Proceedings of the 2004 Winter Simulation Conference
R .G. Ingalls, M. D. Rossetti, J. S. Smith, and B. A. Peters, eds.

NEW ADVANCES AND APPLICATIONS FOR MARRYING SIMULATION AND OPTIMIZATION

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ABSTRACT

This tutorial will focus on several new real-world applications that have been developed using an integrated set of methods, including Tabu Search, Scatter Search, Mixed Integer Programming, and Neural Networks, combined with simulation. Applications include project portfolio optimization and supply chain management.

1 INTRODUCTION

Many real world problems in optimization are too complex to be given tractable mathematical formulations. In a wide range of applications, classical formulations such as integer and mixed integer programming problems may take many days to run using the best available solvers. The resulting solutions can be drastically short of being optimal or even fail to satisfy feasibility requirements. Moreover, often, such formulations omit key aspects of real world settings.

Practical problems often contain nonlinearities, combinatorial relationships and uncertainties that cannot be modeled effectively by simply listing an objective and a collection of constraints in the "approved mathematical programming manner." Simulation becomes a highly valuable tool in these settings, but is not sufficient by itself to yield the quality of outcomes desired. An extra step is needed – a step that joins simulation and optimization. We propose to present two of the latest applications where combining simulation and optimization provides solutions that are achieved quickly and reliably. We will show how problems are identified, formulated, and analyzed, and demonstrate, using a software package, how solutions are achieved.

The applications chosen are relevant to participants since they are derived from ongoing work with client firms. They illustrate the process requirements and economic benefits derived from using the simulation optimization approach. The applications draw from current work in project portfolio optimization and supply chain management.

2 OPTMIZATION METHODS

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 cope with the complexities and uncertainties posed by many real world problems of the form treated by simulation. The area of stochastic optimization 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 complex 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 real world 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 Campos, et. al. (1999a and 1999b), Glover (1998), Glover et. al. (1997, 2000 and 2003) and Laguna (2002). One of those engines is the search algorithm embedded in the OptQuest optimization system (OptTek 2004). OptQuest® is designed to search for optimal solutions to the following class of optimization problems:

Max or Min $\quad F(x)$

Subject to $Ax \le b$ (Constraints)
$g_l \le G(x) \le g_u$ (Requirements)
$l \le x \le u$ (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 "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 modeled as $Ax \le b$ and the limit on WIP is achieved by a requirement modeled as $G(x) \le g_u$. 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 does allow the user to input problem structure through the use of constraints and has specialized mechanisms for analyzing specific types of problems. In particular, OptQuest contains an highly-efficient algorithm for determining solutions to problems that contain sequencing decisions. Additionally, OptQuest contains algorithms for problems of the type encountered in design where the decisions are of the form "pick one of the following choices."

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 optimization procedure decides upon a new set of input values (see Figure 1).

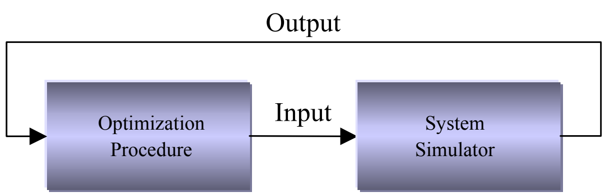

Figure 1: Coordination between Optimizer and Simulator

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).

3 PROJECT PORTFOLIO OPTIMIZATION

The Energy industry uses project portfolio optimization to manage investments in exploration and production, as well as power plant acquisitions (Haskett 1999 and 2003). Each project's cash flow pro-forma is modeled as a Monte Carlo simulation capturing the uncertainties of revenues and expenses.

The following example involves models of sixty-one potential projects at three different stages in the investment funnel: (1) *Identified*, (2) *Entered*; and (3) *Captured*. Each type of project requires a certain number of business development, engineering and earth sciences personnel.

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 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. Also, the projected revenue and expense data are considered. *Captured* projects are those projects that the company has determined will be capable of providing a revenue stream, or from which it is currently 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 included 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 could be suspended for no more than three years. After that time, rights to pursue the opportunity are deemed to have expired.

Other than cash, we also considered personnel and time to be scarce resources. In terms of personnel, we need three categories to 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 combines simulation and optimization into a single system specifically designed for portfolio optimization (April et. al. 2002, 2003a and 2003b, and Kelly 2002). 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 also be specified 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.

