Portfolio Analysis Made Effective and Simple

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Abstract

Effective portfolio analysis strategies rely on robust recognition of resource constraints, competing priorities, interdependencies, and executability. They transform complexity into simplicity.

Our strategy details a flexible, efficient, and analytically rigorous evaluative framework that integrates complex sets of interconnected analyses to assist leadership with data-driven resource allocation. The framework offers solutions in data cleaning, optimization algorithms, and visualization tools that enable stakeholders to effectively navigate complicated portfolio landscapes.

Applicability of the framework is demonstrated through a use case that details a facility construction portfolio expected to grow aggressively in the coming years. Aside from a few key projects, prioritization is becoming increasingly complex. For example, building at one site depends on timely completion of construction at another site; planning for decade-long projects relies on consistent and predictable budgets. This paper addresses both these problems amongst other issues and outlines their corresponding solutions.

Keywords: *Portfolio Analysis*

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Introduction

The Nuclear Security Enterprise (NSE) has existed since World War II and has undergone many transformations over the decades. During the cold war, the NSE grew aggressively to meet production demands to compete with a near-peer geopolitical power. This trend continued until the dissolution of the USSR in 1991.

Under a United States (US) hegemon, demand for nuclear weapons production and maintenance declined, which led to a corresponding decline in infrastructure investment. This position existed for decades until changes in geopolitics motivated a change in the U.S. nuclear weapons posture back towards a new period of expansion. The 2018 Nuclear Posture Review (NPR) describes that the U.S. "has reduced the nuclear stockpile by over 85 percent since the height of the Cold War and deployed no new nuclear capabilities for two decades." Meanwhile, as stated in the 2018 NPR, Russia and China have expanded their nuclear weapons while North Korea has continued to pursue nuclear weapons.

The projected costs of recapitalization to address the additional risks are shown to rise to 3.7% of the DoD budget at its peak in 2029 according to the 2018 NPR.[1] However, the ability to execute a new expansionary plan has been challenging. After years of little to no significant investments in NSE capabilities, the enterprise accumulated technical debt and deferred infrastructure maintenance and construction across the entire infrastructure portfolio. The isolation of some of the labs, plants, and sites (LPS) within the NSE compounds the difficulties in effectively scaling up construction projects. This has led new-start construction to experience widespread schedule delays and budget overruns.

As the challenges facing the National Nuclear Security Administration (NNSA) have compounded, the need to establish a robust portfolio analysis planning process to

[1] Nuclear Posture Review (2018)

analyze the investment portfolio has increased. The objectives of this process can be summarized as follows:

1. Develop transparent, centralized data organization systems to standardize the way portfolio data is collected and normalized across the NSE.
2. Improve communication across the NSE's numerous stakeholders through more transparent prioritization and planning systems, from LPS organizations to federal program offices.
3. Develop thorough analysis and simulation models to accurately depict the cost, schedule, risk, and interdependencies associated with the NNSA's infrastructure portfolio to conduct a comprehensive portfolio analysis.

This paper will primarily focus on a start-to-finish *portfolio analysis methodology* developed to address NNSA's most pressing planning and programming challenges. In addition, we will describe the analytical tools and capabilities developed to support portfolio analysis across NNSA.

Portfolio Analysis Overview

A *portfolio* is a collection of assets, projects, programs, or portfolio sub-elements that are managed as a group to achieve strategic objectives. *Portfolio analysis* centers around methods for modeling and analyzing portfolios to better align investments to agency-wide goals.

Portfolio analysis provides the ability to analyze a portfolio of assets (projects, facilities, vehicles, etc.) in order to create a realistic, executable plan to complete the portfolio of work. In practice, portfolio analysis requires multiple sequential and interconnected analyses – where each analysis builds upon the previous analysis. Performing effective, trustworthy portfolio analysis therefore requires planning and foresight.

At a high level, portfolio analysis requires three steps: foundational analysis, sub-portfolio (asset-level) analysis, and portfolio level analysis:

1. Foundational analysis builds the base of the next two steps. It defines the portfolio and narrows the scope of analysis. It also identifies what information is important and how to analyze the information.
2. The second step involves a deeper look into the sub-portfolio subcomponents or sub-elements. In the case of NNSA, sub-elements are synonymously referred to as assets or projects. Weights and scores are assigned to sub-elements, and sensitivity analysis is performed.
3. The final step, portfolio level analysis, involves the application of constraints at the portfolio level and the run of simulations to identify optimal portfolio alternatives.

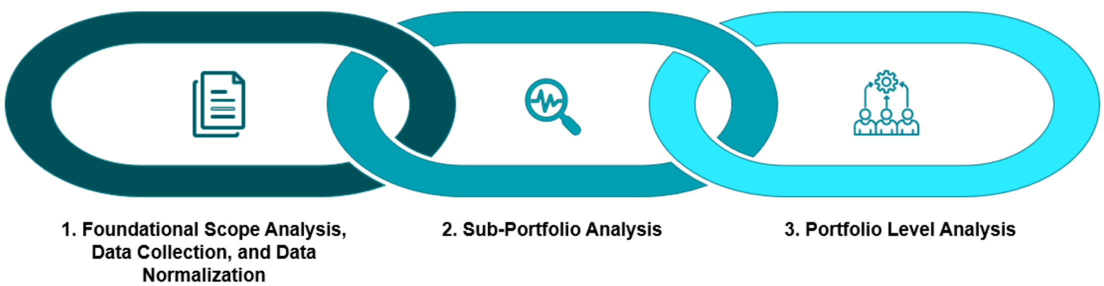

Figure 1: Portfolio Analysis Process Flow

The portfolio analysis explained in this paper applies to the major construction project portfolio of the NNSA today and the near future. The paper discusses key metrics and criteria valuable to the NNSA, though they are not unique to the NNSA. The NNSA offers a great use case for portfolio analysis because of their expanded mission requirements and constraints on funding and capacity. Regardless of organizational environment or complexity, portfolio analysis is valuable for planning and managing portfolios because it prepares leaders for expected and unexpected changes.

Step 1: Foundational Analysis

Foundational analysis encompasses many sub-steps that build upon each other to form the basis for down-stream analyses. These processes require a clearly defined objective, comprehensive data collection, and effective data normalization. Mistakes or oversights in this step will impact all subsequent steps, so special attention must be given when conducting the foundational analysis. While the foundational analysis capabilities discussed in this paper focus on an especially complex organization, NNSA, these capabilities are readily transferable to other organizations.

Step 1.1: Foundational Analysis – Portfolio Definition and Scoping

The first step in foundational analysis is to better understand the problem the organization faces. Some typical questions asked at this stage include:

1. Who decides what investments are approved within the organization?
2. Who are the stakeholders with a vested interest in the outcome of the portfolio analysis?
3. What are the respective roles of each stakeholder? Are some stakeholders more important than others?
4. How do the stakeholders relate to each other? Do some stakeholders have equities / needs that directly conflict with the needs of other stakeholders?
5. What funding mechanisms are currently in-place to get funding to stakeholders?
6. How do organizations communicate with each other? If these organizations have interdependencies and do not communicate, what barriers are preventing effective cross-collaboration?
7. What data exists on each respective investment/program? Does this information exist for *all investments/programs?*

This step is important because it defines the scope of the portfolio and the relevant parties, and therefore bounds the portfolio analysis problem by clearly outlining what analysts need to examine in subsequent steps. Bounding the portfolio is critical to avoiding scope-creep – the increase in portfolio requirements over-time. Clear bounds also avoid over-complicating the size of the portfolio.

The output from this step is a comprehensive, well-documented understanding of how the organization of interest is structured, each organization group's stake in the portfolio, how the organization performs planning and programming activities, and a proposed analytical structure for how the portfolio will be analyzed.

