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# Postoptimality Analysis in the Selection of Technology Portfolios


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# Presentation Outline

- Rationale
- Technology Portfolio Selection Problem
- Postoptimality Analysis
  - Parametric Screening
  - Monte Carlo Analysis
  - K-Best Analysis
- Conclusions

# Rationale

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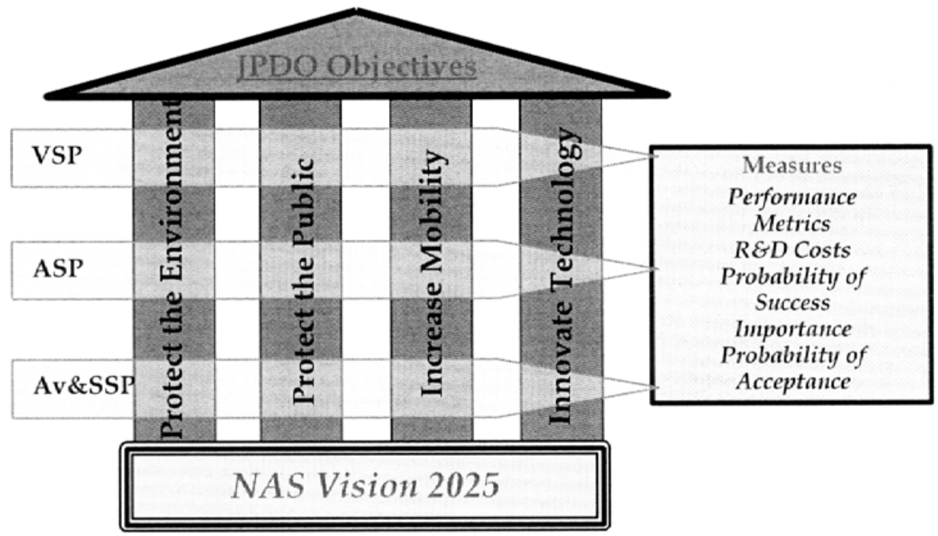
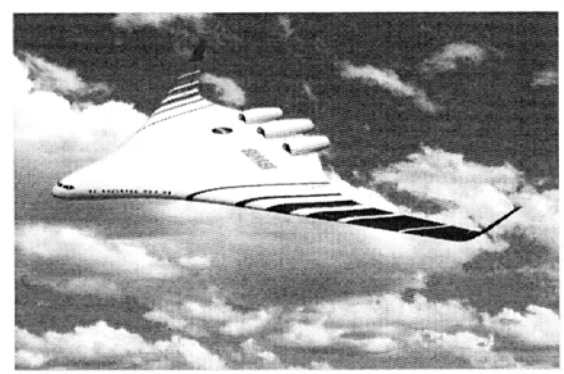
- Stems from the need for consistent, transparent and auditable decision-making processes and tools
- Project investments are selected through optimization of net mission value as a function of capability level achieved, subject to cost and time constraints.
- The uncertainty in the input data must be combined into a global confidence range, which provides the decision maker with an overall sense of quality and likelihood of success of the investment strategy.
- Main intent: to gauge the degree of confidence in the optimal solution and to provide the decision-maker with an array of viable selection alternatives, which take into account input uncertainties and possibly satisfy non-technical constraints.

# Technology Portfolio Selection

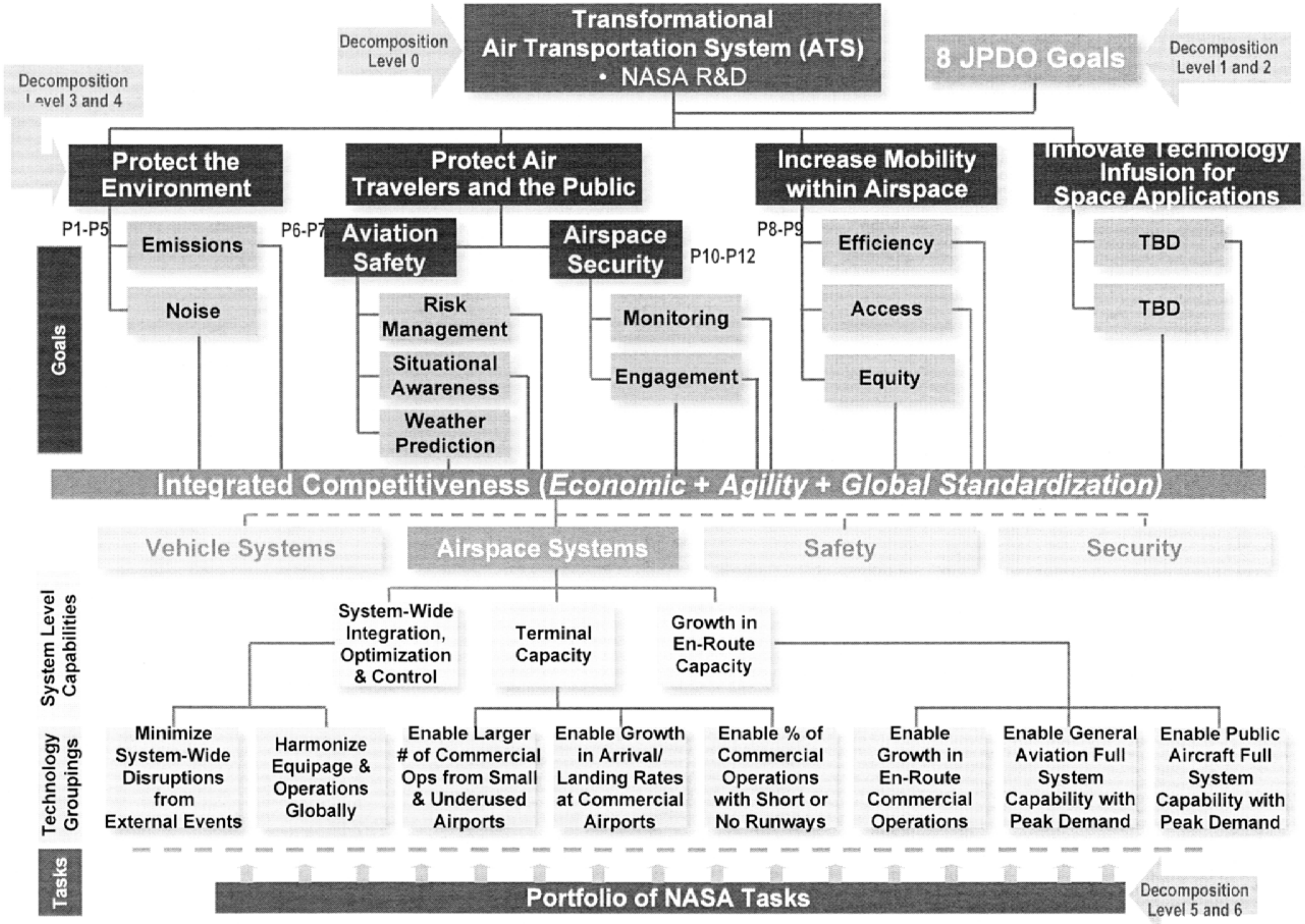
- Quantify NASA goals/sub-goals in the context of the Next Generation Air Transportation System (JPDO). Capture the entire research program, and provide initial illustrative results for Return on Investment.




