ANL/NSE-23/22

Cost Benefit Analyses through Integrated Online Monitoring and Diagnostics

Final Report

Argonne National Laboratory
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Cost-Benefit Analyses through Integrated Online Monitoring and Diagnostics

Final Report

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1 Introduction

The objective of this research is to improve the economic competitiveness of advanced reactors through the optimization of cost and plant performance, which can be achieved by coupling intelligent online monitoring with asset management decision-making. As advanced reactors are early in the development life-cycle, online monitoring systems and associated sensor networks can be incorporated directly into the design without constraints related to retrofitting and system upgrades.

1.1 Motivation

Economic competitiveness is the greatest barrier facing the U.S. nuclear power sector. The U.S. operating light water reactor (LWR) fleet is struggling to remain profitable in a challenging market environment, leading the federal and state governments to provide incentives to ensure that the U.S. retains its largest source of carbon-free electricity. While these efforts aid in addressing the issue in the short-term, sustainable changes are needed to improve the long-term economic outlook.

Nuclear power plant operating costs are constrained by many factors, such as security requirements or fuel costs. However, improvements in asset-management and operational strategies offer one avenue for cost reduction that is within the control of utilities. For advanced reactor designs, this includes maintenance activities associated with systems and components, along with potential changes in operational modes, such as power reductions. The difficulty is optimizing asset-management and operational decision-making in a complex and interconnected environment. There are numerous factors that can influence the course of action, including the current status of plant components, projected revenue, regulatory compliance, etc. A comprehensive assessment of these factors must be conducted for a truly optimized solution to be found.

1.2 Project Overview

The current research is focused on the optimization of advanced reactor operation and asset management using online monitoring and diagnostics and intelligent decision-making. To achieve this goal, the project developed the high-level analysis methodology outlined in Figure 1-1, which is briefly discussed here.

First, during the reactor design phase, it is necessary to develop a sensor network that can properly monitor and diagnose important component faults and degradation throughout the lifetime of the plant. This is a difficult task as there are many unknowns regarding long-term operational reliability and the associated costs of additional sensors and system penetrations can be prohibitive. Therefore, development of the sensor network must be optimized based on these criteria while ensuring necessary system diagnostic capabilities. For the current project, the Ohio State University (OSU) Integrated System Failure Analysis (ISFA) method it utilized for this assessment.

Once reactor operation begins, the sensor network is utilized by an online monitoring and diagnostic tool (such as the Argonne PRO-AID tool [1]), which provides a real-time picture of component and system performance. Specifically, both slow degradation phenomena (wear and tear of components and sensors) and abrupt events (leakages, valves failures, etc.) are diagnosed. Based on the analysis performed by the diagnostic tool, the plant risk profile must be updated to accordingly to represent the real-time condition of the plant. For an operating plant, the plant risk profile includes not only safety considerations, which are evaluated through the probabilistic risk assessment (PRA), but also productivity concerns, which are gauged through the use of a generation risk assessment (GRA).

Utilizing the real-time plant risk profile, a risk-informed decision-making process then attempts to optimize plant operations and asset management plans. The challenges of this task include cost-benefit decision-making in multivariate space while ensuring the plant does not approach risk or safety limits. Markov Decision Processes (MDPs) are utilized to perform this task in an efficient and intelligent manner.

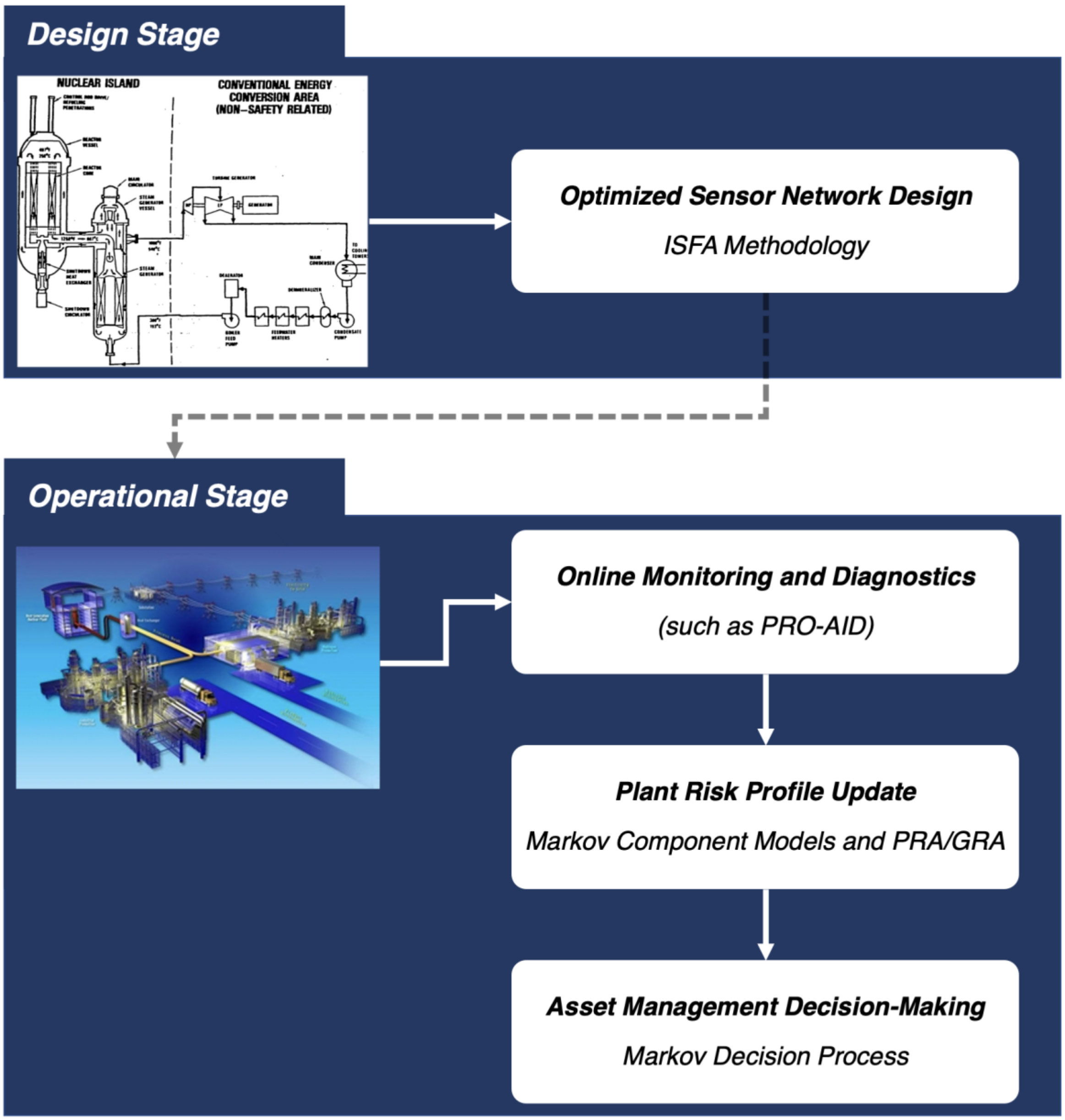


Figure 1-1: Overall Project Methodology and Structure

1.3 Project Objectives

The project has two main objectives, as detailed below:

- **Sensor Network Design**:
  - Further development of the OSU ISFA methodology capabilities to permit additional optimization criteria and refine the optimization analysis approach.

- **Asset-Management Decision-Making Optimization**:
  - Creation and development of an approach for asset-management and operational strategy optimization that comprehensively and seamless incorporates all available data stream into the optimization analysis, including online plant monitoring, component models, and the plant risk profile.

In addition to the methodology tasks outlined above, the project seeks to perform a preliminary demonstration of the approaches as part of the effort to commercialize the developed technologies.

1.4 Report Structure

The following report provides an overview of the research and its findings and is structured based on the major project initiatives, as outlined in Figure 1-2. The Introduction section gives a brief overview of the project and its structure. The section is followed by sections on Sensor Network Optimization, Intelligent Asset-Management Decision-Making, and a Time-to-Market (T2M) Analysis for the developed technology. The last section provides concluding remarks on the project, along with the list of accomplishments and the possible next steps towards further enhancing the proposed methodology.

Section 2: Sensor Network Optimization

- ***2.1: Methodology***
- ***2.2: Demonstration***

Section 3: Intelligent Asset-Management Decision-Making

- ***3.1: Methodology***
- ***3.2: Demonstration***

Section 4: Time-to-Market Analysis

- ***4.1: Findings***

Section 5: Conclusions

- ***5.1: Accomplishments***
- ***5.2: Next Steps***

Figure 1-2: Report Outline

2 Sensor Network Optimization

The first focus of the project was the further refinement of the OSU ISFA methodology [2-4] for the development of an optimized sensor network design. This section briefly introduces the methodology and the experiments designed to verify the effectiveness and performance of the sensor selection method developed to generate optimal sensor deployment configurations for online monitoring (OLM) systems for advanced nuclear reactors. In the experiments, several important capabilities of the OLM system, such as the capability of observing various states of the target system, the capability of fault detection and discrimination, the capability of fault prognostics, and various other characteristics that sensor systems should fulfill such as functionality, integrability, reliability, and cost, are taken into account when generating optimal sensor deployment configurations. A reactor cavity cooling system (RCCS) of the General Atomics (GA) Modular High-Temperature Gas Reactor (MHTGR) is selected as the case study system in these experiments. This section proposes a multiple-objective optimization algorithm which outputs a series of sensor deployment solutions, including the numbers, types, and positions for deploying the sensors required by the OLM system.

