INL-EXT-19-55819

Light Water Reactor Sustainability Program

Combined Data Analytics and Risk Analysis Tool for Long Term Capital SSC Refurbishment and Replacement

September 2019

U.S. Department of Energy

Office of Nuclear Energy

INL-EXT-19-55819

Combined Data Analytics and Risk Analysis Tool for Long Term Capital SSC Refurbishment and Replacement

D. Mandelli, C. Wang, S. StGermain, C. Smith (INL)
D. Morton (Northwestern University)
I. Popova (Texas State University)
S. Hess (Jensen Hughes)

September 2019

Prepared for the
U.S. Department of Energy
Office of Nuclear Energy

EXECUTIVE SUMMARY

The objective of this report is to summarize the research and development activities performed during FY19 for the Risk Informed Asset Management (RIAM) project under the Risk Informed System Analysis (RISA) pathway for the Light Water Reactor Sustainability (LWRS) program. This project started in October 2018 in response to the need to develop data analytics tools coupled with risk-informed methods to manage plant assets over periods of extended operation (including licensne renerwal and second license renewal). The first application of this project targets replacement/refurbishment expenditures of plant capital assets (i.e., Structures, Systems and Components - SSCs) as part of the plant license renewal process. The objective is to optimize the SSC replacement/refurbishment schedule based on economic constraints, data uncertainties and SSC reliability data.

We started our work by formalizing, from a mathematical perspective, the SSC optimization replacement schedule by identifying its requirements, degrees of freedom and constraints. We then proceeded to develop computational tools able to solve this class of problems. We proceeded in two development directions: the first direction consists of stand-alone algorithms designed to optimize the SSC replacement/refurbishment schedule while the second one consists of methods that evaluate the impact of data uncertainties (e.g., budget and costs) on the replacement/refurbishment schedule.

The outcome of this project during FY19 has been the creation of a software tool which contains a library of methods that can be employed to solve SSC replacement/refurbishment schedule optimization problems. The developed methods integrate both safety/reliability and cost models in a single decision-making tool, which also provides the user with data analysis capabilities to explore and analyze the generated solution.

Several examples with increasing levels of complexity are presented and analyzed in detail in order to demonstrate the developed capabilities and tools. The objective is to present a pragmatic workflow that can be followed by plant management workers, which considers the type of analysis, the type of constraints, data uncertainties and provides the most suited method and computational tool to be employed. The intent of this worlflow and tool is to provide nucelar plant and fleet decision-makers with the capability to effectively and efficienlty evaluate long-term asset management strategies to select the most effective and profitable investment portfolio.

CONTENTS

FIGURES

TABLES

ACRONYMS

AHP	Analytic Hierarchy Process
AM	Asset Management
CDF	Core Damage Frequency
CNAQ CR	Condition Not Adverse to Qualify Condition Report
CAQ-S CR	Condition Adverse to Qualify Station Level Condition Report
DOE	Department of Energy
EPRI	Electric Power Research Institute
ER	Equipment Reliability
ESF	Engineered Safety Features
ET	Event Tree
FT	Fault Tree
GA	Genetic Algorithm
I&C	Instrumentation and Controls
ILCM	Integrated Life Cycle Management
INL	Idaho National Laboratory
IPOP	Investments Portfolio Optimal Planning
IRR	Internal Rate of Return
JH	Jensen-Hughes
LCMP	Life Cycle Management Plan
LCO	Limiting Condition of Operation
LER	License Event Report
LERF	Large Early Release Frequency
LHS	Latin Hypercube Sampling
LTAM	Long-Term Asset Management
LWRS	Light Water Reactor Sustainability
MC	Monte-Carlo
MCS	Minimal Cut Set
MHRS	Labor hours
MWe	Megawatt of Electrical power
MWh	Megawatt hour of energy
NAM	Nuclear Asset Management

NEI	Nuclear Energy Institute
NHPP	Nonhomogeneous Poisson Process
NPP	Nuclear Power Plant
NPV	Net Present Value
O&M	Operations and Maintenance
PDF	Probability Density Function
PRA	Probabilistic Risk Assessment
PWR	Pressurized Water Reactor
RAVEN	Risk Analysis Virtual Environment
RCP	Reactor Coolant Pump
REM	Roentgen Equivalent Man, dose of radiation
RIAM	Risk Informed Asset Management
RI-PSH	Risk Informed Plant System Health
RISA	Risk-Informed Systems Analysis
RUL	Remaining Useful Life
R&D	Research and Development
SCAQ CR	Significant Condition to Qualify Condition Report
SLR	Second License Renewal
SQA	Software Quality Assurance
SSCs	Structures, Systems, and Components
T&M	Testing and Maintenance
UQ	Uncertainty Quantification

Combined Data Analytics and Risk Analysis Tool for Long Term Capital SSC Refurbishment and Replacement

1. INTRODUCTION

As indicated in the RISA use case milestone [1], one industry relevant use case that was proposed and chosen was focusing on risk-informing capital investment decisions related to Structures, Systems, and Components (SSCs) replacement plans. As commercial Nuclear Power Plants (NPPs) pursue extended plant operation in the form of Second License Renewal (SLR), opportunities exist for these plants to provide capital investments to ensure long-term safe and economic performance. At the current time, several utilities have announced an intention to pursue extended operation for one or more of their NPPs via SLR[a]. The goal of this research is to enhance the long-term safety and economics of NPPs during the SLR period of operation by providing a structured risk-informed approach to evaluate and prioritize plant capital investments made in preparation for, and during the period of, extended plant operation.

In this respect, the objective is to develop a comprehensive enterprise risk analysis framework with the goal of decreasing the operational cost of nuclear power plants and supporting long-term economic and safe operation during the period of extended operation (i.e., during SLR). This framework combines into a unified analysis environment: classical Probabilistic Risk Assessment (PRA) tools; risk and reliability evaluation methods; degradation models for plant SSCs; and, plant cost models.

This report summarizes the activities of the Risk Informed Asset Management (RIAM) project regarding the development of data analytics tools coupled with risk-informed methods to manage plant assets. The work has been conducted by Idaho National Laboratory (INL), Northwestern University, Texas State University and Jensen Hughes.

The outcome of this project during FY19 has been the creation of a software tool, which contains a library of methods that can be employed to solve SSC replacement/refurbishment schedule optimization problems. The developed methods integrate both safety/reliability and cost models in a single decision-making tool, which also provides to the user data analysis capabilities to explore and analyze the generated solution.

In this document we summarize how this tool has been structured and how it can be employed in several examples with increasing levels of complexity in order to demonstrate the developed capabilities. In order to maximize the effectiveness of this document we have condensed and summarized the activities of this year in the main section of this report. We have left most of the technical details such as the mathematical models and the method development in the appendices.

2. CAPITAL BUDGETING

Capital budgeting can be approached using a class of discrete optimization models that allocate scarce resources among competing activities. Furthermore, as we will see, when accounting for random parameters in such capital budgeting models, the approach falls under the umbrella of decision making under uncertainty. Different entities such as businesses and government agencies, make decisions regarding replacement, refurbishment, expansion or abandonment of assets. Examples of capital budgeting problems are cost cutting decisions related to improving efficiency, streamlining operations, eliminating waste or

[a] http://www.world-nuclear-news.org/Articles/Duke-Energy-to-seek-fleetwide-second-licence-renew?feed=feed

reducing liabilities; or, expansion of operations including opening of new facilities or expanding capability within existing facilities. Replacement or refurbishment of assets, changing processes or changing locations of assets can also be analyzed from a capital budgeting point of view. The decision to abandon, cease production, close a facility, retire equipment, or to replace, expand, and acquire new equipment are important economic decisions, which require the type of rigorous analytical justification that we describe in this report.

As a practical matter, capital budgeting decisions are usually conducted in a dynamic and uncertain environment. Regardless of when the decision is made, there are three possible outcomes regarding a proposal for a specific project: accept, reject, or delay. The steps in the decision-making process include recognizing the problem or opportunity, generating solution alternatives, developing cash-flow forecasts, evaluating the alternatives, selecting and implementing the best set of alternatives, and post-decision analysis and evaluation.

A key step in such problems is carrying out the requisite analysis to forecast cash flows associated with selecting, rejecting, or delaying a project. In addition, the analyst must choose an appropriate discount rate. Cash flows are functions of the initial investment cost and forecasted revenues and costs. The discount, or hurdle rate, should be uniquely linked to the risk of the projects at hand and depend on the risk-free rate in the economy (typically represented by the rate of the 10-year U.S. Treasury bond).

Projects can be analyzed individually or collectively as a portfolio of candidate projects. Textbook analysis typically begins with the former type of approach, and the evaluation of alternatives for individual projects is done by computing and comparing numerical values under different *rules*. The most common rule is based on the Net Present Value (NPV), which gives the dollar value created today by undertaking an investment in a project. When analyzing an individual project, the NPV allows decisions to be made in a simple fashion: if the NPV is positive, we accept the project; otherwise, we reject the project. A second rule is based on the Internal Rate of Return (IRR), which is the discount rate that makes the NPV of an investment equal to zero. An investment is acceptable if the IRR exceeds the required/hurdle rate of return and is rejected otherwise. For more details on the development and analysis using these types of rules see, e.g., Chapter 9 of [2].

The computation of the discount rate depends on the riskiness of individual projects, and once computed is kept fixed. Variables that can vary are the cash flows of the projects. There are different ways to incorporate uncertainty in the capital budgeting process, and one of them is having uncertain cash flows. We detail how this can be done in this report, both in deriving scenarios for NPVs based on uncertain failure rates, yielding uncertain cash flows, and in using those scenarios for NPVs within an optimization model for capital budgeting.

We will describe and propose solution procedures for deterministic and stochastic capital budgeting problems. These approaches go beyond simple rules for evaluating a single project, and account for resources required to implement multiple projects simultaneously. In other words, we might have a collection of projects with attractive NPVs or IRRs, but because of associated costs, we simply cannot afford to simultaneously select all of the projects.

When dealing with multiple projects simultaneously, we can simply enumerate possibilities when the total number of options is small, but as the problem scales this quickly becomes computationally intractable. For example, if we have 30 attractive investment projects, but can only afford to implement 15, there are about 155 million combinations, which can be enumerated on a computer. However, if each of the 30 projects can be done via multiple palns of execusion (e.g., plan A, plan B, plan C) or not at all, and we can only afford 15 of the projects, the number of combinations is over 1 quadrillion (1×10^{15}). Of course, real-world situations are more complex, and often involve more projects, multiple colors of money (e.g., capital funds and Operations and Maintenance - O&M - funds), multiple years in the planning horizon, piggybacking opportunities, the existence of mutually exclusive alternatives, and incorporation of uncertainty, all of which these simple enumerative calculations ignore. This motivates the need for the type of mathematical models and the solution technology that we describe in this report.

There is a long history and significant literature on the type of *deterministic* capital budgeting models that we describe (e.g., see [3,4,5]). There is much less work on optimization models for capital budgeting under uncertainty although we can point to [6], which takes a contingent claims approach, coupled with integer programming as well as the work upon which we build in this report in [7] and [8].

3. MEASURING RISK IN CAPITAL BUDGETING

Cash flow estimation must involve modeling of a variety of factors or variables. In order to create an incremental cash flow, two different types of costs are needed: current annual costs and proposed annual costs. Current and proposed costs or savings can also be split in two categories: hard costs/savings and soft costs/savings.

The actual cash flow estimation depends on the project considered but the following variables can play a role in the proposed annual estimation of hard costs, including costs for purchase and installation of new or replacement equipment:

- Initial design
- Materials
- Physical implementation
- Ongoing baseline support
- Impact on other programs (i.e., Does this support another approved initiative/project? Will this impact any other on-going initiatives, projects or plans?)
- Continuing contract labor (i.e., Does this increase station headcount? Will site or group training be required?, etc,)
- Impact on licenses and annual fees
- New preventive maintenance actions

Soft costs/savings in general will involve higher uncertainty and may need to be discounted with a factor depending on the degree of certainty and overall impact of the item on the station. Such decisions may ultimately be revised, but the initial evaluation should be made by the person doing the evaluation.

4. SSC REPLACEMENT USE CASE

Industry Equipment Reliability (ER) and Asset Management (AM) programs are essential to support the safe and economic plant operation of commercial NPPs. These programs are addressed in several industry-wide and regulatory programs. For example, U.S. NPPs have implemented the ER process defined in INPO AP-913 "Equipment Reliability Process Description" [9] for which Section 3.5 focuses attention on long-term planning and plant life-cycle management. This industry guidance specifies that NPPs identify and assess issues related to long-term equipment performance in the plant Long-Term Asset Management (LTAM) process. The identified issues are prioritized by assessing the consequences and probabilities of failure of the affected equipment. The various identified issues associated with the long-term performance of plant SSCs is then subject to comprehensive technical and business analyses to identify appropriate cost-effective solutions, which are then input into the plant's Life Cycle Management Plan (LCMP).

One such outcome of plant LCMP is the specification and scheduling of refurbishment and replacements for major plant (i.e., high capital cost) SSCs. Plant LCMPs are intended to be living documents that are updated to reflect changing conditions and priorities over time. One important example of such a change is the decision for a plant to extend its operating license beyond its current specified operating limit. Since 2000, 97 U.S. NPPs have received extensions to their operating licenses from the original 40-year lifetime to permit operation out to 60 years (although several of these have since permanently shut down due to issues related to economic competitiveness) [10]. In addition to these extensions, several plants have indicated the intension to seek an additional 20 years of operational life (i.e., from 60 to 80 years) via a SLR application. Currently six units (Turkey Point Units 3 and 4, Surrey Units 1 and 2, and Peach Bottom Units 2 and 3) have submitted applications for a second license extension with two more units (North Anna Units 1 and 2) having indicated an intent to also submit an application [11].

In one utility's evaluations of capital expenditures to support SLR decisions, the utility has identified an integrated list of capital improvements that should be considered. Initial estimates for these improvements represent ~1 to 2 billion dollars of investment. With such a large investment need, the host utility is interested in methods and tools to support risk management throughout the project lifecycle. One particular issue of concern is that if a decision is made not to replace a particular SSC, what would be the risks, likelihoods, and consequences of subsequent failure of the SSC? Example projects within the set of potential investments include:

- Digital I&C upgrades,
- Reactor Coolant Pump (RCP) refurbishment or replacement,
- Buried piping replacement (including potential use of reinforced C fiber type pipes),
- Main generator replacement,
- Main condenser replacement.

An important outcome of this research will be the capability to risk rank (i.e., prioritize) the capital investments in SSCs to account for the possibility that the level of funding that can be obtained would not be sufficient to address all of the proposed improvements.

For this Use Case application, the host utility must identify a list of potential capital improvements to support plant operation throughout the period of SLR. The primary objective of this Use Case application is to develop and apply methods and tools that are capable of assessing and managing the risks and likelihood of failure of these SSCs during the extended operating period. Additional objectives for this application are to identify an optimal allocation of the capital expenditures for these SSCs and to manage these expenditures (via re-optimization) as circumstances change from initial approval through the end of the SLR operating period.

A structured approach will be necessary to address the objectives indicated above. First, the anticipated operational lifetimes for critical plant SSCs will need to be evaluated to determine the likelihood that they could fail prior to the end of the SLR operational period. In this Use Case application, this set consists of those high capital cost SSCs identified by the host utility for which refurbishment or replacement may be necessary to support operation during the period of SLR. Once the likelihood of failure estimates for the critical SSCs are developed, the next step will be to develop applicable replacement or refurbishment strategies. For the purpose of this Use Case application, the strategic alternatives (i.e., refurbishment or replacement) previously developed by the host utility will be used as a starting point for the analyses. Once the various strategic alternatives are reviewed and modified as appropriate, the projected life cycle costs associated with the SSCs of interest will be determined and evaluated for key financial metrics – e.g., cash flow, NPV, or other metrics used by the utility decision-makers – using applicable economic cost/benefit models. The final step will then perform optimization studies that evaluate proposed investment alternatives to identify the strategy that provides maximal value to the utility over the projected plant lifetime (i.e., through the period of SLR). The intent is to complete initial characterization, evaluation, and prioritization of the identified enhancements for use in the host utility business process evaluations during government Fiscal Year 2020.

5. OVERVIEW OF PLANT ASSET MANAGEMENT METHODS

RIAM consists of a combination of financial and engineering evaluation methods that apply risk management technology to support plant long-term planning and investment decisions at the corporate, fleet, plant, system, or equipment levels. RIAM is intended to provide decision makers with both qualitative and quantitative information related to investments in asset management. The approach is intended to be used at the levels of individual projects and also across a portfolio of projects. The objective of RIAM is to optimize long-term economic value while effectively identifying and controlling enterprise risks.

RIAM is a subset of a broader range of activities that are put in place at operating NPPs to cost-effectively manage these capital-intensive assets. This overall approach, often referred to as Nuclear Asset Management (NAM), is defined as the process of making operational, resource allocation and risk management decisions across all levels of a nuclear generation business to maximize the value of the NPP to stakeholders while maintaining adequate levels of safety to the public and the plant staff. The objectives of Nuclear Asset Management are to provide methods and tools to support management decisions related to:

- Plant investments and operational strategies that maximize value to all stakeholders
- Project prioritization and resource allocation within and among plants in a fleet
- Reduce production costs while maintaining adequate levels of safety
- Optimize capital additions to maintain or improve plant performance and availability

From approximately 2002 through 2012, the Electric Power Research Institute (EPRI) conducted research into RIAM. In this work, RIAM was developed to provide a systematic approach to the assessment and analysis of plant economic performance while maintaining high degrees of confidence that adequate levels of safety were maintained [12]. The RIAM process involves modeling and evaluation of various performance indicators to provide decision-makers with information to support improved investment planning and resource allocation. Examples of such key information include:

- Projected costs and revenues
- Financial metrics such as NPV, IRR, etc.
- Nuclear safety; e.g., Core Damage Frequency (CDF) and Large Early Release Frequency (LERF)
- Plant power production and efficiency; availability factor, capacity factor, heat rate, etc.
- System and equipment performance; availability, reliability, equipment failure rates, etc.

A fundamental premise of RIAM is that decisions that impact the long-term design, operation and maintenance of plant SSCs will impact plant economic performance. This impact is in addition to any impacts on plant safety and regulatory performance. In published EPRI research, this was illustrated via the interactions in Figure 1 [13]. This schematic shows that RIAM uses a series of interrelated technical and financial models to evaluate the integrated effects of changes to the plant and provide information to key personnel to support better and more timely decision making.

Use of a RIAM approach is considered to be important to achieve effective management of risks associated with the extended operation of NPPs. A key aspect of RIAM is to identify the risks and opportunities associated with extended plant operational lifetimes. and to classify them based on their potential impact. These risks and opportunities can be effectively classified into one of three categories [14]:

1. The issue is potentially life-limiting for a particular plant. An example of such an issue is failure of a high capital cost SSC (such as failure of the plant turbine generator or steam generator, significant degradation of structural materials in the reactor vessel, containment, or spent fuel pool structure) where the cost to repair or replace would exceed the value of the plant as an economic asset.
2. The issue can be addressed via effective active asset management but requires use of improved monitoring, diagnostics and prediction techniques. An example of this is the application of more

extensive on-line monitoring, diagnostics, and prognostics (including the use of artificial intelligence) to more cost effectively assess equipment, system, and plant performance.
3. The issue represents an opportunity for modernization and enhanced performance. An example of this type of issue is the deployment of an integrated plant refurbishment with extended power uprate capability.

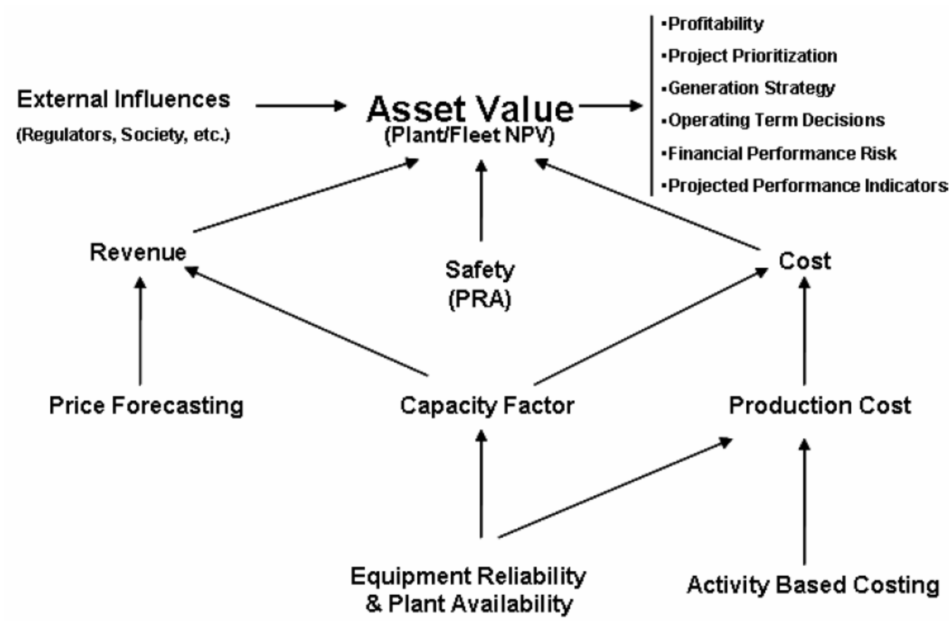

Figure 1. Risk-informed asset management framework (from [13]).

Because of the long timeframes and the large uncertainties associated with the desired period of extended nuclear plant operation, there exist significant risks which must be managed successfully to permit the plant to perform both safely and economically throughout this period. Several important challenges to achieving this objective have been identified and are expected to become more acute as time progresses [14]:

1. **Aging Degradation**. Age related degradation can result in failures, high costs of replacement and repairs to avoid failures, and real or perceived reductions in safety margin (which, if substantial could result in additional costs due to heightened regulatory scrutiny).
2. **Obsolescence**. Obsolescence can result in high costs to procure equipment, high costs to maintain out-of-date systems, inability to attract a knowledgeable workforce, and old technology which renders the plant non-competitive with alternative generation sources.
3. **Constrained Supply Chain**. In a global competitive environment, the demand for equipment and services is not limited to any specific industry or geographic region. For capital intensive industries such as commercial nuclear power, procurement of essential replacement equipment and services will be a significant challenge and will place a premium on effective, integrated, long-term planning.

An example where all three of these items are manifest is in the area of plant instrumentation and controls in which the deployment of digital control systems to replace analog systems in safety related applications has proven to be challenging and expensive.

Within the commercial nuclear industry, operating utilities typically are structured such that details of the business and technical (i.e., engineering) functions are performed by separate organizations. Because of this situation, the accomplishment of many of the objectives of the asset management process are accomplished by different programs within the plant. For example, as discussed in Section 4 of this report, the LTAM function at U.S. NPPs is addressed in Section 3.5 of INPO AP-913 "Equipment Reliability Process Description" [15]. These functions typically are the responsibility of System Managers at the plant or Fleet Engineering Managers at the corporate engineering offices (or a combination thereof). Other functions are accomplished across different areas within the organization. As a result, coordination and efficient information transfer are needed to support effective and efficient decision-making.

In recognition of the distributed nature of decision-making with respect to capital assets, the industry developed high level guidance that addressed the key elements of the capital asset management process. This document, AP-940 "Nuclear Asset Management: Process Description and Guideline" [16], was published in 2005 and was intended to provide a process model (within the nuclear industry Standard Nuclear Process Model – SNPM) to provide a foundation for activity-based management and a structure for making business performance comparisons and benchmarking. The document provides an overview of the critical activities related to business processes that are necessary to achieve safe and economical NPP operation. Within this framework, NAM represents a support function in the context of providing various business services to the NPP. These services include the development and administration of the nuclear asset management, strategic planning, long-range planning, and the development, monitoring, forecasting and reporting of plant budgets. The primary activities addressed in AP-940 are the following:

- Strategic Planning
- Generation Planning
- Project Evaluation and Ranking
- Long Range Planning
- Budgeting
- Plant / Fleet Valuation

Critical interfaces discussed in AP-940 are the important links between NAM process activities and ER process activities described in AP-913 [15]. The RIAM approach is intended to address this critical interface between NAM and ER that focuses on the aspects of project evaluation and ranking related to long-range planning (also referred to as previously as LTAM).

An important set of methods and tools to support NPP LTAM programs and, in particular, their application to NPPs that are anticipating operating during extended periods of operation (i.e., periods of license renewal and second licenase renewal) is Integrated Life Cycle Management (ILCM) developed by EPRI. The ILCM method [17] addresses the management and optimization of large capital projects for the purposes of extended plant operation. As part of the ongoing collaboration between the DOE LWRS Program and the EPRI Long Term Operation (LTO) Program, the Use Case application described in Section 4 of this report will utilize ILCM as a starting point to develop mechanisms to meet the Use Case objectives. The ILCM approach is an evaluation method that consists of a sequence of structured evaluations. The ILCM method and accompanying software is available to EPRI member utilities; it should be noted that since all U.S. NPP owner operators are EPRI members, ILCM is available to all operating U.S. NPPs. Note that some of the elements of ILCM related to the Use Case discussed in Section 4 of this report were previously presented in [18] using information that is publicly available. Important elements of ILCM, and its anticipated application for this Use Case, are repeated here for the benefit of the reader.

As indicated previously, ILCM provides a structured approach to evaluate LTAM related to refurbishing or replacing high capital cost SSCs. The first step in the ILCM process is to evaluate the anticipated operational lifetimes for critical plant SSCs to determine the likelihood that they could fail during the period of extended operation [19]. In this Use Case application, this set consists of those high capital cost SSCs identified by the host utility for which refurbishment or replacement may be necessary to support operation during the period of SLR. To accomplish this, a number of different approaches could be applied. These approaches employ methods such as developing physics of failure models and fitting them using plant data or via the use of expert elicitation approaches such as the Delphi technique or Analytic Hierarchy Process (AHP). Note that the EPRI ILCM process was developed to permit use of one or more of these methods based on the preference of the operating NPP. For illustrative purposes, an example likelihood of failure curve from an early ILCM pilot application is provided in Figure 2 [19].

Once the likelihood of failure curves for the identified SSCs are developed, the next step is to develop appropriate LTAM strategies (which can include replacement or comprehensive refurbishments). For the purpose of this Use Case application, the strategic alternatives (i.e., refurbishment or replacement) previously developed by the host utility will be used as a starting point for the analyses. Once the various strategic alternatives are developed, the projected life cycle costs associated with the SSCs are determined and evaluated for key financial metrics (e.g., cash flow, NPV, or other metrics used by the utility decision-makers) using applicable economic models. The final step is to conduct optimization studies that evaluate proposed investment alternatives to identify the strategy that provides maximal value to the utility over the projected plant lifetime (i.e., through the period of SLR). It should be noted that this represents a complicated optimization problem due to the myriad constraints that are imposed (e.g., prescribed system outage start dates and durations, annual cash flow limitations, supply chain constraints, etc.).