- Objective: to substantially increase transport capacity while improving or keeping constant any harmful effects on the environment (emissions, noise), safety, and security.



# Example - Airspace Systems Program



# Example - NASA JPDO Efforts

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**ASP: 8@ $8600M**

| | |
|---|---|
| *Minimize System-wide Diruptions(ASP)* | *600* |
| *Harmonize Equipage & Operations(ASP)* | *400* |
| *Larger #of Commercial Ops,SUA (ASP)* | *200* |
| *Growth in LTO at Com. Airports (ASP)* | *1000* |
| *Enable Com Op at Short Runways(ASP)* | *1000* |
| *Enable Growth in Com OP in NAS (ASP)* | *4000* |
| *Enable Full System Gen. Aviation (ASP)* | *1000* |
| *Enable Public Aircraft Capability (ASP)* | *400* |

The Participants assembled data on these 38 Capabilities fulfilled to completion and targeted for R&D in support of tripling capacity without further eroding safety, security, and environment. They total to ~35B.

**VSP: 15@ $22935M**

| | |
|---|---|
| Subsonic Vehicles Emissions (VSP) | 1500 |
| Supersonic Vehicles Emissions (VSP) | 85 |
| ESTOL Vehicles Emissions (VSP) | 1500 |
| Personal Air Vehicles Emissions (VSP) | 100 |
| Subsonic Vehicles Noise (VSP) | 2400 |
| Supersonic Vehicles Noise (VSP) | 392 |
| ESTOL Noise (VSP) | 460 |
| Personal Air Vehicles Noise (VSP) | 17 |
| Rotor Vehicles Noise (VSP) | 390 |
| Subsonic Aerodynamics,Structures & Efficiency (VSP) | 10100 |
| Super Sonic Aerodynamics,Structures & Efficiency (VSP) | 1867 |
| ESTOL Aerodynamics,Structures & Efficiency (VSP) | 808 |
| RV Aerodynamics,Structures & Efficiency (VSP) | 851 |
| PAV Aerodynamics,Structures & Efficiency (VSP) | 376 |
| UAV Aerodynamics,Structures & Efficiency (VSP) | 2089 |

**AvSSP: 15 @ $3302.5M**

| | |
|---|---|
| Incidents,Abnormal Operations (AvSSP) | 340 |
| Incidents, System Failure (AvSSP) | 340 |
| Detection of Natural Hazards (AvSSP) | 260 |
| Mitigation, Natural Hazards (AvSSP) | 260 |
| Human Error, Unsafe Flights (AvSSP) | 340 |
| Machine Error, Unsafe Flight (AvSSP) | 340 |
| Human/Machine Interface. (AvSSP) | 340 |
| Hostile Aircraft Takeover (AvSSP) | 170 |
| Protection, MANPADS (AvSSP) | 170 |
| EME & Cyber Attack Protection (AvSSP) | 127.5 |
| Hostile Info Protection (AvSSP) | 127.5 |
| Flight Path Dev Detection (AvSSP) | 130 |
| Airport Security Breach Detection (AvSSP) | 97.5 |
| Detection of Cargo Threat (AvSSP) | 130 |
| Detection of Chems. & Biologicals(AvSSP) | 130 |

# Technology Portfolio Selection Problem

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- The portfolio analysis targeted identifying the best set of capabilities that would support the implementation of desirable future scenarios that contribute to the high-level Joint Planning and Development Office (JPDO) goals, subject to performance requirements, and budget and development time constraints

- For each capability, the capability utility, probability of development success, and the probability of acceptance are combined to compute an overall expected utility of the capability

- The expected utility, together with the development cost of the capability, are the key quantities used in computing an optimal portfolio.

