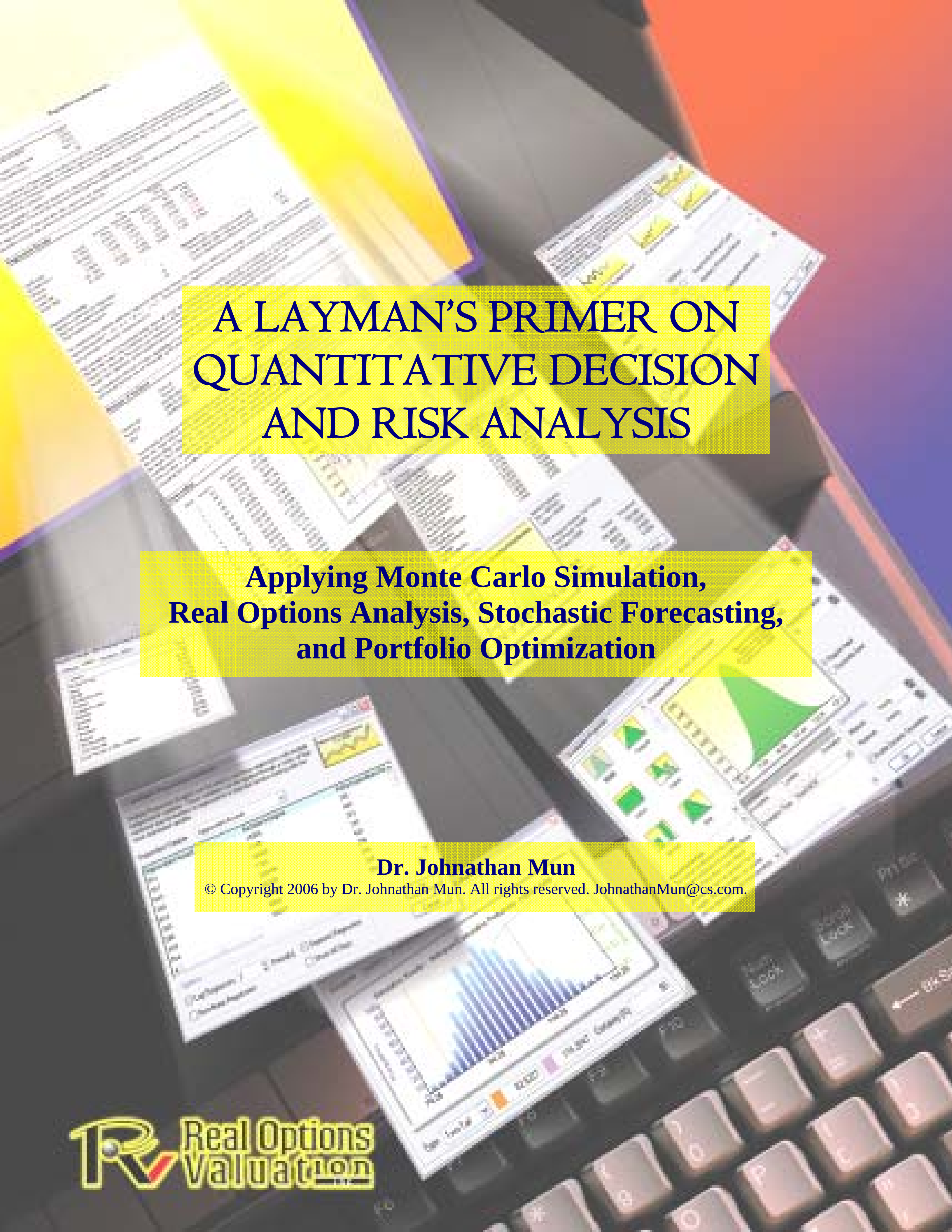

A LAYMAN'S PRIMER ON QUANTITATIVE DECISION AND RISK ANALYSIS

Applying Monte Carlo Simulation, Real Options Analysis, Stochastic Forecasting, and Portfolio Optimization

Dr. Johnathan Mun

Real Options Valuation

A Layman's Primer on Quantitative Decision and Risk Analysis: Monte Carlo Simulation, Real Options, Forecasting, and Optimization[1]

Since the beginning of recorded history, games of chance have been a popular pastime. Even in Biblical accounts, Roman soldiers cast lots for Christ's robes. In earlier times, chance was something that occurred in nature, and humans were simply subjected to it as a ship is to the capricious tosses of the waves in an ocean. Even up to the time of the Renaissance, the future was thought to be simply a chance occurrence of completely random events and beyond the control of humans. However, with the advent of games of chance, human greed has propelled the study of risk and chance to evermore closely mirror real-life events. Although these games were initially played with great enthusiasm, no one actually sat down and figured out the odds. Of course, the individual who understood and mastered the concept of chance was bound to be in a better position to profit from such games of chance. It was not until the mid-1600s that the concept of chance was properly studied, and the first such serious endeavor can be credited to Blaise Pascal, one of the fathers of modern choice, chance, and probability. Fortunately for us, after many centuries of mathematical and statistical innovations from pioneers such as Pascal, Bernoulli, Bayes, Gauss, LaPlace, and Fermat, and with the advent of blazing fast computing technology, our modern world of uncertainty can be explained with much more elegance through methodological hands-on applications of risk and uncertainty. Even as recent as two decades ago, computing technology was only in its infancy and running advanced analytical models would have been a fantasy, but today, with the assistance of software packages, we have the ability to, in a very practical sense, apply such techniques with great ease. We should, in this case, choose not to repeat but to learn from human history that with innovation comes the requisite change in human behavior, to accept these new methodologies as the norm.

To the people who lived centuries ago, risk was simply the inevitability of chance occurrence beyond the realm of human control. Albeit many phony soothsayers profited from their ability to convincingly profess their clairvoyance by simply stating the obvious or reading the victims' body language and telling them what they wanted to hear. We modern-day humans, ignoring for the moment the occasional seers among us, with our fancy technological achievements, are still susceptible to risk and uncertainty. We may be able to predict the orbital paths of planets in our solar system with astounding accuracy or the escape velocity required to shoot a man from the Earth to the Moon, or drop a smart bomb within a few feet of its target thousands of miles away, but when it comes to say, predicting a firm's revenues the following year, we are at a loss. Humans have been struggling with risk our entire existence, but through trial and error, and through the evolution of human knowledge and thought, have devised ways to describe, quantify, hedge, and take advantage of risk.

