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The Value of Refining Buy-up Alternatives for Portfolio Decision Analysis

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1. Introduction

Portfolio project selection and in particular portfolio decision analysis (DA) approaches at their most basic rely on a simple economic notion – rank investments in order of value gained per dollar spent and fund them in this order until the budget is spent. But the quality of the recommendations generated by such an approach is only as good as the quality of the assumptions about projects that are used. In this paper we consider how much effort is worth expending to improve definition of alternatives at the project level.

Much of the time-consuming work in project portfolio management consists of efforts to obtain and improve these inputs in a variety of ways. Because analyst and managerial time and attention are limited resources, it is desirable to understand when different efforts are valuable, and to focus accordingly. For example, Keisler (2004) explored portfolio characteristics that determine the benefit of efforts to refine estimates of project value. But analysts do more than tighten value estimates. One of the main activities in standard portfolio DA (e.g., Allen, 2000) is defining project level alternatives. We shall explore some different strategies for this and what conditions make them valuable.

A standard approach to creating a richer set of alternatives (and one that lends itself very naturally to hierarchical portfolio management) is to have project managers present several different project alternatives based on different budgets, e.g., current budgeted level, blue-sky proposal (or buy-up), barebones (or buy-down) proposal, maybe some other target amount, with zero funding being a standard alternative (see Sharpe and Keelin, 1998). Clearly, portfolio analysis is applied in situations with a variety of characteristics, e.g., portfolios of projects vs.

portfolios of business units (Allen, 2000). Different levels of refinement can be used at these different levels (Anderson and Jogelkar, 2004), for example stage-gate type portfolio management methods (Cooper et al, 2001) may include more funding level alternatives for investments at higher levels of the hierarchy. Presumably, such additional efforts yield economic benefit.

1.1 Conceptual example

Consider the simple situation depicted in figure 1. In this portfolio, there are only two projects, 1 and 2. The portfolio manager has C available to fund projects. The manager of project 1 has requested funding of C and promises to deliver value V1, and the manager of project 2 has promised to deliver value V2. If this was all that was specified, the portfolio manager would fund project 1 rather than project 2, because V1 > V2. If instead the full value trajectories (i.e., graphs charting value versus investment, also called buy-up curves) for each project were specified, the portfolio manager would allocate the available funding to both projects so that each would have the same marginal return per dollar invested, at funding levels C1' and C2'. This changes the frontier of the portfolio from the lower curve to the upper curve in figure 2, and the value added by including the full range of funding alternatives is V1'+V2'–V1.

Figure 1: A two project example

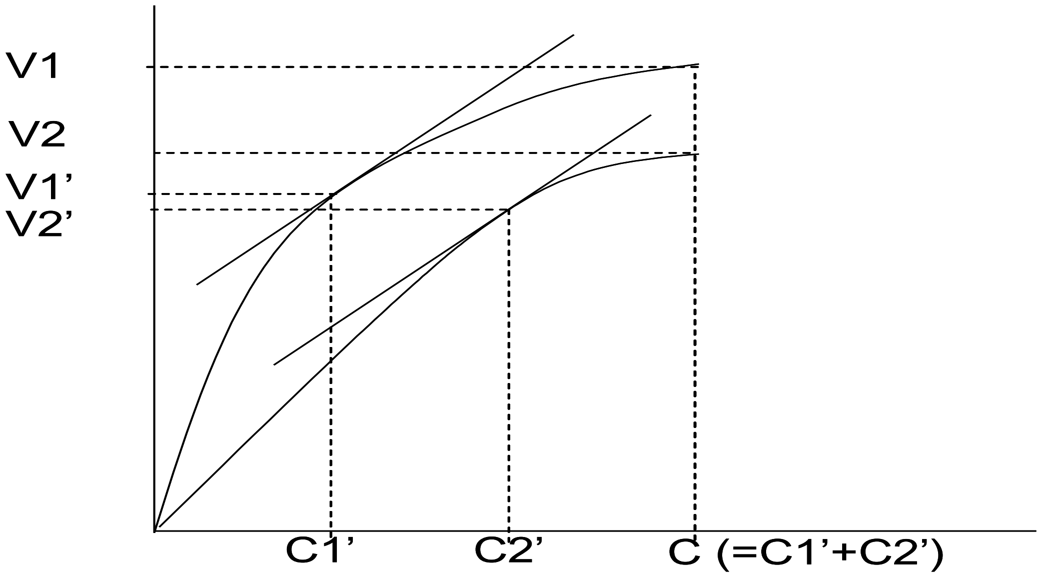
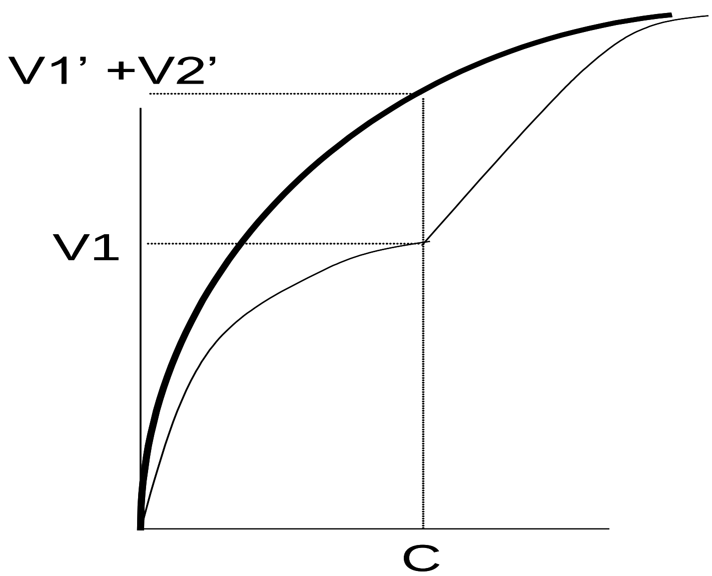


Figure 2: Value trajectories when partial funding of projects is / is not allowed.



