration of Control Methods and Digital Twins for Advanced Nuclear Reactors

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ABSTRACT

Advanced nuclear reactors offer a new set of features to energy generation, due to their ability to adapt to variable energy demand, operate autonomously, be deployed in rural locations and monitored remotely, afford compact size and lower power ratings, and rely on novel technologies to achieve safer operations. Thus, a requirement for the success of these reactors is the use of intelligent forms of control to track changing power demands, make autonomous decisions, and reduce the need for human involvement.

Regulatory requirements pertaining to control of nuclear reactors could be met via historical means of control; however, these are not expected to enable the level of highly autonomous operations desired in advanced nuclear reactors. Historical control methods rely on both logical and high-performance (HP) control. These two types of control are usually used separately, with a human element being introduced whenever decisions are cascaded from one science to another. AI/ML control, on the other hand, can replace the human element in the current U.S. fleet of nuclear power plants (NPPs) by acting as a supervisory optimizer that understands the plant internal/external variables in order to make control decisions, and can easily handle non-linear and multi-input/multi-out (MIMO) decisions—another requirement for advanced nuclear reactors that could be difficult to handle via logical and HP control. Because of the harsh operating environments produced in advanced reactors, resulting in the frequent failure of sensors and other types of equipment, and considering the lack of operating history for advanced nuclear reactors, control of advanced nuclear reactors would necessitate relying on a model that can track and adapt to the actual process (i.e., a digital twin). This digital twin can make approximations when knowledge and data are unavailable and would evolve as more knowledge is gained. The reactor control must also be risk-informed to account for the high-consequence nature of advanced reactors.

This report introduces a high-level (i.e., not method- or process-specific) integration of the three different control and digital twinning methods able to meet the requirements for advanced nuclear reactors. These methods could be applied during both the operational and design stages of these reactors. The aim is to demonstrate how each method interfaces with and highlights enabling solutions necessitated by the unique features of advanced nuclear reactors.

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ACRONYMS

AI	artificial intelligence
D	derivative
DCS	distributed control system
HIL	hardware-in-the-loop
HP	high-performance
INL	Idaho National Laboratory
M&S	modeling and simulation
MAGNET	Microreactor Agile Non-Nuclear Experimental Testbed
MIMO	multi-input/multi-out
ML	machine learning
MPC	model predictive control
NASA	National Aeronautics and Space Administration
NPP	nuclear power plants
NRC	Nuclear Regulatory Commission
O&M	operation and maintenance
P	proportional
PID	proportional integral derivative
ROM	reduced-order model
SISO	single-input/single-output
SSCs	systems, structures, and components

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Integration of Control Methods and Digital Twins for Advanced Nuclear Reactors

1. INTRODUCTION

The evolution of U.S. and global energy needs has led to demand for a new type of nuclear reactor. Many classical characteristics of nuclear power plants (NPPs) must now be evolved, including their large power capacities (typically ≥1 GWe), large sizes, strong reliance on manpower, onsite construction, immobility, challenges to deployment in rural locations, and primary function as baseload sources of electricity. Also desired are further improvements to nuclear reactor safety, reduced operational costs and nuclear waste, and enabled usage of energy to support processes other than electricity generation. This has motivated the development of novel new reactor types referred to collectively as advanced nuclear reactors. Advanced nuclear reactors possess one or more of the following key features:

- Can operate at lower and/or variable power ratings. In some cases, the power rating may be on the order of a few megawatts, enough to meet the demand entailed by a specific application.
- Can operate in rural areas that are not grid connected, or can primarily be used to support processes other than electricity generation (e.g., a chemical plant).
- Are made highly autonomous due to increased application of automation technologies to such activities as monitoring and control. This is because advanced reactors can be deployed in remote locations, and each central control room takes charge of monitoring and operating several reactors simultaneously. Autonomous operations are also needed to reduce the cost per MWh generated, as manpower is a primary cost driver for the current U.S. nuclear reactor fleet.
- Are small or compact in size. This is often achieved via forms of cooling and neutron moderation (for thermal reactors) that differ from those used in typical light-water reactors.
- Are built in a manufacturing facility or are modularly assembled onsite, thanks to their small size, thus enabling them to be built faster and with mobility in mind.
- Are safer to operate, thanks to several key technological advances such as increased reliance on passive forms of cooling, a lower power, a strong negative feedback coefficient, and a lower radioactive inventory.

Due to these features, advanced nuclear reactor research, design, and development have seen rapidly growing interest in recent decades, with different advanced reactor technologies currently under development having reached various levels of maturity. However, while those features increase the deployment potential for advanced nuclear reactors, they also introduce several unique requirements that must be met before these reactors can be used in the manner envisioned.

The highly autonomous and dynamic nature of advanced nuclear reactors, as well as their potential abilities to operate remotely, necessitates smarter and more powerful forms of reactor control. Control theory can be divided into two different subcategories: passive and active control. Passive control refers to a system's ability to track a desired state without the use of actuation. This feature is often designed into the system by using the laws of physics (e.g., gravity and natural convection). An example of this in the nuclear power industry is seen when making a reactor "walk-away safe," meaning that under loss of power, it will employ natural convection or other physics-based means to passively cool itself until fully shut down. By contrast, active control (the focus of this report) uses actuation to achieve the desired outcome. Active control loops are abundant in light-water reactors and include control of pressurizer pressure and level, primary-side water temperatures, and reactor power output.

Active control is the science and engineering of methods and tools for initiating actions (through the use of actuators) based on measurements captured either by sensors or by humans. The controller design translates the reactor requirements, which are fed into a control loop along with the plant conditions, to determine the necessary process changes needed to achieve the desired outcomes. For advanced reactors, control must enable autonomous decision making, be robust enough to accommodate every fault (both intentional and non-intentional [i.e., adverse]), be adaptive in properly tracking and adjusting to plant and environmental conditions, and be optimized to accommodate conflicting constraints and requirements. Both control methods (i.e., passive and active) often simultaneously co-exist within a given system. For example, researchers are working to develop and couple a model predictive control algorithm to those components that support the passive control of high-temperature gas-cooled reactors—comparing the results against the outcomes of advanced model-based controllers and then assessing the level of accuracy required by the state-space model in order to successfully achieve an efficient model-based controller [1].

Historically, active control methods have leveraged both logical control and high-performance (HP) control, each of which offers its own advantages and limitations. In other words, each corresponds to a certain type of ideal application (discussed in Sections 2.2 and 2.3). Recently, artificial-intelligence (AI) and machine-learning (ML)-based types of control have received increased interest (discussed in Section 2.4). While logical control is based on a human-defined set of rules, both HP and AI/ML-based control were developed and optimized against a model of the system being controlled. Fidelity of the model is critical for achieving optimal control performance, and during the control method development, the model is usually designed to reflect the ideal plant conditions at the reactor design stage (i.e., it does not mirror the plant in an operational environment). HP control includes methods of accounting for model uncertainties by reducing their impact on the control or tracking of the plant states (see Section 2.3). AI/ML-based control makes it possible to retrain the models so as to track the plant conditions. While this approach could potentially serve to meet the need for design basis operations, it would falter whenever the plant begins to operate in new and unknown/unexpected domains, since these control methods were not designed to operate under such regimes. A better understating of the plant processes during reactor operations is thus required, as is achievable by creating—in a digital simulated environment—a dynamic "twin" of the plant (i.e., a digital twin) to either partially or completely emulate the plant's behavior (see Section 3). This digital twin could serve several other functions besides replicating the behavior of a plant or process. For example, it could also be used to simulate failure scenarios or virtualize sensor data (i.e., generate sensor measurements for uninstrumented process locations) so as to ensure that proper control actions are taken.

In the present work, the use of control methods and digital twins are reviewed, summarizing the current status of both in relation to various industrial applications such as NPPs (Sections 2 and 3). This information is then utilized in Section 4, which covers converting the features of advanced reactors into a set of unique aspects. Some of the aspects can be addressed via existing solutions. Others result in technology gaps that must be closed by meeting a set of control requirements, some of which can be met using digital twins. In Section 5, an approach is introduced to demonstrate how the requirements can be met so as to achieve fully autonomous advanced reactor control. Also demonstrated within this overarching approach to control is the role of certain key enabling technologies that are critical to advanced nuclear reactors.

2. STATE OF CONTROL

A controller or control law is an algorithm that determines how actuators should be applied within a dynamical system in order to drive that system toward a desired state. This is in contrast to monitoring algorithms (e.g., anomaly detection), which may influence the control law but do not directly control the system. This section provides background information on control theory and the various controller concepts, with a particular focus on those that can be implemented for the control of advanced nuclear reactors.

2.1 Background

By answering some key questions, this section describes basic control theory concepts that are then built upon throughout the remainder of this report:

- What are the parts of a control system?
- What are the different control objectives?
- What makes a controller design good?
- What are some complications that make controller design more difficult?

Discussing complications that make controller design more difficult is useful for exploring the advantages and disadvantages of various control strategies. While control theory is a mathematically rigorous field, the intent here is to be as conceptual as possible. The aim of this section is not to provide a comprehensive review of control, as such can already be found in the literature and in textbooks [2][3][4].

2.1.1 Anatomy of a Control System

Control systems are comprised of systems, inputs, and outputs. The relationships between these are often shown graphically using block diagrams. In simplified terms, the primary systems are the dynamical system of interest (i.e., the plant, which here includes the actuators and sensors) and the controller. The plant has several inputs (i.e., variables that influence plant behavior) and outputs (i.e., variables that describe the state of the system). The inputs include known control inputs (e.g., actuator signals) and unknown disturbance inputs (e.g., unmodeled dynamics), and the outputs can include measured sensor values and inferred performance metrics. Starting with basic open-loop control (meaning the controller has no knowledge of the measured signals), the controlled input is defined as the reference input (i.e., desired state), and the controller output is defined as the control signal. A block diagram of these connections is shown in Figure 1. This open-loop control is extended to closed-loop control (i.e., incorporating knowledge of the measured signal) in Section 2.1.2 below.

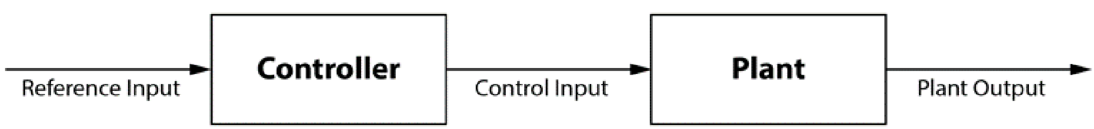


Figure 1. Block diagram of the open-loop control system.

