INL/RPT-22-68899

Reliability and Integrity Management Program Implementation Approach

September 2022

Final Report

Diego Mandelli, Todd Anselmi, Curtis Smith, Svetlana Lawrence, Courtney Otani

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Prepared for the
U.S. Department of Energy
Office of Nuclear Energy
Under DOE Idaho Operations Office
Contract DE-AC07-05ID14517

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ABSTRACT

Nuclear energy is the most reliable and environmentally sustainable energy source available today. In the United States, nuclear-generated power accounts for approximately 20% of total electricity and over 55% of clean energy. New advanced reactors have enormous potential to help further decarbonize the energy market, enhance grid resiliency, create new jobs, and build a stronger economy. More than 50 new reactors are being developed in the United States, and the federal government realizes an urgent need to deploy nuclear technologies to meet the country's energy, environmental, and national security goals. As such, the U.S. Department of Energy launched multiple programs to support advanced reactor deployment. The research described in this paper explores implementation strategies for the Reliability and Integrity Management Program that directly supports the U.S. Department of Energy goal to enable the near-term deployment of the advanced reactor technologies. The project is conducted under the Regulatory Development Program for advanced reactors sponsored by the U.S. Department of Energy.

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ACKNOWLEDGEMENTS

The authors would like to acknowledge support of this project provided by X-Energy team members Steve Vaughn, Patrick Robinson, Glen Lawson, Renee Fales, and Luke McSweeney along with Electric Power Research Institute researchers Mark Albert and Greg Shelby.

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ACRONYMS

AOO	Anticipated Operational Occurrence
AR	Advanced reactors
ASME	American Society of Mechanical Engineers
BDBE	Beyond Design Basis Event
BPVC	Boiler & Pressure Vessel Code
CLR	Component-Level Requirement
DBA	Design Basis Accident
DBE	Design Basis Event
DID	Defense-in-depth
DMA	Degradation mechanism assessment
DOE	Department of Energy
FOM	Figure of merits
GA	Genetic Algorithms
HTGR	High-temperature gas reactor
INL	Idaho National Laboratory
LBE	Licensing Basis Event
LMP	License Modernization Project
LOCA	Loss of coolant accident
LWR	Light-Water Reactor
MANDE	Monitoring and Non-destructive Examination
MCS	Minimal cut sets
NDE	Non-destructive examination
NEI	Nuclear Energy Institute
NPP	Nuclear power plant
NRC	Nuclear Regulatory Commission
O&M	Operations and maintenance
OLLD	On-line leak detection
PBMR	Pebble-bed modular reactor
POD	Probability of Detection
PRA	Probabilistic Risk Assessment
PWR	Pressurized-Water Reactor
RCCS	Reactor cavity cooling system
RIM	Reliability and Integrity Management

RSF	Required safety function
SSC	Structures, systems, and components
AOO	Anticipated Operational Occurrence
ASME	American Society of Mechanical Engineers
BDBE	Beyond Design Basis Event
BPVC	Boiler & Pressure Vessel Code
CLR	Component-Level Requirement
DBA	Design Basis Accident
DBE	Design Basis Event
DID	Defense-in-depth
DMA	Degradation mechanism assessment
DOE	Department of Energy
FOM	Figure of merits
GA	Genetic Algorithm
HTGR	High-temperature gas reactor
INL	Idaho National Laboratory
LBE	Licensing Basis Event

TERMS AND DEFINITIONS

This section defines terms used in this report. Definitions are consistent with terms and definitions presented in 2019 edition of ASME Boiler and Pressure Vessel Code Section XI Division 2 code “Requirements for Reliability and Integrity Management (RIM) Programs for Nuclear Power Plants” [1] herein after referred to as ASME Section XI Div. 2 and with NEI Technical Report 18-04, Revision 1 “Risk-Informed Performance-Based Technology-Inclusive Guidance for Non-Light Water Reactor Licensing Basis Development” [2] herein after refereed as NEI 18-04.

Accident Sequence	A representation in terms of an initiating event followed by a sequence of failures or successes of events (i.e., system, function, or operator performance) that can lead to undesired consequences with a specified end state.
Alternate Requirements	Monitoring or augmented non-destructive examination (NDE) methodologies used to assess and evaluate component degradation other than the prescribed NDE methods contained in [1] Mandatory Appendix V and any augmented provisions contained in the applicable reactor design supplement of Mandatory Appendix VII.
Anticipated Operational Occurrence (AOO)	Anticipated event sequences expected to occur one or more times during the life of a nuclear power plant (NPP), which may include one or more reactor modules. Event sequences with mean frequencies of 1×10-2/plant-year and greater are classified as AOOs. AOOs take into account the expected response of all structures, systems, and components (SSC) within the plant, regardless of safety classification.
Availability	The probability that a system or component is capable of supporting its function.
Beyond Design Basis Event (BDBE)	Rare event sequences that are not expected to occur in the life of a NPP, which may include one or more reactor modules, but are less likely than a Design Basis Event (DBE). Event sequences with frequencies of 5×10-7/plant-year to 1×10-4/plant -year are classified as BDBEs. BDBEs take into account the expected response of all SSCs within the plant regardless of safety classification.
Component Exposure Population	The set of equipment included in the scope of the Reliability and Integrity Management (RIM) Program for which a particular RIM strategy is applied to influence reliability.
Component-Level Requirement (CLR)	CLRs are the allowable degradation limits of an individual component from a safety point of view. CLRs are described in accordance with the plant safety evaluation, using quantities such as the break size postulated in an accident scenario.
Condition Monitoring	The process of systematic data collection and evaluation to identify and quantify usage factors or changes in performance or condition of an SSC, such that remedial action may be planned to maintain SSC Reliability Targets.
Containment Failure Frequency (CFF)	CFF is the sum of frequencies of various containment failure modes ranging from small leaks to a large and early break of the containment.
Defense-in-Depth	An approach to designing and operating nuclear facilities that prevents and mitigates accidents that release radiation or hazardous materials. The key is creating multiple independent and redundant layers of defense to compensate for potential human and mechanical failures so that no single layer, no matter how

	robust, is exclusively relied upon. Defense-in-depth includes the use of access controls, physical barriers, redundant and diverse key safety functions, and emergency response measures.
Degradation Mechanism	A phenomenon or process that attacks (e.g., wears, erodes, corrodes, cracks) the material under consideration.
Design Basis Accident (DBA)	Postulated accidents that are used to set design criteria and performance objectives for the design of safety-related SSCs. DBAs are derived from DBEs based on the capabilities and reliabilities of safety-related SSCs needed to mitigate and prevent accidents, respectively. DBAs are derived from the DBEs by prescriptively assuming that only safety-related SSCs classified are available to mitigate postulated accident consequences to within the 10 CFR 50.34 dose limits.
Design Basis Event (DBE)	Infrequent event sequences that are not expected to occur in the life of a NPP, which may include one or more reactor modules, but are less likely than AOOs. Event sequences with mean frequencies of 1×10-4/plant-year to 1×10-2/plant-year are classified as DBEs. DBEs take into account the expected response of all SSCs within the plant regardless of safety classification. The objective and scope of DBEs form the safety design basis of the plant.
Design Basis External Hazard Level (DBEHL)	A design specification of the level of severity or intensity of an external hazard for which the safety-related SSCs are designed to withstand with no adverse impact on their capability to perform their required safety function (RSF).
End State	The set of conditions at the end of an Event Sequence that characterizes the impact of the sequence on the plant or the environment. In most probabilistic risk assessments (PRA), end states typically include success states (i.e., those states with negligible impact) and release categories.
Event Sequence	A representation of a scenario in terms of an Initiating Event defined for a set of initial plant conditions (characterized by a specified POS) followed by a sequence of system, safety function, and operator failures or successes, with sequence termination with a specified end state (e.g., prevention of release of radioactive material or release in one of the reactor-specific release categories). An event sequence may contain many unique variations of events (minimal cut sets) that are similar in terms of how they impact the performance of safety functions along the event sequence.
Failure	Events involving conditions that would disable a component’s ability to perform its intended safety function.
Failure Mechanism	Any of the processes that results in failure modes, including chemical, electrical, mechanical, physical, thermal, and human error.
Frequency-Consequence Target (F-C Target)	A target line on a frequency-consequence chart that is used to evaluate the risk significance of LBEs and to evaluate risk margins that contribute to evidence of adequate defense-in-depth.
Fundamental Safety Function (FSF)	Safety functions common to all reactor technologies and designs; includes control heat generation, control heat removal and confinement of radioactive material.

Human Error (HE)	Any human action that exceeds some limit of acceptability, including inaction where required, excluding malevolent behavior.
Indication of Degradation (ID)	A signal or response that degradation exists that could lead to the exceedance of a CLR.
Initiating Event	Any event that perturbs the steady state operation of the plant, if operating, or the steady state operation of the decay heat removal systems during shutdown operations such that a transient is initiated in the plant that leads to the need for reactor subcriticality and decay heat removal.
Level of Rigor	The level of confidence to which a given examination system must be demonstrated based upon factors such as user needs, degradation mechanisms, and required Reliability Targets.
Licensing Basis Event (LBE)	The entire collection of event sequences considered in the design and licensing basis of the plant, which may include one or more reactor modules. LBEs include AOOs, DBEs, BDBEs, and DBAs.
Mechanistic Source Term	A source term that is calculated using models and supporting scientific data that simulate the physical and chemical processes that describe the radionuclide inventories and the time-dependent radionuclide transport mechanisms that are necessary and sufficient to predict the source term.
Mitigation Function	An SSC function that, if fulfilled, will eliminate or reduce the consequences of an event in which the SSC function is challenged. The capability of the SSC in the performance of such functions serves to eliminate or reduce any adverse consequences that would occur if the function were not fulfilled.
Monitoring	The systematic process of observing, tracking, and recording activities or data for the purpose of evaluating plant SSC conditions.
Monitoring and Non-destructive Examination (MANDE)	A term used in ASME Section XI, Div.2 that includes the activities of monitoring, non-destructive examination (NDE), and use of surveillance specimens.
Non-Safety-Related with No Special Treatment SSCs (NST SSCs)	All SSCs within a plant that are neither safety-related SSCs nor non-safety-related SSCs with special treatment SSCs.
Non-Safety-Related with Special Treatment SSCs (NSRST SSCs)	Non-safety-related SSCs that perform risk-significant functions or perform functions that are necessary for defense-in-depth adequacy.
Performance-Based	An approach to decision-making that focuses on desired objective, calculable or measurable, observable outcomes, rather than prescriptive processes, techniques, or procedures. Performance-based decisions lead to defined results without specific direction regarding how those results are to be obtained. At the NRC, performance-based regulatory actions focus on identifying performance measures that ensure an adequate safety margin and offer incentives and flexibility for licensees to improve safety without formal regulatory intervention by the agency.

Probabilistic Risk Assessment (PRA)	A quantitative assessment of the event sequences involving the release of radioactive material, an estimate of accident frequencies, consequences and uncertainties.
PRA Safety Function	Reactor design-specific SSC functions modeled in a PRA that serve to prevent and/or mitigate a release of radioactive material or to protect one or more barriers to release.
Prevention Function	An SSC function that, if fulfilled, will preclude the occurrence of an adverse state. The reliability of the SSC in the performance of such functions serves to reduce the probability of the adverse state.
Probability of Detection (POD)	The percentage resulting from dividing the number of detections by the number of flawed specimens or flawed grading units examined. POD indicates the probability that an examination system will detect a given flaw.
Reliability	The probability that a system or component will perform its specified function under given conditions upon demand and for a prescribed mission time.
Reliability and Integrity Management (RIM)	Those aspects of the plant design process that are applied to provide an appropriate level of reliability of SSCs and a continuing assurance over the life of the plant that such reliability is maintained. These include design features important to reliability performance such as design margins, selection of materials, testing and monitoring, provisions for maintenance, repair and replacement, leak testing, and NDE.
Reliability Target	A performance goal established for the probability that an SSC will complete its specified function in order to achieve plant-level risk and reliability goals.
Required Functional Design Criteria (RFDC)	Reactor design-specific functional criteria that are necessary and sufficient to meet the required safety functions.
Required Safety Function (RSF)	A PRA Safety Function that is required to be fulfilled to maintain the consequence of one or more DBEs or the frequency of one or more high-consequence BDBEs inside the F-C Target.
Risk-Informed	An approach to decision-making in which insights from probabilistic risk assessments are considered with other sources of insights.
Risk-Significant LBE	An LBE whose frequency and consequence meet a specified risk significance criterion. In the LMP framework, an AOO, DBE, or BDBE is regarded as risk-significant if the combination of the upper bound (95%tile) estimates of the frequency and consequence of the LBE are within 1% of the F-C Target and the upper bound 30-day total effective dose equivalent at the exclusion area boundary exceeds 2.5 mrem.
Risk-Significant SSC	An SSC that meets defined risk significance criteria. In the LMP framework, an SSC is regarded as risk-significant if its PRA Safety Function is: (a) required to keep one or more LBEs inside the F-C Target based on mean frequencies and consequences; or (b) if the total frequency LBEs that involve failure of the SSC PRA Safety Function contributes at least 1% to any of the LMP cumulative risk targets. The LMP cumulative risk targets include: (i) maintaining the frequency of exceeding 100 mrem to less than 1/plant-year; (ii) meeting the NRC safety goal quantitative health objective for individual risk of early fatality; and (iii) meeting

	the NRC safety goal quantitative health objective for individual risk of latent cancer fatality.
Safety Design Approach	The strategies that are implemented in the design of a NPP that are intended to support safe operation of the plant and control the risks associated with unplanned releases of radioactive material and protection of the public and plant workers. These strategies normally include the use of robust barriers, multiple layers of defense, redundancy, and diversity and the use of inherent and passive design features to perform safety functions.
Safety-Related Design Criteria	Design criteria for SR SSCs that are necessary and sufficient to fulfill the required functional design criteria for those SSCs selected to perform the required safety functions.
Safety-Related SSCs (SR SSCs)	SSCs that are credited in the fulfillment of RSFs and are capable to perform their RSFs in response to any DBEHL.
Safety-Significant SSC	An SSC that performs a function whose performance is necessary to achieve adequate defense-in-depth or is classified as Risk-Significant SSC.
Sizing Accuracy	The difference between the actual length, depth, flaw separation, and remaining ligaments and the values measured using a non-destructive sizing technique as determined during the performance demonstration process.
Surveillance Samples	Specimens of SSC representative materials for monitoring the material performance, relevant to meeting the RIM target reliabilities, of inservice SSCs subjected to environmental stressors. Surveillance samples are located in the same or higher levels of environmental stressors as the inservice SSCs. They are unique for each reactor design, SSC design and degradation mechanisms of concern.
Uncertainty (as used in MANDE)	A quantification representing the variability associated with monitoring and non-destructive examination (MANDE) data and includes many technique and application specific parameters such as the minimum detection capability, sizing accuracy, resolution tolerance, repeatability, consistency, etc.
Uncertainty (as used in PRA)	A representation of the confidence in the state of knowledge about the parameter values and models used in constructing the PRA.

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Reliability and Integrity Management Program Implementation Approach

SUMMARY

Every nuclear power plant (NPP) in the United States and around the world is obligated to maintain high levels of safety with measures that ensure plant reliability and integrity. These programs have become increasingly risk-informed in recent years. New reactor designs are very focused on risk-informed approaches to support all stages of development—from initial design and licensing to plant operation and retirement. The License Modernization Project (LMP) initiative by the U.S. Nuclear Regulatory Commission (NRC) is just one example of a risk-informed approach being encouraged for implementation.

The LMP initiative resulted in the issuance of Regulatory Guide (RG) 1.233, "Guidance for a Technology-Inclusive, Risk-Informed, and Performance-Based Methodology to Inform the Licensing Basis and Content of Applications for Licenses, Certifications, and Approvals for Non-Light Water Reactors" [3]. RG 1.233 endorses Nuclear Energy Institute (NEI) 18-04, Revision 1, "Risk-Informed Performance-Based Guidance for Non-Light Water Reactor Licensing Basis Development" [2] as one acceptable method for non-light-water reactor (LWR) designers to use for selection of licensing basis events (LBEs); classification and special treatments of structures, systems, and components (SSCs); and assessment of defense-in-depth (DID). All of these activities are fundamental to the safe design of non-LWRs.

The NEI 18-04 document provides guidance for the following technology-inclusive, risk-informed, and performance-based (TI-RIPB) processes that must be completed to satisfy the requirements of RG 1.233:

- Systematic definition categorization and evaluation of event sequences for selection of LBEs, which include anticipated operational occurrences (AOOs), design basis events (DBEs), design basis accidents (DBAs), and beyond design Basis events (BDBEs)
- Systematic safety classification of SSCs, development of performance requirements, and application of special treatments
- Systematic adherence to guidelines for evaluation of DID adequacy.

Some of the above processes are well-known since they were and still are used for licensing of LWRs, such as systematic definition and evaluation of event sequences and evaluation of DID. However, the systematic safety classification of SSCs, development of performance requirements, and application of special treatments are somewhat unfamiliar to LWRs. More specifically, development and monitoring of performance requirements are a completely new problem that does not exist in the LWR domain. The reason is that development and monitoring of performance requirements is the essence of a performance-based approach, a methodology not yet fully embraced and employed by LWRs. While a performance-based approach for risk management is very beneficial, LWRs have historically leaned toward deterministic methods, and only recently started shifting towards risk-informed approaches and in lesser degree to performance-based approaches. Given the novelty of the process, the advanced reactor industry has an understandable difficulty in its interpretation and proper implementation. Fortunately, another industry initiative led by the American Society of Mechanical Engineers (ASME) has been in development for a few years—requirements for a reliability and integrity management (RIM) program for NPPs [1]. The objective of the RIM program is to define, evaluate, and implement strategies to ensure that performance requirements for SSCs are defined, achieved, and maintained throughout the plant lifetime. As such, the ASME RIM program fits extremely well with the objectives of the TI-RIPB approach described in RG 1.233 and, given its acceptance by the NRC, can serve as an acceptable and

satisfactory approach to addressing the process of systematic safety classification of SSCs, development of performance requirements, and application of special treatments.

In August 2020, the NRC communicated to ASME [4] that it has initiated efforts to review and endorse the 2019 Edition of ASME Boiler & Pressure Vessel Code (BPVC) Section XI, Division 2 [1] for application to non-LWRs. Draft Regulatory Guide DG-1383 [5] was issued for public comments in September 2021 with full issuance expected in 2022. This endorsement adds urgency for developers of new reactor designs to understand how ASME Section XI, Division 2 is to be implemented.

Regulatory Guide DG-1383 "describes an approach that is acceptable to the staff of the NRC for the development and implementation of a preservice (PSI) and in-service (ISI) program for non-light water reactors" [5]. ASME Section XI, Division 2 also provides the requirements for the creation of the RIM program for any type of non-LWR NPP. The RIM program can be beneficial to the industry by reducing implementation costs and providing consistency in implementation for users. However, because ASME Section XI, Division 2 complies with ISI requirements through application of processes that are common to current LWR designs, there is limited experience to draw from and limited guidance on meeting the requirements for the development of the risk-informed RIM program.

Therefore, Regulatory Framework Modernization Program within Regulatory Development supporting the Department of Energy's (DOE's) Office of Nuclear Energy initiated a project to develop guidance based on the pending ASME Section XI, Division 2 requirements for non-LWR developers through the establishment of the risk-informed RIM program. INL's project covers a limited scope focused on two key steps:

- SSC reliability target allocations
- Identification and evaluation of RIM strategies.

The scope was selected based on industry feedback about the development of the RIM program and most urgent needs as related to the licensing process based on RG 1.233. INL's project demonstrates the RIM development process using a case study that presents various possibilities and options for meeting RIM program requirements, including considerations of a tradeoff between reliability and economics, and optimization of design options.

The draft report presents simple, publicly available case studies to allow greater focus on the methodology demonstration. The draft report is being issued to solicit industry feedback on these initial efforts which will help guide future research and development. Use of publicly available information enables wide distribution of the report without proprietary information concerns which facilitates collection of feedback. The next step is to apply the developed framework to a reactor-specific design via technology-specific case studies.

1. PROJECT DESCRIPTION

1.1 Scope and Objectives

The scope of this project is to develop a framework supporting RIM implementation strategies for advanced reactors. This work supports the establishment of a defined and predictable regulatory framework by providing guidance for implementing of the ASME code addressing the development of a RIM program.

The objective of this project is to support the design and continuous performance assessment of advanced nuclear power reactors with a framework and a guidance document that provides directions on the use of reliability targets, associated reliability allocation, and RIM strategies as part of implementation of ASME Section XI, Division 2 based on a risk-informed and performance-based approach to system performance management. The results obtained from this effort directly address the goal of enabling the deployment of advanced nuclear reactors by reducing the regulatory risks and uncertainties associated with their commercial deployment.

The outcome for this project is a framework that the nuclear power industry can use when developing ways to establish and meet reliability targets to comply with the requirements of ASME Section XI, Division 2. The future implementation of this framework will allow analyzing early lessons learned to occur simultaneously as experience is gained in a RIM program strategies selection that can subsequently be factored into the development of a software tool that would expedite this process.

1.2 Description of RIM Program Development

Figure 1 presents the conceptual framework for a RIM program. The development of RIM program requires determination of:

- WHAT to monitor/examine to meet the end-goal plant operational requirements (i.e., safety, investment protection, and licensing)
- HOW to monitor/examine the “selected what”

As the result of RIM program implementation, a RIM strategy is developed to monitor the performance of the system at each level, at either the complete system or multiple sub-systems, and for each SSC.

The focus of the project is represented by ASME Section XI, Division 2 Figure I-1.1-2 [1] presented as Figure 2 below. The outlined portions represent the scope to develop the initial RIM strategy based on the degradation mechanisms present, the allocation of reliability targets, and understanding the uncertainties of the non-destructive evaluation (NDE) assigned to a strategy.

Each task in the RIM program development is very broad and complex; however, some tasks are more straightforward because they are similar to processes implemented by existing NPPs. For example, the damage mechanism assessment is a well-known process within the industry used in activities such as risk-informed in-service inspection (RI-ISI) and license renewal. While damage phenomena and mechanisms may be different between advanced reactors and LWRs, the process of their assessment follows similar steps.

Other tasks are more complicated because they are newly introduced in ASME Section XI, Division 2, or they use methodologies and approaches that are novel to the industry. Therefore, these tasks are selected as the focus of this project and are discussed in the following sections.

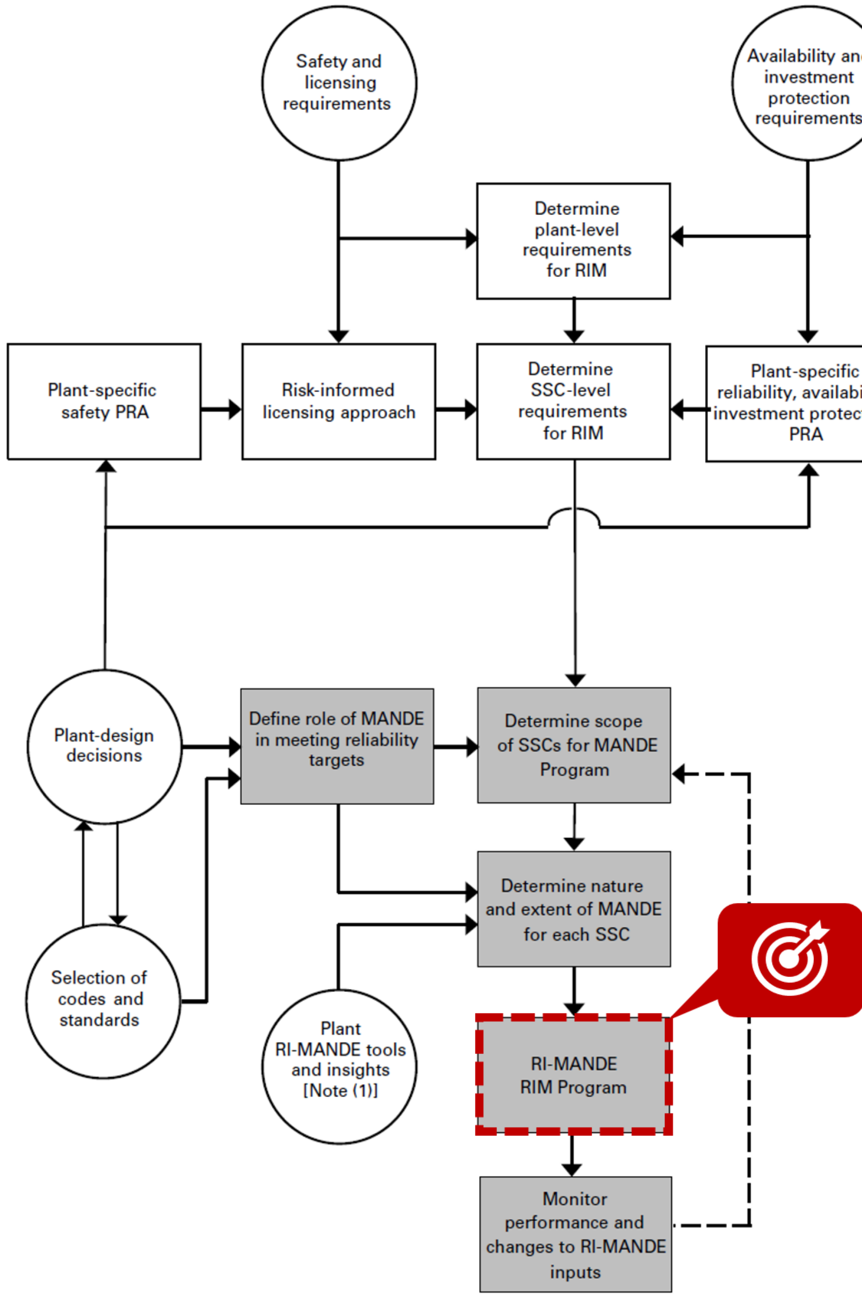


Figure 1. RIM program conceptual framework [1].

