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OPTFOLIO – A SIMULATION OPTIMIZATION SYSTEM FOR PROJECT PORTFOLIO PLANNING

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ABSTRACT

OptFolio is a new portfolio optimization software system that simultaneously addresses financial return goals, catastrophic loss avoidance, and performance probability. The innovations embedded in the system enable users to confidently design effective plans for achieving financial goals, employing accurate analysis based on real data. Traditional analysis and prediction methods are based on mean variance analysis -- an approach known to be faulty. The new software system takes a much more sophisticated and strategic direction. State-of-the-art technology integrates simulation and metaheuristic optimization techniques and a new surface methodology based on linear programming into a global system that guides a series of evaluations to reveal truly optimal investment scenarios. In this paper we will present new techniques that increase the flexibility of optimization tools and deepen the types of portfolio analysis that can be carried out. We include examples applied to energy, pharmaceutical, and information technology portfolios.

1 BACKGROUND

The beneficiaries of the technology discussed here include executives responsible for capital investments, finance department analysts charged with capital budgeting, and technology managers responsible for project planning and implementation. Their needs provide compelling reasons to use the technology.

There is growing evidence that executives are dissatisfied with their current risk-assessment methods and are under continual pressure to improve capital investment performance. They seek technology to help communicate the analysis and clearly identify the reasons for specific investment decisions and simultaneously worry that competitors may adopt new and more advanced technology.

Capital investment decisions are usually accomplished with traditional analyses that include net present value and mean-variance analysis. Consequently most organizations use similar methods to evaluate and select capital spending options. Many organizations evaluate projects by estimating their net present value (NPV). NPV is calculated by projecting expected future cash flows, "discounting" the future cash flows by the cost of capital, and then subtracting the initial investment. Conventional wisdom directs us to undertake projects if NPV is positive, but this does not guarantee funding. Organizations typically consider other factors, which incorporate their ability to fund the initial investment given their capital structure, current operating cash flow positions, strategic considerations and financial expectations.

In public and private organizations, the decisions of committing limited resources to multiple uses can either strengthen or deteriorate their very financial foundation. On one end of the spectrum, capital budgeting procedures often employ traditional operations research (OR) techniques to guide and support decisions. On the other end, executives admit that selections come down to intuition, combined with seat-of-the-pants "guestimates," and peppered with squeaky wheel assignments. Typically, however, what is common is to build models that employ pro-forma plans centering on measures of the benefits of the investments – returns, payback period, and risk. The list may expand to include cash flow, cost of capital, market share, etc.

Evaluations of alternatives are also made in a variety of ways, from one-at-a-time comparisons of returns and risks to more sophisticated portfolio optimization and real options. In companies using these sophisticated methods, portfolio selection usually includes mean-variance analysis.

In a seminal paper in 1952 in the *Journal of Finance* (Markowitz 1952) Nobel laureate Harry Markowitz laid down the basis for modern portfolio theory. 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 practice, mean-variance efficient portfolios have been found to be quite unstable. Typically, input parameters like expected returns, correlation among projects and project variance are estimated using either historical data or forecasts. Researchers have found that estimation errors in the input parameters overwhelm the theoretical benefits of the mean-variance paradigm.

Although cracks in the foundation are becoming too conspicuous to ignore, capital budgeting participants have been dedicated to traditional ideas for so long that they are not able to pull away, even at the expense of severely hampering their financial growth. More progressive analysts have insistently sounded the alert about the crumbling structure underlying mainstream investment strategies. Still, the best response has been to cobble together various ad-hoc measures in an attempt to shore up the framework, or erect a makeshift alternative. Recognition that this response is far from ideal has persuaded many to cling to the old ways, in spite of their apparent defects.

The inability to devise a more effective alternative has been due in large part to limitations in the technology of decision-making and analysis, which has offered no reliable method to conquer the complexity of problems attended by uncertainty. As a result, the goal of evaluating investments effectively and accurately accounting for tradeoffs between risk and potential return, has remained incompletely realized and ripe for innovation.