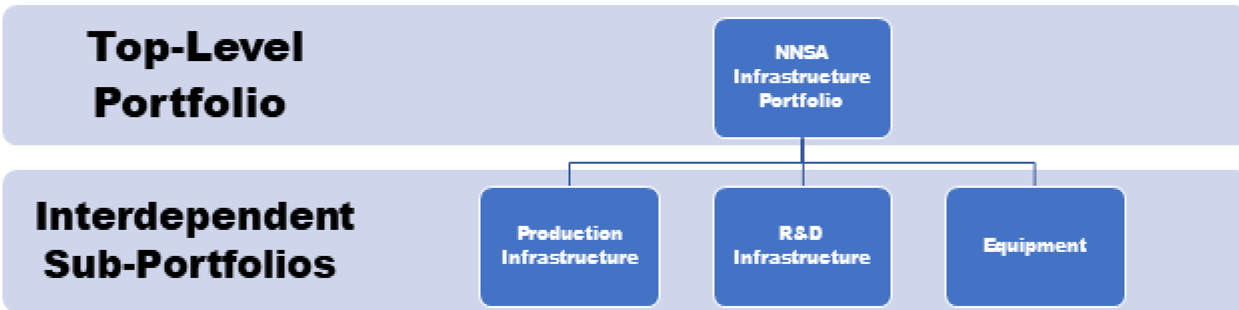

Figure 2: Example Output - Portfolio Structure Diagram

One of the primary objectives of foundational is to scope out the portfolio. Figure 2 represents a diagram of NNSA's infrastructure portfolio, including sub-portfolios that comprise NNSA's infrastructure portfolio writ large. The diagram is an over-simplification of the actual portfolio structure but a useful illustration for what this step is meant to accomplish.

Other sub-portfolios could be considered part of the cumulative infrastructure portfolio (for example, infrastructure maintenance); however, clear lines must be drawn as to what is considered sufficiently important to include in the analysis. Typical questions to draw delineations are listed below:

1. How large of a role does the sub-portfolio play in the cumulative portfolio? If it is small, can it be excluded for the purposes of simplicity? For example, if a sub-portfolio only comprises 1% of the total infrastructure portfolio, it could be excluded to simplify the analysis.
2. Can data be collected to model the sub-portfolio? If data cannot be collected (i.e., it is a non-modellable portfolio), then it can be excluded for simplicity.

Once the portfolio has been effectively scoped and defined, analysts can define in greater detail how potential investments are valued within the portfolio. Without effective portfolio scoping, portfolio prioritization and valuation techniques will likely need to be re-worked in the future.

Step 1.2: Foundational Analysis – Criteria Identification and Definition

Foundational analysis allows analysts to better understand how each stakeholder evaluates the merits or value of any given *sub-portfolio element* (a specific project, portfolio, or program) to the overarching portfolio, as well as the organization's overarching portfolio objectives. This pays dividends in future analyses, as it creates a *standard prioritization and analysis framework through development of both sub-portfolio and portfolio-level evaluation criteria.*

Prioritization criteria can generally be categorized into two groups: sub-portfolio criteria and portfolio-level criteria. *Sub-portfolio criteria* are used to compare the relative importance of one portfolio sub-element to another. Figure 3 identifies examples of sub-portfolio elements. Put simply, sub-portfolio criteria are used to compare the relative merits of one asset to another.

Portfolio-level criteria approximate portfolio-level objectives or characteristics that the portfolio is trying to achieve. Both types of criteria will be explored in further detail in the proceeding sections.

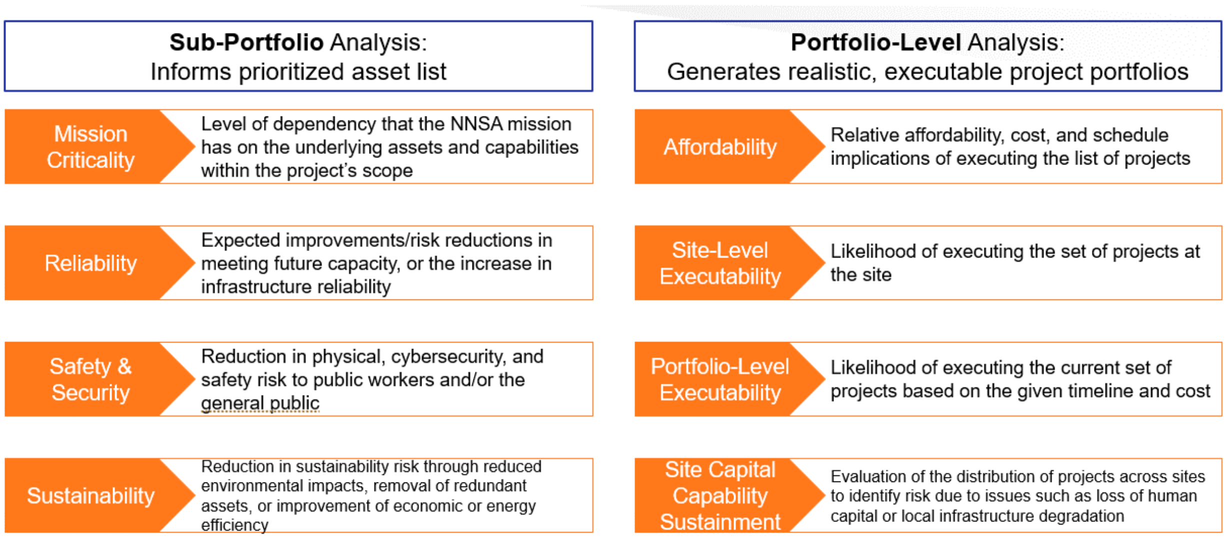

Figure 3: Sub-Portfolio vs. Portfolio-Level Evaluation Criteria

Sub-Portfolio Criteria:

A sample of typical questions used to develop sub-portfolio criteria are:

1. How do different stakeholders evaluate the merits of a given investment? In other words, what *program, project, or investment* characteristics are considered when evaluating whether an investment should be undertaken?
2. Are these characteristics uniform across all sub-portfolios? What are the *common* evaluation criteria that portfolio stakeholders consider when evaluating the merits of a given investment?
3. Is there structural overlap between the criteria? If so, how can this overlap be reduced/removed?
4. How are investments or program benefits and priorities communicated to decision-makers? Are these communication methods standard across all stakeholders?

Capability

Category Name	Description	Score
Highest	There are substantial & tangible capability benefits from execution of the project; the project is primarily focused on capability concerns, and will directly mitigate an existing capability issue	100
High	The project will produce notable capability benefits, but will not fully mitigate existing capability issues	75
Moderate	There are capability benefits from the project, but they are moderate in nature; the project is not primarily focused on capability concerns.	50
Low	There are very minor capability benefits that result from the project. Capability is not a primary driver for executing a project.	25
None	There are no tangible capability benefits, or capability will decrease as a result	0

Capacity

Category Name	Description	Score
Highest	There are substantial & tangible capacity benefits from execution of the project; the project is primarily focused on capacity concerns, and will directly mitigate an existing capacity issue	100
High	The project will produce notable capacity benefits, but will not fully mitigate existing capacity issues	75
Moderate	There are capacity benefits from the project, but they are moderate in nature; the project is not primarily focused on capacity concerns.	50
Low	There are very minor capacity benefits that result from the project. Capacity is not a primary driver for executing a project.	25
None	There are no tangible capacity benefits, or capacity will decrease as a result.	0

Mission Dependency

Mission Dependency				
Replaceability	Impact			
	Minor	Moderate	Substantial	Critical
Easy	0	25	75	80
Challenging	25	50	80	85
Very Challenging	75	80	90	95
Nearly Impossible	80	85	95	100

Figure 4: Example Sub-Portfolio Prioritization Criteria

Figure 4 shows three example sub-portfolio criteria. Each criteria represents a different desirable characteristic for an asset. The objective of this step is to develop a standardized set of evaluative criteria for use in determining the relative importance of different portfolio sub-elements. This, in turn, indirectly informs subsequent portfolio-level analyses. Our example model includes 10 prioritization criteria, each with unique quantification methods ranging from discrete qualitative scoring rubrics to continuously distributed parametric analyses.