From a controls perspective, the two systems (i.e., controller and plant) can be thought of as functions that map inputs to outputs. The controller is a known function that maps the reference input (and measured signals for closed-loop control) to the control input, and the plant is an unknown function (often approximated using a model) that maps the control and disturbance inputs to the plant outputs. The goal of the controls engineer is to design the control function (i.e., control law) in a manner that meets the design requirements and performance objectives.

2.1.2 Feedback and Feedforward Control

In the area of controller design, the two control objectives most often discussed are the regulator and tracking problems. The regulator problem assumes the controller is trying to regulate around a fixed reference input; the tracking problem assumes the controller is trying to track a time-varying reference input. In the context of advanced or autonomous NPPs, the regulator problem corresponds to baseload or fixed-power scenarios, whereas the tracking problem corresponds to load following or automated startup/shutdown scenarios. In other words, for fully autonomous operation, both problems must be considered. The regulator and tracking problems are often addressed using feedback and feedforward control, respectively.

Given zero disturbances and perfect knowledge of the system being controlled, open-loop control would demonstrate good performance. In practice, this is unrealistic, so feedback control uses the error (defined as the difference between the reference input and the sensor output) to drive the system toward the reference value in the presence of disturbances and despite imperfect knowledge of the system. This is a purely reactive mechanism: it reacts to present and past errors but does not consider future reference inputs. This makes it well suited to the regulator problem but not to the tracking problem.

To properly handle the time-varying tracking problem, feedforward control utilizes knowledge of the current and future values of the reference input to design a control input. This assumes some knowledge of system dynamics in order to calculate the feedforward control input. This description of feedforward control is identical to that of the open-loop control mentioned above. Control systems can combine feedback and feedforward control to properly account for both time-varying reference inputs and disturbances (Figure 2).

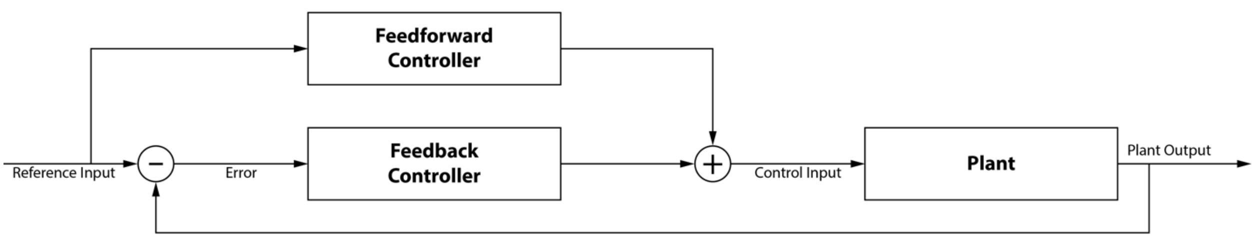


Figure 2. Block diagram of the closed-loop control system, including both feedback and feedforward control.

2.1.3 Performance Metrics

When designing a control system, many different metrics (e.g., stability, transient response, steady-state accuracy, and robustness) can be used to assess candidate controllers and compare various designs. In the context of advanced reactors, these metrics all play an important role in controller design.

Stability is a basic but essential characteristic of closed-loop systems. Stability takes many forms, but for the sake of simplicity, a system is considered stable if bounded inputs and bounded initial states either excite a bounded response (or error) or excite a bounded response that approaches zero error over time. If this condition is not met (i.e., the system is unstable), the response could grow unbounded and result in damage, dangerous conditions, etc.

For a stable closed-loop system, transient response and steady-state accuracy are the next two metrics assessed. The term “transient” can have many meanings but generally refers to abrupt changes in inputs, disturbances, and anything that causes significant deviation from steady-state conditions. In this light, transient response refers to any metrics that measure the system response to transient conditions. This includes measuring the overshoot or speed of response regarding reference signal changes, or measuring the oscillations and settling time as the system recovers from the transient. After this recovery, steady-state accuracy becomes a measure of how closely the system response aligns with the reference signal.

Finally, assuming the use of a system model to design a control law that enables a stable closed-loop system with good transient response and steady-state accuracy, robustness then refers to how sensitive the system performance is to variations in the model parameters (i.e., uncertainty in the system model). This is a key consideration because uncertainty will always exist in the system model, whether because the system is difficult to model or because its parameters can change over time.

2.1.4 Constraints

One complication of great relevance to NPPs is the fact that systems can have constraints. These may come in the form of limits to inputs (e.g., maximum wattage and flow rate) or operating limits to outputs (e.g., the plant shuts down if the reactor pressure falls outside certain upper and lower bounds). Many of the traditional control strategies are poorly equipped to handle constraints defined as hard thresholds, as these are considered a form of non-linearity that complicates the control process.

2.1.5 System Models

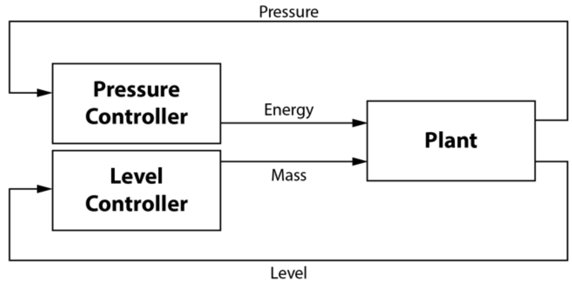
Earlier in this report, the plant was introduced as an unknown function, often approximated with models. This can be done using either a purely physics-based or data-driven approach, or a hybrid of the two. These models are then incorporated into the various controller design strategies to help achieve strong performance.

Regardless of the modeling approach, a degree of error will always exist in the model—a complication that several of the control strategies aim to overcome.

2.1.6 Single-input Single-output and Multi-input Multi-output Control

Another complication that must be considered is whether the control system is attempting to control a single variable using a single actuator (single-input single-output [SISO]) or multiple variables using multiple actuators (multi-input multi-output [MIMO]). SISO systems feature a single input-output pairing, and other variables generally need not be considered. By contrast, MIMO systems feature multiple correlated inputs/outputs that should generally be considered together to maximize performance.

For MIMO systems featuring distinct input-output pairings, one strategy often used at NPPs is to treat each input-output pairing as a SISO system, and ignore the interactions from the other variables. However, this generally leads to decreased performance. This idea of treating a MIMO system as multiple SISO systems is exemplified by the pressurizer system of a pressurized-water reactor. The pressurizer is a saturated system that controls the pressure and coolant inventory by using pressure and level feedback controllers. In greatly simplified terms, the system pressure is controlled by adding or removing energy, while the level is controlled by adding or removing mass. These two control loops can be treated as two distinct input-output pairings. However, adding or removing mass changes the energy as well, meaning that changes to the level also alter the pressure. If these systems were controlled as two distinct SISO systems, any actuation to change the level would create pressure transients that would need to be handled by the pressure controller. By contrast, if they were treated as a MIMO system, the single controller should know that changes in level would change the pressure, and could compensate for that by adding or removing energy while changing mass, thus producing the desired pressure behavior. The two different configurations are shown in Figure 3.



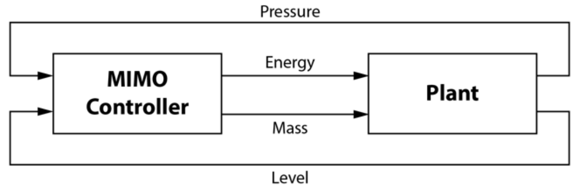


Figure 3. Block diagrams of treating the pressurizer as two distinct SISO control loops (left) or one MIMO control loop (right).

2.1.7 Linear and Nonlinear Control

Functions can be broadly classified as either linear or nonlinear, with linear functions taking the form $y = ax$, where a is a parameter, x is the function independent variable, and y is the function dependent variable. Nonlinear functions deviate from that linear form. Control system design and theory vary significantly from each other, depending on whether the system model equations and controller equations are linear (or approximately linear) or nonlinear, with the nonlinear equations potentially requiring much more involved calculations to demonstrate performance metrics.

2.1.8 Output and State Feedback Control

To discuss output and state feedback control, the notion of the state of the system must be introduced. Consider a robotic arm consisting of motors to rotate each link and sensors to measure the positions of the links. The question then becomes: is the sensor information at a given time (i.e., the positions of all the links) sufficient to summarize the dynamic information about the robot? The answer is no, because the robot arm possesses inertia. A robot arm that is motionless will progress differently from one that is moving. Thus, the state encompasses information on both the position and velocity of each link, meaning that the sensor set does not measure the full state of the system.

In this example, the controller using this sensor set would be considered an output controller because it uses the plant output but cannot access the state. To access the state, two options are available: add velocity sensors or use state estimation techniques to estimate the system state. Examples of state estimation techniques include Luenberger observers, Kalman filters, and particle filters [3][5]—all of which estimate the state via a model of the system combined with the available measurement data collected over time. These techniques would be necessary in any controller design requiring state feedback (also referred to as full state feedback).

2.2 Logical Control

Historically, logical control has been the most common form of control in power plants (both fossil and nuclear alike). It is usually achieved via simple logic decisions (i.e., combinations of AND and/or OR gates and variations thereof [e.g., XOR, flip flops, and threshold functions]). These are often based on piping and instrumentation diagrams that describe process decision making and are developed by process or nuclear engineers when designing the plants. In old installations, analog forms of control—the predecessor to logical control—followed an approach similar to that of current forms of logical control, but relied on operators to perform the control logic in accordance with pre-specified procedures or operator knowledge of the process.

A specific example of a logical controller is a bang-bang controller (also called an on-off controller), which monitors the parameter of interest and turns the actuator either on or off to match the desired setpoint. The simplest example of this is a household heating (or cooling) thermostat. When the temperature drops a certain amount below the setpoint, the heat turns on until the temperature then exceeds that setpoint by a certain amount, at which point it turns back off. This process is repeated in oscillatory fashion to maintain the temperature within the specified operating range. The primary advantage to bang-bang control is that it is simple to understand and implement, and can work well for systems that do not require strict operating margins. The disadvantages are that the oscillating signals and/or frequent switching could be undesirable or create additional wear.