Over the last several years, alternative methods have emerged A new portfolio optimization software system simultaneously addresses financial return goals, catastrophic loss avoidance, and performance probability. The innovations embedded in the system enable users to confidently design effective plans for achieving financial goals, employing accurate analysis based on real data. Traditional analysis and prediction methods are based on mean variance analysis -- an approach known to be faulty. The new software system takes a much more sophisticated and strategic direction. State-of-the-art technology integrates simulation and metaheuristic optimization techniques and a new surface methodology based on linear programming into a global system that guides a series of evaluations to reveal truly optimal investment scenarios.

Portfolio analysis tools are designed to aid senior management in the development and analysis of portfolio strategies, by giving them the capability to assess the impact on the corporation of various investment decisions. To date most of the commercial portfolio optimization packages have been relatively inflexible and are often not able to answer the key questions asked by senior management. In this paper we will present new techniques that increase the flexibility of optimization tools and deepen the types of portfolio analysis that can be carried out. We also include some examples applied to energy, pharmaceutical, and information technology portfolios.

2 OPTIMIZATION

Due to the complexity and uncertainty in real systems, simulation often becomes a basis for handling complex decisions. 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 (simulations) with the goal of finding optimal values for decision variables (Glover and Laguna 1997). One example is the search algorithm embedded in the OptQuest® optimization system developed by OptTek System, Inc. OptQuest is designed to search for optimal solutions to the following class of optimization problems:

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

where x can be continuous or discrete (Glover, Kelly, and Laguna 1999) . The objective function, $F(x)$, 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 Nonlinear Constraints are simple upper and/or lower bounds imposed on a nonlinear function. The values of the bounds "g_l" and "g_u" must be known constants. All 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 NPV of a portfolio by judiciously choosing projects subject to budget restrictions and a limit on risk. In this case, x represents specific project participation levels, and $F(x)$ is the expected NPV. The budget restriction is modeled as $Ax \leq b$ and the limit on risk is a requirement modeled as $G(x) \leq g_u$ where $G(x)$ is a percentile value. Each evaluation of $F(x)$ and $G(x)$ requires a Monte Carlo simulation of the portfolio. By combining simulation and optimization, a powerful tool results.

The optimization procedure uses the outputs from the system evaluator (simulation), 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.

The optimization procedure is designed to carry out a special search, where successively generated inputs produce varying evaluations, which over time provide a highly efficient trajectory to the best solutions (Glover, Laguna, and Marti 2000). The process continues until an appropriate termination criterion is satisfied (usually based on users' preference for the amount of time to be devoted to the search).

The integration of simulation with optimization has been shown to be a powerful approach for portfolio optimization. At times, however, the computational cost of multiple simulations can be quite high. At the beginning of 2003, OptTek received a National Science Foundation Small Business Innovative Research (SBIR) award to develop a method to minimize the number of simulations required to determine the optimal project portfolio. The method, which is called the layer envelope response method, is forecast to significantly improve the efficiency in achieving the optimal solutions.

3 EXAMPLES

The following examples demonstrate the power and versatility of OptFolio.

3.1 Example 1: The Petroleum and Energy Industry

The Petroleum and Energy (P&E) industry uses project portfolio optimization to manage investments in oil and gas exploration and production. Each project's cash flow pro-forma is modeled as a Monte Carlo simulation capturing the uncertainties of expenses and revenues. The following example involves models of fifteen potential projects with multiple types of uncertainty in drilling, production, and market conditions. The data were provided by Landmark Graphics using their Terras Portfolio system. The OptFolio system requires pro-forma information for each project, as well as budget information. 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. 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). We used a 10% cost of capital rate for all of our analyses. The user specifies performance metrics and constraints to tailor the portfolio for his needs. We examined multiple cases to demonstrate the flexibility of OptFolio to enable a variety of decision alternatives that significantly improve upon traditional mean variance portfolio optimization.

3.1.1 Case 1.1: Traditional Markowitz Approach

In Case 1.1, 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. An initial investment budget was also imposed on the portfolio.