- The optimal portfolio selection problem is to determine the set of capabilities that provide the maximum composite value while fitting within the available budget.

# Optimal Portfolio Investment

- The optimization problem:
  - Find $X_i$ such that it maximizes $z = \Sigma_i EU_i * X_i$
  - subject to the cost constraint $\Sigma_i C_i * X_i \leq B$
  - with $i = 1, N$ (N number of capabilities) and $X_i = \{0,1\}$.

- Solved with the "Branch and Bound" algorithm (Martello & Toth, 1988)

- The optimal set of selected capability is denoted by $(X_i)^{opt}$

- The cost of the optimal portfolio is $C^{opt} = \Sigma_i C_i * (X_i)^{opt}$

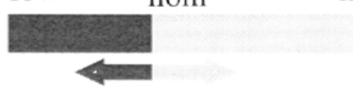
- The remaining budget ("investment slack ") $S = B - C^{opt}$

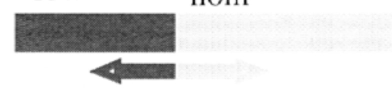
# Postoptimality Analysis - Parametric Screening

- This approach identifies the bounds of each parameter for which the given optimal selection is valid.
- From a different point of view, this kind of analysis effectively provides the independent uncertainty range for the cost and expected utility of each capability.
- Capabilities close to the "optimal frontier" and weakly dominant are sensitive to cost and utility variation.
- Two caveats regarding the nature of the results obtained:
  - The cost and the expected utility are assumed independent and varied independently of each other;
  - In the expected utility analysis no physical constraints have been taken into account to limit the improvement in performance of each capability.

# Parametric Screening

- Solve the optimization problem with one parameter - cost $C_i$ or expected utility $EU_i$ - varied from the base value (first incremented and then decremented by $\Delta C$ or $\Delta EU$, respectively) until a change relative to the nominal solution is observed:




- This determines the parameter limits of each capability for which the base optimal portfolio $(X_i)^{opt}$ is obtained:

$$C_{low} \leq C_{nom} \leq C_{high}$$
$$EU_{low} \leq EU_{nom} \leq EU_{high}$$

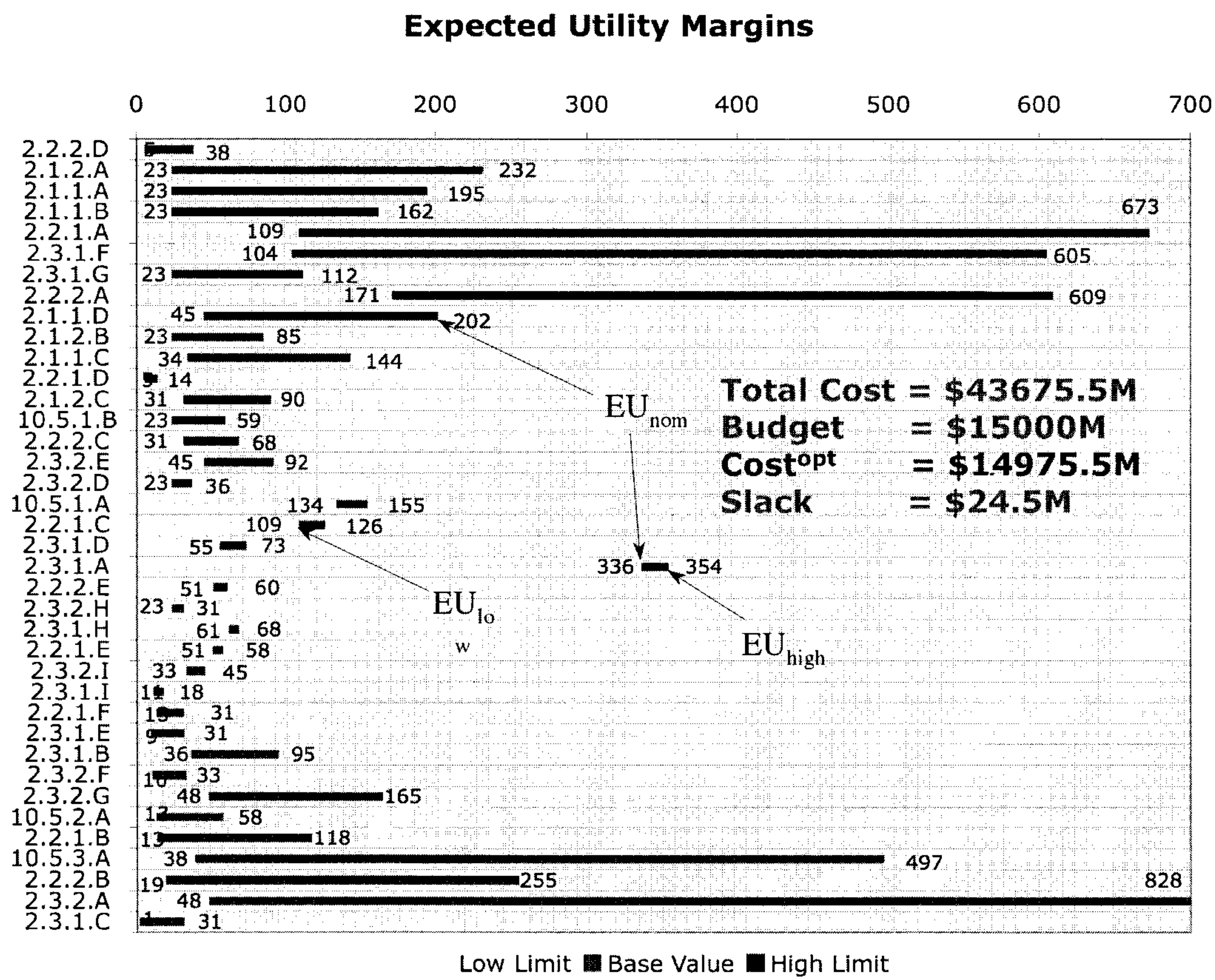
- Track the capabilities which have a tendency to exit/enter the base optimal portfolio.
- Sensitivity measure: cumulated changes over the runs = $\Sigma[X_i-(X_i)^{opt}]$.