2.1 Methodology

When a safety-critical system is still in the development phase, it is difficult to select a sensor deployment strategy for designing the OLM system related to such a system due to the shortage of operational data. This section introduces a model-based method that can determine the best candidate sensors to be used by an OLM system by utilizing the inferred signal features of the system in the development phase. These signal features and the corresponding sensor selection criteria can be derived from the outcomes of a qualitative model-based fault analysis method, the ISFA method, which infers the impacts of system faults and their evolutions. Six sensor selection criteria were identified. Table 2-1 displays the sensor selection criteria used by the proposed methodology.

Table 2-1: Sensor selection criteria used by the proposed methodology

Criteria	Description
1. Fault Detection and Discrimination (FDD)	Evaluate the capability of the OLM system in detecting and identifying various types of faults in the target system.
2. Fault Prognostics	Evaluate the capability of the OLM system in forecasting component failures during system operations.
3. Observability	Evaluate the capability of the OLM system in observing system signals and states.
4. Functionality	Evaluate whether the functions of a sensor satisfy the requirement of the OLM system
5. Integrability	Evaluate the difficulty in installing a sensor into the monitored system.
6. Cost	Evaluate the expenses for adding a sensor to the OLM system.

Applying the methodology to a safety-critical system includes several steps, which are introduced below:

1. Create qualitative ISFA models for the target system (i.e., the RCCS in this report). This step identifies the system components, their functions, and the flows transmitted by these

components (e.g., the airflow delivered by the inlet pipes) since sensors will be deployed to measure the physical variables related to these flows (e.g., the flow rate and the pressure of the airflow).

2. Run ISFA simulations and generate signal features under various failure scenarios. The simulations utilize the qualitative models of the identified components, flows, and functions to infer the trends in the physical variables under various failure scenarios and generate signal features based on the trends.
3. Apply the sensor selection criteria to evaluate the effectiveness of the OLM system. These criteria can be used to rank and evaluate the important aspects (e.g., the ability to diagnose faults, etc.) of the OLM system.
4. Use a Multiple Objective Optimization Algorithm to select the optimal sensor deployment configuration. The optimization algorithms leverage the selection criteria as objective functions for evaluating various sensor selection solutions.

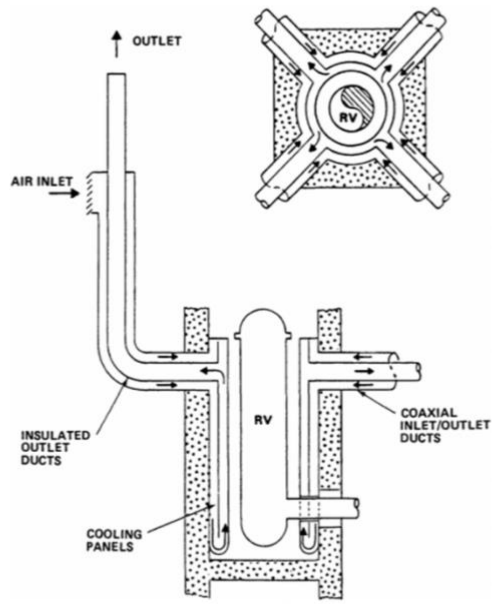


Figure 2-1: Structure of the Reactor Cavity Cooling System [5]

Due to a recent invention disclosure and potential patent submission, a detailed discussion of the methodology is deferred to future publications.

2.2 Demonstration

2.2.1 Case Study System

An MHTGR RCCS [5] was selected as the case study system for the proposed methodology. The RCCS removes heat from the reactor cavity in a passive manner by the natural convection of outside air through cooling panels located in the reactor cavity. The cavity cooling panels form a cylindrical wall completely external to the primary coolant pressure boundary and surround the uninsulated reactor vessel. The cooling panels and ducting collect the heat transferred from the vessel by radiation and natural convection, transporting the heated air to the environs. They protect the cavity walls from overheating during normal operations and provide an alternate means of decay heat removal when the reactor is shut-down. The structure of the RCCS is displayed in Figure 2-1. In the figure, the RCCS includes the inlet pipes, the outlet pipes, the cooling panels, etc. It is worth noting that the RCCS has four sets of inlet and outlet pipes, but the sketch at the bottom of Figure 2.1 only displays one of them. The detailed list of components considered in the case study is displayed in Table 2-2. Four sets of pipelines in the RCCS are numbered as inlet/outlet pipes 1, 2, 3, and 4, respectively. The labels defined for each component will be reused in the experiment result sections.

Table 2-2: The important components and their labels

Labels	Components	Labels	Components	Labels	Components	Labels	Components
FI1	The filter at inlet pipe 1	FI2	The filter at inlet pipe 2	FI3	The filter at inlet pipe 3	FI4	The filter at inlet pipe 4
FO1	The filter at outlet pipe 1	FO2	The filter at outlet pipe 2	FO3	The filter at outlet pipe 3	FO4	The filter at outlet pipe 4
PI1V	The vertical part of inlet pipe 1	PI2V	The vertical part of inlet pipe 2	PI3V	The vertical part of inlet pipe 3	PI4V	The vertical part of inlet pipe 4
PI1H	The horizontal part of inlet pipe 1	PI2H	The horizontal part of inlet pipe 2	PI3H	The horizontal part of inlet pipe 3	PI4H	The horizontal part of inlet pipe 4
PO1V	The vertical part of outlet pipe 1	PO2V	The vertical part of outlet pipe 2	PO3V	The vertical part of outlet pipe 3	PO4V	The vertical part of outlet pipe 4
PO1H	The horizontal part of outlet pipe 1	PO2H	The horizontal part of outlet pipe 2	PO3H	The horizontal part of outlet pipe 3	PO4H	The horizontal part of outlet pipe 4
CP1	The cooling panel connected to pipe set 1	CP2	The cooling panel connected to pipe set 2	CP3	The cooling panel connected to pipe set 3	CP4	The cooling panel connected to pipe set 4
CP	The cooling panel of the reactor wall						

2.2.2 Candidate Sensors

The physical variables of the RCCS taken into account include the temperature, the flow rate, the pressure, the particle density, and the radiation density of the airflow transferred through the RCCS. According to these types of signals, ten candidate sensors were selected for the OLM system. The sensors are listed in Table 2-3. The labels shown in the table will be reused in the result section.

Table 2-3: Specification of the candidate sensors

Labels	Measures	Range	Cost ($)	MTTF(h)
TS1	Temperature	-200 ~ 1100C	1,500	1e6
TS2	Temperature	-50 ~ 500C	1,000	1e7
FS1	Flow rate, Temperature (Multifunctional)	0 ~ 200L/min, 0 ~ 500C	4,500	1e5
FS2	Flow rate	0 ~ 250L/min	2,500	1e6
PS1	Pressure	0 ~ 10 MPa	3,200	1e6
PS2	Pressure	0 ~ 1 MPa	1,000	1e7
DS1	Particle Density	0 ~ 0.02 kg/m^3	5,000	1e6
DS2	Particle Density	0 ~ 0.2 kg/m^3	1,500	1e6
RS1	Radiation	0.1u ~ 100mSv/h	7,000	1e6
RS2	Radiation	0.1u ~ 10mSv/h	5,000	1e5

2.2.3 Considered Failure Modes

An essential function of the OLM system is to detect and distinguish faults during system operations. Table 2-4 introduces the failure modes of the system components considered in this report. It is worth noting that this report considers single fault scenarios only (i.e., in each fault scenario used to generate signal features, only one fault was injected). But the proposed method can be applied to multiple fault scenarios as well.

Table 2-4: Failure modes of components considered

Component	Failure Modes	Description
Inlet Filters	Inner Leakage	Some of the dirty air passes the filter since there are small holes in the filter.
	Clog	The air cannot pass the filter smoothly since too much dust is accumulated on the filters.
Inlet Pipes	Leak to the environment	Small leakage at the shell of the pipes.
	Collapse	Large leakage at the shell of the pipes.
Cooling Panels	Degradation due to rust/scaling	
Outlet Pipes (inside the inlet pipe)	The leakage from the inlet pipe	Some of the air leaks from the inlet pipe into the outlet pipe.
Outlet Pipes (outside the inlet pipe)	Leak to the environment	Small leakage at the shell of the pipes
	Collapse	Large leakage at the shell of the pipes.
Outlet Filters	Inner Leak	Some of the dirty air passes the filter since there are small holes in the filter.
	Clog	The air cannot pass the filter smoothly since too much dust is accumulated on the filters.
Sensors	Bias	There are discrepancies between measured and true values.
	Drift	The output of the sensor keeps increasing or decreasing linearly from the normal state.
	Spike	Spikes are fast, short-duration electrical transients in voltage (voltage spikes), current (current spike), or transferred energy (energy spikes) in an electrical circuit of sensors.
	Stuck	The output of a sensor signal becomes constant.
	Hardover	The output of the sensor increases above the maximum threshold

2.2.4 Other Constraints

The following constraints/assumptions are introduced when performing sensor selection:

- One sensor can measure physical variables at one location only, i.e., the case in which a sensor can simultaneously sample data at different locations is not considered
- No more than three sensors can be deployed at one location. This constraint is introduced because of the limited space available for sensor installation.