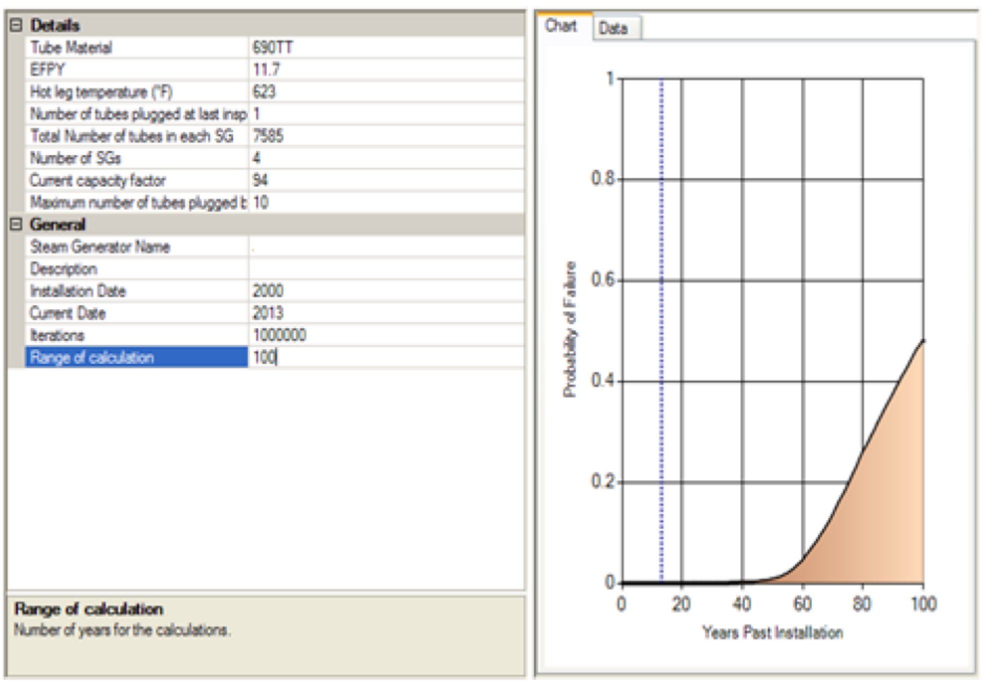

Figure 2. Example of steam generator likelihood of failure curve (from [19]).

To perform the optimizations described above, use of several methods will be investigated. First, it should be noted that the EPRI ILCM software contains an optimization approach that was developed by Électricité de France (EDF). The Investments Portfolio Optimal Planning (IPOP) approach provides a general framework for the optimization of constrained maintenance scheduling problems by coupling a Genetic Algorithm (GA) and Monte-Carlo (MC) simulation algorithm [20]. IPOP consists of three different modules shown schematically in Figure 3:

- Mean Value Calculation Program
- Optimization Algorithm

- Risk Indicators Calculation Program.

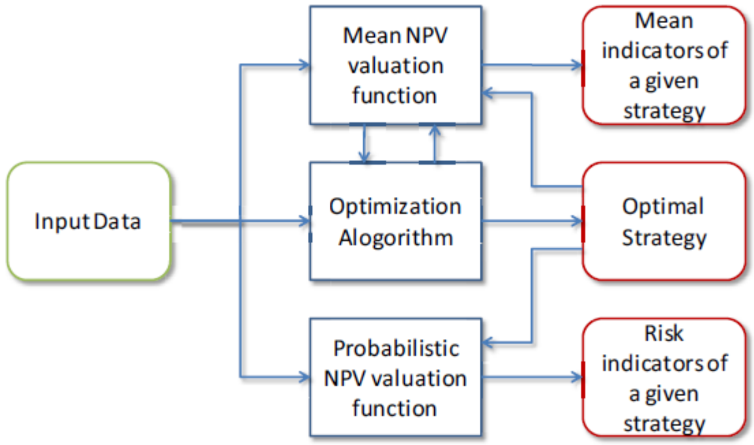

Figure 3. Optimization steps for risk assessment of long-term capital investments (from [21]).

IPOP is intended to be used to assess optimization across the spectrum from a single component to the analysis of all major components across a fleet. IPOP also is intended to support decision-making on maintenance alternatives, prioritization of investments, and comparison of alternate strategies. A discussion of the specific modules and algorithms, as well as demonstration applications of IPOP on NPP test cases are provided in [21].

In addition to the use of IPOP, the application of additional optimization methods will be investigated during this Use Case. These approaches address issues that are common practice in industrial capital budgeting. In particular, it is common practice to develop a rank ordering of projects by application of some metric of value to the enterprise. Typically, this can consist of a financial metric (such as NPV or Benefit-to-Investment Ratio, BIR). However, for the case of LTAM applications, during the course of the period over which the investments are made, emerging events can have a significant impact on the planned budget and on project costs. This can result in the need to perform periodic reevaluations that can result in significant revisions to the original ranked order list. These events also can require the expenditure of considerable resources to reallocate the remaining budget to both address the issues and obtain a new rank-ordered list.

In budget allocation problems, the research literature has recommended forming an optimal portfolio of projects using variants of a Multi-Knapsack model. The Multi-Knapsack approach to capital budgeting [22, 23, 24] takes as input a budget forecast, along with the stream of liabilities and the anticipated profit for each project. The output of the Multi-Knapsack model is a collection (or portfolio) of projects that are optimal assuming the point forecasts of input parameters are correct. In this Use Case, one such approach that has been developed for use on long-term capital asset management at NPPs is applied [25, 26]. This approach is discussed more extensively in the following sections of this report.

6. ALGORITHMS FOR SSC REPLACEMENT SCHEDULING OPTIMIZATION

In what follows we first describe a deterministic optimization model for capital budgeting. Next we introduce a stochastic optimization model, which allows for probabilistic forecasts for budgets, NPVs, and project cost streams. The stochastic optimization model is relatively complex, and so we start with a relatively simple setting prior to extending it the what we label the full stochastic optimization model.

Prior to discussing the models and algorithms we briefly describe options for software. Optimization models of the type we formulate can be solved with off-the-shelf commercial software, and with open-source software. When it comes to optimization with continuous variables, open-source software competes well with commercial alternatives. For the types of discrete optimization problems we describe, expressed as mixed-integer linear programming models, commercial solvers such as CPLEX, Gurobi, and Xpress can significantly outperform open-source alternatives like CBC. That said, there are obvious advantages to open-source solvers. In addition to solvers, there are modeling languages that facilitate rapid prototyping of optimization models. Commercial modeling languages include AMPL and GAMS, and open-source modeling languages include PYOMO (Python based) and JuMP (Julia based). The models that we describe have been implemented in GAMS [27] and PYOMO [28].

6.1 Deterministic Capital Budgeting

We consider a capital budgeting problem for a nuclear generation station, with possible extension to a larger fleet of plants. Due to limited resources, we can only select a subset from a list of several candidate capital projects. Our goal is to maximize overall NPV associated with the selected subset. In doing so, we must respect resource limits and capture key structural and stochastic dependencies of the system, although in this section we start with the simpler deterministic case, ignoring randomness. Example projects include upgrading a steam turbine, refurbishing or replacing a set of reactor coolant pumps, and replacing a set of feed-water heaters. We provide a specific example in Appendix A that illustrates the steps of the mathematical model and solutions from the optimization algorithm. The example is relatively simple so that we can illustrate ideas concisely. Realistic problems will naturally be larger in scale.

Indices and sets:

$i \in I$	candidate projects
$j \in J_i$	options for selecting project i (e.g., initiate project i in year t or $t+2$ and in a standard (three year) or in an expedited (two year) manner)
$(i', j') \in IJ_{ij}$	piggybacking situations, i.e., option j' for project i' can be selected only if option j is selected for project i
$k \in K$	types of resources, e.g., capital funds, O&M funds, labor-hours, time during outage
$t \in T$	time periods (years)

Data:

a_{ij}	reward (revenue less financial cost) of selecting project i via option j
b_{kt}	available budget for a resource of type k in year t
c_{ijkt}	consumption of resource of type k in year t if project i is performed via option j

Decision variables:

$$x_{ij} \quad \begin{cases} 1 & \text{if project } i \text{ is selected via option } j \\ 0 & \text{otherwise} \end{cases}$$

Optimization model formulation:

$$
\begin{aligned}
\max_{x} \quad & \sum_{i\in I, j\in J_i} a_{ij}\, x_{ij} \\
\text{s.t.} \quad & \sum_{j\in J_i} x_{ij} \; = 1, i \in I \\
& \sum_{i\in I, j\in J_i} c_{ijkt}\, x_{ij} \;\; \le b_{kt}, \qquad k \; \in K, t \in T \\
& x_{i'j'} \;\le x_{ij}, \qquad (i', j') \in IJ_{ij}\,, j \in J_i, i \in I \\
& x_{ij} \in \{0,1\}, \qquad j \in J_i\,, i \in I
\end{aligned}
\tag{6.1}
$$

The decision variables, x_{ij}, indicate whether we choose to do project i by means j. Restated, if $x_{ij} = 1$, then we recommend doing project i via option j, and taken together these decision variables produce both a portfolio of selected projects and a schedule for performing those projects over time. The set of available options, $j \in J_i$, can explicitly include the "do-nothing" option, and the first constraint ensures that we choose exactly one option from the available set for each project, including the possibility of selecting the do-nothing option. Even if we select the do-nothing option for a project, it induces an NPV, a_{ij} , which may be negative, representing growing O&M costs, losses in plant efficiency, etc. The second structural constraint ensures that the budget of each resource k is respected in each year t. The third structural constraint captures piggybacking situations in which option j' for project i' (which may have cheaper costs) may be selected only if project-option pair (i, j) is also selected. The objective function includes the NPV for each project-option pair, a_{ij} , and the correct NPV is selected by the 0-1 decision variable, x_{ij}.

We note that sometimes there are projects that must be done, e.g., for safety and/or regulatory reasons. This can be handled within the mathematical formulation just given, without introducing additional constructs. The set J_i typically includes a *do-nothing option* for each project, but when project i must be done, we simply do not include the do-nothing option. Mathematically, an alternative is to *not* include an explicit do-nothing option, to replace the first structural constraint with an inequality, and to add an additional set of must-do projects with an equality constraint. Both options are mathematically equivalent and simply represent a choice to be made by the analyst. The mathematical model is simpler using our approach in this section, but the set of input data is a bit more complicated. Handling the do-nothing option implicitly leads to the opposite situation. To illustrate ideas, we include an explicit do-nothing option in this section, and later we illustrate the implicit alternative. We do note that the choice that we make affects the NPV calculations. The scheme described in this section requires NPV calculations that are *absolute* and includes an NPV value for the do-nothing case. In contrast, if the do-nothing option is implicit then the NPV of plan A, plan B, etc., should be calculated *relative* to that of the do-nothing option. We discuss this in detail in Section 7.

The deterministic model can be repeatedly solved by changing the input values, a_{ij} , b_{kt} , c_{ijkt} . This will allow for what-if sensitivity analysis to identify the crucial drivers behind the optimal project selection decision. Monte Carlo simulation permits a powerful variant of this approach in which we model a_{ij} , b_{kt} , c_{ijkt} as random variables, sample from their distributions, and perform a form of uncertainty quantification in terms of the resulting distributions governing the binary decisions selected, x_{ij}, and the overall NPV of the selected portfolio. We discuss analysis using this Monte Carlo approach in detail in Sections 10.2.2 and 10.3.2.

6.1.1 Deterministic Capital Budgeting Workflow

Input: data structure

- Candidate projects: I [Set]
- Project options: J [Set]
- Project-option pairs: IJ [Set within $I \times J$]
- Resources: K [Set]
- Time periods: T [Set]
- NPV: $a[i, j]$: two-dimensional real array on IJ
- Budget: $b[k, t]$: two-dimensional real array on $K \times T$
- Cost: $c[i, j, k, t]$: four-dimensional real array on $IJ \times K \times T$

Output:

- Yes-no project-option pairs: x [two-dimensional binary array on IJ]
- Overall NPV for portfolio of selected projects: NPV [scalar, real]

6.2 Initial Stochastic Capital Budgeting

We now turn to the issue of how to incorporate uncertainty in a capital budgeting model. This report considers two approaches to do so, which we briefly sketch here. We allow for uncertainty in the three key parameters that drive our capital budgeting model: the available budget, the cost streams induced by selecting a project, and the NPV associated with a project. Moreover, we assume that probability distributions can be specified that govern these uncertain parameters. In this setting one approach is to perform what-if analysis by using the deterministic capital budgeting model as a "black box," and repeatedly solving that model under different inputs. Monte Carlo simulation can be used to do so many times, and the output of the black box is itself random, meaning the specific projects selected and the overall NPV. In this way, we can understand which projects are most frequently selected, and what distribution of NPV we may see. This approach is sometimes called a wait-and-see approach in the stochastic programming literature.

The second approach, which we begin describing in this section, and expand in the next, formulates a large optimization model in which we simultaneously consider a set of scenarios for budget realizations, costs, and NPVs. The model is an example of a two-stage stochastic program. In the first stage, a decision is made which cannot depend on the scenarios. In our case that decision is a prioritization of the projects, which specifies whether project i is higher priority than project i' or vice versa. The second stage decisions specify which projects are implemented in each scenario, respecting the cost- and budget realizations for that scenario and, importantly, also respecting the first-stage prioritization decisions. For concreteness an example is provided in Appendix B, and detailed examples and analysis are discussed in Section 10.

The following stochastic capital budgeting model has, as its core, the deterministic capital budgeting model, indexed by scenario, but uses additional constructs to build the first-stage prioritization decisions. In this section, to help first illustrate ideas in a simpler setting we do *not* include the full fidelity of the deterministic model developed above. In particular, we do not consider options (Plan A, B, etc.), multiple types of resources (e.g., capital budgets and O&M funds), or the piggybacking scheme. The full model is developed in the next section. For the reader making comparisons with the literature we note that the model we specify here is an implementation of model (14a)-(14f) from [8]. We note that this model has better computational performance than the model with additional decision variables in [7]. Moreover, the $s_{ii'}$ variables defined below are analogous to the $y_{ii'}$ variables in [7].

Indices and sets:

$i, i' \in I$	candidate projects
$\omega \in \Omega$	scenarios
$t \in T$	time periods (years)

Data:

a_i^ω	profit of project i under scenario ω (NPV)
b_t^ω	budget at time t under scenario ω
c_{it}^ω	cost of project i for time t under scenario ω
q^ω	probability of scenario ω

Decision variables:

$$s_{ii'} = \begin{cases} 1 & \text{if project } i \text{ has no lower priority than project } i' \\ 0 & \text{otherwise} \end{cases}$$

$$x_i^\omega = \begin{cases} 1 & \text{if project } i \text{ is selected under scenario } \omega \\ 0 & \text{otherwise} \end{cases}$$

Optimization model formulation

$$\begin{aligned} \max_{s,x} \sum_{\omega \in \Omega} q^\omega \sum_{i \in I} a_i^\omega x_i^\omega & \\ \text{s.t.} \quad & s_{ii'} + s_{i'i} \geq 1, \qquad i < i', i, i' \in I \\ & x_i^\omega \geq x_{i'}^\omega + s_{ii'} - 1, i \neq i', i, i' \in I, \omega \in \Omega \\ & \sum_{i \in I} c_{it}^\omega x_i^\omega \leq b_t^\omega, \qquad t \in T, \omega \in \Omega \\ & s_{ii'} \in \{0,1\}, \qquad i \neq i', i, i' \in I \\ & x_i^\omega \in \{0,1\}, \qquad i \in I, \omega \in \Omega \end{aligned} \tag{6.2}$$

The first structural constraint effectively enforces that either project i has higher priority than project i' or vice versa, with the nuance that both are allowed so that the projects have the same priority. (For this reason, strictly speaking we should use the more awkward, if precise, phrase that project i has no lower priority than project i'.) If $s_{ii'} = 1$, i.e., project i has higher priority than project i', then the next constraint reduces to $x_i^\omega \geq x_{i'}^\omega$, which implies that if we select the lower priority project i' ($x_{i'}^\omega = 1$) in scenario ω then we must also select the higher priority project. If $s_{ii'} = 0$ or if $x_{i'}^\omega = 0$ then the constraint is vacuous. The next constraint simply states that we must obey the budget under all scenarios and in each year under consideration. Moreover, in the objective function we maximize the *expected value* of the NPV we obtain.

6.2.1 Stochastic Optimization Process Flow

Input: data structure

- Candidate projects: I [Set]
- Time periods: T [Set]
- Scenarios: W [Set]
- NPV: $a[i,w]$: two-dimensional real array on $I \times W$
- Budget: $b[t,w]$: two-dimensional real array on $T \times W$
- Cost: $c[i,t,w]$: three-dimensional real array on $I \times T \times W$
- Probabilities: $q[w]$: one-dimensional real array on W

Output:

- Yes-no on project i higher priority than i': s: two-dimensional binary array on $I \times I$
- Yes-no on selecting a project under a scenario: x: two-dimensional binary array on $I \times W$
- Overall expected NPV for portfolio of prioritized projects: NPV: scalar, real

6.3 Full Stochastic Capital Budgeting

The deterministic capital budgeting model previously developed allows for multiple options in how we select a project. For example, we might select a project via Plan A, Plan B, Plan C, or not select the project at all. In addition, the deterministic model allows for multiple types of resources (e.g., capital budgets and O&M budgets), and further allows for piggybacking constraints.

Our initial stochastic capital budgeting model illustrates the ideas of prioritization without the additional features of multiple types of resources, piggybacking, and multiple options for selecting each project. The former two features integrate with the prioritization scheme in a straightforward way, as we will describe below. The latter-most feature proves to have subtle interactions with the notion of prioritization, and we discuss that in some detail in this section and Section 10. The model sketched here is new and, to our knowledge, has not appeared in the literature. Even though the notation has been sketched above, we develop the full model here so that this section is self-contained, given that it specifies our "full" mathematical model for stochastic capital budgeting.

Indices and sets:

$i, i', i'' \in I$	candidate projects
$j, j' \in J_i$	options for selecting project i (e.g., initiate project i in year t or $t+2$ and in a standard (three year) or in an expedited (two year) manner)
$M \subseteq I$	must-do projects (e.g., due to safety reasons even if their NPV is negative)
$(i', j') \in IJ_{ij}$	option j' for project i' can be selected only if option j is selected for project i, i.e., piggybacking
$k \in K$	types of resources, e.g., capital funds, O&M funds, labor-hours, time during outage
$t \in T$	time periods (years)
$\omega \in \Omega$	scenarios

Data:

a_{ij}^{ω}	NPV (revenue less financial cost) of selecting project i via option j under scenario ω
b_{kt}^{ω}	available budget for a resource of type k in year t under scenario ω
c_{ijkt}^{ω}	consumption of resource of type k in year t if project i is performed via option j under scenario ω
q^{ω}	probability mass of scenario ω

Decision variables:

$$s_{ii'} = \begin{cases} 1 & \text{if project } i \text{ has no lower priority than project } i' \\ 0 & \text{otherwise} \end{cases}$$

$$y_i^{\omega} = \begin{cases} 1 & \text{if project } i \text{ is selected for } some \text{ option under scenario } \omega \\ 0 & \text{otherwise} \end{cases}$$

$$z_{ij} = \begin{cases} 1 & \text{if project } i \text{ is selected via option } j \text{ under } some \text{ scenario} \\ 0 & \text{otherwise} \end{cases}$$

$$x_{ij}^{\omega} = \begin{cases} 1 & \text{if project } i \text{ is selected via option } j \text{ under scenario } \omega \\ 0 & \text{otherwise} \end{cases}$$

Because the optimization model is large, we explain each component as we go rather than first listing the large model.

6.3.1 Optimization Model Formulation

As indicated in the previous stochastic optimization model, we maximize NPV of the selected portfolio of projects in (6.3a).

$$\max_{s,x,y,z} \sum_{\omega \in \Omega} q^{\omega} \sum_{i \in I} \sum_{j \in J_i} a_{ij}^{\omega} x_{ij}^{\omega} \tag{6.3a}$$

$$\text{s.t.} \quad s_{ii'} + s_{i'i} \geq 1, \qquad i < i', i, i' \in I \tag{6.3b}$$

$$y_i^\omega \geq y_{i'}^\omega + s_{ii'} - 1, \qquad i \neq i', i, i' \in I, \omega \in \Omega \tag{6.3c}$$

For simplicity, in what follows we will say that variable $s_{ii'} = 1$ means that project i is higher priority than i' even though the variable definition allows for ties, i.e., the projects being the same priority. Constraint (6.3b) indicates that either project i is higher priority than project i' or vice versa, and further allows both (i.e., a tie). Constraint (6.3c) indicates that if project i is higher priority than project i' ($s_{ii'} = 1$) then if we select the lower priority project *under some option* then we must also select the higher priority project; if $s_{ii'} = 0$ or if $y_{i'}^\omega = 0$ then the constraint is vacuous.

$$\sum_{i \in I} \sum_{j \in J_i} c_{ijkt}^\omega x_{ij}^\omega \leq b_{kt}^\omega, \qquad k \in K, t \in T, \omega \in \Omega \tag{6.3d}$$

Constraint (6.3d) requires that we be within budget in each time period, for each resource type, and under each scenario.

$$\sum_{j \in J_i} x_{ij}^\omega = y_i^\omega, \qquad i \in I, \omega \in \Omega \tag{6.3e}$$

$$y_i^\omega = 1, \qquad i \in M, \omega \in \Omega \tag{6.3f}$$

Constraint (6.3e) defines binary variable y_i^ω and simultaneously ensures that we select project i via at most one option. Constraint (6.3f) ensures that we select all must-do projects. We note that this illustrates the alternative to the situation in which we must include the “Do Nothing” option among the alternatives for optional projects; see the related discussion in Section 6.1.

$$x_{i'j'}^\omega \leq x_{ij}^\omega, \qquad (i', j') \in IJ_{ij}, j \in J_i, i \in I \tag{6.3g}$$

Constraint (6.3g) captures piggybacking conditions.

$$s_{ii'} + s_{i'i} \leq 1, \qquad i < i', i, i' \in I \tag{6.3h}$$

$$s_{ii'} + s_{i'i''} + s_{i''i} \leq 2, \qquad i \neq i', i' \neq i'', i'' \neq i, i, i', i'' \in I \tag{6.3i}$$

Constraints (6.3h)-(6.3i) require that we produce a total ordering of the projects rather than allowing for ties. If we remove constraints (6.3h)-(6.3i) then it will not change the optimal NPV that we obtain, but including the constraints can facilitate easier parsing of the solutions.

$$x_{i'j}^\omega + s_{ii'} - 1 \leq \sum_{\substack{j' \in J_i \\ j' \leq j}} x_{ij}^\omega, \qquad i \neq i' \; i, i' \in I, j \in J_{i'}, \omega \in \Omega \tag{6.3j}$$

Constraint (6.3j) is a type of consistency constraint with respect to the notion of options; the constraint matters only when project i is higher priority than project i' ($s_{ii'} = 1$). In this case, if we select Plan A for the lower priority project then we must select plan A for the higher priority project. If we select Plan B for the lower priority project, then we can select Plan A or Plan B for the higher priority project. And, if we select Plan C for the lower priority project then we can select Plan A, B, or C for the higher priority project. Inclusion of constraint (6.3j) is "optional" and reflects how the decision maker prefers to interpret the notion of priorities.

$$\sum_{\omega \in \Omega} x_{ij}^{\omega} \leq |\Omega| \, z_{ij} \, , i \in I, j \in J_i \tag{6.3k}$$

$$\sum_{j \in J_i} z_{ij} \leq 1, \;\; i \in I \tag{6.3l}$$

$$s_{ii'}, x_{ij}^{\omega}, y_i^{\omega}, z_{ij} \in \{0,1\}, i \neq i', i, i' \in I, j \in J_i \, , \omega \in \Omega \tag{6.3m}$$

Constraints (6.3k) and (6.3l) taken together indicate that, for each project separately, we cannot mix use of Plans A, B, and C across different scenarios. For example, if for project #4, we select Plan B under any scenario then we must use Plan B for project #4 (or not select the project) under all other scenarios.

6.3.2 Full Stochastic Optimization Process Flow

Input: data structure

- Candidate projects: I [Set]
- Project options: J [Set]
- Project-option pairs: IJ [Set within $I \times J$]
- Must Do projects: M [Set within I]
- Resources: K [Set]
- Time periods: T [Set]
- Scenarios: W [Set]
- NPV: $a[i, j, w]$: three-dimensional real array on $IJ \times W$
- Budget: $b[k, t, w]$: three-dimensional real array on $K \times T \times W$
- Cost: $c[i, j, k, t, w]$: five-dimensional real array on $IJ \times K \times T \times W$
- Probabilities: $q[w]$: one dimensional real array on W

Output:

- Yes-no on project i higher priority than *i*': *s* [two-dimensional binary array on $I \times I$]
- Yes-no on project-option pairs under a scenario: *x* [three-dimensional binary array on $IJ \times W$]
- Yes-no on project under some option: *y* [two-dimensional binary array on $I \times W$]
- Yes-no on project-option under some scenario: *z* [two-dimensional binary array on IJ]
- Overall expected NPV for portfolio of prioritized projects: NPV [scalar, real]

7. NPV MODELS

7.1 Simple NPV Models

Assume we have a portfolio of candidate projects, in which some of the decisions involve either replacing an item now or postponing its replacement to the future and facing potentially higher maintenance and replacements costs. Here, we assume that the item must either be replaced now, or in the future, and in this context, we describe the appropriate cash-flow calculations. Then, we extend the discussion to allow the planned replacement to occur in year 2 or 3, say, rather than year 1.

We assume that there is not an option of "doing nothing" because the items under consideration are of significant importance, and if not replaced in due course, would impose an unacceptable risk to either safety or production.

Notation:

- p: probability of item failure for one year
- C_P: cost of planned replacement
- C_U: cost of unplanned replacement
- C_D: cost of shutdown per day
- D: number of days plant is off-line, if a shutdown occurs
- N: number of years
- R: discount rate

We could incorporate additional parameters, like weekly or monthly inspection costs, fixed costs of shutdown in addition to the daily costs specified above, etc. That said, the setting that we describe allows us to illustrate key ideas in the cash-flow calculations for computing the NPV.

We further assume that if we do not replace the item, then its failure time is a random variable that follows a Geometric distribution, where the probability of failure in one year is denoted by p; i.e., the probability of survival over one year is $1-p$. Thus, if the plant faces a 20-year decision period then the probability of survival up to year t, is $(1-p)^t$, and the probability of failing in year t is given by $p(1-p)^{t-1}$.

A pedantic but useful construct for thinking about the calculations that follow is this: there is a "coin flip" for each year, which yields a "fail" or "no fail" event for that year. Immediately after the coin flip, appropriate costs are incurred. In other words, this discrete view of time with Bernoulli trials is useful to simplify the logic of the calculations, rather than viewing time as a continuum and needing to tease out "what happened when" during a year.

If the item is not replaced today (time $t=1$), then we can compute the expected replacement cost in any year $t=1,2,\ldots,N-1$ as:

$$Expected\ Replacement\ Cost\ in\ Year\ t = C_U p(1-p)^{t-1} \tag{6.4}$$

Here, we incur this cost only if the coin flips yielded "no fail" events in years $t=1,2,\ldots,t-1$, and then a "fail" event in year t, i.e., we incur the cost with the Geometric random variable's probability mass of having the first failure in year t, which is given by $p(1-p)^{t-1}$.