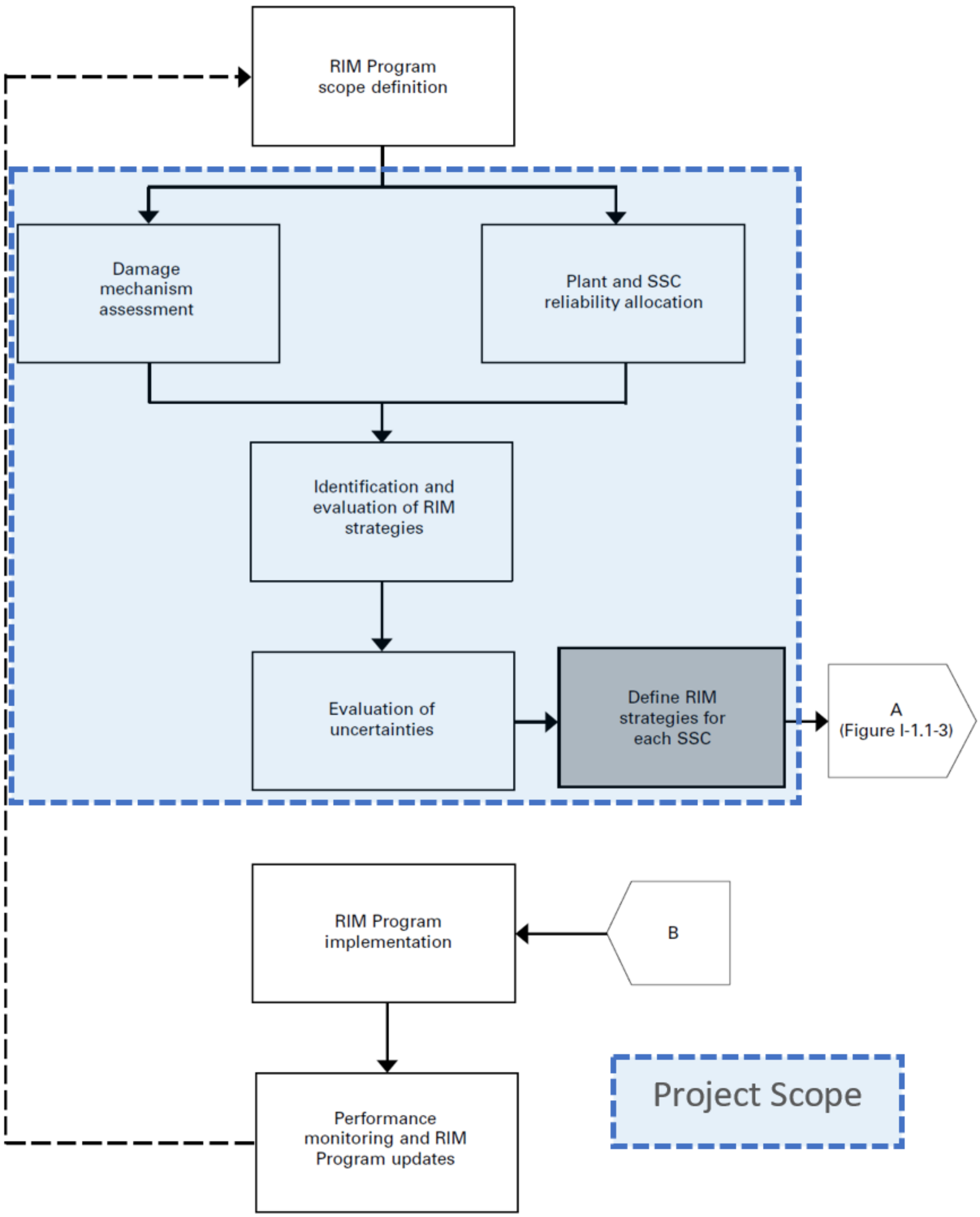


Figure 2. RIM program scope and project scope.

1.2.1 Plant and SSC Reliability Target Allocation

The reliability target allocation is a complex process because it involves considering multiple aspects largely grouped into two categories:

- Regulatory limits on the risks, frequencies, and radiological consequences of LBEs determined based on multiple considerations including deterministic analyses and evaluations, insights obtained from the plant probabilistic risk assessment (PRA), and defense-in-depths aspects.

- Requirements for plant availability and investment protection defined by the limits on the risks related to the loss of production and/or loss of assets determined by the plant reliability, availability, investment protection PRA.

The objective of selecting reliability targets is to establish a benchmark that will be used for evaluating system performance. As such, reliability targets are developed during the initial phase of the RIM program, and later, the actual plant performance is measured against the reliability targets to identify deviations from the expected performance.

A simplified overview of the steps in the reliability target allocation process is presented below:

Step 1: Plant-level reliability targets, radiation dose limits. The starting point is the radiation dose limits to the public which are specified by the NEI 18-04 frequency-consequence curve. The radiation dose limits are the same regardless of reactor design, but compared to LWRs, new designs may have additional requirements for dose limits due to different release sources.

Step 2: Plant-level reliability targets, accident scenarios. The accident scenarios that could lead to a release associated with source terms identified in Step 1 are defined. The accident parameters include failure modes of SSCs and associated probabilities of failure which may lead to an accident. As the result of this step, frequency of each possible accident scenario is determined.

Step 3: System-level reliability targets. The reactor design must meet the radiation dose regulatory limits with various options to meet the requirement. Meaning one plant could accomplish it through high redundancy of mechanical systems (e.g., three train system) while another design may accomplish it through very high reliability of the primary system (e.g., passive cooling system) supported by a backup system for DID. The system-level reliability targets are assigned in a way that the plant-level reliability targets remain in the designated LBE category—AOO, DBE, and BDBE—including uncertainty considerations.

Step 4: Component-level reliability targets. This is the step where failure modes and failure probabilities are defined for each SSC to inform the SSC-level reliability targets. The SSC reliability targets are then input into the system-level reliability targets, and the evaluation is performed to check if the initially set system-level reliability targets are met. If not, SSC-level reliability targets are adjusted (i.e., reliability values increased) until the system-level reliability targets are satisfactory.

The difficulty with reliability target allocation is due to an uncertainty as to how much of a risk increase (or reliability decrease) each SSC can afford before regulatory limits in steps 1 and 2 are compromised. This is a tricky question because an incremental risk increase for one SSC may not change anything at the plant-level whereas the same small risk increase in multiple SSCs can have a detrimental effect.

Figure 3 presents a schematic of the reliability target allocation process, which also demonstrates the previously mentioned difficulty where multiple options for reliability targets are available at each level.

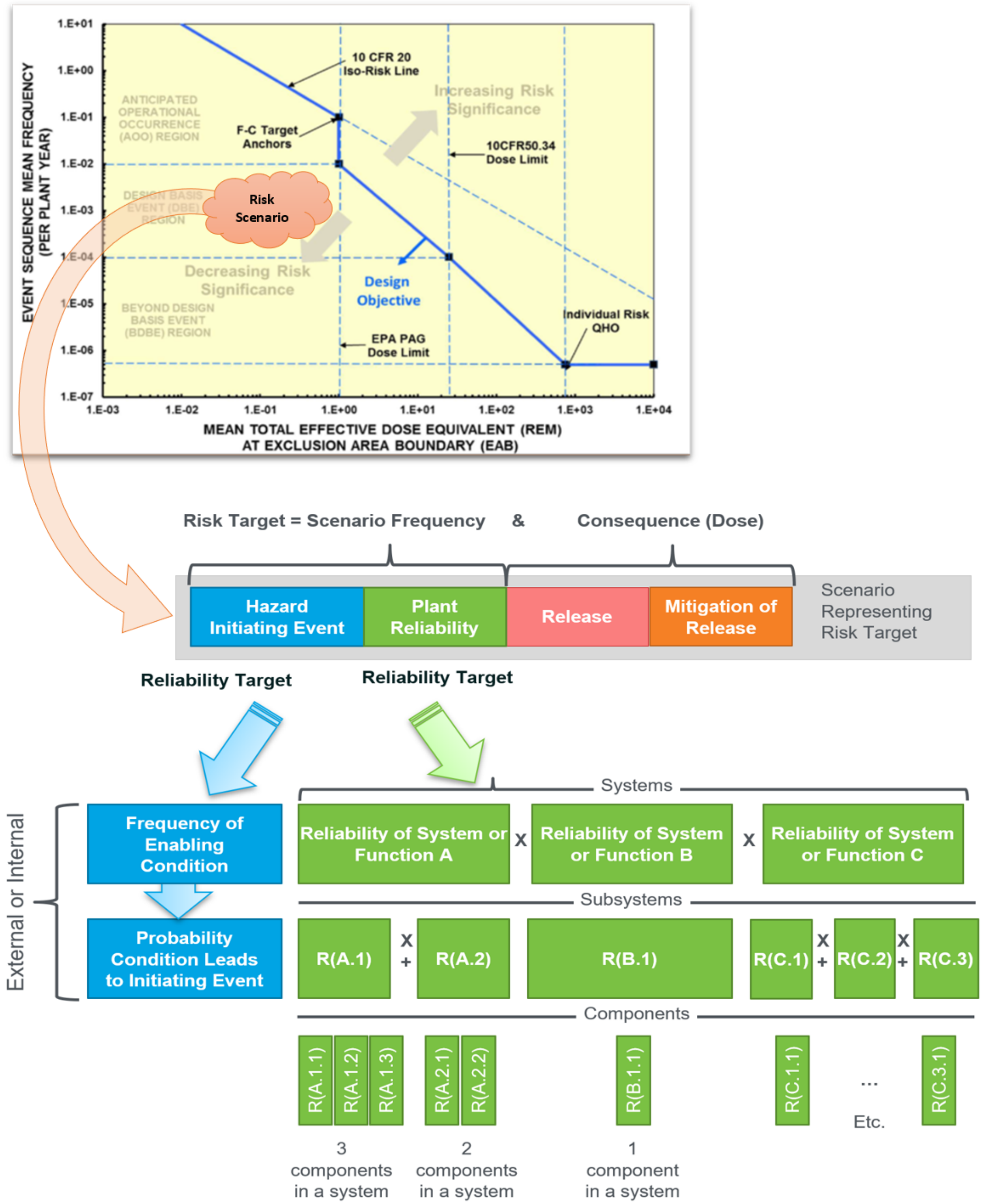


Figure 3. Schematic of reliability target allocation process.

1.2.2 Damage Mechanism Assessment

The material and operating conditions for an SSC are used to identify degradation mechanisms and associated failure modes that an SSC may be subject to. Mandatory Appendix VII of ASME Section XI, Division 2 provides supplements for different reactor types (many of which are still in development). Similar to the approach taken for RI-ISI, the identified degradation mechanism attributes and attribute criteria within Appendix VII can be used to identify what the SSC may be susceptible to and where the area of interest for inspection/examination may best be applied.

1.2.3 Identification and Evaluation of RIM Strategies

The objectives of this task are:

- Identify available RIM strategies that will meet the reliability targets.
- Evaluate and select combinations of strategies that are necessary and sufficient to meet and maintain reliability targets.
- Ensure that selected strategies are optimized in terms of both reliability and costs (i.e., meet reliability targets while using the most cost-effective combinations of RIM strategies).

The first two objectives are driven by system and/or SSC physical parameters (e.g., degradation mechanisms to consider, performance parameters to monitor). As such, they must be both necessary and sufficient to demonstrate that they meet regulatory requirements for reliability targets. However, selection of cost-effective RIM strategies is a desirable but not a regulatory-driven objective. Many combinations of strategies would be available for a new reactor that would meet reliability targets. This project focuses on providing a solution using multi-objective optimization techniques.

Multiple approaches to creating RIM strategies are possible. We can group these approaches into three categories:

1. *Modifications to system reliability focused on an individual component-level*. This approach targets the facility and system behavior through a technical evaluation that is focused on possible reliability characteristics of components. Multiple possible methods of evaluation include:
    a. Rule-based adjustments. This approach uses simple heuristics to modify a component's individual reliability allocation (either more or less reliable) to perturb a system reliability until its target is met. This approach is not guaranteed to optimize a system since it is essentially a brute-force approach that modifies a system by focusing on components. Even if a particular RIM strategy is found using this approach, there may be other strategies that are more cost-effective for the same overall reliability since not every combination of change can be evaluated for complex systems.
    b. Random adjustments. Similar to the rule-based adjustments, the approach randomly modifies a component's reliability allocation in order to perturb the system reliability. However, since the process is stochastic, it is not guaranteed to be optimal. Further, random adjustments to component reliability allocations may produce many cases that do not meet higher-level reliability targets thereby being computationally inefficient.
    c. Engineering judgement-based adjustments. This approach requires engineering input into the selection of and adjustment to component's reliability allocation. Specific components are targeted for reliability allocation changes due to judgement. This approach also suffers from some of the issues previously discussed in 1a and 1b.
    d. Importance measure based adjustments. This approach relies on the calculation of reliability- or risk-focused importance measures. Typical importance measures include a risk achievement worth (how much will system reliability decrease if a component fails), a percent-contribution (how much does a component contribute to the overall system), and sensitivity worth (how sensitive is a system to changes in a component's reliability).
    e. Prevention worth-based adjustments. This approach relies on the calculation of prevention worth sets, i.e., a combination of components that—if guaranteed to work—will prevent failure of the system or facility. Components that fall outside of the prevention set are candidates for reliability decrease modifications since these components will have a secondary impact on overall system or facility performance.

2. *Modifications to system reliability focused on a functional or subsystem level*. These approaches are similar to that described in 1 above with the exception of the focus being on a higher level than at the component-level for evaluation.
    a. Functional level-based adjustments
    b. System or sub-system-level-based adjustments
    c. Initiating event impact-based adjustments.
3. *Modifications to system reliability focused on a global system-level*. This approach embodies the idea that all elements of the system model (from lowest to highest) be considered—including all potential combinations of reliability adjustments. However, for most complex systems, the computational requirement for this complete global-level optimization is not achievable due to the extremely large number of potential options available to consider. Consequently, in the remainder of this report, we consider approximation options to approach 3 in addition to items 1 and 2.

Since multiple technical approaches are possible, we also need to consider a metric that can help to define what is "better" when considering different allocation suggestions that might be available. At a high level, we consider reliability of components and systems along with the costs associated with the reliability management of these components and systems. An approach that provides adequate reliability while minimizing cost would be preferred over one that has higher cost. Attributes that are not directly translatable to either cost or reliability are not considered in this project. However, the RIM strategies for each SSC are defined based on the optimization analysis where both system reliability and costs associated with various RIM strategies are considered.

1.2.4 Evaluation of Uncertainties

The TI-RIPB licensing approach requires consideration of uncertainties. There are multiple sources of uncertainty associated with both the frequency and consequence estimates and equipment performance metrics are significant contributors to the overall uncertainty estimate. As such, it is important to properly identify, characterize, and account for uncertainties associated with equipment performance that can and should be accomplished as part of the RIM program scope.

Uncertainties from multiple sources should be included and propagated through the entire model quantification. This is explicitly accounted for by using the INL-developed RAVEN software [6] which is a flexible and multipurpose uncertainty quantification, regression analysis, data analysis, and model optimization platform.

2. RELIABILITY TARGET ALLOCATION CASE STUDY

Reliability target allocation is the key task in the risk-informed, performance-based licensing bases development following RG 1.233 [3] and in the RIM program development [1]. Figure 3 in Section 1.2.1 presents a schematic of the reliability target allocation process and demonstrates the difficulty of this process since multiple options for reliability targets are available. As part of this project, we performed a reliability target allocation for a simplified case study as discussed below.

However, this guidance does not specify process or provide directions as to how to establish reliability targets that would meet the requirements. The high-level requirement identified in NEI 18-04 is that "the reliability targets are set to ensure that the underlying LBE frequencies and consequences meet the LBE evaluation criteria with sufficient margin" and that "information from the PRA is used as input to the selection of reliability targets. [2]"

Guidance for reliability targets allocation in ASME Section XI, Division 2 is also very narrow: "plant-level reliability shall be derived from regulatory limits on the risks, frequencies, and radiological consequences of licensing basis events that are defined in the [PRA]" and "the PRA model shall be used to allocate SSC Reliability Targets from and consistent with the plant-level reliability goals." As such, one of the top requests from the industry is to develop methodologies and guidance to support the reliability target allocation process in a consistent, repeatable, defensible, and verifiable manner that could be followed regardless of reactor technology. This project addressed this undertaking with preliminary results and findings discussed in the following sections.

Both NEI 18-04 and ASME Section XI, Division 2 indicate that reliability target allocation should be done at the plant-level first with the final goal of having reliability targets assigned to every SSC. Given that a plant will have hundreds of SSCs, many SSCs contributing to multiple accident sequences, and each SSC reliability target having a range of acceptable values, the problem becomes extremely large.

For example, let's consider a plant with only 100 SSCs and only two options for a reliability target assignment (e.g., one option uses a realistic reliability value, and second option uses a more conservative value). This scenario would result in total of 1.27E+30 possible combinations (2 options ^ 100 components = 1.27E+30 possibilities) of a reliability target allocation for plant SSCs. The goal of reliability target allocation is to find the appropriate reliability target values that would (1) satisfy all regulatory requirements; (2) be feasible to achieve (i.e., SSC actual performance can meet the assigned reliability target); and (3) be acceptable from economic perspective. Given these goals and the extremely large number of possible combinations reliability target allocation process is certainly a great challenge.

2.1 Framework for Reliability Target Allocation

2.1.1 Case Study Description

A PRA model for a generic pressurized-water reactor (PWR) was selected to demonstrate the proposed methodology for the reliability target allocation process. The PRA model is limited to a Level 1 and internal events only. The selected reactor design and PRA model are intentionally simple to support the initial demonstration of the proposed technical framework where the problem is small. This way, the demonstration is focused on the methodology rather than addressing computational complexities, specifics of new technologies, unavailability of data, and other similar constraints that are expected when the reliability target allocation is performed for advanced reactors.

While the ASME Section XI, Division 2 guidance is developed specifically for non-LWRs, the methodology for the reliability target allocation task would be similar in concept. The goal of the initial demonstration of the framework is to collect industry feedback, not for a specific reactor technology, but rather for the methodology. The use of a well-known PWR technology with established PRAs is expected to facilitate the feedback. In addition, a demonstration that is based on the publicly available information allows a wide, unrestricted distribution of the results, which is also a significant benefit for solicitation of feedback.

After the initial demonstration of the proposed framework using a generic PWR model, the same, improved framework will be applied to the reliability target allocation task performed for an advanced reactor.

2.1.2 Problem Formulation

A single initiating event can be seen as a single point in the regulatory plot shown in Figure 4 where the main constraint is to avoid an initiating event occurring above the regulatory curve (blue line of Figure 4). The degree of freedoms here considered are the probability values of the basic events that are queried in the initiating event risk model. By changing these parameters, the location of the initiating event in the regulatory plot moves vertically (see Figure 4). More specifically:

- If the probability value of a basic event increases, the location of the initiating event moves upward.

- If the probability value of a basic event decreases, the location of the initiating event moves downward.

Note that changing the probability value of a basic event also has economic implications in terms of procurement costs and surveillance/testing costs. As an example, more frequent surveillance/testing activities would increase component reliability, and, hence, it would reduce the probability of the basic event that is part of such a component; consequently, the location of the initiating event moves consequently downward (see Figure 4).

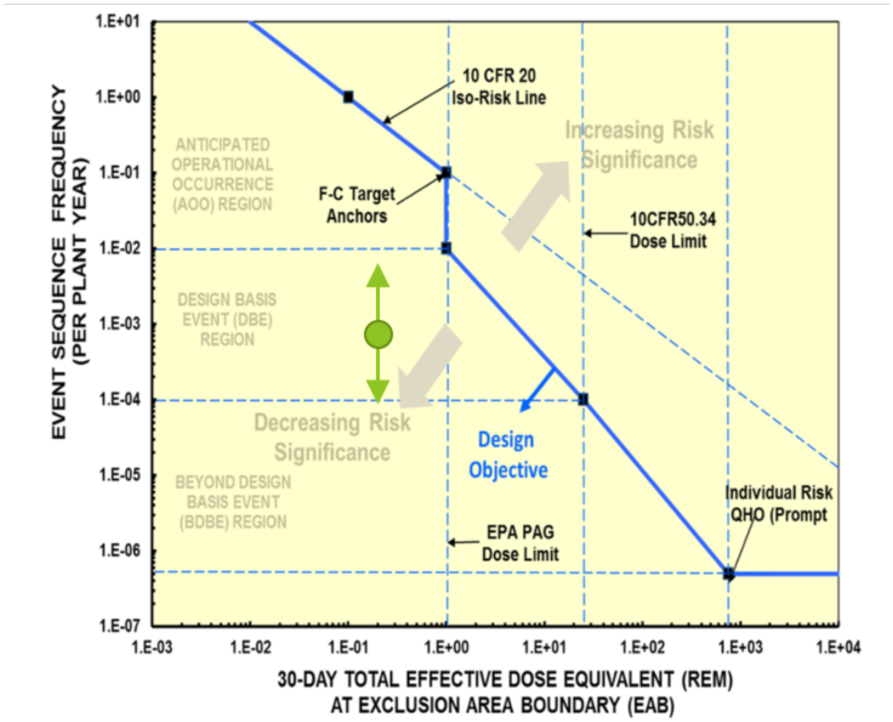


Figure 4. Graphical presentation of the impact of varying basic event probability values on location of event sequence frequency.

An initial formulation of the reliability target allocation problem can be framed as follows: given an initiating event, the objective is to determine the optimal probability values for the basic events queried in the given initiating event such that the frequency of the event sequence is as close as possible to the regulatory limits as indicated in Figure 5.

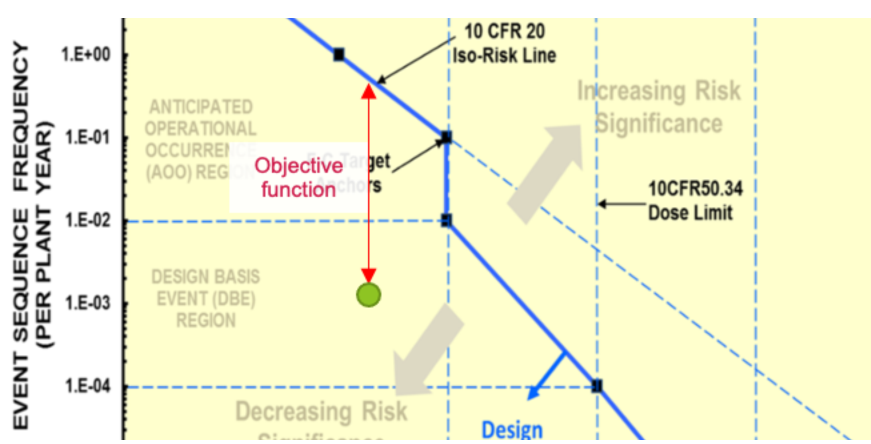


Figure 5. Graphical presentation of the objective function that it is needed to be minimized.

A different formulation of the reliability target allocation problem can be also framed as follows: determine the optimal probability values for the basic events queried in the given initiating event such that they minimize costs, and they keep the frequency of the event sequence below the regulatory limits. Note that these two formulations origin from the nature of model that is used in the optimization problem; this model, given a set of basic events, determines the event sequence frequency and the corresponding costs. These two generated variables are each used in a formulation of the reliability target allocation problem.

To simplify the analysis in this project, it is assumed that the probability value for a basic event cannot be arbitrarily chosen in space continuum (i.e., cannot be treated as a continuous variable in the [0,1] interval). Instead, it can be chosen from a discrete set of options. Mathematically speaking, we are dealing with an optimization problem where the decision variables are discrete and finite. An example set of options for a single basic event is given in Table 1 where three options are available along with their corresponding probability and cost values (e.g., procurement and testing/surveillance costs). The goal of the optimization process is to choose the optimal option for each basic event.

Table 1. Example of list of options for a basic event.

ID	Option	Probability	Cost
1	Base reliability	P^{base}	C^{base}
2	Low reliability	$P^{low} > P^{base}$	$C^{low} < C^{base}$
3	High reliability	$P^{high} < P^{base}$	$C^{high} > C^{base}$

The solution of such an optimization process can be challenging when the number of basic events and options are high. As an example, assume 30 basic events are considered where three options are available for each of them. The overall number of option combinations is: $3^{30} = 2.06\ 10^{14}$. Assume the evaluation of the event sequence frequency takes 0.1 seconds given an option combination, the, the evaluation of the initiating event sequence frequency for all combinations would take $6.53\ 10^5$ years. Even optimization methods (see Appendix A) have convergence issues when dealing with so many degrees of freedoms (30 in this example).

