SELECTING PROJECT PORTFOLIOS BY OPTIMIZING SIMULATIONS

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New advances in the area of simulation optimization allow managers to go beyond traditional ranking rules, CAPM and real options analysis in order to select optimal sets of projects to fund. Furthermore, these advances make use of portfolio performance measures and goals that can be defined to directly relate to corporate strategy and are easy to communicate and understand. We present a real-world example to illustrate this methodology.

In industry, managers must select portfolios of projects for funding, in order to advance the corporate goals. There are generally many more projects than funding can support. Ideally, managers aim to select an optimal subset of projects to meet the company's goals while complying with budgetary restrictions. At the same time, they seek to control the overall risk of a portfolio of projects and ensure that cash flow or other such performance objectives are maximized.

Modern portfolio theory is still largely based on the Markowitz model of mean-variance efficiency [16], or on assumptions related to it. An underlying assumption for this theory is that portfolio returns are normally distributed. While the mean-variance efficiency theory is still used throughout industry for securities portfolio selection, there is a growing body of evidence that suggests that actual portfolio returns are not normally distributed [17]. This is especially true when the task is to select a portfolio of *projects*, as opposed to financial assets. In such a setting, it has been shown that mean-variance is not an appropriate risk measure for a portfolio, and in practice, mean-variance efficient portfolios have been found to be quite unstable [2, 3].

Determining how to allocate investment capital among projects in order to maximize performance is a common endeavor with multiple approaches to solutions. These investment decisions can have a significant, direct impact on the financial health of an organization. A wide variety of models and solution techniques – such as CAPM and, more recently, Real Options Analysis (ROA) – center around measures of the benefits of the investments, such as return, payback period and cash flow. Most of these techniques, however, still rely on a series of assumptions that limit the complexity of the model. For example, a deterministic measure of market risk must be known (or estimated), project returns must follow a known and tractable type of probability distribution, a risk-aversion level must be assumed for the firm, and so forth.

A recently developed modeling and solution approach that has proved capable of overcoming these limitations is simulation optimization. Simulation becomes essential whenever a situation arises that is very difficult (or even impossible) to represent by tractable mathematical models. In project portfolio selection, for example, it can be important to consider different types of risk associated with prospective decisions, including both macroeconomic risk (variability in interest rates), and project-specific risk (probability of success of each project, uncertainties in the magnitude and variability of sales and cost projections, estimation errors in projected investment requirements, etc.) Furthermore, complex situations cannot be easily analyzed by trial-and-error mechanisms, because the range of parameter values and the number of parameter combinations is too large for an analyst to simulate. Today, there exist very powerful optimization algorithms to guide a series of simulations to produce high-quality solutions in the absence of tractable mathematical structures. Furthermore, we are now able to precisely compare and rank different solutions in terms of quality [19].

As we subsequently demonstrate, by this means we are able to optimize project portfolios by a variety of measures and with built-in safeguards against risk, including Net Present Value measures and Value-at-Risk measures that cannot normally be addressed in real world situations exhibiting the complexity we are now able to handle effectively.

SIMULATION OPTIMIZATION

Theoretically, the issue of identifying best values for a set of decision variables falls within the realm of optimization. Until quite recently, however, the methods available for finding optimal decisions have been unable to effectively handle the complexities and uncertainties posed by many real world problems of the form treated by simulation. The area of stochastic optimization (as in ROA, for example) has attempted to deal with some of these practical problems, but the modeling framework limits the range of problems that can be tackled with such technology.

The complexities and uncertainties in real world systems are the primary reason that simulation is often chosen as a basis for handling the decision problems associated with those systems. Consequently, decision makers must deal with the dilemma that many important types of optimization problems can only be treated by the use of simulation models, but once these problems are submitted to simulation there are no optimization methods that can adequately cope with them.

Recent developments are changing this picture. Advances in the field of metaheuristics—the domain of optimization that augments traditional mathematics with artificial intelligence and methods based on analogs to physical, biological or evolutionary processes—have led to the creation of optimization engines that successfully guide a series of complex evaluations with the goal of finding optimal values for the decision variables, as in [6, 7, 8, 9, 10, 11, 15].