# Parametric Screening - *A Priori* Observations

| | Selected capability ($X_k = 1$) | Capability not selected ($X_k = 0$) |
|---|---|---|
| Cost | $C_{low} =$ TBD (1)<br>$C_{high} = C_{nom} + S$ (2) | $C_{low} =$ TBD (5)<br>$C_{high} = \infty$ (6) |
| Expected Utility | $EU_{low} =$ TBD (3)<br>$EU_{high} = \infty$ (4) | $EU_{low} = 0$ (7)<br>$EU_{high} =$ TBD (8) |

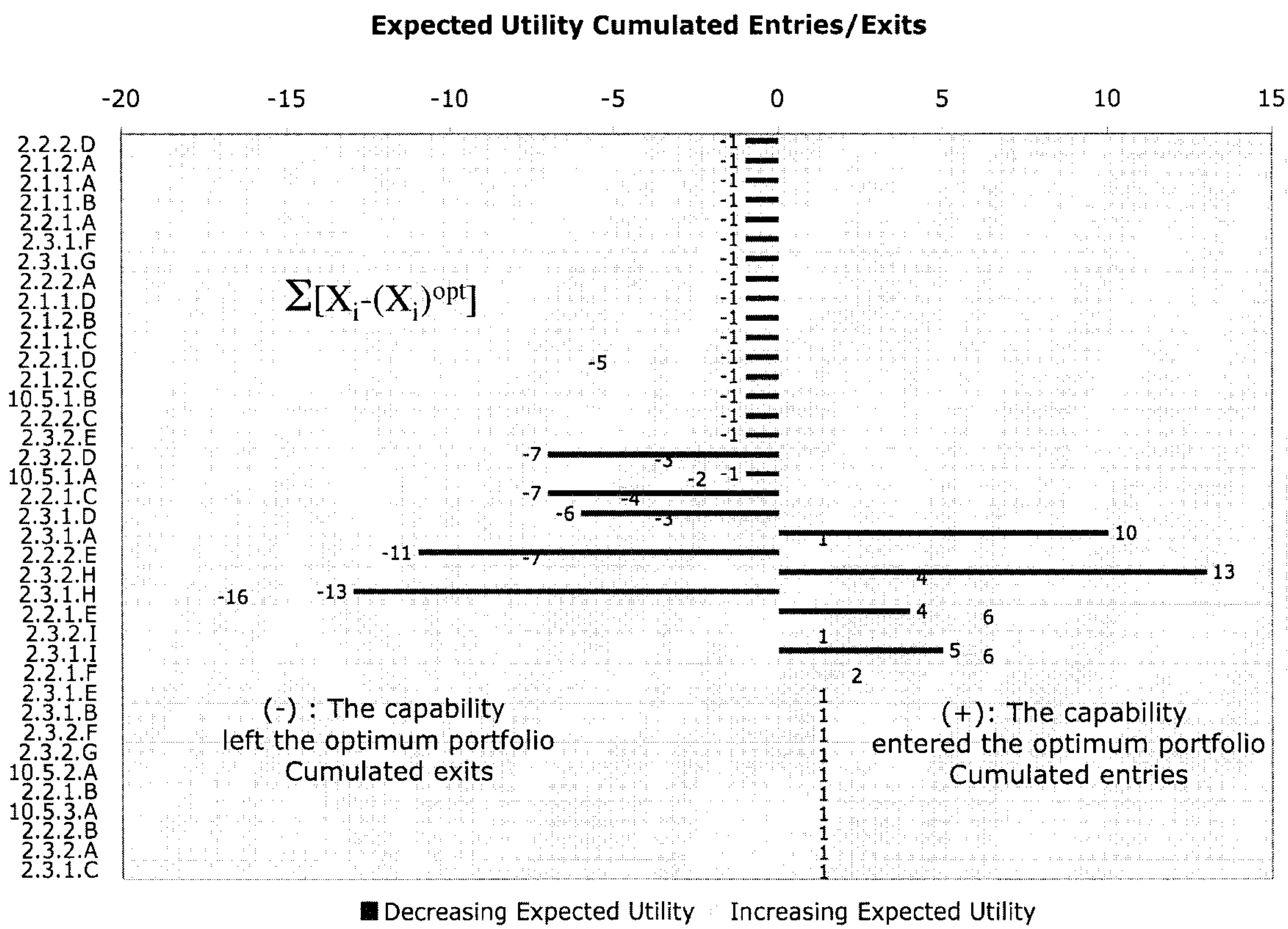
(1) Lowering the cost of a selected capability will introduce other capabilities in the portfolio.
(2) Non-intuitive changes can occur. $S = B - C^{opt}$.
(3) Lowering the expected utility will displace the capability.
(4) Selected capabilities have already a high expected utility.
(5) Can induce complex changes.
(6) Capabilities not selected are already too expensive.
(7) Capabilities not selected are already less performing.
(8) Can induce complex changes. In this quadrant, to avoid unrealistic changes, the expected utility is screened only up to twice the best expected utility in the capability set.