More sophisticated means of logical controls (e.g., sequence development) are seldom used. Sequential control often reflects a series of process changes or plant configuration steps implemented into logic so as to ensure that the process follows those steps—as opposed to an operator using a procedure to implement this process. Due to its simplicity, explainability, and ease of design/deployment, logical control is often resorted to as the plant operation method by industries in need of automated control. Often, a single or redundant controller is assigned a certain part of the plant process, and multiple controllers are linked together through signals or measurements that must be transferred from one process to another. Breaking down the control of a plant into several controllers is often required due to the computational limitations of each controller, as well as to improve overall reliability (i.e., failure of one or a pair of controllers would have a limited impact on the plant processes). Thus, in the logical control world, the control system is referred to as a distributed control system (DCS). Furthermore, it must often adhere to certain performance standards (e.g., an International Electrotechnical Commission safety integrity level of three) defining the “minimum failure rates on demand” requirement (i.e., how high a failure rate can be tolerated given the overall and specific process risks). U.S. NPPs often rely on operators to perform control functions, but have recently been upgrading to digital logical control and using a DCS to achieve this objective, thereby following in the footsteps of the fossil fuel power industry, which in the 1990s and 2000s converted to the use of DCSs.

In parallel to DCS, other systems usually held to higher failure requirements are relied on to operate safety-critical areas of the plant. For example, because fire protection systems, reactor core control, and emergency shutdown systems follow a more rigorous approach to hardware and software design, they thus require lower failure rates (e.g., an International Electrotechnical Commission safety integrity level of four). Such systems have already been adopted for the most critical areas of NPPs. However, many decisions that could potentially impact safe operation of the plant remain the responsibility of operators.

2.3 High-performance Control

HP control was developed to overcome the limitations of purely logical control, and is the most powerful tool used in control theory. It differs from logical control in that it functions based on continuous tracking and modification of the process (i.e., it is not discretized into logical decisions). This field of control is needed for HP applications. For example, to protect against increased pressure in a certain section of a process, the pressure measurement could be fed to a relief valve that then gradually opens to ensure that the process pressure is sustained. This can be contrasted to a logical control process, in which the valve would be opened once the pressure reached a certain threshold. The simplest form of HP controller will track the measured value and use the difference between it and the desired value as the error to be relied upon in determining how quickly and extensively an actuator must be adjusted to reduce this difference.

This section provides a high-level overview of the proportional integral derivative (PID) controller and robust, adaptive, and optimal control frameworks, along with a control strategy example within each of the frameworks. While this report distinguishes among robust, adaptive, and optimal control, these have also been combined to form, among other things, robust optimal controllers. The ability to handle constraints (as defined in Section 2.1.4) is important for NPPs, as they may undergo shutdown when process parameters exceed certain predefined limits. Of the methods presented in this section, only optimal control is capable of directly handling these constraints, though the others may be able to account for them indirectly.

2.3.1 Proportional Integral Derivative Control

In nuclear (and fossil fuel) plants, PID controllers are the most common controller design. Though the most primitive of the HP control methods, they are often selected for their simplicity.

A PID controller calculates the actuation level via a three-part function: a term that is proportional to the error (P), and is used to account for the current value of the error; a term that is proportional to the integral of the error (I), and is used to account for what the long-term behavior of the error has been; and a term that is proportional to the derivative of the error (D), and is used to account for what the short-term behavior of the error currently is [6]. Each of these terms is associated with a parameter that is tuned to make the closed-loop system behave as desired. For example, increasing the gain (or P) parameter of the controller could speed up the controller response but can also cause undesired issues such as overshoot, which is usually dampened by altering the other two parameters (I and D). Operators usually observe how the process is responding and then alter those parameters to achieve the desired performance. As the plant ages, or changes are made to the process equipment, those controllers get re-tuned by the operators. While models can be used to design PID controllers, these controllers are often tuned online, guided by the process, often as trial and error. The primary advantages of PID controllers are that they are easy to implement and understand, and can perform well when applied to SISO linear systems.

Unlike the current nuclear reactor fleet, which has dedicated operators for each unit in a plant, advanced reactors cannot afford having an operator continuously re-tune the PID controllers. Furthermore, the performance of those controllers is insufficient to support very dynamic processes. For example, supercritical CO_2 reactors operate under conditions in which a slight change in fluid dynamics significantly alters the CO_2 properties and requires rapid tracking of the process and adjustment of the actuators [7]—something perhaps unachievable via PID. Additionally, the three degrees of freedom introduced by the PID controller (due to the three tunable parameters) are insufficient for high-dimensional processes that require a higher order control function. Because they are still relatively simple, there is little theory around the implementation of PID controllers for MIMO systems, and they do not address the robustness metric mentioned earlier.

2.3.2 Robust Control

To make control systems more robust, methods of robust control are used. Whereas the use of system models is optional for PID control, robust approaches rely on them. A primary aspect of robust control theory is to quantify the plant uncertainty and then design a controller that can handle any plant dynamics that fall within that uncertainty range. One common approach to robust control is H_∞ (H-infinity) control [8], which aims to minimize the infinity norm of the system model (which includes model uncertainty), with this norm quantifying the extent of plant disruptions due to disturbance inputs.

Robust control techniques are advantageous because they are readily applicable to MIMO systems and can directly include uncertainty and other performance metrics into the optimization. However, their primary disadvantage is that, because they try to account for a set of models (i.e., any model that falls within the uncertainty range), they can be overly conservative, resulting in worse performance than that of a controller designed to more precisely align with the true system. As a result of this disadvantage, robust control techniques are often most useful when the model contains large unmodeled dynamics, large amounts of noise, or rapid and unpredictable changes in model parameters, thus necessitating methods for ensuring adequate performance under such conditions.

2.3.3 Adaptive Control

Another approach to enhancing the robustness of control systems is adaptive control, which also relies on the use of system models. Rather than designing a single controller to handle the uncertainty—as was the case with robust control—adaptive control uses a parametric controller to adapt the control law to the current state of the system. One common adaptive control approach is model reference adaptive control [9]. This control strategy starts with a user-selected reference model featuring the desired ideal performance characteristics, then tunes the controller online using measurement data, such that the closed-loop performance approximates that of the reference model.

Adaptive control overcomes some of robust control's disadvantages—namely, it can provide superior performance in the presence of certain types of uncertainty, since it tunes the controller to the state of the system rather than accounting for multiple states. However, to remain stable, this tuning process tends to occur slowly, meaning that adaptive control is poorly suited to large or rapidly changing types of uncertainty. As such, adaptive control techniques are often most useful when the model contains slowly changing or predictable variations. Another disadvantage of adaptive control is that the theory behind implementing it in MIMO systems is less developed than for robust control techniques.

2.3.4 Optimal Control

Whereas the robust and adaptive control techniques focus on making control systems more robust to uncertainties, optimal control techniques focus on transforming the control problem into an optimization problem by defining control laws as minimizing a cost function. One powerful optimal control approach is model predictive control (MPC) [10], which operates on some fixed horizon, meaning it considers some fixed duration in the future. An actuator sequence is then designed to minimize the cost function over that horizon. This optimization is rerun at every sampling period (or as often as possible in light of the computational constraints), and the actuator sequence is updated as the controller receives feedback from measured signals.

A primary advantage of MPC is that, because it transforms the controls problem at each sampling period into an optimization problem, it gains the flexibility of generic optimization problems. For example, it can handle constraints, disturbances, MIMO systems, delays, etc.—all while maintaining approximate optimality properties. However, because of this added flexibility, its primary disadvantages are its heavy model reliance and the increased design, analysis, and computational effort involved.

2.4 AI/ML Control

AI/ML control can be used to directly control the process. For example, AI/ML control can use data to generate a ML model compatible with more standard control techniques (i.e., some of those listed above), or can utilize reinforcement learning to directly learn a control law that maps sensor information to control signals [11][12][13]. In reinforcement learning, the model (called an intelligent agent—here, the controller) learns the proper actions to take in a given environment (the system), reducing the effort needed to design a control. AI/ML control can also be defined as informing the control function by either modifying the model, adjusting the control loop parameters, influencing feedback or feedforward control mechanisms, or utilizing a combination of all three. When this second definition is used, AI/ML control adopts a supervisory role and is thus referred to as a supervisory controller. Supervisory controllers can correspond to any of the three control types discussed earlier; however, recent advances in AI/ML make it a strong candidate for the supervisory controller. Recently, novel AI/ML-based control has gained momentum, thanks to its ability to address certain gaps associated with common control methods.

A key advantage of AI/ML control is the ability of AI/ML to create—either autonomously or with minimal human effort—data-driven models of non-linear systems. This implies the possibility of controlling poorly understood/modeled systems. However, this would require significant computational power, and would increase the processing time for control actions. This could prove a critical disadvantage when used as direct plant controllers—a key requirement in HP applications. Other limitations on using AI/ML for direct control are that stability and other types of performance metrics are never guaranteed, and that AI/ML operation uncertainty (i.e., ambiguity regarding the control output) exists due to the stochastic nature of AI/ML and the black box nature of the controllers (i.e., their lack of transparency and explainability).

As a result of these limitations, several industries have not yet accepted AI/ML control for use in the direct control of plants. And when used, AI/ML control is often integrated with a more deterministic approach that operates the process and ultimately serves as the main interface to the process. In the nuclear power industry, usage of AI/ML for direct control remains largely theoretical, and is expected to be realized in the form of an indirect or supervisory application for advanced reactors, since the level of autonomy needed for these reactors is higher, and what is desired is a solution capable of understanding the process condition in a supervisory fashion (similar to a human operator) and then adjusting the process control accordingly.

3. STATE OF DIGITAL TWINS

A unified definition of a digital twin does not yet exist in the literature, because various interpretations of digital twins may exist based on different technologies, applications, etc. However, it is possible to define certain primary characteristics of digital twins. A recent report published by the U.S. Nuclear Regulatory Commission (NRC) [14] identifies the following four characteristics of a nuclear digital twin system (see Figure 4):

1. Exists in Digital Form: The technologies and information that form part of the digital twin must exist in a digital format that can be managed, processed, communicated, and executed using digital technology. It is important that this characteristic be explicitly defined for applications in the nuclear industry, which has a legacy of information-sharing via non-digital formats (e.g., paper).
2. Maintains State Concurrence: The digital twin must be able to update dynamically to represent the current state of a physical entity or phenomenon, and it must be able to maintain that state. This vital condition differentiates a digital twin from existing modeling or simulation capabilities that can run in digital form but do not maintain concurrence with the actual system in real-time.
3. Ensures State Cognizance: The digital twin must be able to provide new and integrated sets of insights, information, relationships, and outcomes—all pertaining to the physical entity being twinned, and all made possible, feasible, or efficient thanks to implementing the digital twin. This is another vital condition ensuring that digital twins do not simply re-create preexisting capabilities, but add unique and novel value to the selected application.
4. Serves an Underlying Purpose: The technology must have an underlying purpose that relates to an NPP lifecycle activity, and that purpose should inform decisions about the system or component being represented.