2.2.5 Experiment Results

The Non-dominated Sorting Genetic Algorithm (NSGA-II) [6, 7] is selected to implement the sensor selection methodology discussed in this study to design the OLM system. NSGA-II handles each objective function separately. After crossover and mutation, the NSGA-II algorithm creates a Non-dominated Pareto Front for all the solutions and the best result is chosen from the Non-dominated Pareto Front. The number of optimal solutions obtained in this study are 100 and the values of each objective function for 5 optimal solutions are presented in Table 2-5.

Table 2-5: Values of objective functions for 5 optimal solutions

Number of solution	Cost	Observability	Fault diagnostics	Fault prognostics	Integrability
1	24700	293682.3	30795.25	270523.2	12.2
2	213000	1209887	121322.9	1100068	22.4
3	30400	325039	33887.72	300701.9	12.2
4	26200	309106.2	30795.25	285103.6	12.4
5	169200	1071693	110270.5	970182.2	22.2

The flowchart describing the application of the NSGA-II algorithm for obtaining the optimal solutions for the sensor placement optimization problem is shown in Figure 2-2. It can be observed from Figure 2-2 that, the objective functions and the constraints for sensor selections are defined for the NSGA-II algorithm based on the sensor selection criteria. Sensors are sampled at each location and crossover and mutation are applied to sensors to re-evaluate the objective functions and select the optimal solutions until the predefined maximum number of generations is reached.

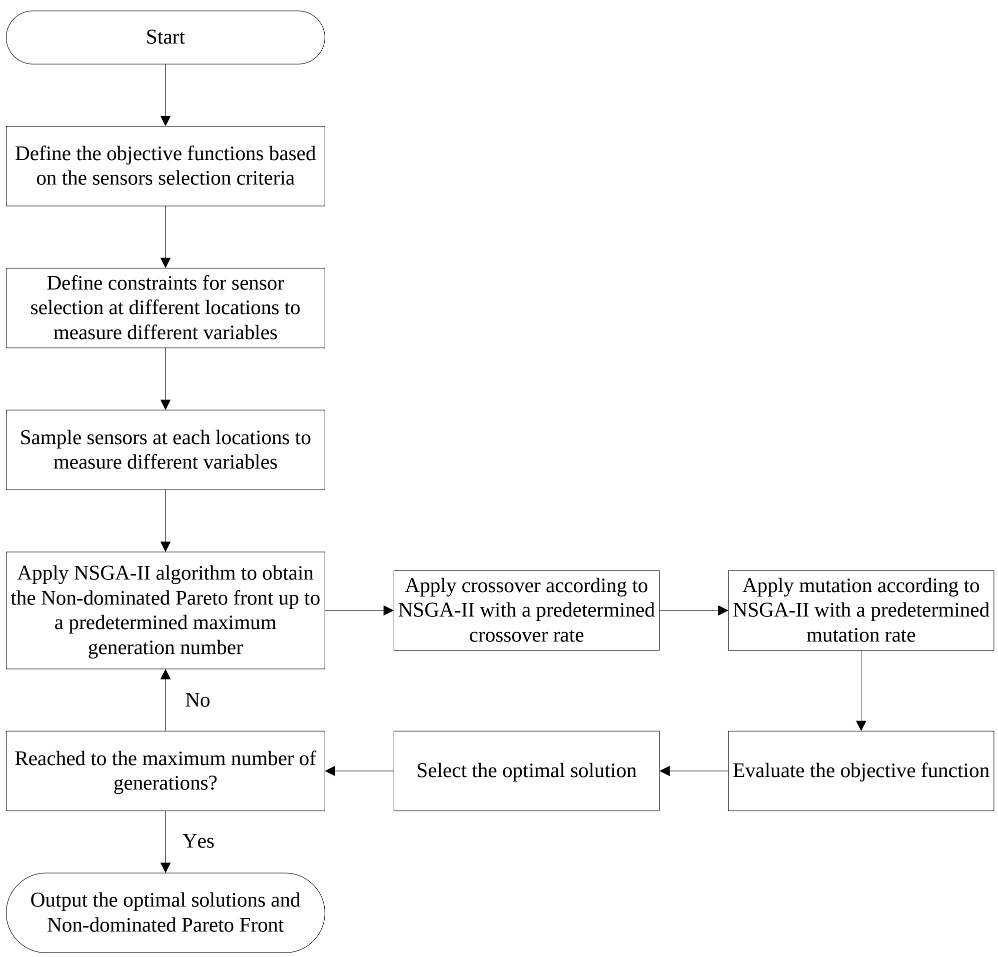
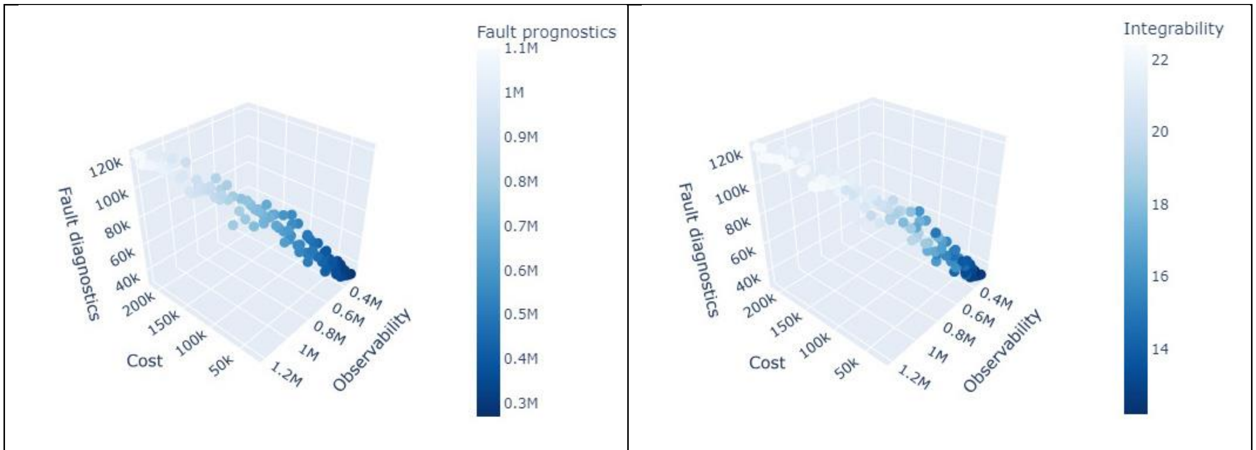


Figure 2-2: Flowchart of the implementation of the Non-dominated Sorting Genetic Algorithm (NSGA-II) for the sensor placement optimization problem

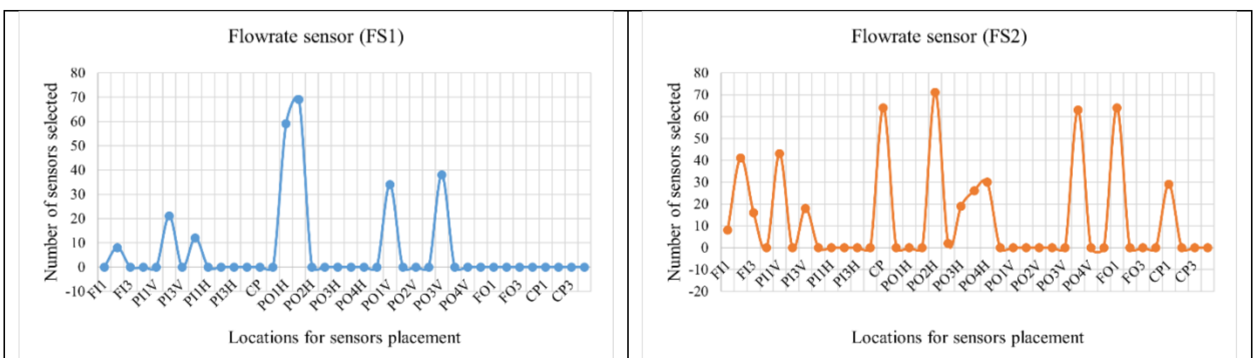
The Non-dominated Pareto Front found for different sensor selection criteria is presented in Figure 2-3, where each figure provides values for 4 sensor selection criteria. It can be observed that, both Figure 2-3(a) and Figure 2-3(b) depict a Non-dominate Pareto Front where each of the points of the Non-dominate Pareto Front corresponds to an optimal solution for sensor placement.