Since we assume that the item must be replaced in year N if it has not already failed, the expected replacement cost does *not* depend on the result of a coin flip in year N, in the same way that replacement in year 1 precludes dependence on the year 1 coin flip. Rather, we incur this cost with certainty in year N, conditional on the item having not failed in previous years $t=1,2,\ldots,N-1$; i.e., the expected cost is given by:

$$Expected\ Replacement\ Cost\ in\ Year\ N = C_P(1-p)^{N-1} \tag{6.5}$$

where we use the planned replacement cost.

In order to illustrate the computation of the cash flows, we further assume that if the item is not replaced now, the plant faces a loss of revenue due to a shutdown at a cost of C_D per day. Then, the expected downtime cost incurred in year $t = 1, 2, \dots, N-1$ is given by:

$$Expected\ downtime\ cost\ in\ Year\ t = DC_D p(1-p)^{t-1}. \tag{6.6}$$

Again, we assume that the planned replacement in year $t = N$ precludes dependence on the coin flip and hence precludes incurring any downtime cost in that year, although we acknowledge other assumptions are possible. Thus, for practical purposes there is no coin flip in year N.

More generally, if the item is not replaced now, the plant will face the possibility of increased costs due to reliability issues, where example costs include increased inspection costs, downtime costs for a weeklong shutdown, lost revenue from a 6-hour shutdown, costs associated with an emergency replacement of an item, etc. We can express the above costs in the following functional form: $Re\_Cost(p, t, C_1, C_{2,\dots,}C_M)$, where $C_1, C_{2,\dots,}C_M$ are costs relevant for the considered item and, in general, p could be a vector that incorporates multiple types of shutdown. In our case the expected downtime cost in year $t = 1, 2, \dots, N$ is given by a function: $Re\_Cost(p, t, C_P, C_U, C_D, D, N)$, with just a scalar value for p.

There are two relevant time-series of cash flows, one for replacing the item now and another for replacing it later, either at failure or at the horizon year N. Consider first replacing the item today; in this case, we simply incur the cost of planned replacement at time $t = 1$, i.e., we incur cost C_P.

The second time-series of cash flows is for replacing the item in the future. In this case, for every year t, we have the expected replacement cost and the expected downtime cost. So, for any year $t = 1, 2, \dots, N-1$, the cash flows will be computed as:

$$Cash\ Flow\ Replaced\ in\ Year\ t = -[(C_U + DC_D)\ p(1-p)^{t-1}] \tag{6.7}$$

and for the final year as:

$$Cash\ Flow\ Replaced\ in\ Year\ N = -[C_P(1-p)^{N-1}]. \tag{6.8}$$

Note that we have a minus sign in front of the cash flows because all of them are costs, i.e., cash outflows. The timelines of the two options are illustrated as follows:

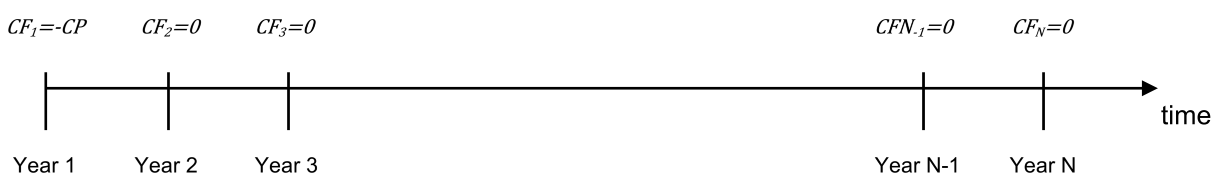

Figure 4. Graphical representation of option 1: replace now.

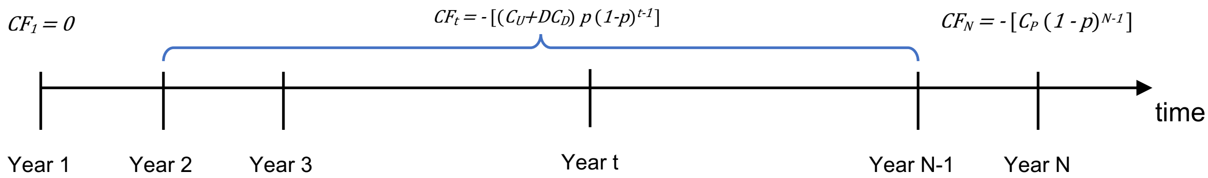

Figure 5. Graphical representation of option 1: replace later.

The NPV of Option 1 is:

$$NPV\ Option\ 1 = -C_P \tag{6.9}$$

The NPV of Option 2 is:

$$NPV\ Option\ 2 = -\left[\sum_{t=1}^{N-1} \frac{(C_U + DC_D)p(1-p)^{t-1}}{(1+R)^{t-1}} + \frac{C_P(1-p)^{N-1}}{(1+R)^{N-1}}\right] \tag{6.10}$$

We can compare the two options in two ways. The first way is to simply compute the "net" NPV as the difference between the NPV of Option 1 and that of Option 2, i.e., $Net\ NPV = NPV\ Option\ 1 - NPV\ Option\ 2$. The resulting equation is:

$$Net\ NPV = -C_P + \left[\sum_{t=1}^{N-1} \frac{(C_U + DC_D)p(1-p)^{t-1}}{(1+R)^{t-1}} + \frac{C_P(1-p)^{N-1}}{(1+R)^{N-1}}\right] \tag{6.11}$$

If the project in question is the only one under consideration, then if $Net\ NPV > 0$ the decision is to replace the item today, and otherwise we replace later. As we discuss in detail in Section 6, we employ an optimization model when multiple projects are considered simultaneously, and we need to stay within annual budgets in terms of, for example, capital costs.

We now extend the logic of what we have above to the planned replacement occurring in year T_0. In what we have presented above, we assumed $T_0 = 1$, but we now allow for delaying this planned replacement to a later year, albeit at the risk of incurring a failure prior to T_0 along with associated unplanned replacement costs and downtime costs. If the planned replacement happens at time T_0, the corresponding time-series of cash flows will become: one for replacing the item at time T_0, either at failure before T_0 or at T_0, and another for replacing it later, either at failure or at the horizon year N.

The first time-series of cash flows is for replacing the item at T_0. In this case, for every year $t = 1, 2, \ldots, T_0 - 1$, we have the expected replacement cost and the expected downtime cost. So, for any year $1, 2, .., T_0 - 1$, the cash flows will be computed as:

$$Cash\ Flow\ Replaced\ in\ Year\ t = -[(C_U + DC_D)\ p(1-p)^{t-1}] \tag{6.12}$$

for $t = T_0$ the expected cash flow is:

$$Cash\ Flow\ Replaced\ in\ Year\ T_0 = -[C_P(1-p)^{T_0-1}] \tag{6.13}$$

The timeline of this option is illustrated as follows:

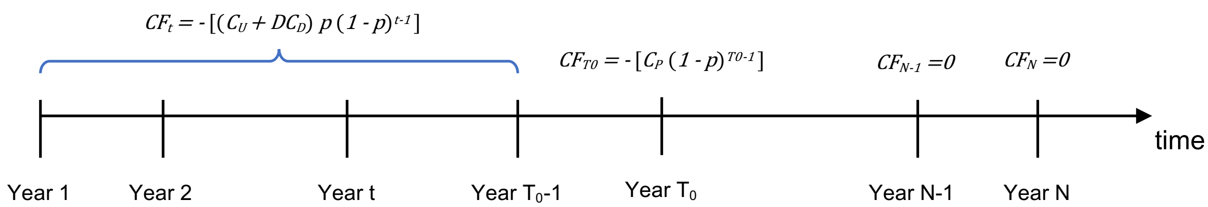

Figure 6. Graphical representation of option 1: planned replacement at T_0.

The NPV of Option 1 is:

$$NPV\ Option\ 1 = -\left[\sum_{t=1}^{T_0-1} \frac{(C_U + DC_D)p(1-p)^{t-1}}{(1+R)^{t-1}} + \frac{C_P(1-p)^{T_0-1}}{(1+R)^{T_0-1}}\right] \tag{6.14}$$

Note that if $T_0 = 1$ then the first term yields zero, and the NPV of Option 1 reduces to that discussed above, i.e., it equals $-C_P$.

The second time-series of cash flow is for attempting to delay replacement of the item to time N, and incurring the risk of an unplanned replacement and downtime in the meantime, and it is the same as we calculated before. The NPV of Option 2 is:

$$NPV\ Option\ 2 = -\left[\sum_{t=1}^{N-1} \frac{(C_U + DC_D)p(1-p)^{t-1}}{(1+R)^{t-1}} + \frac{C_P(1-p)^{N-1}}{(1+R)^{N-1}}\right] \tag{6.15}$$

We can compute $Net\ NPV$ as:

$$\begin{aligned} Net\ NPV &= NPV\ Option\ 1 - NPV\ Option\ 2 = \\ &= \left[\sum_{t=T_0}^{N-1} \frac{(C_U + DC_D)p(1-p)^{t-1}}{(1+R)^{t-1}} + \frac{C_P(1-p)^{N-1}}{(1+R)^{N-1}} - \frac{C_P(1-p)^{T_0-1}}{(1+R)^{T_0-1}}\right] \end{aligned} \tag{6.16}$$

7.2 Reliability and Maintenance Cost Models

Here, we discussion the possibility of using higher fidelity mathematical models governing the reliability and maintenance of key systems or components, henceforth *items*, which are driven by three elements:

1. A *stochastic model* represents failure times and degradation of the item in question.
2. A specific class of *maintenance policies* is considered, which governs how and when preventive and corrective maintenance is performed.
3. A *cost model* that represents, typically, either long-run average cost or a time-discounted cost associated with maintaining the item.

We note that we develop these ideas here, but we do not employ results from such models elsewhere in this report. The desired output of a reliability and maintenance model is a schedule for performing preventive maintenance, and in this section, we describe such models with an emphasis on the corresponding cost models. Here, a cost model can incorporate costs associated with system failure, cost of corrective maintenance, and cost of preventive maintenance. There is a huge literature on such models, and we do not attempt to review that literature here. Rather, we classify and characterize commonly used mathematical models that are considered the most useful, and discuss their application to maintain structures, systems, and components at a nuclear power plant. We emphasize that even though the mathematical models we discuss might suggest repeated replacement of an item, we recognize that many large and important systems in a plant will be replaced at most one time in a plant's life.

First, we introduce key terminology. *Preventive maintenance* of an item means that the item is replaced before if fails. *Corrective maintenance* of an item means that maintenance is performed only when the item fails. Depending on the class of maintenance policies under consideration, corrective maintenance can either: (i) repair the item minimally to a state which is "as good as old", i.e., to its stochastic state immediately prior to failure, or (ii) replace the item to a "good as new" state.

Two of the most commonly used modeling frameworks differ with how corrective maintenance is treated and are known as the *block replacement model* and the *age replacement model*. The block replacement model derives its name from the fact that it is often applied jointly to a block of items. The model recommends replacing the item at times $t_0, 2t_0, 3t_0, \ldots$ And, if the item fails in the meantime, it undergoes corrective maintenance to the as-good-as-old state. The age replacement model differs in that the item is replaced, i.e., to the as-good-as-new state either at failure (corrective maintenance) or at age t_0 (preventive maintenance), whichever occurs first.

These block-replacement and age-replacement modeling frameworks admit a number of variants that differ in the following respects:

1. Costs can be computed in a time-discounted manner or they can be computed via a long-run average cost per unit time.
2. Corrective maintenance can imply replacement, minimal repair, or both options can be available and can depend on other factors.
3. Time can be treated in a discrete or in a continuous manner.
4. Repair and/or replacement can be immediate, or the system may be down, and the maintenance action can take time to perform.
5. The time horizon can be treated as infinite or it may have a finite termination.

We again emphasize that the mathematical models that we detail here are far from exhausting the relevant literature. Other models include, for example, group replacement policies, maintenance schemes that hinge on the item's condition, and so-called opportunistic replacement policies. In the next section we detail the block replacement model as an example.

7.3 Block Replacement Models

This section details a block replacement model using the constructs of Section 7.2. The block replacement model is an important example of scheduling maintenance under uncertain failure times. The calculations are insightful, and they allow for a higher fidelity model than we consider in Section 7.1 in that a richer class of models for stochastic failure times are considered. That said, the model is stylized in that it neglects the time value of money; i.e., time discounting of cash flows is not included. The constructs we use involve:

1. *Stochastic model:* Under the block replacement model the stochastic model governing failure times is quite general, for the moment. In particular, we let $f(t)$ denote the Probability Density Function (PDF) and $F(t)$ denote the Cumulative Distribution Function (CDF) governing the time to failure so that a continuous random variable governs time to failure.
2. *Class of maintenance policies:* We assume that the item is replaced at $t_0, 2t_0, 3t_0, \ldots$ And, if the item fails in the meantime we assume it is corrected to an as-good-as-old state.
3. *Cost model:* We let $C_{CM} > C_{PM} > 0$ denote the costs of corrective maintenance and preventive maintenance, respectively, and we employ a *long-run average cost model*, as detailed below. Here, C_{PM} can incorporate all costs associated with a planned replacement of the item. Similarly, the corrective maintenance cost, C_{CM}, can incorporate the expected cost associated with a plant trip. In a simple model, the plant trips when the item fails, with probability p_{trip}, and we can express $C_{CM} = p_{trip}\, C_{CM,trip} + \left(1 - p_{trip}\right) C_{CM,no\ trip}$, where $C_{CM,trip}$ and $C_{CM,no\ trip}$ represent costs with, and without, a plant trip.

The above assumptions on the stochastic model and the class of maintenance policies combine to yield a result, which greatly simplifies the analysis, at least for the long-run-average cost model. In particular, a classic result characterizes the random number of failures in between each of the planned replacements.

Fact ([29]): Let $f(t)$ denote the PDF of the failure time distribution, and let the random variable $N(kt_0, (k+1)t_0)$ denote the number of failures between two replacement times for $k = 1, 2, \ldots$. Then, $N(kt_0, (k+1)t_0)$ is a Nonhomogeneous Poisson Process (NHPP) with rate function given by $z(t) = \frac{f(t)}{\int_t^\infty f(u)du} = \frac{f(t)}{1-F(t)}$, where $F(t)$ is the CDF of the failure time distribution.

This fact allows us to conveniently express the expected number of failures in an arbitrary time interval, say (t_1, t_2), via $E[N(t_1, t_2)] = \int_{t_1}^{t_2} z(u)du$, and if the item is as-good-as-new at times $0, t_0, 2t_0, 3t_0, \ldots$ then the expected number of failures in each interval is $E[N(0, t_0)] = \int_0^{t_0} z(u)du$.

As a simple, but useful, example suppose that the item's failure time follows a Weibull distribution with parameters α and λ, with PDF $f(t) = \alpha\, \lambda^\alpha t^{\alpha-1} \exp\left(-(\lambda t)^\alpha\right)$, and hence with failure rate function $z(t) = \alpha\, \lambda^\alpha t^{\alpha-1}$. As a result, we can compute the expected number of failures in interval $(0, t_0)$, and all subsequent intervals, as $E[N(0, t_0)] = (\lambda t_0)^\alpha$. We note that the exponential (memoryless) distribution is the special case of the Weibull distribution in which $\alpha = 1$. When $\alpha > 1$ the Weibull distribution has an increasing failure rate, and when $\alpha < 1$ the failure rate is decreasing.

We can represent the expected cost over time interval $(0, t_0)$ as $C_{CM}\, E[N(0, t_0)] + C_{PM}$, and hence the cost per unit time is:

$$Cost(t_0) = \left(C_{CM}\, E[N(0, t_0)] + C_{PM}\right) / \; t_0 \tag{7.1}$$

First consider the unusual case in which the failure rate function, $z(t)$, is *decreasing*. Then, the item becomes more reliable over time, and hence we should never perform preventive maintenance, i.e., in this case the optimal solution is to select $t_0 = \infty$. In the case of the Weibull distribution this occurs if $\alpha \leq 1$.

More generally, differentiating $Cost(t_0)$ yields:

$$\frac{d\ Cost(t_0)}{d\ t_0} = \{C_{CM}\ [\ t_0 z(t_0)\ -\ E[N(0,t_0)] -\ C_{PM}\} /\ t_0^2 \tag{7.2}$$

Assuming that the failure rate function, $z(t)$, is *increasing* and $\frac{d\ Cost(t_0)}{d\ t_0}$ is positive when t_0 is sufficiently large, then we can set the derivative to zero and solve the following equation for t_0:

$$C_{CM}\ [\ t_0 z(t_0)\ -\ E[N(0,t_0)] =\ C_{PM} \tag{7.3}$$

In this case we are ensured a unique solution. In the case of the Weibull distribution with $\alpha > 1$ the optimal value of t_0 is given by:

$$t_0 = \frac{1}{\lambda}\left[\frac{C_{PM}}{(\alpha-1)C_{CM}}\right]^{1/\alpha} \tag{7.4}$$

which has intuitive tendencies with respect to the parameters. As C_{PM} grows, so does t_0. As C_{CM} or α grow then t_0 becomes shorter.

We note that there are other cases in which a unique value of t_0 is not ensured via the method just sketched. If the failure rate function has a bathtub shape (i.e., $z(t)$ is first decreasing and then increasing) then, even though there is not a unique root, we naturally want to select the larger root, which corresponds to when the failure rate is increasing.

8. ANALYSIS METHODS

In Section 7.1 we describe how we develop the NPV for individual projects using a relatively simple model of failure based on a Geometric random variable with Bernoulli failure trials each year. This section begins with a more detailed example of how NPV calculations can be performed. Next we describe analysis using with the Monte Carlo method applied to the capital budgeting model; see discussion in Section 6.2. Finally, we describe the analysis associated with the full stochastic model of Section 6.3.

8.1 Detailed NPV Development for Four Batteries Replacement

This section gives an example of how we can compute the NPV associated with two options for replacing a set of batteries. We assume that it is currently year 2019, and our plant has two units, U1 and U2. In addition to diesel generators, Class 1E batteries provide backup power of plant safety equipment. The existing Class 1E batteries–specifically, type E1(2)D(B)11–have a manufacturing defect in which the post seals can leak, and the leaks can cause the posts to corrode. If we choose *not* to replace the batteries, then we must inspect the batteries weekly. In contrast, we will inspect new batteries monthly. If we do not replace the batteries, we assume that each battery may trigger a 6-hour shutdown of the corresponding unit due to corrosion at which time the posts are cleaned. Furthermore, if batteries are not replaced then they can fail, requiring immediate unplanned replacement and incurring a week-long shutdown for the corresponding unit.

Options:

(i) Replace four batteries in 2019.

(ii) Do not replace the batteries at this time and incur larger maintenance costs, unplanned replacement costs, and lost revenue due to plant shutdowns. Under this option we replace all four batteries in 2035. Here, 2035 is the start of the second 20-year license renewal period, and replacement reflects either a licensing commitment or planned replacement to ensure appropriate management of aging.

Assumptions *without* replacement:

- The posts on the batteries may start to corrode in 2020 for U1 and U2.
- As a result, each year the following scenarios may occur:
  - Corrosion on each battery may cause an unplanned shutdown of the corresponding unit for six hours. This can occur separately for each battery with probability p=0.05. We note that such a shutdown is a complex event, and the reflected costs associated with lost generation are meant to capture an order of magnitude with respect to financial impact to the station.
  - Corrosion on each battery will cause a total battery failure and an unplanned shutdown of the corresponding unit. This occurs with probability p=0.01 for each battery. Under such a failure event, we require replacement of all four batteries, and we incur an unplanned battery replacement cost of $350k per battery. Furthermore, in the event of an unanticipated battery failure, one week (168 hrs) is needed to procure the new batteries, install and test them, and we account for lost revenue due to the loss of one unit. (We assume that only one unit is lost.)

Costs:

- The cost of a *planned* replacement of a Class 1E battery is $70,000 per battery.
- The cost of an *unplanned* battery replacement is five times the cost of planned replacement, i.e., $350,000 per battery, which includes expedited procurement, installation, and testing.
- Cost of a six-hour shutdown (i.e., first scenario above) is 32 ($/MWh) x 1250 (MW) x 6 (hrs) x 4 (batteries) = $960,000.
- Cost of a week-long shutdown (i.e., the second scenario above) is 32 ($/MWh) x 1250 (MW) x 168 (hrs) x 1 (shutdown) = $6,720,000.
- Each inspection costs $160/week.
- With the exception of the first bullet, each of the costs are multiplied by the appropriate probability to compute the expected cost.

Proposed Project Soft Savings

- With new Class 1E batteries, the frequency of inspection will decrease from one inspection per week to one inspection per month. Each inspection costs $160/week. Weekly inspection costs are incurred each year if the batteries haven't been replaced and monthly inspection costs are incurred if the batteries have been replaced.
- For each battery, we have a probability of incurring a six-hour shutdown or a week-long shutdown with lost revenue if the batteries have not been replaced. We assume that soft savings terminate after 2034.

In the actual estimation of the current cash flows we consider three different types of cost categories (hard costs/savings): ongoing O&M, major non ongoing O&M, capital, each with three subcategories: labor, contract labor, and services and materials. For the projected hard costs/saving we have direct O&M implementation cost, direct capital implementation costs, ongoing O&M, each with the three subcategories used in the current cash flows estimation. In the soft cost/savings we include projected savings, reliability savings and efficiency savings. Hard savings are kept at 100%, projected soft savings are discounted at 90%, reliability savings at 80% and efficiency savings at 65%. The discount factors are subjective and constructed to reflect the uncertainty of the projected soft savings.

Based on the above assumptions we can compute the expected cash flows for the proposed four battery replacement project. We can start by calculating:

- Probability no battery fails in a year = $(1-0.01)^4 = 0.960596$
- Probability at least one battery fails in a year = $1 - 0.960596 = 0.0394$

Using a Geometric distribution with p =[Prob at least one battery fails in a year] = 0.0394 we can compute probabilities of first failure for years 2020-2035 as shown in Table 1.

Table 1. Reliability calculation for battery test case.

Year t	Probability of survival	Probability of first failure at year *t*
2019		
2020	0.9606	0.0394
2021	0.9227	0.0379
2022	0.8864	0.0364
2023	0.8515	0.0349
2024	0.8179	0.0336
2025	0.7857	0.0322
2026	0.7547	0.0310
2027	0.7250	0.0297
2028	0.6964	0.0286
2029	0.6690	0.0274
2030	0.6426	0.0264
2031	0.6173	0.0253
2032	0.5930	0.0243
2033	0.5696	0.0234
2034	0.5472	0.0224
2035	0.5256	0.0216

For example, probability of survival in year 2020 is obtained by $0.960596^{2020-2019} = 0.9606$. Probability of first failure in year 2020 is equal to the probability of at least one failure, 0.0394. All consecutive probabilities follow the geometric rule, and the probability in 2021 is $0.9606 \times 0.0394 = 0.0379$.

To compute the expected replacement cost we multiply the probability of first failure by the cost of unplanned replacement and the number of batteries. This is summarized in Table 2. We treat year 2035 differently since the assumption is that 2035 is the year of the planned replacement. As a result:

- Expected replacement cost = probability of survival x cost of planned replacement x number of batteries.
- Expected weekly inspection costs each year if the batteries have not been replaced = Number of batteries x Weekly inspection cost x Probability of survival x 4 x 12
- Expected monthly inspection costs each year if the batteries have been replaced = (1 – Probability of survival) x Weekly inspection cost x 12 x Number of batteries

- Soft savings from inspections = Expected monthly inspection costs each year if the batteries have been replaced - Expected weekly inspection costs each year if the batteries have not been replaced
- Expected lost revenue from 6-hour shutdown if the batteries have not been replaced = Probability of incurring a shutdown in current year x MWs of Units x Number of batteries x Cost of shutdown of MW/hour x 6
- Expected downtime cost for week-long shutdown = Probability of first failure at time t x Downtime cost

Table 2. Replacement costs calculation for battery test case.

Year	Probability of survival	Probability of first failure at year *t*	Expected replacement cost
2019			
2020	0.9606	0.0394	$55,165.59
2021	0.9227	0.0379	$52,991.84
2022	0.8864	0.0364	$50,903.75
2023	0.8515	0.0349	$48,897.94
2024	0.8179	0.0336	$46,971.17
2025	0.7857	0.0322	$45,120.32
2026	0.7547	0.0310	$43,342.40
2027	0.7250	0.0297	$41,634.53
2028	0.6964	0.0286	$39,993.97
2029	0.6690	0.0274	$38,418.04
2030	0.6426	0.0264	$36,904.22
2031	0.6173	0.0253	$35,450.05
2032	0.5930	0.0243	$34,053.17
2033	0.5696	0.0234	$32,711.34
2034	0.5472	0.0224	$31,422.38
2035	0.5256	0.0216	$147,167.02

Next we use the calculated expected costs to construct current costs and projected costs. Expected replacement costs will be accounted for under current ongoing O&M – services and materials. If batteries are not replaced in 2019, there will be a replacement based on unplanned costs. For the projected cash flows, hard costs are the planned replacement in 2019. There will be projected soft savings from inspection and reliability soft savings from 1) lost revenue from 6-hour shutdown if the batteries have not been replaced and 2) downtime cost for a week-long shutdown. We combine the hard and soft savings and create incremental cash flows by subtracting projected cash flows and current cash flows. We use an assumed rate of inflation (1.5%) to adjust future cash flows and an assumed discount rate of 9% to compute the NPV. Table 4 shows the cumulative NPV.

Table 3. Reliability induced cost calculations for battery test case.

Year	Expected replacement cost	Expected weekly inspection costs if the batteries haven't been replaced	Expected monthly inspection costs if the batteries have been replaced	Soft savings from inspections	Probability of incurring a shutdown in current year	Expected lost revenue from 6-hour shutdown if the batteries have not been replaced	Expected downtime cost for week-long shutdown
2019							
2020	$55,165.59	$29,509.51	$302.62	$29,206.89	0.04803	$46,108.61	$264,794.81
2021	$52,991.84	$28,346.72	$593.32	$27,753.40	0.04614	$44,291.75	$254,360.84
2022	$50,903.75	$27,229.74	$872.56	$26,357.18	0.04432	$42,546.47	$244,338.01
2023	$48,897.94	$26,156.78	$1,140.80	$25,015.98	0.04257	$40,869.97	$234,710.12
2024	$46,971.17	$25,126.10	$1,398.47	$23,727.63	0.04090	$39,259.53	$225,461.60
2025	$45,120.32	$24,136.03	$1,645.99	$22,490.04	0.03928	$37,712.55	$216,577.51
2026	$43,342.40	$23,184.98	$1,883.76	$21,301.22	0.03774	$36,226.53	$208,043.50
2027	$41,634.53	$22,271.40	$2,112.15	$20,159.24	0.03625	$34,799.06	$199,845.75
2028	$39,993.97	$21,393.81	$2,331.55	$19,062.27	0.03482	$33,427.83	$191,971.03
2029	$38,418.04	$20,550.81	$2,542.30	$18,008.52	0.03345	$32,110.64	$184,406.61
2030	$36,904.22	$19,741.03	$2,744.74	$16,996.29	0.03213	$30,845.36	$177,140.25
2031	$35,450.05	$18,963.15	$2,939.21	$16,023.94	0.03086	$29,629.93	$170,160.22
2032	$34,053.17	$18,215.93	$3,126.02	$15,089.91	0.02965	$28,462.39	$163,455.23
2033	$32,711.34	$17,498.15	$3,305.46	$14,192.69	0.02848	$27,340.86	$157,014.44
2034	$31,422.38	$16,808.65	$3,477.84	$13,330.82	0.02736	$26,263.52	$150,827.44
2035	$147,167.02						

Table 4. Savings calculation for battery test case.