Section 2.3.4 provides a detailed description of three methods that have been investigated to solve such optimization problem. Before jumping on the solution methods, it is important to make few observations:

- Not all basic events might be under RIM scrutiny. In this case the basic events that are outside RIM scrutiny will not be part of the optimization process, and their probability value will be set to the nominal value determined from reliability databases or from previous reliability analyses (e.g., through Bayesian update).
- Data uncertainties should be explicitly considered. This is particularly relevant since uncertainties associated with probability of multiple basic events impact overall event sequence frequency (see Figure 6). Basic event uncertainties can be included in the reliability determination methodology described above through the definition of the objective function that we want to minimize. Rather than looking at the distance of the mean value of event sequence frequency to the regulatory limit, we look at the distance of the 95% percentile (or any point estimate of event sequence probability distribution) of event sequence frequency to the regulatory limit (see red segment of Figure 6).
- The definition of objective function shown in Figure 4 needs to include additional regulatory constraints. As an example, event sequences should be contained within their corresponding classification region (i.e., AOO, DBE, and BDBE). An alternative of objective function for three event sequences is shown in Figure 7.

- A missing aspect of the reliability determination methodology presented here is the concept of margin management. Once the plant is operating, some components might be taken offline either for corrective/preventive maintenance or for testing/surveillance purposes. In this situation, event sequency frequency would increase and overall plant safety margin may be affected. Therefore, impact of maintenance and testing/surveillance activities should be considered, and adequate safety margins should be built into account for variations in plant operation.
- DID requirements might be present in real operational contexts, and they could be translated into constraints that need to be considered in the optimization process.
- The reliability determination methodology can be performed at the basic event level or at the system-level. Thinking in terms of system reliability targets might simplify the analysis. This would be the case if these three conditions are simultaneously satisfied:
    a. Each system function is represented by its own fault tree
    b. Components are not shared among systems
    c. Basic events associated with a system are only explicitly included in the fault trees of that system.
- Here it is assumed that both active and passive components should be part of the same RIM optimization process since they all have impact on plant risk. Optimizing the active and passive components separately could lead to non-optimal solutions.
- In this work we have considered only one single initiating event. In a typical nuclear industry context, multiple initiating events are being analyzed in a plant PRA. Event sequence risk models might query a subset of common basic events. In this case, the application of the reliability determination methodology presented above could lead to different optimal options for the same basic event. This situation requires a modification of the reliability determination methodology such that it is applied to all initiating events simultaneously rather than one initiating event at a time.

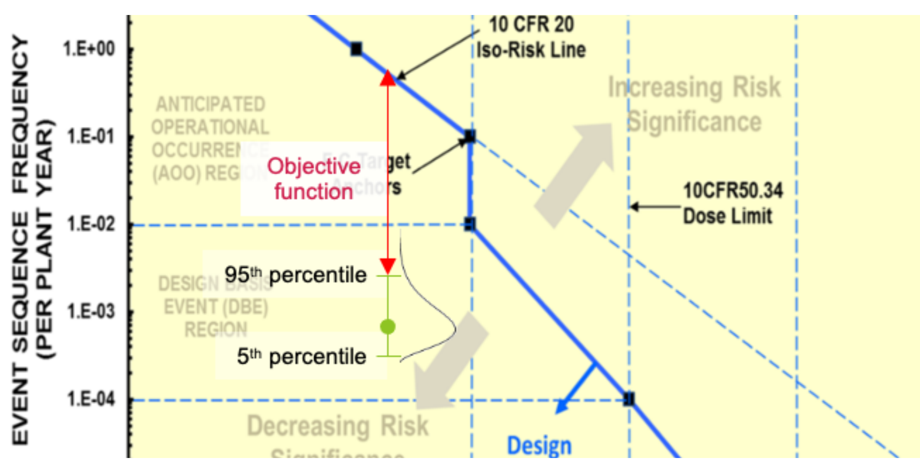


Figure 6. Graphical representation of the impact of basic event probability uncertainties on event sequence frequency.

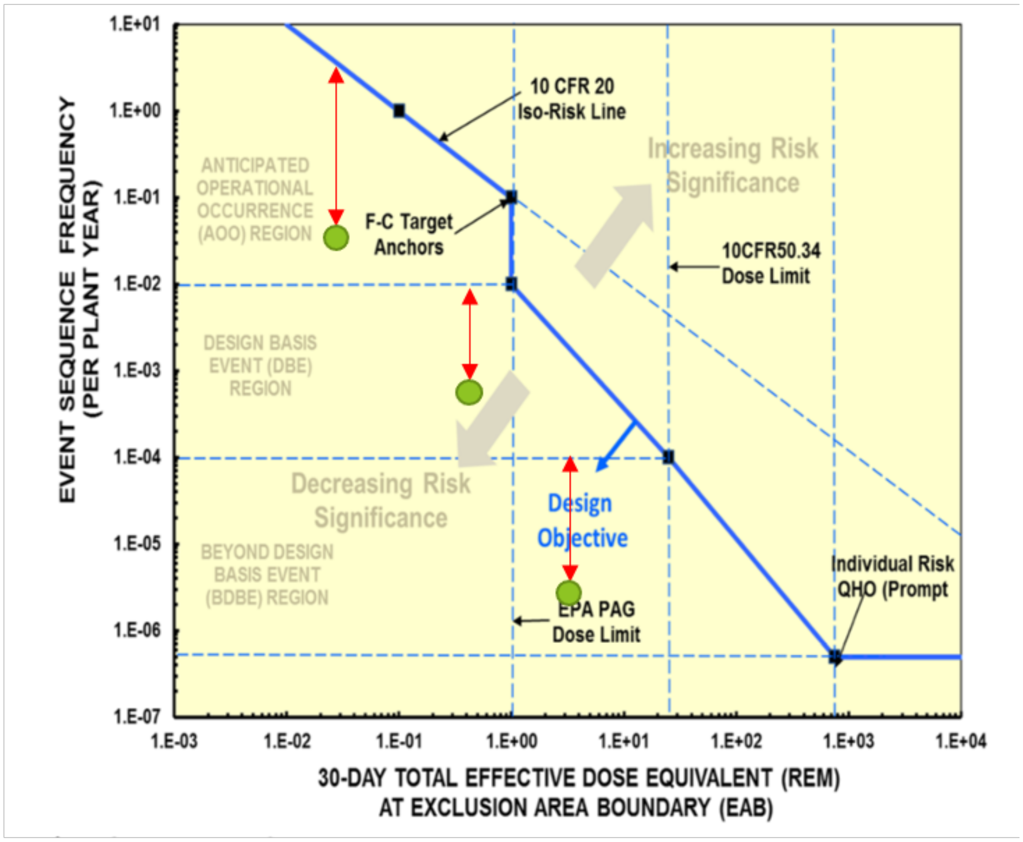


Figure 7. Definition of objective functions depending on event sequence location.

2.1.3 Available Tools

For the scope of this project, we are planning to employ two main software tools developed in the past year under the Light Water Reactor Sustainability (LWRS) program: RAVEN and SR^2ML.

RAVEN is a flexible and multipurpose modeling and simulation platform designed to perform uncertainty quantifications, regression analyses, data analyses, and model optimization analyses. Depending on the tasks to be accomplished and on the probabilistic characterization of the problem, RAVEN perturbs the response of the system by altering its parameters through Monte Carlo, Latin hypercube, and other reliability surface search sampling methods.

The data generated by the sampling process are analyzed using classical and more advanced data mining methods. RAVEN also manages the parallel dispatching (i.e., both on desktop, workstation, and large high-performance computing machines) of the software representing the physical model. RAVEN heavily relies on machine learning algorithms to construct surrogate models of complex physical systems to perform uncertainty quantification, reliability analyses, system optimization, and parametric studies.

Table 2 provides a summary of the subset of methods and models contained in RAVEN that are being used within the RIM project. More specifically, RAVEN is actively used to:

- Link models (e.g., contained in SR^2ML) together using, for example, the ensemble and logical model
- Sample the constructed models (e.g., for data uncertainty propagation and model optimization) using RAVEN samplers, optimizers (e.g., genetic algorithms), and the RAVEN running RAVEN capability (e.g., mix of uncertainty propagation and model optimization)
- Postprocess the generated data using classical statistical and data mining methods.

Table 2. List of RAVEN models and methods and their corresponding use case.

Model/Method/Capability	Use Case
Samplers (e.g., Monte Carlo, Latin hypercube, grid)	Methods designed to perform uncertainty quantification by sampling model input variables according to specific strategy
Pareto frontier	Method designed to determine the Pareto frontier from a multidimensional dataset
Optimizers (e.g., gradient-based, genetic algorithms, simulated annealing)	Methods designed to determine the global minima and maxima of the output variable of a model by smartly changing input variable values
Ensemble model	Capability to link models together in a linear data workflow
Logical model	Capability to choose which model to run (out of two) based on a set of logical conditions
Code interface	Capability to link external codes (e.g., PRA, economic or thermohydraulic codes) and treat them as RAVEN models
RAVEN running RAVEN	Capability to perform a two-level analysis where the first RAVEN is considered as a model (child mode) while the second RAVEN (parent mode) performs any sampling strategy (e.g., sampling or optimization)
Basic statistics	Postprocessor designed to analyze large datasets with the goal of determining the statistical moments (e.g., mean and variance) and perform sensitivity analysis
Data mining	Postprocessor designed to perform clustering of large datasets to evaluate similarities and patterns from the generated data

The Safety Risk Reliability Model Library (SR^{2}ML) is a software package that contains a set of reliability models designed to be interfaced with the INL-developed RAVEN code. These models can be employed to perform both static and dynamic system risk analysis and determine the risk importance of specific elements of the considered system. Two classes of reliability models are included:

- The first class includes all classical reliability models (fault trees, event trees, Markov models, and reliability block diagrams), which have been extended to deal not only with Boolean logic values but also time-dependent values. These models have been designed to mainly perform simulation-based reliability analyses where time needs to explicitly be taken into account.
- The second class includes several reliability models designed to incorporate the effect of component aging and maintenance on component unavailability. These models have been designed to support decision-making regarding maintenance posture at the plant and system-level (e.g., optimal maintenance operations that best balance cost and reliability).

Models included in these two classes are designed to be included in a RAVEN ensemble model to perform time-dependent system reliability analysis (e.g., dynamic analysis). Similarly, these models can be interfaced with system analysis codes within RAVEN to determine the failure time of systems and evaluate accident progression (static analysis).

The reliability analyses that can be performed in SR^{2}ML are not only classical (i.e., probability based) but also more innovative using a margin-based language. Classical reliability modeling is performed by coupling existing PRA quantification codes (e.g., Systems Analysis Program for Hands-on Integrated Reliability Evaluation [SAPHIRE]) with SR^{2}ML models. The main goal of margin-based reliability analyses is to better integrate equipment reliability data in order to assess system health. We still employ current reliability models (e.g., fault trees), but we are deploying a different calculation engine based on metric spaces rather than set theory (typically used in a "probability of occurrence of an event" language). The most important point of this method is how equipment reliability data generated by a component under different maintenance strategies (e.g., corrective or condition-based) can be used directly to measure component margin. Note that this method is not designed to be an alternative strategy to current PRA methods, but instead, a complementary solution designed for different kinds of decisions. We are, in fact, aiming to make decisions that target plant resources and asset management activities, such as work scheduling and project prioritization.

The reliability model at the system-level typically consists of a hierarchical set of fault trees, which are made up of a Boolean logic structure designed to link the top event under consideration (e.g., system failure to perform its desired function) given the Boolean status of its basic components, the basic events. The fault tree structure can be solved in probability terms with the goal of determining the probability of top event occurrence, given the probability values associated to each basic event. This can be achieved by first generating a list containing combinations of basic events that lead to the top event under consideration (i.e., the MCSs). Then, the probability associated with the top event can be calculated as the probability of the union of all MCSs.

SR^2ML contains a model designed to determine top event probability provided the list of MCSs and the probability associated to each basic event —the `MCSSolver` model— which can be directly employed within RAVEN and linked to component reliability models. Below, we indicate how the computation of the top event probability is performed. From a model perspective, the `MCSSolver` model input-output variables are the following

- Inputs variables:
  - Basic event probability $P(BE_l)\ \ l = 1, \dots, L$
  - Set Ξ of MCSs, $MCS_n \in \Xi\ \ (n = 1, \dots, N)$
- Output variables: top event probability $P(TE)$.

For the scope of the RIM project, we are planning to employ the following features/models of these two software tools:

- The `MCSSolver` model from SR^2ML that will receive the MCSs generated by SAPHIRE (or any PRA code).
- The RAVEN genetic algorithm optimization method to perform single-objective optimization over a set of discrete variables.
- RAVEN sampling capabilities to propagate data uncertainties (e.g., basic event probabilities).
- RAVEN Pareto frontier postprocessor to perform multi-objective optimization.
- The RAVEN running RAVEN capability to perform embedded analysis that combine multiple model sampling steps (e.g., optimization plus uncertainty propagation).

Currently, we are investigating the optimal software design that will be able to perform desired optimization processes. Once this is completed, we will proceed to construct the full RAVEN workflows and test it for different test cases (see Section 2.3). We will also investigate the need of high-performance computing systems to speed up optimization calculations.

2.2 Importance Identification

To support reliability target allocation studies, importance measures were identified as a potentially necessary input. The importance measures are PRA metrics that show various metrics of a given BE and how it contributes to the overall risk.

Baseline identification of the importance values of systems and components—from the same case study introduced in Section 2.1.1—was completed in three ways. These were differentiated by the way the systems were defined and by the manipulation of the failure rate of the components for three LOCA initiating events: small, medium, large. All cases were solved with a core damage frequency (CDF) truncation of 1E-13. Further explanation and results are presented in the following sub-sections.

2.2.1 System Importance Identification

2.2.1.1 Approach 1: By Fault Tree Definition

The first approach to determine the importance of the systems was to define the systems by their function. Their function is defined by the logic that makes up the top event that represents those systems and then by calculating their importance measures. Components that make up the front-line of the system as well as the support systems (such as electrical systems) are considered.

To calculate the importance measures for each top event fault tree, the following values were used:

- $F(x)$ total CDF of event tree related to the initiating event sequence
- $F(1)$ risk of the top event basic event failure probability set to 1
- $F(0)$ risk of the top event basic event failure probability set to 0
- $F(i)$ sum of CDF of sequences including the failure of the top event of interest, i.

To solve for F(1) and F(0), the fault tree was considered to be a calculated basic event whose probability could be set to 0 or 1. Sequences are cut sets of the failure or success of fault trees that lead to core damage due to the initiating LOCA event. The CDF of each sequence for the entire LOCA event tree is equal to the total CDF of the event tree. These values were used to calculate the four importance measures as defined below. The results are presented in Table 3.

- Risk Reduction Worth (RRW) $F(x)/F(0)$
- Risk Achievement Worth (RAW) $F(1)/F(x)$
- Birnbaum (Bi) $F(1) - F(0)$
- Fussell-Vesely (FV) $F(i)/F(x)$.

Table 3. LOCA event tree/sequence importance measures of functional systems defined by top event fault trees.

Initiating Event	Total CDF	Fault Tree	RRW	RAW	Bi	FV
LLOCA	6.381E-10					
		ACC-FT	1.00	9.26E+03	5.91E-06	2.25E-03
		LPI-FT	1.19	9.26E+03	5.91E-06	7.70E-01
		LPR-FT	1.30	9.26E+03	5.91E-06	2.28E-01
MLOCA	1.682E-07					
		ACC-FT	1.00	8.92E+02	1.50E-04	2.16E-04
		HPI-FT	1.00	8.92E+02	1.50E-04	6.84E-03
		HPR-FT	12.8	8.92E+02	1.50E-04	9.22E-01
		LPI-FT	1.01	8.92E+02	1.50E-04	6.81E-02
		RPS-FT	1.00	8.92E+02	1.50E-04	3.10E-03
SLOCA	3.825E-08					
		AFW-FT	1.01	2.22E+02	8.45E-06	5.94E-03
		F&B-FT	1.01	1.26E+00	1.02E-08	5.38E-03
		HPI-FT	1.09	1.05E+04	4.01E-04	8.20E-02

Initiating Event	Total CDF	Fault Tree	RRW	RAW	Bi	FV
		HPR-FT	8.08	6.42E+01	2.45E-06	8.76E-01
		LPI-FT	1.00	1.00E+00	0.00E+00	0.00E+00
		LPR-FT	1.00	1.00E+00	0.00E+00	0.00E+00
		RHR-FT	5.87	1.17E+01	4.41E-07	8.30E-01
		RPS-FT	1.04	1.05E+04	4.01E-04	3.64E-02
		SSC-FT	1.05	1.16E+01	4.09E-07	1.28E-01

These definitions and treatments of the probabilities of the fault trees result in inaccurate representation of the coupled nature of the fault trees. Components that are used in multiple fault trees will effectively have different values within the same calculation of F(1) or F(0) because only one top event basic event probability was changed, not the basic events in the other top event fault trees it is queried in. In an attempt to decouple the systems more, a second approach was developed.

2.2.1.2 Approach 2: By Basic Event Identification

The second approach to determine the importance of the systems was by defining them by the components that belong to each physical system. For the generic PWR PRA model, each basic event failure is tagged as belonging to a certain system. This was used to group the importance measure results of the basic events that appeared in the LOCA cut sets. The FV of all the basic events for each system were summed and normalized by the sum of the FV of basic events for all systems to come up with a normalized contribution of each system to the LOCA event. This is defined mathematically here:

$$Contribution\ of\ System\ X = \left(\sum_X FV\right)/\left(\sum_{LOCA} FV\right) \times 100\%.$$

Non-component related basic events were either removed from the set of events considered in the calculation or set as their own category of events. Events that could not be optimized—like the occurrence of a LOCA in a cold leg segment—were removed from the calculation. Their contribution was not calculated and their FV was not included in the summation of all FV for the LOCA. Events that could potentially be optimized—like human operations—were combined into a separate system called "Operator Actions" despite their system tag. The results are presented in Table 4.

Table 4. LOCA event tree/sequence physical system contributions.

Initiating Event	Total CDF	Physical System	System Contribution
SLOCA	3.83E-08		
		AC Power	3.08%
		Auxiliary Feedwater System	0.50%
		Component Cooling Water	5.76%
		Containment Spray System	0.00%
		Chemical and Volume Control System	0.01%
		DC Power	0.08%
		Emergency Power	2.51%
		High Pressure Injection/Recirculation	11.07%
		Low Pressure Injection/Recirculation	67.60%
		Main Feedwater System	0.00%
		Primary Pressure Relief System	0.00%
		Reactor Cooling System	0.10%
		Reactor Protection System	2.75%
		Safety Injection Actuation System	0.01%
		Service Water System	0.92%
		Operator Action	5.61%
MLOCA	1.68E-07		
		Accumulator	0.01%
		AC Power	0.41%
		Component Cooling Water	0.63%
		Containment Spray System	0.03%
		Chemical and Volume Control System	0.01%
		DC Power	0.01%
		Emergency Power	0.33%
		High Pressure Injection/Recirculation	0.64%
		Low Pressure Injection/Recirculation	11.50%
		Reactor Cooling System	0.01%
		Reactor Protection System	0.30%
		Safety Injection Actuation System	0.01%
		Service Water System	0.11%
		Operator Action	85.99%
LLOCA	6.38E-10		
		Accumulators	0.09%
		AC Power	2.30%
		Component Cooling Water	5.00%
		Containment Spray System	0.26%
		DC Power	0.03%
		Emergency Power	2.01%
		High pressure injection / recirculation	5.35%
		Low pressure injection / recirculation	84.55%
		Reactor Cooling System	0.09%
		Service Water System	0.33%

2.2.2 Sensitivity Study on Failure Rate of Component Types

One of the approaches for reliability target allocation can be based on component types rather than a system or component-level. For example, all the motor-operated valves at a plant can be assigned the same reliability target. This approach could be beneficial for the plant owners and operators because it simplifies procurement and maintenance conducted for the same type of components.

The importance of component types was evaluated in a sensitivity study of the overall LOCA CDF. The study was based on the application of multiplication factors to the component failure rates. Three multiplication factors were used: 20, 50, 100.

These multipliers were applied to the failure rates and, as a result, they affected all BEs related to the component types and their systems that show up in the cut sets of the nominal case. For example, for check valve events, this includes check valve BEs associated with the accumulator, low pressure injection, reactor cooling system, and service water systems because they appeared in the nominal cut sets. All check valve BEs in those systems were multiplied by a multiplier, one at a time, then the CDF of each case was solved for at a truncation of 1E-13. If a multiplication resulted in a probability greater than one, the probability was set to one. Events that weren't included were failures due to external events or human operator actions. These were considered to be events that could not be optimized like a component where a better-quality component could be utilized in place of a nominally performing component.

Across all three LOCA events, the circuit breakers (CRB), motor driven pumps (MDP), and motor-operated valves (MOV) were the most influential components. These are indicated in the plots in Figure 8, Figure 9, and Figure 10 by triangle data points. The rate of increase of the total CDF due to the increased basic event probabilities for the above components was the greatest as well as the overall magnitude of increased CDF. The only exception is for SLOCA, the heat exchangers (HTX) had a slightly greater contribution to the increasing of total CDF compared to motor-operated valves. The SLOCA case was also the only one where increased failure probabilities of the motor-operated valves resulted in the least increase in the total CDF of the top three component types. In the large loss of cooling accident (LLOCA) and MLOCA case, it resulted in the greatest increase in total CDF.

The least influential events were the components that were added to the analysis with the decreased size of the LOCA. In the plots, the components added in the MLOCA from the LLOCA case are plus sign data points. The components added in the SLOCA case from the MLOCA case are X sign data points. Circle or triangle data points are used for components included in all LOCA cases. As the plots show, none of the multiplications of these events resulted in a change in order of magnitude. For the MLOCA case, all the component types added to the ones in the LLOCA case, when multiplied by 100, the total CDF experiences at most a 14% change. For the SLOCA case, all the component types added to the ones in the LLOCA case, when multiplied by 100, the total CDF experiences at most a 167% increase. For the component types unique to the SLOCA case, when multiplied by 100, the total CDF experiences at most a 34% increase.

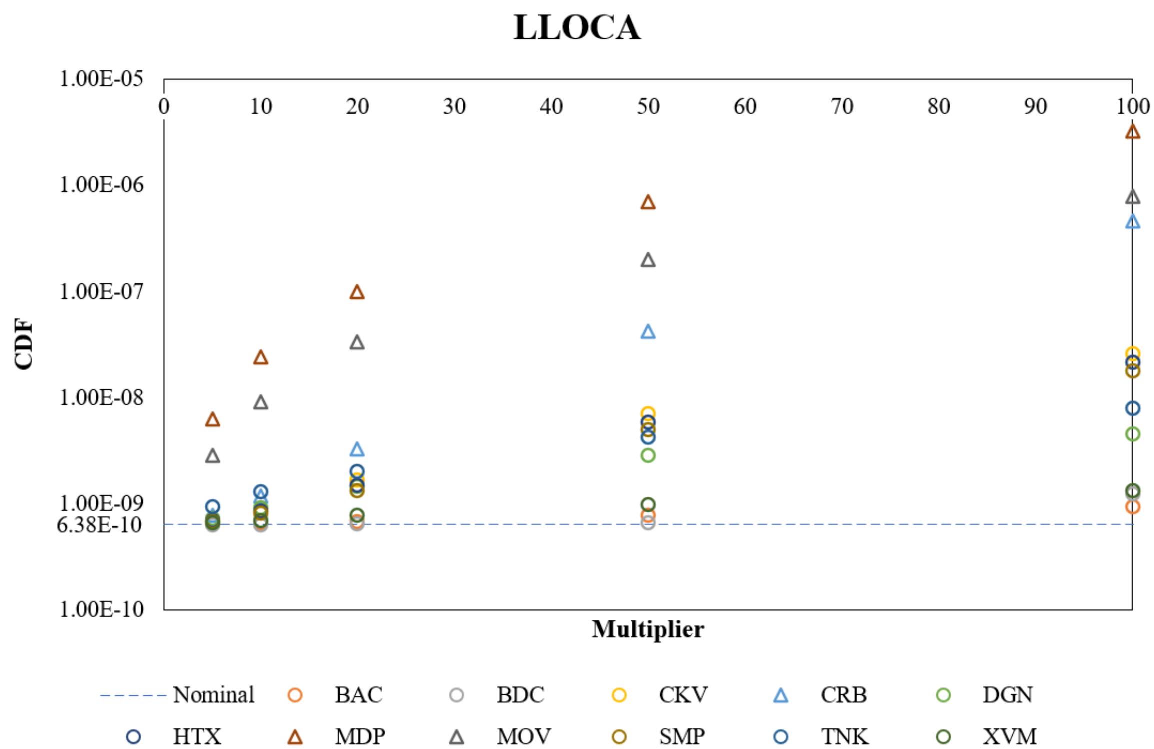


Figure 8. CDF of LLOCA due to multiplication of component failure rates being multiplied by a factor of 5, 10, 20, 50, and 100.