This paper is essentially about this nature of portfolio buy-up curves, how they depend on the individual buy-up curves and the method by which they are integrated, and how important it is to correctly characterize the curves and make decisions based on them. In section 2, we define a model that formalizes this notion of what goes on in a portfolio including characteristics of projects in the portfolio and the way information about these projects may be transformed by various analytic strategies. In section 3, we consider some real data to derive assumptions for simulating portfolios with which to compare the analytic strategies. We describe simulation results for a base case and a number of variations in section 4, to see what tends to make the different strategies more or less effective. We conclude with a discussion of implications of these findings for decision analytic and project portfolio management practice.

2. Model

2.1 Form

We start with a set of independent candidate projects within a portfolio vying for funding from a total budget B. For project i, there is a value function that relates the funds expended on the project (C_i) to the value of the project, call it $V_i(C_i)$, up to some maximum cost (investment) level, C_i^{max}, i.e., the requested level of funding level. In practice, V_i could be expected net present value (ENPV) or expected single or multiple attribute utility. We shall denote the cost of the portfolio $C = \Sigma C_i$ and the value of the portfolio as $V = \Sigma V_i(C_i)$.

We assume that the V_i, which represent the way that dollars of input are converted into use value, follow a common form for multi-attribute utility functions:

$$V_i(C_i) = r_i[1–EXP(–k_iC_i/C_i^{max})]/[1–EXP(–k_i)].$$

At $C_i = C_i^{max}$, the quantity within the brackets is equal to one, i.e., 100% of the potential value achieved, and at $C_i = 0$, the quantity within the brackets is 0. The parameter r_i, therefore, represents the value achieved per dollar for at the maximum investment level. The parameter k_i represents the level of curvature, where the higher the value of k_i, the more returns to scale are decreasing. Some portfolio applications (e.g., public policy) literally do use utility functions, while for others this function is a flexible proxy for a range of possible value trajectories.

2.2 Strategies

In practice, projects generally only receive funding levels corresponding to some proposal that they have submitted, that is, something up to our C_i^{max}. The portfolio manager must still determine what proposed funding levels should be developed for each project prior to the resource allocation decision. We consider several analytic strategies (S) for making this decision, and we denote the value of the portfolio under strategy S as V(S). We shall first consider three hypothetical strategies.

S1) *Random* funding: In this strategy, we randomly pick projects to fund at C_i^{max} until the budget is exhausted. This strategy is not one that we would consciously pursue. It serves as a practical lower bound so that we can compare how much value is added by the other strategies.

S2) *Discrete* funding: With this in-or-out strategy there is no additional definition of alternatives prior to project selection. We consider only the binary choice between including projects in the funded portfolio by funding them at their maximum cost or rejecting them by not funding them at all. Formally, the decision maker solves Max $V_{\{Ci\}}$ s.t. $C \leq B$, $C_i = 0$ or $C_i = C_i^{max}$.

S3) *Continuous* funding levels: This is an ideal where for each project the value for the entire funding range has been computed and therefore the decision maker can choose to fund at any level between 0 and C_i^{max}, i.e., the decision maker solves Max $V_{\{Ci\}}$ s.t. $C \leq B$, $C_i \geq 0$ and $C_i \leq C_i^{max}$.

Note, if the V_i are smooth, and $d^2V_i/dC_i^2 < 0$ for all i, a single optimal solution will exist and all projects that are funded at a level between 0 and C_i^{max} will have the same derivative of value with respect to cost at their chosen funding level.

We consider the additional variations:

S4) *Step*-levels for each project: The general case of a set of equally spaced increments in funding for a project in between the extreme cases of S2 and S3, i.e., Max $V_{\{Ci\}}$ s.t. $C \leq B$, $C_i = C_i^{max} n/k$, where n is an integer between 0 and k, for some $k > 1$. If $k = 2$, this would mean including the option of a 50% funding level, etc. In the base case, $k = 4$ and so the alternative funding levels for project i are 0%, 25%, 50%, 75% and 100% of C_i^{max}.

S5) Haircuts: With this strategy, we treat all projects alike and cut each project down by the same proportion until the total cost is equal to the budget, i.e., $C_i = C_i^{max} B/(\Sigma_i C_i^{max})$.

S6) Layered haircuts: Each project is funded in such a way that the marginal value of each project would be equal and the total budget would be spent, assuming that the curvature parameter (as defined below) for each project is equal to the mean curvature.

We can think of each strategy as facilitating the use of different information about the value trajectories, as in table 1. Assuming the portfolio manager sets the optimal funding levels for each project based on the information available at the time of decision, the increase portfolio expected value due to each strategy is analogous to the decision analytic expected value of the information brought to bear by that strategy. To compare the prospective benefit of these different strategies, we simulate portfolios of candidate projects with varying individual buy-up curves, and calculate the various V(S).

Table 1. Analysis reveals information, so value of analysis is analogous to value of information about parameter values.