In this quick primer, advanced quantitative risk-based concepts will be introduced, namely, the hands-on applications of Monte Carlo simulation, real options analysis, stochastic forecasting, and portfolio optimization. These methodologies rely on existing techniques (e.g., return on investment, discounted cash flow, cost-based analysis, and so forth), and complements these traditional techniques by pushing the envelope of analytics, and not to replace them outright. It is not a complete change of paradigm, and we are not asking the reader to throw out what has been tried and true, but to shift one's paradigm, to move with the times, and to *improve* upon what has been tried and true. These new methodologies are used in helping make the best possible decisions, allocating budgets, predicting outcomes, creating portfolios with the highest strategic value and returns on investment, and so forth, where the conditions surrounding these decisions are risky or uncertain. These new techniques can be used to identify, analyze, quantify, value, predict, hedge, mitigate, optimize, allocate, diversify, and manage risk. Find out how multinationals like 3M, Airbus, Boeing, BP, Chevron, GE, Motorola, Pfizer, Johnson & Johnson, and many others are relying on these advanced analytical techniques.

[1] This primer is written by Dr. Johnathan Mun, and is based on his two latest books, "Modeling Risk," (Wiley 2006) and "Real Options Analysis, Second Edition," (Wiley 2005).

Why Is Risk Important in Making Decisions?

Before we embark on the journey to review these advanced techniques, let us first consider why risk is critical when making decisions, and how traditional analyses are inadequate in considering risk. Risk should be an important part of the decision-making process; otherwise bad decisions may be made without an assessment of risk. For instance, suppose projects are chosen based simply on an evaluation of returns alone or cost alone; clearly the highest-return or lowest-cost project will be chosen over lower-return or higher-cost projects. In theory, projects with higher returns will in most cases bear higher risks, or to truly minimize cost, just fire everyone! Therefore, instead of relying purely on bottom-line profits or costs, a project or strategy should be evaluated based on its returns, costs, as well as its risks. Figures 1 and 2 illustrate the errors in judgment when risks are ignored.

Figure 1 lists three *mutually exclusive* projects with their respective costs to implement, expected net returns (net of the costs to implement), and risk levels (all in present values). Clearly, for the budget-constrained manager, the cheaper the project the better, resulting in the selection of Project X. The returns-driven manager will choose Project Y with the highest returns, assuming that budget is not an issue. Project Z will be chosen by the risk-averse manager as it provides the least amount of risk while providing a positive net return. The upshot is that, with three different projects and three different decision makers, three different decisions will be made. Who is correct and why?

Why is Risk Important?

Name of Project	Cost	Returns	Risk
Project X	$50	$50	$25
Project Y	$250	$200	$200
Project Z	$100	$100	$10

Project X for the cost and budget-constrained manager

Project Y for the returns driven and nonresource-constrained manager

Project Z for the risk-adverse manager

Project Z for the smart manager

Figure 1: Why is Risk Important?

Figure 2 shows that Project Z should be chosen. For illustration purposes, suppose all three projects are independent and mutually exclusive, and that an unlimited number of projects from each category can be chosen but the budget is constrained at $1,000. Therefore, with this $1,000 budget, 20 project Xs can be chosen, yielding $1,000 in net returns and $500 risks, and so forth. It is clear from Figure 2 that project Z is the best project as for the same level of net returns ($1,000), the least amount of risk is undertaken ($100). Another way of viewing this selection is that for each $1 of returns obtained, only $0.1 amount of risk is involved on average, or that for each $1 of risk, $10 in returns are obtained on average. This example illustrates the concept of *bang-for-the-buck* or getting the best value (benefits and costs both considered) with the least amount of risk. An even more blatant example is if there are several different projects with identical single-point average net benefit or cost of $10 million each. Without risk analysis, a decision maker should in theory be indifferent in choosing any of the projects. However, with risk analysis, a better decision can be made—for instance, suppose the first project has a 10 percent chance of exceeding $10 million, the second a 15 percent chance, and the third a 55 percent chance, additional critical information is obtained on the riskiness of the project or strategy and a better decision can be made.

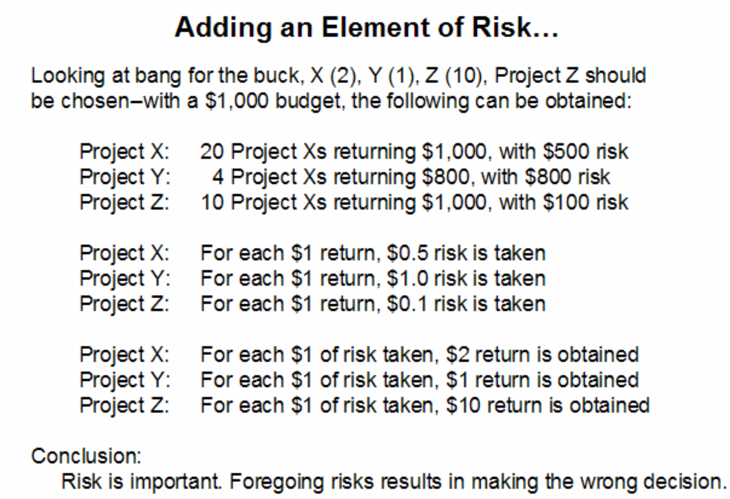

Figure 2: Adding an Element of Risk

From Dealing with Risk the Traditional Way to Monte Carlo Simulation

Businesses have been dealing with risk since the beginning of the history of commerce. In most cases, managers have looked at the risks of a particular project, acknowledged their existence, and moved on. Little quantification was performed in the past. In fact, most decision makers look only to single-point estimates of a project's profitability. Figure 3 shows an example of a single-point estimate. The estimated net revenue of $30 is simply that, a single point whose probability of occurrence is close to zero.[2] Even in the simple model shown in Figure 3, the effects of interdependencies are ignored, and in traditional modeling jargon, we have the problem of *garbage-in, garbage-out* (GIGO). As an example of interdependencies, the units sold are probably negatively correlated to the price of the product, and positively correlated to the average variable cost, ignoring these effects in a single-point estimate will yield grossly incorrect results. For instance, if the unit sales variable becomes 11 instead of 10, the resulting revenue may not simply be $35. The net revenue may actually decrease due to an increase in variable cost per unit while the sale price may actually be slightly lower to accommodate this increase in unit sales. Ignoring these interdependencies will reduce the accuracy of the model.