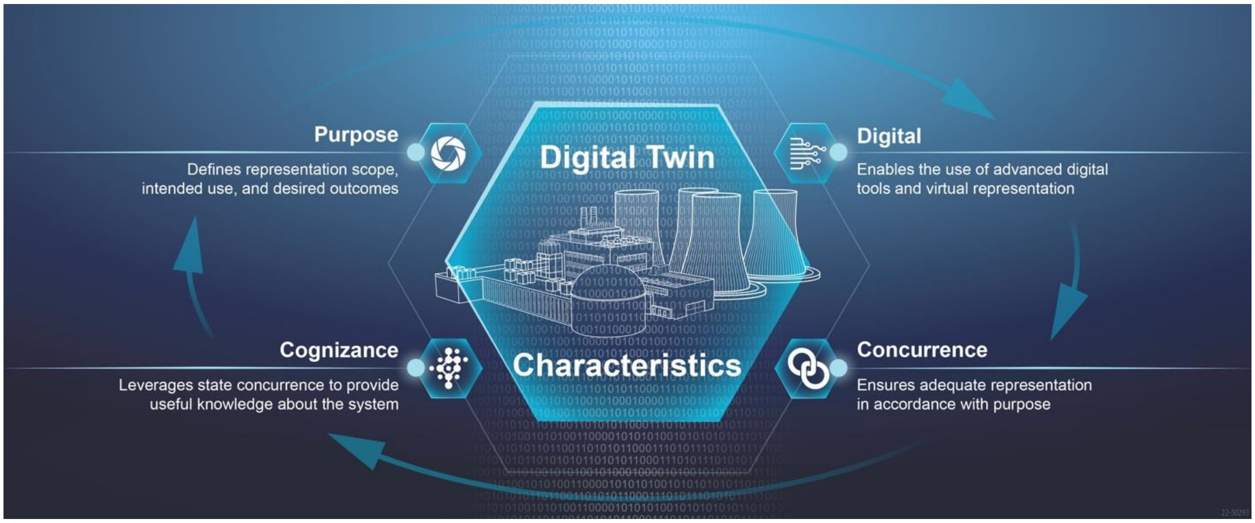


Figure 4. The four characteristics of a nuclear digital twin system [14].

More recently, the concept of a digital twin maturity spectrum has emerged [15]. It is hard to determine when exactly a digital model can be called a digital twin, partly because the capabilities of a digital twin are developed through an evolutionary process. However, digital twins offer value even in their early evolutionary stages. For example, consider a Level 1 digital twin created during the concept and preliminary design phases. Its primary purpose is to mitigate technical risks and uncover issues prior to the construction of a physical asset [16]. Such digital twins can be used for iterative design optimization, maintaining data integrity among different stakeholders, virtual prototyping and testing, etc. [17]. The twin will then mature through the various levels, until reaching full connectivity with the physical asset. At the highest level of the maturity spectrum, the digital twin will afford some degree of autonomous operation and maintenance (O&M) of the physical asset [16].

Digital twins can also feature various fidelities and be based on either physics or empirical data. For example, the development of hybrid digital twins that leverage both model-based and data-driven techniques has been discussed [18]. The effort focuses on how to best construct the reduced-order models (ROMs) from known physics, determine which ML and data-driven methods best represent certain physics that are necessarily neglected in a ROM, and integrate uncertainty quantification into the hybrid models.

3.1 Digital Twin Interface with a Nuclear Power Plant

Considering their characteristics and applications for the nuclear power industry, this section gives a detailed description of a NPP digital twin system (or simply a nuclear digital twin system). A digital twin system for NPPs can consist of four parts, as shown in Figure 5 and discussed below [14].

3.1.1 The Nuclear Power Plant

NPPs contain complex parts that can be categorized in numerous ways, depending on their objective and purpose. From a digital twin system perspective, these parts can be categorized into the following five broad technical areas.

1. Physical Assets. These are commonly referred to as systems, structures, and components (SSCs). As examples, they include the reactor and plant buildings (structures); the cooling, feedwater, power generation, and electrical systems (systems); and pumps, motors, valves, chillers, circuit breakers, compressors, fans, and batteries (components).
2. Physical Phenomena. These are forms of reactor thermal hydraulics, corrosion, concrete degradation, etc., that influence both the plant performance and changes to plant states.
3. Advanced Sensors and Instrumentation. This category includes powering requirements and communication or data transfer infrastructure (e.g., cable or wireless technologies). Connection to the control systems within the NPP may provide a means for digital twins to autonomously influence NPP operational states.
4. Computing and Networking Systems. This category includes both hardware and software for enabling regular plant O&M, and ranges from complex computing clusters to simple handheld devices.
5. Procedures and Human Actions. This category includes normal reactor operations, refueling, engineering, maintenance, safe shutdown, chemical control, etc., as well as control actions. These actions can be continuous (e.g., procedural operator actions to control power) or periodic (e.g., scheduled testing, maintenance, and upgrades).

Of these technical areas, Physical Assets, Physical Phenomena, and Procedures and Human Actions can be considered the *physical twin*, meaning they encompass those entities that can be potentially modeled in digital form, resulting in their respective *digital twin*. The other two—Advanced Sensors and Instrumentation and Computing and Networking Systems—would be required not only for plant operations, but also to enable and support the digital twins of the NPP physical assets, physical phenomena, and procedures and human actions.

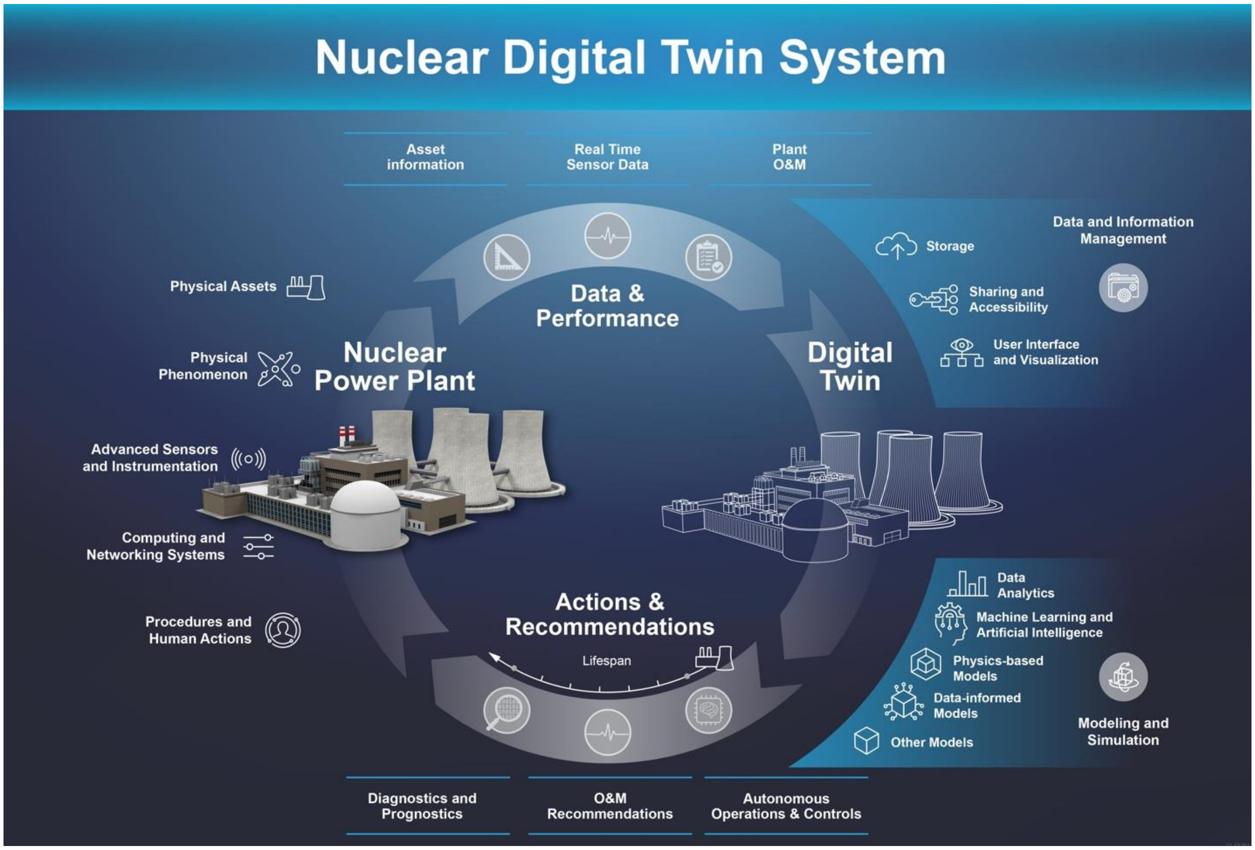


Figure 5. Description of a digital twin for NPP applications [14].

3.1.2 Digital Twin

Digital twins are a representation of one or more NPP entities that fall into the relevant areas identified in the previous section. For producing a digital twin, especially one for an NPP, two broad technological needs that must be met have been identified: modeling and simulation (M&S) and data and information management [14].

M&S is described as consisting of one or more of the following: data analytics, AI/ML, physics-based models, data-informed models, and other model types. Data and Information Management encompasses infrastructure for gathering, processing, and disseminating information in a logical, organized manner that complies with all applicable requirements and presents information to users and computer interfaces in a manner that can be clearly visualized, absorbed, and verified for integrity and correctness [14]. Included within this umbrella are data storage systems such as local plant servers, fleet-wide data infrastructure, and cloud-based storage systems; software solutions to ensure seamless integration of the heterogenous plant data, uninterrupted data availability, and real-time interaction across digital twin models and data storage; and user interfaces outside the main control room, such as a plant monitoring and diagnostic center, a M&S interface, and even handheld digital devices.

3.1.3 Data and Performance

Information on the plant and its SSCs, physical phenomena, procedures and actions, and sensor/instrumentation data is vital for enabling sustained, accurate, reliable, and efficient digital twin operation. Asset information includes dimensions, geometries, topologies, materials, chemical makeups, etc., all of which depend on factors such as SSC type/function and the requirements of the digital representation. Real-time data acquisition in NPPs is primarily intended to support NPP control room information (e.g., reactor power level and pressurizer level/pressure). In the rest of the plant, it is aimed at ensuring safe, reliable operation of SSCs and is generally performed both manually and periodically. Advanced digital sensors that foster wireless capabilities, high bandwidths, and quick installation enable real-time data acquisition and a large number of sensor modalities (e.g., vibration, temperature, pressure, flow rate, voltage, and current) on a much larger and more diverse subset of plant SSCs. Data on plant O&M activities include corrective and preventive work-order logs, outage logs, and licensee event reports, all of which provide comprehensive details on O&M activities—details that can be valuable to digital twin applications.