Information level about parameters for *strategy*	**Productivity**	**Curvature**
(S1) Random	None (but portfolio wide average assumed > 0)	None (assume = 0)
(S2) Traditional	Project specific	None (assume = 0)
(S3) Optimal	Project specific	Project specific
(S4) Steps	Project specific	Project specific (partial) assume piecewise linear
(S5) Haircut	None (but portfolio wide average assumed > 0)	Portfolio-wide average
(S6) Layered haircut	Project specific	Portfolio-wide average

3. Determining assumptions

3.1 Descriptive data about portfolios

In order to calibrate the simulation model, I obtained two sets of data. The first is a family of capital investments and expenditures related to remediation of geographically distributed nuclear waste handling sites. These results are from a study led by Ronald G. Whitfield of the Argonne National Laboratory (Baldwin *et al*, 1994) , in conjunction with the development of a decision support system. A portfolio of 33 candidate projects was identified, and for each project detailed estimates of impact across many performance criteria were developed (by the proposers) and vetted (by a peer review process), for one or more of the following funding levels: Core, Intermediate, Operations, and Long-Range. A multi-attribute value function was assessed and the results were used to identify optimal portfolios for various assumptions regarding funding levels, value functions, etc.

Out of the 33 projects, there were 32 projects with at least two different funding levels having different values. For 17 projects three funding levels with different values were specified and for three projects four distinct funding levels were specified.

I fitted exponents (k_i) for the value function for each project. There was an implied exponent for each of the interior points. The quantity within the brackets can range from 0% to 100%. In some cases, the low cost alternative was clearly to have zero funding. In the other cases, the lowest funding level was treated as a baseline, that is, C_i for each alternative was calculated as an increment to the baseline. There were 17 three-level curves each containing one midpoint, and there were three four-level curves each containing two midpoints, i.e., the second and third highest funding levels. The project level cost and value data and the derived parameters are shown in table 2.

There were two outlier points in the set of exponents thus derived, with values of approximately –8 and 16, while the rest of the values fell between approximately –3 and 9. The projects corresponding to the two outliers did not have meaningful *curves* to represent the benefit of increased funding, but essentially had step functions instead. Of the remaining points, six of the exponents were below zero, indicating increasing returns to scale, and this number is large enough that it would not be reasonable to assume that buy-up curves always show diminishing marginal returns. The mean value of the exponents is 2.35. If we exclude the outliers, the distribution has mean 2.1 and standard deviation 3.2.

Table 2. Data from one of the portfolios used to estimate simulation parameters

PROJECT	Core investment	First step investment	Second step investment	Third step investment	Core value	First step value	Second step value	Third step value	Maximum investments' bang for the buck	First midpoint implied exponent	Second midpoint implied exponent
1	0	3016	5408		32	33.2	34.3		0.425295858	-0.2903912	
2	0	8265	10080		28.8	47.4	49.4		2.043650794	1.3341932	
3	5304	6635	11066		30.5	40.1	40.3		1.700798334	16.84797	
4	0	2600			34.3	34.5			0.076923077		
5	0	1144			33.7	34			0.262237762		
6	808	5580	6662		0	22.8	34.2		5.842159207	-1.7374891	
7	788	1786	5170	5645	27	44.5	89.4	100	15.02985382	0.4044793	-0.9598412
8	140	625	1624		28.9	30.8	33.4		3.032345013	0.8381046	
9	572	3614	5726	11290	27.5	30.3	31.5	33.1	0.522485538	1.9913243	1.9981897
10	248	291			34.4	34.5			2.325581395		
11	0	2585	5171		34.1	34.2	34.6		0.096693096	-2.7716965	
12	0	493			33.8	34.2			0.811359026		
13	832	1424			33.9	34			0.168918919		
14	1436	1748			33.7	33.9			0.641025641		
15	0	4264	6396		33.8	34.1	34.2		0.062539087	0.7934905	
16	4425	5621	7701		33.8	34.3	34.3		0.152625153	-21.150831	
17	328	361			32.6	33.7			33.33333333		
18	0	118	501		33.9	34.1	34.2		0.598802395	4.5780823	
19	265	529			34.1	34.2			0.378787879		
20	0	416	832		33.6	34.2	34.5		1.081730769	1.3862936	
21	208	2430	5046		30.3	31.5	33.4		0.640760645	-0.5902268	
22	10400	15823	19764	29952	29.6	31.1	31.5	32	0.122749591	3.3266821	2.8665923
23	0	16245	23712		22.9	29.5	35.6		0.535593792	-1.462334	
24	28600	28600	28600		20.5	36.1	43.4		NA		
25	0	1088	5451		30.7	32.3	33.1		0.440286186	5.4618009	
26	0	2188			34.1	34.2			0.045703839		
27	156	15200	35770		21.2	21.3	29.4		0.230246532	-7.5579047	
28	3224	4673	6545		60.2	60.2	60.4		0.060222824		
29	33488	53470			21.5	50.2			1.436292663		
30	6240	6240	10033		27.9	32.1	33.4		1.450039547		
31	0	357	357		28	32.4	32.5		12.60504202		
32	459	1045	4056		37.1	37.8	38		0.250208507	9.2302573	
33	10400	16640	19282		27.4	36.5	37.3		1.114613826	2.8753521	

The data set is too small to productively use goodness-of-fit tests. As a rough approximation from visual inspection, the data appear consistent with a uniform distribution ranging from –3 and 7 (that is, within a range of ± 5 of the mean). The distribution on costs and productivity index (the ratio of expected net present value to remaining cost, which is sometimes called bang for the buck) can be estimated by calculating the increment from the baseline to the maximum for each of the 32 projects and using these as data points. The values of $\log(C_i^{max})$, where costs are in thousands of dollars, follow a distribution that appears approximately normal, with mean 7.5 and standard deviation 1.75. The values of $\log[V_i(C_i^{max})]/\ C_i^{max}$, that is the logarithm of the productivity index (in dimensionless units of utility) follow a distribution that is approximately normal with mean –0.3, and standard deviation 1.65.