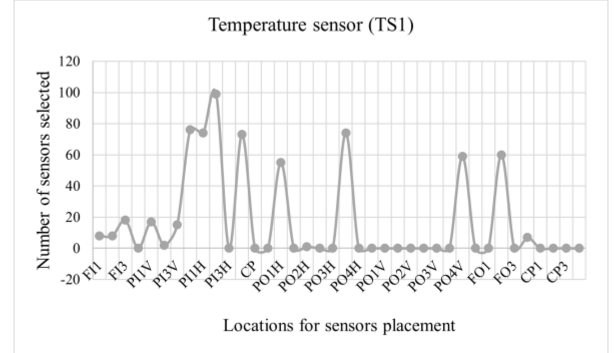
(a) (b)

Figure 2-3: Non-dominated Pareto fronts for sensors placement optimization for different sensors selection criteria

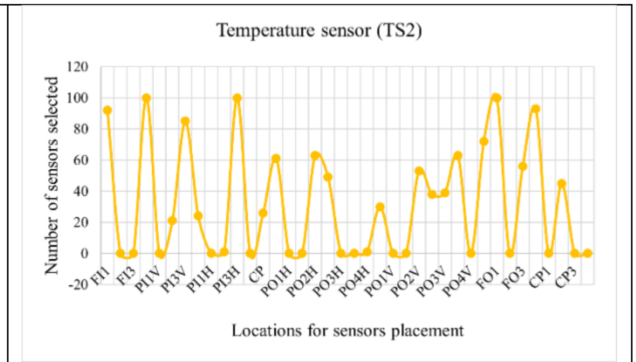
The number of sensors selected at different locations after optimization is shown in Figure 2-4. It can be observed from Figure 2-4(a) and Figure 2-4(b) that the flowrate sensor (FS1) is selected at only a few locations compared to the flowrate sensor (FS2). Therefore, it is concluded that, the flowrate sensor (FS1) is more location sensitive, and should be used at those few locations to measure the corresponding variables, while the flowrate sensor (FS2) is more location agnostic. According to Figure 2-4, a similar behavior can be observed for other sensors too. Some sensors are very location sensitive and can be used at only a few locations while other sensors are location agnostic.



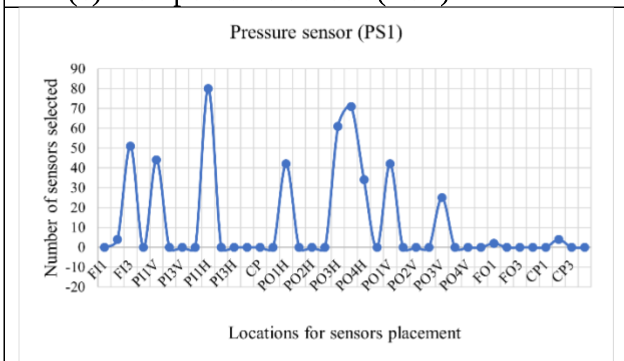
(a) Flowrate sensor (FS1) (b) Flowrate sensor (FS2)



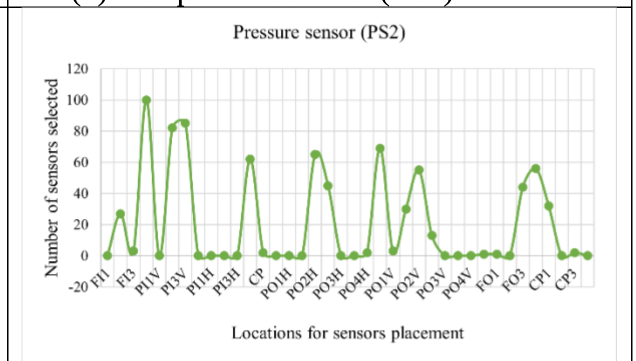
(c) Temperature sensor (TS1)



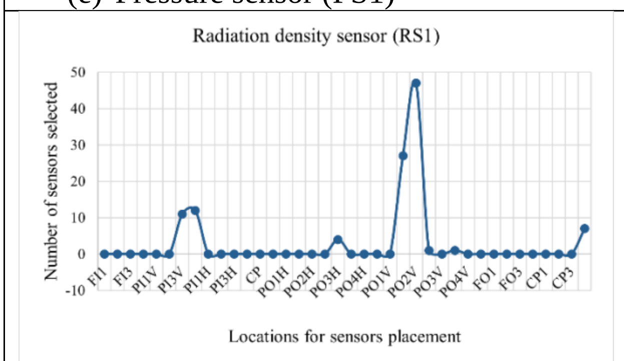
(d) Temperature sensor (TS2)



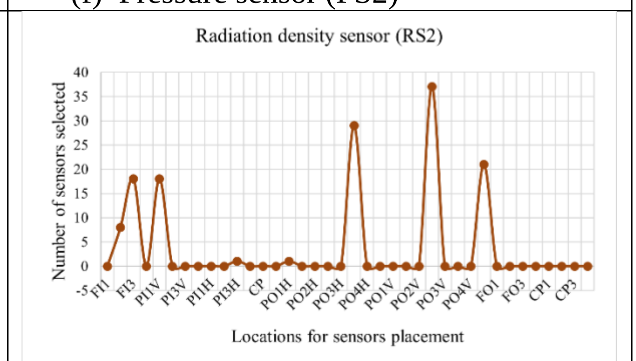
(e) Pressure sensor (PS1)



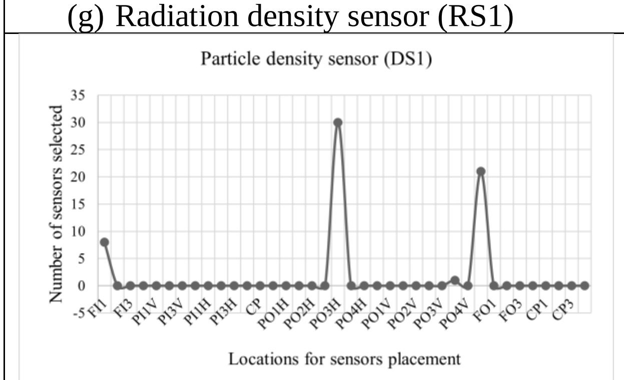
(f) Pressure sensor (PS2)



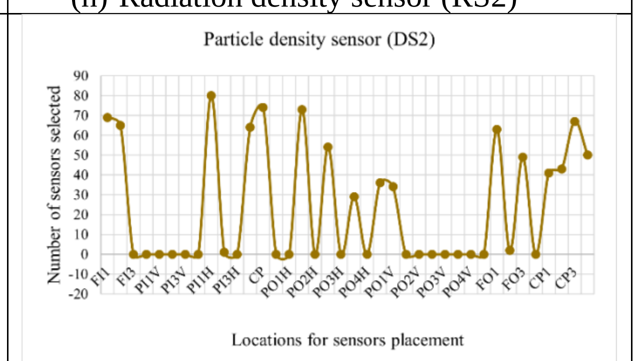
(g) Radiation density sensor (RS1)



(h) Radiation density sensor (RS2)



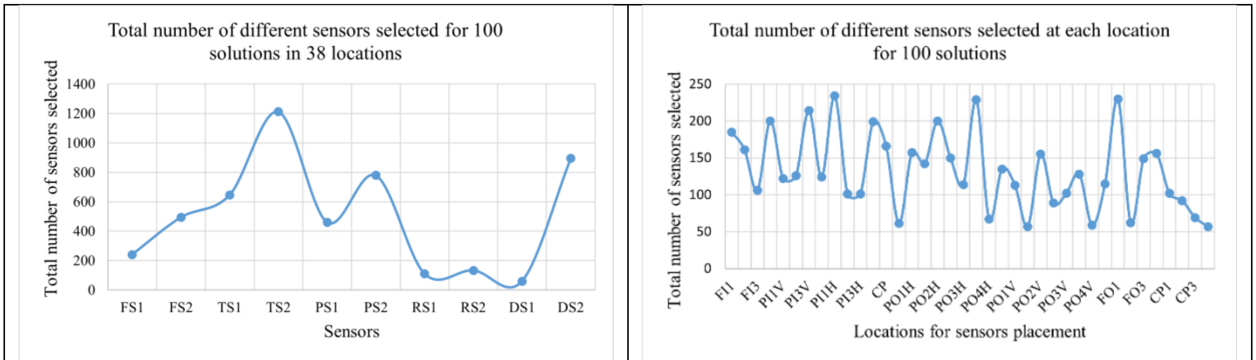
(i) Particle density sensor (DS1)



(j) Particle density sensor (DS2)

Figure 2-4: Number of different sensors selected at different locations for 100 solutions

The total number of sensors selected for 100 solutions at 38 different locations is presented in Figure 2-5(a) for different types of sensors. It can be observed that, Temperature sensor (TS2) is selected the most and Radiation density sensor (RS1), Particle density sensor (DS1) are selected the least. In Figure 2-5(b), the total number of sensors selected at different locations is presented.