One traditional approach used to deal with risk and uncertainty is the application of scenario analysis. Suppose three scenarios were manufactured: the worst-case, nominal-case, and best-case scenarios, and different values are applied to the unit sales, the resulting three scenarios' net revenues are obtained. As earlier, the problems of interdependencies are not addressed. The net revenues obtained are simply too variable. Not much can be determined from such an analysis.

A related approach is to perform *what-if* or *sensitivity* analysis. Each variable is perturbed a prespecified amount (e.g., unit sales is changed ±10%, sales price is changed ±5%, and so forth) and the resulting change in net revenues is captured. This approach is great for understanding which variables drive or impact the bottom line the most. Performing such analyses is tedious and provides little benefit at best. A related approach is the use of Monte Carlo simulation and tornado-sensitivity analysis, where all perturbations, scenarios, and sensitivities are run hundreds of thousands of times automatically.

[2] On a continuous basis, the probability of occurrence is the area under a curve, e.g., there is a 90% probability revenues will be between $10 and $11 million. However, the area under a straight line approaches zero. Therefore, the probability of hitting exactly $10.0000 is close to 0.00000001%.

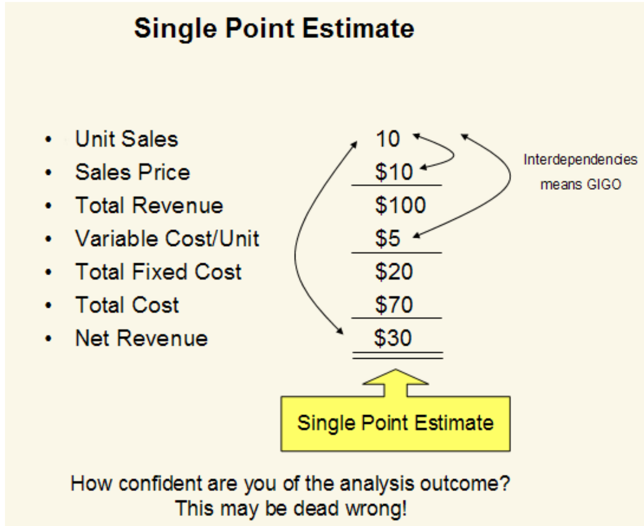

Figure 3: Single-point Estimates

Therefore, Monte Carlo simulation, one of the advanced concepts introduced in this paper, can be viewed as simply an extension of the traditional approaches of sensitivity and scenario testing. The critical success drivers or the variables that affect the bottom-line variable the most, which at the same time are uncertain, are simulated. In simulation, the interdependencies are accounted for by using correlations. The uncertain variables are then simulated tens of thousands of times automatically to emulate all potential permutations and combinations of outcomes. The resulting net revenues from these simulated potential outcomes are tabulated and analyzed. In essence, in its most basic form, simulation is simply an enhanced version of traditional approaches such as sensitivity and scenario analysis but automatically performed for thousands of times while accounting for all the dynamic interactions between the simulated variables. The resulting net revenues from simulation, as seen in Figure 4, show that there is a 90 percent probability that the net revenues will fall between $19.44 and $41.25, with a 5 percent worst-case scenario of net revenues falling below $19.44. Rather than having only three scenarios, simulation created 5,000 scenarios, or trials, where multiple variables are simulated and changing simultaneously (unit sales, sale price, and variable cost per unit), while their respective relationships or correlations are maintained.

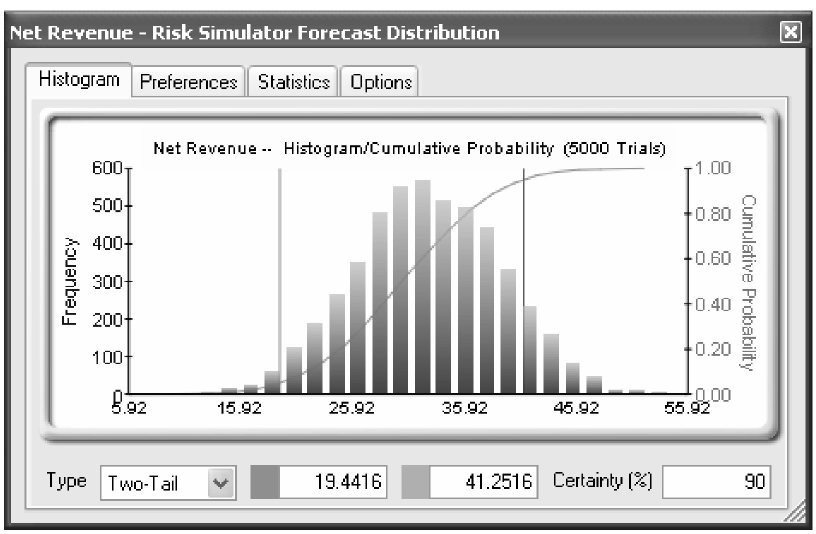

Figure 4: Simulation Results

Monte Carlo simulation, named for the famous gambling capital of Monaco, is a very potent methodology. For the practitioner, simulation opens the door for solving difficult and complex but practical problems with great ease. Perhaps the most famous early use of Monte Carlo simulation was by the Nobel physicist Enrico Fermi (sometimes referred to as the father of the atomic bomb) in 1930, when he used a random method to calculate the properties of the newly discovered neutron. Monte Carlo methods were central to the simulations required for the Manhattan Project, where in the 1950s Monte Carlo simulation was used at Los Alamos for early work relating to the development of the hydrogen bomb, and became popularized in the fields of physics and operations research. The Rand Corporation and the U.S. Air Force were two of the major organizations responsible for funding and disseminating information on Monte Carlo methods during this time, and today there is a wide application of Monte Carlo simulation in many different fields including engineering, physics, research and development, business, and finance.