# Expected Utility Margins




✓ The high limit of non-selected capabilities represents the utility to fit the capability in the optimum portfolio for a given budget

# Expected Utility Sensitivity Sets



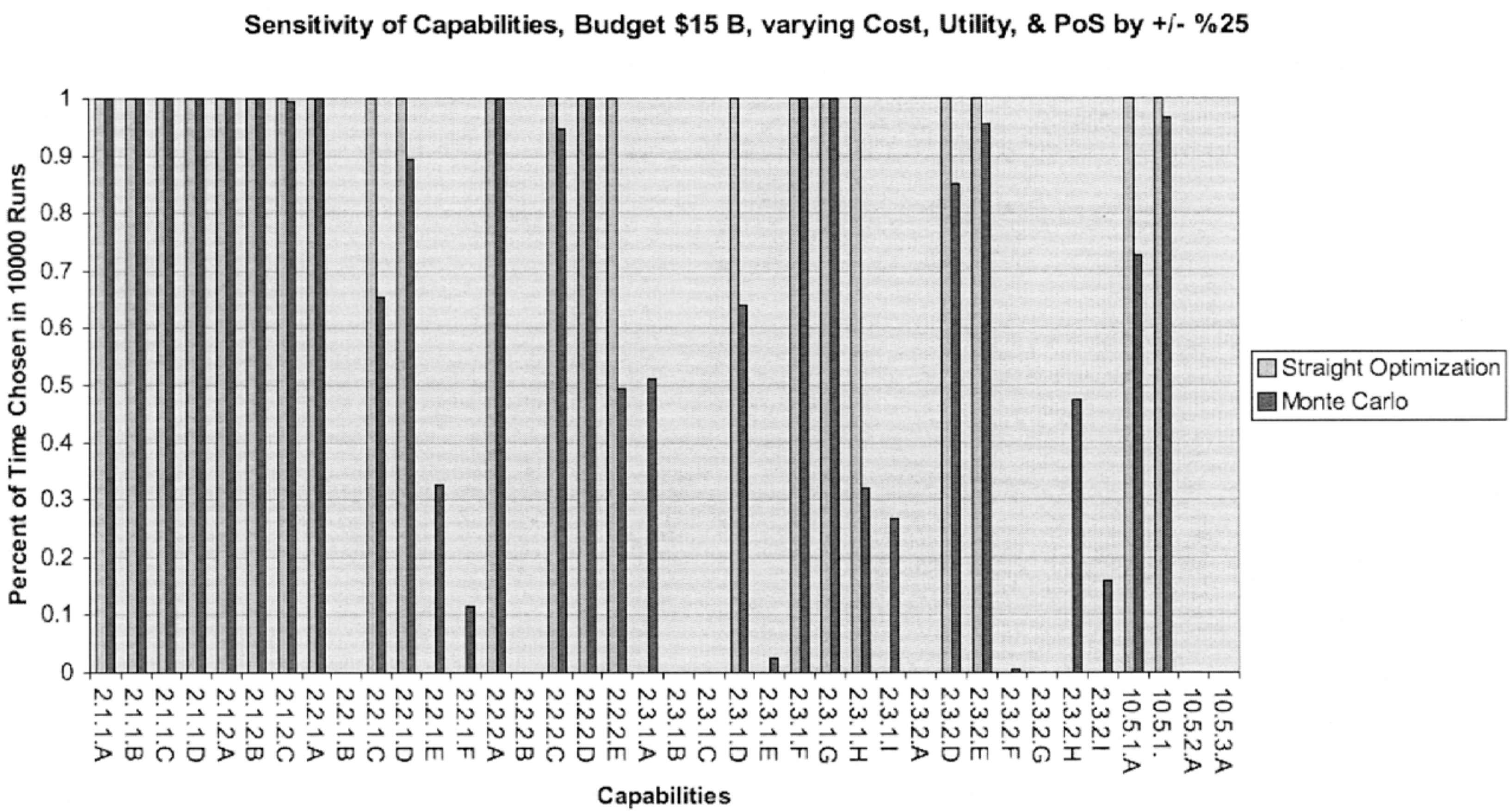

- The capabilities sensitive to expected utility increase are near the the optimal front and they have close [utility/Cost] ratios.
- The capabilities sensitive to expected utility decrease are also close to the optimal frontier, but their [utility/Cost] ratios have a wider spread and weak dominance.

# Monte Carlo Analysis

- Simultaneous variation of cost and expected utility
- Varied all capabilities with Monte Carlo sampling in two trials
  - +/- 10%
  - +/- 25%

  random variation relative to the initial assigned value
- Performed 1000 optimization runs for each case
- The status (in or out) of each capability is accumulated from each run such that a selection frequency is computed from this stage of the parametric screening.