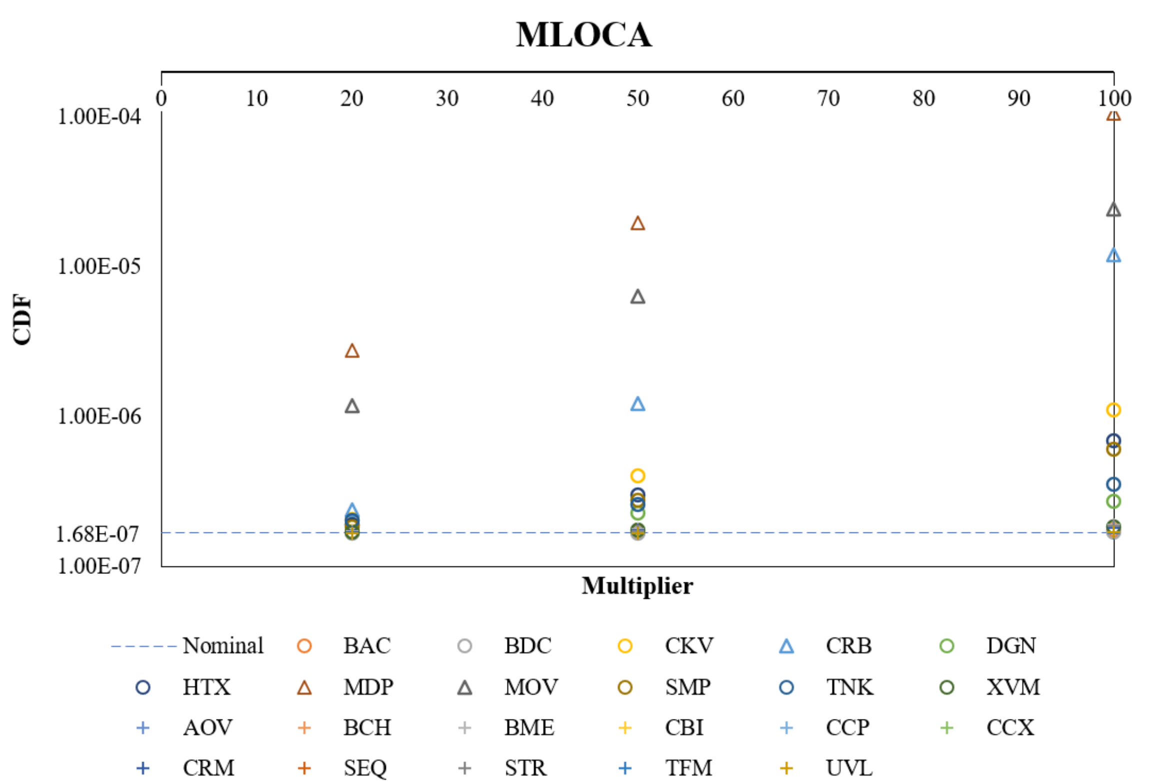


Figure 9. CDF of MLOCA due to multiplication of component failure rates being multiplied by a factor of 20, 50, and 100.

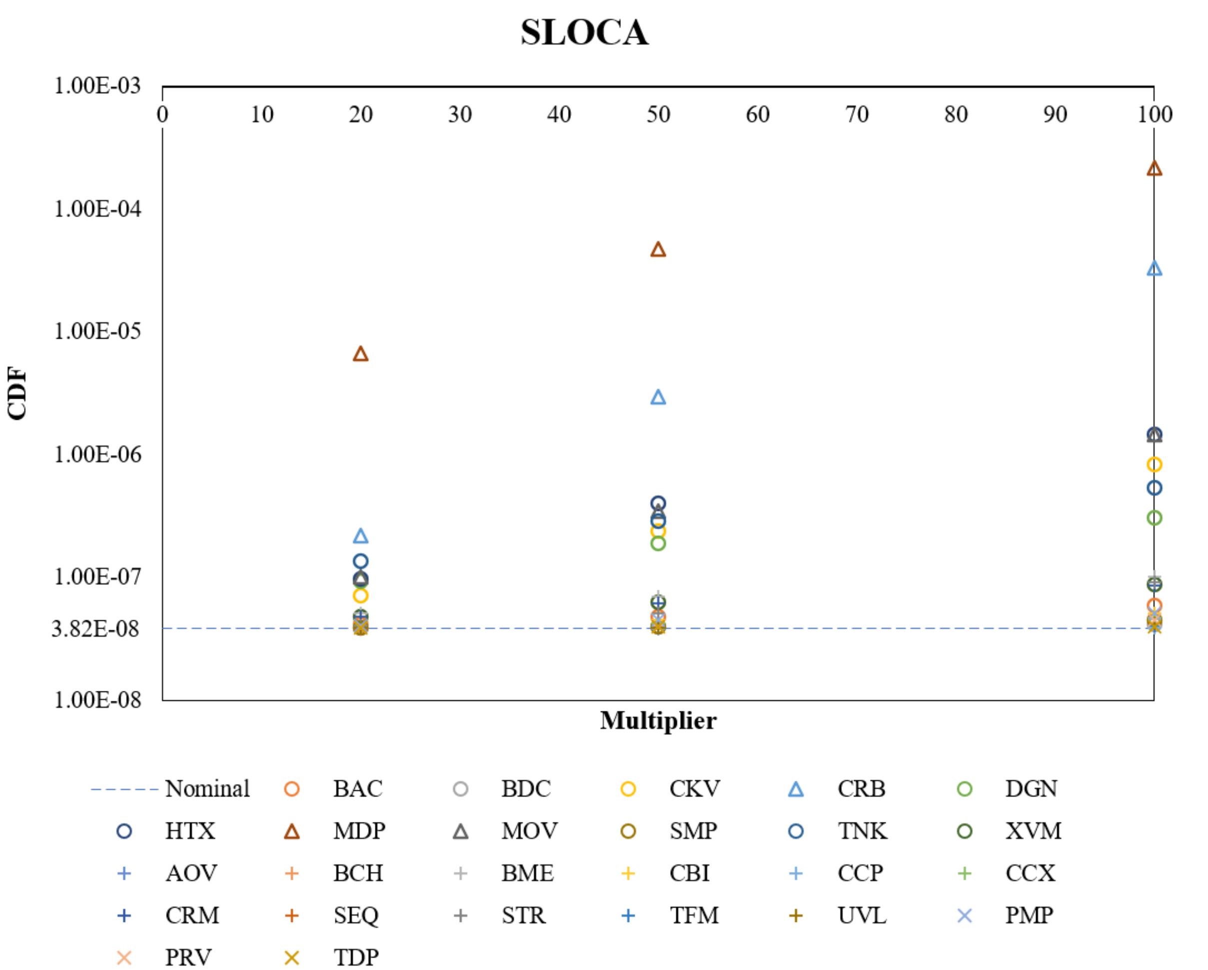


Figure 10. CDF of SLOCA due to multiplication of component failure rates being multiplied by a factor of 20, 50, and 100.

2.3 Optimization Of Reliability Target Allocation Methods

2.3.1 Problem Setting

We are here considering a generic advanced reactor plant characterized by the following constituent elements:

1. The plant consists of N systems (e.g., AC power system, core injection system).
2. Each system is designed to support one or a few functions.
3. A system is not an isolated entity but it either supports or it is supported by other system(s).
4. Plant is comprised of S assets (e.g., centrifugal pumps, motor-operated valves) designed to support system functions.
5. Each asset is modeled from a reliability standpoint by one or more basic events (BEs). We indicate with R the number of the complete set of BEs.
6. At the design phase, each asset can be chosen out of a set of options; without loss of generality, we are considering two options for a generic asset:
    - Option 1: high quality and highly reliable asset (high procurement cost)
    - Option 2: lower quality and less reliable asset (low procurement cost).

7. A set of M initiating events (IEs) are considered IE_m $(m = 1, \dots, M)$ where:
   a) The frequency f_m of occurrence of each IE_m is known
   b) A PRA model $\mathbb{R}_m$ is available for each IE. $\mathbb{R}_m$ determines for IE_m the frequency f_m of an undesired event called event sequence (e.g., frequency f_m^{CD} of core damage –CD–, or frequency f_m^{RR} of radioactive release). The $\mathbb{R}_m$ consists of a set of fault trees and event trees
   c) For each IE_m it is possible to calculate $f_m = \mathbb{R}_m(f_m, P_1, \dots, P_r, \dots, P_R)$ where P_r indicates the probability of each basic event BE_r $(r = 1, \dots, R)$.

Figure 11 presents a graphical representation of a plant composed by seven systems (indicated as Sys1 to Sys7) designed to counteract effects of an initiating event IE_m. A combination of failures within a subset of systems can lead to an event sequence (e.g., radioactive release).

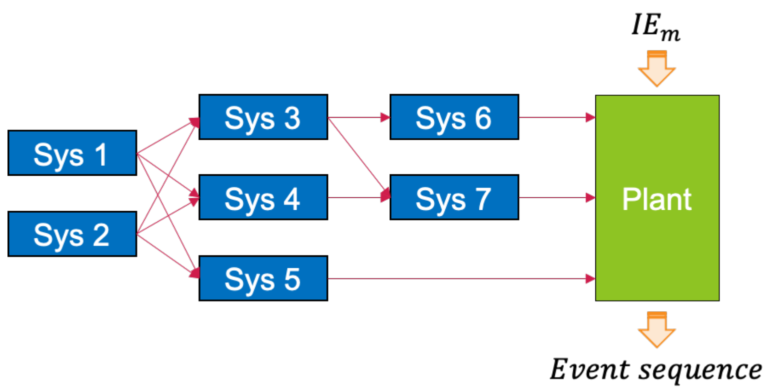


Figure 11. Graphical representation of a system composed by seven sub-systems.

2.3.2 Single IE Optimization Formulation

As a first step, let's consider a single IE. The goal of the RIM project is to determine the optimal configuration of asset options that minimize costs and maximize plant reliability. With that in mind, note that:

- The degree of freedom are the options (see element 6 listed in Section 2.3.1) of the considered assets (see element 4 listed in Section 2.3.1)
- The objective function to be minimized is the sum of all the option costs for the considered assets
- Plant reliability can be considered either as a constraint (i.e., single-objective optimization) or as an additional objective function to be maximized (i.e., multi-objective optimization).

For the scope of this project, we employed the following optimization formulation in a single-objective form which can be described as follows

$$\min_{\boldsymbol{opt}} \quad cost(\boldsymbol{opt})$$
$$s.t. \quad f_m^{RR}(\boldsymbol{opt}) \leq f_{reg}^{RR}$$

where:

- $\boldsymbol{opt} = [opt_1, \dots, opt_S]$ represents the "decision space" and it consists of the set of options of the considered S assets

- $cost(\boldsymbol{opt})$ represents the cost of a generic option $\boldsymbol{opt}$. In its most simple form (which is considered in this work), it is formulated as the sum of the costs associated with each asset option

$$cost(\boldsymbol{opt}) = \sum_{s=1}^{S} cost(opt_s)$$

- The frequency of radioactive release $f_m^{RR}(\boldsymbol{opt})$ for the considered IE_m is upper bounded and such bound is dictated by the regulatory limit (e.g., limit identified by the LMP approach [2]).

Figure 12 presents a graphical representation of a single-objective optimization problem for a single initiating event. In this case, the regulatory limit is the constraint for the optimization function. The reliability target is not a single value, it is a range of values that satisfy predetermined requirements. From the regulatory standpoint of view, it is desirable to set reliability targets in such a way that the event sequence frequency represented by a point on the frequency-consequence (F-C) curve (i.e., the green circle on Figure 12) is as low as possible on the y axis (i.e., the event sequence frequency is minimized). However, from the cost perspective, it is more desirable for the point on F-C curve to be as high as allowable by regulatory limits since system reliability is proportional to system procurement costs.

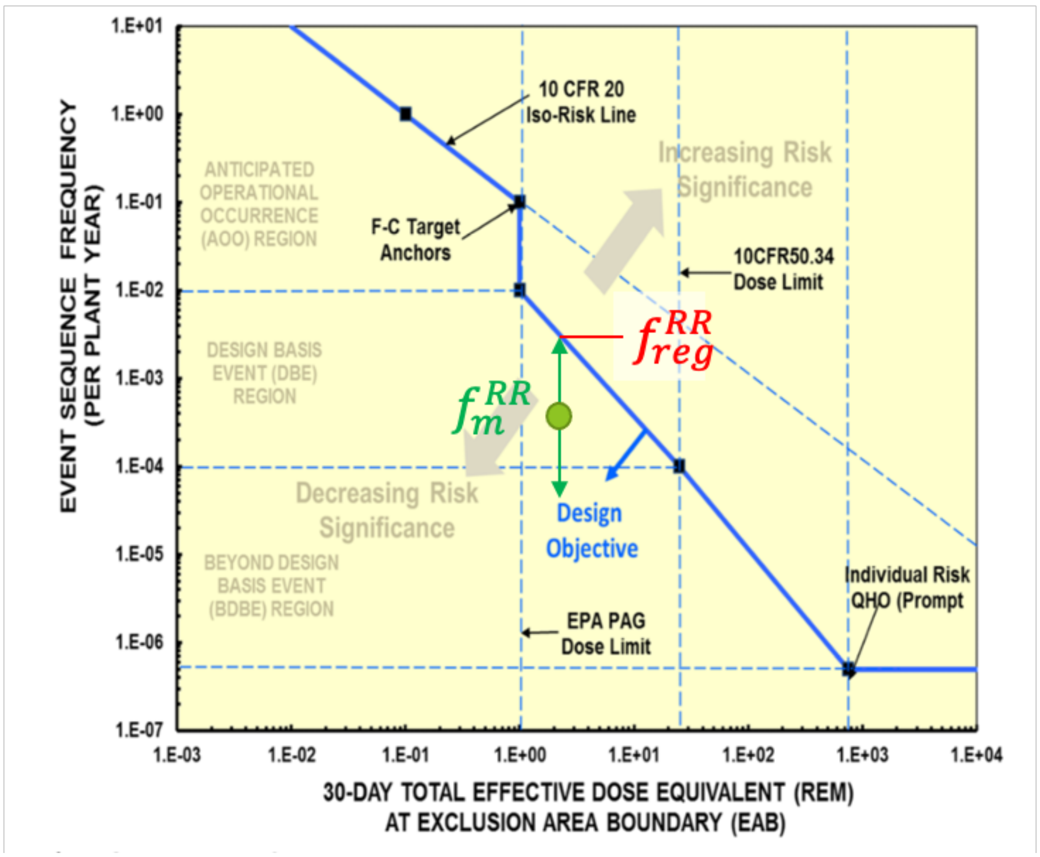


Figure 12. Single-objective optimization problem for a single initiating event.

2.3.3 Multi IEs Optimization Formulation

The reliability target allocation task becomes significantly more complex when it is performed with consideration of all applicable IEs. For a LWR, there are metrics that represents a cumulative risk which are CDF and large early release frequency (LERF). However, under the LMP approach, each IE (or a family of IEs) is represented by its only risk metric which is the 30-day total effective dose equivalent. The difficulty that arises for the reliability target allocation process is how to select SSC reliability targets given that the same SSCs may be contributing to multiple event sequences. Meaning, the change of a reliability target of one SSC may affect multiple points on the F-C curve and the effect may be of a different magnitude.

The economic objective for reliability target allocation is having most points on the plant F-C curve close to the F-C Target curve, which is represented by the blue line marked "Regulatory curve (RC)" in Figure 13. The challenge is how to express this preference mathematically as a limiting function. One of the possibilities is to use a complimentary cumulative distribution function (CCDF) proposed by Denning et al in [7]. The CCDF is presented as a red line in Figure 13.

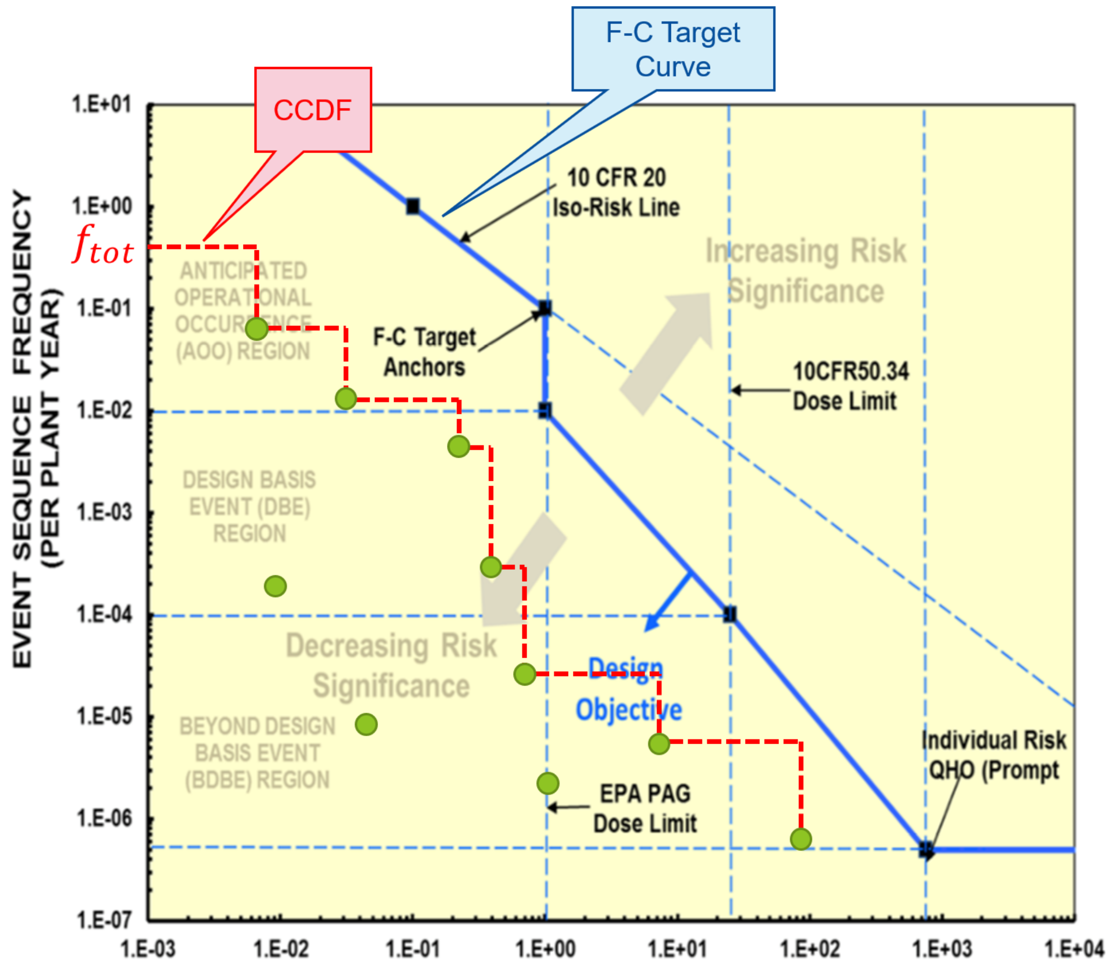


Figure 13. Single-objective optimization problem for multiple initiating events.

The objective function becomes getting the CCDF curve as close as possible to the F-C Target curve which will ensure that 1) safety limits are met, and 2) it is accomplished by selection of most cost-effective options for reliability target allocation.

2.3.4 Numerical Solution of the Optimization Problem

The problem formulation indicated in Section 2.3.1 presents few challenges as indicated below:

- The dimensionality of the problem is very high, i.e., the number S of assets that are considered is very high (over a hundred assets)
- The number of options of each asset is very small; as an example, element 6 listed in Section 2.3.1 presents two options (a highly reliable and expensive asset vs. a less reliable and less expensive asset)

- The numerical evaluation of $f_m^{RR}(\boldsymbol{opt})$ throughout the optimization problem can be computationally expensive.

In this configuration, the optimization is intractable, i.e., it cannot be solved using available optimization techniques. In order to solve the problem formulation indicated in Section 2.3.2, we have identified three possible directions to follow:

1. Straight through (or brute-force) Monte Carlo approach (see Section 2.3.5)
2. System centric approach (see Section 2.3.6)
3. Importance based iterative approach (see Section 2.3.7).

2.3.5 Straight Through Monte Carlo Approach

The solution of the problem indicated in Section 2.3.2 can be numerically solved using a classical Monte Carlo approach by performing these steps:

1. Randomly sample the option opt_s of each asset ($s = 1, \dots, S$)
2. Construct the vector $\boldsymbol{opt} = [opt_1, \dots, opt_s, \dots, opt_S]$
3. Evaluate $cost(\boldsymbol{opt})$ and $f_m^{RR}(\boldsymbol{opt})$
4. Repeat Steps 1, 2 and 3 N_{MC} times
5. Identify the vector $\boldsymbol{opt}$ out of the N_{MC} generated that
   - Has lowest value of $cost(\boldsymbol{opt})$, and,
   - Satisfies the requirement $f_m^{RR}(\boldsymbol{opt}) \leq f_{reg}^{RR}$.

Pros	Cons
• Easy implementation • Easier management of computational resources • Analysis can be refined by generating new samples	• Required large number N_{MC} of Monte Carlo samples to be generated • The obtained solution is not guaranteed to be the optimal one

2.3.6 System Centric Approach

This approach replicates a top-bottom process where reliability targets are determined at the system-level first and then reliability targets at the asset level are established. The decomposition plant-system-asset provides a middle step (system-level), and it tackles directly the first two challenges listed in Section 2.3.4. A graphical representation of this approach is shown in Figure 14. At the asset level, there is a direct link between assets and PRA BEs; similarly, there is usually a direct link between a system and a PRA fault tree. At the accident level, the event sequence is determined by the plant PRA model which combines event trees and fault trees to generate a set of MCSs. Note that the concept of system reliability target is not directly a specific part of the plant PRA model, but reliability targets are required to be allocated using the plant PRA model [1].

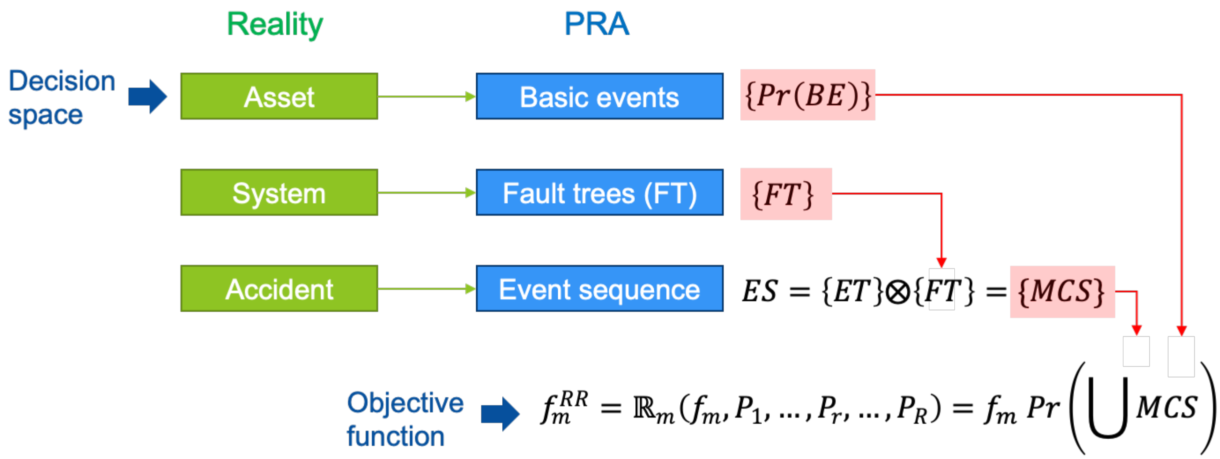


Figure 14. Asset and system levels in a RIM optimization setting.

The system centric approach is structured in two steps, each involving an optimization process:

1. System optimization step – determine Pareto frontier for each system S_n
   - *Model employed*: set of MCSs from system fault tree model
     (a) Here we are considering the supporting systems to be perfectly reliable which is needed to separate the system of interest S_n from the rest of the systems
   - *Data required*: Asset options (BEs probability, cost)
   - *Data generated*: Optimal set of asset options at the system-level
2. Event sequence optimization step
   - *Degrees of freedom*: Set of options for each system (see Step 1)
   - *Model employed*: set of MCSs for the considered IE
   - *Objective function*: minimization of plant costs and maintain plant reliability regulatory constraints
   - *Data generated*: Optimal Pareto option for each system.

Note the following:

- The Pareto frontiers obtained in Step 1 are used primarily to filter out non-optimal system configurations and keep the problem tractable by making it smaller (dimensionality wise).
- The decision space is reduced since the dimensionality of the problem is dictated by the considered number of systems rather than then number of assets.
- The number of options for each dimension is larger and it is equal to the number of points that compose the system Pareto frontier.
- The model employed in Step 2 is the full PRA model for the considered IE.