Simplistically, Monte Carlo simulation creates artificial futures by generating thousands and even hundreds of thousands of sample paths of outcomes and analyzes their prevalent characteristics. In practice, Monte Carlo simulation methods are used for risk analysis, risk quantification, sensitivity analysis, and prediction. An alternative to simulation is the use of highly complex stochastic closed-form mathematical models. For a high-level decision maker, taking graduate level advanced math and statistics courses is just not logical or practical. A brilliant analyst would use all available tools at his or her disposal to obtain the same answer the easiest and most practical way possible. And in all cases, when modeled correctly, Monte Carlo simulation provides similar answers to the more mathematically elegant methods. In addition, there are many real-life applications where closed-form models do not exist and the only recourse is to apply simulation methods. So, what exactly is Monte Carlo simulation and how does it work?

Today, fast computers and powerful software like *Risk Simulator* have made possible many complex computations that were seemingly intractable in past years. For scientists, engineers, statisticians, managers, business analysts, and others, computers have made it possible to create models that simulate reality and aid in making predictions, one of which is used in simulating real systems by accounting for randomness and future uncertainties through investigating hundreds and even thousands of different scenarios. The results are then compiled and used to make decisions.

Monte Carlo simulation in its simplest form is a random number generator that is useful for forecasting, estimation, and risk analysis. A simulation calculates numerous scenarios of a model by repeatedly picking values from a user-predefined *probability distribution* for the uncertain variables and using those values for the model. As all those scenarios produce associated results in a model, each scenario can have a forecast. Forecasts are events (usually with formulas or functions) that you define as important outputs of the model. Think of the Monte Carlo simulation approach as picking golf balls out of a large basket repeatedly with replacement. The size and shape of the basket depend on the distributional *input assumption* (e.g., a normal distribution with a mean of 100 and a standard deviation of 10, versus a uniform distribution or a triangular distribution) where some baskets are deeper or more symmetrical than others, allowing certain balls to be pulled out more frequently than others. The number of balls pulled repeatedly depends on the number of *trials* simulated. Each ball is indicative of an event, scenario or condition that can occur. For a large model with multiple related assumptions, imagine the large model as a very large basket, where many baby baskets reside. Each baby basket has its own set of colored golf balls that are bouncing around. Sometimes these baby baskets are linked with each other (if there is a *correlation* between the variables), forcing the golf balls to bounce in tandem whereas in other uncorrelated cases, the balls are bouncing independently of one another. The balls that are picked each time from these interactions within the model (the large basket) are tabulated and recorded, providing a *forecast output* result of the simulation.

By applying Monte Carlo simulation to simultaneously change all critical inputs in a correlated manner within a model, you can identify, quantify, and analyze risk.[3] The question then is what next? Simply quantifying risk is useless unless you can manage it, reduce it, control it, hedge it, or mitigate it. This is where strategic real options analysis comes in. Think of real options as a strategic road map for making decisions. Suppose you are driving from point A to point B, and you only have or know one way to get there, a straight route. Further suppose that there is a lot of *uncertainty* as to what traffic conditions are like further down the road, and you *risk* being stuck in traffic, and there's a 50% chance that will occur. Simulation will provide you the 50% figure. But so what? Knowing that half the time you will get stuck in traffic is valuable information, but the question now is, so what? Especially if you have to get to point B no matter what. However, if you had several alternate routes to get to point B, you can still drive the straight route but if you hit traffic, you can make a left, right, or U-turn, to get around congestion, mitigating the risk, and getting you to point B faster and safer, that is, you have *options*. So, how much is such a strategic road map or global positioning satellite map worth to you? In situations with high risk, real options can help you create strategies to mitigate these risks. In fact, businesses and the military have been doing real options for hundreds of years without really realizing it. For instance, for the military, they call it *courses of action* or *analysis of alternatives*—do we take Hill A so that it provides us the option and ability to take Hill B and Valley C, or do we only take Valley C, and so forth. The piece that is missing is the structure and analytics which real options provides. Using real options analysis, we can quantify and value each strategic pathway, and frame strategies that will hedge or mitigate, and sometimes take advantage of risk.

In the past, corporate investment decisions were cut-and-dried. Buy a new machine that is more efficient, make more products costing a certain amount, and if the benefits outweigh the costs, execute the investment. Hire a larger pool of sales associates, expand the current geographical area, and if the marginal increase in forecast sales revenues exceeds the additional salary and implementation costs, start hiring. Need a new manufacturing plant? Show that the construction costs can be recouped quickly and easily by the increase in revenues it will generate through new and more improved products, and the initiative is approved. However, real-life conditions are a lot more complicated. Your firm decides to go with an e-commerce strategy, but multiple strategic paths exist. Which path do you choose? What are the options that you have? If you choose the wrong path, how do you get back on the right track? How do you value and prioritize the paths that exist? You are a venture capitalist firm with multiple business plans to consider. How do you value a start-up firm with no proven track record? How do you structure a mutually beneficial investment deal? What is the optimal timing to a second or third round of financing?