3.1.4 Actions and Recommendations

The objective of implementing a digital twin system is to provide actions and recommendations in support of safe, reliable, and efficient system operation. To this end, digital twin actions and recommendations have been classified into the following categories: Diagnostics and Prognostics, O&M Recommendations, and Autonomous Operations and Controls [14]. Diagnostics and Prognostics (e.g., anomaly detection, sensor malfunction identification, differentiation between true anomalies and sensor malfunctions, failure predictions, and critical event predictions) can be enabled in real-time by digital twins, thus providing plant staff with real-time notification and recommendations on emergent or future conditions. Predictive algorithms in digital twins can even go beyond diagnostics and prognostics to generate recommendations for efficient O&M practices.

Most operations and controls in existing NPPs are manual in nature; however, digital twin technologies offer the potential to not only recommend but also enable autonomous performance of certain operations and control actions in NPPs.

3.2 Digital Twins in Nuclear and Other Industries

The digital twin concept was initially proposed in the late 90s by the National Aeronautics and Space Administration (NASA) to support the design and operation of air vehicles [19]. Since that time, the range of applications has expanded to include many other industries. Digital twins are of particular interest to the energy industry, due to recent trends in integrated energy systems (IES) and flexible operations having made electricity production processes more complex [20]. However, successful implementations of digital twins in the energy industry remain limited [21]. A 2022 survey found few research publications on digital twins applied to fossil fuel power plants, NPPs, renewable energy systems, and the powering of plant components [21]. However, research on the future adoption of digital twins in the energy industry is being carried out across U.S. national laboratories [22][23][24]. Researchers at Idaho National Laboratory recently performed their first digital twin test of a simulated microreactor. A virtual model of the Microreactor Agile Non-Nuclear Experimental Testbed (MAGNET) used sensor data and open-source technologies to create a consistent flow of information and real-time data sharing, allowing researchers to test, evaluate, and predict microreactor behaviors under different operating conditions [22].

Most digital twin applications in the field of nuclear power have pertained to condition monitoring of equipment or processes. For example, physics-based digital twins are being developed to study the stability of boiling-water reactor feedwater systems in order to address the oscillatory behavior of feedwater heater levels [25]. The digital twin provides a better understanding of this oscillation phenomena, and is useful for investigating different hypotheses about the cycling behavior regarding its origin. Furthermore, a means is being developed of conducting real-time operating performance optimization via a data-driven digital twin focused on predicting moisture carryover in a boiling-water reactor and providing input to a plant's operational plan during a power cycle in order to mitigate high moisture carry-over [26][27].

Both physics-based and data-driven digital twin modeling are being used to assess target systems' current and future states [28]. This includes developing diverse health assessment algorithms and statistics-based approaches that are fused with uncertainty-aware ML algorithms to quantifiably detect statistically significant changes in system health.

Digital twins can also be used to inform maintenance decisions. For example, maintenance advisories are being developed that yield optimal system behavior in accordance with operator-defined objectives and constraints [29]. This approach utilizes digital twins and algorithmic interventions in reinforcement learning algorithms to enable reasoning in the selection of maintenance options.

Outside energy generation, digital twins are also being implemented in industries such as the healthcare, smart cities, manufacturing, automotive, retail, mining, maritime and shipping, agricultural, education, construction, and retail industries [30][31][32].

The manufacturing industry is leading the digital twin implementation efforts by producing the greatest number of publications on the topic [32][33]. This stems from the industry's rapid developments in connectivity due to Industry 4.0 [34][35][36][37][38][39]. Industry 4.0, the latest phase of the Industrial Revolution, focuses heavily on interconnectivity, real-time data usage, and automation. Due to Industry 4.0, digital twins can collect real-time data on machine status, allowing manufacturers to more quickly identify issues and perform process control actions [40]. Digital twins also allow manufacturers to integrate all the phases of the manufacturing lifecycle (i.e., design, manufacture, operation, and disposal) [41][32]. In fact, digital twins have already been implemented in manufacturing processes that support the energy industry [42][43], transportation industry [44][45], and many others.

Another interesting use case of digital twins as applied to a process-oriented industry is found in construction. Just as with manufacturing, digital twins can be used in different lifecycle phases of construction projects (i.e., the designing and engineering, construction, O&M, and demolition and recovery phases) [46]. Construction projects are traditionally challenged by fragmented processes and stakeholders. By integrating information across teams and project phases, implementations of digital twins are able to overcome these challenges [46]. Building information modeling, a technology for creating and managing a digital model containing information on project assets, has aided in the adoption of digital twins by this industry [47][48].

As with manufacturing, smart cities are another area in which the application of digital twins is rapidly evolving due to developments in connectivity [31][32] [33]. By embedding the Internet of Things—a network of interconnected sensing devices—into the core services offered within a city, data can be gathered, analyzed, and monitored to aid in city planning and development [49][50], resource optimization [51][52][53][54][55][56], mobility optimization [57][58][59][60], monitoring of the built environment [61], and identification and management of system interdependencies [62].

In the healthcare industry, digital twins have been used to simulate the effects of certain drugs [63][64]; plan and perform surgical procedures [65][66][67]; monitor, diagnose, and predict various aspects of individuals' health [68][69][70][71]; manage hospitals [72][73], etc.

Though the spread of digital twins from the aerospace industry outward is a fairly recent occurrence, the number of digital-twin-related publications across these varied sectors is growing exponentially, and is expected to continue doing so as more industries undergo a digital transformation [74].

3.3 Digital Twin in Control

In regard to controlling NPPs, digital twins can serve various functions throughout the phases of the control system lifecycle:

During control system design: In the design stage, digital twins can be used as representations of the plant to optimize the controller model. They can also be used to optimize virtual and control-driven sensors, as well as the control response (within the design bases).

During plant testing: During testing, digital twins can be used to evaluate, qualify, and validate the control response (within the design bases—and for some selected use cases, beyond design bases). They can be interfaced with hardware when partial plant hardware is available (i.e., hardware-in-the-loop [HIL]), and coupled to other models such as of external process variables. For example, a digital twin model and a HIL simulation were combined to design a lifting control system for a jackup rig prototype [75]. The digital twin model was used to optimize the control system design, and the HIL simulation was used to test the prototype control system, based on the digital twin model.

During plant operations. Digital twins can be used to determine the plant's external operational state and inform the controllers in real-time. This can be achieved by creating training data otherwise unavailable, then benchmarking the plant performance to the model. Digital twins can also be used to estimate the internal system state and attempt to understand and react to beyond design control scenarios. Digital twins can simulate system operation, and ML can utilize the simulation to optimize or reconfigure a control system, as required, or even to recover from faults when they occur [76]. Digital framework and workflow models can be developed for optimally controlling IES in real-time, based on the system state and desired outcomes [77]. This is demonstrated by full digital-twin coupling, with real-time communication between the physical components, virtual system state, and optimized controls. Digital twins can also be used to model the broader interactions between plants. For example, a control architecture comprised of an automated reasoning system is being developed that closely interacts with a multi-layer advanced control system and is supported by a digital twin [78]. In another case involving multi-generation units, an economically optimal method is being developed of electricity dispatch for IES [79]. This dispatch method uses a high-fidelity digital twin to capture the system dynamic response and inform a MIMO supervisory control system. In addition, digital-twin-based reinforcement learning methods are being developed in order to maintain and/or restore power in communities via a novel coupling of power engineering aspects to sociotechnical aspects and objectives [29]. This research unlocks methods of coupling power-engineering/sociotechnical problems, reinforcement-learning-driven adaptation, and a network synthesis module to augment existing grids in order to optimize the ensuing AI-driven power restoration response.

For maintenance: Digital twins can be used to evaluate the impact of changing/dropping control functions in the event of failures. The digital twin concept was applied to reoptimize a controller [80]. The control system was expected to maintain continuous operation in the event of an anomaly. By applying a digital twin, different failures could be detected and the controller reoptimized to permit continued production. The digital twin can also reoptimize control response (to compensate for aging or maintenance). For example, in the energy industry, a near-autonomous management and control system was developed and assessed for advanced reactors [81]. A set of digital twins was implemented, each serving as a knowledge acquisition system to support different near-autonomous management and control functions (e.g., diagnosis, strategy planning, prognosis, and strategy assessment). The assembly of digital twins supported operator decision making and/or directly suggested operational recommendations based on knowledge of the current plant state, predictions of future state transients, and knowledge of uncertainties—all extracted via ML algorithms and stored in digital twins serving various functions.

As with digital twins, modern control systems are found across many different industries, including transportation, energy, water, healthcare, communications, and manufacturing [82]. Hence, this effort explored the implementation of digital twins across different applications. Control systems that stand to benefit from interactions with digital twins have also been encountered. Although these works have begun to pave the way for the use of digital twins in control systems, the literature still reflects a great need for contributions toward interfacing them [76].

4. CONTROL METHODS FOR ADVANCED REACTORS

Because of their unique aspects (see Section 1), advanced reactors have a unique set of requirements that directly impacts control system design and deployment. This section discusses the unique aspects of advanced reactors and how those aspects leverage existing solutions and result in control gaps that, in turn, introduce a set of requirements for the control of advanced reactors.

4.1 Regulatory Requirements

4.1.1 Unique Aspect

As with any nuclear reactor, advanced reactors are regulated by NRC, making them subject to NRC Regulations Title 10, Code of Federal Regulations (CFR) 50. Specifically, control regulatory requirements, including the need for redundancy, diversity, and defense in depth, are based on ensuring reliable system functionality in the face of a wide range of failure modes. The regulatory requirements also include considerations of design control, verification (for design and configuration), redundancy, diversity, independence, deterministic behavior, simplicity, explainability, clear functional allocation, maintainability, and configuration and obsolescence management. This applies to both control system software and hardware. Other aspects such as cybersecurity, radiofrequency interference (for hardware), and robustness must also be considered. Details on each of those requirements are discussed in the regulatory framework, often citing several standards (e.g., IEEE) for control purposes.

4.1.2 Control Gap

Despite the extensive set of requirements established to ensure that the regulations are met, logical and HP control methods are expected to conform with most—if not all—of them, if designed and developed in compliance with the regulatory framework. However, use of AI/ML control requires the development of special forms of models capable of meeting the requirements. For example, the black box nature of AI/ML models can present an explainability and simplicity challenge that may require increased dependence on validation via tools that could be enabled by systems (e.g., digital twins) that represent the plant process. Concepts such as continuous training and learning during beyond design basis scenarios could be challenged by the configuration control requirements, since methods that adapt to new operation requirements would, in essence, result in new and unvalidated performance behaviors. Those are just some examples of the challenges associated with AI/ML control.