# Selection Frequency Results



# Recommended Portfolio Composition

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### Robust Selection

Less than 10 exits for a selected capability in the deterministic analysis.
*Greater than 85% selection record for a selected capability in the Monte Carlo.*

- 2.1.1.A Protect/Prevent Abnormal Operations & System Failures
- 2.1.1.B Detect & Mitigate Natural Hazards
- 2.1.1.C Prevent Breakdown of Human/Machine Interface
- 2.1.1.D Integrity & Efficiency of Accepting Advanced Software Systems
- 2.1.2.A Detect & Inform Potential System Vulnerabilities
- 2.1.2.B Mitigate Consequences from Intentional Attack
- 2.1.2.C Detect & Contain Diseases & Bio/Chem Agents
- 2.2.1.A Low emission subsonic vehicles
- 2.2.1.D Low emission personal air vehicles
- 2.2.2.A Low noise subsonic vehicles
- 2.2.2.C Low noise ESTOL vehicles
- 2.2.2.D Low noise personal air vehicles
- 2.3.1.F Increase Arrival/Landing Rates at Commercial Airports
- 2.3.1.G Commercial Operations from Small/Underused Airport
- 2.3.2.E Efficient all-weather rotorcraft
- 10.5.1.B Conduct Routine UAV in NAS

### Not Recommended

Less than 10 entries for a non-selected capability in the deterministic analysis.
*Less than 15% selection record for a non-selected capability in the Monte Carlo*

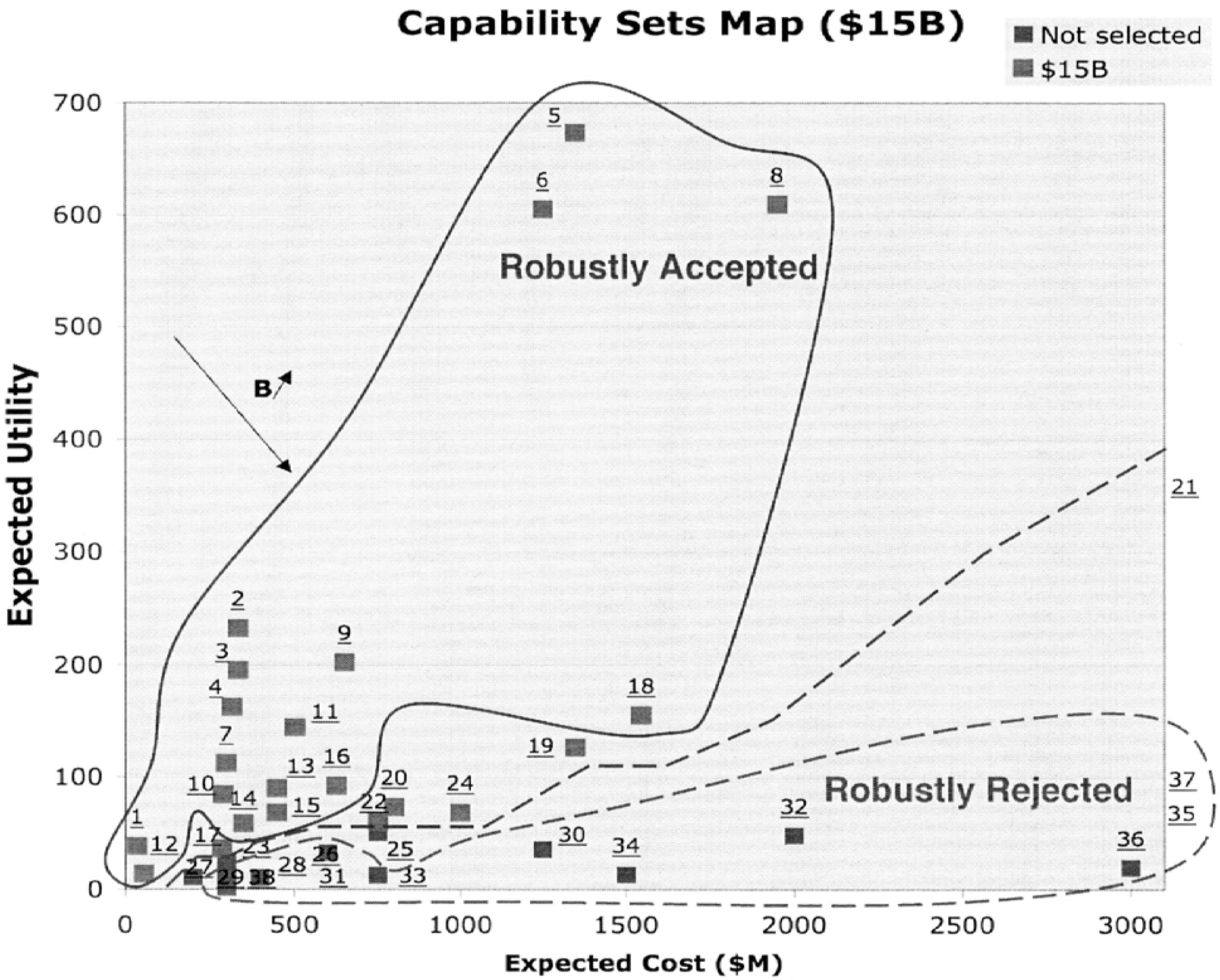
- 2.2.1.B Low emission supersonic vehicles
- 2.2.1.F Low emission UAVs
- 2.2.2.B Low noise supersonic vehicles
- 2.3.1.B General Aviation During Peak Demand
- 2.3.1.C Public Service Aircraft During Peak Demand
- 2.3.1.E Globally Harmonized Equipage & Operations
- 2.3.2.A Efficient subsonic vehicles
- 2.3.2.F Complete Decision Information to All in NAS
- 2.3.2.G Low Cost Vehicles for Bulk Cargo
- 2.3.2.I Minimum Impediments of Mode Change
- 10.5.2.A Extended Autonomous Flight in Mars Atmosphere
- 10.5.3.A Incorporating Hypersonic Air-Breathing Propulsion