Portfolio-Level Criteria:

A portfolio-level characteristic can only be evaluated at the portfolio-level and is meant to be a statistical representation of that characteristic. It is used to represent desirable characteristics for any given portfolio. Typical questions used to generate portfolio-level evaluation criteria are listed below:

1. What portfolio-level characteristics are desirable by the organization? A typical example would be that the portfolio can stay under a notional budget constraint (i.e., the portfolio is *affordable*).
2. Do these portfolio-level characteristics have structural overlap? In other words, would you expect a structural correlation to exist between different portfolio-level statistics? Structural overlap is not desirable.
3. Is there existing data that can help measure any given portfolio's performance relative to the portfolio-level characteristics?

Portfolio-Level Characteristics			
Characteristic	**Affordability**	**Executability**	**Mission Risk**
Description	The degree to which a portfolio can fit under a budget constraint	Statistics that approximate the likelihood of successfully executing the investments in the portfolio	The degree to which the portfolio minimizes schedule risk

Figure 5: NNSA Portfolio-Level Criteria

Figure 5 represents NNSA's desirable characteristics for their infrastructure portfolio grouped into three portfolio-level characteristics. Once defined, these characteristics can be used to develop statistics to approximate any given portfolio's performance. Multiple different statistics are developed within each group to approximate each characteristic (i.e., multiple affordability statistics). In subsequent steps, the model leverages these statistics to perform a multi-objective optimization analysis.

For the NNSA example, there were two affordability statistics: Cumulative Budget Overrun and Maximum Budget Overrun. Examples of these statistics are shown in Table 1. In Step 3 (Portfolio-Level Analysis), the portfolio analysis simulation model can then be used to move sub-elements within the portfolio around to minimize these affordability statistics.

	Year			
	1	**2**	**3**	**Sum**
Total Budget	$100	$100	$100	-
Total Cost	$115	$120	$130	-
% Budget Overrun	15%	20%	30%	65%
Maximum Budget Overrun	-	-	30%	

Table 1 – Example Affordability Statistics

Within the NNSA portfolio, another consideration is mission risk or schedule risk. This characteristic is measured by taking each project's expected end-date and each project's mission need date (the date when the project would ideally be completed) and summing up the deltas to create one cumulative mission risk statistic. Table 2 highlights a very basic example.

	Original End-Date	Shifted End-Date	Mission Need Date	Mission Need Delta
Project A	2030	2032	2030	2
Project B	2035	2031	2035	-4
Project C	2040	2046	2040	6
				4

Table 2 – Mission Risk Statistic Example

In subsequent steps, these calculated statistics are used to evaluate the relative merits of any given portfolio alternative.

Step 1.3: Foundational Analysis – Data Structuring and Normalization

Once the portfolio has been defined, its objectives clearly outlined, and its evaluative criteria identified, a comprehensive data structure must be developed to support all subsequent analytical steps.

Figure 6 outlines a typical data structure to support subsequent analysis. The example below is an oversimplification of NNSA's data structure. The specific data structure would depend on the responses from the problem scoping and definition step.

Project ID	Project Name	Project Start Date	Project End Date	Mission Need Date	Project Cost	Mission Dependency: Replaceability	Mission Dependency: Impact	Capability	Capacity
1	Build Facility 1	2012	2017	2035	$ 29,477,172	Challenging	Substantial	High	Highest
2	Modify Capability 2	2013	2042	2042	$ 64,050,000	Challenging	Moderate	High	Moderate
3	Replace Facility 3	2024	2029	2029	$ 40,104,436	Easy	Moderate	None	Highest
4	Build Capability 4	2035	2040	2040	$ 32,730,557	Very Challenging	Substantial	Highest	High
5	Replace Facility 5	2029	2032	2032	$ 3,000,000	Very Challenging	Critical	High	Moderate
6	Repair Capacity 6	2029	2036	2036	$ 50,000,000	Very Challenging	Minor	Moderate	Highest
7	Modify Capability 7	2022	2025	2025	$ 1,356,000	Very Challenging	Minor	Moderate	Low
8	Build Facility 8	2029	2034	2034	$ 33,192,901	Easy	Substantial	Low	High
9	Build Capacity 9	2029	2033	2033	$ 12,978,000	Nearly Impossible	Substantial	Low	Low
10	Build Capability 10	2035	2041	2041	$ 112,000,006	Nearly Impossible	Critical	Highest	None
11	Replace Capability 11	2022	2029	2029	$ 138,852,804	Nearly Impossible	Moderate	Moderate	Low
12	Repair Facility 12	2046	2052	2052	$ 71,344,381	Challenging	Critical	Moderate	Low
13	Build Capability 13	2023	2028	2027	$ 59,780,283	Challenging	Substantial	Highest	High
14	Build Capacity 14	2025	2031	2031	$ 62,543,816	Challenging	Substantial	Moderate	Moderate
15	Repair Capacity 15	2025	2040	2040	$ 124,823,827	Nearly Impossible	Critical	High	Highest
16	Build Capability 16	2024	2031	2031	$ 50,000,000	Challenging	Minor	High	Low
17	Repair Capacity 17	2026	2038	2038	$ 21,504,677	Challenging	Minor	Low	High
18	Replace Capability 18	2024	2033	2033	$ 3,528,490	Easy	Minor	Moderate	Moderate
19	Replace Capability 19	2027	2036	2036	$ 54,000,000	Challenging	Moderate	Moderate	Low
20	Modify Capability 20	2024	2031	2031	$ 29,092,300	Challenging	Moderate	High	Low
21	Repair Facility 21	2043	2050	2050	$ 132,027,034	Challenging	Minor	High	Low
22	Modify Capability 22	2030	2048	2048	$ 76,521,002	Very Challenging	Critical	High	None
23	Repair Capacity 23	2040	2054	2054	$ 147,527,034	Challenging	Substantial	None	Moderate
24	Repair Capacity 24	2025	2042	2042	$ 28,557,148	Very Challenging	Critical	Low	Low
25	Modify Capacity 25	2024	2031	2031	$ 106,789,217	Challenging	Substantial	High	High
26	Build Facility 26	2027	2035	2035	$ 36,377,582	Very Challenging	Substantial	High	Low
27	Modify Capacity 27	2037	2055	2055	$ 26,190,051	Very Challenging	Minor	Moderate	High
28	Modify Capability 28	2028	2032	2032	$ 4,451,685	Challenging	Moderate	High	High
29	Build Facility 29	2024	2032	2032	$ 58,969,853	Easy	Minor	Low	Moderate
30	Repair Facility 30	2026	2038	2038	$ 173,121,462	Nearly Impossible	Substantial	Moderate	Moderate
31	Build Facility 31	2010	2012	2012	$ 23,205,000	Very Challenging	Critical	Highest	High
32	Repair Capability 32	2011	2019	2019	$ 32,146,830	Very Challenging	Critical	Moderate	Low
33	Modify Capability 33	2012	2021	2021	$ 32,183,791	Challenging	Substantial	High	Moderate
34	Repair Capability 34	2015	2021	2021	$ 47,932,008	Easy	Substantial	Moderate	None
35	Modify Capability 35	2015	2021	2021	$ 31,735,200	Nearly Impossible	Substantial	High	None
36	Build Facility 36	2015	2021	2021	$ 93,150,926	Challenging	Minor	Low	Low
37	Build Facility 37	2017	2021	2021	$ 32,830,000	Easy	Substantial	Highest	Moderate
38	Replace Capability 38	2010	2017	2017	$ 259,971,163	Very Challenging	Critical	High	Moderate
39	Modify Capacity 39	2010	2013	2013	$ 33,822,000	Challenging	Substantial	High	Moderate
40	Repair Capacity 40	2012	2016	2016	$ 112,256,407	Very Challenging	Critical	Moderate	Highest

Figure 6: Example Portfolio Analysis Data Structure

Figure 6 includes a list of the portfolio sub-elements (i.e., projects, programs, etc.), including their respective costs and schedules, as well as their performance on the identified sub-portfolio criteria (more details on quantification methods for sub-portfolio criteria in Step 2: Sub-Portfolio Analysis). This example set of data typically constitutes the minimum data requirements to execute subsequent analyses.