A second data set consisting of 28 usable projects was provided by Strategic Decisions Group, and these data are largely consistent with the Argonne data. This dataset is a by-product of an R&D portfolio analysis for a company in the pharmaceutical industry. The ENPVs for project-level alternatives were not uniformly increasing in cost, so the dominated alternatives were excluded from this study. The number of funding alternatives per project was not constrained, and the number of non-dominated alternatives (funding levels) varied between 2 and 7, averaging just under 4 per project. A total of 41 points were available to estimate curvature, and I fitted exponents to them. For 17 points, the implied exponent was below zero. If one outlier data point is excluded (with an implied exponent of approximately 32), the mean value of the exponents is 0.8 and the standard deviation is 3.08, consistent with a uniform distribution between –4 and 6. Across all projects, the values of $\log[V_i(C_i^{max})]/ C_i^{max}$ at the maximum funding levels follow a distribution which is approximately normal with mean 3.0 and standard deviation 1.2. The cost figures here only include direct R&D costs, and the actual productivity if full costs were available would likely be somewhat lower. The distribution of $\log(C_i^{max})$, where C_i is in millions of dollars, is approximately normal with mean 3.3 and standard deviation 2 – a rather wide variation.

3.2 Simulation parameter values

To simulate the generic portfolio, we generate n projects with parameters drawn from known distributions. For each project i, a set of random parameter values are generated for maximum cost (C_i^{max}), curvature (k_i), and productivity index at maximum cost (r_i). We define the base-case value function as before: $V_i(C_i) = r_i[1–EXP(–k_iC_i/C_i^{max})]/[1–EXP(–k_i)]$. The C_i^{max}, r_i, and k_i are each independent and identically distributed and follow distributions as follows:

- C_i^{max} follow a lognormal distribution with mean 3 and standard deviation 2; because the value function uses only (C_i/C_i^{max}), results should be scaleable with respect to the mean of the distribution – so any findings would be independent of the actual mean value chosen here.
- We assume that r_i follow a lognormal distribution with mean 2 and variance 2, similar to previous findings on ranges of estimated values described in Keisler (forthcoming), which were based on a limited amount of data. Results on the relative values of portfolios under different strategies are independent of the mean, because it is a scaling factor that applies to all projects equally. Thus, for present purposes only the variance matters.
- Most critical to this analysis, k_i follow a uniform distribution with minimum –3.5 and maximum 6.5. To give an idea of what these values mean, k_i = 4 implies a trajectory in which 50% of the cost leads to 85% of the value, while k_i = 8 approximates the 80-20 rule where 20% of the cost leads to 80% of the value.

  To illustrate what this means for curvature of buy-up curves, figure 3 shows a set of buy-up curves (normalized for budget level) for one simulated portfolio. Figure 4 shows how this would appear in a typical portfolio, where curves are scaled by size of project, i.e., not normalized (here, including the highest budget projects would distort the scale of the graph, so they are censored).

Figure 3. Base case simulation – distribution of normalized buy-up curves

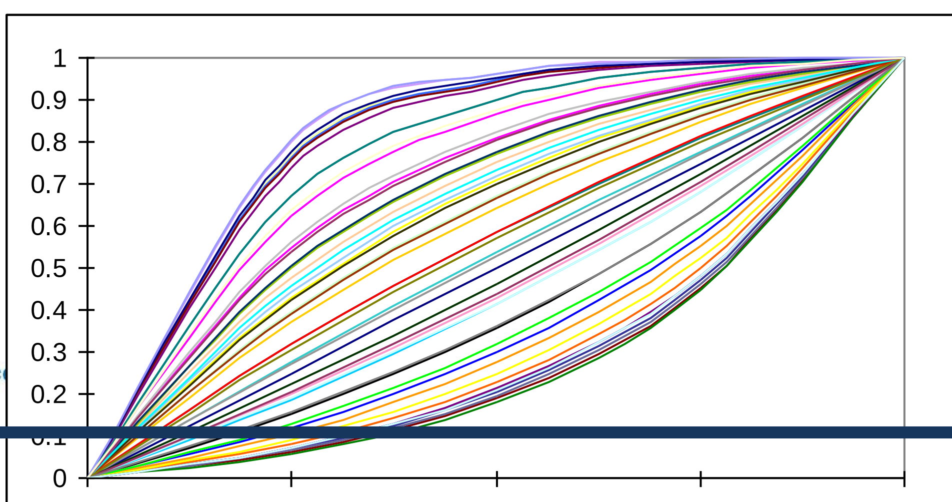
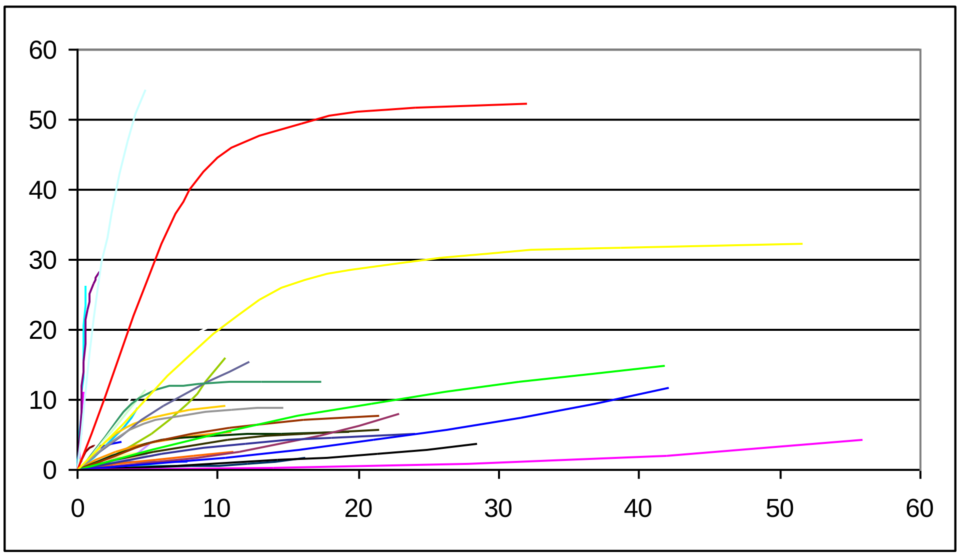


Figure 4. Representative Buy-up curves from base case (excluding highest cost curves).