Real options are useful not only in valuing a firm through its strategic business options but also as a strategic business tool in capital investment decisions. For instance, should a firm invest millions in a new open architecture initiative, and if so, what are the strategies and how do they proceed? How does the firm choose among several seemingly cashless, costly, and unprofitable information-technology infrastructure projects? Should it indulge its billions in a risky research and development initiative? The consequences of a wrong decision can be disastrous and lives could be at stake. In a traditional analysis, these questions cannot be answered with any certainty. In fact, some of the answers generated through the use of the traditional analysis are flawed because the model assumes a static, one-time decision-making process while the real options approach takes into consideration the strategic options certain projects create under uncertainty and a decision maker's flexibility in exercising or abandoning these options at different points in time, when the level of uncertainty has decreased or has become known over time.
The real options approach incorporates a learning model, such that the decision maker makes better and more informed strategic decisions when some levels of uncertainty are resolved through the passage of time, actions, and events. Traditional analysis assumes a static investment decision, and assumes that

[3] The outcomes from a Monte Carlo simulation include probabilities and various risk statistics that can be used to make better decisions.

strategic decisions are made initially with no recourse to choose other pathways or options in the future. Imagine real options as your guide when navigating through unfamiliar territory, providing road signs at every turn to guide you in making the best and most informed driving decisions. This is the essence of real options. Figure 5 illustrates a very basic real options framing exercise—clearly more complex situations can be set up. From the options that are framed, Monte Carlo simulation, stochastic forecasting, coupled with traditional techniques are applied. Then, real options analytics are applied to solve and value each strategic pathway and an informed decision can then be made.[4]

Real options analysis can be used to frame strategies to mitigate risk, value and find the optimal strategy pathway to pursue, and generate options to enhance the value of the project while managing risks. Sample options include the option to expand, contract, abandon, or sequential compound options (phased stage-gate options, options to wait and defer investments, proof of concept stages, milestone development and research and development initiatives).

Portfolio Optimization

In most decisions, there are variables over which you have control, such as how much to charge for a product or how much to invest in a project or which projects you should choose in a portfolio when you are constrained by a budget or resources. These controlled variables are called decision variables. Finding the optimal values for decision variables can make the difference between reaching an important goal and missing that goal. These decisions could also include allocating financial resources, building or expanding facilities, managing inventories, and determining product-mix strategies. Such decisions might involve thousands or millions of potential alternatives. Considering and evaluating each of them would be impractical or even impossible. An optimization model can provide valuable assistance in incorporating relevant variables when analyzing decisions, and finding the best solutions for making decisions. Optimization models often provide insights that intuition alone cannot. An optimization model has three major elements: decision variables, constraints, and an objective. In short, the optimization methodology finds the best combination or permutation of decision variables (e.g., which projects to execute) in every conceivable way such that the objective is maximized (e.g., strategic value, revenues, and return on investment) or minimized (e.g., risk and costs) while still satisfying the constraints (e.g., time, budget, and resources).

Obtaining optimal values generally requires that you search in an iterative or ad hoc fashion. This search involves running one iteration for an initial set of values, analyzing the results, changing one or more values, rerunning the model, and repeating the process until you find a satisfactory solution. This process can be very tedious and time consuming even for small models, and often it is not clear how to adjust the values from one iteration to the next. A more rigorous method systematically enumerates all possible alternatives. This approach guarantees optimal solutions if the model is correctly specified. Suppose that an optimization model depends on only two decision variables. If each variable has 10 possible values, trying each combination requires 100 iterations (10^2 alternatives). If each iteration is very short (e.g., 2 seconds), then the entire process could be done in approximately three minutes of computer time. However, instead of two decision variables, consider six, then consider that trying all combinations requires 1,000,000 iterations (10^6 alternatives). It is easily possible for complete enumeration to take many years to carry out. Therefore, optimization has always been a fantasy until now, with sophisticated software and computing power, coupled with smart heuristics and algorithms, such analyses can be done within minutes.

[4] The pathways can be valued using partial differential closed-form equations, lattices, and simulation. The Real Options SLS software by Real Options Valuation, Inc. (www.realoptionsvaluation.com) is used to value these options with great ease.