Data normalization is also critical to effective data structuring. Within the context of this paper, data normalization is defined as the standardization of a variable or set of variables to a common scale. An example would be taking a variable with a notional distribution between {-2,000, 14,000} and normalizing that distribution to be between {0, 100}. These techniques are utilized to perform more like-to-like comparisons of portfolio performance across multiple variables. These techniques are particularly useful for portfolio-level statistics, which typically are not on the same scale (affordability statistics measured as a percentage, mission risk measured in years).

Step 2: Sub-Portfolio Analysis

Once foundational analysis has been completed, sub-portfolio analysis is performed to better understand the relative importance of different sub-elements of the cumulative portfolio. Many different prioritization model specifications exist across the operations research body-of-knowledge.

The specific model specification should be reviewed based on the individual portfolio use-case; however, a common model specification is a simple additive weight (SAW) model. This model performs cross-product addition to compile a composite “score” for each portfolio sub-element. That is, it produces a discrete first to nth list of prioritized portfolio sub-elements using a combination of criteria scores and weights.

Figure 7 illustrates a simple example of a SAW model in practice. The subsequent steps will discuss key considerations while developing and implementing a SAW prioritization model.

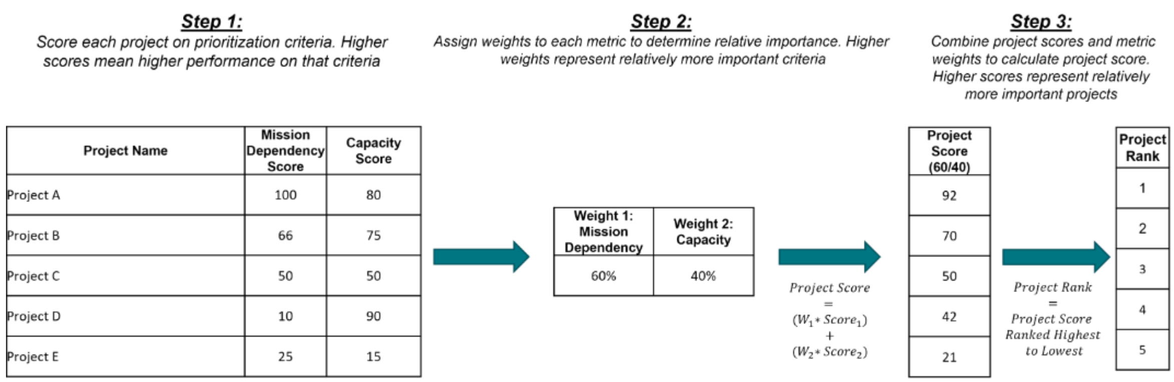

Figure 7: Simple Additive Weight Model

Step 2.1: Develop Criteria Weights

Many techniques exist for calculating criteria weights; however, for simplicity, this paper will not perform an exhaustive description of potential weighting techniques. This paper will, instead, describe the method used to calculate weights for the NNSA infrastructure portfolio. NNSA calculated criteria weights using a *pairwise comparison* method. This method entails comparing each sub-portfolio criteria to every other sub-portfolio criteria exactly once using a direct quantitative, or calculable, value judgement. An example of a pairwise comparison evaluation would be the user judging that, "Criteria A is three times more important than Criteria B."

The output from this method is a set of weights that mathematically represent the relative importance of each portfolio sub-criteria compared to all other portfolio sub-criteria. Tables 3 – 5 highlight this process.

Pairwise Comparison Questions

Important Note: All questions must be answered for a criteria ranking to be calculated. Only fill out Column C.

Question ID	Question	Response	Points assigned to Criteria 1	Points Assigned to Criteria 2
1	Please assign one of the following importances to the following project criteria: Criteria 1: Mission Dependency; Criteria 2: Capability	Criteria 1 is significantly more important than Criteria 2	5	1
2	Please assign one of the following importances to the following project criteria: Criteria 1: Mission Dependency; Criteria 2: Capacity		3.5	2.5
3	Please assign one of the following importances to the following project criteria: Criteria 1: Capability; Criteria 2: Capacity	Criteria 1 is slightly less important than Criteria 2	2.5	3.5

Criteria 1 is significantly more important than Criteria 2
Criteria 1 is slightly more important than Criteria 2
Criteria 1 is equally as important as Criteria 2
Criteria 1 is slightly less important than Criteria 2
Criteria 1 is significantly less important than Criteria 2

Table 3 - Step 1: Perform pairwise comparison to determine criteria preferences.

Criteria Matrix			
	Mission Dependency	Capability	Capacity
Mission Dependency		1	2.5
Capability	5		3.5
Capacity	3.5	2.5	
Score Summation	8.5	3.5	6

Key			
Definition	Importance Hierarchy	Score	Inverse
Y is significantly more important than X	Y > X	5	1
Y is slightly more important than X	Y ~> X	3.5	2.5
Y is equally as important as X	Y = X	3	3
Y is slightly less important than X	Y ~< X	2.5	3.5
Y is significantly less important than X	Y < X	1	5

Table 4 - Step 2: Develop pairwise matrix based on answers in Step 1

Project Criteria Ranking Table					Exponent: 2
Project Criteria	Total Points	Ordinal Rank	Selected Weights	Linear Proportionate Weight	Exponentiated Proportionate Weight
Mission Dependency	8.50	1	47.22%	47.22%	59.96%
Capability	3.50	3	19.44%	19.44%	10.17%
Capacity	6.00	2	33.33%	33.33%	29.88%
Sum	18		100.00%	100.00%	100.00%

Table 5 - Step 3: Criteria weights calculated based on users' selection of weighting method

Step 2.2: Score Sub-Portfolio Elements

There are two general methods used to quantify and score criteria: quantitative and qualitative. Quantitative criteria utilize data that is already on a numerical scale. Examples include cost data, building gross square footage, acreage, and schedule data. This data is typically collected for all portfolio sub-elements and normalized to a common scale for scoring.

Qualitative data is non-numeric. Therefore, analysts must transform qualitative data into quantitative data. One example of qualitative data is the “capability” of a project or asset (which may not be easily measurable). An analyst can develop a “rubric” to categorize qualitative information (typically blocks of text) into scores. A basic scoring rubric is shown in Figure 8.

Category	Description	Score
Highest Benefit	The project's primary objective is to create a completely novel capability.	100
Moderate Benefit	The project advances an existing capability, but it is not novel.	50
No Benefit	No capability improvements.	0

Figure 8: Qualitative Scoring Rubric Example

To develop the integrated prioritized list of sub-elements, each sub-element is scored on each prioritization criteria. Those scores are then multiplied by the criteria’s weights, and the sum of all sub-elements and criteria weights is compiled. With this method, higher scores indicate higher-priority projects. There are many important considerations when developing appropriate scoring methods; however, these considerations are best covered through other bodies of operations research literature.

Step 2.3: Sensitivity Analysis

Sensitivity analysis is then performed on the compiled prioritized list to test for potential issues in the system, identify major drivers, and highlight outliers. By adjusting one variable, the user can see how other variables change and understand how impactful the different parts of the model are on the outputs. While more sophisticated sensitivity analysis tests exist for SAW models, only rudimentary sensitivity analyses are outlined in this paper.