(a)	(b)

Figure 2-5: Total number of sensors selected (a) for different sensor types and (b) at different locations

3 Intelligent Asset-Management Decision-Making

The second focus of the project was the creation and development of an approach for asset-management and operational strategy decision-making that comprehensively and seamlessly incorporates all avenues of available data, including online plant monitoring, component models, and the plant risk profile. An overview of the developed approach and preliminary demonstration analysis are provided here.

3.1 Methodology

A central aspect of the research project is the utilization of an intelligent decision-making approach to optimize asset-management strategies. The system of interest (the nuclear power plant) can be in any of a finite number of states, and the transition between system states follows a Markov process. At discrete time steps, the decision-maker can take actions to influence system state transition. So, the transitions between system states depend not only on "nature," i.e., the inherent randomness in system state transition, but also on decision-maker actions. At each time step, different decision-maker actions and different system state transitions lead to varying rewards for the decision-maker. The decision-maker's objective is to maximize the sum of the rewards that will be received from the current time step into the future.

As shown in Figure 3-1, the approach for asset-management decision-making during plant operation requires multiple steps and tools but fundamentally relies on a Markov decision processes/partially observable Markov decision processes (MDP/POMDP) optimization assessment. The steps before the MDP are necessary to supply the MPD calculation with the information required to form a real-time assessment of plant status.

First, sensor information from the operating plant is provided to the online monitoring and diagnostic tool (PRO-AID [1] for the approach discussed here), which assesses component status based on the sensor data and physical system models. To inform this calculation, Markov component models provide additional insights regarding component behavior (such as estimated component failure probability). Both PRO-AID and the Markov component models work in tandem to assess the condition of components within the system.

The output of PRO-AID are real-time probabilities regarding component status (healthy, degraded, failed, etc.). The output from PRO-AID and the Markov component models are utilized to develop a real-time plant risk profile, which consists of a PRA and a GRA. The PRA analyzes plant risk from a safety perspective, while the GRA assesses economic risk.

Lastly, the output from PRO-AID and the real-time plant risk profile are fed to the MDP analysis. The MDP analyzes different operational strategies to determine the optimal asset-management strategy to maximize revenue.

Due to a pending patent regarding the developed approach, a detailed discussion of the methodology is deferred to future publications.

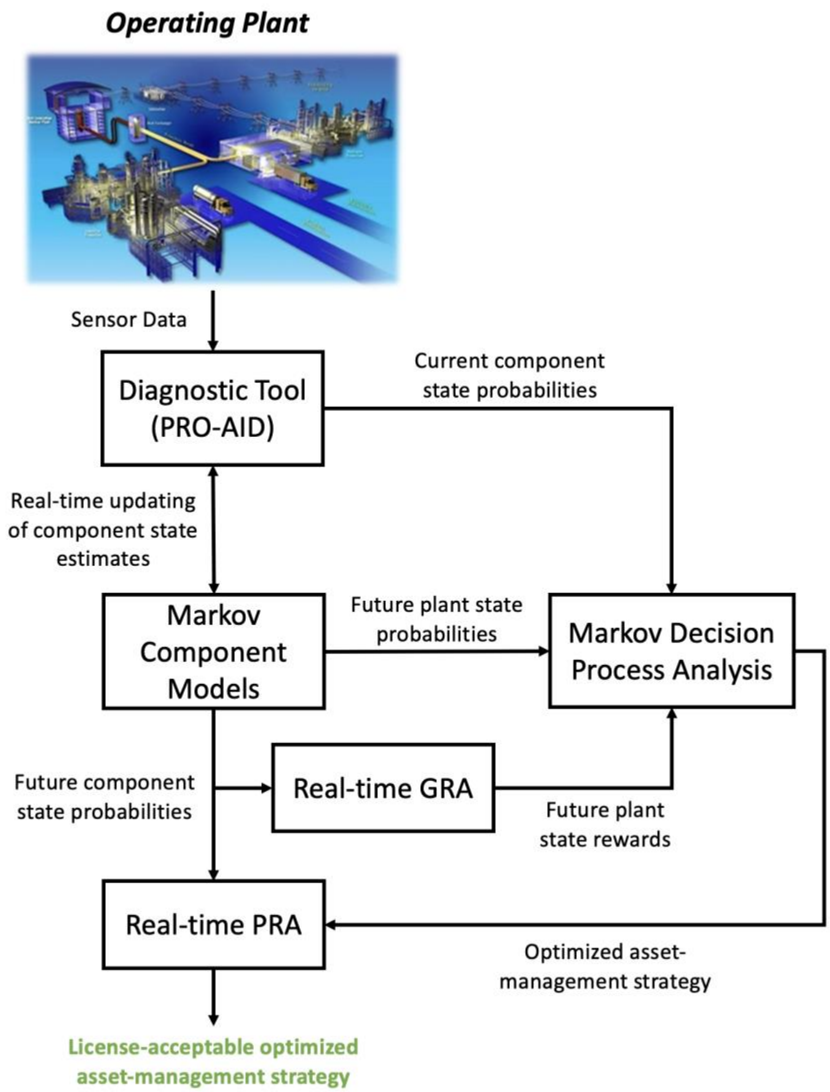


Figure 3-1: Intelligent Asset-Management Decision-Making Approach

3.2 Demonstration

As the focus of the project was the applicability of the developed approaches to advanced nuclear reactor designs, a non-light water reactor was selected for the demonstration analysis. The following sections describe the selected reactor design and system analyzed, in addition to the process utilized to make the selection.

3.2.1 Reactor Overview

The advanced reactor design selected for the demonstration analysis was the MHTGR, which was selected for several reasons. First, the general reactor design is similar to the Framatome SC-HTGR design but there is significant design information available in the public domain (described below), which alleviated concerns regarding university students who are part of the current project and unable to access controlled information. Second, as highlighted above, was the availability of detailed design and licensing documentation, which expedited the development of the demonstration problem. This included System and Subsystem Design Description (SDD and SSDD) documents and a PRA. The MHTGR licensing approach also utilized a risk-informed performance-based method, similar to that of LMP [8]. Lastly, the multi-module design of the MHTGR plant, described below, also permits additional operating modes.

Significant work was completed on the MHTGR design and licensing case as part of a DOE-sponsored effort in the 1980s and early 1990s led by GA Technologies, Combustion Engineering, Bechtel National, Inc., and Stone and Webster. Although the project was cancelled before construction began, there was regulatory interaction through submittal and review of the Preliminary Safety Information Document (PSID) [5] and the NRC's published draft Preapplication Safety Evaluation Report (PSER) [9].

The documentation developed as part of the MHTGR project was initially considered under the Applied Technology (AT) DOE designation. Given the elimination of the AT category by DOE, the project worked with the DOE Office of Scientific and Technical Information (OSTI) to get the MHTGR documents listed in Table 3-1 properly cleared for public release. This information was then utilized for the demonstration analysis and is also now openly available on OSTI.gov for use as part of other research efforts.

Table 3-1: Cleared MHTGR Documents

Report Number	Title
HTGR-86-024*	Preliminary Safety Information Document for the Standard MHTGR
NUREG-1338*	Preapplication Safety Evaluation Report for the Modular High-Temperature Gas-Cooled Reactor (MHTGR)
HTGR-86-011*	Probabilistic Risk Assessment for the Modular HTGR Plant
HTGR-87-086	Modular High Temperature Gas-Cooled Reactor plant capital and busbar generation cost estimates
HTGR-86-020	Heat transport system design description
HTGR-86-101	Shutdown Cooling Circulator SDD
HTGR-87-039	Circulating Water SSDD
HTGR-87-027	Feedwater and condensate SDD
HTGR-86-069	Forced Outage Assessment
HTGR-86-051	NSSS Control SSDD
HTGR-86-076	Plant control, data, and instrumentation SDD
HTGR-86-052	NSSS Analytical Instrumentation SSDD
HTGR-86-047	Plant protection and instrumentation SDD
HTGR-86-049	Investment protection SSDD
HTGR-86-048	Safety protection SSDD
HTGR-87-028	Steam and water dump SDD
HTGR-87-033	Heater drains and condensate returns SSDD
HTGR-87-034	Condensate polishing SSDD
HTGR-87-035	Steam vents and drains SSDD
HTGR-86-129	Steam generator SDD
HTGR-86-028	Shutdown Cooling SDD
HTGR-87-068	RCCS SDD

* Previously cleared for public release

Within the Vessel System, helium coolant flows to the reactor vessel in the outer annular region of the crossduct, flows down through the core, returns through the center region of the crossduct, down through the steam-generator bundle, then back up the annular region around the steam-generator back to the inlet of the single helium circulator. On the secondary coolant side, feedwater enters the separate steam generator vessel at the bottom and flows through a helical coil tube bundle, exiting as superheated steam at the side of the vessel (see Figure 3-2).

When the reactor is shut down for maintenance or refueling, decay heat can be removed from the core by the normal Heat Transport System (HTS), or alternatively by an independent Shutdown Cooling System (SCS). The SCS consists of a motor-driven circulator coupled with a water-cooled heat exchanger mounted beneath the reactor core within the reactor vessel. The SCS is provided for investment protection and flexibility of operation. The SCS and HTS are not "safety-related".