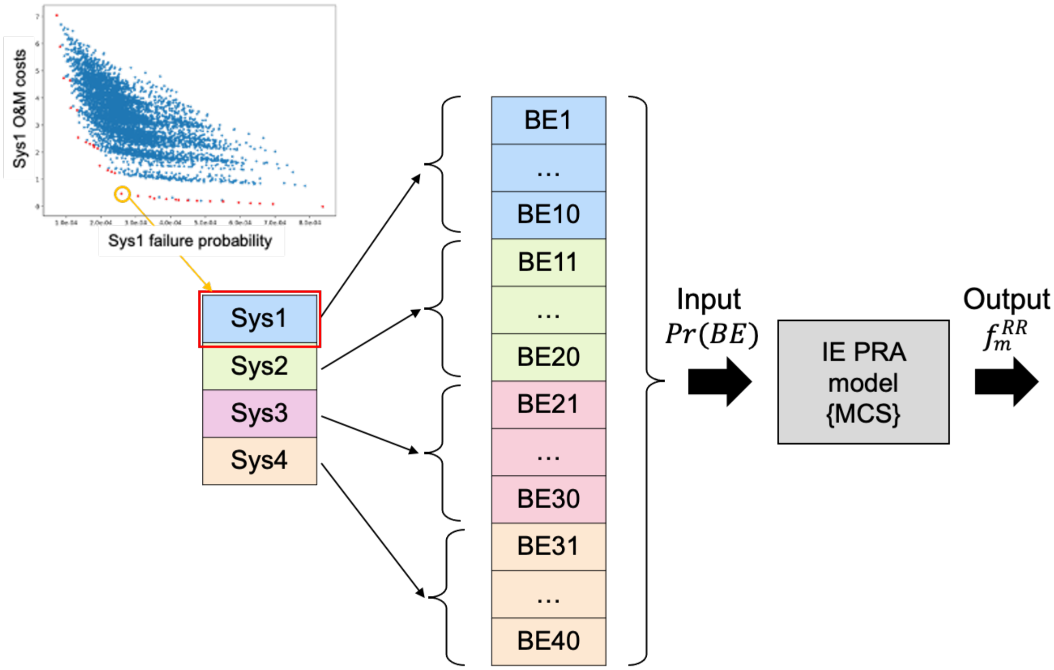


Figure 15. Graphic representation of system centric optimization approach for a system composed by four sub-systems and 40 basic events.

Pros	Cons
• Optimal solution can be obtained • Each optimization step can be performed with well-known optimization algorithms	• Several optimization operations need to be performed • System fault trees need to be quantified with manual manipulations required • Computational time can be high

2.3.7 Importance Based Iterative Approach

Another approach that can be employed to solve this problem decomposes the original problem into sub-problems and iteratively solve the optimization problem for each sub-problem. The identification of these sub-problems can be performed by observing the relative importance of each basic event. In this context, basic events with highest importance should be optimized first, while basic events with lowest importance should be optimized last.

The importance measure for each basic event can be reliability driven, cost driven, or both (reliability-cost driven). We initially focused on the identification of reliability driven importance measures. In this case we aim to identify those basic events that have the highest impact on the frequency of the event sequence $freq(ES)$. Mathematically speaking, we are looking at an importance measure for a generic basic event BE as

$$I_{BE} = \frac{\partial\, freq(ES)}{\partial\, Prob(BE)}$$

where $Prob(BE)$ indicates the probability of the basic event. Out of the available risk importance measures that can be generated by PRA codes, the Birnbaum measure I_{BE}^{Birn} is the one that exactly matches the above definition of I_{BE}. The Birnbaum measure is defined as

$$I_{BE}^{Birn} = freq(ES|BE = 1) - freq(ES|BE = 0).$$

Given that $freq(ES)$ is a linear function of $Prob(BE)$, it can be shown that $I_{BE}^{Birn} = I_{BE}$.

Again, assuming that we are dealing with one single initiating event, the determination of the optimal probability values for the basic events that are queried of the initiating event can be performed by performing the reliability determination methodology which consist of the following steps:

Step 1: Generate the minimal cut sets (MCSs) for the considered event sequence.

Step 2: Calculate I_{BE}^{Birn} for all basic events using base probability values P^{base} (see Table 1).

Step 3: Rank all basic events based on I_{BE}^{Birn} in descending order.

Step 4: Consider the first R basic events from the list obtained in Step 3 (i.e., the R most important basic events).

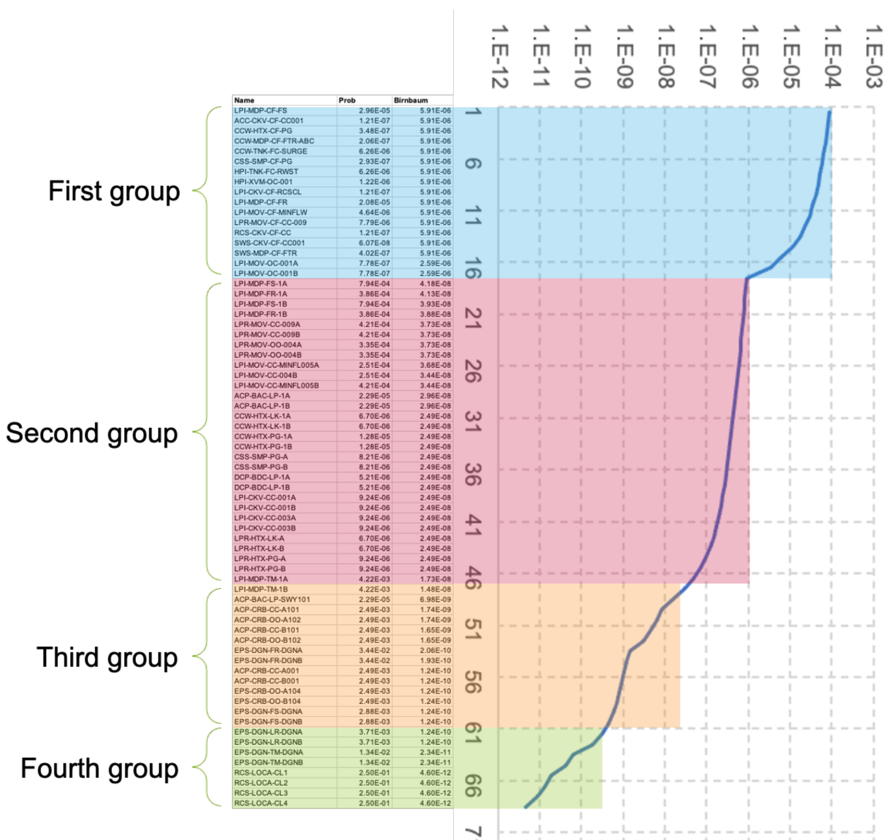
Step 5: Perform the optimization over the R basic events (i.e., determine the optimal option of the considered R basic events such that the $freq(ES)$ is as close as possible to the regulatory limit).

Step 6: Recalculate the importance measure for the lower basic events and re-rank them

Step 7: Consider the next R basic events, and GOTO Step 5 until all basic events are considered

a. Set lower BEs with mean probability values

b. Set upper BEs with probability values obtained by the optimization process.



Name	Prob	Birnbaum
LPI-MDP-CF-FS	2.96E-05	5.91E-06
ACC-CKV-CF-CC001	1.21E-07	5.91E-06
CCW-HTX-CF-PG	3.48E-07	5.91E-06
CCW-MDP-CF-FTR-ABC	2.06E-07	5.91E-06
CCW-TNK-FC-SURGE	6.26E-06	5.91E-06
CSS-SMP-CF-PG	2.93E-07	5.91E-06
HPI-TNK-FC-RWST	6.26E-06	5.91E-06
HPI-XVM-OC-001	1.22E-06	5.91E-06
LPI-CKV-CF-RCSCL	1.21E-07	5.91E-06
LPI-MDP-CF-FR	2.08E-05	5.91E-06
LPI-MOV-CF-MINFLW	4.64E-06	5.91E-06
LPR-MOV-CF-CC-009	7.79E-06	5.91E-06
RCS-CKV-CF-CC	1.21E-07	5.91E-06
SWS-CKV-CF-CC001	6.07E-08	5.91E-06
SWS-MDP-CF-FTR	4.02E-07	5.91E-06
LPI-MOV-OC-001A	7.78E-07	2.59E-06
LPI-MOV-OC-001B	7.78E-07	2.59E-06
LPI-MDP-FS-1A	7.94E-04	4.18E-08
LPI-MDP-FR-1A	3.86E-04	4.13E-08
LPI-MDP-FS-1B	7.94E-04	3.93E-08
LPI-MDP-FR-1B	3.86E-04	3.88E-08
LPR-MOV-CC-009A	4.21E-04	3.73E-08
LPR-MOV-CC-009B	4.21E-04	3.73E-08
LPR-MOV-OO-004A	3.35E-04	3.73E-08
LPR-MOV-OO-004B	3.35E-04	3.73E-08
LPI-MOV-CC-MINFL005A	2.51E-04	3.68E-08
LPI-MOV-CC-004B	2.51E-04	3.44E-08
LPI-MOV-CC-MINFL005B	4.21E-04	3.44E-08
ACP-BAC-LP-1A	2.29E-05	2.96E-08
ACP-BAC-LP-1B	2.29E-05	2.96E-08
CCW-HTX-LK-1A	6.70E-06	2.49E-08
CCW-HTX-LK-1B	6.70E-06	2.49E-08
CCW-HTX-PG-1A	1.28E-05	2.49E-08
CCW-HTX-PG-1B	1.28E-05	2.49E-08
CSS-SMP-PG-A	8.21E-06	2.49E-08
CSS-SMP-PG-B	8.21E-06	2.49E-08
DCP-BDC-LP-1A	5.21E-06	2.49E-08
DCP-BDC-LP-1B	5.21E-06	2.49E-08
LPI-CKV-CC-001A	9.24E-06	2.49E-08
LPI-CKV-CC-001B	9.24E-06	2.49E-08
LPI-CKV-CC-003A	9.24E-06	2.49E-08
LPI-CKV-CC-003B	9.24E-06	2.49E-08
LPR-HTX-LK-A	6.70E-06	2.49E-08
LPR-HTX-LK-B	6.70E-06	2.49E-08
LPR-HTX-PG-A	9.24E-06	2.49E-08
LPR-HTX-PG-B	9.24E-06	2.49E-08
LPI-MDP-TM-1A	4.22E-03	1.73E-08
LPI-MDP-TM-1B	4.22E-03	1.48E-08
ACP-BAC-LP-SWY101	2.29E-05	6.98E-09
ACP-CRB-CC-A101	2.49E-03	1.74E-09
ACP-CRB-OO-A102	2.49E-03	1.74E-09
ACP-CRB-CC-B101	2.49E-03	1.65E-09
ACP-CRB-OO-B102	2.49E-03	1.65E-09
EPS-DGN-FR-DGNA	3.44E-02	2.06E-10
EPS-DGN-FR-DGNB	3.44E-02	1.93E-10
ACP-CRB-CC-A001	2.49E-03	1.24E-10
ACP-CRB-CC-B001	2.49E-03	1.24E-10
EPS-CRB-OO-A104	2.49E-03	1.24E-10
EPS-CRB-OO-B104	2.49E-03	1.24E-10
EPS-DGN-FS-DGNA	2.88E-03	1.24E-10
EPS-DGN-FS-DGNB	2.88E-03	1.24E-10
EPS-DGN-LR-DGNA	3.71E-03	1.24E-10
EPS-DGN-LR-DGNB	3.71E-03	1.24E-10
EPS-DGN-TM-DGNA	1.34E-02	2.34E-11
EPS-DGN-TM-DGNB	1.34E-02	2.34E-11
RCS-LOCA-CL1	2.50E-01	4.60E-12
RCS-LOCA-CL2	2.50E-01	4.60E-12
RCS-LOCA-CL3	2.50E-01	4.60E-12
RCS-LOCA-CL4	2.50E-01	4.60E-12

Figure 16. List of Large LOCA basic events (see list on left side) and corresponding complementary cumulative importance measure curve (see curve on the right side).

Optimization window

Shift step

BE Name	BE Description	Prob. Of Failure	I^{BE}	Physical System
ACC-CKV-CF-CC001	CCF OF ACC CKV-001 TO OPEN	1.21E-07	1.12E-03	ACC
ACP-BAC-LP-1A	4160 V VITAL AC BUS 1A FAILS	2.29E-05	1.06E-03	ACP
ACP-BAC-LP-1B	4160 V VITAL AC BUS 1B FAILS	2.29E-05	1.06E-03	ACP
ACP-BAC-LP-SWY101	SWITCHYARD-101 AC BUS FAILS	2.29E-05	2.51E-04	ACP
ACP-CRB-CC-A001	CRB-A001 FAILS TO STRIP OFF FROM BUS TO	2.49E-03	4.85E-04	ACP
ACP-CRB-CC-A101	CIRCUIT BREAKER-A101 FAILS TO OPEN FOR T	2.49E-03	6.78E-03	ACP
ACP-CRB-CC-B001	CRB-B001 FAILS TO STRIP OF FROM BUS TO P	2.49E-03	4.85E-04	ACP
ACP-CRB-CC-B101	CIRCUIT BREAKER-B101 FAILS TO OPEN FOR T	2.49E-03	6.45E-03	ACP
ACP-CRB-OO-A102	CIRCUIT BREAKER-A102 FAILS TO CLOSE FOR T	2.49E-03	6.78E-03	ACP
ACP-CRB-OO-B102	CIRCUIT BREAKER-B102 FAILS TO CLOSE FOR T	2.49E-03	6.45E-03	ACP
CCW-HTX-CF-PG	CCF OF HEAT EXCHANGER PLUGGING	3.48E-07	3.22E-03	CCW
CCW-HTX-LK-1A	CCW-A Heat Exchanger External Leakage (Sma	6.70E-06	2.62E-04	CCW
CCW-HTX-LK-1B	CCW-B Heat Exchanger External Leakage (Sma	6.70E-06	2.62E-04	CCW
CCW-HTX-PG-1A	CCW HEAT EXCHANGER 1A PLUGGING	1.28E-05	5.00E-04	CCW
CCW-HTX-PG-1B	CCW HEAT EXCHANGER 1B PLUGGING	1.28E-05	5.00E-04	CCW
CCW-MDP-CF-FTR-ABC	System Generated Event based upon Rasp CCF	2.06E-07	1.91E-03	CCW
CCW-TNK-FC-SURGE	CCW SURGE FAILS	6.26E-06	5.80E-02	CCW
CSS-SMP-CF-PG	CCF OF CONTAINMENT SUMP PLUGGING	2.93E-07	2.71E-03	CSS
CSS-SMP-PG-A	CONTAINMENT RECIRC SUMP PLUGGING IN TF	8.21E-06	3.21E-04	CSS
CSS-SMP-PG-B	CONTAINMENT RECIRC SUMP PLUGGING IN TF	8.21E-06	3.21E-04	CSS
DCP-BDC-LP-1A	125V VITAL DC BUS 1A FAILS	5.21E-06	2.04E-04	DCP
DCP-BDC-LP-1B	125V VITAL DC BUS 1B FAILS	5.21E-06	2.04E-04	DCP
EPS-CRB-OO-A104	CIRCUIT BREAKER-A104 FAILS TO CLOSE FOR T	2.49E-03	4.85E-04	EPS
EPS-CRB-OO-B104	CIRCUIT BREAKER-B104 FAILS TO CLOSE FOR T	2.49E-03	4.85E-04	EPS
EPS-DGN-FR-DGNA	DGN-A FAILS TO RUN	3.44E-02	1.11E-02	EPS
EPS-DGN-FR-DGNB	DGN-B FAILS TO RUN	3.44E-02	1.04E-02	EPS
EPS-DGN-FS-DGNA	DGN-A FAILS TO START	2.88E-03	5.61E-04	EPS
EPS-DGN-FS-DGNB	DGN-B FAILS TO START	2.88E-03	5.61E-04	EPS
EPS-DGN-LR-DGNA	DGN-A FAILS TO LOAD AND RUN, EARLY TERM	3.71E-03	7.23E-04	EPS
EPS-DGN-LR-DGNB	DGN-B FAILS TO LOAD AND RUN, EARLY TERM	3.71E-03	7.23E-04	EPS

Figure 17. Excerpt of importance based iterative approach.

Note the following:

- The choice of the parameter R (see Steps 4 and 7) should be carefully chosen. A large value would imply large computational time for optimization instances (see Step 5). A small value would bias the analysis to a non-optimal solution. Rather than dealing with a fixed value of R, a possible alternative is to let R vary at each iteration (see Step 7). This can be accomplished by considering the complementary cumulative importance measure curve (see Figure 16). The value of this curve of a basic event can be determined by subtracting the sum of basic events I_{BE}^{Birn} prior to it to the full sum of basic events I_{BE}^{Birn}. By partitioning the range of the complementary cumulative importance measure curve into equally spaced segments, it is possible to determine the group of basic events that are contained in each segment. In Figure 16, the complementary cumulative importance measure curve is partitioned into four segments, and the corresponding groups of basic events is shown.
- A plant asset (e.g., a centrifugal pump) might be represented in a PRA model by several basic events (e.g., fail to start, fail to run) where their options (see Table 1) are coupled (i.e., the same option should be assigned to each basic event). In this case, the optimization process must consider only one basic event and propagate the chosen option to the coupled basic events. Further, for this report, we are not considering the implications of common-cause failures in the model.
- Step 3 in the method presented above is not mandatory, but it has been introduced to consider situations where, after an optimization iteration (see Step 5), the importance values of the basic events located underneath are largely changed.
- The optimization method presented here considers only the plant reliability aspect of a basic event option, and it neglects the economic aspect of such option. In other terms, only the probability value of each option drives the optimization method while the cost is not part of the method. A possible alternative method would employ a multi-objective optimization algorithm (see Appendix A) in Step 5 in a cost vs. $freq(ES)$ space where constraints in the $freq(ES)$ dimension are imposed by regulatory limits. Another method is to group basic events that need to

be optimized by considering not only risk factors (i.e., Birnbaum importance I_{BE}^{Birn}) but also economic factors. This can be accomplished by plotting each basic event as a point in a two-dimensional space, I_{BE}^{Birn} vs. cost variance (see Figure 18), where cost variance of a basic vent is determined as the difference between the most expensive and the cheapest option for that basic event. The I_{BE}^{Birn} vs. cost variance space can be partitioned into regions (e.g., nine regions as shown in Figure 18):

1. Basic events contained in the red region of Figure 18 are basic events with highest impact on both risk and economic aspects while.
2. Basic events contained in the green region of Figure 18 are basic events with very low impact on both risk and economic aspects.

At this point, the multi-objective optimization process can be performed in each region separately.

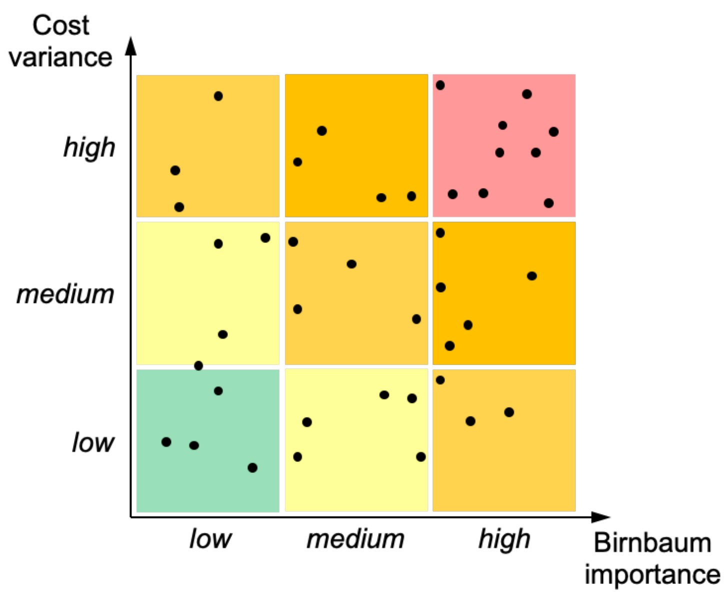


Figure 18. Basic event ranking based on their risk importance and the variance on their option costs, each dot corresponds to one single basic event.

Pros	Cons
• Optimal solution can be obtained • Each optimization window can be performed with well-known optimization algorithms	• Computational time can be high

2.4 LLOCA Example

In order to test the proposed approaches, we have selected a well-known IE for existing LWR plants: a LLOCA scenario. We employed a publicly available PWR PRA model. The LLOCA PRA model is composed by a single event tree and by multiple fault trees. The systems shown in Table 5 are credited for the mitigation of a LLOCA event.

Table 5. List of system identified in the LLOCA PRA model.

System ID	Description
ACC	Accumulator tanks
ACP-480	480V AC power system
ACP-4160	4160V AC power system
CCW	Component cooling water
DCP-125	125V DC power
EPS-SWS	Emergency power system service water system
LPI	Low pressure injection system
LPR	Low pressure recirculation system
RWST	Refueling water storage tank
SWS-TRNA	Service water system train A

More observations about the LLOCA PWR PRA model are listed below:

- 92 assets out of the 10 systems listed in Table 5 have been identified. They represent the decision space of the reliability target allocation example problem, and, hence, it is required to determine the optimal configuration of reliability targets for these 92 assets.
- The number of BEs is slightly larger (i.e., 118) than the number of assets since more than one basic event is associated with some assets. These correlations between assets and BEs needs to be captured.
- The association between assets and the system is typically well defined, i.e., an asset is associated with a unique system. However, it is common that a system supports multiple functions in the PRA model. In such cases, multiple assets are associated with multiple systems.
- We employ here a regulatory constraint set to $f_{reg}^{RR} = 6.23\text{E} - 9\ 1/\text{yr}$.

A simulation model of the PWR LLOCA system was created and it consisted of the following three sub-models (see Figure 19):

- *Option model*: this model receives in input the selected option for each asset (or for each system), and it generates the corresponding basic event probability values and asset cost values. This model was created ad-hoc for this specific application. In the near future, we are planning to create a general-purpose model such that it can be re-used for multiple RIM applications.
- *Reliability model*: this model contains the MCSs generated by SAPHIRE and it determines frequency of the LLOCA sequence provided basic event probability values. We employed here the `MCSsolver` available in the SR^{2}ML repository. The reader might query why a PRA code was not here employed. The `MCSsolver` was designed and developed only to perform fast probability calculations on MCSs on multiple machines (from laptops to high performance computing machines) without the computational overhead of PRA codes such SAPHIRE or CAFTA. Note that `MCSsolver` is not a PRA since it does not have capabilities to generate MCSs from event trees and fault trees. For the specific PWR LLOCA test case, the evaluation of the generated set of MCSs (about 20,000) takes about 1.6 seconds.
- *Cost model*: this model simply sums up all the cost values for all the considered assets. Here we have considered only procurement and installation costs. Note that depending on the use case being considered, this model can be more complex to include several economic aspects that can

be projected over the planned lifetime of the plant such as: maintenance costs, and monitoring and surveillance costs.

The communications between these three models were completed using RAVEN `EnsembleModel` capability which allows passage of data elements between models in a linear fashion.

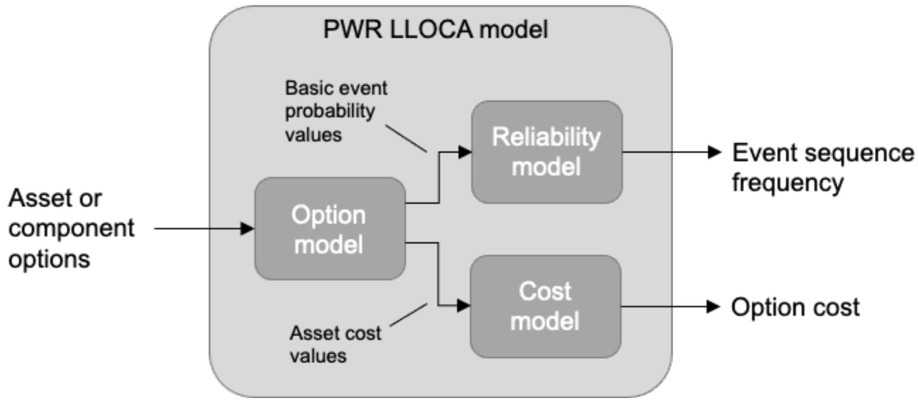


Figure 19. Graphical representation of the PWR LLOCA model employed to optimize RIM strategy.

Assuming that only two options are available for each component (i.e., lower and higher reliability), there are $2^{92} = 4.95\ 10^{27}$ possible combinations. Even if the same option is assigned to identical assets belonging to different trains, the number of combinations drops to $2^{42} = 4.40\ 10^{12}$ possible combinations. Assuming the evaluation of the PWR LLOCA model for each combinations takes 3.5 seconds, the evaluation of all combinations would take 488,114 years. Obviously, this option for reliability target allocation is not feasible and other alternatives are considered.

For the scope of this report, we have solved the RIM optimization problem using the methods presented in Sections 2.3.5 and 2.3.6. The results are indicated in Sections 2.4.1 and 2.4.2 for the Monte Carlo and GA optimization respectively.

2.4.1 LLOCA Monte Carlo Analysis

The RIM analysis of the PWR LOOCA test scenario we first performed using the Monte Carlo analysis shown in Section 2.3.5. an initial evaluation set of $N_{MC} = 65{,}000$ Monte Carlo samples were generated. Note that this number of samples N_{MC} covers a very small fraction of the possible combinations (i.e., $1.47\ 10^{-6}\%$). The search of the optimal sample was performed by filtering out the samples that would not satisfy regulatory constraints and identify the sample with lowest cost value. From the generated samples, the optimal sample which satisfies regulatory constraint ($f_m^{RR}(\boldsymbol{opt}) \leq f_{reg}^{RR}$) and minimizes costs had a value of $cost(\boldsymbol{opt}) = 29{,}320\ K\$$ (and a corresponding $f_m^{RR}(\boldsymbol{opt}) = 2.92\ E - 9\ 1/yr$).The histogram of the generated samples is shown in Figure 20.