Year	Total Hard Savings	Total Soft Savings	Total Savings
2019	(280,000.00)	0.00	(280,000.00)
2020	(228,630.21)	256,086.30	27,456.09
2021	(182,679.94)	484,919.32	302,239.38
2022	(141,577.42)	689,390.52	547,813.10
2023	(104,811.22)	872,085.22	767,274.00
2024	(71,923.86)	1,035,314.92	963,391.06
2025	(42,506.11)	1,181,146.30	1,138,640.19
2026	(16,191.94)	1,311,427.11	1,295,235.18
2027	7,346.09	1,427,809.32	1,435,155.40
2028	28,400.85	1,531,769.81	1,560,170.66
2029	47,234.34	1,624,628.94	1,671,863.28
2030	64,080.89	1,707,567.10	1,771,647.99
2031	79,150.13	1,781,639.51	1,860,789.64
2032	92,629.56	1,847,789.46	1,940,419.02
2033	104,686.91	1,906,860.20	2,011,547.12
2034	115,472.22	1,959,605.49	2,075,077.71
2035	162,509.60	1,959,605.49	2,122,115.09

The NPV and IRR are:

Table 5. NPV and IRR summary for battery test case.

Measure	Hard Savings	Hard and Soft Savings
NPV	$ 162,509.60	$ 2,122,115.09
IRR	17.3%	117.1%

Clearly the NPV based on hard and soft savings is positive and the IRR in both cases is greater than the assumed discount rate of 9% and the replacement of batteries in 2019 should be accepted. The approximate savings from taking such action is close to 2 million dollars. Note also that the NPV for the battery replacement becomes positive in 2020; thus the payback period for this investment is less than one year (a the assumed failure probabilities, inflation rate, and discount rate).

9. METHODS DEVELOPMENT

The methods described in Sections 6, 7, and 8 have been implemented by developing several models:

- Optimization PYOMO Models: which perform capital and stochastic budgeting optimization (see Appendix F)
- NPV models: which perform the risk-informed NPV calculation associated to each project
- Reliability models: modeled component failure probabilities

These models are available in the following software repositories:

- RAVEN code (see Appendix C): INL developed code which is employed to perform simulation-based optimization
- CashFlow plugin (see Appendix D): a repository which contains models designed to perform NPV calculation and which can be directly linked to RAVEN
- Logos plugin (see Appendix E): a repository which contains a set of reliability and optimization models and which can be directly linked to RAVEN

10. USE CASES

In order to show how the developed methods can be applied to capital SSC replacement scheduling, we have developed a series of test cases. We consider a capital budgeting problem for a nuclear generation station, with possible extension to a larger fleet of nuclear plants. Due to limited resources, we can only select a subset from several candidate capital projects. Our goal is to maximize overall NPV. In doing so, we must respect resource limits and capture key structure and stochastic dependencies of the system. Example projects under consideration include upgrading high pressure feedwater heaters, improving emergency diesel generators, and replacing a set of reactor coolant pumps. To understand the nature of the proposed methodologies, we consider a numerical example with 16 projects (see Table 6) each having liabilities in some or all of the next five years. These projects were selected because they constituted a set of projects that were close to the budget cutoff point, with some being funded and others not. Thus, the subset of projects identified in Table 6 was selected to provide a useful validation of the applicability of the methods proposed in the report.

Table 6. List of considered projects for the considered SLR plan.

ID	Project name	Category	Options
1	HP feedwater heater upgrade	Optional	Plan A, B, don't do
2	Pressurizer replacement	Must do	Plan A, B, C
3	Improvement to emergency diesel generators	Optional	Plan A, B, don't do
4	Secondary system PHM system	Optional	Plan A, B, don't do
5	Replacement of two reactor coolant pumps	Must do	Plan A, B
6	Seismic modification, requalification, reinforcement, improvement	Optional	Plan A, B, C, don't do
7	Fire protection	Must do	Plan A, B
8	Service water system upgrade	Optional	Plan A, B, don't do
9	Batteries replacement	Optional	Plan A, don't do
10	Replace CCW piping, heat exchangers, valves	Must do	Plan A, B, C
11	Reactor vessel internals	Optional	Plan A, B, don't do
12	Reactor vessel upgrade (head included)	Must do	Plan A
13	Replace LP turbine	Optional	Plan A, B, don't do
14	Replace instrumentation and control cables	Must do	Plan A
15	Condenser retubing	Optional	Plan A, B, don't do
16	Replace moisture separator reheater	Optional	Plan A, B, C, don't do

In this example, we only consider two colors of money, i.e., capital and operation and maintenance (O&M) funds. Additional types of resources could include labor-hours and time during an outage. The planning horizon for this set of projects is set to five years although NPV is computed with a horizon of 20 years. Plans A, B, and C represent different timing options to do planned replacement. Table 7 summarizes the considered use cases which are presented in more detail in Sections 10.1, 10.2, and 10.3.

Table 7. Summary of the analyzed use cases.

No.	Name	Features	Inputs
1	Capital budgeting	Prioritize SSC projects and provide optimal schedule	Yearly budget (capital) and project constraints
2	Plant asset management under uncertainty	Same as model 1 + uncertainties associated to costs and budget	Same as model 1 + uncertainty distributions associated to input data (budget and constraints)
3	Risk informed plant asset management	Same as model 2 + risk associated to SSC failure	Same as model 2 + SSC reliability data and cost associated to SSC failure (e.g., loss of production, regulatory cost)

10.1 Use Case 1

In the first use case, we have two budgetary constraints: capital budgets and O&M budgets, and Table 8 provides the planned capital and O&M budgets for the next five years. We use the solution methodology described in Section 6.1 to obtain the optimal solution, which we also describe below.

Table 8. Available capital and O&M budget for each year.

	Year 1	Year 2	Year 3	Year 4	Year 5
Capital budget [M$]	22.6	36.7	20.6	23.6	22.7
O&M budget [M$]	0.08	0.17	0.05	0.15	0.14

Table 6 shows the descriptions of these 16 projects, and their available options and importance. Table 9 shows the project cost and NPV values for each project-option pair. Note that there are “Plan A” or “Plan A and Plan B” or “Plan A, Plan B, and Plan C” options for the projects. In the current example we associate “Plan A” with the initial timing of the projects. “Plan B” or “Plan C” can be considered as the timing option where we shift some of the projects starting time. As shown in Table 9, projects 2, 5, 7, 10, 12, and 14 have negative NPVs. However, these must-do projects have been mandated for inclusion in the portfolio. Safety goals are of foremost concern in a NPP with failure to meet safety or regulatory goals having significant consequence Thus, in our example, projects 2, 5, 7, 10, 12, and 14 are forced to be selected when solving the optimization model; see constraint (6.3f). These projects reduce the budget available for choosing the best portfolio of projects, and they do decrease overall NPV of the portfolio by almost $45M.

The solution results for three examples of Use Case 1 are listed in Table 10. The first example represents the simple situation in which there is only Plan A and all funds are aggregated in a single budget, labeled “Plan A CapitalFunds.” The second example involves all available options in terms of timing, and the third example is identical to the second except that it distinguishes capital funds and O&M funds. Table 10 specifies the optimal selection of projects and their implementation plans, and the corresponding value for the objective function, i.e., the maximum NPV for the portfolio of selected projects.

Table 9. NPV calculation for Use Case 1.

Project-option	Capital costs [M$]					O&M costs [M$]					Total NPV [M$]
	Y1	Y2	Y3	Y4	Y5	Y1	Y2	Y3	Y4	Y5	
1: PlanA	12.99	1.30				0.02	0.01				27.98
1: PlanB		12.99	1.30				0.02	0.01			27.17
2: PlanA	9.15	0.92				0.04	0.01				-10.07
2: PlanB		9.15	0.92				0.04	0.01			-9.78
2: PlanC				9.15	0.92				0.04	0.01	-9.22
3: PlanA				10.08	1.10				0.01	0.01	20.23
3: PlanB			10.08	1.10				0.01	0.01		20.84
4: PlanA		4.50	0.30	0.20			0.01	0.01	0.01		35.00
4: PlanB			4.50	0.30	0.20			0.01	0.01	0.01	33.98
5: PlanA		18.60					0.03				-18.60
5: PlanB					18.60					0.03	-17.02
6: PlanA		2.24					0.20				9.48
6: PlanB				2.24					0.20		8.94
6: PlanC					2.24					0.20	8.68
7: PlanA	1.31	0.13				0.01	0.01				-1.44
7: PlanB				1.31	0.13				0.01	0.01	-1.32
8: PlanA	2.34					0.01					5.18
8: PlanB			2.34					0.01			4.88
9: PlanA	0.28					0.01					2.10
10: PlanA			4.57	0.46				0.01	0.01		-5.03
10: PlanB		4.57	0.46				0.01	0.01			-5.18
10: PlanC				4.57	0.46				0.01	0.01	-4.88
11: PlanA		19.82					0.03				41.14
11: PlanB					19.82					0.03	37.65
12: PlanA	5.25					0.02					-5.25
13: PlanA			18.77					0.02			167.94
13: PlanB				18.77					0.02		163.05
14: PlanA	5.92	0.60				0.02	0.01				-6.52
15: PlanA	5.24					0.02					16.72
15: PlanB			5.24					0.02			15.76
16: PlanA	3.16					0.01					8.26
16: PlanB				3.16					0.01		7.56
16: PlanC					3.16					0.01	7.34

Table 10. Results for deterministic capital budgeting case study.

ID	Category	Project name	PlanA CapitalFunds	PlanA, PlanB, PlanC, CapitalFunds	PlanA, PlanB, PlanC, CapitalFunds, O&Mfunds
1	Optional	HP feedwater heater upgrade	Do Nothing	PlanB	PlanB
2	Must do	Pressurizer replacement	PlanA	PlanC	PlanC
3	Optional	Improvement to emergency diesel generators	PlanA	Do nothing	Do Nothing
4	Optional	Secondary system PHM system	PlanA	PlanA	PlanA
5	Must do	Replacement of two reactor coolant pumps	PlanA	PlanA	PlanA
6	Optional	Seismic modification, requalification, reinforcement, improvement	PlanA	PlanB	Do Nothing
7	Must do	Fire protection	PlanA	PlanB	PlanB
8	Optional	Service water system upgrade	Do Nothing	PlanA	PlanA
9	Optional	Batteries replacement	PlanA	PlanA	PlanA
10	Must do	Replace CCW piping, heat exchangers, valves	PlanA	PlanC	PlanC
11	Optional	Reactor vessel internals	Do Nothing	PlanB	PlanB
12	Must do	Reactor vessel upgrade (head included)	PlanA	PlanA	PlanA
13	Optional	Replace LP turbine	Do Nothing	PlanA	PlanA
14	Must do	Replace instrumentation and control cables	PlanA	PlanA	PlanA
15	Optional	Condenser retubing	Do Nothing	PlanA	PlanA
16	Optional	Replace moisture separator reheater	Do Nothing	PlanA	PlanB
			NPV=19.90	**NPV = 263.17**	**NPV=253.53**

The three right-most columns of Table 10 show the optimal plans for the selected projects for the three example instances. Note that projects 1, 8, 11, 13, 15 and 16 are not selected under the first instance. However, when the timing option is allowed, and all funds are aggregated under capital funds, all projects are selected except for project 3, and the NPV grows considerably, from \$19.90M to \$263.17M. When capital funds and O&M funds are distinguished, the NPV naturally drops to \$253.53M, and in this example only projects 3 and 6 are not selected. Clearly, the additional flexibility associated with the timing of Plans B and C is of significant value, and accounting separately for capital budgets and O&M budgets is a modest detriment.

In capital budgeting we often encounter the concept of "real options." In particular, the decision maker has the right but not the obligation to make a business decision in the future. A real option allows managers to evaluate opportunities and select the right one. Real options are similar to financial options, e.g., the option to purchase shares of Microsoft one month from today at a given stock price. There are a variety of real options related to decisions to: expand, abandon, wait, contract or switch. In the above example we have an illustration of the option to delay initiation of a project. And, as we see from the results, the value of this option in our case is quite high. In our view, it makes sense for risk managers at nuclear power plants to consider such options when it can be done safely. Our methodology and software implementation allow decision makers to consider different what-if scenarios and make an informed decision regarding project selection.

10.2 Use Case 2

For the second use case, some numerical values of the capital budget, which were deterministic in Use Case 1, are modified to incorporate uncertainty through uniform distributions (indicated as $U[a, b]$ as for a uniform distribution between a and b); see Table 11.

Table 11. Capital budget uncertanites.

Capital budget [M$]				
Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**
U[20,23]	U[34,38]	U[17,22]	U[20,25]	U[18,24]

10.2.1 Stochastic Optimization Approach

We implement the stochastic optimization model of Section 6.3 with the data for the 16-project portfolio. We start with a simpler setting than in Table 11 in order to observe the behavior of the solution depending on different constraints as described below. We first solve the problem *only* with uncertain budgets and using the same scenarios for all five years. Using a uniform distribution U[19,40] for the annual budget, we create the 10 scenarios in Table 12, which are applied to all five years with perfect correlation across the years.

Table 12. List of scenarios identified for the stochastic optimization approach for Use Case 2.

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
19.00	22.15	24.25	26.35	28.45	30.55	32.65	34.75	36.85	40.00

First, we solve the stochastic optimization problem including constraints (6.3a), (6.3d), (6.3e), (6.3f), (6.3g), and (6.3m). This is the minimal set of constraints ensuring the budget is met and that Must Do projects are selected, but the model does not seek a prioritized solution. Table 13 shows the optimal solution with an optimal objective value of $266.707M.

As can be seen, all "Must Do" projects are selected, but the solutions "jump" between different plans and switch on and off between scenarios; see, e.g., the project "Service water system upgrade" as the budget grows: For the first scenario S1 = $19M budget, the optimal solution is Plan A. However, for the second and fourth scenarios this project is not selected. Clearly this is not a desired behavior of the solution.

Next, we solve the stochastic optimization problem by adding constraints (6.3b), (6.3c), and (6.3h). Table 14 shows the optimal solution with an optimal objective value of $264.994M.

Table 13. Results for the stochastic capital budgeting approach for the considered scenarios indicated in Table 12.

	Budget	19	22.15	24.25	26.35	28.45	30.55	32.65	34.75	36.85	40
HP feedwater heater upgrade	Optional		Plan B		Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Presurizer replacement	***Must do***	Plan B	Plan A	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C
Improvement to emergency diesel generators	Optional		Plan B	Plan A	Plan A	Plan A	Plan A	Plan B	Plan B	Plan B	Plan B
Secondary system PHM system	Optional		Plan A	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replacement of two reactor coolant pumps	***Must do***	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Seismic modification, requalification, reinforcement, improvement	Optional	Plan A	Plan A	Plan A	Plan C	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A
Fire protection	***Must do***	Plan A	Plan B	Plan A	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Service water system upgrade	Optional	Plan A		Plan A		Plan B	Plan A	Plan A	Plan B	Plan A	Plan A
Batteries replacement	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace CCW piping, heat exchangers, valves	***Must do***	Plan B	Plan A	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C
Reactor vessel internals	Optional			Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Reactor vessel upgrade (head included)	***Must do***	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace LP turbine	Optional	Plan B	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace instrumentation and control cables	***Must do***	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Condenser retubing	Optional	Plan B	Plan B	Plan A	Plan B	Plan B	Plan B	Plan A	Plan A	Plan A	Plan A
Replace moisture separator reheater	Optional	Plan A	Plan C	Plan A		Plan A	Plan A	Plan B	Plan A	Plan A	Plan A

Table 14. Results for the stochastic capital budgeting approach for the considered scenarios indicated in Table 12 by adding constraints (6.3b), (6.3c), and (6.3h).

	Budget	19	22.15	24.25	26.35	28.45	30.55	32.65	34.75	36.85	40
HP feedwater heater upgrade	Optional					Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Presurizer replacement	***Must do***	Plan B	Plan A	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C
Improvement to emergency diesel generators	Optional			Plan A	Plan A	Plan A	Plan A	Plan B	Plan B	Plan B	Plan B
Secondary system PHM system	Optional		Plan B	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replacement of two reactor coolant pumps	***Must do***	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Seismic modification, requalification, reinforcement, improvement	Optional	Plan A	Plan B	Plan A	Plan B	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A
Fire protection	***Must do***	Plan A	Plan A	Plan A	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Service water system upgrade	Optional	Plan A	Plan B	Plan A	Plan A	Plan B	Plan A	Plan A	Plan B	Plan A	Plan A
Batteries replacement	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace CCW piping, heat exchangers, valves	***Must do***	Plan B	Plan A	Plan C	Plan A	Plan C	Plan C	Plan C	Plan C	Plan C	Plan C
Reactor vessel internals	Optional		Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Reactor vessel upgrade (head included)	***Must do***	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace LP turbine	Optional	Plan B	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace instrumentation and control cables	***Must do***	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Condenser retubing	Optional	Plan B	Plan B	Plan A	Plan A	Plan B	Plan B	Plan A	Plan A	Plan A	Plan A
Replace moisture separator reheater	Optional	Plan A	Plan C	Plan A	Plan A	Plan A	Plan A	Plan B	Plan A	Plan A	Plan A

Note, that the undesired behavior of selecting and then not selecting a project as the budget is gone, but there is still "jumping" between different plans. For example, see the project involving the "Replace moisture separator reheater". For S1 it starts with Plan A, under S2 jumps to Plan C, then back to Plan A and later even goes to Plan B. Here, Plan A starts now, Plan B delays one year and Plan C delays two years. In this and subsequent tables, we use colors to highlight these types of instabilities. We note than in Figure 13 and Figure 14 (and in subsequent figures in this section), these types of instabilities are easily identifiable from the use of color coding which we have provided.

To remedy this, we include constraint (6.3j). Table 15 shows the optimal solution with an optimal objective value of $241.623M.

Table 15. Results for the stochastic capital budgeting approach for the considered scenarios indicated in Table 12 by adding constraints (6.3j).

	Budget	19	22.15	24.25	26.35	28.45	30.55	32.65	34.75	36.85	40
HP feedwater heater upgrade	Optional								Plan B	Plan B	Plan B
Presurizer replacement	*Must do*	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Improvement to emergency diesel generators	Optional				Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Secondary system PHM system	Optional		Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan A
Replacement of two reactor coolant pumps	*Must do*	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Seismic modification, requalification, reinforcement, improvement	Optional		Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Fire protection	*Must do*	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Service water system upgrade	Optional	Plan B	Plan B	Plan B	Plan B	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A
Batteries replacement	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace CCW piping, heat exchangers, valves	*Must do*	Plan B	Plan A	Plan A	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Reactor vessel internals	Optional		Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Reactor vessel upgrade (head included)	*Must do*	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace LP turbine	Optional	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan A
Replace instrumentation and control cables	*Must do*	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Condenser retubing	Optional	Plan B	Plan B	Plan B	Plan B	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace moisture separator reheater	Optional			Plan C	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B

Note that the solution behavior is much improved but there is still jumping between different plans; e.g., see the project involving "Replace CC piping, heat exchangers and valves". By incorporating constraints (6.3k) and (6.3l) we fix this problem by requiring that only one type of plan can be selected for each project. Table 16 shows the optimal solution with an optimal objective value of 225.708M. Now, once a particular plan is selected, the solution stays there for the selected scenarios. These results indicate that there is a price to be paid for achieveing this stabilization; i.e. the realized portfolio NPV will be somewhat reduced (by ~15% from the largest calculated NPV in this example).

In addition to the analysis just presented, we now rerun the full stochastic optimization model with *different* uniform budget distributions for the five years (but still no uncertainty in cost streams or in NPVs) indicated in Table 11. Similarly, to the first budget scenarios, we create a set of 10 budget scenarios as specified in Table 17.

Table 16. Results for the stochastic capital budgeting approach for the considered scenarios indicated in Table 12 by adding constraints (6.3k) and (6.3l).

	Budget	19	22.15	24.25	26.35	28.45	30.55	32.65	34.75	36.85	40
HP feedwater heater upgrade	Optional					Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Presurizer replacement	***Must do***	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Improvement to emergency diesel generators	Optional		Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Secondary system PHM system	Optional		Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Replacement of two reactor coolant pumps	***Must do***	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Seismic modification, requalification, reinforcement, improvement	Optional			Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Fire protection	***Must do***	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Service water system upgrade	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Batteries replacement	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace CCW piping, heat exchangers, valves	***Must do***	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Reactor vessel internals	Optional										Plan B
Reactor vessel upgrade (head included)	***Must do***	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace LP turbine	Optional	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Replace instrumentation and control cables	***Must do***	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Condenser retubing	Optional	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Replace moisture separator reheater	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A

Table 17. List of scenarios identified for the stochastic optimization approach for Use Case 2.

Budget	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
Year 1	20.0000	20.3333	20.6667	21.0000	21.3333	21.6667	22.0000	22.3333	22.6667	23.0000
Year 2	34.0000	34.4444	34.8889	35.3333	35.7778	36.2222	36.6667	37.1111	37.5556	38.0000
Year 3	17.0000	17.5556	18.1111	18.6667	19.2222	19.7778	20.3333	20.8889	21.4444	22.0000
Year 4	20.0000	20.5556	21.1111	21.6667	22.2222	22.7778	23.3333	23.8889	24.4444	25.0000
Year 5	18.0000	18.6667	19.3333	20.0000	20.6667	21.3333	22.0000	22.6667	23.3333	24.0000

Table 18 shows the optimal solution with an optimal objective value of 221.736M. Note that the model solved here is analogous to that in Table 16 in that switching between different plans is not allowed. Some projects (e.g., seismic modification and replace moisture separator reheater) can only be selected when the budget realizations are sufficiently large, and some projects are not selected at all (HP feedwater heater upgrade), but the solution cannot switch between Plan A and Plan B, for example, across different budget scenarios.

Table 18. Results for the stochastic capital budgeting approach for the considered scenarios indicated in Table 17.

		S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
HP feedwater heater upgrade	Optional										
Presurizer replacement	Must do	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Improvement to emergency diesel generators	Optional			Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Secondary system PHM system	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replacement of two reactor coolant pumps	Must do	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Seismic modification, requalification, reinforcement, improvement	Optional							Plan B	Plan B	Plan B	Plan B
Fire protection	Must do	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Service water system upgrade	Optional				Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Batteries replacement	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace CCW piping, heat exchangers, valves	Must do	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Reactor vessel internals	Optional				Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Reactor vessel upgrade (head included)	Must do	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace LP turbine	Optional	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B	Plan B
Replace instrumentation and control cables	Must do	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Condenser retubing	Optional	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A	Plan A
Replace moisture separator reheater	Optional									Plan C	Plan C

10.2.2 Simulation Based Analysis

For the second use case, some numerical values of Use Case 1 are provided in terms of uncertainties through uniform distributions (indicated as $U[a, b]$ as uniform distribution between a and b) in Table 11 and Table 24.

In this case study, a simple model is proposed to compute the NPV of project-option pairs:

$$NPV_{i,j} = \frac{pDC_D + C_u + C_{hs}}{(1+R)^{t_{i,j}-t_{i,A}}} \tag{10.1}$$

where

- $i \in I$: candidate projects
- $j \in J_i$: options for selecting project i, i.e., “Plan A” and “Plan B” for project 1 in this case
- p: probability of item failure
- D: number of days plant is off-line if a shutdown occurs
- C_D: cost of shutdown per day
- C_u: cost of unplanned replacement
- C_{hs}: project hard savings
- R: discount rate
- $t_{i,A}$: the starting year of plan A for project i
- $t_{i,j}$: the starting year of option j for project i

Table 19 shows the corresponding input data and the calculated NPVs assuming given failure probabilities and the discount rate is 3% for all cases.

Table 19. NPVs of project-option pairs.

Project-option	Soft savings [M$]				Hard savings [M$]	Total NPV [M$]
	P_failure	T_shutdown [days]	Repl. cost	NPV		
1: Plan A	0.10	20.00	25.98	27.98		27.98
1: Plan B						27.17
2: Plan A				-10.07		-10.07
2: Plan B						-9.78
2: Plan C						-9.22
3: Plan A	0.01	7.00	20.16	20.23		20.23
3: Plan B						20.84
4: Plan A					35.00	35.00
4: Plan B						33.98
5: Plan A				-18.60		-18.60
5: Plan B						-17.02
6: Plan A	0.50	10.00	4.48	9.48		9.48
6: Plan B						8.94
6: Plan C						8.68
7: Plan A				-1.44		-1.44
7: Plan B						-1.32
8: Plan A	0.05	10.00	4.68	5.18		5.18
8: Plan B						4.88
9: Plan A				2.10		2.10
10: Plan A				-5.03		-5.03
10: Plan B						-5.18
10: Plan C						-4.88
11: Plan A	0.05	30.00	39.64	41.14		41.14
11: Plan B						37.65
12: Plan A				-5.25		-5.25
13: Plan A	0.02	20.00	37.54	37.94	130.00	167.94
13: Plan B						163.05
14: Plan A				-6.52		-6.52
15: Plan A	0.04	25.00	15.72	16.72		16.72
15: Plan B						15.76
16: Plan A	0.03	12.00	7.90	8.26		8.26
16: Plan B						7.56
16: Plan C						7.34

In this case study, the failure probabilities for projects 1, 3, 6, 8, 11, 13, 15, and 16 are drawn randomly from their corresponding distributions, and the NPVs are generated using the proposed simple equation. Monte Carlo sampling is used to calculate the output distributions or risk profiles of probable NPV of each project based on random sampling from probability distributions of uncertain input parameters. For each project with failure probability, a RAVEN external model is constructed to compute the NPV. All above uncertain parameters are sampled via RAVEN using their associated distributions. A Monte Carlo Sampler from RAVEN is used to perform the scenario analysis with a limit of 20,000 samples. The detailed calculation flow is provided in Figure 7.