Finally, we set the number of projects in a portfolio, n, at 50, which is slightly larger than the portfolios described above, and somewhere in the middle of the wide range of portfolio sizes seen in practice. We set the available budget, B, at 2000, so that the budget represents approximately 50% of the total requested funds for a typical iteration (the expected value of C for n = 50 is 50[exp(5)] = 7420, and the theoretical 50^{th} percentile of the distribution of C for the simulated portfolios is closer to 4000).

Where an allocation would lead to a small amount of leftover funds, we assume that the remaining funds in the budget are allocated to the next marginal project. This simplifies some comparisons and avoids knapsack type problems where funds could be allocated differently merely in order to exhaust the budget rather than see it go unused. In these cases, the value of the last project funded is calculated using linear interpolation so that the fraction of its value delivered is equal to the fraction of its cost covered. This underestimates the value of that last project but the difference is very small.

3.3 Key statistics for measuring the portfolio strategies in the simulation

We know *a priori* that V(S3) ≥ V(S4) ≥ V(S2) ≥ V(S1), because the choices in S4 are a subset of those in S3, etc. The question of interest is how much greater the values on the left are than those on the right, and we answer it using the following statistics. First we consider V(S2) – V(S1), which is the increase in value from a randomly portfolio in which projects are funded at random to a well-prioritized portfolio with no refinements of alternatives at the project level (projects are either in at 100% funding or out with 0 funding); we call this the value of prioritization. Next we consider V(S3) – V(S2), which is the increase from a well-prioritized portfolio when there are no refinements to a well-prioritized portfolio when there are continuous funding alternatives at the project level; we call this the value of refinement. We combine these to get the value of complete analysis, V(S3) – V(S1), which is the increase in value from a randomly funded portfolio to one where each project is funded at the optimal level. Strategy S1 is a straw man and S3 is a gold standard. Thus, V(S3) –V(S1) is the maximum possible improvement from this type of decision analytic intervention.

Also of interest are various ratios using the basic statistics:

The percentage of the maximum possible improvement achieved by merely prioritizing existing projects, [V(S2) –V(S1)]/[V(S3) –V(S1)].

The percentage of maximum possible improvement achieved by taking the additional step of enumerating a continuous range alternatives for each project, [V(S3)–V(S2)] / [V(S3)–V(S1)].

The ratio of the value added by the continuous enumeration step to the value added by the prioritization step, [V(S3)–V(S2)]/[V(S2)–V(S1)]

We distinguish between the ratio of the average values and the average value of the ratios, the latter of which do not depend directly on the overall portfolio value and are thus more consistent across the set of simulations than are the portfolio values themselves. We shall compute similar statistics for the remaining strategies (S4-S6).

For a base case and then variations we simulate 250 portfolios of which 143 yield suitable data. Note, because the budget is not assumed to be correlated with the portfolio's cost characteristics, there will be iterations where either the single most productive project requests more funding than the total budget, or all projects together request less funding than the total budget for at least one of the situations considered. We shall exclude those iterations, and use the remaining iterations to calculate statistics for each strategy and scenario of interest. In order to better estimate the comparative performance of the different strategies, we shall use the same raw simulation data for each strategy and each scenario, e.g., if project 1 in portfolio 1 had a curvature exponent set at the 10^{th} percentile of the distribution from which it was drawn when considering S1 in the base case, it will also have cost at the 10^{th} percentile when considering S2 in the case where curvatures have a narrower range.

4. Simulation Results

4.1 Base case (Magnitude of results)

For the initial example, we simulate a number of portfolios and find that on average, portfolios funded under the traditional discrete funding strategy (S2) have an average a total value in thousands of dollars of 93.9 ± 10.0. With refinement, the total value increases to 111.8 ± 13.6. The randomly funded portfolio is worth only 38.9 ± 6.8. The value added by prioritization is 55.6 ± 8.8, and the value of complete analysis is 72.9 ± 11.8. The value of refinement is 17.9 ± 6.6. The ranges given are approximate 95% confidence intervals for each statistic, calculated as +/- 2s/√(143-1), where s is the sample standard deviation. When the contributions of prioritization and refinement are expressed as percentages of either portfolio value or total value-added, the ranges are narrower because the numerator and denominator vary together, as shown in table 3. The tight ranges on these percentages and their general agreement with the portfolio value statistics indicate that our qualitative interpretations based on the latter will be robust.

Table 3. Detailed results for base case

Strategy	Name	Average Portfolio Value	Standard Error	Value added	Standard Error	Percent of value of analysis	Standard Error
1	Random	38929	3410	NA	NA	NA	NA
2	Discrete	93877	4958	54947	4414	78.7%	1.8%
3	Continuous	111801	6818	72872	5916	100%	NA
4	Step	110674	6670	71744	5791	98.4%	0.2%
5	Haircut	65824	5002	26894	4150	18.4%	4.3%
6	Layered haircut	96713	6827	57783	5942	66.9%	2.7%
	Refinement	NA	NA	17925	3320	21.3%	1.8%

For the same simulation, V(S4), in this case using 4 discrete non-zero funding level alternatives per project, was nearly as high (110.7 ± 13.3) as V(S3).

The order of magnitude of the numbers here is worth noting. Under reasonable starting assumptions, the value added by prioritization alone is over half the value of the prioritized portfolio, consistent with Keisler's earlier results. The value added by refinement of alternatives is about half of the value added by refinement of estimates in that study, so there really is something to the argument that portfolio DA adds value in more ways than one. We also find that the strategy with discrete steps (S4) performs nearly as well as the continuous funding level strategy (S3), and it ought to be much easier to implement (consistent with what practitioners describe).