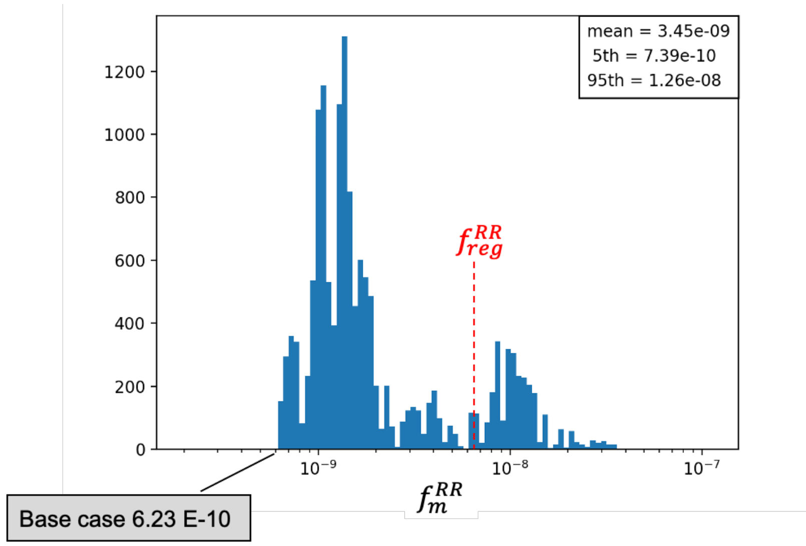


Figure 20. Histogram of f_m^{RR} generated using Monte Carlo analysis (see Section 2.3.5).

2.4.2 LLOCA System Centric Analysis

As indicated in Section 2.3.6, this analysis required several optimization steps. The first step required a multi-objective optimization analysis for all the systems indicated in Table 5. In this respect, Table 6 lists the number of points that are part of the Pareto frontier for all considered systems. Note that in this case the complete number of system combinations obtained by multiplying all numbers listed in Table 6 is $1.317 \cdot 10^9$ (which is three orders of magnitude lower than the number of asset combinations). However, such number is still very high; assuming the evaluation of the PWR LLOCA model for each combinations takes 3.5 seconds, the evaluation of all system combinations would now take 146 years (rather than 488,114 years). A graphical representation of the Pareto frontiers obtained for the ACP480, CCW, ACP4160, and LPI systems are shown in Figure 21.

As an aside analysis, we generated a large number of simulations (again 65,000 samples); in each simulation, a single Pareto point was sampled, and the model described in Figure 19 was then evaluated (the plot of the results are shown in Figure 22). From this analysis we were able to obtain the following optimal system configuration characterized by $cost(\boldsymbol{opt}) = 27880\ K\$$ and $f_m^{RR}(\boldsymbol{opt}) = 3.24\ E-9\ 1/yr$. Note that the obtained optimal point is slightly better than the one obtained in Section 2.4.1.

Table 6. List of number of Pareto frontier points for the system identified in the LLOCA PRA model.

System ID	# Pareto frontier points
ACC	5
ACP-480	8
ACP-4160	23
CCW	17
DCP-125	5
EPS-SWS	9
LPI	13
LPR	6
RWST	4
SWS-TRNA	6

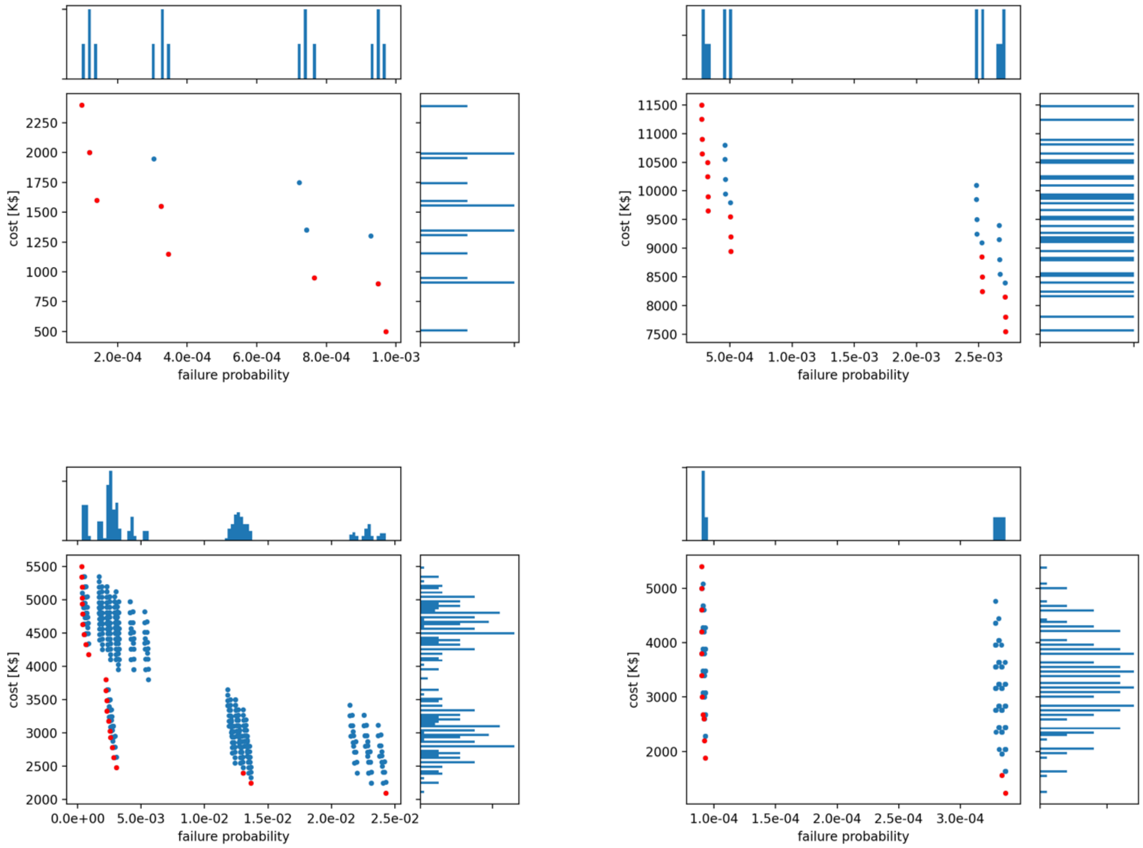


Figure 21. Complete set of options (blue points) and Pareto frontier (red points) options for the ACP480 (top left), CCW (top right), ACP4160 (bottom left), and LPI (bottom right) systems.

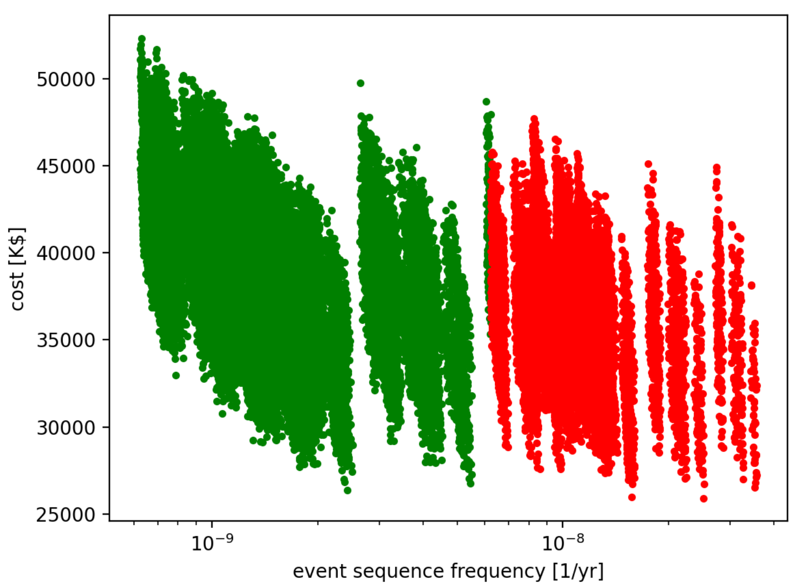


Figure 22. Scatter plot of the samples generated by sampling a Pareto frontier point for each of the 10 systems indicated in Table 6. The points showed in green satisfy the regulatory constraint ($f_m^{RR}(\boldsymbol{opt}) \leq f_{reg}^{RR}$) while the points in red do not.

The second step of the method indicated in Section 2.3.6 consisted of a single-objective optimization that was performed on the 10-dimensional space using GAs where each dimensions is represented by a the Pareto Frontier of each considered system (see Table 6). From this analysis, the sample which satisfies regulatory constraint ($f_m^{RR}(\boldsymbol{opt}) \leq f_{reg}^{RR}$) and it minimizes costs had a value of $cost(\boldsymbol{opt}) = 24{,}670\ K$ and $f_m^{RR}(\boldsymbol{opt}) = 5.53\ E - 9\ 1/yr$

The GA optimization analysis was performed using an initial population of 60 options that were randomly generated again using RAVEN. The size of the initial population strongly affects the likelihood to reach the optimal solution, the convergence rate and the overall computational time. While there is no rule to choose the size of the initial population, we chose a value of 60 based on the dimensionality of the problem but, prior running the optimization analysis, we checked that the initial population was well diversified by plotting it on a parallel coordinate plot.

For clarification we indicate with the term *Batch*, the population of the 60 system options at a specific iteration of the GA optimization. Figure 23 shows the evolution of the population of 60 system option throughout the GA optimization process. From this figure note the following:

- Since each batch comprehend 60 data points, this evolution includes the full envelope of the population (the min, max and average values are hence reported). Note that the envelope is at the beginning very wide since the original population was generated using a Monte-Carlo strategy. Then, as the GA operations indicated in Section A modify the structure of such population, they converge to the optimal solution.
- The considered objective function (i.e., system costs, indicated as *systCost* at the bottom of the plot of Figure 23) that we want to minimize also slowly decreases to its optimal value.
- A large number of subset of systems (i.e., ACC, ACP480, CCW, DCP_125, LPR, RWST, SWS_TRNA) quickly converge to their higher Pareto frontier point which is characterized by lower costs and lower reliability.
- The remaining set of systems (i.e., ACP4160, EPS_SWS, LPI) are the ones that have more variability, and this where the GA optimization process focus on changing.

A more valuable plot that shows more comprehensively the evolution of the population is the parallel coordinate plot. This kind of plots is designed to plot population of points in a multi-dimensional space. This plot consists of a series of parallel axes, one for each dimension, and each point is represented by a line that pass through all axes and it intercept these axes at the corresponding coordinate of such multi-dimensional point in each dimension. Figure 24 shows a parallel coordinate plot for several batch values (i.e., several GA optimization iteration). Unlike the plot shown in Figure 23, the parallel coordinate plot captures the interaction between multiple dimensions throughout the GA optimization iteration process. This plot captures how optimal solution can be found by simultaneously acting on these three systems: ACP4160, EPS_SWS, and LPI for two slightly different configurations.

Lastly, Figure 25 plots the evolution of the GA population in the output space of the model shown in Figure 19, i.e. total costs and event sequence frequency, for different batch instances (i.e., 1, 5, 10, 20, 50, and 120). From here, we expect that the population converges toward the optimal point, and it satisfies the prescribed constraints. In these plots, elements of the population that satisfy the requirements are shown in green, otherwise they are plotted in red. The reached optimal point is shown in the last plot (batch 120).

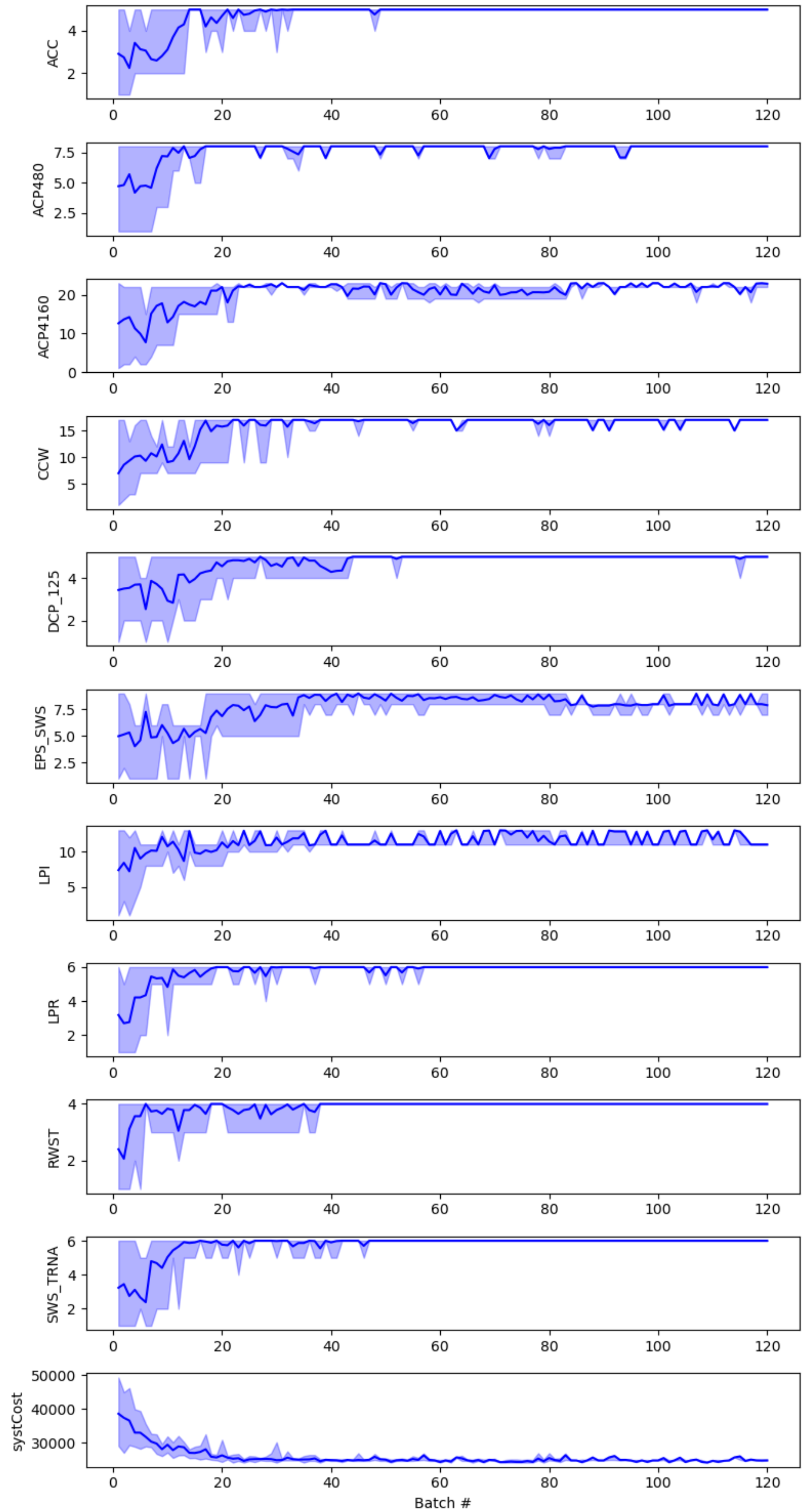


Figure 23. Evolution of the option population throughout the GA optimization process.

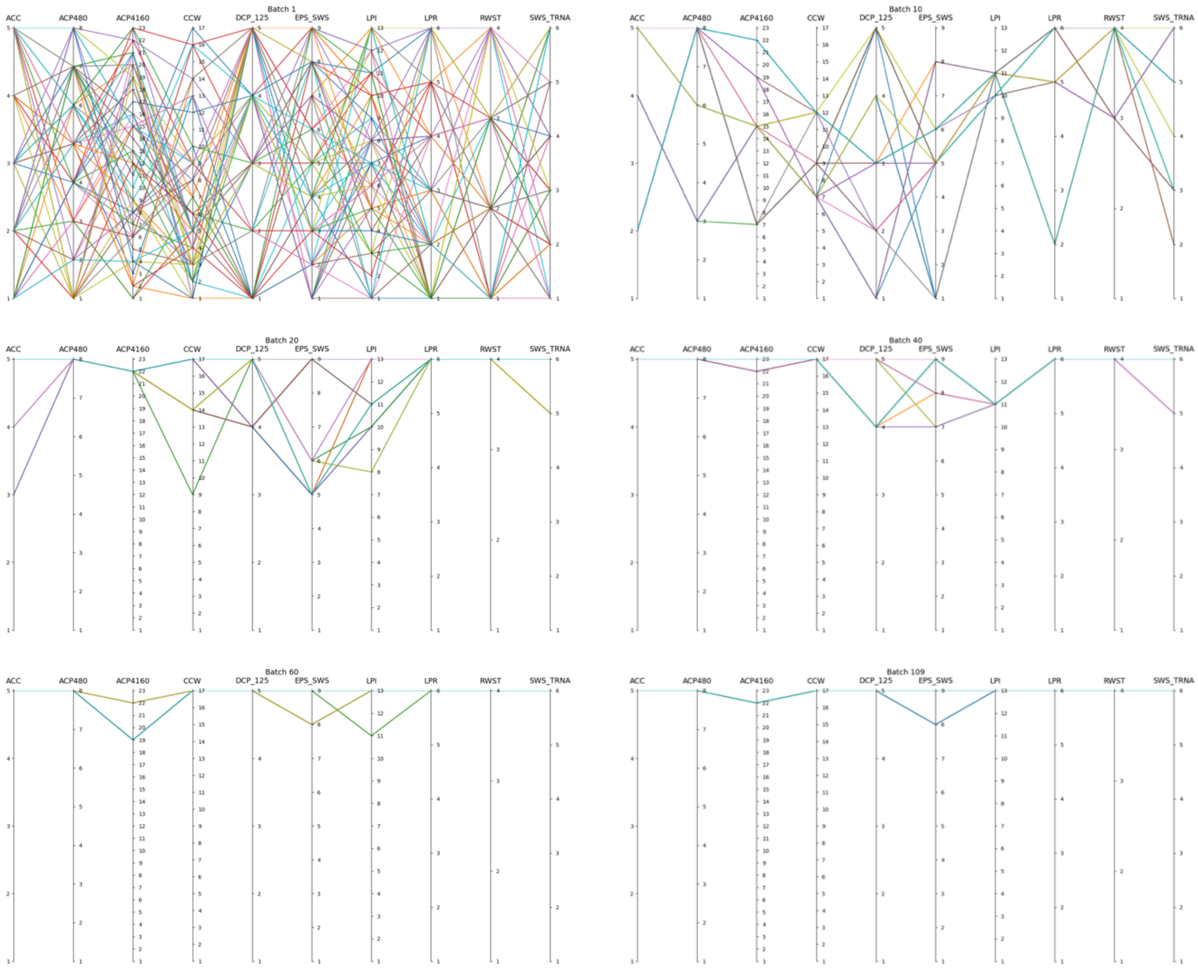


Figure 24. Parallel coordinate plot of the option population for different batch instances (i.e., 1, 10, 20, 40, 60, and 109).

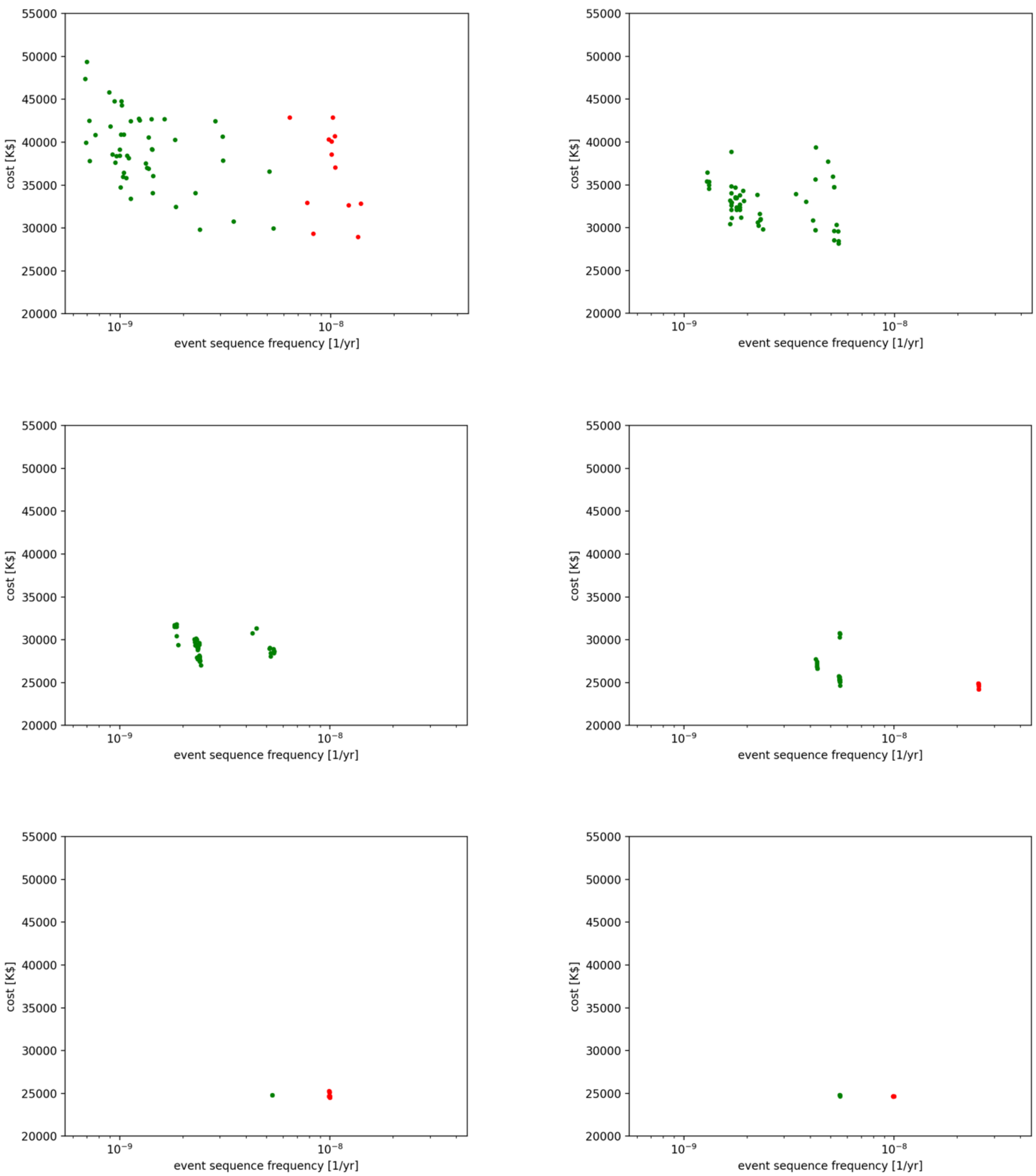


Figure 25. Evolution of the GA population in the output space, total cost and event sequence frequency, for different batch instances (i.e., 1, 5, 10, 20, 50, and 120).

2.5 Identified Difficulties, Gaps, and Needs for Additional Research

Allocating reliability targets proved to be a very complex task due to its multifaceted nature and broad scope. Specific areas of difficulty are discussed below.

2.5.1 Identified Difficulties

Passive-only components consideration for the RIM program. ASME Section XI, Division 2 is developed for passive-only components. However, this brings some concerns since the starting point of reliability target allocation is the plant-level: "the RIM program shall identify plant-level risk and Reliability Targets for RIM. Plant-level reliability shall be derived from regulatory limits on the risks, frequencies, and radiological consequences of licensing basis events that are defined in the probabilistic risk assessment (PRA). [1]" The plant-level reliability targets are addressed per accident sequence to satisfy requirements of NEI 18-04 guidance, and they are determined with consideration of both active and passive components unless a given mitigating system is purely passive. Allocation of reliability targets to only passive components may prove to be problematic because the overall system reliability is not addressed. Also, since the reliability of active components is not specifically considered, the cumulative effect of decreased reliability in both active and passive components is not addressed.

Problem is too large to solve. As discussed in previous chapters, the problem of allocating reliability targets to all plant SSCs at once is too large to solve even with modern computational power. As such, the task must be subdivided to subtasks which brings associated concerns such as:

- Population size of SSCs that would be considered all at once for reliability target allocation
- Selection of SSC groups could be based on a number of factors including importance measures, physical component type (e.g., pipe, valve), system that components belong to, component material, etc.

Interdependence of SSCs. Very few SSCs at a NPP are entirely independent. Most commonly, each SSC is dependent to other SSCs to various extent. This interdependency significantly complicates the optimization process of reliability target allocation.

SSCs supporting multiple event sequences. It is common that a system provides mitigation for multiple accidents. Some event sequences may be similar such as various sizes of LOCAs at LWRs. However, some mitigating systems and their SSCs may support unrelated to each other accidents. For example, an AC power system provides mitigation for most of the accident sequences at LWRs. Given that an SSC may support mitigation for multiple events, difficulty is with the selection of appropriate reliability target that would satisfy all the sequences. The most logical and simple way is to select the most limiting reliability target (i.e., lowest failure probability). However, this solution limits future plant operations flexibility since the SSC's performance will have to satisfy the prescribed reliability target. Another solution that can be considered is having multiple reliability targets, but this creates difficulties with associated performance monitoring strategies.