An acclaimed instance of these engines is the search algorithm embedded in the OptQuest® optimization system [18], which is largely based on a coordinated system of metaheuristic processes that include *scatter search* as a hub [10]. The engine is designed to search for optimal solutions to the following class of optimization problems:

Max or Min	$F(x)$	
Subject to	$Ax \leq b$	(Constraints)
	$g_l \leq G(x) \leq g_u$	(Requirements)
	$l \leq x \leq u$	(Bounds)

where x can be continuous or discrete with an arbitrary step size.

The objective $F(x)$ may be any mapping from a set of values x to a real value. The set of constraints must be linear and the coefficient matrix A and the right-hand-side values of the vector b must be known. The requirements are simple upper and/or lower bounds imposed on a function that can be linear or non-linear. The values of the bounds g_l and g_u must be known constants. All the variables must be bounded and some may be restricted to be discrete with an arbitrary step size.

A typical example might be to maximize the throughput of a factory by judiciously increasing machine capacities subject to budget restriction and a limit on the maximum work in process (WIP). In this case, x represents the specific capacity increases and $F(x)$ is the expected throughput. The budget restriction is represented by $Ax \leq b$ and the limit on WIP is achieved by a requirement modeled as $G(x) \leq g_u$. Each evaluation of $F(x)$ and $G(x)$ requires a discrete simulation of the factory. By combining simulation and optimization, a powerful design tool results.

OptQuest is a generic optimizer that successfully embodies the principle of separating the method from the model. In such a context, the optimization problem is defined outside the complex system. Therefore, the evaluator can change and evolve to incorporate additional elements of the complex system, while the optimization routines remain the same. Hence, there is a complete separation between the model that represents the system and the procedure that is used to solve optimization problems defined within this model.

The optimization procedure uses the outputs from the system evaluator, which measures the merit of the inputs that were fed into the model. On the basis of both current and past evaluations, the method decides upon a new set of input values (see Figure 1).

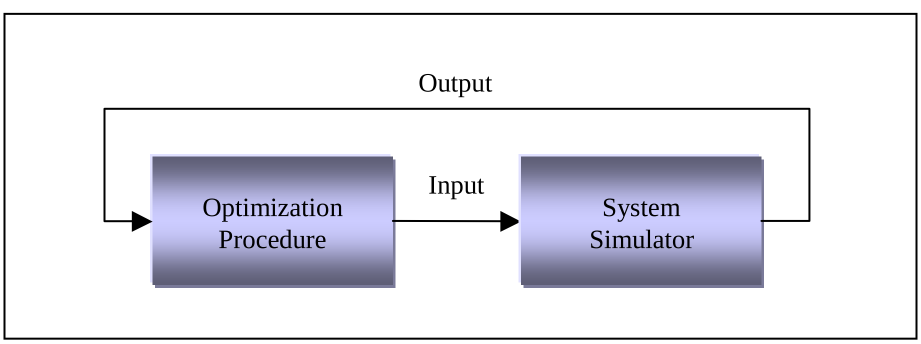

Figure 1: Coordination between Optimizer and Simulator

The optimization procedure is designed to carry out a special "non-monotonic search," where the successively generated inputs produce varying evaluations, not all of them improving, but which over time provide a highly efficient trajectory to the best solutions. The process continues until an appropriate termination criterion is satisfied (usually based on the user's preference for the amount of time to be devoted to the search). We now discuss how this methodology can be applied to optimize the selection of project portfolios.

PROJECT PORTFOLIO OPTIMIZATION

In 1952, Nobel laureate Harry Markowitz laid down the basis for modern investment theory. Markowitz focused the investment profession's attention on *mean-variance efficient portfolios*. A portfolio is defined as mean-variance efficient if it has the highest expected return for a given variance or if it has the smallest variance for a given expected return.