### Trade Candidate

- 2.2.1.C Low emission ESTOL vehicles
- 2.2.1.E Low emission rotorcraft
- 2.2.2.E Low noise rotorcraft
- 2.3.1.A Capacity En-Route Commercial Operations in NAS
- 2.3.1.D Minimize System-Wide Disruptions
- 2.3.1.H Commercial Operations with short/no Runways
- 2.3.1.I Incorporate Full Spectrum of Aircraft to NAS
- 2.3.2.D Efficient easy-to-operate personal air vehicles
- 2.3.2.H Increased Speed & Range for Pedestrian Travel
- 10.5.1.A Autonomous high altitude long-endurance flight

- The results from the two parametric approaches are mutually calibrated in order to issue a common categorization of the projects sets as "robustly selected", "robustly rejected", and "trade candidates".

# Capability Sets Map (EU vs. C)



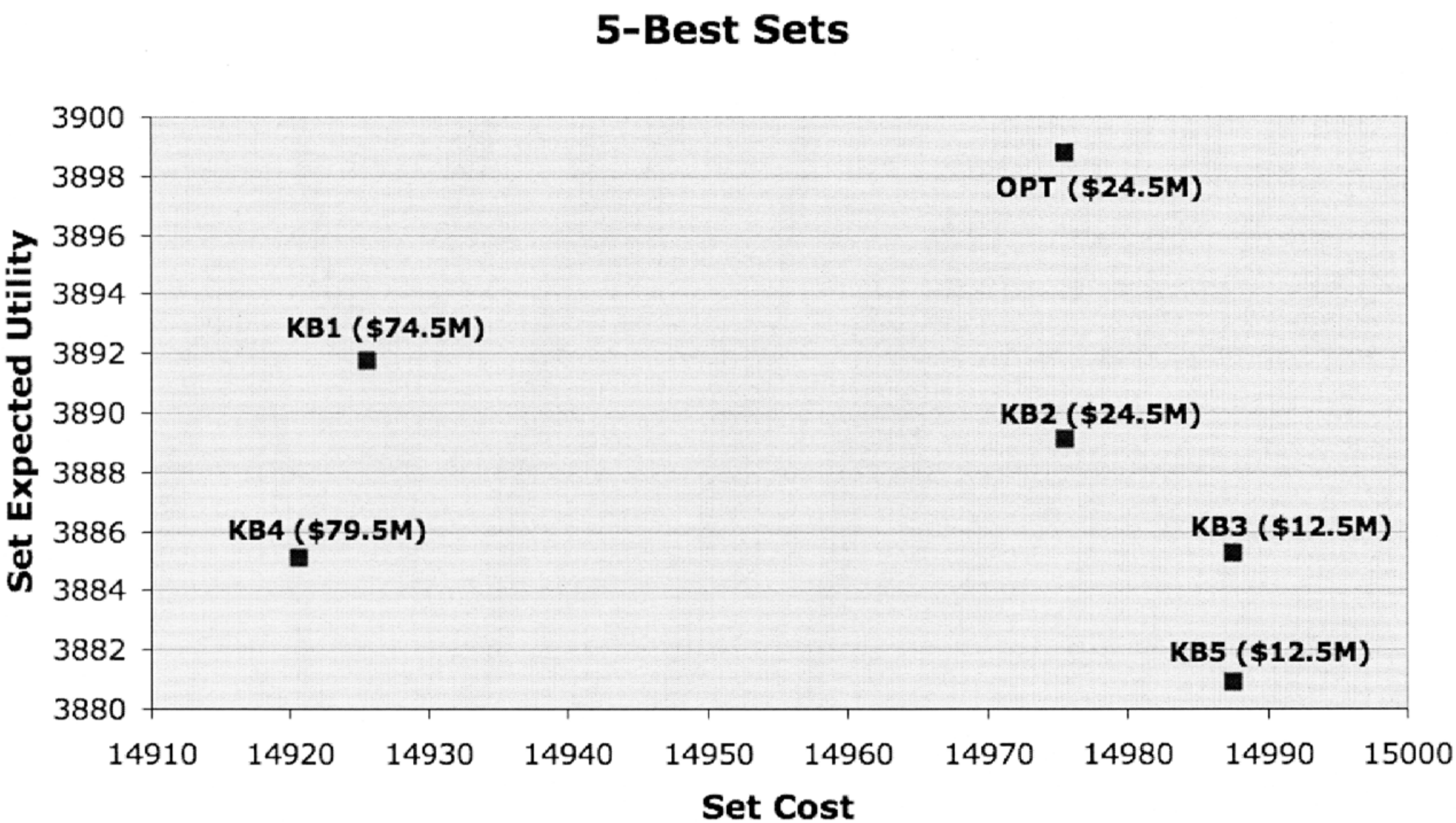

1. Low noise personal air vehicles
2. Detect & Inform Potential System Vulnerabilities
3. Protect/Prevent Abnormal Operations & System Failures
4. Detect & Mitigate Natural Hazards
5. Low emission subsonic vehicles
6. Increase Arrival/Landing Rates at Commercial Airports
7. Commercial Operations from Small/Underused Airports
8. Low noise subsonic vehicles
9. Integrity & Efficiency of Accepting Advanced Software Systems
10. Mitigate Consequences from Intentional Attack
11. Prevent Breakdown of Human/Machine Interface
12. Low emission personal air vehicles
13. Detect & Contain Diseases & Bio/Chem Agents
14. Conduct Routine UAV in NAS
15. Low noise ESTOL vehicles
16. Efficient all-weather rotorcraft
17. Efficient easy-to-operate personal air vehicles
18. Autonomous high altitude long-endurance flight
19. Low emission ESTOL vehicles
20. Minimize System-Wide Disruptions
21. Capacity En-Route Commercial Operations in NAS
22. Low noise rotorcraft
23. Increased Speed & Range for Pedestrian Travel
24. Commercial Operations with short/no Runways
25. Low emission rotorcraft
26. Minimum Impediments of Mode Change
27. Incorporate Full Spectrum of Aircraft to NAS
28. Low emission UAVs
29. Globally Harmonized Equipage & Operations
30. General Aviation During Peak Demand
31. Complete Decision Information to All in NAS
32. Low Cost Vehicles for Bulk Cargo
33. Extended Autonomous Flight in Mars Atmosphere
34. Low emission supersonic vehicles
35. Incorporating Hypersonic Air-Breathing Propulsion
36. Low noise supersonic vehicles
37. Efficient subsonic vehicles
38. Public Service Aircraft During Peak Demand

Most of the selected capabilities "dominate" the rest of the global capability set.
The "optimal frontier" (green line) separates the optimal set region from the remaining domain.

# K-Best Sets

- The k-best sets approach provides solutions near the optimal solution.
- Based on the k-best sets the decision-maker could evaluate aspects of the problem that are not easily modeled quantitatively.
- By finding the k-best sets of technologies with the base-case input parameters, and then comparing the values of these sets over the entire range of possible values for the input parameters, one can identify competitor portfolios.
- The intersection of the k-best portfolios with the optimal portfolio produces a set of project selections deemed as "persistent."

# 5-Best Solutions




- Relative positioning of the five closest competitive portfolios with respect to the optimal recommendation in an aggregated expected utility/total cost mapping.
- KB3 is close to the optimal portfolio, but in addition it minimizes the budget slack.