Circular dependence between SSC failure rate and importance measures. The PRA importance measures (e.g., Fussell-Vesely and Birnbaum) are typical metrics used to identify how important a given component is to the overall undesirable consequence. However, the probability of the undesirable consequence is directly dependent on each contributing component reliability, and a change in a component failure rate affects both the probability of the top event and importance measures of all the contributing events. As such, use of importance measures to assign reliability targets creates a circular dependency that impedes optimization techniques.

2.5.2 Identified Data Gaps

Plant and SSC-level reliability targets are directly related to the state of knowledge and data available for quantification of SSC probabilities of failure. For LWR SSCs, multi-year operational and testing data are available, and techniques for data quantification are well-established. This is not the situation with advanced reactors where operational data is either limited or not available at all. Testing data may be available, but usually it is insufficient to derive failure data with narrow uncertainty ranges. As such, data limitation could complicate RIM program development.

This limitation also affects licensing process that follows RG 1.233 guidance because scarce data typically results in a wider range of uncertainties. It is important because per NEI 18-04, "the upper bound consequences for each DBA, defined as the 95th percentile of the uncertainty distribution, shall meet the 10 CFR 50.34 dose limit at the EAB." The uncertainties also affect DID strategies since "One of the primary motivations of employing DID attributes is to address uncertainties, including those that are reflected in the PRA estimates of frequencies and consequence" [2].

As such, data collection and establishment of proper data processing and quantification methods are vitally important for successful licensing of advanced reactors following RG 1.233 and for development of the RIM program.

2.5.3 Future Research

Additional research is needed to investigate and test methods suitable for reliability target allocation. The methods should:

- Be based on proven and sound technical theories, repeatable, and demonstratable
- Be technology-inclusive (i.e., any reactor design should be able to follow developed methods)
- Be capable of addressing uncertainty considerations
- Be simple and clear in order to minimize industry efforts and reliance on subject-matter experts.

The future efforts will target development of the framework that incorporates methods that meet the above requirements to support industry with the complex task of reliability target allocation.

3. RCCS RIM FRAMEWORK OVERVIEW

The initial framework was developed using publicly available information using a single, simple system to demonstrate the concept of RIM strategy selection. The framework capabilities will be expanded to be applied to more complex systems and eventually to the entire plant.

The system used for the initial framework demonstration is a reactor cavity cooling system (RCCS) for a high-temperature gas reactor. The RCCS for the pebble-bed modular reactor (PBMR) was used as the initial RCCS design. The pilot study performed for the PBMR passive component reliability and integrity management [8] was used as the starting point for the initial setup of the RIM framework developed in this project.

3.1 System Technical Description

The RCCS primary function is to remove thermal radiation from the reactor vessel and to release this heat to the atmosphere. A water-cooled RCCS design is used in this case. Failure of the RCCS does not pose nuclear safety concerns, but the RCCS is relied upon for the DID, and it should remain operable at all times. In addition, RCCS failure could cause flooding of the reactor cavity, an undesirable consequence in terms of availability and investment protection.

A simplified schematic of the RCCS design used in the initial framework is presented in Figure 26. Water flowing through the standpipes around the reactor vessel walls removes heat from the reactor vessel. Water is supplied from outdoor tanks via connecting pipes. Since the system failure mode that is of primary concern is a pipe/weld failure which leads to flooding of the reactor cavity, only a portion of the RCCS is considered, which includes standing pipes and a fraction of connecting pipes. Therefore, there are only two groups of components, standing and connecting pipes, that are modeled in the RCCS RIM framework.

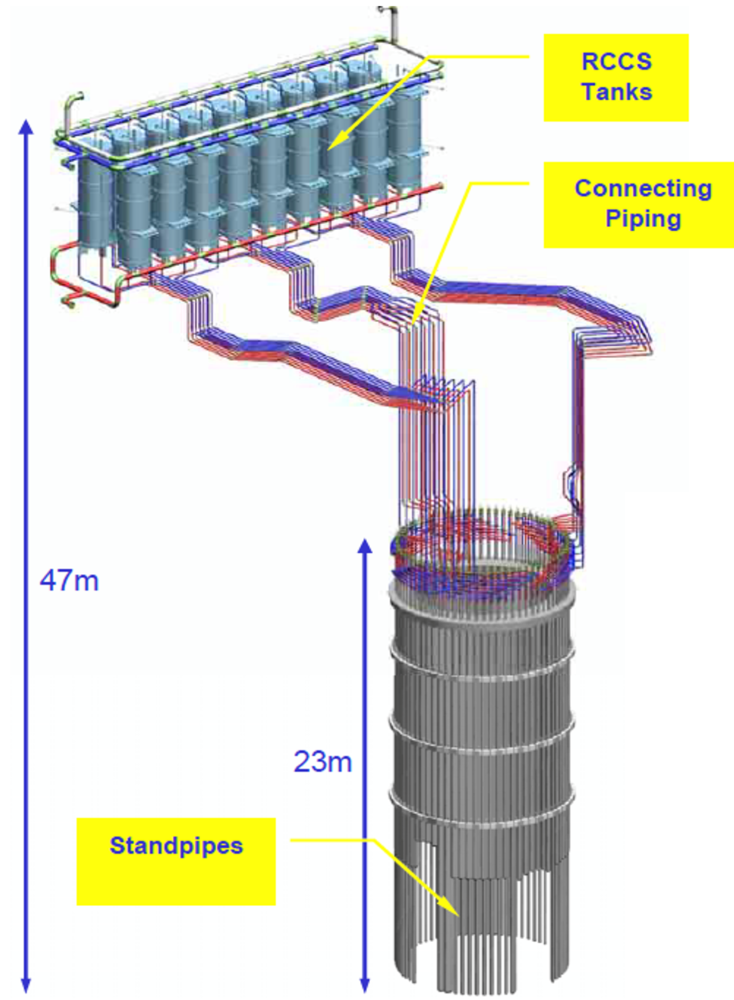


Figure 26. RCCS schematic.

3.2 RCCS RIM Strategies

3.2.1 RCCS Degradation Mechanisms

A RIM strategy is dependent on the type of degradation mechanisms that are present. Degradation mechanisms will vary for different materials in different operating environments and require different approaches to inspection, examination, and condition monitoring. Degradation mechanisms and criteria associated with the degradation mechanism attributes have been provided under Mandatory Appendix VII of ASME Section XI, Division 2 for multiple reactor types, including a high temperature gas reactor. The presentation of this material is separated into the types of degradation mechanisms and is readily applied in a worksheet type format as shown by Appendix A of the PBMR pilot study [8].

For the RCCS, the PBMR pilot study evaluated the potential for degradation mechanisms for the areas shown by the RCCS schematic in Figure 26. The evaluation also included inlet and outlet flow headers providing the flow path through the standpipes as well as flow from the tanks to the standpipes that occurs during the Passive Mode of operation. The Degradation Mechanism Assessment (DMA) for the PBMR RCCS resulted in identifying that there are no potential degradation mechanisms for the components in the RCCS DMA evaluation boundary.

The lack of a degradation mechanism is not unexpected for systems that contain demineralized water and perform in a mild operating environment. When coupled with designing the use of multiple Type 316 stainless steel piping and components, the potential for degradation is further reduced. The design of the

RCCS is such that thermal fatigue induced through vibration or through the combination of hot and cold fluid flows is not present, stresses and corrosive environments are not present to induce stress corrosion cracking, and contributors to corrosive environments are minimal.

Given the results of the PBMR pilot study DMA of the RCCS, no specific degradation mechanism was applied in the development of the RCCS RIM Strategies. This allows for application of general NDE techniques when determining the types of condition monitoring.

3.2.2 RCCS RIM Strategies

For the scope of this work, RIM strategy is defined as the combination of NDE and leak inspection strategies. Three NDE options are considered in the RCCS RIM framework:

- Phased array with assumed simplified probability of detection (POD) = 0.5
- Eddy current + ultrasonic with assumed POD = 0.9
- Do nothing (i.e., perform no NDE at all).

The considered frequencies for the NDE options are 3, 6, 9, and 15 years. The "do nothing" option, (i.e., not doing any SSC monitoring) is included to evaluate its effect on system performance (measured as reliability) vs. overall maintenance costs.

Three on-line leak detection (OLLD) options are considered:

- Visual examination with assumed POD = 0.5
- Imaging spectra with assumed POD = 0.9
- Do nothing (i.e., perform no OLLD at all).

The considered frequencies for the OLLD options are 1.5, 3, 4.5, and 6 years.

Although development of a RIM strategy focuses on meeting a desired reliability measure, costs can be considered when selecting from strategies that achieve the desired reliability since operations and maintenance (O&M) costs become a very important aspect of a successful long-term facility operation. Therefore, cost considerations are included in this evaluation. For the cost portion of the RIM model, both fixed and variable costs are considered. The fixed costs include things like personnel training and equipment costs. The variable costs are estimates for each inspection, and they include trained personnel time, number of people to perform each inspection, supplies needed to perform the inspection, etc. Costs are evaluated for the lifespan of the plant which is assumed to be 60 years. The cost model is setup using a rate of $100 per hour to perform typical inspection activities. The following multipliers are used for the cost model:

- Visual examination: x 1.0
- Imaging spectra: x 2.0
- Phased array: x 2.0
- Eddy current + ultrasonic: x 2.5.

3.3 RCCS Reliability Model

The RCCS RIM model uses a Markov model for predicting the effect from various inspection strategies on the RCCS piping reliability, a method based on the research described in [9]. The schematic of the model is presented in Figure 27 with the frequency of pipe rupture defined in Equation (1) [9].

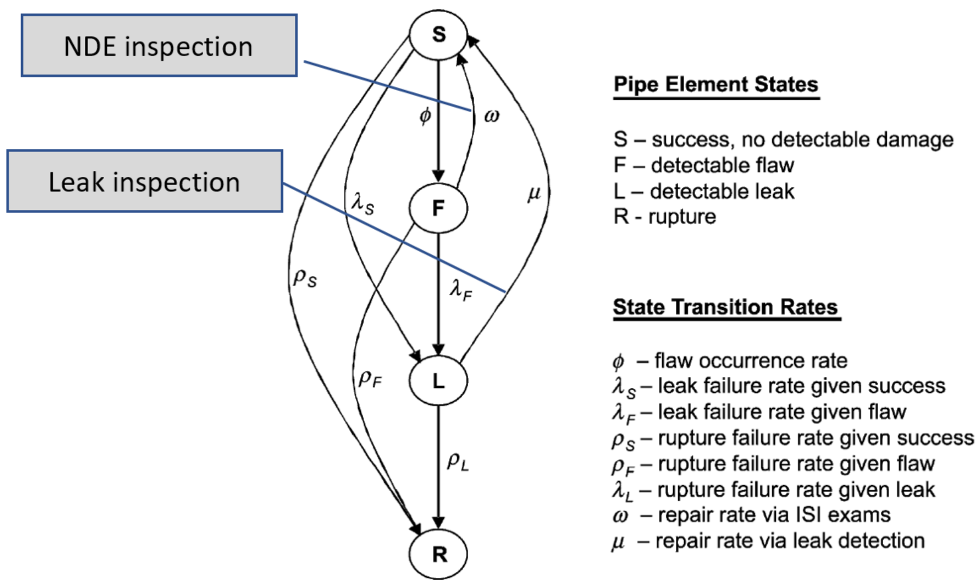


Figure 27. Pipe Markov model.

$$\rho_{ix} = \sum_{k=1}^{M_i} \rho_{ikx} = \sum_{k=1}^{M_i} \lambda_{ik} P_{ik}\{R_x|F\} I_{ik} \tag{1}$$

where

ρ_{ix}	=	Total rupture frequency for pipe component *i* for rupture mode *x*
ρ_{ikx}	=	Rupture frequency of pipe component *i* due to damage mechanism *k* for rupture mode *x*
λ_{ik}	=	Failure rate of pipe component *i* due to damage mechanism *k*
$P_{ik}\{R_x|F\}$	=	Conditional probability of rupture mode *x* given failure for pipe component *i* and damage mechanism *k*
M_i	=	Number of different damage mechanisms for component *i*
I_{ik}	=	Integrity management factor for component *i* and damage mechanism *k*; this factor adjusts the rupture frequency to account for variable integrity management strategies such as leak detection, volumetric NDE, in-service testing, etc. that might be different than the components in the service data.

The failure rate of pipes λ_{ik} is given by Equation (2) [9]:

$$\lambda_{ik} = \frac{n_{ik}}{f_{ik} N_i T_i} \tag{2}$$

where

n_{ik} = Number of failures (all modes including wall thinning, cracks, leaks and ruptures, and any events in which pipe repair or replacement is made are included) events for pipe component *i* due to damage mechanism *k*

T_i = Total exposure time over which failure events were collected for pipe component *i* normally expressed in terms of reactor years

N_i = Number of components per reactor year that provided the observed pipe failures for component *i*

f_{ik} = Fraction of number of components of type *i* that are susceptible to failure from damage mechanism *k* for conditional failure rates given susceptibility to damage mechanism *k*; this parameter is set to 1 for unconditional failure rates.

The repair rate ω and μ are estimated using Equation (3) and Equation (4) [9], respectively:

$$\omega = \frac{P_I P_{FD}}{(T_{FI} + T_R)} \tag{3}$$

$$\mu = \frac{P_{LD}}{(T_{LI} + T_R)} \tag{4}$$

where

ω = Flaw repair rate

μ = Leaks repair rate

P_I = Probability that a pipe with a flaw will be inspected in inspection interval

P_{FD} = Probability that a flaw will be detected given this segment is inspected

T_{FI} = Mean time between inspections for flaws (inspection interval)

P_{LD} = Probability that the leak in the segment will be detected per inspection

T_{LI} = Mean time between inspections for leaks

T_R = Mean time to repair once detected.

The reliability function for the RCCS piping is described by Equation (5):

$$R(t) = S(t) + F(t) + L(t) \tag{5}$$

where

$R(t)$ = Reliability of a pipe over time t

$S(t)$ = Success, no detectable pipe damage over time t

$F(t)$ = Flaw detected successfully over time t

$L(t)$ = Leak detected successfully over time t.

3.4 RCCS RIM STRATEGIES EVALUATION

A RIM strategy is defined here as the combination of the RIM strategy associated to the connecting pipes and the RIM strategy associated to the standing pipes. For each pipe group, a RIM strategy is a combination of NDE and OLLD (i.e., leak) strategies. Given the chosen types of NDE and OLLD options indicated in Section 3.2, the total number of possible RIM strategies is 9801 [$(11\text{x}9)^2 = 9801$]. The choice of the optimal RIM strategies has been performed in a multi-objective optimization fashion where the objectives that need to be minimized are RCCS flooding frequency and RCCS surveillance costs. The RIM strategies that minimize both objective functions are identified in the Pareto frontier as shown in Figure 28.

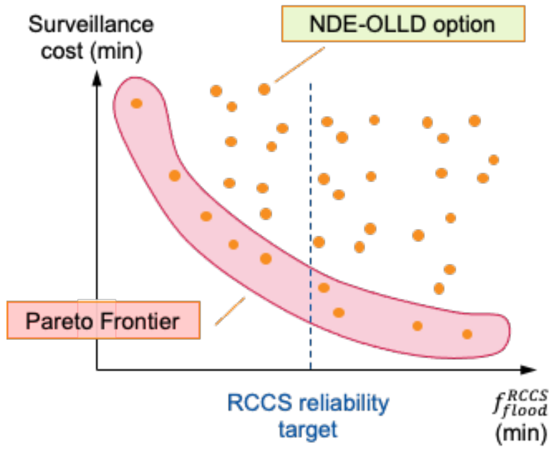


Figure 28. RCCS RIM strategy optimization.

The uncertainty propagation was done for the optimal RIM strategies identified by Pareto frontier distribution using RAVEN. The preliminary results for the reliability values vs. RIM strategies are shown in Figure 29 where it is assumed that the same RIM strategies are followed for standing and connecting pipes.

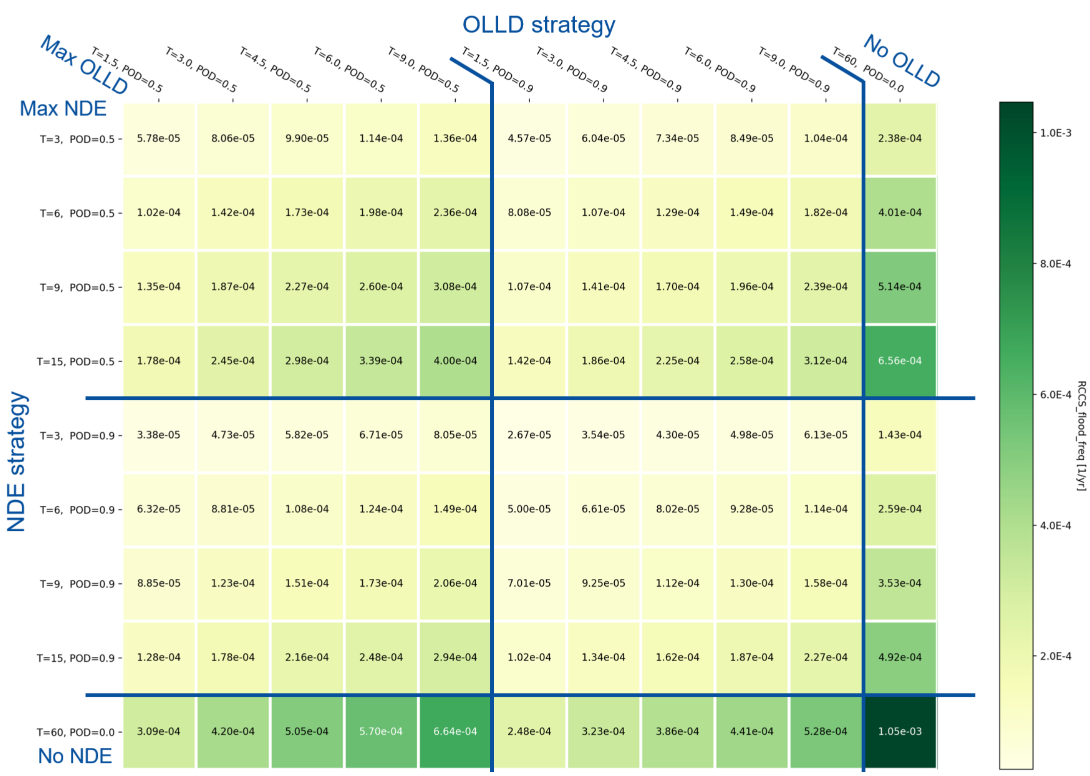


Figure 29. RIM strategies vs. RCCS reliability.

Similarly, the preliminary results for comparison of the surveillance costs over the lifespan of the plant (60 years) for the RIM strategies are shown in Figure 30.

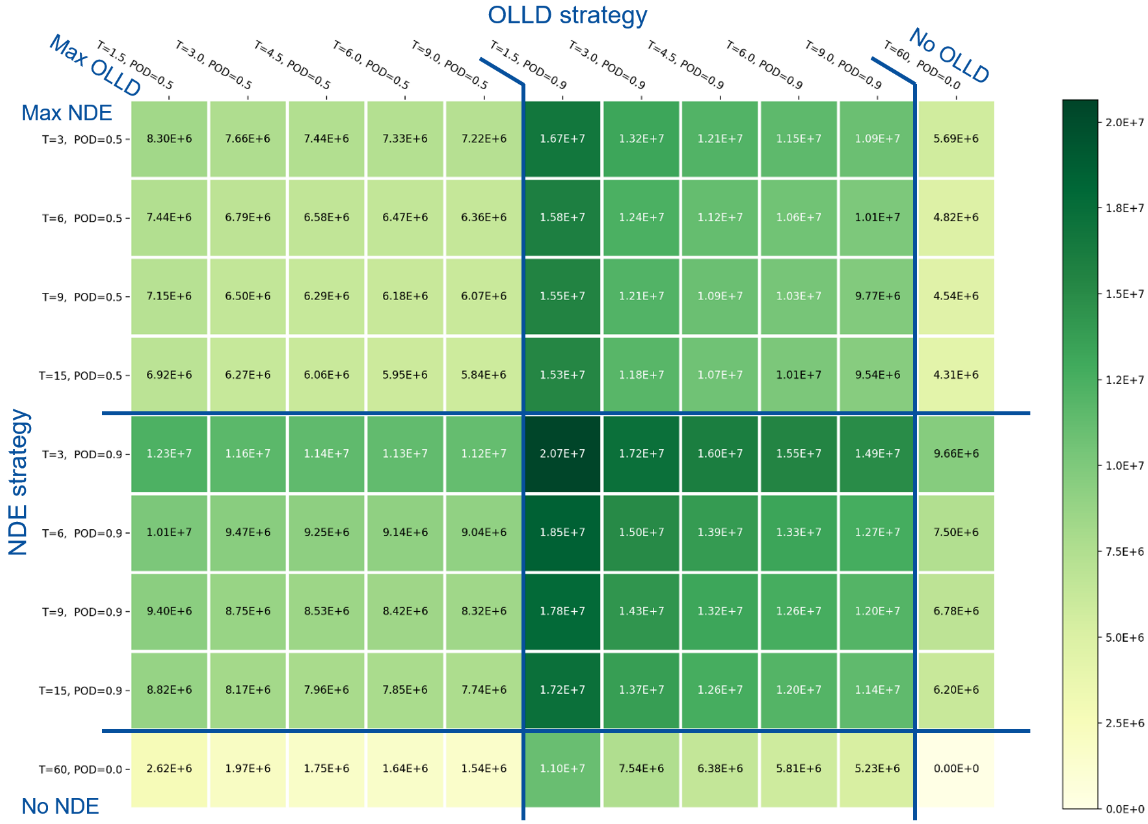


Figure 30. RIM strategies vs. surveillance cost.

The preliminary results for the complete multi-objective optimization of RIM strategies with flood frequency due to a pipe break vs. surveillance costs are presented in Figure 31.

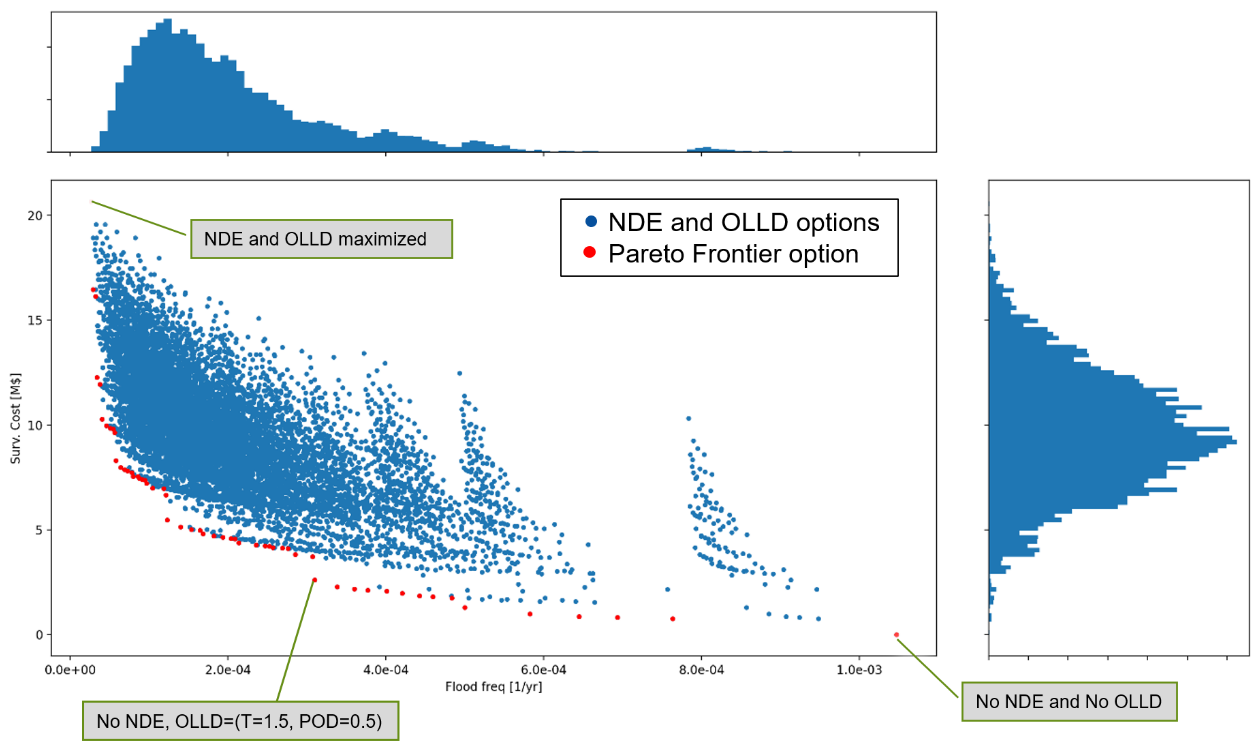


Figure 31. RIM strategies: flood frequency vs. surveillance costs.

It should be noted that RIM strategies have relatively small impact on the overall system reliability determined in the initial RCCS RIM study. This is because pipe failure rates used for this initial evaluation are very low due to the generic data used for the analysis. In this evaluation, the pipe failure rates for a very robust LWR cooling system are used. The framework will be adjusted to use more realistic data for pipe failure rates, POD, and costs. However, the generic data was sufficient to demonstrate the capabilities and applicability of the framework.