Maximize μ_{NPV}
subject to
$\sigma_{NPV} < 5000$
Budget $\leq$ 10,000

This formulation resulted in a portfolio with the following statistics:

$\mu_{NPV} = 11478$
$\sigma_{NPV} = 5000$
5^{th} Percentile = 3989.

We performed this traditional mean variance case to provide a basis for comparison for the subsequent cases. An empirical histogram for the optimal portfolio is shown in Figure 1.

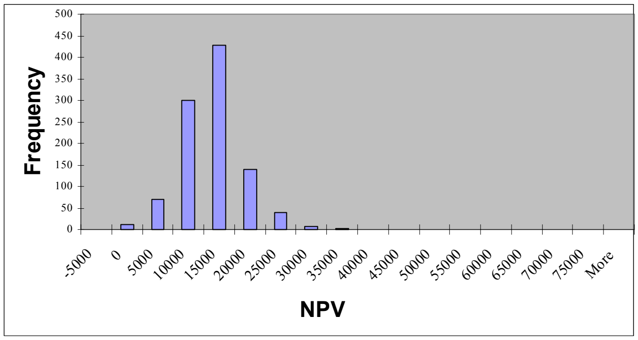

Figure 1: Mean Variance Portfolio

3.1.2 Case 1.2: Risk controlled by 5th Percentile

In Case 1.2, 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 5^{th} percentile of NPV above the value determined in Case 1.1. An investment budget was also imposed on the portfolio.

Maximize μ_{NPV}
subject to
5th Percentile $\geq$ 3,989
Budget $\leq$ 10,000

This case has replaced standard deviation with the 5^{th} percentile for risk containment. The resulting portfolio has the following attributes:

$\mu_{NPV} = 26{,}793$
$\sigma_{NPV} = 15{,}332$
5^{th} Percentile = 4,037.

By using the 5^{th} percentile as a measure of risk, we were able to more than double the expected return compared to the solution found in Case 1.1. Additionally, one could argue that the 5^{th} percentile provides a better understood measure of risk, i.e., there is a 95% chance that the portfolio will achieve a NPV of 4,037 or higher. The NPV distribution is shown in Figure 2.

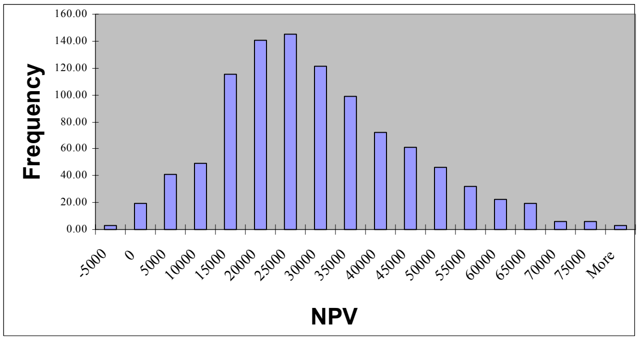

Figure 2: 5th Percentile Portfolio

3.1.3 Case 1.3: Maximizing Probability of Success

In Case 1.3, the decision was 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 1.1. An investment budget was also imposed on the portfolio.

Maximize Probability (NPV $\geq$ 11,478)
subject to
Budget $\leq$ 10,000

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:

Probability (NPV $\geq$ 11,478) = 0.88
μ_{NPV} = 27,980
σ_{NPV} = 16,109
5th Percentile = 3,242.

This portfolio has an 88% chance of achieving the NPV goal of 11,478. This represents a significant improvement over the Case 1.1 portfolio considering that the probability of meeting or exceeding 11,478 in Case 1.1 was only 50%. The NPV distribution is shown in Figure 3.