# Overall Presence in the 5-Best Portfolios

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| Capability | Opt | KB1 | KB2 | KB3 | KB4 | KB5 | Overall |
|---|---|---|---|---|---|---|---|
| 2.2.2.D | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.1.2.A | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.1.1.A | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.1.1.B | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.2.1.A | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.3.1.F | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.3.1.G | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.2.2.A | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.1.1.D | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.1.2.B | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.1.1.C | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.2.1.D | 1 | 1 | 1 | 1 | 0 | 1 | 83.33% |
| 2.1.2.C | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 10.5.1.B | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.2.2.C | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.3.2.E | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.3.2.D | 1 | 1 | 1 | 0 | 1 | 0 | 66.67% |
| 10.5.1.A | 1 | 1 | 1 | 1 | 1 | 1 | 100.00% |
| 2.2.1.C | 1 | 1 | 1 | 1 | 1 | 0 | 83.33% |

| Capability | Opt | KB1 | KB2 | KB3 | KB4 | KB5 | Overall |
|---|---|---|---|---|---|---|---|
| 2.3.1.D | 1 | 1 | 1 | 1 | 1 | 0 | 83.33% |
| 2.3.1.A | 0 | 0 | 0 | 0 | 0 | 1 | 16.67% |
| 2.2.2.E | 1 | 1 | 0 | 1 | 1 | 0 | 66.67% |
| 2.3.2.H | 0 | 0 | 0 | 1 | 0 | 0 | 16.67% |
| 2.3.1.H | 1 | 0 | 1 | 1 | 1 | 0 | 66.67% |
| 2.2.1.E | 0 | 1 | 1 | 0 | 0 | 0 | 33.33% |
| 2.3.2.I | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.3.1.I | 0 | 1 | 0 | 0 | 0 | 1 | 33.33% |
| 2.2.1.F | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.3.1.E | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.3.1.B | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.3.2.F | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.3.2.G | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 10.5.2.A | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.2.1.B | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 10.5.3.A | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.2.2.B | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.3.2.A | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |
| 2.3.1.C | 0 | 0 | 0 | 0 | 0 | 0 | 0.00% |

- The categorization of the capabilities by their overall percent presence in the suboptimal portfolios (including the "persistent" set displayed in green color).

- The parametric sensitivity analysis and the k-best analysis generate consistent choices of "robust" and "persistent" recommendations.

## Conclusions

- Two complementary methods - parametric sensitivity analysis and k-best sets analysis - have been used for qualifying optimal technology portfolios.

- Although the two above approaches are complementary, their results are consistent, in that the "persistent" set is similar in composition to the "robust" set.

- The goal of the postoptimality study is to enhance and improve the decision-making process by providing additional qualifications and substitutes to the optimal solution.

- The methodology proposed here is demonstrated on a NASA technology project selection.

- The results highlight the importance and the usefulness of the postoptimality analysis in providing a higher level of confidence to the technology portfolio recommendations.