Finally, haircut strategies (S5) are generally frowned upon by theoreticians, but are often used by managers and administrators at various levels of companies (Bower, 1970). We find that they are not anywhere near optimal – we would expect them to do rather poorly when many projects have increasing returns to scale – but even so they provide a significant improvement (26.9, or 69%) over random funding. The layered haircut strategy (S6) is even better, performing about as well as S2.

4.2 Sensitivity Analysis

Some of the observations above are rather robust, others depend significantly on the nature of the portfolio, as we shall see. Much of the discussion in this section refers to table 4, which contains the summary results for the base case and several variations.

Table 4. Results for all variations

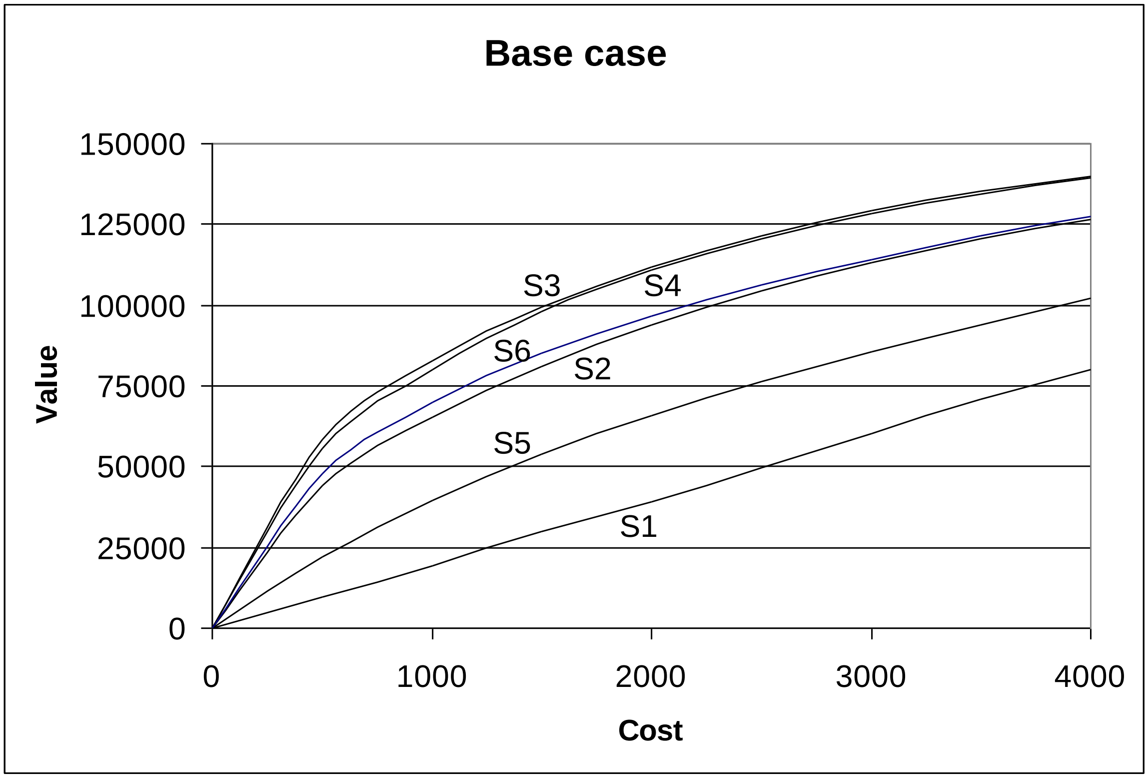
Strategy	V(Si) for scenario distribution on k parameter	Base case U(-3.5, 6.5)	Budget = 1000 U(-3.5, 6.5)	Narrow exponents U(-1.7.5, 3.25)	Normal exponents N(1.5, 2,88)	Positive exponents U(0,10)
1	Random	38929	19171	38929	38929	38929
2	Discrete	93877	65249	93877	93877	93877
3	Continuous	111801	82796	103125	110746	130444
4	Step	110674	80232	102207	109691	127794
5	Haircut	65824	39548	53759	65657	105836
6	Layered Haircut	96713	69791	88240	96740	127473
Strategy	Relative increase over V(S1)					
1	Random	0%	0%	0%	0%	0%
2	Discrete	141%	240%	141%	141%	141%
3	Continuous	187%	332%	165%	184%	235%
4	Step	184%	319%	163%	182%	228%
5	Haircut	69%	106%	38%	69%	172%
6	Layered Haircut	148%	264%	127%	149%	227%
Strategy	Percent of maximum increase					
1	Random	0%	0%	0%	0%	0%
2	Discrete	75.4%	72.4%	85.6%	76.5%	60.0%
3	Continuous	100.0%	100.0%	100.0%	100.0%	100.0%
4	Step	98.5%	96.0%	98.6%	98.5%	97.1%
5	Haircut	36.9%	32.0%	23.1%	37.2%	73.1%
6	Layered Haircut	79.3%	79.6%	76.8%	80.5%	96.8%

Sensitivity to budget level: First, we vary the budget in order to generate the set of buy-up curves for each of the strategies shown in figure 5.

Focusing in particular on the base case results when the budget is halved to $1000, we find at least two interesting differences. We note in particular that the relative value of prioritization is higher at this lower budget level, accounting for 27.6% of the average value added by analysis, as opposed to 22.0% when the budget is doubled to $4000. Intuitively, more projects are likely to be funded at or near 100% when the budget is higher, so the discrete strategy (S2) gives up less then.