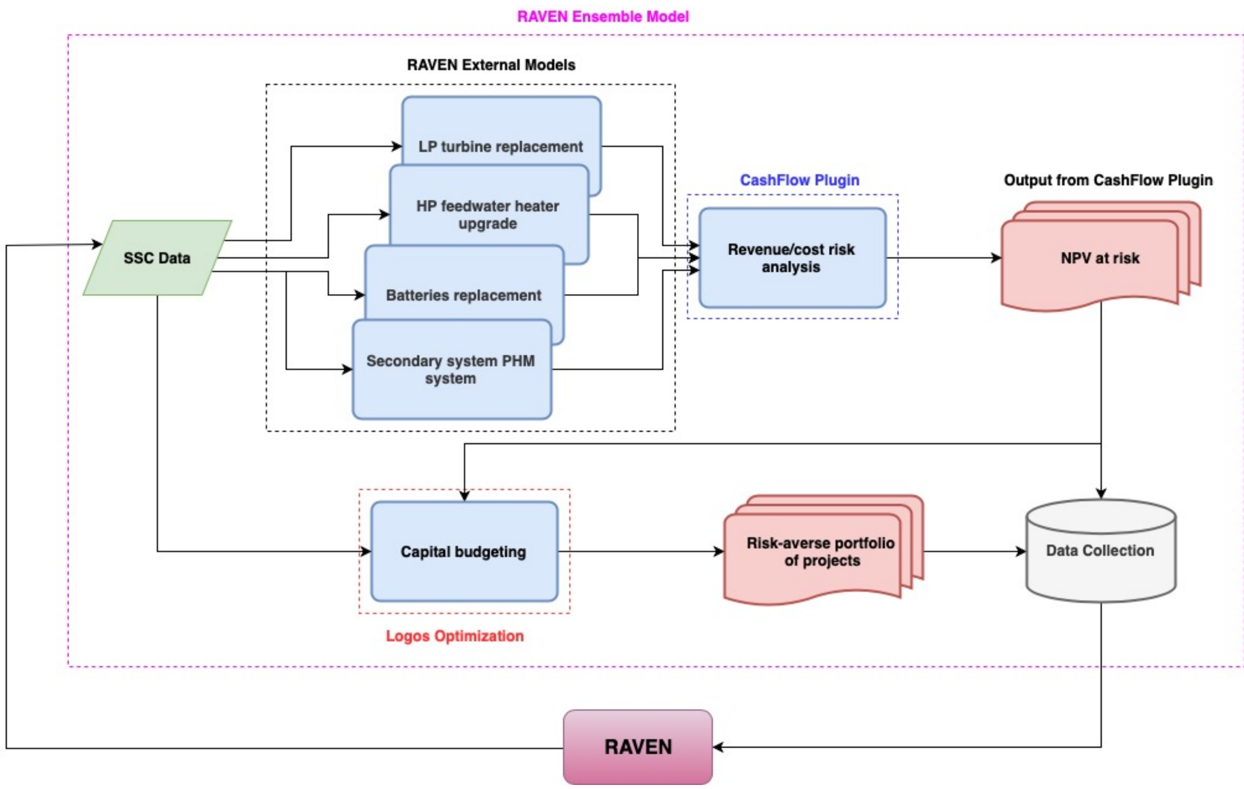

Figure 7. Risk-informed capital budgeting via RAVEN and RAVEN plugins.

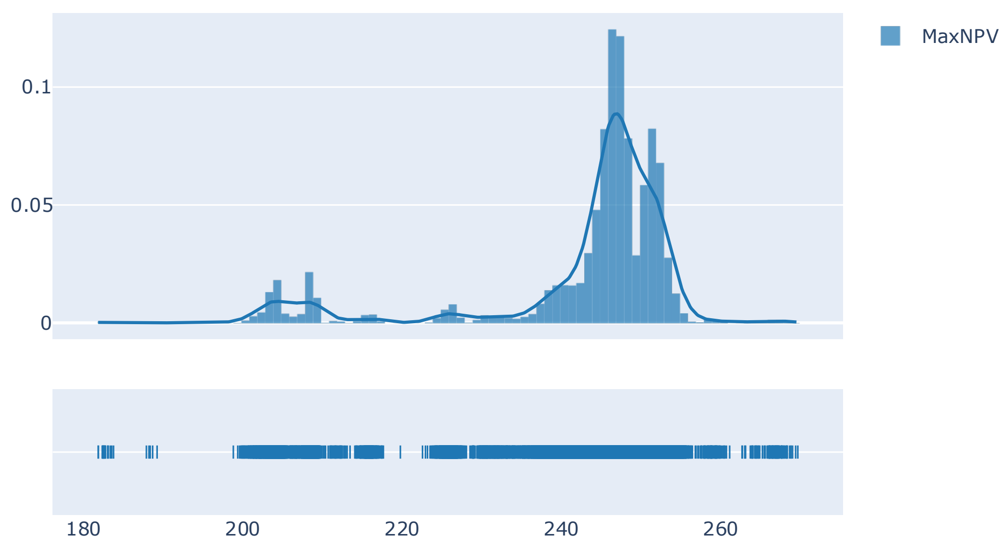

Figure 8. Maximum net-present value (MaxNPV) distribution ($ million) for selected project portfolios (20,000 random scenarios).

Considering all the input uncertainties, the distribution of the selected project portfolios' best NPV, i.e. MaxNPV, is shown in Figure 8, and the statistical moments of best NPV are shown in Table 20. Here, we use the capital budgeting model of Section 6.1 as a black-box function to which we feed the sampled random parameters and from which we obtain the selected projects and the overall NPV. In this study, the expected NPV is $242.94M under 20,000 random scenarios, and the optimal priority list under each scenario is given by Table 21. The top 6 most probable project portfolios are provided in Table 22.

Table 20. Statistical analysis of MaxNPV (20,000 random scenarios).

ID	Average	Minimum	Maximum	σ	5-percentile	95-percentile
MaxNPV	242.94	181.83	269.66	13.03	207.39	252.92

Table 21. Priority lists from scenario analysis (20,000 random scenarios).

ID	Project name	Category	Options	Priorities	Probabilities	Risks (1-Probabilities)
1	HP feedwater heater upgrade	Optional	Plan A	43	0.00E+00	1.00E+00
			Plan B	31	7.76E-02	9.22E-01
			Don't Do	5	9.22E-01	7.76E-02
2	Presurizer replacement	Must do	Plan A	36	8.90E-03	9.91E-01
			Plan B	9	8.00E-01	2.00E-01
			Plan C	25	1.91E-01	8.09E-01
3	Improvement to emergency diesel generators	Optional	Plan A	20	2.96E-01	7.04E-01
			Plan B	13	6.29E-01	3.71E-01
			Don't Do	32	7.51E-02	9.25E-01
4	Secondary system PHM system	Optional	Plan A	6	9.14E-01	8.64E-02
			Plan B	29	8.64E-02	9.14E-01
			Don't Do	42	0.00E+00	1.00E+00
5	Replacement of two reactor coolant	Must do	Plan A	27	1.59E-01	8.41E-01
			Plan B	7	8.41E-01	1.59E-01
6	Seismic modification, requalification, reinforcement,	Optional	Plan A	41	0.00E+00	1.00E+00
			Plan B	40	0.00E+00	1.00E+00
			Plan C	39	0.00E+00	1.00E+00
			Don't Do	3	1.00E+00	0.00E+00
7	Fire protection	Must do	Plan A	21	2.85E-01	7.15E-01
			Plan B	11	7.15E-01	2.85E-01
8	Service water system upgrade	Optional	Plan A	15	5.21E-01	4.79E-01
			Plan B	17	3.96E-01	6.04E-01
			Don't Do	30	8.25E-02	9.18E-01
9	Batteries replacement	Optional	Plan A	10	7.62E-01	2.38E-01
			Don't Do	23	2.38E-01	7.62E-01
10	Replace CCW piping, heat exchangers, valves	Must do	Plan A	14	5.37E-01	4.63E-01
			Plan B	24	2.21E-01	7.79E-01
			Plan C	22	2.42E-01	7.58E-01
11	Reactor vessel internals	Optional	Plan A	8	8.32E-01	1.68E-01
			Plan B	33	6.13E-02	9.39E-01
			Don't Do	28	1.07E-01	8.93E-01
12	Reactor vessel upgrade (head included)	Must do	Plan A	2	1.00E+00	0.00E+00
13	Replace LP turbine	Optional	Plan A	18	3.55E-01	6.45E-01
			Plan B	12	6.45E-01	3.55E-01
			Don't Do	38	0.00E+00	1.00E+00
14	Replace instrumentation and control cables	Must do	Plan A	1	1.00E+00	0.00E+00
15	Condenser retubing	Optional	Plan A	4	9.64E-01	3.55E-02
			Plan B	35	2.93E-02	9.71E-01
			Don't Do	37	6.25E-03	9.94E-01
16	Replace moisture separator reheater	Optional	Plan A	16	4.68E-01	5.33E-01
			Plan B	19	3.10E-01	6.90E-01
			Plan C	26	1.84E-01	8.16E-01
			Don't Do	34	3.77E-02	9.62E-01

Table 22. Ranked project portfolios based on frequencies.

ID	Project name	Category	Options	Project portfolios 1	2	3	4	5	6
1	HP feedwater heater upgrade	Optional	Plan A						
			Plan B						1
			Don't Do	1	1	1	1	1	
2	Presurizer replacement	Must do	Plan A						
			Plan B	1	1	1		1	
			Plan C				1		1
3	Improvement to emergency diesel	Optional	Plan A		1		1		
			Plan B	1		1		1	
			Don't Do						1
4	Secondary system PHM system	Optional	Plan A	1	1	1	1	1	1
			Plan B						
			Don't Do						
5	Replacement of two reactor	Must do	Plan A						1
			Plan B	1	1	1	1	1	
6	Seismic modification, requalification, reinforcement,	Optional	Plan A						
			Plan B						
			Plan C						
			Don't Do	1	1	1	1	1	1
7	Fire protection	Must do	Plan A					1	
			Plan B	1	1	1	1		1
8	Service water system upgrade	Optional	Plan A		1	1	1		1
			Plan B	1				1	
			Don't Do						
9	Batteries replacement	Optional	Plan A	1	1	1	1		1
			Don't Do					1	
10	Replace CCW piping, heat exchangers,	Must do	Plan A	1		1		1	
			Plan B				1		
			Plan C		1				1
11	Reactor vessel internals	Optional	Plan A	1	1	1	1	1	
			Plan B						1
			Don't Do						
12	Reactor vessel upgrade (head included)	Must do	Plan A	1	1	1	1	1	1
13	Replace LP turbine	Optional	Plan A		1		1		1
			Plan B	1		1		1	
			Don't Do						
14	Replace instrumentation and control cables	Must do	Plan A	1	1	1	1	1	1
15	Condenser retubing	Optional	Plan A	1	1	1	1	1	1
			Plan B						
			Don't Do						
16	Replace moisture separator reheater	Optional	Plan A	1				1	
			Plan B		1		1		1
			Plan C			1			
			Don't Do						
MaxNPV		Average		247.35	251.39	246.74	251.63	245.12	253.65
		Minimum		244.88	248.95	244.36	249.28	242.88	250.86
		Maximum		249.84	253.85	249.29	253.78	247.61	256.27
		Standard Deviation		0.92	0.92	0.89	0.91	0.91	1.00
		Frequencies		4393	3006	1023	921	852	779
		Probabilities		0.2197	0.15	0.051	0.0461	0.043	0.039

Sensitivity analysis is performed to identify which variables are important so that special care may be be taken to obtain their precise probability distributions; and which are not so that a single estimate of input parameters may suffice. In Table 23, we have shown the sensitivities for MaxNPV with respect to all the uncertain inputs.

Table 23. Sensitivity analysis of MaxNPV.

Parameters	Sensitivity (MaxNPV)	Normalized Sensitivity (MaxNPV)
Y1	4.87 E-1	4.31 E-2
Y2	5.65 E-01	8.37 E-2
Y3	1.95	1.56 E-1
Y4	1.30	1.20 E-1
Y5	4.47	3.86 E-1
P1	3.73 E+1	4.61 E-3
P3	2.01	2.28 E-4
P6	1.68	6.93 E-4
P8	2.77	3.44 E-4
P11	1.60 E+1	1.97 E-3
P13	3.25 E+1	7.36 E-3
P15	8.12 E-1	1.00 E-3
P16	9.78	2.21 E-3

10.3 Use Case 3

For Use Case 3, the assumptions regarding projects (items to be replaced) and their probability of failure are shown in Table 24.

Table 24. Uncertanities related to component failure probabilities.

ID	Project name	P_Failure
1	HP feedwater heater upgrade	U[0.05,0.15]
3	Improvement to emergency diesel generators	U[0.005,0.0.05]
6	Seismic modification, requalification, reinforcement, improvement	U[0.1,0.5]
8	Service water system upgrade	U[0.01,0.1]
11	Reactor vessel internals	U[0.01,0.1]
13	Replace LP turbine	U[0.01,0.05]
15	Condenser retubing	U[0.01,0.05]
16	Replace moisture separator reheater	U[0.01,0.05]

Here, U[a,b] again stands for a uniform distribution with parameters a and b. The assumptions regarding the yearly budgets are given in Table 11.

10.3.1 Full Stochastic Optimization

This section describes analysis associated with the full stochastic optimization model of Section 6.3. We use the data for candidate projects from the main case study to obtain a solution of the full stochastic optimization model, which in this case includes uncertainty not only the available yearly budgets but also in NPVs as we now describe. We model uncertain NPVs using the fact that items can fail with an unknown probability, and as a result of failure events, the NPVs will change. We described the methods for computing uncertain NPVs in Section 7, taking such failures into account.

The full stochastic optimization model requires as input a set of scenarios. For the budget, we again discretize the uniform interval in 10 equally spaced values and obtain the following scenarios:

Table 25. Scenarios considered for the full stochastic optimization methods for Use Case 3.

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
YEAR 1	20.00	20.33	20.67	21.00	21.33	21.67	22.00	22.33	22.67	23.00
YEAR 2	34.00	34.44	34.89	35.33	35.78	36.22	36.67	37.11	37.56	38.00
YEAR 3	17.00	17.56	18.11	18.67	19.22	19.78	20.33	20.89	21.44	22.00
YEAR 4	20.00	20.56	21.11	21.67	22.22	22.78	23.33	23.89	24.44	25.00
YEAR 5	18.00	18.67	19.33	20.00	20.67	21.33	22.00	22.67	23.33	24.00

For the budget scenarios we assume that the realizations of the budget values are perfectly correlated across the five years. So, if we observe the lowest budget scenario in year 1 we also observe the lowest budget scenario in years 2-5. In addition, for our computation we assume that each of the ten budget scenarios is equally likely; i.e., each scenario occurs with probability 0.1.

To create scenarios for the probabilities of failure, we do a similar discretization by taking three values for each case, namely the lowest, the middle, and the highest values. For example, for the HP feedwater heater upgrade the three realizations of the failure probability are 0.05, 0.1, and 0.15. With this understanding, the following table specifies those realizations:

Table 26. Low, medium and high values of components failure probabilities.

ID	Project name	P_Failure	Low	Medium	High
1	HP feedwater heater upgrade	U[0.05,0.15]	0.05	0.1000	0.15
3	Improvement to emergency diesel generators	U[0.005,0.0.05]	0.01	0.0275	0.05
6	Seismic modification, requalification, reinforcement, improvement	U[0.1,0.5]	0.10	0.3000	0.50
8	Service water system upgrade	U[0.01,0.1]	0.01	0.0550	0.10
11	Reactor vessel internals	U[0.01,0.1]	0.01	0.0550	0.10
13	Replace LP turbine	U[0.01,0.05]	0.01	0.0300	0.05
15	Condenser retubing	U[0.01,0.05]	0.01	0.0300	0.05
16	Replace moisture separator reheater	U[0.01,0.05]	0.01	0.0300	0.05

Additionally, we classify the projects as either No Risk, Low Risk, or Medium Risk using the Monte Carlo simulation results from Section 10.3.2, as we describe below. The low risk and medium risk are assumed to behave independently, and "low risk" means from the Monte Carlo analysis that changes in these failure probabilities were less likely to have a significant impact on the overall portfolio's NPV. Each group has the three realizations discussed above, and the two groups are independent, resulting to a total of nine scenarios. Here, the No Risk, Low Risk, Medium Risk constructs follow the logic of the analysis done for South Texas Project Nuclear Power Station in work described in [7]. Projects in the Low Risk category are assumed to have the following probabilities for each of the three scenarios: P(Low) = 0.1667, P(Medium) = 0.6667, P(High) = 0.1667. For the Medium risk projects, we instead have: P(Low) = 0.3333, P(Medium) = 0.5, P(High) = 0.1667. As a result, in addition to the 10 budget scenarios described earlier, we have 9 scenarios governing the project risk uncertainty, resulting in total of 9x10=90 scenarios. The Low Risk projects are Projects 3, 6, and 15. Medium Risk projects are Projects 1, 8, 11, 13, and 16. The other projects are modeled as having No Risk.

We solve the full stochastic optimization problem described in Section 6.3. The model is implemented in PYOMO. Table 27 shows the optimal results.

Table 27. Solution to the full stochastic optimization model, indicating under which scenarios a project is selected.

ID	Category	Project name	Risk Level	Optimal Solution: No. of Scenarios	Optimal Plan	Scenarios
1	Optional	HP feedwater heater upgrade	Medium	36	Plan B	7,8,9,10
2	Must Do	Pressurizer replacement	None	90	Plan B	All
4	Optional	Secondary system PHM system	None	90	Plan A	All
5	Must Do	Replacement of two reactor coolant pumps	None	90	Plan B	All
7	Must Do	Fire protection	None	90	Plan A	All
8	Optional	Service water system upgrade	Medium	90	Plan B	All
9	Optional	Batteries replacement	None	90	Plan A	All
10	Must Do	Replace CCW piping heat exchangers valves	None	90	Plan B	All
11	Optional	Reactor vessel internals	Medium	6	Plan B	partially 10
12	Must Do	Reactor vessel upgrade	None	90	Plan A	All
13	Optional	Replace LP turbine	Medium	90	Plan B	All
14	Must Do	Replace instrumentation and control cables	None	90	Plan A	All
15	Optional	Condenser retubing	Low	90	Plan A	All
16	Optional	Replace moisture separator reheater	Medium	81	Plan B	2,3,4,5,6,7,8,9,10

The optimal solution does not select projects 3 and 6 (both are Optional), and hence the table does not include rows for these two projects. All "Must Do" projects (see "Category" column) are selected for all 90 scenarios; see projects 2, 5, 7 10, 12, and 14. As a result, their label under the "Optimal Solution: No. of Scenarios" column indicates that they are projects that were selected in all 90 scenarios, either under Plan A or Plan B as indicated in the "Optimal Plan" column. Project 1 is selected for budget scenarios 7, 8, 9, and 10. In other words, when the budget realizations are lower (scenarios 1-6) we cannot afford to select Project 1. The "No. of Scenarios" column indicates that across the nine scenarios of Low-Medium-High for the two groups of Low Risk and Medium Risk projects, that Project 1 was selected in all 9 because 9 NPV scenarios times 4 budget scenarios gives the value of 36 listed in the table. We observe related behavior for Project 16, except that the right-most column indicates that it is selected in all the budget scenarios except for the lowest. The value of 81 under "No. of Scenarios" indicates that it was selected in each of the nine NPV scenarios under each of budget scenarios 2-10. Project 11 is selected only under the highest budget scenario and, even then, not under all nine NPV scenario, but rather only six of the nine as shown in Table 28.

Table 28. Cost scenarios under which project 11 is selected. The SSC is not replaced under scenarios for low failure probability.

Scenario 10, Project 11	Low	Medium	High
Low		x	x
Medium		x	x
High		x	x

If we learn that the failure probability is sufficiently low then we can afford to delay performing Project 11. The optimal value of the objective function is $153.086M. The priority list of the 16 projects is given in Table 29.

Table 29. Priority list for Use Case 3.

ID	Project	Priority List Ranking
12	Reactor vessel upgrade	1-11 (tie)
14	Replace instrumentation and control cables	1-11 (tie)
15	Condenser retubing	1-11 (tie)
7	Fire protection	1-11 (tie)
4	Secondary system PHM system	1-11 (tie)
9	Batteries replacement	1-11 (tie)
10	Replace CCW piping heat exchangers valves	1-11 (tie)
8	Service water system upgrade	1-11 (tie)
2	Pressurizer replacement	1-11 (tie)
5	Replacement of two reactor coolant pumps	1-11 (tie)
13	Replace LP turbine	1-11 (tie)
16	Replace moisture separator reheater	12
1	HP feedwater heater upgrade	13
11	Reactor vessel internals	14
3	Improvement to emergency diesel generators	15-16 (tie)
6	Seismic modification requalification reinforcement improvement	15-16 (tie)

The first 11 projects listed in the table will be executed under all 90 scenarios, and hence the order among their prioritization (1-11) is arbitrary. These 11 include 6 Must Do projects, and these 11 projects are effectively in a tie for highest priority. Project 16 is the next highest priority project as it is done in all scenarios except for the lowest budget scenario. Project 1 has the next highest priority as it is selected in the 36 scenarios with the four highest budget values. Project 11 is only selected among a subset of the nine scenarios for the highest budget scenario, and it is ranked 14th. Finally, Projects 3 and 6 are in a tie for the lowest priority because they are not selected under any scenario. Here, the notion of prioritization is exemplified by the following: Because Project 1 is higher priority than Project 11, if the latter project is selected under some scenario then the former must also be selected; i.e., Project 11 can only be selected in a subset of the scenarios in which Project 1 is selected.

10.3.2 Simulation Based Approach

This simulation-based case study is similar to Use Case 2 reported in Section 10.2.2 except that here the NPVs are generated with more realistic and higher fidelity models. The uncertainties of input data are the same as Use Case 2 provided in Table 11 and Table 24. In this case study, we have a portfolio of candidate projects with options involving either replacing an item today or postponing its replacement to the future and facing potentially higher maintenance and replacements costs. Here, we assume that the item may either be replaced now, or in the future, and in this context, we describe the appropriate cash-flow calculations.

Similar to Use Case 2, the failure probabilities for projects 1, 3, 6, 8, 11, 13, 15, and 16 are randomly drawn from their corresponding distributions, and the incremental NPVs are generated using the same equation as in Section 7.1. Monte Carlo sampling is used to calculate the output distributions or risk profiles of probable NPV of each project based on random sampling from probability distributions of uncertain input parameters. For each project with failure probability, a RAVEN external model is constructed to compute the NPV. All of the uncertain parameters described previously are sampled via RAVEN using their associated distributions. A Monte Carlo Sampler from RAVEN is used to perform the scenario analysis with a limit of 20,000 samples (see Figure 7 for the detailed workflow).

Considering all the input uncertainties, the distribution of the selected project portfolios' best NPV, i.e. MaxNPV, is shown in Figure 9, and the statistical moments of the best NPV are shown in Table 30. In this study, the expected NPV is \$170.76M under 20,000 random scenarios, and the optimal priority list under each scenario is given by Table 31. The top 6 most probable project portfolios are provided in Table 32.

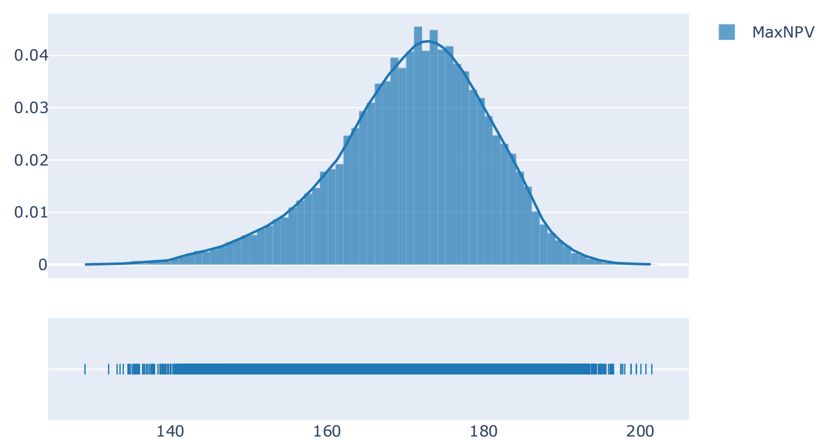

Figure 9. Maximum net-present value (MaxNPV) distribution (\$ million) for selected project portfolios (20,000 random scenarios)

Table 30. Statistical analysis of MaxNPV (20,000 random scenarios).

ID	Average	Minimum	Maximum	σ	5-percentile	95-percentile
MaxNPV	170.76	129.09	201.44	9.86	152.61	185.37

Table 31. Priority lists from scenario analysis (20,000 random scenarios).

ID	Project name	Category	Options	Priorities	Probabilities	Risks (1-Probabilities)
1	HP feedwater heater upgrade	Optional	Plan A	43	0	1
			Plan B	7	0.7287	0.2713
			Don't Do	24	0.2713	0.7287
2	Presurizer replacement	Must do	Plan A	19	0.3709	0.6291
			Plan B	14	0.47375	0.52625
			Plan C	31	0.15535	0.84465
3	Improvement to emergency diesel generators	Optional	Plan A	35	0.0706	0.9294
			Plan B	27	0.22005	0.77995
			Don't Do	8	0.70935	0.29065
4	Secondary system PHM system	Optional	Plan A	10	0.61595	0.38405
			Plan B	18	0.38405	0.61595
			Don't Do	42	0	1
5	Replacement of two reactor coolant	Must do	Plan A	32	0.142	0.858
			Plan B	5	0.858	0.142
6	Seismic modification, requalification, reinforcement,	Optional	Plan A	41	0	1
			Plan B	40	0	1
			Plan C	38	0	1
			Don't Do	2	1	0
7	Fire protection	Must do	Plan A	33	0.1152	0.8848
			Plan B	4	0.8848	0.1152
8	Service water system upgrade	Optional	Plan A	16	0.40855	0.59145
			Plan B	25	0.2632	0.7368
			Don't Do	21	0.32825	0.67175
9	Batteries replacement	Optional	Plan A	13	0.54495	0.45505
			Don't Do	15	0.45505	0.54495
10	Replace CCW piping, heat exchangers, valves	Must do	Plan A	9	0.6957	0.3043
			Plan B	34	0.11285	0.88715
			Plan C	29	0.19145	0.80855
11	Reactor vessel internals	Optional	Plan A	12	0.557	0.443
			Plan B	37	0.04205	0.95795
			Don't Do	17	0.40095	0.59905
12	Reactor vessel upgrade (head included)	Must do	Plan A	1	1	0
13	Replace LP turbine	Optional	Plan A	28	0.20925	0.79075
			Plan B	6	0.79075	0.20925
			Don't Do	39	0	1
14	Replace instrumentation and control cables	Must do	Plan A	3	1	0
15	Condenser retubing	Optional	Plan A	11	0.5758	0.4242
			Plan B	20	0.36085	0.63915
			Don't Do	36	0.06335	0.93665
16	Replace moisture separator reheater	Optional	Plan A	23	0.28675	0.71325
			Plan B	22	0.32305	0.67695
			Plan C	26	0.23315	0.76685
			Don't Do	30	0.15705	0.84295

Table 32. Ranked project portfolios based on frequencies.