4.1.3 Potential Control Solution

An approach utilizing supervisory AI/ML control could be applied. In this case, the AI/ML would act as an optimizer by informing the logical and HP control (connected to the plant), but for the controllers to meet the regulatory requirements regardless of AI/ML input, they would be configured in a manner that limits their adaptability to plant processes. For example, methods for autonomous decision making are being developed for intelligent supervision of energy systems with secure embedded intelligence in mission- and safety-critical systems, utilizing deep reinforcement learning and digital twins [83].

4.1.4 Control Requirement

Requirement 1: Include an interface control layer between the plant and any AI/ML decision-making processes in order to ensure an approach that meets regulatory requirements.

4.2 Operating Environment

4.2.1 Unique Aspect

Due to the small or compact size of advanced reactors, instrumentation and control equipment (e.g., sensors, means of communication, and edge-computing devices) are expected to endure environments made extreme primarily due to high radiation exposure, but also potentially as a result of high temperatures. Exacerbating this challenge is the fact that the equipment is also expected to run for longer durations, and with minimum maintenance.

4.2.2 Control Gap

Control systems are by their very nature highly reliant on sensors and sensor availability (i.e., communication). If designed improperly, the controllers could create unexpected operating conditions in the event of failures.

4.2.3 Potential Control Solution

Given the high autonomy requirement, advanced nuclear reactors must self-identify and compensate for sensor, communication, and electronics failures, and ensure that the control function remains uncompromised by any such failures. Approaches such as observers/state-estimators (see Section 2.1.8) could estimate the state of the equipment by considering the holistic state of the control system sensors and how they should behave (using a pre-set model). These could also include general sensor redundancy (physical and/or analytical) and inferenced (i.e., virtual) sensors. However, the models degrade when the system significantly changes due to reactor aging or the experiencing of internal/external conditions unaccounted for in the model. Comprehensive and novel monitoring methods would thus be needed.

This is one application in which a digital twin capable of tracking the actual system condition and making ideal judgements as to the plant state would benefit control by means of creating virtual sensors to augment the real ones (or replace them when they fail). However, to achieve optimal use of digital twins, the models must have sufficient fidelity to represent the actual system, and these often cannot be run on the fly while the reactor is operating and the conditions changing. Thus, digital twins must be developed to feature a range of fidelity levels. A means of coupling such models during the design and operation of control systems is currently an area of active research.

Additionally, since likely potential sensor failures necessitate a reliance on virtual sensors, the digital twin must be used to determine the optimal placement of sensors in order to ensure that virtual sensors can be used as a redundant means of measurement, when needed. This is an active area of research. For example, data analytic methods are being developed to address the problem of assigning an optimized set of sensors in a nuclear facility, such that a requisite level of process monitoring capability is realized and, in turn, the sensor set is rich enough to enable data analytics for determining the status of the individual sensors with respect to their need for calibration. A research effort targeting sensor placement is detailed in [84]. Researchers are developing methods for efficient sparse data reconstruction by using digital twin models to define sensor requirements. This research supports the development of a virtual sensing framework by determining the minimum number of required sensors, along with where they should be located.

4.2.4 Control Requirement

Requirement 2: Identify and compensate for sensor, communication, and electronics failures by using advanced control methods and digital twins to prevent the control function from being compromised due to such failures, and optimize the placement of sensors to reduce the impact of sensor-related failures.

4.3 High Safety Consequence

4.3.1 Unique Aspect

While the high safety consequences of failure or malfunction are addressed within the regulatory framework, the operational consequences of such failures are also of critical importance to the deployment of advanced reactors, due to power outages, accessibility, and maintenance feasibility (due to the compact assembly, high radiation and contamination, and remote operations). Additionally, some consequences remain unknown (due to lack of experience [see Section 4.6]).

4.3.2 Control Gap

Current NNPs' control decisions typically adopt a conservative approach in which the uncertainty of the plant state is mitigated by decisions to shut down the process and, in some cases, the reactor itself. Human investigation, risk assessment, and intervention are usually possible for current reactors, and failures of the function (due to sensor, communication, or equipment loss) are often mitigated by switching to manual control. Advanced reactors render such responses infeasible, since the goal is to reduce human involvement as much as possible.

4.3.3 Potential Control Solution

The complexity of advanced reactor control systems presents a much greater challenge, given the level of complexity and risk often entailed by reactor control operations. Control systems for advanced reactors must incorporate an element of risk as part of their operation, since a human operator is unavailable to make risk-related decisions. The control system must understand the plant conditions and the challenges that exist in the plant, then incorporate alternative operation methods—possibly using passive control methods, when needed—and make risk-informed decisions as to the best course of action. In addition to the plant's internal conditions, a risk-informed control approach should also consider external factors (e.g., environmental conditions or cyber/physical disturbances or attacks).

Previous efforts in this area have included work on both fault-tolerant and risk-informed control. The field of fault-tolerant control focuses on detecting and identifying faults, then performing a type of controller reconfiguration to ensure that the new closed-loop system (including the fault) can still operate within the strict operating requirements [85]. Methods to enhance control resilience are also being developed by enabling moving target defense and adaptive maneuvering over the space of command, communication, and control modules in dynamically adjusted clusters of energy resources [86]. The research explores capabilities fusing health, risk, and topology information and digital-twin-based technologies, enabling dynamic relocation of command, communication, and control. In another effort, semi-autonomous control systems are being developed that adapt to the presence of plant degradation [87][88][89]. These systems leverage digital twin models to determine safety and power-generation risks in order to evaluate continued plant operation, then they provide an optimized maintenance approach based on these models. The research successfully demonstrates an adaptive control system based on digital twin risk models. Additional research is needed on how to use risk information to influence the control system [90][91].

4.3.4 Control Requirement

Requirement 3: Incorporate risk elements to prevent unnecessary loss of power generation in the presence of known variables and unknown disturbances.

4.4 Highly Coupled

4.4.1 Unique Aspect

Due to the compact nature of their design and the desire for autonomous operations, advanced reactors often contain strongly coupled systems. This is even more challenging, considering that these reactors have smaller thermal inertia and a faster core response and are expected to rapidly respond to condition and demand requirements as part of their mission to achieve flexible operations as well as load following, which entail dynamics that could prove more challenging than what is seen in the typical electricity production process. Furthermore, those reactors are coupled on the grid with other energy sources.

4.4.2 Control Gap

In the current U.S. fleet of NPPs, control functions are often separated into isolated control loops featuring limited interfacing to the rest of the plant. When coupling is needed, the human operator is tasked with coupling the control loops. This is infeasible for advanced reactors, due to the limited supervisory role of the operator, thus introducing the need for highly coupled MIMO control (see Section 2.1.6). This is often made challenging if the system incorporates a high level of non-linearity (see Section 2.1.7).

4.4.3 Potential Control Solutions

As discussed in Section 2, several types of control methods are capable of handling highly coupled systems. These include but are not limited to robust control (Section 2.3.2), optimal control (Section 2.3.4), and AI/ML control (Section 2.4).

If supervisory AI/ML control is used, a means of coupling those methods with either HP or logical control must be developed, as discussed in Section 4.1.3. For example, methods are being developed for integrating low-level controllers (e.g., PIDs) designed for system stability with a reference governor control algorithm to enable the desired dispatch of electricity control [92][93].

4.4.4 Control Requirement

Requirement 4: Integrate highly coupled control loops and state awareness methods to ensure safe and optimal performance of the process variables.

4.5 Evolving Knowledge

4.5.1 Unique Aspect

Unlike the current U.S. reactor fleet, which has been in operation for decades and is well understood, advanced reactors rely on novel physics and operational concepts not yet fully understood or validated. Given the current state of advanced reactors, their design and envisioned operations rely on models based on experts' understanding of the underlying physics and needs. This results in increased uncertainty, presenting an even greater challenge given that these reactors are envisioned to operate with a high degree of autonomy once deployed. Such autonomy depends on those models and the underlying physics assumptions.

4.5.2 Control Gap

While control functions are usually less dependent on models than on sensors and communication, the models must nevertheless be sufficient to develop the core function of the reactor.

4.5.3 Potential Control Solutions

Enhancing model fidelity via digital twins as knowledge is gained could be a way to successfully reflect the evolution of that knowledge. However, controls testing and validation, when based purely on simulations conducted using digital twin lifecycles (e.g., digital twin certification), introduces a degree of uncertainty. A means of generating adaptable digital twins that can operate outside the original knowledge design domain is needed. For example, new extrapolation and validation methodologies are being developed by combining physical models via the representativity and physical coverage mapping scaling methodologies [94]. The research aims to advance these extrapolation and validation methodologies, thus reducing the reliance on expert judgement.

Alternative methods exist for enabling controllers to track the required setpoints, regardless of the model. Section 2 discusses several ways to handle uncertainty, and these include robust control (Section 2.3.2), adaptive control (Section 2.3.3), and AI/ML control (Section 2.4). An example is found in [95]. Researchers are developing a self-learning control system by using control algorithms obtained through reinforcement learning. The aim is to employ this system to design physics-constrained multi-objective agents that enable autonomous supervisory control during power transients. Similar to the above (Section 4.1.3), if supervisory AI/ML control is used, a means of coupling those methods with HP or logical control must be developed.

4.5.4 Control Requirement

Requirement 5: Incorporate robustness into the control loop design to empirically and gradually model the process and adjust the control method as knowledge is gained, thereby ensuring safe and optimal performance amidst uncertainty and changing plant conditions.

4.6 Lack of Operating History

4.6.1 Unique Aspect

In the current U.S. fleet of nuclear reactors, and due to the expected differences between process/plant models and the actual system, current operational methods often rely on historical behavior in order to modify or tune the plant configuration process to achieve optimal performance. This is usually performed by the human operator (e.g., an operator tuning a PID controller), and is also enabled by the simpler and independent process control loop design. This is unlikely in advanced reactors, as they are relatively new, carry a high level of complexity, lack the human element, and feature no operating history. Furthermore, robust prognostics models and failure data do not exist for these reactors, requiring another source of historical behavior data.

4.6.2 Control Gap

Adaptive and auto-tunable control methods are needed, implying the use of more intelligent forms of control that can benefit from limited operational history.