In figure 2 below, the curve is known as the *efficient frontier* and contains the mean-variance efficient project portfolios. The area below and to the right of the efficient frontier contains various risky assets (due to the discrete nature of projects, the efficient frontier in the figure shown here is really a set of points, not a continuous line). The mean-variance efficient portfolios are combinations of these risky projects.

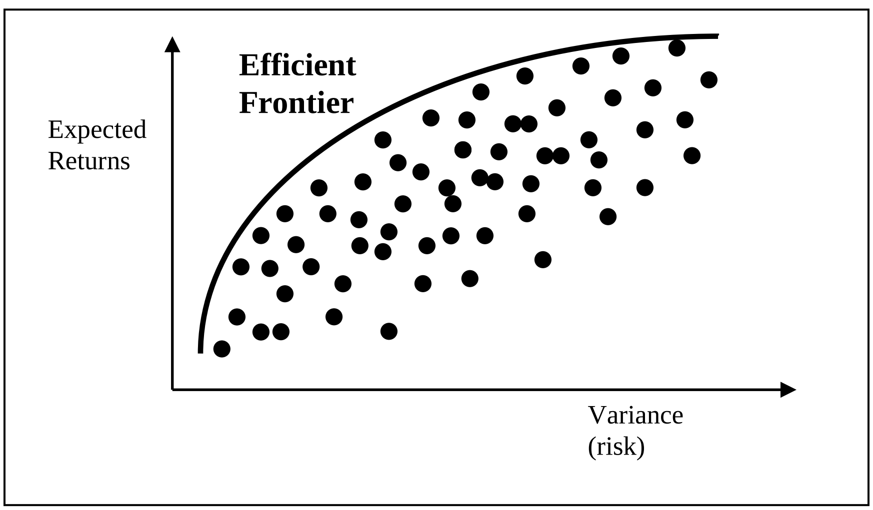

Figure 2. The mean-variance efficient frontier

Certain principles of portfolio theory are fundamental: decision makers are risk-averse; they prefer portfolios with high returns and low risk. From these principles, we can develop optimization models that construct efficient portfolios of projects.

The best-known model for portfolio optimization is based on the assumption that the expected portfolio returns will be normally distributed, with a mean = $\boldsymbol{r}$, and a covariance matrix = $\boldsymbol{Q}$. The model seeks to balance risk and return in a single objective function, as follows:

Given a vector of portfolio returns r, and a covariance matrix Q, then we can formulate the model as follows:

$$\text{Maximize} \quad r^T w - k w^T Q w \quad (1)$$
$$\text{Subject to:} \quad \Sigma_i w_i = 1 \quad (2)$$
$$w \geq 0 \quad (3)$$

where w_i is the proportion of the total capital invested in project *i*, and k is represents a coefficient of the firm's risk aversion.

Equation (3) in the above model imposes no restrictions on w, other than non-negativity, and hence implies that w is a continuous variable. That is, since we are talking about project portfolios, we assume here that a firm can have fractional participation levels in a project. We can easily modify the equation so that the decision is whether or not to invest in a project, by writing $w \in (0, 1)$ instead.

In practice, small changes in the estimated parameter inputs (expected returns, correlation and variance) lead to large changes in the implied portfolio holdings. Typically, these input parameters are estimated using either historical data or forecasts. According to recent research, estimation errors in these input parameters frequently outweigh the benefits of the mean-variance model [2, 3]. In the following practical example, we show alternate models for choosing portfolios that are, in some sense, more robust to estimation parameters, and result in more intuitive measures of risk and performance from the standpoint of a manager.

A PRACTICAL EXAMPLE

The Energy Industry uses project portfolio optimization to manage investments in exploration and production, as well as power plant acquisitions [12, 13].

The following example involves a company that has sixty-one potential projects in its investment funnel. The projects have been classified into three categories according to their stage in the funnel: (1) *Identified*, (2) *Entered*; and (3) *Captured*. Each type of project requires a certain number of business development, engineering and earth sciences personnel, and the company has a budget limit for these investment opportunities.