As a third means of providing decay heat removal, a "safety-related" RCS is provided within each reactor cavity. The RCCS cooling is provided by natural circulation of outside air within enclosed panels along the reactor cavity walls. The panels are designed such that outside air does not communicate with air within the cavity. The RCCS is capable of removing from the reactor vessel, decay heat conducted and radiated from the core. The RCCS is always functioning in its natural circulation mode to provide cooling of the reactor cavity concrete during normal operation and is therefore always available to remove decay heat under accident conditions without reliance on active components, power supplies, or operator action. [5]

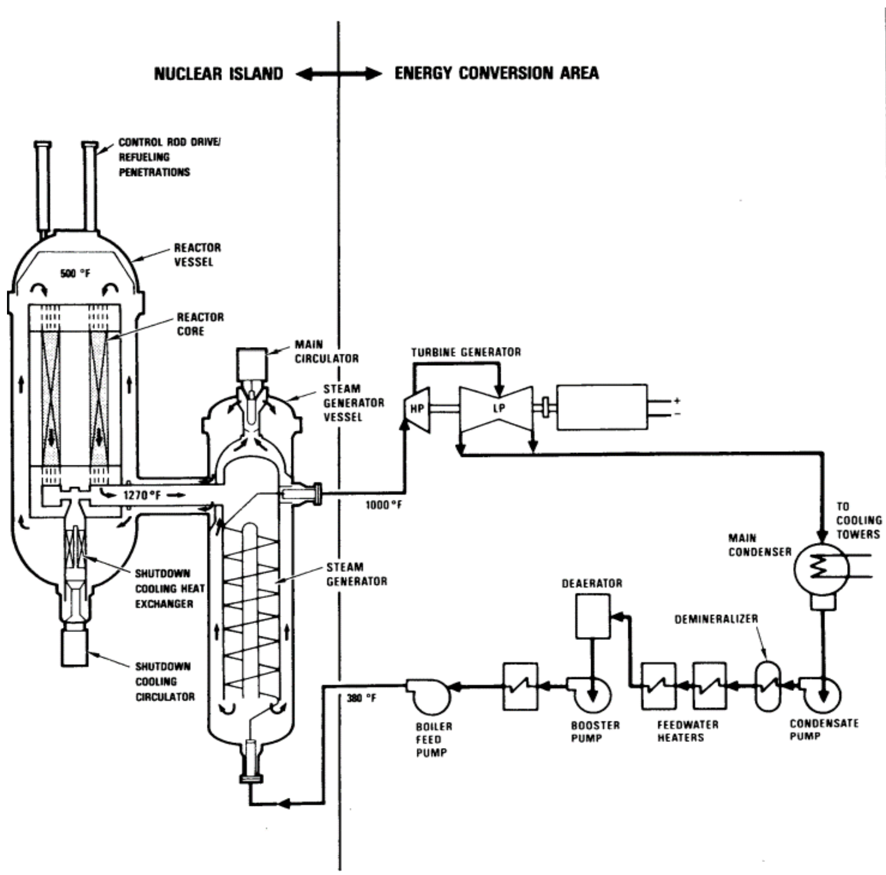


Figure 3-2: MHTGR Plant Overview (Single Reactor) [5]

Table 3-2 summarizes some of the key design features and parameters associated with the Standard MHTGR.

Table 3-2: Features of the Standard MHTGR [5]

Fuel	UCO + ThO_2 Microparticles
Coating	Ceramic (PvC/SiC/PyC)
Moderator	Graphite
Coolant	Helium
Coolant Boundary	Steel Pressure Vessel
Power per Module	140 MWe/ 350 MWt
Power Density	5.9 W/cc
Fuel Temperature (Max/Ave)	1060/677 C (1940/1250 F)
Coolant Temperature	259/687 C (497/1268 F)
Coolant Pressure	6.4 MPa (925 psig)
Steam Temperature	541 C (1005 F)
Steam Pressure	2500 psig

3.2.2 Demonstration System Selection

As developing a component and system monitoring and decision-making framework for the entirety of the multi-reactor MHTGR design was beyond the scope of the current project. A subsystem of the MHTGR design was selected for analysis. It is important to note that while the component monitoring aspect of the demonstration analysis focused on a single subsystem, the decision-making framework accounts for the impact of the operation and availability of the entire plant. To select the subsystem for that would be the focus of the demonstration analysis, MHTGR subsystems were compared on the following criteria:

- Relevance to the generation capacity of the plant and interest from the asset-management perspective
- Availability of detailed piping and instrumentation (P&ID) information
- Complexity of the subsystem network
- Complexity of the boundary conditions to be imposed
- Type of PRA analysis used to assess the network (fault tree versus simulation-based)
- Necessity of online component monitoring
- Complexity of surrogate system model
- Availability of PRO-AID models for the system components

The following five MHTGR subsystems were considered as part of this process:

- Shutdown Cooling System (SCS)
- Reactor Cavity Cooling System (RCCS)
- Main Circulator Subsystem (MCS)
- Feedwater and Condensate System (FW)
- Reactor Plant Cooling Water Subsystem (RPCWS)

The results of the selection analysis are summarized in Table 3-3. Based on this analysis, the FW system was selected for the following reasons. First, the FW system is central to the generation capacity of the plant and has multiple components are key to asset-management decisions. Next, a detailed P&ID was available from the MHTGR Feedwater and Condensate SDD [10]. While complexity of the system and its boundary conditions are high, that is a positive aspect, as it reinforces the need for intelligent decision-making processes given the complexity of the associated analysis. In addition, the components within the system can be assessed utilizing traditional PRA fault tree analysis, with preliminary models already developed as part of the MHTGR PRA. The system requires online monitoring since it is in continuous operation and a key factor in the generation capacity of the plant and also because the included components, such as feedwater heaters, can experience degradation. While the complexity of the corresponding surrogate model is high, the components within the system are fairly standard and also mostly available within the existing PRO-AID database.

Table 3-3: Demonstration Problem Selection Process Results

Evaluation Criteria	SCS	RCCS	MCS	FW	RPCWS
Relevance to generation capacity and asset-management perspective	High	Low	High	High	High
Availability of a detailed P&ID	Yes	No P&ID needed	No P&ID needed	Yes	Yes
Complexity of the subsystem network	Medium	No Network	No Network	High	High
Complexity of the boundary conditions	Low	Low	Low	High	High
Pathway for PRA analysis	Yes - Traditional	Yes – Simulation-Based	Yes – Traditional	Yes – Traditional	Yes – Traditional
Necessity of online monitoring	No (standby system)	Yes	Yes	Yes	Yes
Complexity of the corresponding surrogate model	High	Low	High	High	High
Availability of the PRO-AID models for the system components	Most	No	No	Most	Most

3.2.3 Analysis Development

Several preparation steps were necessary for the demonstration analysis, as outlined below. The following subsections provide a brief overview of each aspect:

- **FW System Surrogate:** Given the lack of an operational facility, a surrogate for the FW system was developed in Dymola, which required a detailed decomposition of the system.
- **Markov Component Models:** A Markov model of each component of the FW system was developed as part of the analysis framework
- **Online Monitoring:** PRO-AID was utilized to monitoring and diagnose faults for the surrogate FW system modeled by Dymola.
- **PRA Development:** The existing MHTGR PRA was recreated and adapted to the needs of the demonstration analysis.
- **GRA Development:** A simplified GRA was developed for the analysis based on available documentation regarding MHTGR performance.

3.2.3.1 Feedwater System Decomposition

While the MHTGR documentation provided extensive detail regarding the design and operation of the FW system, the final design was still in development when the project was ultimately canceled. Therefore, a fully complete system design was not finalized, and certain documentation contains conflicting information, as the design was evolving. Since the demonstration analysis requires a plant surrogate to test the framework's capabilities, it was necessary to further refine the FW system to permit the development of a system surrogate in Dymola (see Figure 3-3).

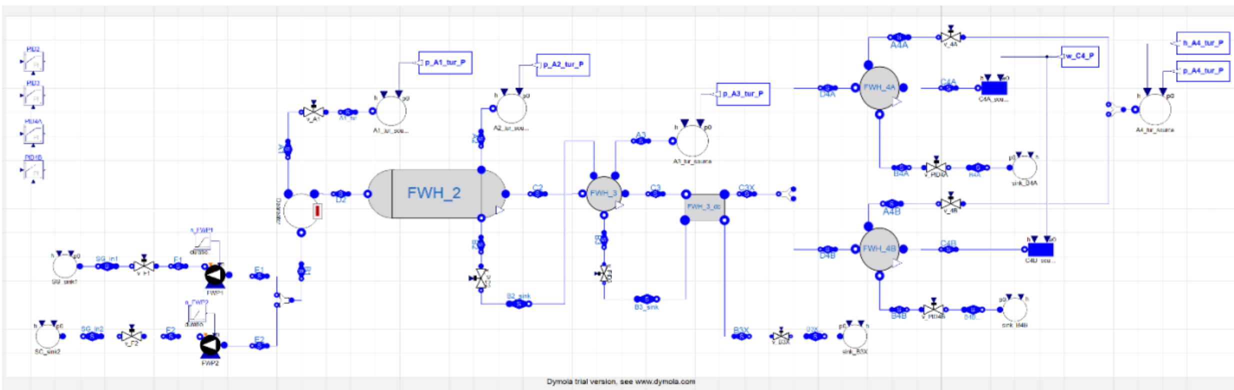


Figure 3-3: Developed FW System Dymola Model

To complete this task, the available FW system information from the MHTGR documentation was reviewed and utilized as a starting point. When conflicting information was found, the project selected the values that were most conducive to the demonstration analysis (while ensuring consistent system design). If information was not available, the missing values were calculated or estimated based on existing design information. The output of this approach was developed FW P&ID shown in Figure 3-4, which formed the basis of the Dymola model of the system. The assumed sensor set for the system is also noted.