Distributional analysis, one example of sensitivity analysis, measures the distribution of scores for each sub-portfolio criteria. Histograms, box-and-whisker plots, and other basic distribution visualization tools are excellent for distributional analysis. The goal of a distributional analysis is to check whether the distribution of scores on a given criteria have sufficient variation. When a criteria's score distribution is low (meaning the criteria scores are consistently "clumped" together), this indicates the criteria will have very little impact on the overall results of the model. This "clumping" is especially easy to spot using distribution visualization tools.

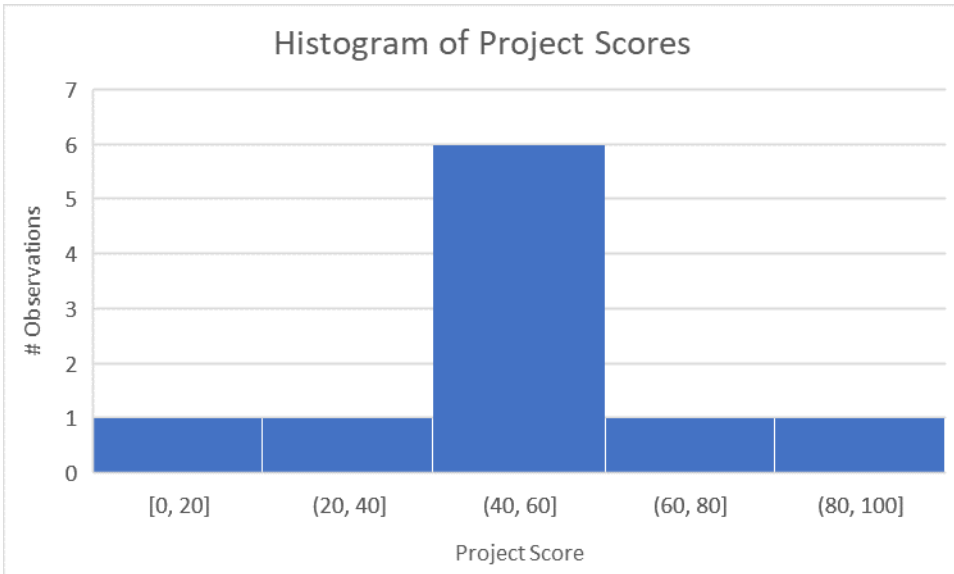

Figure 9 – Histogram Showing "Clumped" Project Scores

Regression analysis is a more robust sensitivity analysis option meant to calculate the "real weights" for each prioritization criteria. This is done by running an ordinary least squares (OLS) regression using each portfolio sub-element's "rank" as the dependent variable and the scores for each criteria as the independent variables.

Table 6 is the first of three tables addressing an example application of regression-based sensitivity analysis. The objective of this regression is to predict the rightmost column, "percentile rank", using columns 1, 2, and 3 as the independent values.

Criteria Weight	55%	30%	15%				**Predicted Value**
Project	**Criteria 1**	**Criteria 2**	**Criteria 3**	**Score**	**Percentile - Score**	**Rank**	**Percentile Rank**
1	60	92	33	65.55	72.40%	9	72.50%
2	83	92	40	79.25	96.50%	2	96.60%
3	70	30	4	48.1	31.00%	21	31.10%

4	68	61	83	68.15	82.70%	6	82.80%
5	2	16	27	9.95	0.00%	30	0.00%
6	37	47	30	38.95	20.60%	24	20.70%
7	93	10	41	60.3	65.50%	11	65.60%
8	1	24	78	19.45	13.70%	26	13.80%
9	98	79	36	83	100.00%	1	100.00%
10	68	52	40	59	58.60%	13	58.70%
11	84	4	52	55.2	51.70%	15	51.80%
12	83	3	91	60.2	62.00%	12	62.10%
13	61	36	1	44.5	24.10%	23	24.20%
14	79	14	19	50.5	37.90%	19	38.00%
15	92	18	0	56	55.10%	14	55.20%
16	68	55	87	66.95	79.30%	7	79.40%
17	3	31	56	19.35	10.30%	27	10.40%
18	27	96	57	52.2	48.20%	16	48.30%
19	30	90	53	51.45	44.80%	17	44.90%
20	37	90	19	50.2	34.40%	20	34.50%
21	73	96	35	74.2	89.60%	4	89.70%
22	12	12	57	18.75	6.80%	28	6.90%
23	76	47	86	68.8	86.20%	5	86.30%
24	47	47	75	51.2	41.30%	18	41.40%
25	98	25	8	62.6	68.90%	10	69.00%
26	92	83	0	75.5	93.10%	3	93.20%
27	71	75	33	66.5	75.80%	8	75.90%
28	11	1	72	17.15	3.40%	29	3.50%
29	65	28	14	46.25	27.50%	22	27.60%
30	48	23	10	34.8	17.20%	25	17.30%

Table 6 – Example OLS Regression Sensitivity Analysis Dataset

As shown in Table 7, the coefficients for the independent variables are then normalized and interpreted to determine whether the criteria's actual weight is statistically significantly different from the "predicted" weight. Criteria that are statistically different from their actual weight are either driving results more or less than originally predicted.

	Coefficients	***Standard Error***	***Lower 95%***	***Upper 95%***
Intercept	0	#N/A	#N/A	#N/A
Criteria 1	0.005687396	0.00059887	0.004458617	0.006916175
Criteria 2	0.003365262	0.000701053	0.001926821	0.004803703
Criteria 3	0.001156138	0.000681217	-0.000241603	0.00255388

Sum	.0102			
Weight Multiplier (WM) = (1 / Sum)	97.95			

Table 7 – Regression Results

Table 8 below shows the results of the regression sensitivity analysis. As an example, criteria 1 has a 95% confidence interval (CI) of {.43, .67}. The actual weight for criteria 1 was .55, meaning that is within the 95% CI.

	Lower 95%	**Lower - Multiplier**	***Upper 95%***	**Upper - Multiplier**	**Weights**	**Reject?**
Intercept	-	-	-	-	-	
Criteria 1	0.004458617	0.437129842	0.006916175	0.677084954	55%	Do Not Reject
Criteria 2	0.001926821	0.189194492	0.004803703	0.470092232	30%	Do Not Reject
Criteria 3	-0.000241603	-0.023225749	0.00255388	0.249724229	15%	Do Not Reject

Table 8 - Normalized Data Hypothesis Test (95% CI)

In the example detailed in Table 6 to 8, the original weights set in the model were not statistically significantly different than the calculated weights from the regression. This result suggests the anticipated influence of each criteria on a project's rank is similar to the weight that was originally used to score the projects.

In other words, the weights used for each criteria are meant to allow certain criteria differentiating influence in affecting the overall ranking of a project. This analysis supports the claim that this differentiation in criteria importance is affecting the model's results.

Step 3: Portfolio-Level Analysis

Once the 1-N list is compiled, the next step is to utilize this data to inform the portfolio-level analysis. Asset-level prioritization alone is insufficient because it does not consider key constraints and interdependencies that arise when evaluating a portfolio at the aggregate level. Additionally, the number of *alternative portfolios* is numerous, necessitating a system for sorting through alternate portfolios to identify "good" alternatives.

In a simple example, portfolio-level analysis with two projects and three funding projections each yields nine possible scenarios. Add one project, and the number of possible scenarios jumps to 27 as shown in Figure 10. It's easy to imagine an overwhelming situation as the number of projects grow and the number of project positions grow.