The relative contribution of analysis, V(S3) / V(S1), decreases as the budget increases, because less of the “low hanging fruit” is available. That is, S3 gets less for the second dollar than for the first, while S1 gets the same value for each dollar allocated. The step strategy degrades slightly relative to the continuous strategy at low budget levels, for similar reasons, but not enough for the fact to be of much interest.

Figure 5. Comparison of strategies for base case parameters and varying budget.



Sensitivity to maximum cost: If the maximum cost is increased and the budget is increased proportionally, then all results are the same except that the units are large. All ratios are the same. If the maximum cost is increased but the budget is not, the effect is the same as lowering the budget (and rescaling units).

Sensitivity to full-cost productivity index: If we start with a given portfolio and multiply the r_i by a constant, we simply change all values proportionately, that is, the value of prioritization and refinement both increase (or both decrease) compared to the value of the random portfolio and so more analysis would be justified in general. Because there would be no change in actual resource allocations compared to the original case, however, the value added from prioritization or refinement remain unchanged as a percentage of portfolio value. More interesting are the next parameters.

Sensitivity to mean of curvature: In the base case, on average 35% of projects will have negative exponents and so are funded at either 0% or 100%. The more such projects there are, the less value there is to refinement. Similarly, haircut strategies are especially inappropriate for projects with negative exponents. We compare the base case with one in which the curvature is uniform between 0 and 10.

Here, the value of prioritization is unchanged (because the value for each project at its maximum funding level is unchanged), while the value of refinement increases to over 36.6 – 67% of the value of prioritization – because there is much more value to be captured at the lower end of the cost range for projects that would be rejected under the binary strategy. By the same token, if the exponent is decreased (not shown), more projects will be funded at 0% or 100% because if one project has a higher productivity index than another at the full cost level, it will likely have a productivity index for much more of the funding range.

The step strategy remains close in value to the full refinement strategy. The haircut strategy adds more value here in absolute terms and relative to the first 3 strategies, also because more of the value arises from the lower end of the cost ranges for each project. In fact, the haircut strategy adds somewhat more value than does prioritization (66.9 vs. 54.9). Given that haircut strategies are much more politically palatable – there are no winners or losers, and everyone sees it as somewhat fair (if not efficient), this may be an attractive option for the portfolio manager. That conflict may not be worth the trouble unless the more refined set of alternatives can be obtained.

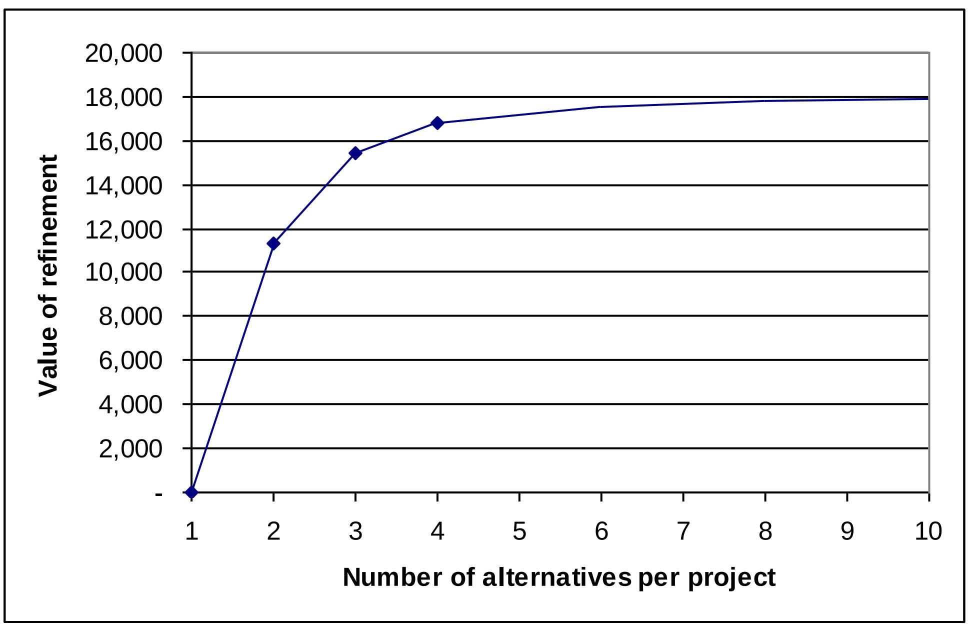
The layered haircut approach combines the general usefulness of the haircut approach (under decreasing returns) with a sort of prioritization, and here approaches the optimal solution, achieving 96.7% of the total possible value of prioritization and refinement combined. As this approach does not require the additional work of generating refined alternatives, and every project gets some funding, its implementation might be both politically palatable and low-cost, and it could be hard to justify using a full-scale portfolio DA with explicit alternatives defined and evaluated for each project.

Sensitivity to variation in curvature: If we modify the base case by halving the range on k_i, so that this parameter is U(–1.75, 3.25), which slightly decreases the average value of k_i to 0.75, we would expect the portfolio to be simpler to manage because there is less variation between projects. Here, because the average is closer to 0, buy-up curves are closer to linear and the value of refinement drops in absolute terms and relative to the value of prioritization. Even if the average did not change, the benefit of refinement is largest at high values of k_i, and by narrowing the range, the benefit of refinement is reduced more for those projects than it is increased on other projects. Layered haircuts would also tend to perform better when the range of k_i is smaller, because the assumption about identical curvature across projects is then more realistic.

Sensitivity to assumption of uniformly distributed curvature parameter: If we assume that k_i are normally distributed with the same mean (1.5) as in the base case, and the same standard deviation (10/√12, for a uniform distribution with range of 10 from minimum to maximum), the relative values from different strategies are simiilar to the base case.