ID	Project name	Category	Options	Project portfolios					
				1	2	3	4	5	6
1	HP feedwater heater upgrade	Optional	Plan A						
			Plan B	1	1	1	1		1
			Don't Do					1	
2	Presurizer replacement	Must do	Plan A	1	1	1			
			Plan B				1	1	
			Plan C						1
3	Improvement to emergency diesel	Optional	Plan A						
			Plan B					1	
			Don't Do	1	1	1	1		1
4	Secondary system PHM system	Optional	Plan A				1	1	1
			Plan B	1	1	1			
			Don't Do						
5	Replacement of two reactor	Must do	Plan A						1
			Plan B	1	1	1	1	1	
6	Seismic modification, requalification, reinforcement,	Optional	Plan A						
			Plan B						
			Plan C						
			Don't Do	1	1	1	1	1	1
7	Fire protection	Must do	Plan A						
			Plan B	1	1	1	1	1	1
8	Service water system upgrade	Optional	Plan A						1
			Plan B				1	1	
			Don't Do	1	1	1			
9	Batteries replacement	Optional	Plan A				1	1	1
			Don't Do	1	1	1			
10	Replace CCW piping, heat exchangers,	Must do	Plan A	1	1	1	1	1	
			Plan B						
			Plan C						1
11	Reactor vessel internals	Optional	Plan A	1	1	1		1	
			Plan B						1
			Don't Do				1		
12	Reactor vessel upgrade (head included)	Must do	Plan A	1	1	1	1	1	1
13	Replace LP turbine	Optional	Plan A						1
			Plan B	1	1	1	1	1	
			Don't Do						
14	Replace instrumentation and control cables	Must do	Plan A	1	1	1	1	1	1
15	Condenser retubing	Optional	Plan A				1	1	1
			Plan B	1	1	1			
			Don't Do						
16	Replace moisture separator reheater	Optional	Plan A				1	1	
			Plan B			1			1
			Plan C		1				
			Don't Do	1					
MaxNPV		Average		174.93	177.6	177.8	166.67	174.8	179
		Minimum		148.03	147.5	149.3	148.8	150	151.1
		Maximum		191.92	195.4	195.4	181.75	191.5	198.8
		Standard Deviation		6.929	7.336	7.527	6.3986	7.192	7.977
		Frequencies		2095	1638	1383	1346	862	728
		Probabilities		0.1048	0.082	0.069	0.0673	0.043	0.036

11. USER GUIDE TO THE DEVELOPED RIAM METHODS

The methods and analysis presented in this have indicated how it is possible to structure a RIAM analysis for different boundary conditions. From a user perspective it would be useful to identify the more suited approach depending on the use needs. The developed methods (see Section 6) assume the availaibility of:

1. A predefined list of selected projects
2. SSC reliability data (SSC failure probability)
3. SSC cost data

SSC cost data are available from plant management databases while the first two items need to be created. The set of projects that would improve plant performances might be determined by plant management as well while the set of SSCs that require replacement/refurbishment might be identified with analytical methods/tools. It should be noted that since all operating NPPs perfrom capital budgeting, they all have processes in place to develop this list. In this case, the EPRI ILCM code (see Section 5) can be used to provide an analytical evaluation of SSC failure probability (see Figure 2) and an initial list of SSCs which should be considered for SLR.

Thus, the set of the available tools would be comprised of: Logos plugin, RAVEN, Cashflow plugin and ILCM. In ordert to show how these tools can be employed, we have developed a guide shown in Figure 10 which shows the three different phases of RIAM analysis: 1) the optimal model, 2) the required data and 3) the tool to be employed:

- *Early phase*: management is starting to consider the issue related to capital SSC replacement (see Table 33)

Table 33. Approach to be employed at an early phase of the RIAM development.

Model	Data	Tool
− Simulation-based approach − Full stochastic optimization approach	Reliability data, data uncertainties, cost data	RAVEN + Logos plugin + Cashflow plugin + ILCM

- *Planning phase*: management has clearer ideas on how the use case is set (in terms of which data to consider) and is deciding on how to set the prioritization rules (see Table 34)

Table 34. Approach to be employed at a planning phase of the RIAM development.

Model	Data	Tool
− Full stochastics optimization approach − Initial stochastic optimization approach	Reliability data, data uncertainties, cost data	Logos plugin + ILCM

- *Late/execution phase*: capital SSC replacement is ready to start or it has recently started and management is evaluating “what if” scenarios based on actual data/budget/boundary conditions (see Table 35)

Table 35. Approach to be employed at a late/execution phase of the RIAM development.

Model	Data	Tool
Deterministic capital budgeting approach	Reliability data, cost data	Logos plugin + ILCM

Note that in Tables 33-35 we have also included the EPRI ILCM code which in this case would be employed to determine:

- SSC failure probability
- Set of SSCs to be replaced/refurbished, i.e., the list of projects to be included in the scheduling optimization

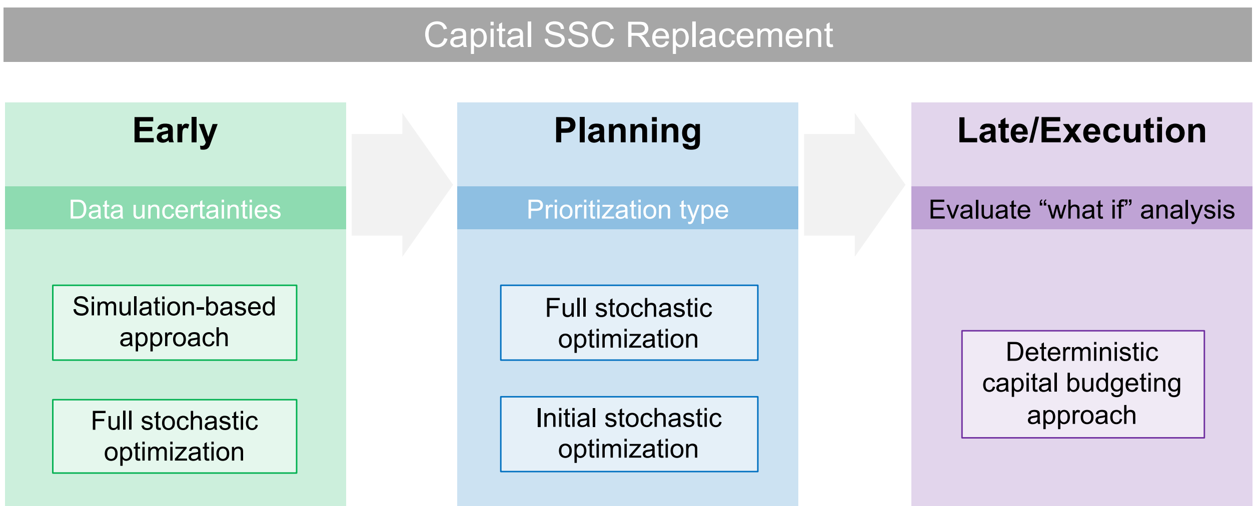

Figure 10. RIAM approaches as function of capital SSC phase (early, planning and late).

12. LINK WITH PHM PROJECT

The Use Case related to development of a RIAM program has significant commonalities to the Use Case that is developing a modern, integrated, risk-informed system health program [31]. Although these two Use Cases are similar in that they focus on plant equipment and system performance, they possess different emphases in objectives and timeframes. This is characterized in Table 36.

Table 36. Emphases and timeframes for system health and asset management Use Cases.

Program	Primary Timeframe	Primary Focus
System Health	Short to Intermediate Term	Engineering
Asset Management	Intermediate to Long Term	Financial

As described in Section 5 of this report, RIAM uses a combination of financial and engineering evaluation methods to apply risk management technology to support plant long-term planning and investment. RIAM is intended to provide decision makers with both qualitative and quantitative information related to investments in asset management with an objective of optimizing long-term economic value while effectively identifying and controlling enterprise risks. As described in Section 5, an important set of methods and tools to support NPP long-term asset management efforts – in particular, with their application to NPPs that are anticipating operating during extended periods of operation (i.e. periods of license renewal) – is the ILCM approach and tool developed by EPRI. The ILCM method [30] addresses the management and optimization of large capital projects for the purposes of extended plant operation. ILCM methods and accompanying software are available to EPRI member utilities; it should be noted that since all U.S. NPP owner operators are EPRI members, ILCM is available to all operating U.S. NPPs.

In contrast, as described in the LWRS System Health Use Case report that is being published simultaneously with this report [31], NPP Equipment Reliability (ER) programs are developed and implemented in accordance with INPO AP-913 [32]. Additionally, regulatory focus via the Maintenance Rule as implemented by the industry in NEI 93-01 [33] focuses, to a large extent, on the reliability and availability of plant SSCs. As a result, plant system health programs have tended to focus predominantly on the engineering aspects related to ER. Additionally, focus on items such as Maintenance Rule performance, in particular addressing performance deficiencies associated with plant SSCs classified as (a)(1) or for SSCs which possess small amounts of margin for the Mitigating Systems Performance Index (MSPI) program [34], has focused attention on issues that are short to intermediate term in nature. One indicator of this focus can be seen in the content of industry sponsored research to support plant ER programs. Research related to ER related issues typically is sponsored by EPRI under the Plant Engineering Program. The results of this research are used by operating NPPs around the world to support plant ER programs. To support widespread adoption of the outcomes of this research EPRI periodically publishes a report (which is publicly available) that lists all of the products developed from this research. A review of the most recent of these reports (see [35]) indicates a large portion of the research focuses on the engineering aspects of plant ER and also focuses on the short and intermediate term needs of the operating NPPs. Important elements associated with the Maintenance Rule and AP-913 are described in the LWRS System Health Use Case report that is being published simultaneously with this report [31]. RIAM is most closely aligned with the LCM portion of AP-913 which has a longer-term focus than the other portions of that industry guidance document.

Although the two Use Cases have different emphases, it is evident that they are closely related. For example, development of long-term asset management plans related to plant life extension will be dependent upon the effectiveness of the management of the health of plant SSCs achieved by the plant ER program. Conversely, anticipated financial restraints related to either current ER programs or for future investments can have an impact on decisions related to the reliability and performance of plant SSCs. As a result, as the two Use Cases related to system health and risk-informed asset management progress, the LWRS collaboration is planning to work with both host utilities to coordinate activities to more fully integrate the approaches to the greatest extent practicable. Some key areas where these collaborations are anticipated to occur are the following:

- Evaluation of the impact of short to intermediate term investments on long-term system performance including potential impacts on plant risk (both safety and economic) and impacts on long term capital investment needs
- Evaluation of the impact of long-term investment alternatives system performance, particularly with respect to the impacts of investment limitations and deferrals on plant risk (both safety and economic).

In [31] we have started the development of a Risk Informed Plant System Health (RI-PSH) framework which would automatize data and model sharing among plant organizational structures by including:

1. *Data* generated by plant SSCs
2. *Models* and data pre-processing functions

3. *Algorithms* which employs data and models to provide services.

As shown in Figure 11: from plant data, the RI-PSH provides risk knowledge from a safety regulatory and economical perspective. In addition, it provides a set of suggested actions such as optimal PM/surveillance frequency and replacement/procurement scheduling. The RIAM project fits in the SSC replacement/procurement scheduling: data streaming from plant PHM monitors and risk data are used to determine the best SSC procurement and replacement schedule.

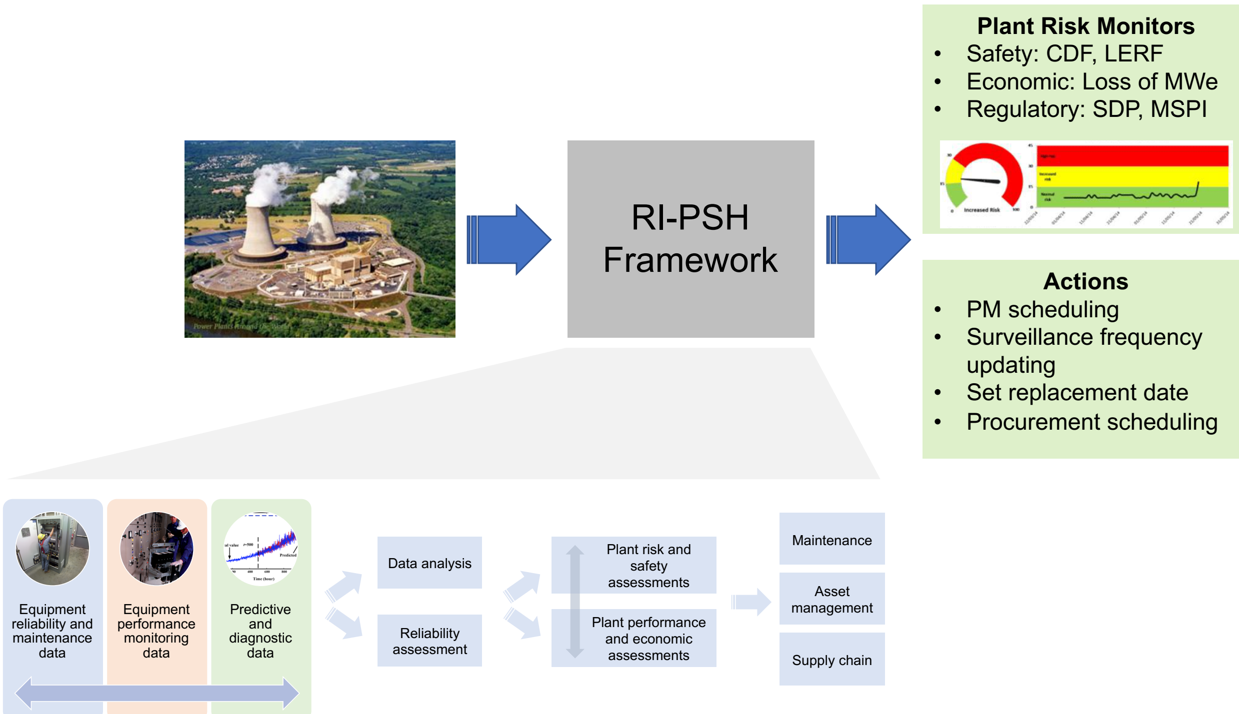

Figure 11. Graphical representation of the RI-PSH framework [31].

13. FUTURE WORK

The activities presented in this report focused mainly on capital SSC replacement scheduling in view of plant SLR planning. These kinds of optimization problems can be extended to different aspects of plant operations management such as maintenance and supply chain management (see Figure 12). In this respect, in the next years we are planning to perform the following:

- Finalize the development of the methods designed for SSC replacement scheduling optimization
- Link developed methods for SSC replacement with the EPRI ILCM code
- Extend methods development to plant operations activities (e.g., maintenance and surveillance)
- Direct integration of plant risk models (e.g., PRA and Generation Risk Assessment - GRA) into optimization analyses
- Integration of economic models regarding market energy price and plant internal cost models such as supply-chain models

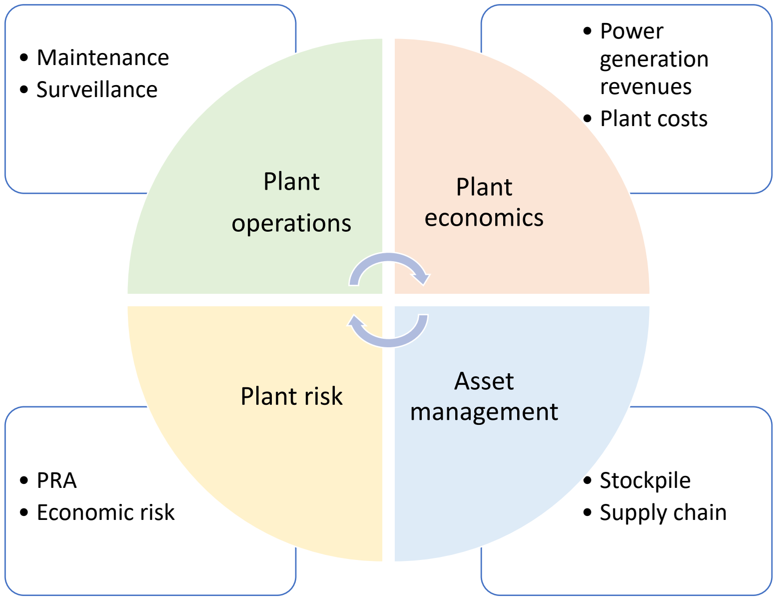

Figure 12. Future vision for RIAM project.

14. CONCLUSIONS

This report has summarized the research activities conducted during FY19 for the RIAM project. This project started with the goal of developing models and methods to optimize capital SSC replacement schedules for SLR types of applications. In this respect we have developed several classes of models which address several variants of schedule optimization problems. Depending on the type of constraints and degrees of freedom, the most appropriate model can be chosen and employed.

We then proceeded to implement such models into software products by employing the PYOMO library available for the PYTHON language. Such software models can be also employed within the RAVEN statistical framework to create complex coupled reliability economic models. As an example, we have shown how it is possible to link project NPV and system/component reliability models to the optimization models by employing the RAVEN EnsembleModel feature. In addition, RAVEN also can be employed to propagate data and model uncertainties and evaluate sensitivity of the obtained optimized schedule to a variation of the input parameters. As part of the development, we have performed several numerical tests to benchmark the developed software products on several example use cases.

A set of example test cases has been presented in order to show the developed capabilities. In this respect we have shown a set of use cases that framed a few examples of project scheduling optimization problems with different boundary conditions in terms of project constraints. The objective of these use cases is to show how these models can be used at different phases of the capital SSC replacement planning process.

As a last comment on this work, we want to highlight the long-term vision for this project which aims to link in a single analysis framework plant safety, efficiency, reliability and economics. Such vision is shared by another LWRS-RISA project, the PHM project, which focuses on the management of plant/system/component health. In this respect the PHM activities target generation of health information which can be used by the RIAM activities to manage and optimize available resources.

REFERENCES

[1] R. Szilard, H. Zhang, S. Hess, J. Gaertner, D. Mandelli, S. Prescott, M. Farmer, "RISA Industry Use Case Analysis," INL Technical Report INL/EXT-18-51012 (2018).

[2] S. A. Ross, R. W. Westerfield, and B. D. Jordan, *Fundamentals of Corporate Finance 8th edition*, McGraw-Hill (2008).

[3] H. Bierman, S. Smidt, *The Capital Budgeting Decision: Economic Analysis of Investment Projects 5th edition*, Macmillan Publishing Co. New York (1980).

[4] G. G. Brown, R. F. Dell, A. M. Newman, "Optimizing Military Capital Budgeting," *Interfaces*, **34**, no. 6, pp. 415-425 (2004).

[5] H. M. Weingartner, "Capital Budgeting of Interrelated Projects: Survey And Synthesis," *Management Science* **12**, pp. 485-516 (1966).

[6] H. Meier, N. Christofides, G. Salkin, "Capital Budgeting Under Uncertainty-An Integrated Approach Using Contingent Claims Analysis and Integer Programming," *Operations Research*, **49**, no. 2, pp. 196-206 (2001).

[7] A. Koc, D. P. Morton, E. Popova, S. M. Hess, E. Kee, D. Richards, "Prioritizing Project Selection," *The Engineering Economist*, **54**, no. 4, pp. 267-297 (2009).

[8] A. Koc, D. Morton, "Prioritization via Stochastic Optimization," *Management Science*, **61**, no.3, pp. 586-603 (2016).

[9] Institute of Nuclear Power Operations (INPO), "AP-913 - Equipment Reliability Process Description, Revision 6," Washington, DC (2018) (limited distribution).

[10] Status of Initial License Renewal Applications and Industry Initiatives; U.S. NRC Website; https://www.nrc.gov/reactors/operating/licensing/renewal/applications.html (Accessed 5 August 2019).

[11] Nuclear News; May 2019; p. 10, American Nuclear Society, Lagrange Park, IL.

[12] Electric Power Research Institute (EPRI), "Risk-Informed Asset Management (RIAM) Development Plan," EPRI Report 1006268, Palo Alto, CA (2002).

[13] Electric Power Research Institute (EPRI), "Risk-Informed Asset Management (RIAM): Method, Process, and Business Requirements," EPRI Report 1009632, Palo Alto, CA (2005).

[14] J. P. Gaertner, S. M. Hess; "Managing Risks Associated with Long Term Operations"; Proceedings of 2009 American Nuclear Society Risk Management Embedded Topical Meeting Washington, DC (2009).

[15] Institute of Nuclear Power Operations (INPO), "AP-913 - Equipment Reliability Process Description, Revision 6," Washington, DC (2018) (limited distribution).

[16] Nuclear Energy Institute (NEI), "AP-940 - Nuclear Asset Management: Process Description and Guideline," Washington, DC (2005) (limited distribution).

[17] Electric Power Research Institute (EPRI), "Integrated Life Cycle Management: Status Report," EPRI Report 1021188 (2010).

[18] R. Szilard, H. Zhang, S. Hess, J. Gaertner, D. Mandelli, S. Prescott, M. Farmer, "RISA Industry Use Case Analysis," INL Technical Report INL/EXT-18-51012 (2018).

[19] S. M. Hess, C. A. Mengers, "Integrated Life Cycle Management for Nuclear Power Plant Long Term Operation," *Probabilistic Safety Assessment and Management PSAM 12*, Honolulu, HI (2014).

[20] J. Longchampt, W. Lair, "Risk-Informed Simulation Optimization for Engineering Asset Management," *Probabilistic Safety Assessment and Management PSAM 12*, Honolulu, HI (2014).

[21] J. Longchampt, K. Fessart, "On the Use of Genetic Algorithm to Optimize Industrial Assets Lifecycle Management Under Safety and Budget Constraints," *Proceedings of American Nuclear Society Mathematics and Computation M&C 2013 Conference*, Sun Valley, ID (2013).

[22] J.C. Hartman, *Engineering Economy and the Decision-Making Process*, Prentice-Hall Inc., Upper Saddle River, NJ (2007).

[23] H. Bierman Jr. and S. Smidt, *The Capital Budgeting Decision*, Macmillan Publishing Co., New York, Fifth Edition (1980).

[24] H.M. Weingartner, "Capital Budgeting of Interrelated Projects: Survey and Synthesis," *Management Science*, **12**, pp. 485–516 (1966).

[25] A. Koc, D. Morton. E. Popova, S. M. Hess, E. Kee, D. Richards, "Prioritizing Project Selection," *The Engineering Economist*, **54**, (2009)

[26] D. Morton, A. Koç, S. Hess, "Application of Stochastic Optimization to Nuclear Power Plant Asset Management Decisions," *Proceedings of American Nuclear Society Mathematics and Computation M&C 2013 Conference*, Sun Valley, ID (2013).

[27] GAMS. 2019. https://www.gams.com.

[28] W. E. Hart, J.-P. Watson, "PYOMO: Modeling and Solving Mathematical Programs in Python," *Mathematical Programming Computation*, **219**, no. 3 (2011).

[29] R. Barlow, L. Hunter, "Optimum Preventive Maintenance Policies," *Operations Research*, **8**, no. 1, pp. 90-100 (1960).

[30] Electric Power Research Institute (EPRI), "Integrated Life Cycle Management: Status Report," EPRI Report 1021188 Palo Alto, CA (2010).

[31] D. Mandelli, Z. Ma, R. Youngblood, S. St Germain, P. Talbot, S. Hess, D. Dube, C. Pope, J. Miller, M. Robbins, D. Das, M. Azarian, J. Coble, "Plant Integral Risk-informed System Health Program," INL Technical Report INL-EXT-19-55808 (2019).

[32] Institute of Nuclear Power Operations (INPO), "AP-913 - Equipment Reliability Process Description, Revision 6," Washington, DC (2018) (limited distribution).

[33] Nuclear Energy Institute (NEI), "Industry Guideline for Monitoring the Effectiveness of Maintenance at Nuclear Power Plants," NEI Report NUMARC 93-01, Rev. 4F, Washington, DC (2018).

[34] Nuclear Energy Institute (NEI), "Regulatory Assessment Performance Indicator Guideline, Revision 7," NEI Report 99-02 Washington, DC (2013) (https://www.nrc.gov/docs/ML1326/ML13261A116.pdf).

[35] Electric Power Research Institute (EPRI), "Plant Engineering: 2018 Complete Product List," EPRI Report 3002007859 Palo Alto, CA (2019).

Appendix A

DETERMINISTIC CAPITAL BUDGETING EXAMPLE

This appendix sketches a deterministic capital budgeting example from the literature [7]. The goal of using this example was to first reproduce results in the literature to support verification of our software implementation, and then to extend the models in a known setting to test new features described in the report. The set of projects are listed in Table 37 [7].

Table 37. Set of projects chosen for the deterministic capital budgeting example.

ID	System
1	Feedwater heater replacement
2	Emergency sump overhaul
3	Transformer replacement
4	Replace turbine-hall crane
5	Replacement of four reactor coolant pumps
6	Corrosion mitigation of buried piping
7	Refurbish turbine governors
8	Service circulation water pumps
9	Maintain RAOC system
10	Replace piping in high-pressure coolant injection system
11	Replace chiller
12	Vessel-head welding remediation
13	Maintain main condenser
14	Replace instrumentation and control cables
15	Upgrade power feeds to large cranes
16	Replace moisture separator reheater

Candidate projects:

Set I :=

FeedwaterHeater

EmergencySump

…

CranePowerFeed

MoisterSeparatorReheater

;

Project options:

Set J := PlanA PlanB DoNothing ;

This set includes all possible options for any project. If a plan could be done in a piggybacking manner, i.e., contingent on another project, then that could be included as another option in this set, but we haven't included that in this example. In the current example, we associate PlanA with the initial timing of the projects. PlanB can be considered as the timing option where we shift some of the projects starting time by, e.g., one year in the future.

Project-option pairs:

Set IJ :=

FeedwaterHeater PlanA

FeedwaterHeater PlanB

FeedwaterHeater DoNothing

EmergencySump PlanA

EmergencySump DoNothing

…

CranePowerFeed PlanA

CranePowerFeed PlanB

MoisterSeparatorReheater PlanA

;

Note that there are "Plan A", "Plan B", and "Do nothing" options for the first project, "Plan A" and "Do nothing" options for the second project, and there is no "Do nothing" option for the final two projects. The first nine projects include do-nothing options, and the last seven projects are projects that must be done for safety reasons, and hence none of these include the do-nothing option. Note that there are two options for how the penultimate project can be performed, but there's only one option for the final project. Similarly, the second project has no "Plan B" option.

Resources:

Set K := CapitalFunds OandMFunds ;

The example distinguishes two colors of money, capital funds and O&M funds. Additional types of resources could include labor-hours and time during outage.

Time periods:

Set T := year1 year2 year3 year4 year 5;

NPV:

param a :=

FeedwaterHeater PlanA 2.315

FeedwaterHeater PlanB 2.205

FeedwaterHeater DoNothing -1.101

EmergencySump PlanA 0.824

EmergencySump DoNothing -0.400

…

```
CranePowerFeed PlanA -0.246
CranePowerFeed PlanB -0.258
MoisterSeparatorReheater PlanA -20.155
;
```

Budget:

```
param b :=
CapitalFunds year1 0.665
CapitalFunds year2 4.686
CapitalFunds year3 6.725
CapitalFunds year4 0.539
CapitalFunds year5 0.500
OandMFunds year1 0.000
OandMFunds year2 2.027
OandMFunds year3 4.917
OandMFunds year4 3.320
OandMFunds year5 1.683
;
```

Cost:

```
param c :=
FeedwaterHeater PlanA CapitalFunds year1 0.219
FeedwaterHeater PlanA CapitalFunds year2 0.257
FeedwaterHeater PlanA OandMFunds year3 0.085
FeedwaterHeater PlanB CapitalFunds year2 0.219
FeedwaterHeater PlanB CapitalFunds year3 0.257
FeedwaterHeater PlanB OandMFunds year4 0.085
FeedwaterHeater DoNothing OandMFunds year1 0.000
FeedwaterHeater DoNothing OandMFunds year2 0.000
FeedwaterHeater DoNothing OandMFunds year3 0.000
FeedwaterHeater DoNothing OandMFunds year4 0.000
FeedwaterHeater DoNothing OandMFunds year5 0.000
…
;
```

The displayed rows concern the first project. Plan A amounts to doing the project over years 1 and 2 with O&M costs incurred in year 3, and plan B is identical except shifted to years 2 and 3 with O&M costs incurred in year 4. The costs incurred in all years that are not listed are zero; i.e., this format allows for sparse data entry. The FeedwaterHeater-DoNothing pair incurs no costs for capital funds (not listed), and similarly incurs no O&M costs (listed explicitly so it is clear these costs truly are meant to be zero) but incurs a negative NPV of -1.101 as indicated earlier.