Identified projects are being considered for entry, and the company has no stake in them yet. There will be investment at risk prior to the determination of successful entry and successful capture. The current period cash flow consideration for these projects is the cost to secure the rights into the project.

Entered projects are those where the company has made the decision to invest in order to determine the presence of a revenue stream (standard project probability of success). Cash flow for these projects consists of investment necessary to assess the opportunity and obtain a revenue stream. Projected revenue and expense data are also considered.

Captured projects are those projects that the company has determined will be capable of providing a revenue stream, or from which it is already realizing revenue. Cash flows for these projects consist only of projected revenues and expenses, including any initial investment necessary to obtain a revenue stream. In addition, associated with each type of project is a probability of successfully entering the following stage.

Real, but significantly disguised portfolio data has been used to populate the funnel. This example consists of 26 *Identified* projects, 21 *Entered* projects and 14 *Captured* projects. We include the assumption that a decision to enter into an *Identified* project could be delayed a maximum of one year, while capturing an *Entered* project could be delayed for two years. *Captured* projects can be suspended for no more than three years. After that time, rights to pursue the opportunity are deemed to have expired.

In common with cash, personnel and time are considered to be scarce resources. Three categories of personnel work on each project: Business Development, Engineering and Earth Sciences. The availability assumptions for each category, during the whole planning horizon were: (1) there are 6 Business Development people available; (2) there are 40 Engineers available; and (3) there are 40 Earth Scientists available. Business Development officers can work on four projects at one time, while Engineers and Earth Scientists work on a single project. The personnel requirements by project type are shown in Table 1.

Table 1: Personnel Requirements

Project Type / Personnel	Identified	Entered		Captured	Total Available
		Exploratory	Other		
Business Development	1	1	1	0	6
Engineering	1	1	1	2	40
Earth Sciences	2	3	2	2	40

For our analysis, we used OptFolio™ a product of OptTek Systems, Inc. that uses the OptQuest engine, and combines simulation and optimization into a single system specifically designed for portfolio optimization [1, 2, and 14]. The cash flows are entered as constants or statistical distributions depending upon the user's knowledge of system uncertainty. The revenues and expenses can be correlated between projects, and mutual exclusivity or dependency conditions can be imposed among projects. A cost of capital rate is used to compute discounted cash flows (the system allows this rate to be specified either by a constant or a distribution). Users specify performance metrics and constraints to tailor the portfolio for their needs. We examined multiple cases to demonstrate the flexibility of this method to enable a variety of decision alternatives that significantly improve upon traditional mean variance portfolio optimization. The results also show the benefits of managing and efficiently allocating scarce resources like personnel and time.

Each of the cases described below was run for 500 iterations, with 1,000 observations (simulations) per iteration. The weighted average cost of capital, or annual discount rate, used for all cases was 12%.

The solution quality of the different cases was evaluated in terms of expected returns of the portfolio, average personnel utilization rate, capture rate and divestment rate. The capture rate is calculated as the number of *Entered* projects *selected* divided by the total number of *Entered* projects in the funnel. The divestment rate is calculated as: 1 minus the number of *Captured* projects *selected* divided by the total number of *Captured* projects in the funnel. This measures how many *Captured* projects were eliminated, and how many were continued.

Base Case: Unconstrained Optimization

The Base Case is set up using the traditional portfolio mean variance case to provide a basis for comparison for subsequent cases. For ease of presentation, we use a modified terminology in this example. We will call μ_{NPV} the mean expected return (i.e. the mean of the distribution of the NPV values) of the selected portfolio, and σ_{NPV} the standard deviation of returns. An empirical histogram for the optimal portfolio is shown in Figure 3. In this case, we do not allow for the possibility of delaying the investment in a project. In other words, all new projects must start immediately, and *Captured* projects cannot be suspended. We impose a budget constraint, but no personnel constraints for this case. The problem can be formulated as follows:

Maximize μ_{NPV} *(mean expected returns)*

Subject to:

$\sigma_{NPV} \leq \$140M$ *(std. dev. of returns)*
All projects must start in year 1
Budget Constraint