Sensitivity to number of funding levels: Using four non-zero funding levels seems to capture most of the value, so there is not much need to look at more levels. That leaves only the question of whether fewer steps might be sufficient for times when that would be substantially simpler to implement (requiring specification of a proposal for only one or two additional funding levels between zero and the maximum for each project).

Figure 6. How many alternatives per project?



When we rerun the base case, allowing for only one intermediate funding level, we find that V(S4) is slightly reduced – averaging around 9% less than when the full curve is used, compared to only 1.6% degradation when three intermediate values are used and 3.4% when two intermediate values are used. Put another way, the first mid-range alternative adds 63% of the potential value of refinement, with a second midpoint 86% of the potential value is achieved, the third midpoint raises that to 94%, and including the rest of the continuum of alternatives adds only the last 6% of the value of refinement, as in figure 6.

One could argue that if managers are already preparing one intermediate funding level case, it would be cost-effective to prepare at least two of them and gain an additional 5% in value-added.

Sensitivity to percentage of maximum funding each project initially requests: Our base case assumed that projects would receive between 0% and 100% of the initially requested funds. It could be argued that one of the benefits of portfolio DA is that project managers are actually encouraged to create the “step-up” alternatives at funding levels beyond what they would have initially requested, rather than merely alternatives ranging from zero funding to their originally desired amount. This certainly does happen (e.g., Sharpe & Keelin, 1998, Matheson & Matheson, 1998). Such instances were not labeled in the data described above, so it is not clear how prevalent this is. If we assume this is always the case, the benefit would indeed be substantial. The value of the portfolio using a binary rule is 61.6. This is unrealistically low, however, because this implies in the base case that most projects are funded. When the budget is 1000, the portfolio value is 44.1, far better than the random strategy (19.2), worse than the original binary strategy (65.2), better than the haircut strategy (39.5), and far worse than the optimal portfolio (82.8).

Obviously, it cannot always be the case that larger initial requests for each project make the entire portfolio more valuable in the face of a fixed budget. Rather, for those projects in particular for which there are reasonable new step-up options to be created, we might expect the value added by considering that alternative to be of the same order of magnitude as the value added by considering the entire range from zero to the original request. That is a large enough benefit that it seems sensible to at least ask project managers to think about whether they have a useful way to use additional funds.

Sensitivity to functional form: The choice of functional form for $V_i(.)$ is important. Specifically, the form used precludes S-shaped value versus cost curves that might be found with new innovative products, as well as curves involving a fixed cost before any value is achieved and curves that provide substantial value for even any non-zero amount of funding (e.g., ongoing projects that require only maintenance funding to avoid being killed). Such projects often do appear in portfolios, but there is not much to be learned by including them in the model and they would complicate it. Comparing ongoing projects alongside new ones gives the illusion that the ongoing projects are more productive and thus merit funding, when a better characterization of them is that their funding decisions were already made. Projects with S-shaped curves, increasing returns, or large fixed costs should be funded at either 0 or at a level above the point at which the second derivative of the value versus cost curve turns negative (or at their maximum possible funding level), except under extraordinary circumstances, so in considering a portfolio consisting entirely of projects with concave buy-up curves, we are not ignoring any likely funding decisions. We observe, without modeling, that any of these conditions would have the practical effect as having a low exponent – pushing more projects to either 100% or 0% funding with fewer in between.

5. Summary

5.1 Findings

We have found that the refinement process can be a significant source of value in portfolio DA, it is comparable in particular to the value of improved estimates of project benefits. Refinement of alternatives has proportionally greater value when budgets are tighter, which implies that portfolio DA ought to focus more on this step during times when a company is facing financial difficulties, e.g., during a recession. Refinement is also of value when investments have notably decreasing returns to scale (curvature). Perhaps this would also be more common in times of recession (when funding levels are already relatively low) or in mature industries.

Haircut strategies have some value as does simple prioritization, but haircut strategies leave value on the table when more nuanced alternatives are available. Under the right circumstances, the layered haircut strategy (which is not common practice, unlike standard haircuts) might be a very useful innovation. When buy-up curves are going to be used, the number of steps needed to adequately approximate the full buy-up curve for each alternative matches well to portfolio DA practice, two to four non-zero funding levels generally being sufficient. Although the model results could support use of just two non-zero funding levels, the presence in practice of buy-up curves with positive second derivatives would make it informative and sometimes useful to add another point This is consistent with the best practice of asking for “blue-sky” proposals whose budgets exceed current plans.

5.2 Future research

This paper considered basic questions about when a decision analyst should refine project level alternatives, or more broadly, when an R&D organization should consider multiple intermediate funding levels for each project . A limiting factor in this work is the lack of real data from companies that use such techniques, but as more data are collected we may consider more detailed questions about analytic strategy. For example, we might consider different functional forms such as Cobb-Douglass functions, or forms such as that described in Ragsdale (2004, p. 377) where a project's expected value is based entirely on probability of success given number of engineers. We might consider different assumptions on the distributions of the input parameters. We might consider more refined strategies, e.g., a triage strategy in which projects with low enough curvature are considered as binary projects, while projects with higher curvature receive more definition throughout the funding range.

5.3 Last words

The extent to which alternatives are refined is one of the aspects of portfolio DA over which analysts may have control. Refining alternatives requires development of plans for using each level of funding and then estimating the resulting values. This step could significantly increase the cost of analysis – which in the worst case could be roughly linear in the number of alternatives considered – and thus should be undertaken only to the extent that it is valuable. In designing a process to make portfolio decisions, portfolio managers and analysts should first aim to understand the general characteristics of the portfolio. Armed with that understanding, they should focus analytic efforts where they are most likely to add value, at both the narrow level of choosing how to refine alternatives, and at the higher level of allocating effort across more diverse modeling tasks.

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