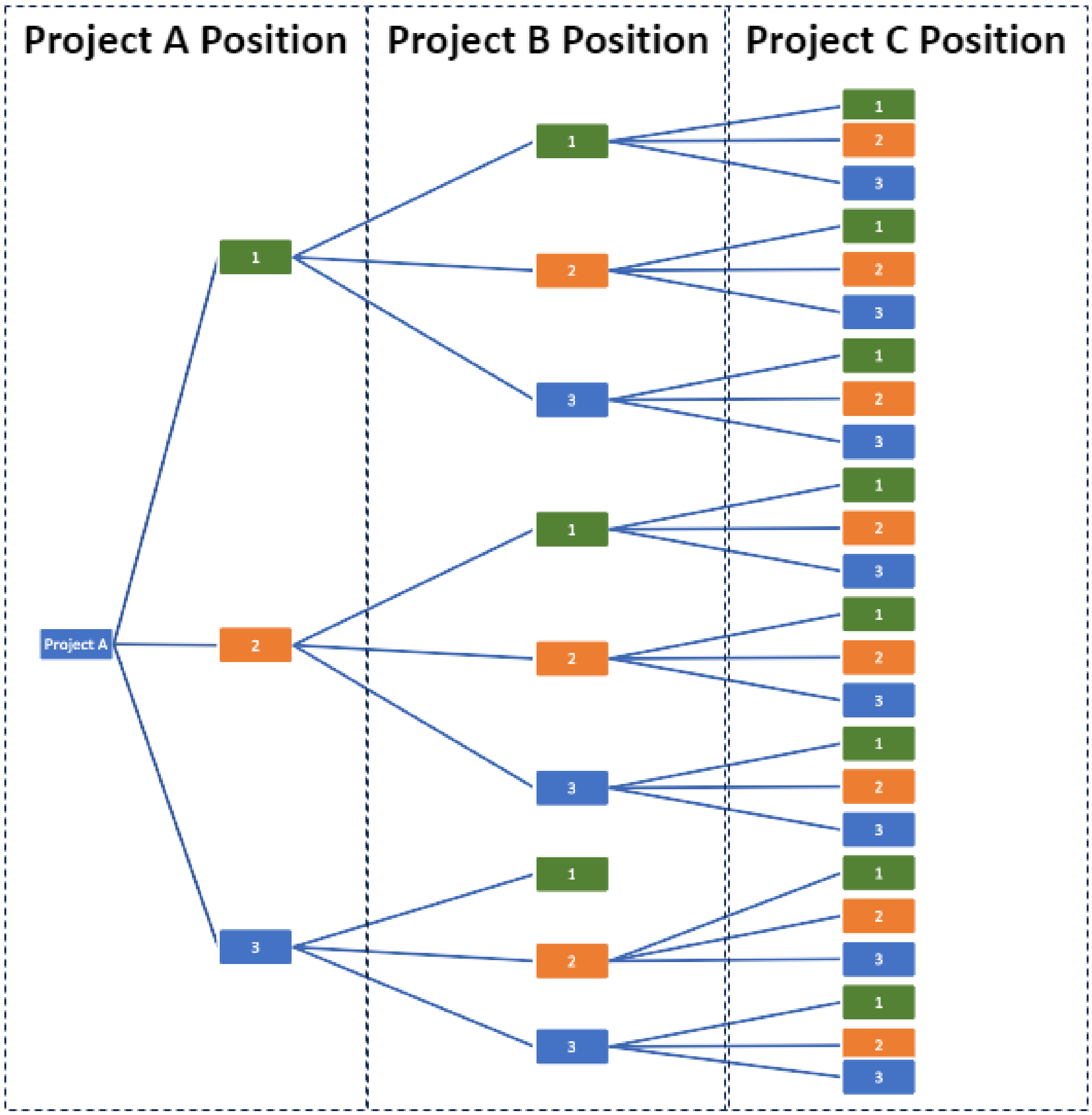

Figure 10: Three Project Portfolio

Mathematically, this scenario is expressed as

$$C(n,r) = \frac{n!}{r!\,(n-r)!}$$

$$n = Set\ or\ population\ size$$

$$r = sample\ size$$

This calculation with 60 projects and 3 unique positions would yield 42,391,158,275,216,203,514,294,433,201 scenarios. In complex environments like the NNSA, it is essential to use a robust method for searching for *sufficient* portfolios because finding and evaluating all of them is resource and time intensive. *Sufficient* portfolios perform well on a suite of portfolio-level statistics or characteristics.

Step 3.1 Define Constraints and Optimization Parameters

Before identifying well-performing portfolios, constraints are imposed to bound portfolio alternatives, and only target “realistic” portfolio scenarios. Examples of constraints include inflation assumptions, mission need date bounding, executability metrics and constraints, affordability, and the inclusion or exclusion of a project.

Once constraints are in place, optimization parameters help identify optimal scenarios. They define what makes one portfolio “better” than another portfolio. Typical examples include budget overruns, schedule overruns, risk reduction metrics or some combination. The model allows for complete customization in what the model targets during optimization.

Part of customization includes predictive analysis, strict budget constraining, and custom logic. As part of predictive analysis, users forecast and mitigate existing constraint violations. Predictive analysis mitigates risk of exacerbating existing issues. Strict budget constraining ensures the portfolio is affordable.

Constraints are typically defined in terms of budget (denominated in dollars) but could be defined as an input resource such as labor. For projects that persistently violate budget constraints, the model allows the user to make individual decisions through user inputs. Users can exclude projects from or add projects to the portfolio analysis by identifying budget overrun minimizing alternatives. By removing projects, users can see the impact on the portfolio if a project is cancelled or put on pause without restructuring the entire model. Additionally, users can add projects to evaluate if they are feasible under some scenarios established by the model that would be challenging for a user to determine without a model.

Where objective value functions of portfolios are hard to define, a relativistic optimization approach can be used. An optimal portfolio is one which performs best on a set of differentiable, weighted, and normalized portfolio statistics. Differentiable statistics must approximate different measures of portfolio health across different portfolios. Weighted statistics are used to differentiate relative impact of performance as defined by the user. Lastly, normalized statistics are necessary to ensure measures are along a common scale. Each of these sets of statistics helps inform the relative optimal portfolio.

Table 9 illustrates relativistic optimization via an example composed of different portfolios. Imagine a baseline portfolio with no mission need overrun, a cumulative budget overrun of 400%, a normalized mission risk score of 100, a normalized affordability score of 0, and a composite performance of 60. These statistics leverage the methodology in the sub-portfolio analysis.

From the baseline, the model identifies three other portfolios that are relatively better than the baseline across different statistics. Each improve the budget overrun but worsen the mission need overrun. The risk scores and affordability scores correspond to the budget overruns and mission need overruns. Because mission risk is weighted more than affordability in this example, the composite performance score shows the Baseline Portfolio as the best performer with a score of 60.

Portfolio Statistic	Baseline Portfolio	Portfolio A	Portfolio B	Portfolio C
Portfolio Optimization Target	None	Mission Risk	Balanced	Affordability/Executability Risk
Average Mission Need Overrun Over Baseline (Years)	0	.5	1	1.5
Cumulative Budget Constraint Overrun	400%	285%	228%	154%
Normalized Mission Risk Score	100	66	33	0
Normalized Affordability Score	0	33	66	100
Composite Performance 60% Mission Risk; 40% Affordability	60	53	46	40

Table 9: Relativistic Optimality Example

Step 3.2: Stress-Test Portfolio

Stress-testing, or changing the conditions that a portfolio experiences, exposes vulnerabilities within the portfolio that asset-level analysis cannot identify. When a budget is cut or need-by dates are moved forward, additional constraints are imposed on the portfolio. Resource constraint analysis and tradeoff analysis tools test those conditions to provide more analytically robust and justifiable portfolio execution alternatives. Stress-testing typically takes the form of running thousands of different portfolio simulations to ensure that an adequate number of alternatives are considered.

Step 3.2.1: Resource Constrain Portfolio

Resource constraint analysis is an algorithm that allows users to work towards a scenario that is constrained efficiently on a resource (such as a budget). The algorithm adds projects to the portfolio from highest priority to lowest priority, which allows projects that are higher priority to be completed closer to their need date.