4.6.3 Potential Control Solution

The operational history can be generated by digital twins able to better represent the process or plant and the coupling to other software or HIL during the design stages, thereby moving from a pure model-based approach to a semi-realistic scenario. Those hybrid systems (comprised of software and HIL with digital twins) can then be used to generate a limited but useful operational history to feed into the optimization of the control method design and development. The coupling should account for the unusual constraints introduced by those technologies (e.g., delay of digital twin simulations or transferable properties of hardware to scale up to deployment in the HIL testing).

For state predictions, faster-than-real-time control technology development for advanced reactors is needed. For example, anticipatory control techniques are being developed to achieve faster-than-real-time prediction and decision-making capabilities for microreactors [96].

Procedures are also needed for when human intervention is needed. Such intervention is to be expected from time to time (at least initially), so the control methods should allow for controlled human intervention activities that compromise neither the operation nor the safety of the reactors, especially during their initial operation.

4.6.4 Control Requirements

Requirement 6: Use software models to identify and react to or track physical phenomena unanticipated due to the lack of operating history.

Requirement 7: Define the human role and what kind of human interventions are allowable, thereby ensuring that humans can monitor the reactor and take appropriate actions as necessary.

4.7 Summary

A summary of the unique aspects, gaps, and control requirements identified in this research is given in Table 1.

Table 1. Summary of identified unique aspects, gaps, and requirements for controlling advanced reactors.

Title	Unique Aspect	Control Gap	Control Requirement
Regulatory Requirements	AI/ML control may not be able to meet some regulatory requirements.	AI/ML control requires the development of a special form of model that meet regulatory requirements.	Include an interface control layer between the plant and any AI/ML decision-making processes in order to ensure an approach that meets regulatory requirements.
Operating Environment	Instrumentation will endure harsh environments for extended periods, increasing probabilities of failures.	The high autonomy requirement makes it necessary to deploy methods that introduce better awareness of the plant and compensate for sensor failure.	Identify and compensate for sensor, communication, and electronics failures by using advanced control methods and digital twins to prevent the control function from being compromised due to such failures, and optimize the placement of sensors to reduce the impact of sensor-related failures.
High Consequence	Operational consequences of failures are of critical importance to the deployment of advanced reactors.	The broader plant conditions and challenges must be understood to make a risk-informed decision as to the best course of action.	Incorporate risk elements to prevent unnecessary loss of power generation in the presence of known variables and unknown disturbances.
Highly Coupled	Compact and autonomous reactors will produce strongly coupled systems, making isolated control less useful.	MIMO control must be able to handle a high level of non-linearity and interface with continuous and discrete states.	Integrate highly coupled control loops and state awareness methods to ensure safe and optimal performance of the process variables.
Evolving Knowledge	Novel concepts of physics and operation will be used that may not be fully understood or validated.	Control method performance depends on the accuracy associated with the system model.	Incorporate robustness into the control loop design to empirically and gradually model the process and adjust the control method as knowledge is gained, thereby ensuring safe and optimal performance amidst uncertainty and changing plant conditions.
Lack of Operating History	A useful operating history to feed into the optimization of the control method design and development does not exist.	Adaptive and auto-tunable control methods are needed	Use software models to identify and react to or track physical phenomena unanticipated due to the lack of operating history. Define the human role and what kind of human interventions are allowable, thereby ensuring that humans can monitor the reactor and take appropriate actions as necessary.

5. THE INTEGRATED ADVANCED CONTROL AND DIGITAL TWIN APPROACH

Building on the requirements developed in the previous section, this section aims to develop a generic approach or framework that enables all the desired control functions for advanced reactors, with all the technological gaps highlighted. This approach will combine digital twins with the three already-discussed forms of control.

Given the inherent differences of control and digital twin methods in terms of operations vs. design, this section introduces a separate approach applicable to each. The main difference between these approaches is that, instead of a physical system, a model is used in the design stage in order to incorporate all or part of the physical process that does not yet exist at the design stage. The following sections discuss each approach—highlighting the role of the requirements discussed in Table 1—to close the overall control loop and meet the unique combinations of requirements associated with advanced nuclear reactors.

5.1 The Operational Approach

Based on Requirement 1, discussed in the previous section, a layered approach to control is proposed, with the direct interface to the plant being achieved through either the logical or HP control (Figure 6). Thus, the AI/ML control layer does not directly control the plant (i.e., takes a supervisory role), but instead influences the other two layers of control. The supervisory AI/ML control makes decisions based on information about the plant or process being controlled (from sensors), the external requirements, and the risk (Requirement 3), and feeds into the input or reference for the controlled process. Therefore, the supervisory AI/ML control layer incorporates broader intelligence to understand linear and nonlinear plant conditions, as fed into the control through multi-input and coupled inputs, and generate multi-outputs that could influence several control loops such as the one in Figure 6 (Requirement 4). In its decision-making capacity, the supervisory layer also uses plant and sensors state information provided by a digital twin (Requirement 2). The supervisory AI/ML control uses models to explain unanticipated conditions due to the lack of operating history (Requirement 6), and adjusts the controllers to adapt to those conditions (Requirement 5). Instead of the supervisory AI/ML control driving the control loop, a human reference can instead be used for control (Requirement 6). The digital twin also controls what sensor values (i.e., physical or virtual) are used in the control process (shown in Figure 6 as a round switch).

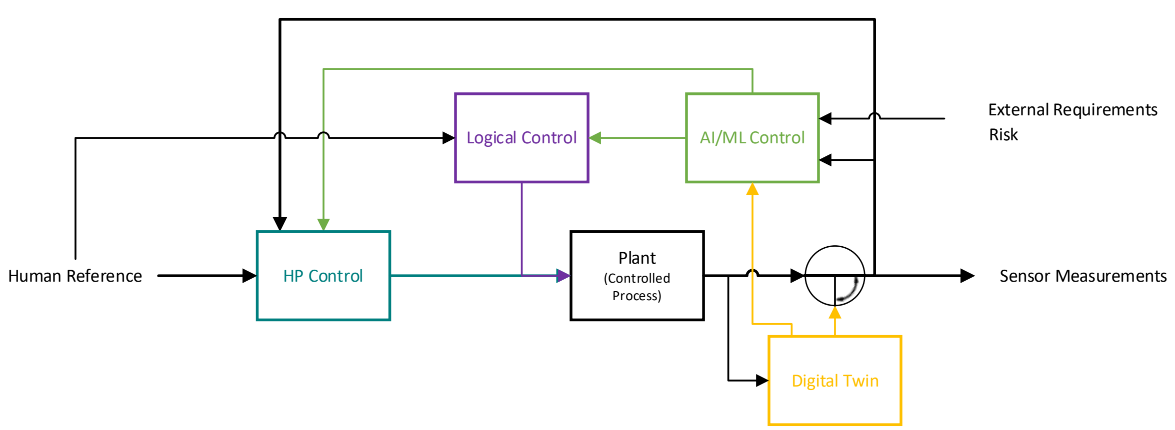


Figure 6. Abstract representation of the operational approach to integrate advanced control methods and digital twins for advanced nuclear reactors.

Figure 7 shows a detailed view of each of the elements in Figure 6. In this figure, the gaps are bordered in red. The plant is represented by physical equipment and certain passive means of control incorporated into the plant and thus not part of the active control introduced by the three layers of control. As discussed earlier, the plant sensor data are fed into a digital twin for deciding which sensors to use. The digital twin is based on two models: high and low fidelity. The high-fidelity model (labeled HF model in the figure) is used for condition monitoring, which is usually not time-critical and thus can afford the longer processing time. The low-fidelity model (labeled LF model in the figure) is an abstraction of the high-fidelity model, and was developed using various reduced-order modeling approaches. Its main characteristic is that it has enough fidelity to develop sufficient state awareness of the controlled process and is informed by the condition monitoring. The low-fidelity model is used for rapid, time-critical decisions, often associated with operational actions. This is the core role of control. Therefore, it is used in determining the operational state of the controlled process or plant.

In addition to its equipment condition monitoring role, the digital twin can also determine the condition of the sensors and, when needed, can isolate or adjust the inaccurate measurements—an important feature of the digital twin, since the harsh environments and long operational lifetimes of advanced reactors increase the probability of sensor failure (see Section 4.2). This ensures that the control loop uses more representative measurements of the plant, regardless of whether the sensor measurement is physical or virtual.

The operational state of the process or plant, as determined by the digital twin, is fed into the supervisory AI/ML control layer, which functions as an optimizer. One common approach to supervisory AI/ML control is the use of reinforced learning, which usually optimizes the decisions made, based on a reward function. While this is an online trial-and-error approach to learning what actions lead to ideal outcomes, a digital twin can be used to train such an optimizer, as is discussed in the design approach covered in the next section. The AI/ML supervisory control receives the external requirements (on the process or plant scale) as well as the plant state from the digital twin. Next, that information is converted into a form usable by the optimizer. The AI/ML supervisory control must also be informed about the risk associated with taken actions. Therefore, a risk model must be developed for the various operational decisions of the plant, and those decisions must be fed into the supervisory AI/ML control optimizer. This is another area critical to advanced reactors, given their nature and the desired level of autonomy (see Section 4.3).

The decisions made by the supervisory AI/ML control layer are passed to one or both of the other two control layers. Logical control methods are mature enough for use in various industries, including the nuclear industry. However, a gap has been identified in the form of a means by which supervisory AI/ML control can interface to this type of control. The same gap also exists for HP control; however, this type of control can take multiple forms, and the interface must be able to couple to each. The three forms of HP control presented herein are:

- Control multiplexing: This is needed when a set of different controllers are required and it is desired to switch from one to another, based on the process or plant state, as a single controller may not be adapted to all states. For a possible example of this, consider that, when the process is operating at normal conditions, actions are taken more rapidly than when the process is degraded. Rapid actions can introduce a form of risk. In control theory, non-linear dynamic compensators are one way of ensuring that transitioning from one controller to another does not introduce instabilities into the controlled process. Instead of conducting multiplexing on standalone controllers, robust controllers (Section 2.3.2) can be developed to address multiple states. These controllers can also be coupled with standalone controllers through control multiplexers.
- Control optimization: Unlike the overall process optimizer in supervisory AI/ML control, this control optimizer focuses on the control metrics discussed in Section 2.1.3. It is therefore more

control-focused, and several methods exist to frame this controller as an optimization problem (e.g., model predictive control [Section 2.3.4]).

- Change control compensators: While digital twins are able to predict sensor issues and compensate for them, change control compensators provide an extra layer of defense, enabling the controller to track the plant state, and adjust the controller to compensate for sensor issues and changing plant conditions (i.e., they adjust the controller instead of the sensors to adapt to changing plant conditions that impact the control model used in designing the controllers). Adaptive controllers discussed in Section 2.3.3 are one type of those change compensators.