The Base Case was set up using the traditional portfolio mean variance case to provide a basis for comparison for the subsequent cases. An empirical histogram for the optimal portfolio is shown in Figure 2. 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 C*aptured* projects cannot be suspended. We imposed a budget constraint, but no personnel constraints for this case. The problem can be formulated as follows:

Maximize μ_{NPV}
Subject to:
$\sigma_{NPV} \leq \$140M$
All projects must start in year 1
Budget Constraint

This formulation resulted in a portfolio with the following statistics:

E(NPV) = \$455M σ = \$136M P(5) = \$266M

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

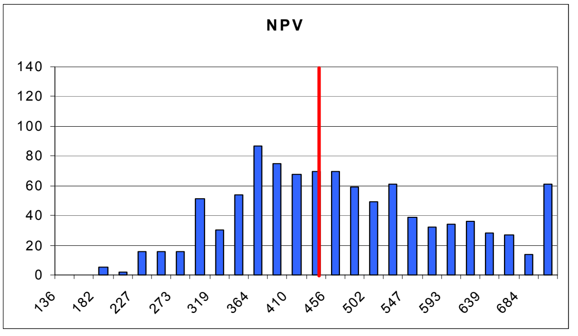

Figure 2: Base Case

In purely financial terms, this case results in higher performance. However, we have deliberately failed to address the scarcity in human resources. The results above imply hiring an additional 12 engineers and 23 earth scientists. 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 cannot be addressed here, such as training, travel, etc.

Case 1: Traditional Markowitz Approach

In a seminal paper in 1952 in the *Journal of Finance*, Nobel laureate Harry Markowitz laid down the basis for modern portfolio theory (Markowitz 1952). Markowitz focused the investment profession's attention to *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 Case 1, we implement the mean-variance efficient portfolio method proposed by Markowitz. The decision was 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:
$\sigma_{NPV} < \$140M$
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 had the following statistics:

E(NPV) = \$394M σ = \$107M P(5) = \$176M

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

The graph of the NPV obtained for 1000 replications of this case is shown in Figure 3.

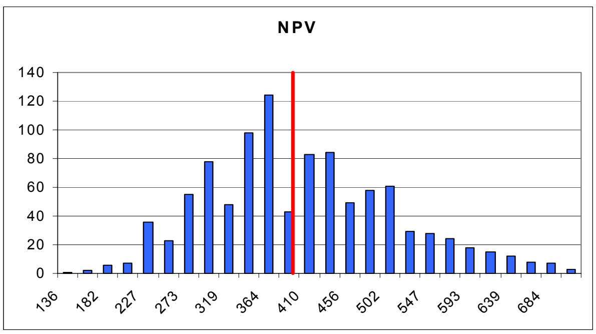

Figure 3: Mean Variance Portfolio

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 may be 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 did just that. The decision was 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 NPV 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 the stated value. In addition, in this case we do allow for delays in the start dates of projects, according to the stated windows of opportunity. The formulation 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 standard deviation with the 5th percentile for risk containment. The resulting portfolio has the following attributes:

E(NPV) = \$438M σ = \$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 4.

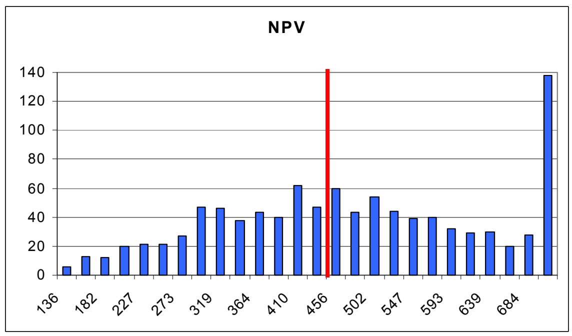

Figure 4: 5th Percentile Portfolio

This case clearly outperforms Case 1. Not only do we obtain much 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 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:

E(NPV) = $440M σ = $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 5, we have succeeded in shifting the probability distribution even further to the right, therefore increasing our chances of beating the returns of the traditional Markowitz case.

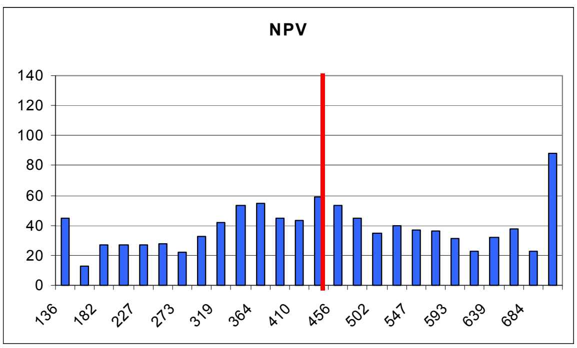

Figure 5: Maximum Probability Portfolio

As we have shown, 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.