Typical constraints imposed before the algorithm is run are project cost, start-dates, duration, a budget/resource constraint, and the relative importance of portfolio sub-elements/projects. By imposing constraints on the portfolio before the algorithm is run, users can evaluate and measure when these constraints are violated (if violations are allowed). Different portfolios may deviate further than each other from projects' need dates. Similarly, tracking the magnitude of budget constraint violations could help evaluate tradeoffs between mission need dates and staying under budget.

The process for resource constraining a portfolio is:

1. Remove all projects from the portfolio.
2. Iteratively add projects into the portfolio, starting with the highest priority projects.
3. Start with lowest shift value.
4. Check if adding in a project at the current shift value allows the portfolio to be "strictly constrained" under the resource constraint.
5. If not under constraint, then shift the project out by one year, and re-evaluate.

6. Continue adding projects until a shift value is found where the portfolio is strictly constrained, or all shift years have been evaluated.
4. If all shift years have been evaluated, select shift value that minimizes the violation of the constraint.
5. Continue adding projects until all projects have been added into the portfolio.

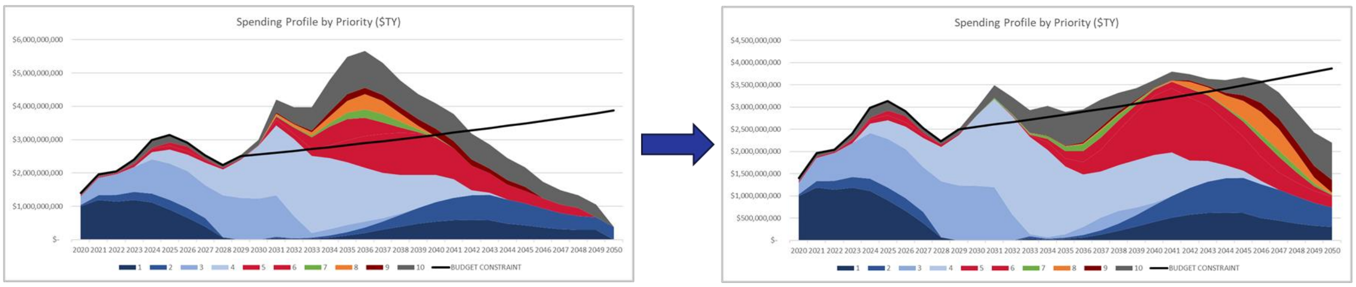

Figure 11 – Resource Constraint Analysis Output Example

Instead of going through this process by hand, an algorithm can go through the steps almost immediately. The resource constraint algorithm is particularly good at finding a portfolio that performs particularly well on one statistic, such as the affordability statistics listed in Table 1.

Step 3.2.2: Perform Tradeoff Analysis Simulations

Once the resource constraint analysis has developed a constrained scenario, a tradeoff analysis algorithm can be run on the portfolio to develop additional scenarios which may perform well on *multiple* statistics, instead of just one statistic.

A basic example of the principle of portfolio-level tradeoffs is shown below in Figure 12. In this example, a user's objective is to concurrently minimize both budget overrun, and schedule overrun. However, in many circumstances, these two objectives directly conflict with each other. This is where a tradeoff analysis is beneficial. The algorithm is useful in defining efficient tradeoffs between competing portfolio-level characteristics.

In Figure 12, let's assume that the baseline portfolio is portfolio B, where budget and schedule performance are poor. Portfolios A, C, D, and E are alternative portfolios that are identified via simulation. Portfolio E is by far the best alternative, as it perfectly minimizes both affordability and schedule risk. However, in practice, perfect alternatives rarely exist. For the rest of the example, let's presume that portfolio E is unattainable.

Portfolio C would be *weakly preferred* over portfolio B, as it reduces budget overrun while not sacrificing any additional schedule overrun. The term for this relationship is *weak dominance*. Portfolio A also *weakly dominates* portfolio B, as A reduces schedule overrun while not sacrificing budget overrun.

Portfolio D *strictly dominates* portfolios A, B, and C as it performs better on both statistics. In this sense, D is better than A, B, and C in every way. Tradeoff analysis logic runs simulations to locate alternative portfolios to *ideally* locate strictly dominant portfolios (i.e., D), but also looks for portfolios which *weakly dominate* other portfolios.

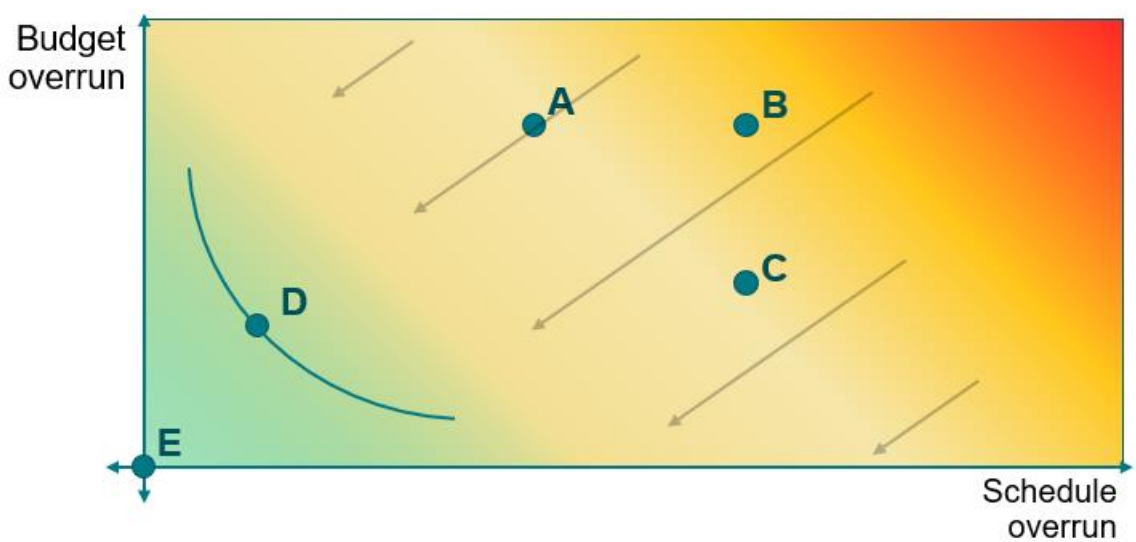

Figure 12 – Tradeoff Analysis Graph: Two Competing Objectives

In many circumstances, finding portfolios like A, C, or D is not easy or even possible without a model; therefore, having a system to define efficient *tradeoffs* between competing statistics is crucial.

Tradeoff analysis logic is implemented via a tradeoff analysis algorithm. The tradeoff analysis algorithm determines portfolio alternatives that efficiently optimize conflicting tradeoffs between multiple portfolio characteristics. Pareto efficiency is a typical way to define efficiency. Pareto efficiency can be defined as, "a situation where no action or allocation is available that makes one entity better off without making another worse off". In the context of this analysis, "entities" are portfolio-level statistics.

Figure 13 highlights the results of running 300 simulations and compiling affordability and mission risk statistics for each alternative. The pareto efficient portfolios from this simulation are indicated in orange. This "short-list" of efficient portfolios warrant presentation to stakeholders, as they are the portfolios that most efficiently optimize the portfolio on competing statistics.