Because both the logical and HP controllers can be used in a control loop, an interface is also needed to couple the two approaches. As was already discussed, current reactors rely on a human to achieve this, but such an approach is infeasible for advanced reactors, given the reduced human role.

Finally, because advanced reactors have no operating history (Section 4.6), the human role must be defined, as it is expected to be of significance during the initial operational phase of the advanced nuclear reactor. This role will phase out as the operational history is developed. However, a margin for human intervention must be designed, and a mechanism for ensuring that this intervention does not impact the condition, risk, or state of the reactor must be incorporated.

5.2 The Design Approach

The design approach shown in Figure 8 mostly resembles the operation approach discussed in the previous section, apart from the aspects relating to the digital twin and the definition of the plant. In this case, the plant is actually part of the physical process being controlled, or is in some cases nonexistent. In cases where the physical system partially exists (e.g., simulating a reactor when the actual core is unavailable but the rest of the plant is), a HIL approach becomes necessary to couple the physical system with the digital twin. Therefore, a suite of interface technologies must be developed to incorporate the different hardware and software tools needed to achieve real-time coupling, which is especially critical to HP control because of its sensitivity to time delays.

Another key difference in the design approach is the need to use the sensor virtualization (already discussed) to feed into the placement of sensors. This is one of the digital twin roles, with the primary consideration being that the sensor placement must account for the redundancy requirement for virtual and physical sensors, as well as the digital twin's ability to diagnose the conditions of the plant and understand its state in order to feed that information to the supervisory control.

Due to lacking part of the real system, and because actual failures take some time to occur, the design approach will use simulated failures to evaluate the digital twin's ability to diagnose and prognose plant conditions. In similar fashion, sensor measurements of the external conditions of the overall reactor or other coupled processes are simulated during the design phase.

Except for the key differences discussed herein, the remaining design approach elements for integrating advanced control methods and digital twins are the same as those seen in the operational approach.

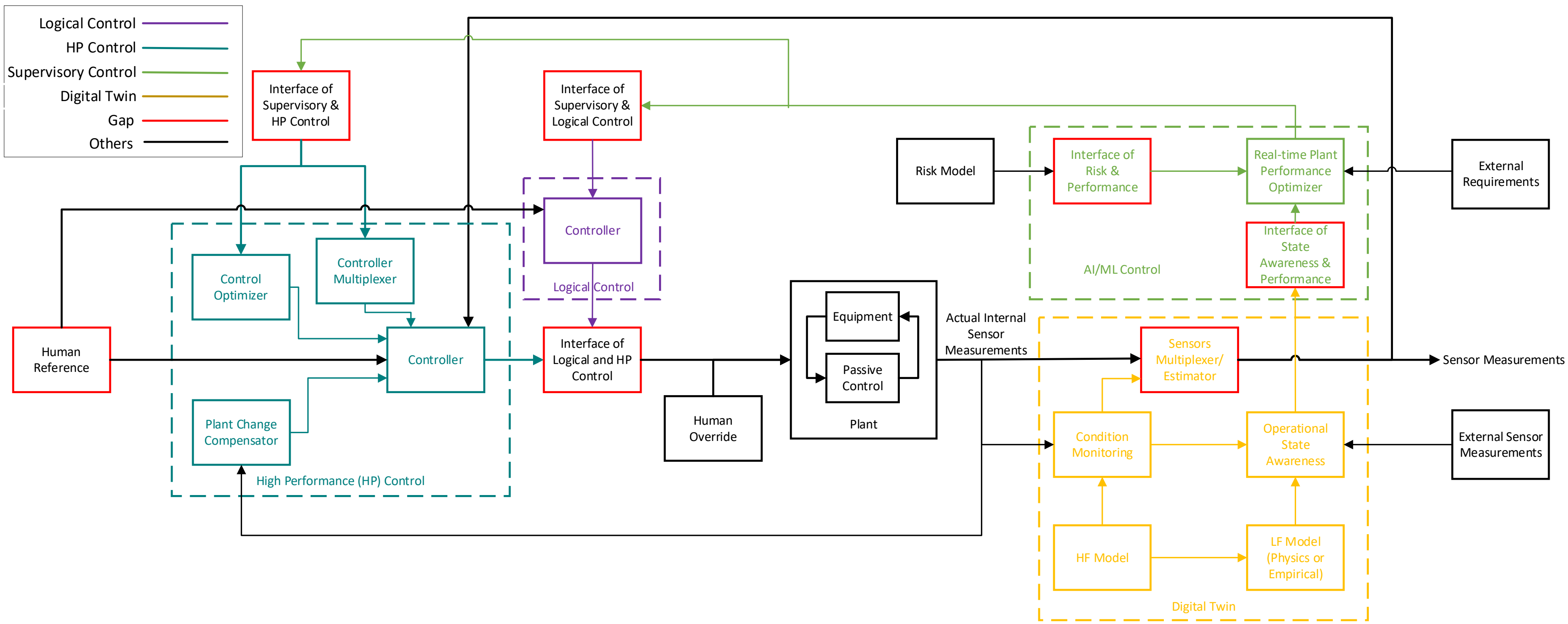


Figure 7. Operational approach to integrate advanced control methods and digital twins for advanced nuclear reactors.

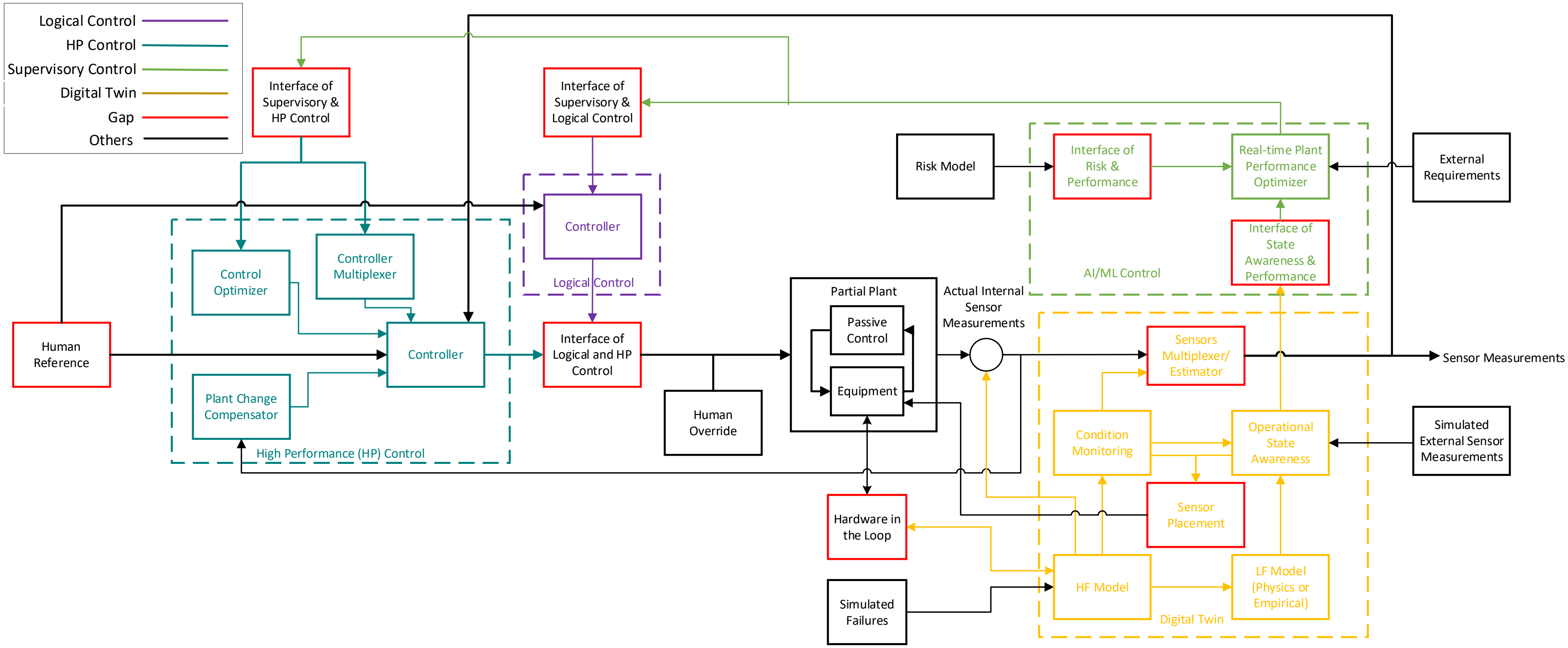


Figure 8. Design approach to integrate advanced control methods and digital twins for advanced nuclear reactors.

6. CONCLUSIONS

Given advanced reactors' unique aspects, several gaps must be addressed to enable their highly autonomous operation. Closing those gaps will result in a set of requirements that can be met using a layered approach to control—one that interfaces with a digital twin. Digital twins are a key enabler for deploying control of advance nuclear reactors. They provide otherwise unavailable information for the design and operation of controllers, and can be used to compensate for the lack of operating history. They can also be used to foster ideal placement of sensors in the design stage of the reactor, and to virtualize sensors during operations. Combining HIL with a digital twin of the other parts of a process would enable partial testing of various control functions.

Another key enabler for autonomous reactor operation related to the use of AI/ML for broader and supervisory intelligence, MIMO optimization, modeling of non-linearity, and integration of risk into the decision-making processes. Because this type of control is not used in the current U.S. reactor fleet, it was necessary to isolate it from the actual control and limit its ability to configure the plant to what the other control methods allow. This is a key research topic identified in this effort, along with determining a means of coupling the two other forms of control. This approach ensures that the control system, including the supervisory AI/ML control, is more likely to successfully meet regulatory requirements.

Though the human role is envisioned to be limited to supervisory decision making, it is expected to be present—even significant—during the initial stages of operation, and to diminish as the operating history is developed and the autonomy is evolved to a level that enables this human role to be reduced. This initial human involvement is due to the nature of supervisory AI/ML control. While it will leverage the digital twin initially, differences between the digital twin and the actual reactor conditions, along with experienced operations that fall outside the digital twin design-basis scenarios, are expected to be observed during operations, and one of the functions of supervisory AI/ML control is to learn from such variation and adjust the process accordingly.

While several research efforts are underway to close the gaps and consequently close the control loop presented in the operation and design approaches, those remain the most critical aspect of deploying advanced control methods for advanced nuclear reactors. Other elements of the control loop are simply common control methods needed in other industries, and are thus sufficiently mature for use in advanced nuclear reactors.

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