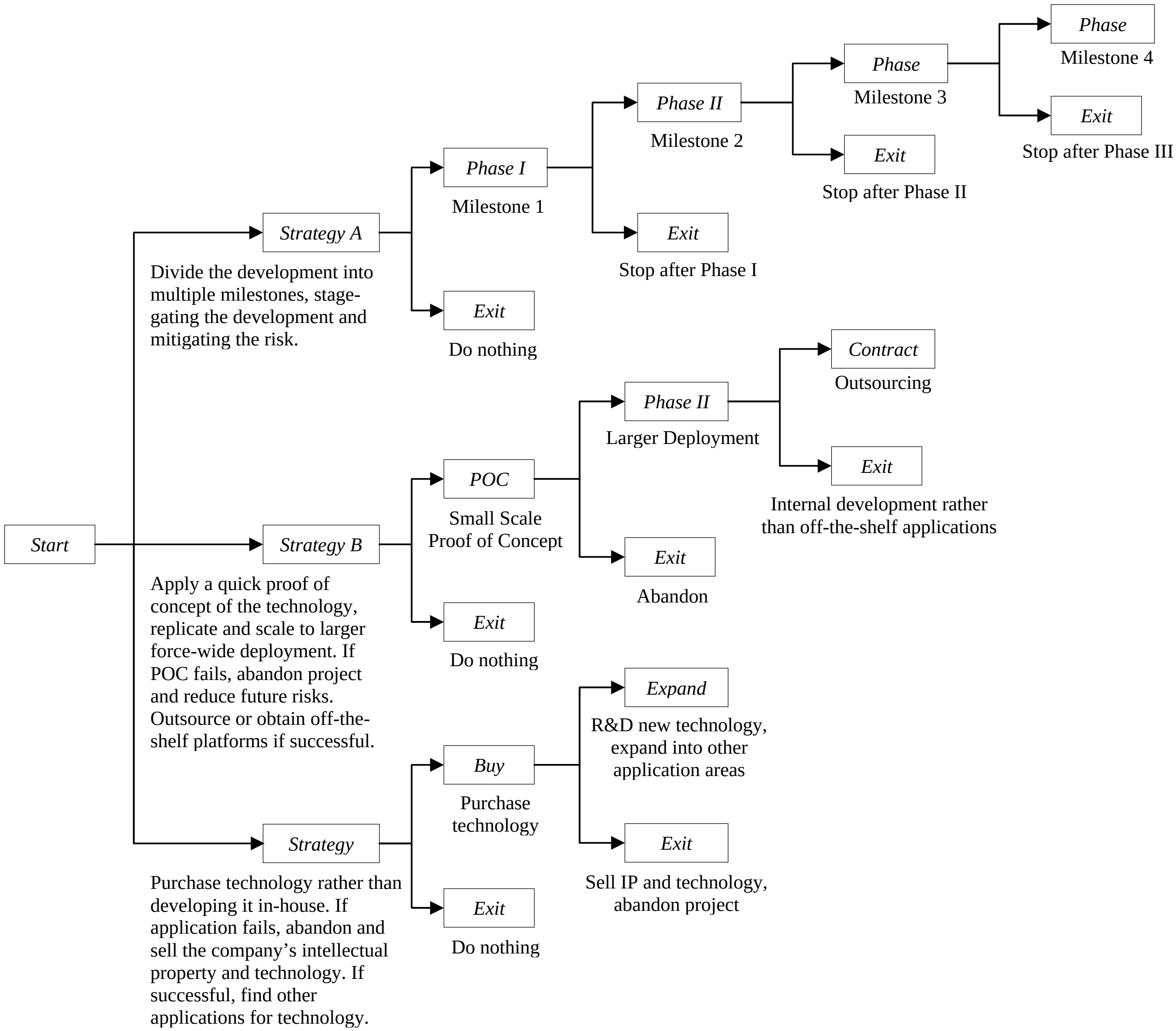

Figure 5: Simple Example of Real Options Framing (Buy vs. Build with Stage-Gate Development)

Figures 6 to 8 illustrate a sample portfolio analysis where in the first case, there are 20 total projects to choose from (if all projects were executed, it would cost \$10.2B), where each project has its own returns on investment or benefits measure, cost, strategic ranking, comprehensive, tactical and total strategic scores (these were obtained from managers and executives through the Delphi method to elicit their thoughts about how strategic a particular project or initiative will be, and so forth). The constraints are full-time equivalence resources, budget, and strategic score. In other words, there are 20 projects or initiatives to choose from, where we want to select the top 10, subject to having enough money to pay for them, the people to do the work, and yet be the most strategic portfolio possible.[5] All the while, Monte Carlo simulation, real options, and forecasting methodologies are applied in the optimization model (e.g., each project's values shown in Figure 6 are linked from its own large model with simulation and forecasting methodologies applied, and the best strategy for each project is chosen using real options analysis, or perhaps the projects shown are nested within one another, for instance, you cannot exercise Project 2 unless you execute Project 1, but you can only exercise Project 1 without having to do Project 2,

[5] There are 2 x 10^{18} possible permutations for this problem, and if tested by hand, would take years to complete. Using Risk Simulator, the problem is solved in about 5 seconds, or several minutes if Monte Carlo simulation and real options are incorporated in the analysis.

and so forth). The results are shown in Figure 6. Figure 7 shows the optimization process done in series, while relaxing some of the constraints. For instance, what would be the best portfolio and the strategic outcome if a budget of $3.8B was imposed? What if it was increased to $4.8B, $5.8B, and so forth? The efficient frontiers depicted in Figure 7 illustrate the best combination and permutation of projects in the optimal portfolio. Each point on the frontier is a portfolio of various combinations of projects that provides the best allocation possible given the requirements and constraints. Finally, Figure 8 shows the top 10 projects that were chosen and how the total budget is best and most optimally allocated to provide the best and most well-balanced portfolio.

Project Name	ENPV	NPV	Cost	Strategy Ranking	Return to Rank Ratio	Profitability Index	Selection	Comprehensive Score	Tactical Score	FTE Resources	Strategic Score
Project 1	$458.00	$150.76	$1,732.44	1.20	381.67	1.09	1	8.10	2.31	1.20	1.98
Project 2	$1,954.00	$245.00	$859.00	9.80	199.39	1.29	1	1.27	4.83	2.50	1.76
Project 3	$1,599.00	$458.00	$1,845.00	9.70	164.85	1.25	1	9.88	4.75	3.60	2.77
Project 4	$2,251.00	$529.00	$1,645.00	4.50	500.22	1.32	1	8.83	1.61	4.50	2.07
Project 5	$849.00	$564.00	$458.00	10.90	77.89	2.23	1	5.02	6.25	5.50	2.94
Project 6	$758.00	$135.00	$52.00	7.40	102.43	3.60	1	3.64	5.79	9.20	3.26
Project 7	$2,845.00	$311.00	$758.00	19.80	143.69	1.41	1	5.27	6.47	12.50	4.04
Project 8	$1,235.00	$754.00	$115.00	7.50	164.67	7.56	1	9.80	7.16	5.30	3.63
Project 9	$1,945.00	$198.00	$125.00	10.80	180.09	2.58	1	5.68	2.39	6.30	2.16
Project 10	$2,250.00	$785.00	$458.00	8.50	264.71	2.71	1	8.29	4.41	4.50	2.67
Project 11	$549.00	$35.00	$45.00	4.80	114.38	1.78	1	7.52	4.65	4.90	2.75
Project 12	$525.00	$75.00	$105.00	5.90	88.98	1.71	1	5.54	5.09	5.20	2.69
Project 13	$516.00	$451.00	$48.00	2.80	184.29	10.40	1	2.51	2.17	4.60	1.66
Project 14	$499.00	$458.00	$351.00	9.40	53.09	2.30	1	9.41	9.49	9.90	4.85
Project 15	$859.00	$125.00	$421.00	6.50	132.15	1.30	1	6.91	9.62	7.20	4.25
Project 16	$884.00	$458.00	$124.00	3.90	226.67	4.69	1	7.06	9.98	7.50	4.46
Project 17	$956.00	$124.00	$521.00	15.40	62.08	1.24	1	1.25	2.50	8.60	2.07
Project 18	$854.00	$164.00	$512.00	21.00	40.67	1.32	1	3.09	2.90	4.30	1.70
Project 19	$195.00	$45.00	$5.00	1.20	162.50	10.00	1	5.25	1.22	4.10	1.86
Project 20	$210.00	$85.00	$21.00	1.00	210.00	5.05	1	2.01	4.06	5.20	2.50
Total	$22,191.00		$10,200.44	162.00			20	**116.32**	**97.65**	116.60	**56.08**
Profit/Rank	$136.98										
Profit*Score	$1,244,365.33	Maximize	<=$3800	<=100			x<=10			<=80	