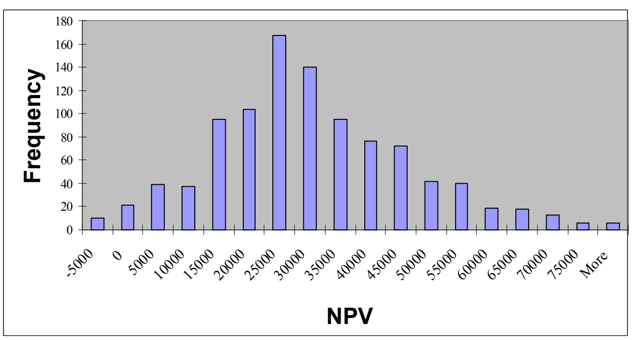

Figure 3: Probability Portfolio

3.1.4 Case 1.4: Minimum Participation

An examination of the optimal participation levels found in Case 1.3 revealed that several of the participation levels were less than 0.1. In may cases, these low levels of participation may be unacceptable. In Case 1.4, we modified the Case 1.3 constraints to prohibit participation levels in the range (0,0.25). In other words, if a project was selected, it must utilize at least a 25% participation or be excluded from the portfolio. An investment budget was also imposed on the portfolio.

Maximize Probability (NPV $\geq$ 11,478)
subject to
Budget $\leq$ 10,000
Participations = 0 or [0.25,1]

The resulting portfolio has the following attributes:

Probability (NPV $\geq$ 11,478) = 0.88
μ_{NPV} = 24,149
σ_{NPV} = 13,252
5th Percentile = 3,664.

In spite of the participation restriction, this portfolio also has an 88% chance of exceeding an NPV of 11,478.

3.1.5 Case 1.5: All or Nothing

Case 1.5 extends the participation restriction to the all or nothing case.

Maximize Probability (NPV $\geq$ 11,478)
subject to
Budget $\leq$ 10,000
Participations = 0 or 1.

The resulting portfolio has the following attributes:

Probability (NPV $\geq$ 11,478) = 0.83
μ_{NPV} = 29,283
σ_{NPV} = 19,046
5th Percentile = 42.

Although the probability measure for this portfolio is still quite high, we can see that the 5th percentile measure has dropped precipitously from the previous cases.

3.1.6 Case 1.6: Exclusivity

In many situations it is desirable to select a single project from a group of projects. In Case 1.6, we limit the portfolio to select a single development project form the set of four development projects considered in this analysis. The other, non-development projects can be selected without restriction. We utilize the Case 1.2 approach.

Maximize μ_{NPV}
subject to
5th Percentile $\geq$ 3,989
Budget $\leq$ 10,000
At most, select one development project.

The resulting portfolio has the following attributes:

$\mu_{NPV} = 19{,}861$
$\sigma_{NPV} = 10{,}453$
5^{th} Percentile = 4,038.

Compared to Case 1.2, the mean NPV is reduced. However, the standard deviation of the NPV is substantially lower.

3.2 Example 2: The Pharmaceutical Industry

Among many other types of initiatives, the Pharmaceutical Industry uses project portfolio optimization to manage investments in new drug development. A pharmaceutical company that is developing a new breakthrough drug is faced with the possibility that the drug may not do what it was intended to do, or have serious side effects that make it commercially infeasible. Thus, these projects have a considerable degree of uncertainty related to the probability of success. Relatively recently, an options-pricing approach, called "real options" has been proposed to model such uncertainties. Although this approach is receiving some attention and may become a competitor, initial feedback has indicated that an obstacle to it's market penetration is that it is difficult to understand and use; furthermore, there are no research results that illustrate better performance than the algorithmic approach we are developing.

The following example is based on data provided by Decision Strategies, Inc., a consulting firm that works with numerous clients in the Pharmaceutical Industry. The data consists of twenty potential projects in drug development. These projects have rather long horizons – 15 to 20 years – and the pro-forma information is given as triangular distributions for both per-period net contribution and investment. The models use a probability of success index – from 0% to 100%. The probability of success index is used in such a way that, if the project fails during a simulation trial, then the investments are realized, but the net contribution of the project is not. In this way, the system can be used to model premature project terminations providing a simple, understandable alternative to real options. In this example, we examined five cases.