Deterministic Capital Budgeting Input Data:

We show numerical results for four different cases:

Case 1: This is the simplest case, where optimal project selection is done using PlanA and DoNothing options and one resource based on CapitalFunds

Note that this is the example from [7], but instead of using the nine projects with positive NPV values, we have extended the model by explicitly entering all sixteen projects, and for the mandatory projects there is no DoNothing option. In other words, the last seven projects must be selected.

Case1-2: This case extends Case1 by adding a second option, PlanB. This option is a timing option, where we shift the starting year for some of the projects

Case 2-1: This case extends Case 1 by adding a second source of funding, OandMFunds

Case 2: This case extends the analysis done in Case 1 by allowing a both second option, PlanB, and a second type of resource, OandMFunds. PlanB shifts the starting time for some of the projects to one year later. The costs and budgets are split between the two available resources CapitalFunds and OandMFunds.

Software Implementation and Verification:

Note that cases 1-2, 2-1 and 2 are new, and there are no published results for such cases in the academic literature. However, as a means of verification of our implementation, we use the same PYOMO [28] code that does replicate the results from Table 2 of the paper [7]. Moreover, for all optimization results described in this report, we have independently implemented the models in code via both PYOMO with the CBC solver and GAMS [27] to cross-validate the results. Taken together, these lend credibility to correctness of the results reported here.

Deterministic Capital Budgeting Output:

Output from PYOMO for all four cases can be found in the Appendix (Optimal Output Case1, Optimal Output Case 1-2, Optimal Output Case 2-1 and Optimal Output Case 2). Note that the CBC solver automatically converts the objective function into minimization, so the optimal objective values printed are the minimums not maximums. We show a summary table with the optimal results.

Table 38. Results for deterministic capital budgeting example for four cases built from [7].

		Column 1	Column 2
Project Number from Koc et al. (2009)	**Project Name**	**PlanA, CapitalFunds optimal total NPV = -68.432**	**PlanA, PlanB, CapitalFunds optimal total NPV = -36.095**
1	FeedwaterHeater	PlanA, CapitalFunds	PlanB, CapitalFunds
2	EmergencySump	PlanA, CapitalFunds	PlanA, CapitalFunds
3	Transformer		PlanA, CapitalFunds
4	TurbineHallCrane		
5	ReactorCoolantPumps	PlanA, CapitalFunds	PlanA, CapitalFunds
6	MitigateBuriedPiping		
7	RefurbishTurbineGovernors		
8	ServiceCircWaterPumps	PlanA, CapitalFunds	PlanB, CapitalFunds
9	MaintainRAOC		PlanA, CapitalFunds
10	ReplaceCoolantInjectPiping	PlanA, CapitalFunds	PlanA, CapitalFunds
11	ReplaceChiller	PlanA, CapitalFunds	PlanB, CapitalFunds
12	VessellHeadWeldRemediate	PlanA, CapitalFunds	PlanB, CapitalFunds
13	MaintainCondensor	PlanA, CapitalFunds	PlanB, CapitalFunds
14	ReplaceConrolCables	PlanA, CapitalFunds	PlanB, CapitalFunds
15	CranePowerFeed	PlanA, CapitalFunds	PlanB, CapitalFunds
16	MoisterSeparatorReheater	PlanA, CapitalFunds	PlanA, CapitalFunds
		Column 3	**Column 4**
Project Number from Koc et al. (2009)	**Project Name**	**PlanA, CapitalFunds, OandMFunds optimal total NPV = -68.432**	**PlanA, PlanB, CapitalFunds, OandMFunds optimal total NPV = -60.852**
1	FeedwaterHeater	PlanA, CapitalFunds, OandMFunds	PlanA, CapitalFunds, OandMFunds
2	EmergencySump	PlanA, CapitalFunds, OandMFunds	PlanA, CapitalFunds, OandMFunds
3	Transformer		
4	TurbineHallCrane		
5	ReactorCoolantPumps	PlanA, CapitalFunds	PlanA, CapitalFunds
6	MitigateBuriedPiping		PlanB, CapitalFunds, OandMFunds
7	RefurbishTurbineGovernors		
8	ServiceCircWaterPumps	PlanA, OandMFunds	PlanA, OandMFunds
9	MaintainRAOC		PlanA, CapitalFunds, OandMFunds
10	ReplaceCoolantInjectPiping	PlanA, CapitalFunds	PlanA, CapitalFunds
11	ReplaceChiller	PlanA, CapitalFunds	PlanA, CapitalFunds
12	VessellHeadWeldRemediate	PlanA, CapitalFunds	PlanA, CapitalFunds
13	MaintainCondensor	PlanA, CapitalFunds	PlanA, CapitalFunds
14	ReplaceConrolCables	PlanA, CapitalFunds	PlanB, CapitalFunds, OandMFunds
15	CranePowerFeed	PlanA, CapitalFunds	PlanA, CapitalFunds
16	MoisterSeparatorReheater	PlanA, CapitalFunds	PlanA, CapitalFunds

Case 1 is reported in column 1 and shows that projects 1, 2, 5, and 8 were selected, as well as all the seven mandatory projects, i.e., projects 10-16. The obtained results are identical to the results from Table 2 in ref. [7], which can be used as a benchmark.

Case 1-2, which allows for performing a project using Plan A or Plan B, and the results are reported in column 2. Comparing columns 1 and 2 illustrates that delaying project 1, 8 and 11-15 frees up funds that enable two additional projects, 3 and 9. Even though we obtain lower NPVs for 1, 8, and 11-15, the new projects bring significant NPV, and as a result the overall NPV grows.

Case 2-1 is identical to Case 1 with the only option being Plan A, but it models capital funds and O&M funds separately. When comparing columns 1 and 3, we have essentially split the CapitalFunds and

OandMFunds and the costs associated with the projects so that the same solution is optimal. In general, the NPV could have degraded, but in this case it did not because O&M costs and budgets are well aligned.

Finally, column 4 represents the most general case (Case 2) in which we have both Plan A and Plan B options and the capital and O&M funds are also distinguished. Comparing columns 2 and 4 is analogous to comparing columns 1 and 3, except this time NPV degrades quite a bit. Of course, a manager would rather have all of the budget aggregated into one pot because it can provide valuable flexibility, and this lack of flexibility decreased significantly in moving from the results of column 2 to those of column 4.

Appendix B

STOCHASTIC CAPITAL BUDGETING EXAMPLE

In this appendix, we use the problem shown in [7] to illustrate simple example input for the stochastic optimization problem of Section 6.2. Some of the projects have negative NPVs because their inclusion is managerially mandated. For the illustrative example we use the projects with positive NPVs only, and we adjust the budget to reflect the mandatory inclusion of the negative NPVs projects. The actual dollar values of the costs are changed in order not to reveal specific power plant information. Table 3938 and Table 4039 show the problem input data.

Table 39. Capital cost values for the problem shown in [7].

Project	Year 1	Year 2	Year 3	Year 4	Year 5	NPV (ai)
1a	0.219	0.257	0.085	0.000	0.000	2.315
1b	0.000	0.219	0.257	0.085	0.000	2.105
1c	0.000	0.000	0.000	0.000	0.000	-1.101
2a	0.000	0.000	0.122	0.103	0.013	0.824
2b	0.000	0.122	0.103	0.013	0.000	0.911
3	5.044	1.839	0.000	0.000	0.000	22.459
4	6.740	6.134	10.442	0.000	0.000	60.589
5	0.425	0.000	0.000	0.000	0.000	0.667
6	2.125	2.122	0.000	0.000	0.000	5.173
7	2.387	0.190	0.012	2.383	0.192	4.003
8a	0.950	0.000	0.000	0.000	0.000	0.682
8apig	0.050	0.000	0.000	0.000	0.000	1.582
8b	0.000	0.950	0.000	0.000	0.000	0.582
8bpig	0.000	0.050	0.000	0.000	0.000	1.482
9	0.030	0.030	0.688	0.000	0.000	0.122
10	0.000	0.200	0.763	0.739	2.539	-2.870
11	0.081	0.032	0.000	0.000	0.000	-0.102
12	0.300	0.000	0.000	0.000	0.000	-0.278
13	0.347	0.000	0.000	0.000	0.000	-0.322
14	4.025	0.297	0.000	0.000	0.000	-3.996
15	0.095	0.095	0.095	0.000	0.000	-0.246
16	5.487	5.664	0.500	6.803	6.778	-20.155

Table 40. O&M cost values for the problem shown in [7].

Project	Year 1	Year 2	Year 3	Year 4	Year 5
1a	0.000	0.000	0.000	0.000	0.000
1b	0.000	0.000	0.000	0.000	0.000
1c	0.000	0.000	0.000	0.000	0.100
2a	0.000	0.000	0.122	0.103	0.013
2b	0.000	0.122	0.103	0.013	0.000
3	5.044	1.839	0.000	0.000	0.000
4	6.740	6.134	10.442	0.000	0.000
5	0.425	0.000	0.000	0.000	0.000
6	2.125	2.122	0.000	0.000	0.000
7	2.387	0.190	0.012	2.383	0.192
8a	0.950	0.000	0.000	0.000	0.000
8apig	0.050	0.000	0.000	0.000	0.000
8b	0.000	0.950	0.000	0.000	0.000
8bpig	0.000	0.050	0.000	0.000	0.000
9	0.030	0.030	0.688	0.000	0.000
10	0.000	0.200	0.763	0.739	2.539
11	0.081	0.032	0.000	0.000	0.000
12	0.300	0.000	0.000	0.000	0.000
13	0.347	0.000	0.000	0.000	0.000
14	4.025	0.297	0.000	0.000	0.000
15	0.095	0.095	0.095	0.000	0.000
16	5.487	5.664	0.500	6.803	6.778

Appendix C

RAVEN

RAVEN, currently under development at Idaho National Laboratory (INL), is a flexible and multi-purpose Uncertainty Quantification (UQ), regression analysis, PRA, data analysis and model optimization software. The framework is capable of constructing the analysis/calculation flow at run-time, interpreting the user-defined instructions and assembling the different analysis tasks following a user specified scheme. In this report, RAVEN will be mainly used to:

- provide stochastic analysis engines
- assess the economic risk of SSCs
- create user specified analysis flows
- determine the best overall portfolio for capital budgeting problems

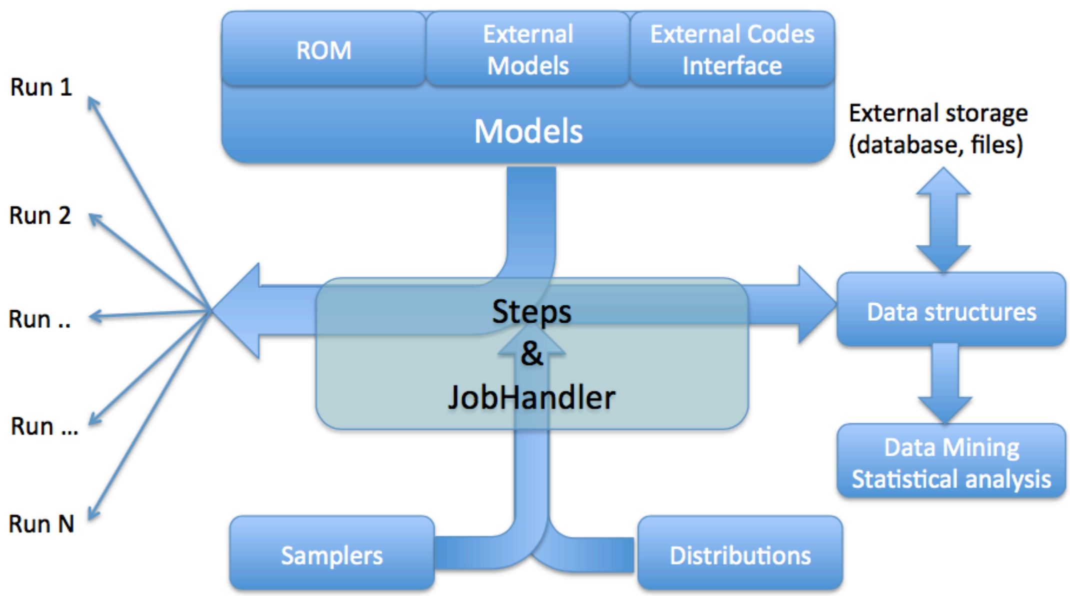

Figure 13. RAVEN abstracted module scheme.

As shown in Figure 13, RAVEN provides a set of capabilities to build analysis flows. *Distributions and Samplers* are used to perturb the input parameters of SSCs, while the models SSCs are perturbed and integrated through the *Models* entity. The parallel dispatching is properly handled by the *Steps and JobHandler*, and the data generated from the *Models* can be analyzed using both classical statistical and more advanced data mining approaches. In addition, automated regression testing system is employed for any development process to assure the quality of the software produced.

Stochastic Analysis Capabilities in RAVEN

The stochastic analysis capabilities, i.e. sampling strategies, inside RAVEN can be used to perform risk/uncertainty analysis for capital budgeting problems. RAVEN provides both classical and advanced sampling strategies to perform uncertainty quantification and dynamic probabilistic risk assessment (DPRA). The most widely used strategies are generally collected in RAVEN as Forward samplers. These strategies sample without exploiting, through learning approaches, the information made available from the outcomes of evaluation previously performed and common system evolution that different calculations can generate in the phase space. RAVEN has several different forward samplers:

- **Monte-Carlo**: approximates the average response of multiple figure of merits relying on multiple random sampling of the input space. It is based on the laws of large numbers in order to approximate the expectations.
- **Grid**: discretizes the domain of the uncertainties in a user-defined number of intervals and record the response of the model at each coordinate of the grid. This method is mainly used to perform parametric analysis of the system response.
- **Stratified including Latin Hyper Cube**: assumes the input space can be separated in regions based on similarity of the responses of the system. The Latin Hyper-cube sampling represents a specialized version of the stratified approach, when the domain strata are constructed in equally probable cumulative distribution function bins.

In addition, RAVEN provides advanced forward sampling strategies including:

- **Sparse Grid Collocation**: builds a grid in the input space selecting evaluation points based on characteristic quadratures as part of stochastic collocation for generalized polynomial chaos method
- **Sobol**: uses high-density model reduction (HDMR) to approximate a function as the sum of interactions with increasing complexity.

To overcome the large number of model evaluations caused by forward sampling strategies, RAVEN also provides several adaptive algorithms that are designed to leverage the information content from previous simulations:

- **Limit Surface Search**: identifies the reliability surface using smart sampling strategy around the transition zones of the system.
- **Adaptive Dynamic Event Tree**: performs dynamic probability risk assessment over aleatory uncertain space.
- **Adaptive Hybrid Dynamic Event Tree**: represents an evolution of the Dynamic Event Tree method for the simultaneous exploration of the epistemic and aleatory uncertain space. The epistemic space is sampled by the Monte-Carlo/Grid-based approach and the aleatory space is exploited by the Dynamic Event Tree.
- **Adaptive Sparse Grid Collocation**: employs an intelligent search for the most suitable sparse grid quadrature to characterize a model.
- **Adaptive Sobol**: decomposes an uncertainty space into subsets and adaptively includes the most influential ones.

Ensemble Modeling in RAVEN

Ensemble modeling in RAVEN is a process where multiple diverse models are coupled with each other to compute the responses of interest. A model entity named *EnsembleModel* is used to assemble multiple models of other categories (i.e. Code, External Model and Reduced Order Models), identifying the input/output connections, and, consequentially the order of execution and which sub-models can be executed in parallel. Two simple structured coupling are provided in Figure 14 and Figure 15 for serial sequential coupling and coupling with feedbacks, respectively. The *EnsembleModel* entity in RAVEN is made to be able to detect any dependent model connections and activate the non-linear solver to resolve the feedbacks in the coupled system.

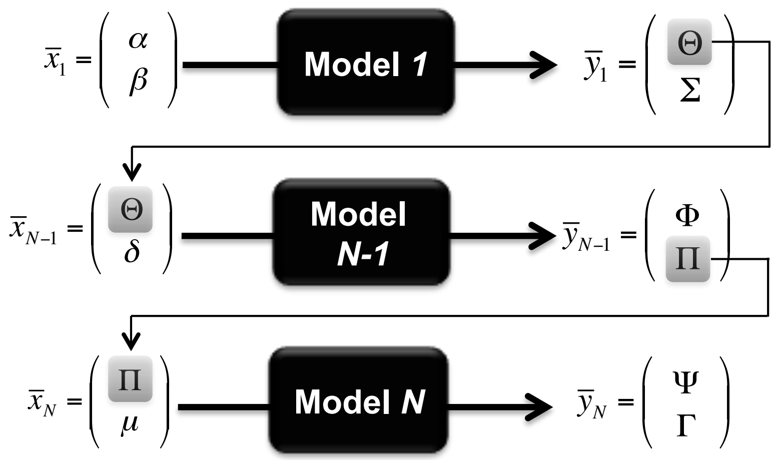

Figure 14. Example of an EnsembleModel constituted by 3 sequential sub-models.

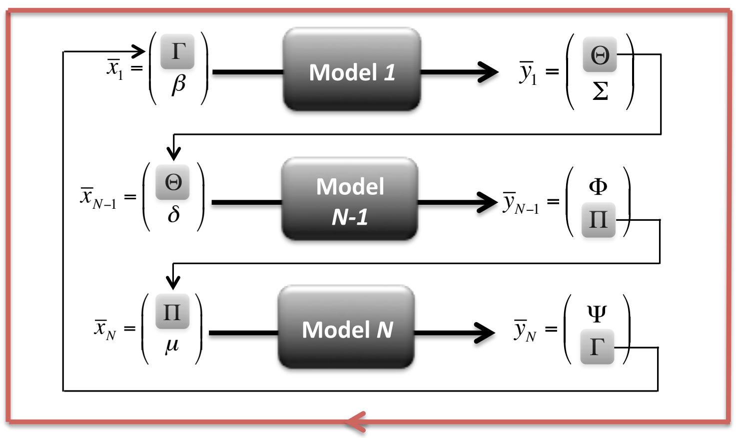

Figure 15. EnsembleModel resolving in a non-linear system of equations.

In RAVEN all the models' outputs (e.g. whatever code output, etc.) are collected in internal containers (named *DataObjects*) that are aimed to store time-series and input/output data relations in a standardized fashion; in this way, the communication of the output information among different entities (i.e. Models) can be completely agnostic with respect to the particular type of output generated by a model. As shown in Figure 16, the *EnsembleModel* entity fully leverages this peculiarity in order to transfer the data from a Model to the other(s). Based on the Input/Output relations of each sub-models, the *EnsembleModel* entity constructs the order of their execution and, consequentially, the links among the different entities.

When considering economical models for each candidate projects, the NPV values calculated from these models will be provided to capital budgeting model. In this case, *EnsembleModel* from RAVEN will be used to combine these models, identifying the connections, and, consequentially the order of execution and which sub-models can be executed in parallel.

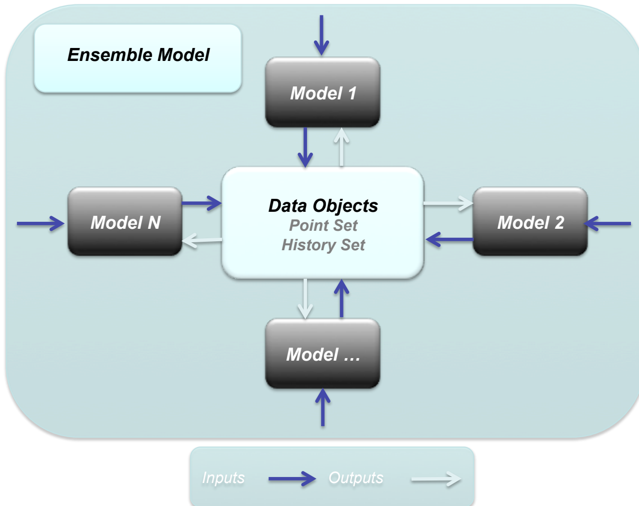

Figure 16. EnsembleModel data exchange.

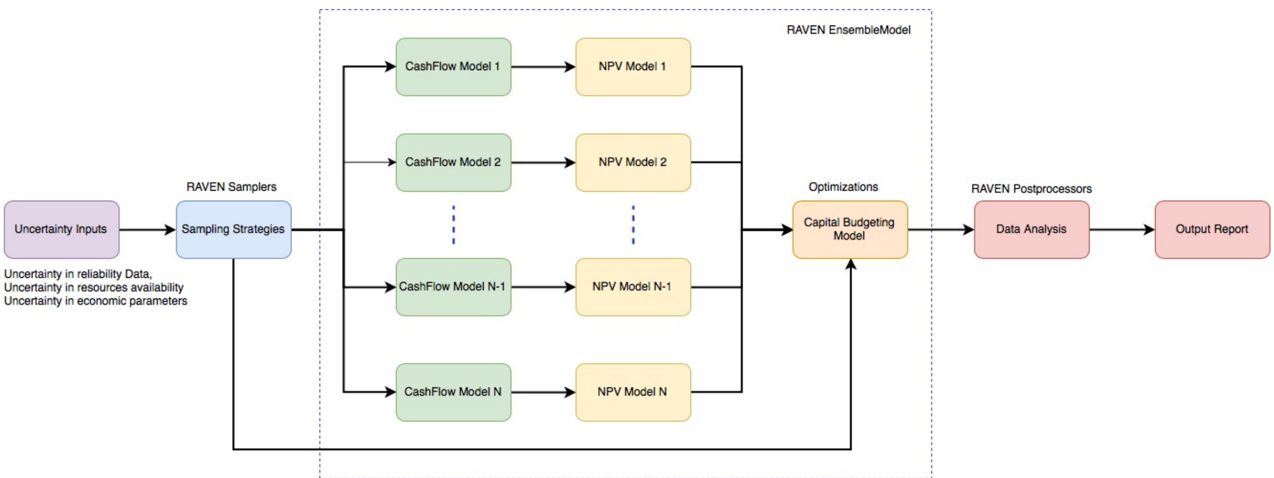

Figure 17. Ensemble model for capital budgeting analysis.

As shown in Figure 17, the risk/uncertainty in the safety/economical parameters will be sampled by RAVEN and provided to the *EnsembleModel*. As it can be noticed:

- The sampled safety/economical parameters will be passed to the *CashFlow models* to compute the net cash flows;
- The net cash flows will be passed to *NPV models* to compute NPV for each candidate projects;
- The *Capital Budgeting model* is connected with the *NPV models* via the NPVs to compute the optimal portfolio of projects;

In addition, advanced data analysis techniques from RAVEN will be used to compute NPV at risk, risk-informed priority list of projects, etc.

Advanced Data Analysis Capabilities in RAVEN

RAVEN provides both basic statistical analysis and advanced data mining analysis capabilities. Data mining is a generic concept that entails the generation of information/knowledge from data sets. The overall goal of data mining is to extract information from a dataset and transform it into understandable structure.

The full list of data mining approaches is present in RAVEN user manual. The following are list of techniques that can be used for capital budgeting:

- Basic statistical relational analysis, such as covariance, correlation, sensitivity analysis
- Clustering: partition the data based on a set of defined similarity measures, including K-Means, Density-Based Spatial Clustering of Applications with Noise (DBSCAN), etc.

Appendix D

CASHFLOW PLUGIN

The CashFlow plugin distributed with RAVEN is employed to compute the NPV or internal rate of return (IRR) of SSC's replacement. The bottom-up cash flow calculations including incremental, capex and amortization are shown in Figure 18, and the total NPV or IRR of given system will be computed and available for other RAVEN entities.

Notation

R: discount rate

x: multiplicative factor

N: project lifetime

C_0: initial cash inflow

C_t: net cashflow at year t

C_t^x: cashflow depend on x

C_t^o: cashflow not depend on x

The main capabilities of CashFlow plugin include:

1) NPV calculation:

$$NPV = \sum_{t=0}^{N} \frac{C_t}{(1+R)^t} \tag{D.1}$$

2) Internal Rate of Return (IRR) calculation: similar to NPV except that the discount rate is the rate that reduces the NPV of an investment to zero. This method is used to compare projects with different lifespans or amount of required capital

$$IRR = NPV = \sum_{t=0}^{N} \frac{C_t}{(1+R)^t} = \sum_{t=1}^{N} \frac{C_t}{(1+R)^t} - C_0 = 0 \tag{D.2}$$

3) Profitability Index (PI) calculation

$$PI = 1 + \frac{NPV}{Initial\_investment} \tag{D.3}$$

4) NPV search, i.e. CashFlow plugin will compute a multiplicative value so that the NPV has a desired value:

$$desired\ value = \sum_{t} \frac{C_t^x}{(1+R)^t} x + \sum_{t} \frac{C_t^o}{(1+R)^t} \tag{D.4}$$

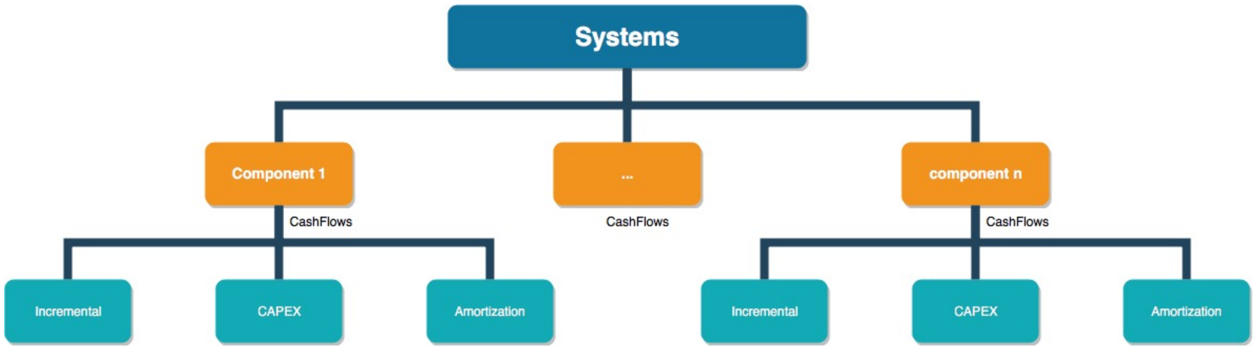

Figure 18. Structure of CashFlow plugin.

Appendix E

RIAM REPOSITORY

The infrastructure of the GitLab repository hosting the software developed for RIAM, i.e. **Logos S**afety, **R**isk, **R**eliability and **H**ealth **M**anagement toolkit (SR2HM), has been built (see Figure **19**19). The current capabilities of **Logos/SR2HM** include:

- Probability risk assessment
  - Event tree model: designed to read from OpenPSA format file of the event tree and construct a RAVEN external model with given Boolean logic structure.
  - Fault tree model: designed to read from OpenPSA format file of the fault tree and construct a RAVEN external model with given Boolean logic structure.
  - Markov Model with generic Markov chain
  - Reliability block diagram model
- Risk-informed asset management
  - Deterministic capital budgeting
  - Optimal project prioritization with stochastic capital budgeting
  - Multi-choice capital budgeting
- Risk-informed economic analysis, i.e. NPV at risk, risk-adjusted NPV etc.
  - Replacement models for SSCs

In this section, we will not provide the detailed algorithms implemented for RIAM capital budgeting problem, while this information can be found in the appendix. In addition, the automated regression testing system of RAVEN is used to ensure that independent software developments will not interfere with one another. A set of challenging tests have been performed to demonstrate the capability of the simulation framework and to characterize the behavior of RIAM. Up to this point coverage of the regression testing system has been made to all developed algorithms.