Figure 6: Portfolio Optimization and Allocation

Budget	Strategic Score	Tactical Score	Comprehensive Score	Allowed Projects	ROI-RANK Objective
$3,800.00	33.15	62.64	58.58	10	$470,235.60
$4,800.00	36.33	68.85	66.86	11	$521,645.92
$5,800.00	38.40	70.46	75.69	12	$623,557.79
$6,800.00	39.94	72.14	82.31	13	$659,947.99
$7,800.00	39.76	70.05	86.54	14	$676,279.81

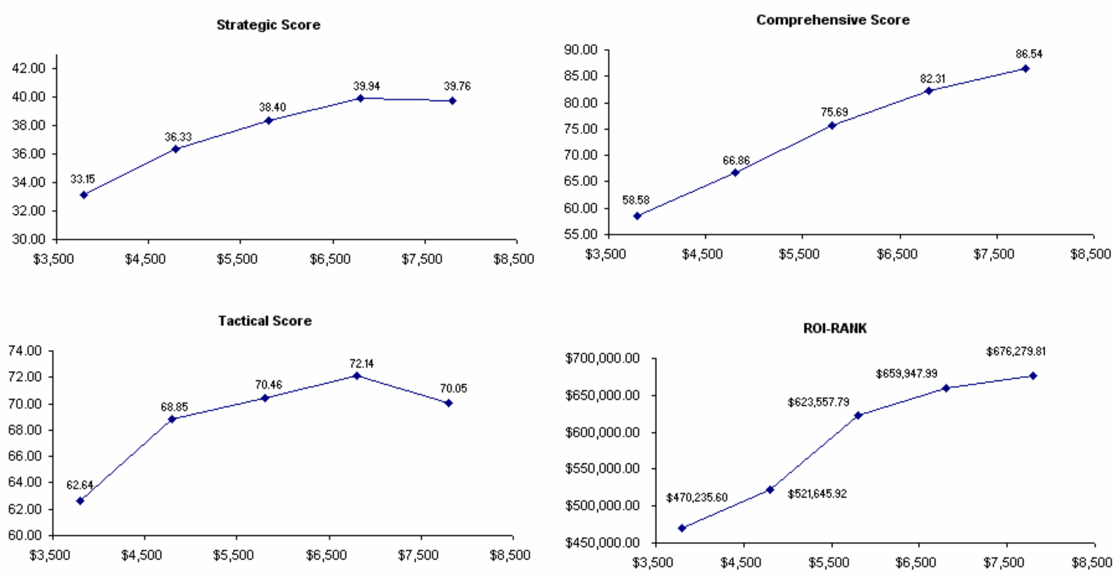

Figure 7: Efficient Frontiers of Portfolios

ASSET ALLOCATION OPTIMIZATION MODEL

Asset Class Description	Annualized Returns	Volatility Risk	Allocation Weights	Required Minimum Allocation	Required Maximum Allocation	Return to Risk Ratio	Returns Ranking (Hi-Lo)	Risk Ranking (Lo-Hi)	Return to Risk Ranking (Hi-Lo)	Allocation Ranking (Hi-Lo)
Selected Project 1	10.50%	12.38%	11.10%	5.00%	35.00%	0.8483	9	2	7	4
Selected Project 2	11.12%	16.36%	6.74%	5.00%	35.00%	0.6799	7	8	10	10
Selected Project 3	11.77%	15.81%	7.63%	5.00%	35.00%	0.7445	6	7	9	9
Selected Project 4	10.77%	12.33%	11.49%	5.00%	35.00%	0.8738	8	1	5	3
Selected Project 5	13.49%	13.35%	12.26%	5.00%	35.00%	1.0102	5	4	2	2
Selected Project 6	14.24%	14.53%	10.94%	5.00%	35.00%	0.9800	3	6	3	5
Selected Project 7	15.60%	14.30%	12.36%	5.00%	35.00%	1.0908	1	5	1	1
Selected Project 8	14.95%	16.64%	8.75%	5.00%	35.00%	0.8983	2	10	4	7
Selected Project 9	14.15%	16.56%	8.36%	5.00%	35.00%	0.8545	4	9	6	8
Selected Project 10	10.08%	12.55%	10.37%	5.00%	35.00%	0.8027	10	3	8	6
Portfolio Total	*12.7270%*	*4.54%*	*100.00%*							
Return to Risk Ratio	*2.8021*									

Figure 8: Portfolio Optimization (Continuous Allocation of Funds)

Integrated Risk Analysis Framework

We are now able to put all the pieces together into an *integrated risk analysis framework* and see how these different techniques are related in a risk analysis and risk management context. This framework comprises eight distinct phases of a successful and comprehensive risk analysis implementation, going from a qualitative management screening process to creating clear and concise reports for management. The process was developed by the author based on previous successful implementations of risk analysis, forecasting, real options, valuation, and optimization projects both in the consulting arena and in industry-specific problems. These phases can be performed either in isolation or together in sequence for a more robust integrated analysis.

Figure 9 shows the integrated risk analysis process up close. We can segregate the process into the following eight simple steps:

1. Qualitative management screening.
2. Time-series and regression forecasting.
3. Base case KVA and net present value analysis.
4. Monte Carlo simulation.
5. Real options problem framing.
6. Real options modeling and analysis.
7. Portfolio and resource optimization.
8. Reporting and update analysis.

1. Qualitative Management Screening

Qualitative management screening is the first step in any integrated risk analysis process. Decision makers have to decide which projects, assets, initiatives, or strategies are viable for further analysis, in accordance with the organization’s mission, vision, goal, or overall business strategy. The organization’s mission, vision, goal, or overall business strategy may include strategies and tactics, competitive advantage, technical, acquisition, growth, synergistic, or globalization issues. That is, the initial list of projects should be qualified in terms of meeting the decision maker’s agenda. Often the most valuable insight is created as decision makers frame the complete problem to be resolved. This is where the various risks to the organization are identified and flushed out.