This formulation results in a portfolio with the following statistics:

μ_{NPV} = \$455M, σ_{NPV} = \$136M, P(5) = \$266M

Number of Projects: 33
Capture Rate: 76%
Divestment Rate: 36%

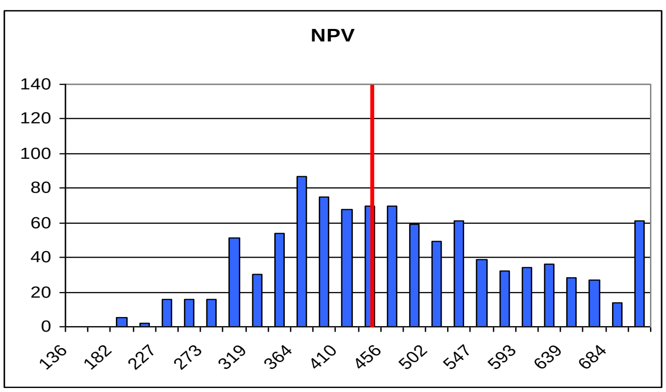

Figure 3: Base Case

In purely financial terms, this case results in high performance. However, we have deliberately failed to address the scarcity in human resources in order to have a base case for comparison to other scenarios. The results above imply the need for an additional 12 engineers and 23 earth scientists beyond those available. If we consider the cost of these resources to be, on average, approximately \$70K per year, then we would have an additional annual operating cost of 35 x \$70K = \$2.45M, equivalent to a present value over the planning horizon of \$18.31M. This amount is not accounted for, and may exceed the budget constraint. There are additional costs usually related to new personnel that are not addressed here, such as training, travel, etc.

Case 1: Traditional Markowitz Approach

In this case, we again implement the mean-variance efficient portfolio method proposed by Markowitz. The decision is to determine participation levels (0,1) in each project with the objective of maximizing the expected NPV of the portfolio while keeping the standard deviation of the NPV below a specified threshold. This case is similar to the Base Case, but here we introduce constraints based on the availability of the different types of personnel.

Maximize μ_{NPV}

Subject to:

σ_{NPV} *< \$140M*

All projects must start in year 1

Budget Constraint

Personnel Constraints:

Bus. Devel. ≤ 6 per year

Engineers ≤ 40 per year

Earth Scientists ≤ 40 per year

The resulting portfolio has the following statistics:

μ_{NPV} = \$394M σ_{NPV} = \$107M P(5) = \$176M

Average Personnel Utilization:	70%
Number of Projects:	22
Capture Rate:	33%
Divestment Rate:	50%

Figure 4 shows the graph of the NPV obtained for 1000 replications of this case.

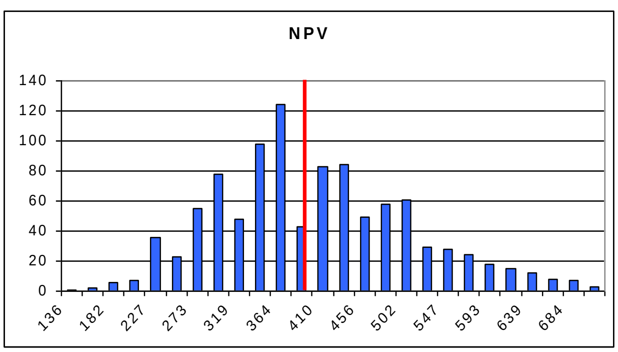

Figure 4: Mean Variance Portfolio

Case 2: Risk controlled by 5th Percentile

For most managers, statistics such as variance or standard deviation of returns are not easy to interpret. It is clearer to say: "there is a 95% chance that the portfolio return is above some threshold value." This can be achieved by imposing a requirement on some percentile of the resulting distribution of returns. In Case 2, we do just that. The decision is to determine participation levels (0,1) in each project with the objective of maximizing the expected NPV of the portfolio, while keeping the 5th percentile of the NPV distribution above the value determined in Case 1. In other words, we want to find the portfolio that produces the maximum average return, as long as no more than 5% of the observations fall below $176M. In addition, in this case we do allow for delays in the start dates of projects, according to the windows of opportunity defined earlier for each type of project. In order to achieve this, we have created copies of a project that are shifted by one, two or three periods into the future (according to the windows of opportunity defined for each project type). We use mutual exclusivity clauses to ensure that only one start date for each project is selected. For example, we have a project (i.e. Project A) that can start at time t = 0, 1 or 2. We use the following mutual exclusivity clause as a constraint:

$$\text{Project } A_0 + \text{Project } A_1 + \text{Project } A_2 \leq 1,$$

The subscript following the project name corresponds to the allowed start dates for the project, and the constraint only allows at most one of these to be chosen. The formulation of this case scenario is as follows:

Maximize μ_{NPV}
Subject to:
- $P(5)_{NPV} \geq \$176M$
- *Projects may start at any time, as allowed*
- *Budget Constraint*
- *Personnel Constraints:*
  - *Bus. Devel. ≤ 6 per year*
  - *Engineers ≤ 40 per year*
  - *Earth Scientists ≤ 40 per year*

This case has replaced the standard deviation with the 5th percentile as a measure of risk containment. The resulting portfolio has the following attributes:

μ_{NPV} = \$438M σ_{NPV} = \$140M   P(5) = \$241M

Average Personnel Utilization:	94.5%
Number of Projects:	27 (7 delayed)
Capture Rate:	43%
Divestment Rate:	29%

By using the 5th percentile instead of the standard deviation as a measure of risk, we were able to shift the distribution of returns to the right, compared to Case 1, as shown in Figure 5.

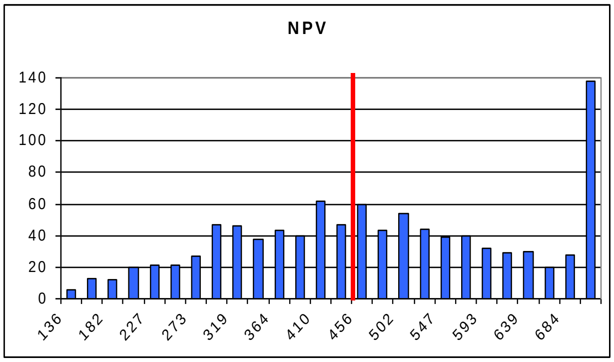

Figure 5: 5th Percentile Portfolio

This case clearly outperforms case 1. Not only do we obtain significantly better financial performance, but we also achieve a higher personnel utilization rate, and a more diverse portfolio with a higher capture rate and lower divestment rate. With respect to the base case, this case also performs better – even financially – if we take into account the trade-off between hiring new personnel and the difference in expected returns.

Case 3: Maximizing Probability of Success

In Case 3, the decision is to determine participation levels (0,1) in each project with the objective of maximizing the probability of meeting or exceeding the mean NPV found in Case 1. As in Case 2, start times for projects are allowed to vary according to the stated limits. The problem can be formulated as follows:

Maximize *Probability(NPV ≥ \$394M)*
Subject to:
Projects may start at any time, as allowed
Budget Constraint
Personnel Constraints:
Bus. Devel. ≤ 6 per year
Engineers ≤ 40 per year
Earth Scientists ≤ 40 per year

This case focuses on maximizing the chance of obtaining a goal and essentially combines performance and risk containment into one metric. The resulting portfolio has the following attributes:

μ_{NPV} = \$440M σ_{NPV} = \$167M P(5) = \$198M

Average Personnel Utilization:	94.5%
Number of Projects:	27 (7 delayed)
Capture Rate:	38%

Divestment Rate: 21%

Although this portfolio is similar in performance to the one in Case 2, this portfolio has a 70% chance of achieving or exceeding the NPV goal. As can be seen in the graph of Figure 6, we have succeeded in shifting the probability distribution even further to the right, therefore increasing our chances of exceeding the returns obtained with the traditional Markowitz case. In addition, in cases 2 and 3, we need not make any assumption about the distribution of expected returns.