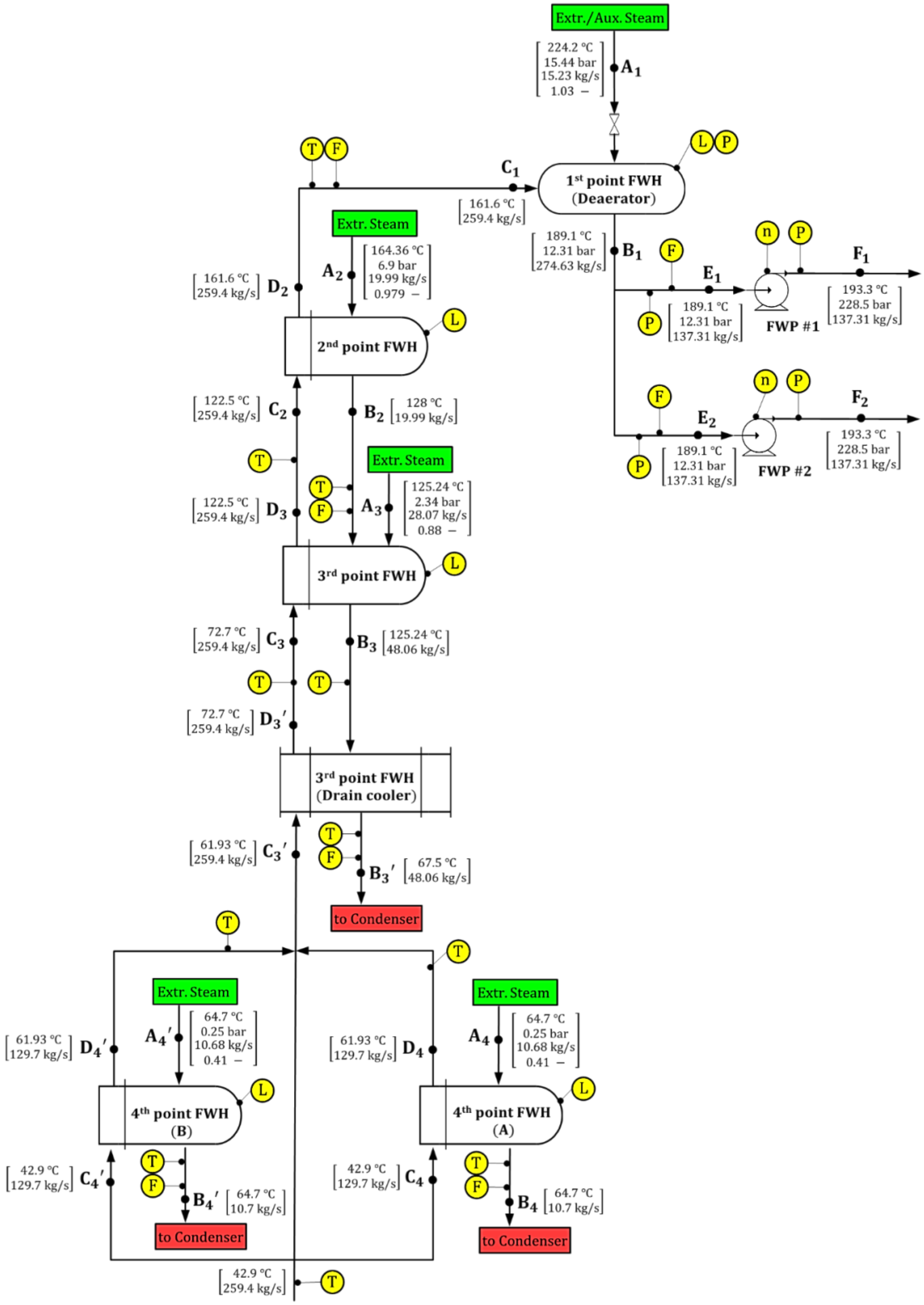


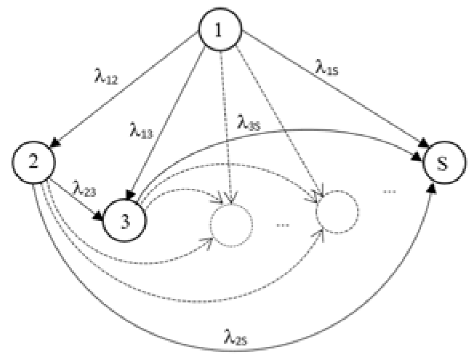
Figure 3-4: Developed FW System P&ID

3.2.3.2 Markov Component Model Development

For the analysis performed, Markov component models were developed for each element of the FW system to aid in the prediction of future system status (which are updated by the online monitoring and diagnostic tool using the system sensor network). Figure 3-5 shows a generic Markov Model created and used in this analysis, along with a generalized form of the analytical solution derived.

Markov Diagram

Consider a component with ***S*** possible states (may range from fully operational/healthy to failed).



Assumptions

1. At time $t = 0$ the system is in state 1 (aka as "Healthy")
2. State transition rates are constant (λ)
3. No Repair

Analytical Solution

The probability for the component to be in state s, $s = 1, 2, \ldots, \boldsymbol{S}$ can be expressed as:

$$P_s = \sum_{k=1}^{S} M(k,s) \cdot e^{-m(k)\cdot t}$$

where $M(k,s)$ is the $(k,s)^{th}$ element of matrix $\widehat{\boldsymbol{M}}$:

$$\widehat{\boldsymbol{M}} = \begin{array}{c} \begin{matrix} 1 & 2 & 3 & \ldots & S \end{matrix} \quad s/k \\ \begin{pmatrix} M_{1,1} & M_{1,2} & M_{1,3} & \ldots & M_{1,S} \\ M_{2,1} & M_{2,2} & M_{2,3} & \ldots & M_{2,S} \\ M_{3,1} & M_{3,2} & M_{3,3} & \ldots & M_{3,S} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ M_{S,1} & M_{S,2} & M_{S,3} & \ldots & M_{S,S} \end{pmatrix} \begin{matrix} 1 \\ 2 \\ 3 \\ \vdots \\ S \end{matrix} \end{array}$$

and defined as

$$M(k,s) = \begin{cases} 0 & , \qquad k < s \\ P_s(t=0) - \sum\limits_{\substack{i=1 \\ i \neq k}}^{S} M_{k,i} & , \qquad k = s \\ \left(\sum\limits_{i=1}^{k-1} \lambda_{ik} \cdot M_{i,s} \right) / (m_k - m_s), & k > s, \quad m_k \neq m_s, \quad = 0 \; otherwise \end{cases}$$

$m(k)$ is k^{th} element of vector of exponent coefficients, $\vec{m}$ is

$$\vec{m} = \{m_1, m_2, \ldots, m_S\}$$

where m_s is the total out-of-state transition rate for state s.

Figure 3-5: Generalized form of Analytical Solution for Markov Component Models

3.2.3.3 On-line Monitoring

As was mentioned in Section 1.2, PRO-AID [1] is the tool to be used for online monitoring and diagnosis of component faults during plant operations. For the demonstration analysis, PRO-AID was linked to the Dymola model of the FW system and the Markov component models. PRO-AID and the Markov component models work in tandem to provide real-time probabilities of system status.

3.2.3.4 PRA Model

Incorporation of the PRA into the intelligent asset-management decision-making approach is a necessary step to ensure that plant operations remain within acceptable safety bounds. The insights from the PRA provide critical insights into the acceptability of proposed asset-management strategies, including whether such actions would preserve plant operating status within the limits of the plant license. To accomplish this task, the real-time PRA developed based on the project approach is utilized in conjunction with the risk-informed performance-based licensing approach of the Licensing Modernization Project (LMP). [11]

As was mentioned in Section 3.2.1, a preliminary MHTGR PRA model is publicly available [12, 13]. For this analysis, the original MHTGR PRA model of the Feedwater and Condensate System was used with some modifications (see Table 3-4 for the list of modifications).