3.2.1 Case 2.1: Simple Ranking of Projects

In Case 2.1, we ranked the projects according to a specific objective criterion. This is an approach often taken by currently available Project Portfolio Management tools in order to select projects under a budgetary constraint. In this case we chose the following objective measure:

$$R = \frac{PV(Revenues)}{PV(Expenses)}$$

All 20 projects were ranked in descending order according to this measure, and projects were added to the final portfolio as long as the budget constraint was not violated. This procedure resulted in a portfolio with the following statistics:

$\mu_{NPV} = 7{,}342$
$\sigma_{NPV} = 2{,}472$
5^{th} Percentile = 3,216.

In this case, 15 projects were selected in the final portfolio. What follows is a discussion of how using OptFolio can help improve these results.

3.2.2 Case 2.2: Traditional Markowitz Approach

In Case 2.2, 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 of 1000. An investment budget was also imposed on the portfolio.

Maximize μ_{NPV}
subject to
$\sigma_{NPV} \leq 1{,}000$
Budget Period 1 $\leq$ 125
Budget Period 2 $\leq$ 140
Budget Period 3 $\leq$ 160

This formulation resulted in a portfolio with the following statistics:

$\mu_{NPV} = 4{,}140$
$\sigma_{NPV} = 1{,}000$
5^{th} Percentile = 2,432.

We performed this traditional mean variance case to provide a basis for comparison for the subsequent cases. An empirical histogram for the optimal portfolio is shown in Figure 4.

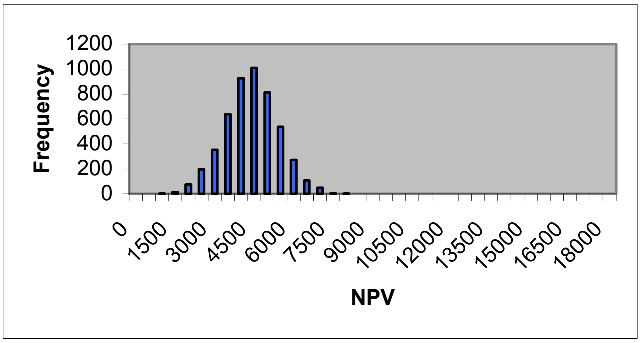

Figure 4: Mean Variance Portfolio

3.2.3 Case 2.3: Risk Controlled by 5th Percentile

In Case 2.3, 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 2.2 (2,432). The same investment budget was also imposed on the portfolio.

Maximize μ_{NPV}
subject to
5th Percentile $\geq 2{,}432$
Budget Period 1 ≤ 125
Budget Period 2 ≤ 140
Budget Period 3 ≤ 160

This case has replaced standard deviation with the 5th percentile for risk containment, which is an intuitive way to control catastrophic risk. The resulting portfolio has the following attributes:

$\mu_{NPV} = 7{,}520$
$\sigma_{NPV} = 2{,}550$
5th Percentile = 3,294.

By using the 5th percentile as a measure of risk, we were able to almost double the expected return compared to the solution found in Case 2.2, and improved on the simple ranking solution. Additionally, as previously discussed the 5th percentile provides a more intuitive measure of risk, i.e., there is a 95% chance that the portfolio will achieve a NPV of 3,294 or higher. The NPV distribution is shown in Figure 5. It is interesting to note that this solution has more variability but is focused on the upside of the distribution. By focusing on the 5th percentile rather than standard deviation, an superior solution was created.

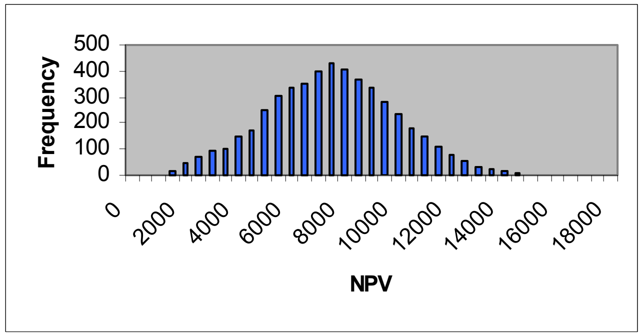

Figure 5: 5th Percentile Portfolio

3.2.4 Case 2.4: Maximizing Probability of Success

In Case 2.4, the decision was 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 2.2. An investment budget was also imposed on the portfolio.