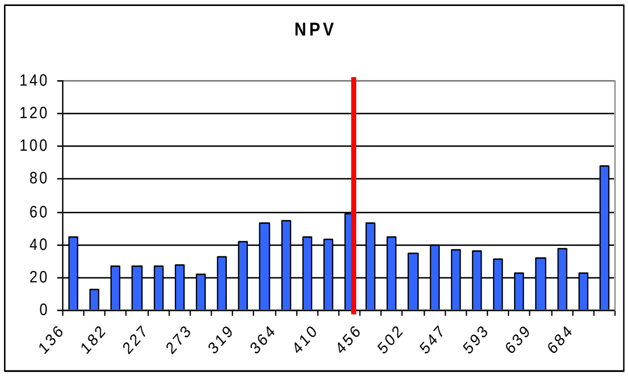

Figure 6: Maximum Probability Portfolio

From the results of this case, we can conduct an interesting analysis that relates to Value-at-Risk (VaR). In traditional (securities) portfolio management, VaR is defined as the worst expected loss under normal market conditions over a specific time interval and at a given confidence level. In other words, VaR measures how much the holder of the portfolio can lose with α% probability over a certain time horizon [4]. In the case of project portfolios, VaR can be defined as the probability that the NPV of the portfolio will fall below a specified value. Going back to our present case, the manager may want to limit the probability of incurring negative returns. In that case, we can formulate the problem in a slightly different way: we still want to maximize the expected return, but we limit the probability that we incur a loss to $\alpha = 1\%$, as follows:

Maximize μ_{NPV}

Subject to:

P(NPV<0) ≤ 1%

Projects may start at any time, as allowed

Budget Constraint

Personnel Constraints:

- *Bus. Devel. ≤ 6 per year*
- *Engineers ≤ 40 per year*
- *Earth Scientists ≤ 40 per year*

The results of this scenario are:

μ_{NPV} = \$411M σ_{NPV} = \$159M P(5) = \$195M

Average Personnel Utilization: 90%

Number of Projects: 27 (4 delayed)

Capture Rate:	38%
Divestment Rate:	21%

These results turn out to be slightly inferior to the case where the probability was maximized. This is no surprise, since the focus was on limiting the probability of downside risk, whereas before the goal was to maximize the probability of obtaining a high expected return. However, this last analysis may prove valuable for a manager that wants to control the VaR. As shown here, for this particular set of projects, a very good portfolio can be selected with that objective in mind.

CONCLUSIONS AND FURTHER RESEARCH

As the above example shows, the expected returns of project portfolios are seldom normally distributed. This creates the need for optimization methods that do not rely solely on theory derived from Markowitz's model, but whose underlying principles are distribution-independent. We have also shown that in project portfolio management and optimization it is not enough to worry about capital budget constraints. If we ignore other scarce resources, such as personnel and time, we may end up selecting a project portfolio that is physically infeasible to implement, given practical limitations in the availability of those resources.

Managers need to assess multiple scenarios in order to select a portfolio that aligns with their strategy and risk profile. By using a methodology and a tool that clearly communicates the performance of the portfolio in each scenario, the manager can make better decisions. Our results show that, through the use of more intuitive performance measures, we can guide our search towards improvements in the performance of the desired portfolio of projects.

Although our example focuses primarily on maximizing expected NPV, there is numerous evidence that managers in industry consider alternate measures such as IRR, payback period and return duration, along with NPV, when making capital budgeting decisions [5]. There is also evidence that non-financial criteria can also play an important role in the ultimate decision to invest in a project. Further work can be done to explore scenarios with different objectives, some of which may not be defined in financial terms. For instance, from a strategic cost perspective, the manager may want to select a portfolio that meets certain financial requirements, but requires the least amount of human resources. Formally, the objective would be to minimize the maximum number of resources required per period in the planning horizon. In addition, other measures may be developed to represent the attractiveness of projects in terms of strategic alignment, geographical diversification or intensification, and other non-financial criteria.

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