3.5 Considerations for RIM Strategies Selection

The results demonstrated by the RIM framework are logical—the reliability of the system as well as surveillance costs increase when more robust RIM strategies are implemented, and the "do nothing" RIM strategy obviously results in the lowest system reliability. However, the "do nothing" strategy does have associated costs measured in terms of a lost production, damaged facility, and expensive repairs. Because the costs associated with these consequences can influence the decision on what RIM strategy should be applied, the framework should be expanded to consider these costs.

The reliability data for new reactors is either limited or non-existent other than data developed from testing. This is a great concern because a lack of data associated with large uncertainties may result in overly conservative (i.e., excessively expensive) compensatory measures to overcome these uncertainties. One way to deal with the data limitation is to rely on a performance-based approach and continuous monitoring to demonstrate adequate system performance. In this case, a traditional preventive maintenance strategy that new reactors may not be able to adequately plan for can be replaced with a condition-based maintenance strategy. The benefit of the condition-based maintenance strategy extends beyond the traditional O&M cost savings due to elimination of unnecessary maintenance. The greatest benefit for new reactors is the ability to adjust the condition-based O&M posture according to the plant/system actual performance. As such, it is important for the new reactor designers to consider future O&M options early in the design process to ensure that the reactor license allows for these beneficial O&M options.

It is expected that with time, as operational data becomes available, maintenance strategies will be adjusted to better reflect degradation mechanisms, critical failure modes, and other contributors to system unreliability. Data obtained via system health monitoring can be used to prioritize maintenance activities based on the SSC performance margin rather than based on probability of failure values based on generic failure data. The RIM framework needs to be expanded to account for the future need to monitor system performance and make adjustments to the RIM strategies as needed given that the RIM program is a "living program" that represents as-built, as-operated plant where credit can be given for various improvements (e.g., added sensors improve monitoring capabilities).

Another consideration related to RIM strategies for new reactors can be referred to as "built-to-inspect." Meaning the plant should be designed in a way that allows various RIM strategies. For example, a visual inspection will not be an option for equipment located in very harsh environment or in physically inaccessible areas. In this case, more expensive RIM strategies, potentially with specialty equipment, will be the only feasible options, which may result in much higher O&M costs. These higher costs might be avoided by a better design solution.

Consideration of the different lifespans for different components within the plant is a feasible RIM strategy. The selection of a specific type of component or component material informs component reliability values. Two different strategies for component selection may be used to achieve the same system-level long-term reliability goals:

- Use expensive components (highly reliable with degradation-resistant material) to ensure adequate component performance over the long lifespan
- Use cheaper components and/or materials and replace them multiple times during the same lifespan.

A combination of design strategies and performance monitoring strategies may provide optimal solutions for meeting the long-term plant performance goals which can be accomplished by expanding the capabilities of the RIM framework.

3.6 Expansion of RIM Framework to Larger Context

In this case, the RCCS RIM strategies selection is rather a simple problem given that this system essentially has only two components of the same type (standing and connecting pipes). The same NDE and OLLD strategies are applied to all the components in the group (i.e., each standing pipe is assumed to have the same RIM strategy), and operational environment is simple (i.e., atmospheric pressure, low temperatures). The problem will become much more complex for a different system or when it needs to be solved for the entire plant vs. a single system. A comparison of RIM program development cases for a simple and more complex system is presented in Table 7.

Table 7. Simple vs. complex system RIM strategies selection.

Inputs	RCCS System Case Study	More Complex System
Number of Components	Two component groups, same component types – all RCCS pipes are grouped into (1) standing pipes or (2) connecting pipes	Many more than two with different component types (e.g., pipes, valves, pumps, heat exchangers)
NDE/OLLD Options	Only two NDE and two OLLD options with simplified assumptions for a POD and cost	Multiple options, each associated with POD and costs estimates, each includes uncertainties
—	The same option is applied for all the components (pipes) in the group	A different strategy and different frequency can be applied for each component or a group of components
Operating Environment	Simple (i.e., atmospheric pressure, low temperature) Same for the entire system	Complex (e.g., high temperature, pressure, and vibration) Varying for different components in the system
Degradation Mechanisms	RCCS has no applicable degradation mechanisms; random failure is postulated instead	Multiple degradation mechanisms possible Different mechanisms could be applicable for different system components
Lifespan	Same for all system components	Possibility of variable lifespan for different components in the system (e.g., 100+ years for not accessible/high SSCs, 20 years for the rest of the system)
Reliability Target	A single reliability target	Hazard-dependent (e.g., internal event, seismic) From nuclear safety risk perspective From investment protection perspective

As mentioned earlier, 9801-available RIM strategies were identified for the very simple RCCS case study. Given considerations presented in Table 7, the RIM strategies optimization problem for a more complex system will have many more degrees of freedom which makes the problem impossible to solve without using a specially developed framework.

4. CONCLUSIONS AND RECOMMENDATIONS

This report describes the research focused on developing the technical framework and implementation strategies supporting establishment of a RIM program for power plants based on advanced nuclear technologies. This research is of a paramount importance because it is directly related to regulatory licensing of advanced reactors and expedited deployment of the new nuclear technologies.

The research and development conducted thus far developed and demonstrated an initial technical framework that can support RIM program development for any advanced reactor. The use of this framework is extremely beneficial because it allows advanced reactor developers to:

- Optimize the selection of strategies for plant performance monitoring that ensure both safety and economic goals are met
- Expedite regulatory licensing review process since the framework is built based on the regulatory-approved approaches.

Additional research and development are warranted to expand the capabilities of the framework to support the entire RIM program development not only on a system-level but most importantly on the plant-level.

5. REFERENCES

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Appendix A
OPTIMIZATION METHODS

Under the RIM project we are informing advanced reactors (ARs) system engineers on the optimal design properties of SSCs along with their optimal lifecycle strategy that minimizes O&M and capital costs and maximizes plant reliability and availability. Some observations regarding this paradigm are as follows:

- Our analyses cannot be only cost driven. In fact, we cannot neglect the fact that SSC design and lifecycle choices may directly affect plant reliability and safety aspects (and, in general, other figure of merits [FOMs] that are outside the O&M realm)
- Such information processing can be performed either at the component or at the system-level depending on how the chosen design and lifecycle choices affect the chosen FOMs.

Figure A-1 shows in graphical form how AR design, which is composed by several SSCs, can be informed using the RIM project to determine optimal SSC design (e.g., SSC material) and lifecycle strategy (e.g., SSC replacement schedule) such that one or more plant FOMs (e.g., O&M-capital costs, system reliability/availability) are optimized (either minimized or maximized).

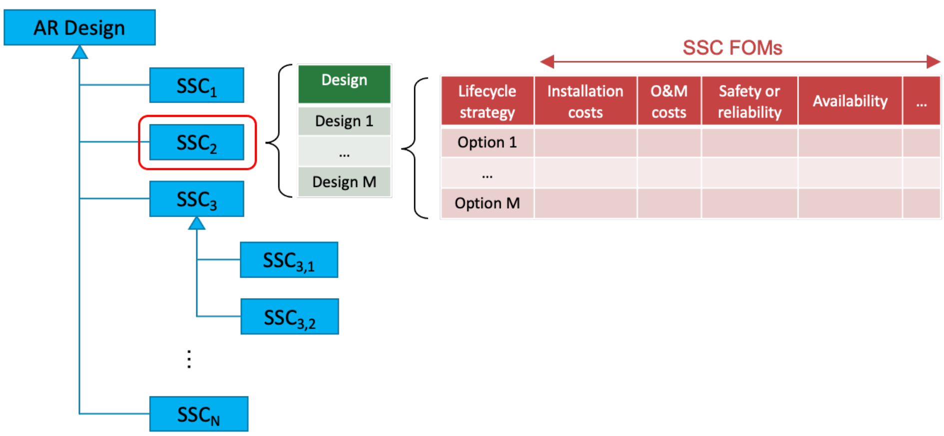

Figure A-1. Representation of a generic AR design as composed by several SSCs and the decision variables to be determined for each SSC: design (e.g., materials) and lifecycle strategy.

This optimization process can be solved numerically, and it requires two main components:

- A model which receives as input the design and lifecycle choices for the considered SSC, and it generates as output the corresponding values of the chosen FOMs (e.g., plant reliability and plant costs). Such a model would be developed for each specific use case under consideration.
- A computational engine designed to perform the actual optimization over the model described above. This computational engine can be developed in a generic form such that it can handle any generic model. The classes of optimization algorithms available from current literature is wide, and then ones considered within this project are presented below.

For the scope of the RIM project, we are considering two types of optimization methods: single- and multi-objective optimization methods. Single-objective optimization methods are designed to determine the global minima (or maxima) of a single-objective function $F(\mathbf{x})$ over a decision variable $\mathbf{x}$. Generally speaking, the decision variable can be defined over an N-dimensional space $\mathbf{x} = [\mathrm{x}_1, \dots, \mathrm{x}_\mathrm{n}, \dots, \mathrm{x}_\mathrm{N}]$ where each element x_n represents a degree of freedom in the decision process. The objective function $F(\mathbf{x})$ is determined uniquely by the employed simulation model. It is not uncommon that constraints might be present in this optimization process; such constraints might target the input or the output spaces. In mathematical terms, single-objective optimization can be translated as follows (see Figure A-2):

$$\begin{aligned} \min_{\boldsymbol{x}} \quad & F(\mathbf{x}) \\ s.t. \quad & \mathbf{x} \in \Xi \\ & G(\mathbf{x}) \leq 0. \end{aligned}$$

The term $\mathbf{x} \in \Xi$ represents a constraint in the input space where, for example, the decision variables are bounded to vary within an upper and a lower bound. The term $G(\mathbf{x}) \leq 0$ represents constraints in the output space where, for example, additional output variables generated by the simulation model are forced to be bounded.

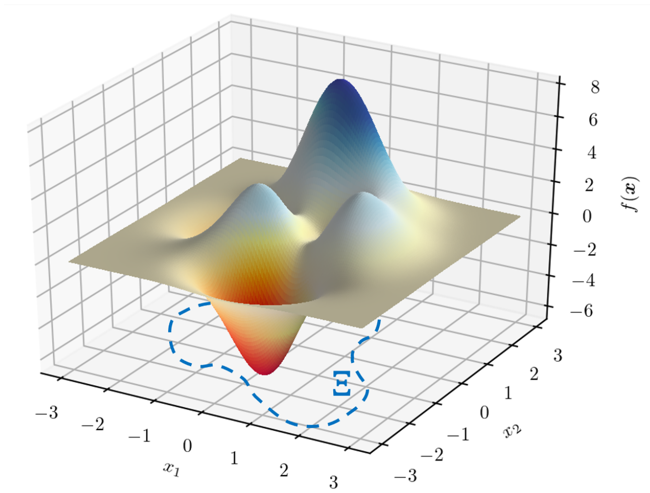

Figure A-2. Graphical representation of single-objective optimization: the goal is to determine the global minima of the objective function $\boldsymbol{f(x)}$ over the 2-dimensional space $\boldsymbol{x_1, x_2}$.

Figure A-3 shows in a flow diagram how model optimization can be performed. In more detail, the function $F(\boldsymbol{x})$ can be modeled by constructing the simulation model for the system under consideration; afterward, it is possible to iteratively loop over the decision variable $\boldsymbol{x}$ to obtain the optimal value of $\boldsymbol{x}$ that minimizes/maximizes the objective function $F(\boldsymbol{x})$ (e.g., minimization of operating costs, maximization of system availability). Under the "build-to-replace" project, the decision variable $\boldsymbol{x} = [x_1, x_2]$ can represent the SSC design (e.g., SSC material), indicated as x_1, and lifecycle strategy (e.g., SSC replacement schedule), indicated as x_2.

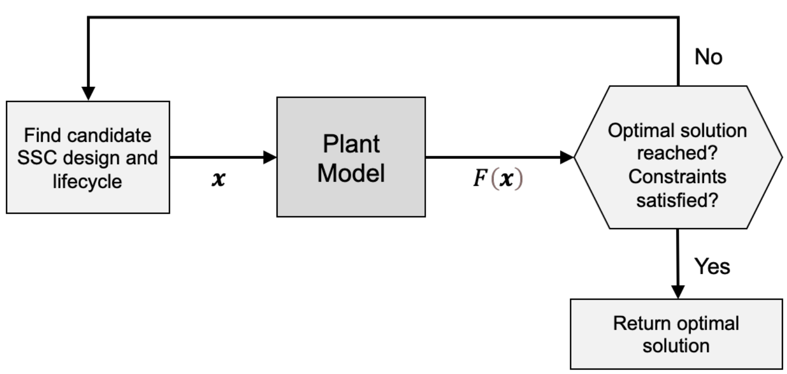

Figure A-3. Model-based optimization scheme.

A-1.1 Gradient-Based Methods

The optimization problem described above can be numerically solved by employing gradient-based optimization algorithms. Gradient-based algorithms are first-order iterative optimization algorithms, and they are ideal for this kind of application. The objective is to find the minimum of a function $F(\boldsymbol{x})$; starting from an initial point $\boldsymbol{x}^0$, this is performed by determining at each iteration r the gradient of $F(\boldsymbol{x})$, $\nabla F(\boldsymbol{x})$, and moving to the next point in the direction of the gradient of the function at the current point.

From a point $\boldsymbol{x}^r$ determined at iteration r, the point $\boldsymbol{x}^{r+1}$ at iteration $r+1$ is calculated as:

$$\boldsymbol{x}^{r+1} = \boldsymbol{x}^r - \boldsymbol{\gamma} \cdot \boldsymbol{\nabla} F(x)$$

The sequence $(\boldsymbol{x}^0, F(\boldsymbol{x}^0)) \longrightarrow (\boldsymbol{x}^1, F(\boldsymbol{x}^1)) \longrightarrow (\boldsymbol{x}^2, F(\boldsymbol{x}^2)) \longrightarrow \cdots$ converges to a local minima of $F(\boldsymbol{x})$.

A-1.2 Stochastic Methods

Stochastic methods are a variation of the gradient-based method shown earlier. They introduce stochastic elements in the selection of point $\boldsymbol{x}^{r+1}$ given $\boldsymbol{x}^r$ obtained from the previous iteration.

- *Simultaneous perturbation stochastic approximation*(*SPSA*): The goal of SPSA is to introduce a stochastic element in the calculation of the gradient $\boldsymbol{\nabla} F(\boldsymbol{x})$ in the equation below:

$$\boldsymbol{\nabla} F(\boldsymbol{x}) = \frac{F(\boldsymbol{x} + \boldsymbol{\epsilon}) - F(\boldsymbol{x})}{\boldsymbol{\epsilon}}$$

  where ϵ is a random perturbation vector.

- *Simulated annealing* (*SA*): SA method determines $\boldsymbol{x}^{r+1}$ by first determining a candidate neighbor $\tilde{\boldsymbol{x}}$ of $\boldsymbol{x}^r$(which is randomly generated), and it accepts it with a probability proportional to $F(\tilde{\boldsymbol{x}}) - F(\boldsymbol{x}^r)$.

A-1.3 Genetic Algorithms (GAs)

GAs represent a relevant class of optimization methods for both continuous and discrete optimization problems. GAs are very well suited for discrete optimization problems (i.e., the decision variable $\boldsymbol{x}$ is discrete in nature and not continuous). In addition, GAs are able to deal with any type of data structure. By data structure, we intend any form of encoding information into a digital format.

GA methods act on a population of sampled points $(\boldsymbol{x}, F(\boldsymbol{x}))$ (rather than focusing on a one-sample-at-a-time mindset), and they iteratively combine pairs of points to generate a new generation of points with higher quality. An initial population of N elements is initially generated (e.g., by Monte Carlo sampling) and evaluated. Each element$(\boldsymbol{x}, F(\boldsymbol{x}))$ of the population has the input coordinates $\boldsymbol{x}$ encoded into a discrete form, a genotype, while the $F(\boldsymbol{x})$ term is encoded into a fitness value $\tilde{f}$. The genotype form of $\boldsymbol{x}$ (here indicated as $\tilde{\boldsymbol{x}}$) is called a data structure, and it can be of several forms depending on the application. In this report we focus on arrays of discrete values. More advanced data structures can be matrices, tree structures, or graph structures (see Figure A-4). When dealing with arrays of length L of discrete values, several options can be chosen: array of L binary values, array of L integers, combination of L integers, permutation of L integers.

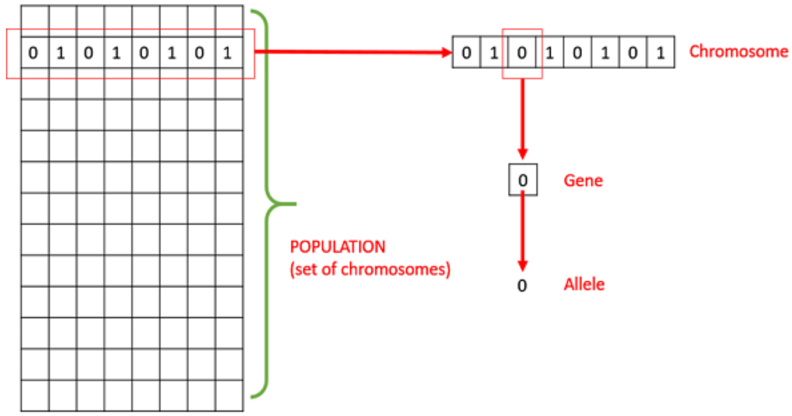

Figure A-4. Graphical representation of the GA data structures.

The main operators that are being employed by GAs are the following:

- Crossover: the encodings of two chromosomes are mixed to generate two new encodings
- Mutation: the encoding of a chromosome is altered by randomly changing the value of a single element of the chromosome
- Replacement: the population of chromosomes is updated by removing chromosomes with low fitness or high generational age value and keeping chromosomes with high fitness or low generational age.

The main structure of a GA optimization algorithm is shown in the box below (refer to Figure A-5).

Algorithm 1. GA optimization.

1. Create initial population: perform uniform sampling of the region of interest:
2. Monte Carlo sampling of N samples $(\boldsymbol{x}, F(\boldsymbol{x}))_n \ \ , n = 1, \dots, N$
3. Perform a genotype representation according to the problem under investigation
4. Calculate fitness of each chromosome: $(\boldsymbol{x}, F(\boldsymbol{x}))_n \rightarrow (\tilde{\boldsymbol{x}}, \tilde{f})_n$
5. Reproduction: create the new generation of offsprings from current population:
6. Perform parent selection from the population based on their fitness
7. Perform crossover: creation of child population by mixing chromosome structure of parents
8. Perform random mutation on the generated offspring
9. Evaluate offspring (i.e., determine $F(\boldsymbol{x})$) and calculate their fitness $\tilde{f}$
10. Return to Step 4 until convergence is met.

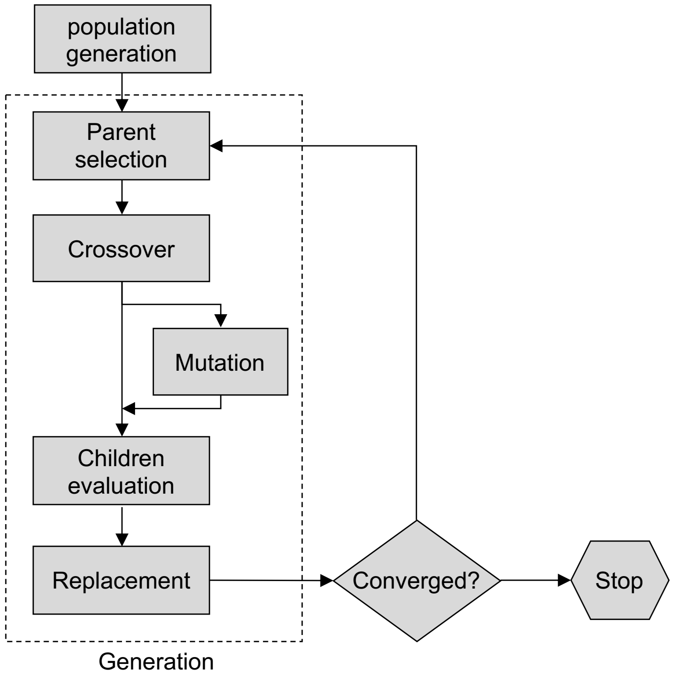

Figure A-5. GA workflow.

A-1.4 Multidimensional Pareto Frontier

The multi-attribute utility analysis is a structured methodology in decision theory designed to handle the tradeoffs among multiple objectives. Provided several options, the goal is to identify the "best" option that satisfies a specific set of needs or requirements.

The first step is to identify the set of attributes that affect the decision at hand. Typically, these attributes can be condensed into two, utility and cost, but, in some applications, the number of attributes might be higher (e.g., lifecycle cost and performance).

Let's assume that a decision can be taken from a set of options by considering the utility and cost of each option. Using a graphical representation (see Figure A-6), it is possible to plot each option as a point in a two-dimensional space, cost vs. utility[a]:

- *Cost*: this axis represents the cost associated with each option ranging from 0 (i.e., cheapest option) to a maximum value C_{max} (i.e., the most expensive option)
- *Utility*: this axis represents the added value (or the performance) associated with each option ranging from 0 (i.e., lowest performance option) to a maximum value U_{max} (i.e., option with highest performance).

[a] As indicated earlier, the number of attributes considered in complex settings can be $N > 2$. Thus, in such cases, the space would be N -dimensional.

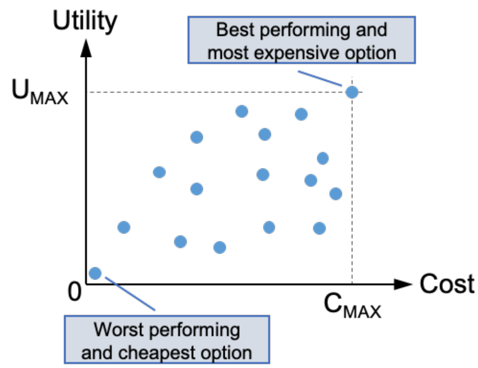

Figure A-6. Set of options (blue dots) plotted in a cost vs. utility space.

Once the complete set of options have been generated and the utility and cost values have been determined for each option, the next step is the determination of the Pareto optimal frontier which is fundamentally an envelope of options that dominates (in terms of both utility and cost) the set of remaining options (see A-7).

The final step in the analysis is to impose the utility and cost constraints (see Figure A-8) and select those points that satisfy both of these requirements. In some applications, the data provided to each option to generate its values of utility and cost might be affected by uncertainties. In such cases, data uncertainties are propagated for each selected option; the final outcome is that rather than having a single point for each option, we have a cloud of options centered around the selected option. By performing this analysis, now it is possible to determine not only the best options but also how uncertainties affect such a decision process.

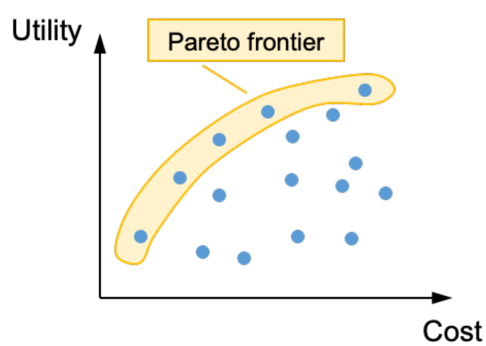

Figure A-7. Pareto frontier obtained from a set of options plotted in a cost vs. utility space.

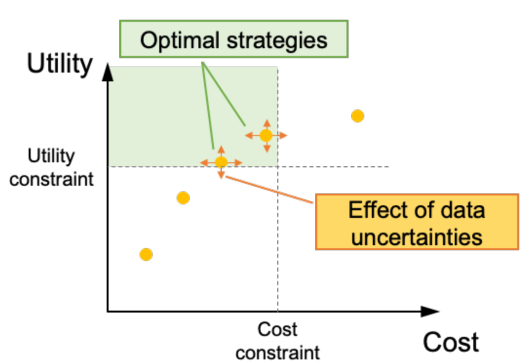

Figure A-8. Propagation of uncertainties for the points on Pareto frontier and imposition of cost and utility constraints.

This kind of analysis requires a model $\boldsymbol{\Psi}$ (or a set of models) that determines the value of M objective functions $y_1, \ldots, y_M$ given a set of N input variables $x_1, \ldots, x_N$ (also known as decision functions):

$$\boldsymbol{Y} = \boldsymbol{\Psi}(\boldsymbol{X}) \quad \text{where: } \boldsymbol{Y} = [y_1, \ldots, y_M] \text{ and } \boldsymbol{X} = [x_1, \ldots, x_N].$$

The set of input variables $\boldsymbol{X}$ are sampled, and the corresponding output variables $\boldsymbol{Y}$ are obtained from the model $\boldsymbol{\Psi}$. The Pareto frontier is then obtained from the generated set of $\boldsymbol{Y}$ as indicated in the workflow shown in Algorithm 2. This method is very effective when the input variables are discrete in nature, and the possible combination of values for the input variables are limited.

Algorithm 2. Pareto-frontier-based multi-objective optimization.
1. Generate all possible combinations of values for the input variables $x_1, \ldots, x_N$
2. Generate the objective functions $y_1, \ldots, y_M$ for each combination of the input variables generated in Step 1
3. Determine the Pareto frontier from the data set generated in Step 2.