Maximize Probability (NPV $\geq 4{,}140$)
subject to
Budget Period 1 ≤ 125
Budget Period 2 ≤ 140
Budget Period 3 ≤ 160

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:

$\mu_{NPV} = 7{,}461$
$\sigma_{NPV} = 2{,}430$
5th Percentile = 3,366.

This portfolio has a 91% chance of achieving or exceeding the NPV goal of 4,140. This represents a significant improvement over the Case 2.2 portfolio considering that the probability of meeting or exceeding 4,140 in Case 2.2 was only 50%. The NPV distribution is shown in Figure 6.

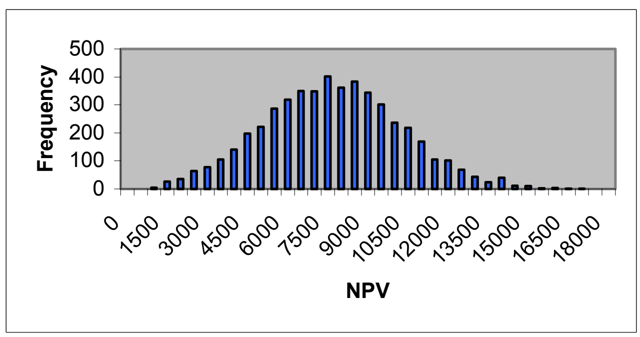

Figure 6: Probability Portfolio

3.2.5 Case 2.5: All-or-Nothing

In many real-world cases, these types of projects have all-or-nothing participation levels. However, in Case 2.4 most of the optimal participation levels found were fractional. In Case 2.5, we modified the Case 2.4 constraints to allow only 0 or 1 participation levels. In other words, a project must utilize 100% participation or be excluded from the portfolio. An investment budget was also imposed on the portfolio.

Maximize Probability (NPV $\geq$ 4,140)
subject to
Budget Period 1 $\leq$ 125
Budget Period 2 $\leq$ 140
Budget Period 3 $\leq$ 160
Participations = 0 or 1

The resulting portfolio has the following attributes:

μ_{NPV} = 7,472
σ_{NPV} = 2,503
5th Percentile = 3,323.

In spite of the participation restriction, this portfolio also has a 91% chance of exceeding an NPV of 4,140, and has a high expected return. In this case, as in Case 2.1, 15 out of the 20 projects were selected in the final portfolio. However, the expected returns are significantly higher than in Case 2.1.

These cases illustrate the benefits of using alternative measures for risk. Not only are percentiles and probabilities more intuitive for the decision-maker, but they also produce solutions with better financial metrics.

The OptFolio system can also be used to optimize performance metrics such as Internal Rate of Return (IRR) and Payback Period. The following examples address these cases.

3.3 Example 3: Information Management Projects

One of the fastest growing areas of application for Project Portfolio Management is Information Technology (IT). Traditionally, firms have not had a systematic approach for tracking the returns on investment projects. Also, it is estimated that more than 30% of IT projects ultimately fail, after a considerable amount of money and resources has been invested (AMR Research, October 2002). Therefore, there is a trend across all industries to improve the ways in which decisions are made whether to undertake specific projects. The following example involves models of five potential IT projects. These projects involve data processing, network integration and enterprise management solutions. Data for these projects were provided by Decision Strategies, Inc. As in our previous examples, we used OptFolio for our analysis. In all cases, we considered budgetary restrictions.

3.3.1 Case 3.1: Traditional Markowitz Approach

In this case, we maximize mean NPV, while limiting the standard deviation to at most 3.0. The resulting statistics for the final portfolio are:

μ_{NPV} = 12.15
σ_{NPV} = 0.50
5th Percentile = 11.36
μ_{IRR} = 95.90%.

The NPV distribution for this portfolio is shown in Figure 7.