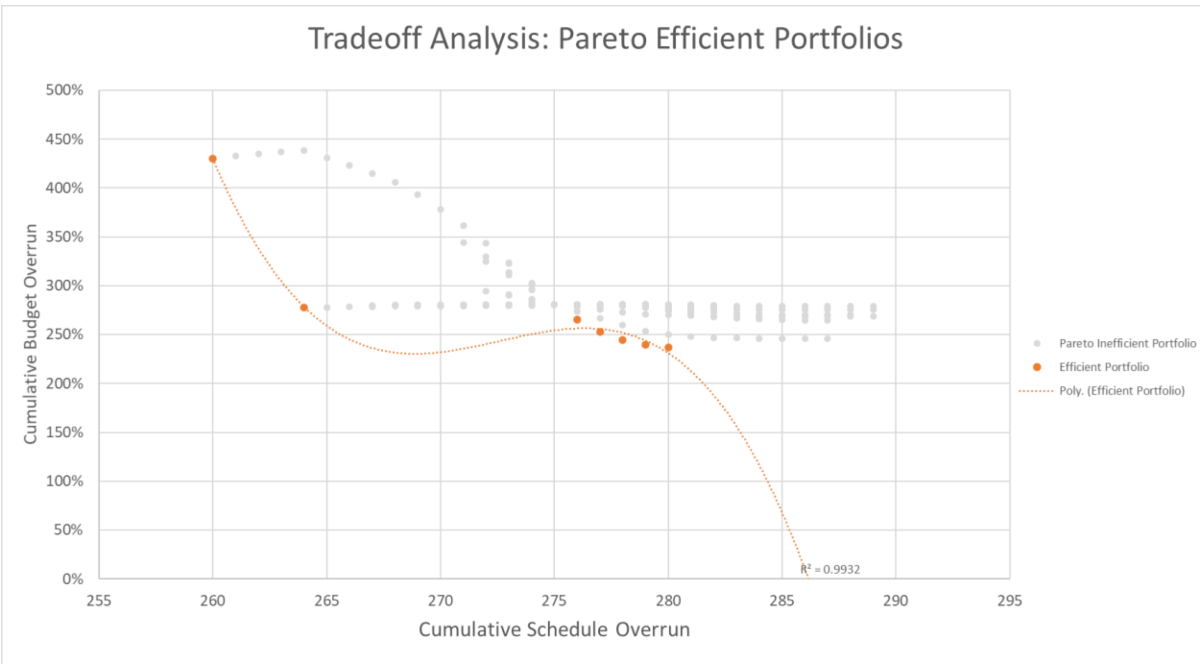

Figure 13: Pareto Efficient Portfolios

To determine "efficient" tradeoffs between different portfolio characteristics, the tradeoff analysis algorithm runs thousands of simulations and directly compares the alternatives against each other to determine efficient alternatives. The tool works by finding all possible one-shift alternative portfolios. One-shift alternative portfolios have exactly one difference compared to a baseline portfolio. Table 10 outlines an example of a one-shift alternative portfolio, where project B has a modified schedule while all other projects stay the same.

Project Portfolio	Baseline Portfolio: Project Completion Date	One-Shift Alternative Portfolio
Project A	2035	2035
Project B	2040	2042

Project C	2029	2029

Table 10: One-Shift Alternative Portfolio

In the example above, only one project is modified compared to a baseline portfolio. This allows for *marginal analysis* to be performed on each alternative portfolio, making it easier to characterize the marginal impact of making one single modification to a baseline portfolio.

Usually, finding all one-shift alternative portfolios involves hundreds or thousands of alternatives to compare. An algorithm can help the model more efficiently find and compare all alternatives in a few minutes.

The general logic of the algorithm operates through multiple layered logic loops to collect key statistics on each portfolio. In the outer loop, the algorithm looks at each project, skips over projects the user excluded, and finds all one-shift alternative portfolios *specific to that project*. For each portfolio, statistics such as the ones shown in Table 11 are stored in a database.

General Portfolio Stats	Affordability Statistics	Executability Statistics	Mission Risk Statistics
Shifted Project Name	Max BC Violation	Investment Smoothing	Total Years Shifted
Portfolio ID	Cumulative BC Violation	# Concurrent Projects	
Original Portfolio Stats		Max $ Executed	
Tradeoff Value		Site Statistics	

Table 11: Example Portfolio Statistics Calculated for Each Portfolio Alternative

After storing the information, the algorithm compares the stored alternatives against each other based on user-defined optimality calculated in the “tradeoff value” statistic.

Figure 14 depicts the logic diagram for the tradeoff analysis. The primary benefit of using tradeoff analysis logic is that if the baseline portfolio is already relatively acceptable, then it effectively accomplishes a detailed marginal analysis, finding portfolios that are only slightly different, and comparing performance. Before running tradeoff analysis, the initial portfolio is ideally already well-performing across multiple portfolio statistics. The resource constraint analysis is a useful pre-cursor to ensure this condition is met.

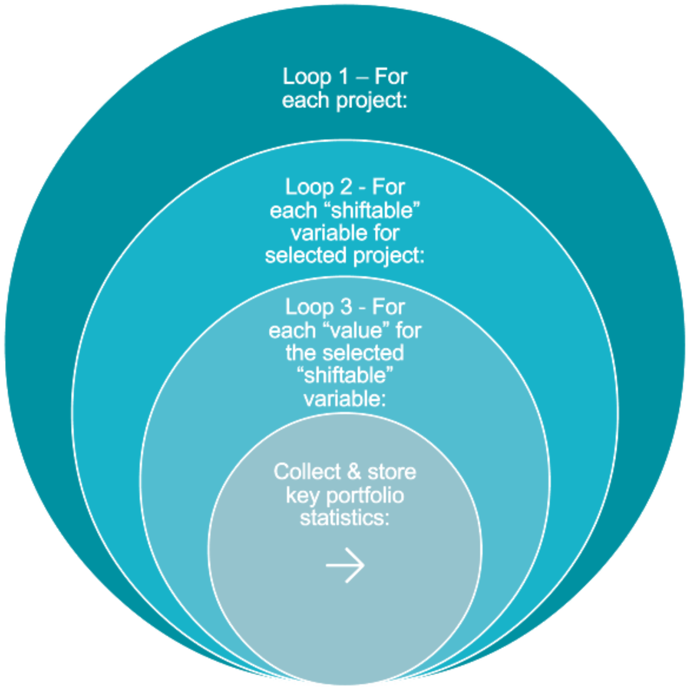

Figure 14: Tradeoff Analysis Logic Diagram

Between resource constraint analysis and tradeoff analysis, a portfolio can be evaluated to adjust under different conditions. If the foundational analysis is robust, when obstacles hamper a portfolio, decisions can be made quickly using these tools.

Step 3.3: Develop Short-List of Portfolio Alternatives

Once thousands of portfolio alternatives have been simulated and their respective tradeoffs documented, a short list of alternatives is extracted from the simulation database for decision-maker consideration.

Each simulation should have unique performance characteristics. Some will excel in one characteristic but perform poorly in other characteristics. Others will perform moderately well on multiple statistics, but not excel in any statistic.

The point of developing a diverse short list of alternatives is that it allows the decision-maker to understand the different possible alternatives and make an informed decision on which risks to mitigate and which to accept. In other words, providing a short list of *efficient portfolio alternatives* enables decision-makers differentiated and actionable alternatives.

Conclusion

With many complex, costly construction projects on the horizon, NNSA planners need effective portfolio analysis tools to ensure that the enterprise meets its goals. Unstable budgets and unexpected costs can have major impacts on construction schedules and mission needs. The portfolio analysis tools highlighted in this paper offer the NNSA the analytical rigor to make informed portfolio decisions, increasing the chance to achieve its goals.

The analysis gives leaders answers in the face of uncertain conditions. It does not just provide one solution, but offers multiple solutions that can fit budget constraints, mission needs, and schedule changes. With multiple solutions, decision-makers can identify and adjust portfolios to meet the current environment at any point in time.

It is also worth mentioning that while this methodology provides an analytical framework for solving portfolio analysis problems, a model alone cannot solve challenging planning problems that organizations face. The application of this process is meant to *inform faster, better decision-making*, but ultimately this process is only as good as the analysts implementing the steps and analyzing the results for the decision-maker.

While the simple methodology discussed in this paper was developed for NNSA, the same process can be employed by any organization managing a portfolio of projects. Furthermore, the same process can also be used to support Analyses of Alternatives, affordability analyses, contingency funding analysis, sustainment reviews, force design, and many other analyses. Through application of this process, organizations can consistently perform traceable, actionable, and reliable portfolio analysis to inform better decision-making.