Test Automation

Automated regression testing is a development methodology that is generally used to verify the correctness and performance of software after each modification. This methodology is integrated directly into GitHub and GitLab for RAVEN and RAVEN supported Plug-Ins. In this case, testing is performed automatically as part of the continuous integration system (CIS) process when a user commits a change to the repository. Tests of changes across multiple platforms are executed with each pull request. Results from each test execution are maintained in the CIS database, in an approved records repository along with results from the timing executions.

Testing System Prerequisites

The module test system consists of scripts written in the bash shell language and Python. It may be used on any platform that is supported by RAVEN (i.e. Linux, Mac, and Windows). The following conditions must be satisfied for the module test system to function properly:

1. RAVEN should be installed and updated. This is because RAVEN is used to run the module tests;
2. The system running the tests must be configured with the software prerequisites necessary to build and run RAVEN. These include a Python interpreter, Python libraries (h5py, matplotlib, numpy,

scipy, and scikit-learn), and development tools (C++ compiler, Miniconda package manager for Python, and git source code control);
3. RAVEN must be built with the appropriate compiler before it can be used to run the tests;
4. The **Logos/SR2HM** submodule must be initialized and fully updated. Addition prerequisites include PYOMO, glpk and coincbc;

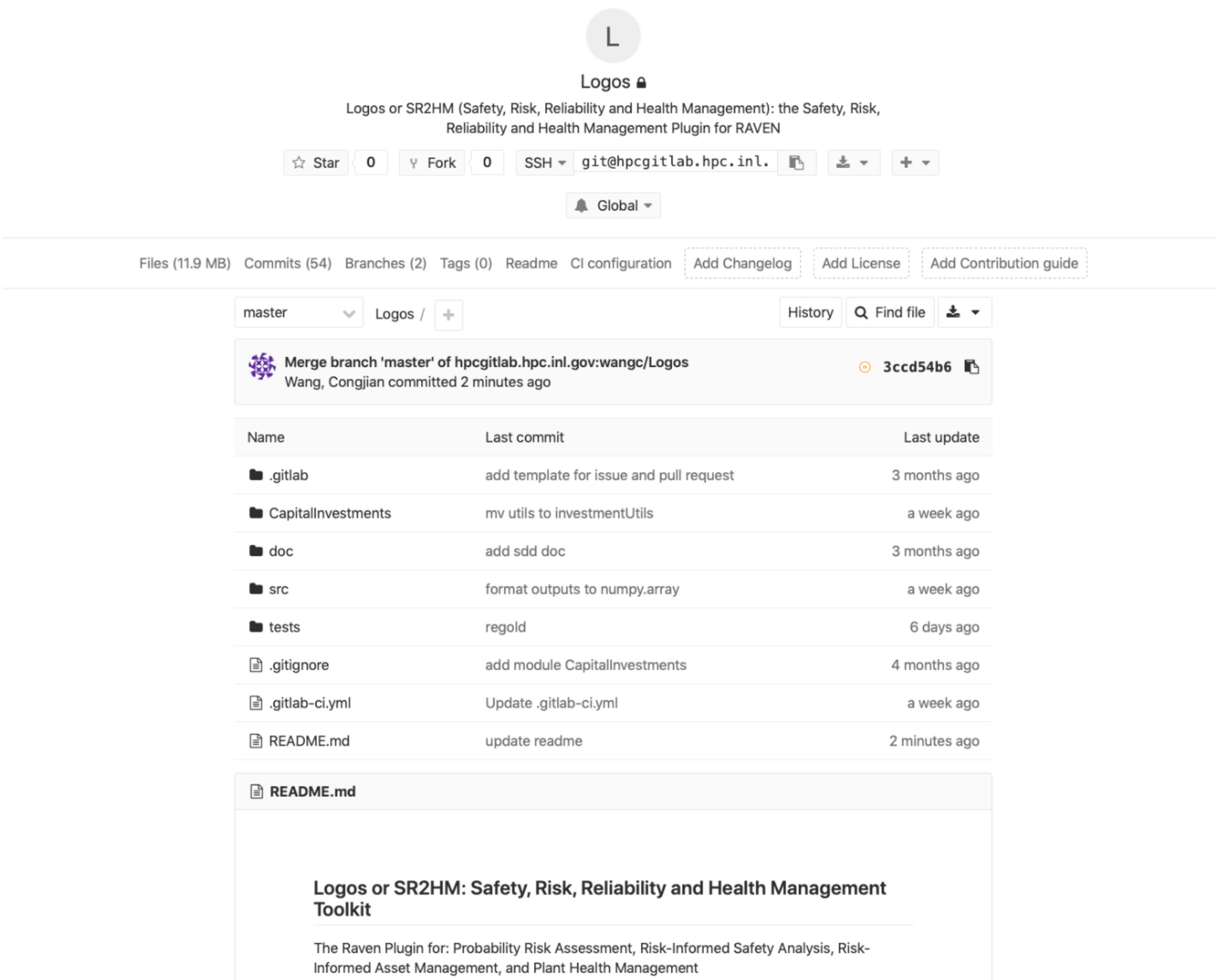

Figure 19. Screenshot of the Logos repository.

Test Location and Definition

The **Logos/SR2HM** is one of RAVEN supported Plug-Ins and managed by Git. Plug-Ins in RAVEN are an option to associate a workflow or a set of RAVEN external models to RAVEN without having them included in the RAVEN main repository. The benefits include modularity, access restriction, and regression testing for compatibility with RAVEN as it continues to grow. In this case, we are able to treat these two repositories as separate yet still be able to use one from within the other. The main structure of RIAM repository is shown in Figure 20. The folder *tests* contains the input of the tests and the corresponding output (in the *gold* folder) which are used to assure that the behavior of the code is not changed for new modifications. These tests can be also collected in subfolders based on their characteristics.

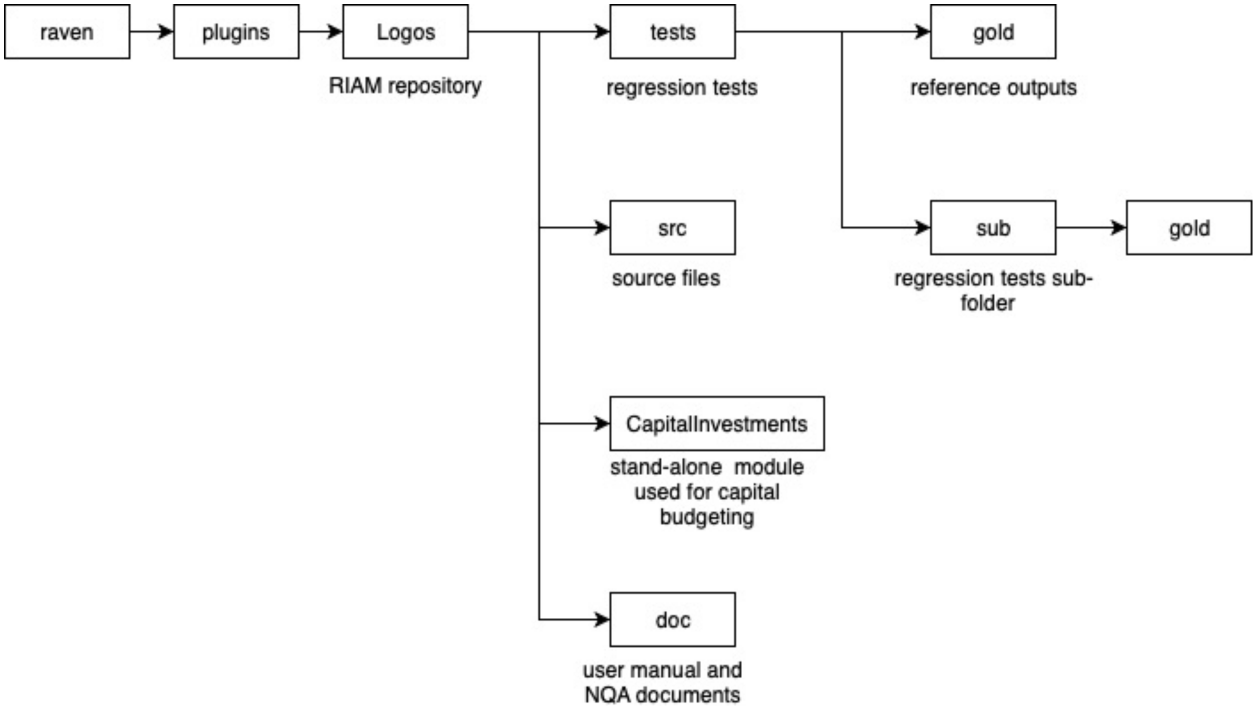

Figure 20. Folder tree of Logos repository.

The RAVEN repository contains a complete testing system used to provide regression testing for itself and Plug-Ins. The **Logos/SR2HM** module tests are defined in the same manner as they are for RAVEN. A single test consists of a RAVEN input file along with associated data needed to perform that run. That can include input data, external models, and Python files. These may be placed in the *tests* directory, or in subdirectories of *tests*. Every directory that contains tests to be run by the framework must contain a test specification file named "tests". The syntax of these files is defined by the RAVEN test framework, which controls how each test is run and sets the criteria used to determine whether it passed or not. An example of a test specification file is presented here:

```
[Tests]
  [./TestGraphModel]
    type  = 'RavenFramework'
    input = 'test_graphModel.xml'
    UnorderedCsv   = 'graphModel/Print_sim_PS.csv'
  [../]
[]
```

In the above example, one test is defined, named "TestGraphModel", using RAVEN test module (defined in the test file as "type = 'RavenFramework'"). Comparison criteria are also defined in the "tests" file. In most cases, one or more output files generated by running the specified input file with RAVEN are compared against a gold standard provided by the developer and stored in the repository. Typically, comparisons are performed on numeric values contained in Comma-Separated Values (CSV) files to defined tolerance. When these file comparisons are specified by the test developer, reference files must have the same name and be placed in the *gold* subdirectory below that containing the "tests" file.

Running the Tests

The integrated tests can be run separately as indicated by following

```
PathToRaven/raven/raven_framework   PathToTest/TestDir/TestName
```

As mentioned above, these tests can be also executed and tested by the RAVEN regression system automatically.

Continuous Integration System (CIVET)

CIVET, developed at INL, is used for continuous integration, verification, enhancement and testing of RAVEN and **Logos/SR2HM**. Each time a developer proposes modification of the contents of the **Logos/SR2HM** repository, CIVET will cause the automated tests to be run on the modified version. These tests must all pass before a proposed change may become part of the official repository. In this way the **Logos/SR2HM** project is protected from the accidental introduction of flaws into the software that required significant investment of resources to develop.

Appendix F

OPTIMIZATION MODELS AND ALGORITHMS

One of the RIAM objectives is to optimize the capital budgeting to support decisions for NPP operations. Since the RIAM are influenced by various factors, such as markets, safety and regulatory, the decision-making process of RIAM should take into account relevant factors for balancing risks, costs and profits. The traditional method of capital budgeting is based on the priority list of candidate projects using economic measures such as benefit-investment ratio, NPV and IRR. In the literatures, the problem of capital budgeting or the variant can be represented by an appropriate knapsack problem. The knapsack approach to capital budgeting takes as input as investments, along with the cost and profit of each project.

The objective of capital budgeting is to find the combination of the binary decisions for every investment such that the overall profit is as large as possible. The output is a collection of projects to be carried out, and we refer this selected collection of projects as a project portfolio. However, as it is frequently the case for capital budgeting with NPP applications, in practice several additional constraints, such as resources/liabilities, dependencies/synergies, options, time windows for every investment etc., have to be fulfilled. This leads to a various extensions and variations of the basic knapsack problem. Because this need for extension of the basic knapsack problem arose in many practical applications, we will present several more general variants of knapsack problem and their implementations in the following sections.

Risk-Free Decision Making for Capital Budgeting

If the costs and profits of the candidate projects as well as the budgets are known with certainty, the knapsack model provides an effective tool for selecting a project portfolio. The basic Knapsack Problem (KP) for capital budgeting can be defined as follows: We are given an instance of the capital budgeting problem with investment set N, consisting of n investments i with profit p_i, e.g. NPV, and cost w_i, and the available budget c. Then the objective is to select a subset of N such that the total profit of the selected investments is maximized and total cost does not exceed c. Alternatively, KP can be formulated as a solution of the following linear integer programming formulation:

$$\max \sum_{i \in N} p_i x_i \tag{F.1}$$

$$subject\ to \sum_{i \in N} w_i x_i \leq c \tag{F.2}$$

$$x_i \in \{0,1\}, i \in N \tag{F.3}$$

Constraint in (F.2) ensures that the cost of the project portfolio is within the budget. The binary variables x_i in (F.3) which correspond to the selection in the ith binary decision (1 if project i is selected; 0 otherwise). This is the simplest non-trivial integer programming model with binary variables. The variants and extensions of KP will be treated in following sub-sections.

Bounded Knapsack Problem

In the capital budgeting problem described above it may be the case that not all investments/projects are different from each other. In particular, in practice there may be given a number b_i of identical pumps/valves to be replaced. In this case the number of decision variables is equal to the number of different investments instead of the total number of investments. Formally, constraint (F.3) is replaced by non-negative integer decision variable x_i

$$0 \le x_i \le b_i, i \in N$$

The resulting problem is called the bounded knapsack problem (BKP) formally defined by

$$\max \sum_{i \in N} p_i x_i \tag{F.4}$$

$$subject\ to \sum_{i \in N} w_i x_i \le c \tag{F.5}$$

$$0 \le x_i \le b_i, x_i\ integer, i \in N \tag{F.6}$$

Multi-Dimensional Knapsack Problem (DKP)

Moving in a different direction, we consider again the basic capital budgeting problem, i.e. (F.1) ~ (F.3), and now take into account not only the cost constraint but also the limited commitment of critical resources, including: (i) capital cost, (ii) operation and maintenance costs, (iii) time and labor-hours during a planned outage, (iv) personnel, installation and maintenance equipment, space, and more. Denoting the cost of every investment by $w_{i,d}$ for each resource d and introduce the corresponding limited resource c_d we can formulate the extended capital budgeting problem by replacing constraint (F.2) in KP by:

$$\sum_{i \in N} w_{i,d} x_i \le c_d, d \in D \tag{F.7}$$

The resulting problem is called multi-dimensional knapsack problem or D-dimensional knapsack problem (DKP) formally defined by:

$$\max \sum_{i \in N} p_i x_i \tag{F.8}$$

$$subject\ to \sum_{i \in N} w_{i,d} x_i \le c_d, d \in D \tag{F.9}$$

$$x_i \in \{0,1\}, i \in N \tag{F.10}$$

Where the limited resources set is denoted by D, consisting of d “colors” of money within capital costs, within operation and maintenance costs, within personnel availability, etc.

Another example is that the plant has multi-year investments. Consider a DKP problem in which the costs of each investment and the available capitals vary according to time period t. By defining $w_{i,t}$ as the cost of investment i at time period t, and c_t as the available capital at time period t, we get:

$$\begin{gathered} \max \sum_{i \in N} p_i x_i \\ subject\ to \sum_{i \in N} w_{i,t} x_i \leq c_t \\ x_i \in \{0,1\}, i \in N \\ t \in [0, T] \end{gathered} \tag{F.11}$$

Multiple Knapsack Problem (MKP)

Another interesting variant of the capital budgeting problem arises from the original version described above if we consider a maintenance for multi-units NPP in parallel, i.e. it has to be decided whether to accept a particular replacement and in the positive case in which unit to conduct the corresponding replacement. This can be formulated by introducing a binary decision variable for every combination of a maintenance with a unit. If there are n investments (investment set N) on the list of maintenance requests and m unit (unit set M) available, we use binary variables:

$$x_{i,m} \in \{0,1\}, i \in \ N, m \in M$$

The resulting problem is called the Multiple Knapsack Problem (MKP), and the mathematical formulation is given by

$$\max \sum_{m \in M} \sum_{i \in N} p_i x_{i,m} \tag{F.12}$$

$$subject\ to \sum_{i \in N} w_i x_{i,m} \leq c_m, m \in M \tag{F.13}$$

$$\sum_{m \in M} x_{i,m} \leq 1 \tag{F.14}$$

$$x_{i,m} \in \{0,1\}, i \in N, m \in M \tag{F.15}$$

Multiple-Choice Knapsack Problem

Another quite different variant of the capital budgeting problem appears if there may be multiple ways to carry out each investment/project. Each investment i however exists in a number of options where the *j-th* option has cost $w_{i,j}$ and profit value $p_{i,j}$. This problem may be expressed as the Multiple-Choice Knapsack Problem (MCKP). Assume J_i is the set of different options of investment i. Using the decision variables $x_{i,j}$ to denote whether option j was chosen from the set J_i, the mathematical formulation of MCKP is given by

$$\max \sum_{j \in J_i} \sum_{i \in N} p_{i,j} x_{i,j} \tag{F.16}$$

$$subject\ to \sum_{j \in J_i} \sum_{i \in N} w_{i,j} x_{i,j} \leq c \tag{F.17}$$

$$\sum_{j \in J_i} x_{i,j} = 1, i \in N \tag{F.18}$$

$$x_{i,j} \in \{0,1\}, i \in N, j \in J_i \tag{F.19}$$

Constraint (F.18) ensures that exactly one option is chosen from each investment. Considering the limited resources and multi-year investments mentioned in section 0, the MCKP may be extended to D-dimensional MCKP problem (D-MCKP). For example, a project may be performed over a three-year period, say, years $t, t + 1, t + 2$, or the start of the project could instead be two years hence with project implementation over years $t + 2, t + 3, t + 4$. Alternatively, at increased cost and increased benefit, it may be possible to complete the project in two years, $t, t + 1$ or $t + 2, t + 3$. When selecting a project to uprate plant capacity, we may have two options that increase capacity by 3% or 6%. In these cases, the problem can be expressed as the D-MCKP. This problem is formally defined as follows

$$\max \sum_{j \in J_i} \sum_{i \in N} p_{i,j} x_{i,j} \tag{F.20}$$

$$subject\ to \sum_{j \in J_i} \sum_{i \in N} w_{i,j,t} x_{i,j} \leq c_t, t \in [0, T] \tag{F.21}$$

$$\sum_{j \in J_i} x_{i,j} = 1, i \in N \tag{F.22}$$

$$x_{i,j} \in \{0,1\}, i \in N, j \in J_i \tag{F.23}$$

Or

$$\max \sum_{j \in J_i} \sum_{i \in N} p_{i,j} x_{i,j} \tag{F.24}$$

$$subject\ to \sum_{j \in J_i} \sum_{i \in N} w_{i,j,d,t} x_{i,j} \leq c_{d,t}, d \in D, t \in [0, T] \tag{F.25}$$

$$\sum_{j \in J_i} x_{i,j} = 1, i \in N \tag{F.26}$$

$$x_{i,j} \in \{0,1\}, i \in N, j \in J_i \tag{F.27}$$

Prioritizing Project Selection to Hedge Against Uncertainty

One limitation of traditional optimization models for capital budgeting is that they do not account for risk/uncertainty in profit and cost streams associated with individual projects, they do not account for risk in resource availability in future years. Projects can incur cost over-runs, especially when projects are large, performed infrequently, and when there is risk regarding technical viability, external contractors, and/or suppliers of requisite parts and materials. Occasionally, projects are performed ahead of schedule and with cost savings. Planned budgets for capital improvements can be cut and key personnel may be lost. Or, there may be surprise windfalls in budgets for maintenance activities due to decreased costs for "unplanned" maintenance. In these cases, how should we resolve capital budgeting when we have risk forecasts for costs, profits and budgets? One approach is to re-solve the models described in the previous section when refined forecasts for these parameters become available. However, it is not always practical to fully revise a project portfolio whenever better forecasts become available.

In order to prioritize the project selection with risk forecast for these parameters, the two-stage stochastic optimization model [7] is employed to provide priority lists to decision-makers to support better risk-informed decisions. Its inputs include those described in above sections for different variant of the capital budgeting problem, except that a probabilistic description of the uncertain parameters is integrated in the optimization process. The two-stage stochastic optimization model forms a priority list as its first-stage decision and then forms a corresponding project portfolio for each scenario as its second-stage decision. When forming the optimal second-stage project portfolio under a specific scenario, the stochastic optimization model ensures that the portfolio is consistent with the first-stage prioritization; i.e., a project can be selected only if all high-priority projects are also selected. Thus, the portfolios of projects corresponding to different scenarios are nested.

The risk-free capital budgeting models presented in above sections assume that there is no risk in the problem data. And, as was demonstrated in [7], the models do not naturally produce a priority list. The need to deal with these risk forecasts for costs, profits and budget motivates extending risk-free models to risk-informed models that can form a priority list with the goal of maximizing profits of the investments. The notation and formulation of the risk-informed models are as follows:

Indices and Sets:

$i, i' \in N$	candidate projects
$j \in J_i$	options for selecting project i, e.g., initiate project i in year t or $t + 2$ and in a standard (three year) or in an expedited (two year) manner. Note that the last option for project i is always used to indicate "non-selection", i.e. the investment i is not selected.
$d \in D$	types of resources, e.g., capital funds, O&M funds, labor-hours, time during outage
$t \in T$	time periods (years)
$\omega \in \Omega$	scenarios

Data:

p_i^{ω}	profit of investment i under scenario ω (NPV)
$p_{i,j}^{\omega}$	profit of investment i via option j under scenario ω (NPV)
c	available budget under scenario ω
c_d^{ω}	available budget for a resource of type d under scenario ω
c_m^{ω}	available budget for unit m under scenario ω
c_t^{ω}	available budget in year t under scenario ω

$c_{d,t}^{\omega}$	available budget for a resource of type d in year t under scenario ω
w_i^{ω}	cost of investment i under scenario ω
$w_{i,d}^{\omega}$	consumption of resource of type d if investment i is selected under scenario ω
$w_{i,j,t}^{\omega}$	consumption of resource in year t if investment i is performed via option j under scenario ω
$w_{i,j,d,t}^{\omega}$	consumption of resource of type d in year t if investment i is performed via option j under scenario ω
q^{ω}	probability of scenario ω

Decision variables:

$$y_{i,i'} = \begin{cases} 1 & if\ project\ i\ has\ no\ lower\ priority\ than\ project\ i' \\ 0 & otherwise \end{cases}$$

$$x_i^{\omega} = \begin{cases} 1 & if\ project\ i\ is\ selected\ under\ scenario\ \omega \\ 0 & otherwise \end{cases}$$

$$x_{i,m}^{\omega} = \begin{cases} 1 & if\ project\ i\ is\ selected\ for\ unit\ m\ under\ scenario\ \omega \\ 0 & otherwise \end{cases}$$

$$x_{i,j}^{\omega} = \begin{cases} 1 & if\ project\ i\ is\ performed\ via\ option\ j\ is\ selected\ under\ scenario\ \omega \\ 0 & otherwise \end{cases}$$

The risk-free capital budgeting models could be reformulated into risk-informed models as shown in the following:

(Risk-Informed SKP Model: RI-SKP)

$$\max \sum_{\omega \in \Omega} q^{\omega} \sum_{i \in N} p_i^{\omega} x_i^{\omega} \tag{F.28}$$

$$\sum_{i \in N} w_i^{\omega} x_i^{\omega} \leq c^{\omega} \tag{F.29}$$

$$y_{i,i'} + y_{i',i} \geq 1\ and\ i < i' \tag{F.30}$$

$$x_i^{\omega} \geq x_{i'}^{\omega} + y_{i,i'} - 1\ and\ \ i \neq i' \tag{F.31}$$

(Risk-Informed DKP Mode: RI-DKP)

$$\max \sum_{\omega \in \Omega} q^{\omega} \sum_{i \in N} p_i^{\omega} x_i^{\omega} \tag{F.32}$$

$$\sum_{d \in D} w_{i,d}^{\omega} x_i^{\omega} \leq c_d^{\omega} \tag{F.33}$$

$$y_{i,i'} + y_{i',i} \geq 1\ and\ i < i' \tag{F.34}$$

$$x_i^{\omega} \geq x_{i'}^{\omega} + y_{i,i'} - 1 \ and \ i \neq i' \tag{F.35}$$

(Risk-Informed MKP Model: RI-MKP)

$$\max \sum_{\omega \in \Omega} q^{\omega} \sum_{m \in M} \sum_{i \in N} p_i^{\omega} x_{i,m}^{\omega} \tag{F.36}$$

$$\sum_{i \in N} w_i^{\omega} x_{i,m}^{\omega} \leq c_m^{\omega} \tag{F.37}$$

$$y_{i,i'} + y_{i',i} \geq 1 \ and \ \ i < i' \tag{F.38}$$

$$\sum_{m \in M} x_{i,m}^{\omega} \geq \sum_{m \in M} x_{i',m}^{\omega} + y_{i,i'} - 1 \ and \ i \neq i' \tag{F.39}$$

$$\sum_{m \in M} x_{i,m}^{\omega} \leq 1 \tag{F.40}$$

(Risk-Informed MCKP Model: RI-MCKP)

$$\max \sum_{\omega \in \Omega} q^{\omega} \sum_{j \in J_i} \sum_{i \in N} p_{i,j}^{\omega} x_{i,j}^{\omega} \tag{F.41}$$

$$\sum_{i \in N} w_{i,j}^{\omega} x_{i,j}^{\omega} \leq c^{\omega} \tag{F.42}$$

$$y_{i,i'} + y_{i',i} \geq 1 \ and \ i < i' \tag{F.43}$$

$$\sum_{j=1}^{J_i - 1} x_{i,j}^{\omega} \geq \sum_{j=1}^{J_i - 1} x_{i',j}^{\omega} + y_{i,i'} - 1 \ and \ i \neq i' \tag{F.44}$$

$$\sum_{j \in J_i} x_{i,j}^{\omega} = 1 \tag{F.45}$$

All these models are a two-stage stochastic integer program. The first-stage decision variable, y, form the priority list. The second-stage decision variable, x, selects the portfolio of projects to implement for each scenario. The objective function (F.28), (F.32), (F.36) or (F.41) captures the expected total profit, forming the weighted sum of profits over all scenarios. Constraint (F.29), (F.33), (F.37) or (F.42) ensures that the implemented investments stay within budget under each scenario, for each year and/or for each resources/liabilities. Given a pair of investments, constraint (F.30), (F.34), (F.38) or (F.43) ensure either they have the same priority or one has higher priority than the other. Constraint (F.31), (F.35), (F.39) or (F.44) requires that the investment selected by x^{ω}, under each scenario, are consistent with the priority list's ordering. The last constraint of RI-MKP, i.e. F.40, ensures each investment can be selected at most by one unit, and the last constraint of RI-MCKP, i.e. F.45, requires only one option per investment can be selected.