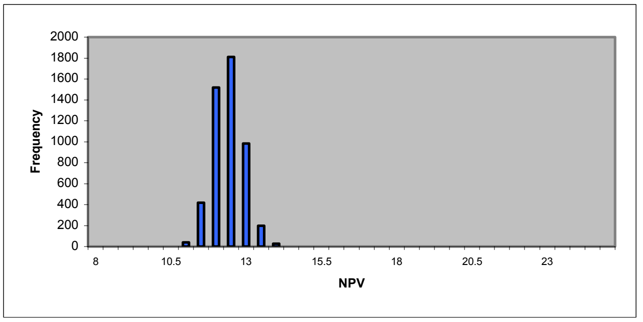

Figure 7: Traditional Markowitz Approach

3.3.2 Case 3.2: Risk Controlled by the 5th Percentile

In Case 3.2, we maximize mean NPV, while holding the 5th percentile to at least 11.36. The statistics for the final portfolio are:

μ_{NPV} = 19.42
σ_{NPV} = 1.26
5th Percentile = 17.33
μ_{IRR} = 45.80%.

The NPV distribution for Case 3.2 is shown in Figure 8.

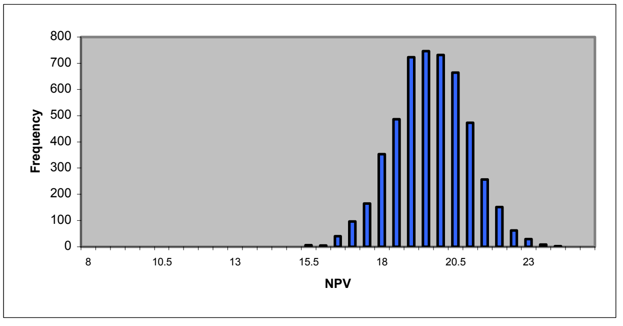

Figure 8: Risk Controlled by 5th Percentile

3.3.3 Case 3. 3: Maximize Probability of Success

In Case 3.3, we maximize the probability that the NPV is greater than 12.15. The resulting portfolio is the same as in Case 3.2.

3.3.4 Case 3.4: All-or-nothing

Case 3.4 is the same as Case 3.3, but we restrict participation levels to the all-or-nothing case. Since the results are the same as cases 2 and 3, we conclude that in all three cases the solution was only involved all-or-nothing participation levels.

3.3.5 Cases 3.5 and 3.6: Maximizing IRR

In some cases, the user may decide that NPV is not the best measure for selecting projects. Cases 5 and 6 seek to maximize Internal Rate of Return (IRR) in order to obtain a better portfolio; however, a NPV smaller than 12.15 (obtained in Case 3.1) is considered unacceptable.

In Case 3.5, we maximize the mean IRR while holding the mean NPV to at least 12.15. The resulting portfolio outperforms the Case 3.1 portfolio in terms of NPV.

In Case 3.6, we maximize the probability that the IRR is greater than 60.8%, the mean IRR value obtained in Case 3.5. We also keep the constraint on the mean NPV, as in the last case. In the resulting portfolio, although the NPV values are lower than in Case 3.5, the IRR has a 100% probability of exceeding 60.8%, with a mean IRR of 101.8%, which is the highest of all the cases analyzed.

We can conclude from these examples that the application is very effective for complex, as well as simple, sets of projects, where different measures of risk and return can produce improvements over the traditional Markowitz (mean-variance) approach, as well as over simple project ranking approaches.

OptFolio offers the user the flexibility to choose various measures and statistics, both as objective performance measures as well as constraints. This enables the user to select better ways of modeling and controlling risk, while aligning the outcomes to specific corporate goals.

OptFolio also provides ways to define special relationships that often arise between and among projects. Correlations can be defined between the revenues and/or expenses of two projects. In addition, the user can define projects that are mutually exclusive, or dependent. For example, in some cases, selecting Project A *implies* selecting Project B; such a definition can easily be done in OptFolio.

Portfolio analysis tools are designed to aid senior management in the development and analysis of project portfolio strategies, by giving them the capability to assess the impact on the corporation of various investment decisions. To date, commercial portfolio optimization packages are relatively inflexible and are often not able to answer the key questions asked by senior management. With OptFolio, we present new techniques that increase the flexibility of portfolio optimization tools and deepen the types of portfolio analysis that can be carried out.