Table 3-4: Summary of MHTGR PRA Modifications

Fault Tree	Modifications to the MHTGR version
FW Subsystem Fails	1. Removed condensate portion
Loss of Pumping	1. Removed condensate portion 2. Added two simultaneous independent failures 3. Added CCF Failure 4. Incorporated two 80% capacity varying speed pumps, thus replacing the 1-out-of-2 100% capacity pumps logic.
LP FW Heater Failure	1. Added basic event for heater fouling (for each FW heater) 2. The BE for FW heater excessive leakage was replaced by a OR gate for heater leakage with two basic events under it, one for the tube-side leakage and the other for the shell-side leakage

The set of input data needed for the PRA model was taken from the MHTGR PRA [13]. The values were then updated using the current industry average performance for components and initiating events (IEs) at U.S [14].

3.2.3.5 GRA Model

A GRA is the process of predicting the risk of generation loss during future operation by estimating the probability and duration of plant trip or derate due to equipment degradation or failure. [15] GRA is a key activity in assuring productivity and profitability as plants worldwide face increasingly competitive power markets. Nuclear power plant operators require tools to assist management in making decisions involving the operation and maintenance of equipment whose failure can cause reactor trips or down-power events. A GRA model, whether rudimentary or detailed, is an important element of nuclear asset management risk-informed tools for analyzing effects of equipment reliability and availability on plant value and resource allocation decision-making.

Central to the assessment of generation risk is the development of a trip model. A trip model is similar in function and construction to that used for PRA with the exception that the end-state of the trip model is the frequency of plant trip as opposed to the frequency of core damage or offsite dose consequence. The trip model is generally used to estimate the frequency of instantaneous trip and down-power at the plant based on actual plant configuration and condition.

Another model important for a GRA analysis is a derate power model, a model where the end-state is the frequency of plant to operate at decreased (derated) power level. The two models, trip and derate power, when built, help to identify different plant states and the awards (generation) associated with them which are key input parameters for any asset management decision at the plant level.

For the demonstration analysis, a simplified MHTGR GRA was developed that considered three plant states (100% power, 80% power, and 0% power (plant trip)) and two subsystems (the FW subsystem and Transformer subsystem). Only the FW system is directly considered in the resulting optimization analysis, but the Transformer subsystem was also provided to demonstrate how additional systems can be incorporated into the framework.

3.2.4 Demonstration Analysis

The demonstration analysis centered on the operation of the FW system described in Section 3.2.3. For the preliminary analysis presented here, the goal was to test the integrated analysis framework for a large, complex problem to ensure that the model produced useful results and that the calculation could be performed in a reasonable amount of computational time. Therefore, many of the values utilized in the analysis were either based on preliminary analysis or postulated.

Before proceeding to the complete demonstration, a limited-scope FW system test analysis was performed. The test analysis permitted a trial run of the data communication pathways and formatting. In addition, and most importantly, the overall size and complexity of the test analysis was far less than the full demonstration analysis. Therefore, potential errors in the input preparation approaches, solution methodology, and output results could be more easily identified. For example, the determination of optimal actions is fairly trivial given the size of the problem, so it would provide a validation of the analysis output result. The results of the test analyses were successful and matched the optimal actions selected by direct analysis.

The full demonstration analysis focused on the online monitoring and diagnostics of six FW system components (two FW pumps and four FWHs). The online diagnostic information for these components was utilized to develop a real-time risk profile for the plant. Although only these six components are monitored in real-time for this analysis, the status and behavior of the complete plant is taken into account within the developed risk profile. The details of the demonstration analysis are omitted here, given that they include information regarding the approach that is current undergoing patent submittal preparation.

In conclusion, the preliminary demonstration analysis calculations appeared successful for several reasons. First, the solution approach was able to perform an assessment of a system that was highly complex with over 2 billion possible transition pathways. In addition, the program was able to calculate the result in a reasonable period of time (less than 30 minutes when utilizing a desktop machine), which is a promising indicator for future cases with further complexity. In addition, the results for the initial analyses matched intuition for the simple cases assessed, providing a preliminary level of confidence in the solution scheme and overall framework. This is an important factor as the purpose of the integrated framework is to assess scenarios where the complexity is too great for simple calculations or intuition. In such scenarios, it may become difficult to gauge the accuracy of the suggested actions, without in-depth investigation.

4 Time-to-Market Analysis

To aid in the further development and commercialization of the developed technology, a T2M report has been prepared, which identifies and examines remaining steps to deployment. The focus of the T2M assessment was the commercialization of the intelligent asset-management decision-making approach utilizing MDPs, as it was a technology developed as part of the project and includes shared intellectual property amongst the project team.

The purpose of the T2M report is to support the development, commercialization, and deployment of the technology through an assessment of the following factors:

- Technology Motivation – Customer needs and value proposition
- Target Markets – Market size, customer feedback, market drivers
- Competitive Landscape – Existing competition, alternatives
- Risk Strategy – Identified risks, mitigation strategies
- Roadmap – Financial plans, sales strategy, next steps

Details of the assessment are not provided here, given the sensitive nature of the content and pending patent submittal for the developed asset-management approach.

4.1 Findings

There were several main findings based on the T2M assessment, outlined below:

1. **Patent finalization:**
    a. Complete patent submittal to support future licensing of the approach or direct tool development
2. **TCF award submittal:**
    a. Pursue funding for further approach development (including the following action items) through a TCF award
3. **Additional demonstration analyses:**
    a. Complete additional demonstration analyses to improve confidence in analysis performance, provide use cases for advertising and demonstration of cost savings, and to allow development of new visualization techniques.
    b. Discuss potential for industry involvement with demonstration analysis to increase realism, advertise approach, and gather customer needs.
4. **Further customer interviews:**
    a. Conduct additional customer research with operating LWR fleet and advanced reactor vendors concerning operational needs.
5. **Competition review:**
    a. Conduct further research regarding the tools/products currently being used by the operating LWR fleet for asset-management decision-making.

5 Conclusions

The NEET project reviewed here focused on improving the economic competitiveness of advanced reactors by reducing operational costs through intelligent asset-management decision-making. To achieve this goal, technical efforts centered on the following:

- **Sensor Network Design**: Optimizing the design of the plant sensor network based on multiple criteria, such as fault detection and cost.

- **Operational Asset-Management**: Optimizing plant operations and maintenance activities utilizing online monitoring in conjunction with component models and the plant risk profile.

5.1 Accomplishments

Several significant efforts were completed regarding the sensor network design optimization task, with a focus on expanding the capabilities of the OSU ISFA approach. First, new optimization criteria were added, such as observability and cost. Next, multiple optimization algorithms were explored to determine the best approach for the methodology. Lastly, a demonstration analysis of the sensor network design process was performed utilizing the MHTGR RCCS.

A major focus of the project was the creation and development of the intelligent asset-management decision-making approach. A novel methodology was outlined that utilizes MDPs in conjunction with online plant monitoring, component models, and a real-time risk profile of the plant. Significant effort established a seamless process of integrating these factors directly into the MDP, providing a single, comprehensive analysis structure. A preliminary demonstration of the approach was completed utilizing the MHTGR feedwater system. In addition, a T2M analysis was completed, with a focus on the developed technology, to outline next steps towards commercialization.

Additional highlights of the project include the following:

- **Patents:** A patent application is being prepared regarding the integrated MDP approach for intelligent asset-management decision-making, with submittal scheduled for mid-2023.

- **Invention Disclosures:** An invention disclosure has been submitted regarding the selection criteria for optimal sensor placement in online monitoring systems.

- **Publications:** In additional to the limited technical reports submitted to DOE as part of the project, two conference papers and journal articles were submitted regarding the sensor network design approach. Based on guidance from Argonne legal, publications regarding the integrated MDP approach for asset-management decision-making are being deferred until patent submittal occurs.

- **Student Support:** Three post-doctoral students/researchers and one PhD candidate at OSU were supported through the research conducted under this NEET award. One of the post-doctoral students/researchers is now an assistant professor at the University of Maryland.

5.2 Next Steps

Regarding the ISFA-based sensor selection and optimization methodology, several future actions are planned as outlined below:

- **Invention Disclosure:** A invention disclosure regarding the selection criteria for optimal sensor placement in online monitoring systems has been submitted and is currently being reviewed for possible submission as a patent.

- **Further Method Development:** Additional sensor selection criteria, such as reliability of candidate sensors and uncertainty in sensor measurements, will be developed and integrated into the approach for sensor network optimization, and the scalability and maintainability of the proposed methodology will be studied so that the proposed method can be applied to large-scale and more complex systems.

Regarding the integrated MDP approach for intelligent asset-management decision-making, several future actions are planned, as outlined below:

- **Patent Completion:** A patent application is being prepared for the integrated MDP approach to asset-management decision-making, with submittal scheduled for mid-2023.

- **Further Development Toward Commercialization**: The T2M analysis identified several main tasks requiring completion before commercialization of the technical can be achieved. Avenues for funding these activities, such as TCF awards, are currently being pursued.

First, in coordination with Argonne and OSU technology commercialization teams, a patent application is being prepared for the integrated MDP approach to asset-management decision-making, with submittal planned for mid-2023. Second, based on the findings of the T2M analysis, several funding avenues are being pursued to complete the outstanding tasks necessary for commercialization. These tasks include a demonstration of the cost savings potential of the approach utilizing a real-world example and further development of the approach regarding scalability and usability. A TCF application has been submitted concerning these efforts.

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