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 the optimum portfolio that 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.

4 SUPPLY CHAIN MANAGEMENT

Simulation Optimization has recently become a “hot” technology in supply chain planning and management. The latest advancements in integrating optimization technology with simulation techniques that model the complex supply chain environment have contributed to enabling improved and more focused decisions by the diverse set of managers involved in extracting the most value from the supply chain. Expected benefits from these improved decisions include:

- Increased throughput
- Reduced inventories
- Lower supply chain costs
- Increased return on assets
- Greater customer satisfaction
- Reduced lead times

OptTek Systems, in partnership with Flextronics (a multi-billion dollar outsourcing manufacturing company: `<http://www.flextronics.com/ValueAdded/SimFlex/simflex.asp>`) has created a simulation optimization system for modeling complex supply chains. The optimizer is based on the OptQuest system described earlier. The simulator is a discrete event simulation system that models production and distribution functions while considering uncertainty. To briefly illustrate the application of the method in a typical supply chain environment, the following case study is presented.

Consider the supply chain lead times, capacity constraints and forecasting errors what are the minimum safety stock levels required for a finished product and six of its components at two Flextronics facilities. To analyze this scenario, two objective functions are considered.

Function 1: MIN Cost = Inventory Cost;
SUBJECT TO delivery time <= 2 days

Function 2: MAX Revenue = (Sales) – (Lost Sales when not shipping in time) – (Inventory Cost)

It is usual to analyze situations such as this using alternate objective functions to best address multiple concerns. Figures 6 and 7 show the improvements projected using the simulation optimization system.

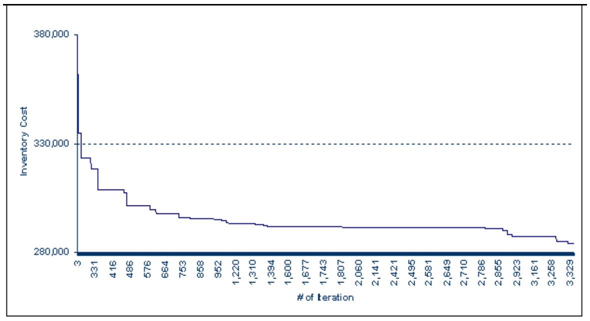

Figure 6: Minimizing Cost

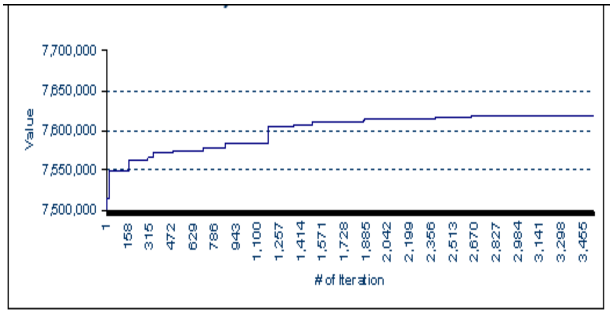

Figure 7: Maximizing Profit

Iteration 1 shows the performance of the initial design and the last iteration shows the objective values for the best supply chain designs.

A confident process for supply chain planning and scheduling enables dramatic improvements in customer response time for deliveries, inventory management, throughput, and purchasing and operating expenses. The improvements in overall supply chain response times also enables increased market share and higher profitability. The overall improvement of the supply chain planning and management that can be accomplished through the use of optimization methods can be significant. The availability of these new methods opens the door to handling decision-making problems in purchasing, manufacturing, and distribution that could not be adequately approached in the past.

5 OPTTEK SYSTEMS, INC.

OptTek Systems, Inc. is an optimization software and services company located in Boulder, Colorado. We are the leading optimization software provider to the simulation software market and are confident that our products and services will add significant value to our customers.

OptTek software is recognized throughout the simulation and optimization market for its quality, speed, and customer service. Independent evaluations of our software demonstrate that our technology yields faster and higher quality solutions when compared to other optimization methods currently on the market. While other methods currently being applied in complex and highly uncertain environments have value, they either identify feasible solutions or locally optimal solutions. Both are typically improvements over the status quo but neither identifies the global optimum or "best" solution.

OptTek's methods, which are well known in both the simulation and optimization communities, are based on the contributions of Professor Fred Glover, one of the founders of OptTek and a winner of the von Neumann Theory Prize in operations research, who developed the adaptive memory method called Tabu search, and the evolutionary method called Scatter Search, singularly powerful search techniques in global optimization.

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