4 PERFORMANCE COMPARISON

The following figures demonstrate OptFolio's performance compared to the system prior to this research. The LEVER method has had significant impact on the efficiency of our approach. In all the cases below, OptFolio was run with and without the LEVER method. We provide examples from the four data sets tested in the previous section. For these cases, we let both applications run for the same number of iterations. The total number of iterations was the same used for our test trials described in the previous section, to ensure we obtained the solutions reported above for OptFolio. In Figures 9, 10 and 11, not only does OptFolio with the LEVER method find the best portfolio significantly sooner, but, given the total number of iterations allotted, the non-enhanced system never finds a solution of equal or higher quality. These performance results show that OptFolio with the LEVER method is more than 1000% more efficient than our previous system. The LEVER method has been a technical success and contributes to our attainment of Objective 4.

5 SUMMARY

The approach discussed here brings intelligence to software for corporate decision-making, and gives a new dimension to optimization and simulation models in business and industry. The method empowers decision makers to look beyond conventional decision-making approaches and actually pinpoint the most effective choices in uncertain situations. The implementation of the software should al-

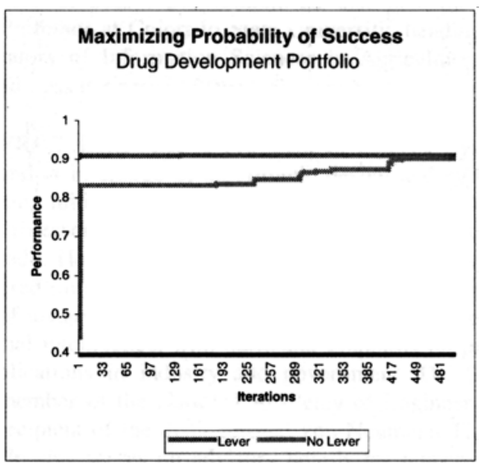

Figure 9: Maximizing Probability of Success

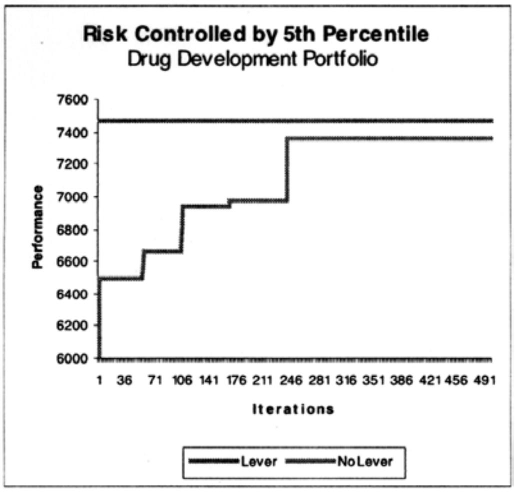

Figure 10: Controlling Risk by 5th Percentile

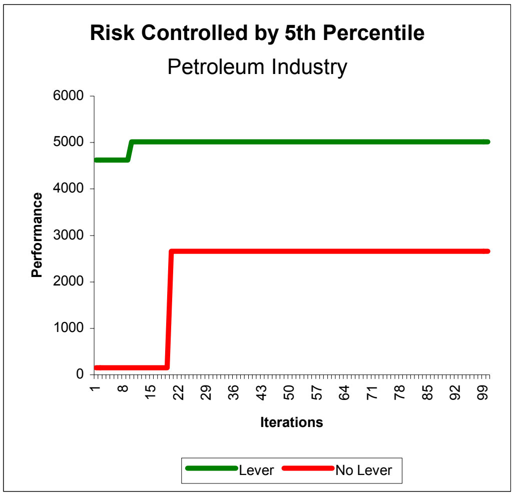

Figure 11: Controlling Risk by 5th Percentile

low senior management to confidently maximize financial return while accurately measuring and controlling risk.

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