2. Time-Series and Regression Forecasting

The future is then forecasted using time-series analysis, stochastic forecasting, or multivariate regression analysis if historical or comparable data exist. Otherwise, other qualitative forecasting methods may be used (subjective guesses, growth rate assumptions, expert opinions, Delphi method, and so forth).[6] *Risk Simulator* can also be used to run more advanced forecasting techniques such as nonlinear extrapolation, stochastic processes (mean-reversion, random walk, jump-diffusion, and mixed processes) as well as Box-Jenkins ARIMA econometric models.

3. Base Case Net Present Value Analysis

For each project that passes the initial qualitative screens a discounted cash flow model is created. This model serves as the base case analysis where a net present value or ROI is calculated for each project, using the forecasted values in the previous step. This step also applies if only a single project is under evaluation. This net present value is calculated using the traditional approach of using the forecast revenues and costs, and discounting the net of these revenues and costs at an appropriate risk-adjusted rate. The return on investment and other metrics are generated here. For nonprofit organizations, governmental, or military organizations, we can also apply Knowledge Value-Added (KVA) analysis in this phase. KVA provides the required *benefits* or revenue proxy to run ROI analysis. KVA measures the value provided by human capital assets and IT assets by analyzing an organization, process or function at the process-level. It provides insights into each dollar of IT investment by monetizing the outputs of all assets, including intangible assets (e.g., such as that produced by IT and humans). By capturing the value of knowledge embedded in an organization's core processes (i.e., employees and IT), KVA identifies the actual cost and revenue of a process, product, or service. Because KVA identifies every process required to produce an aggregated output in terms of the historical prices and costs per common unit of output of those processes, unit costs and unit prices of can be calculated. The methodology has been applied in 45 areas within the Department of Defense, from flight scheduling applications to ship maintenance and modernization processes.

4. Monte Carlo Simulation[7]

Because the static discounted cash flow produces only a single-point estimate result, there is oftentimes little confidence in its accuracy given that future events that affect forecast cash flows are highly uncertain. To better estimate the actual value of a particular project, Monte Carlo simulation should be employed next. Usually, a sensitivity analysis is first performed on the discounted cash flow model; that is, setting the net present value or ROI as the resulting variable, we can change each of its precedent variables and note the change in the resulting variable. Precedent variables include revenues, costs, tax rates, discount rates, capital expenditures, depreciation, and so forth, which ultimately flow through the model to affect the net present value or ROI figure. By tracing back all these precedent variables, we can change each one by a preset amount and see the effect on the resulting net present value. A graphical representation can then be created in Risk Simulator, which is oftentimes called a tornado chart because of its shape, where the most sensitive precedent variables are listed first, in descending order of magnitude. Armed with this information, the analyst can then decide which key variables are highly uncertain in the future and which are deterministic. The uncertain key variables that drive the net present value and hence, the decision are called critical success drivers. These critical success drivers are prime candidates for Monte Carlo simulation. Because some of these critical success drivers may be correlated, a correlated and multidimensional Monte Carlo simulation may be required. Typically, these correlations can be obtained through historical data. Running correlated simulations provides a much closer approximation to the variables' real-life behaviors.

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[6] See Chapters 8 and 9 of "Modeling Risk," (Wiley 2006) by Dr. Johnathan Mun for details on forecasting and using the author's *Risk Simulator* software to run time-series, extrapolation, stochastic process, ARIMA, and regression forecasts.

[7] See Chapters 4 and 5 of "Modeling Risk," (Wiley 2006) by Dr. Johnathan Mun for details on running Monte Carlo simulation using the author's *Risk Simulator* software.

5. Real Options Problem Framing[8]

The question now is that after quantifying risks in the previous step, what next? The risk information obtained somehow needs to be converted into *actionable intelligence*. Just because risk has been quantified to be such and such using Monte Carlo simulation, so what and what do we do about it? The answer is to use real options analysis to hedge these risks, to value these risks, and to position yourself to take advantage of the risks. The first step in real options is to generate a strategic map through the process of framing the problem. Based on the overall problem identification occurring during the initial qualitative management screening process, certain strategic optionalities would have become apparent for each particular project. The strategic optionalities may include among other things, the option to expand, contract, abandon, switch, choose, and so forth. Based on the identification of strategic optionalities that exist for each project or at each stage of the project, the analyst can then choose from a list of options to analyze in more detail. Real options are added to the projects to hedge downside risks and to take advantage of upside swings.

In this phase, complex systems modeling, system dynamics, and game theory can also be applied. That is, the model can be set up as a system of multiple links or nested options, where one option is linked to another in unison (e.g., complex simultaneous and sequential compound options) and the ramifications of competitors' actions can be included in the model (e.g., strategic competitive games played in an oligopoly situation, where your opponent takes very different actions depending on the actions that you take, generating multiple potential scenarios and payoffs).

6. Real Options Modeling and Analysis

Through the use of Monte Carlo simulation, the resulting stochastic discounted cash flow model will have a distribution of values. Thus, simulation models, analyzes, and quantifies the various risks and uncertainties of each project. The result is a distribution of the NPVs and the project's volatility. In real options, we assume that the underlying variable is the future profitability of the project, which is the future cash flow series. An implied volatility of the future free cash flow or underlying variable can be calculated through the results of a Monte Carlo simulation previously performed. Usually, the volatility is measured as the standard deviation of the logarithmic returns on the free cash flow stream. In addition, the present value of future cash flows for the base case discounted cash flow model is used as the initial underlying asset value in real options modeling. Using these inputs, real options analysis is performed to obtain the projects' strategic option values.

7. Portfolio and Resource Optimization[9]

Portfolio optimization is an optional step in the analysis. If the analysis is done on multiple projects, decision makers should view the results as a portfolio of rolled-up projects because the projects are in most cases correlated with one another, and viewing them individually will not present the true picture. As organizations do not only have single projects, portfolio optimization is crucial. Given that certain projects are related to others, there are opportunities for hedging and diversifying risks through a portfolio. Because firms have limited budgets, have time and resource constraints, while at the same time have requirements for certain overall levels of returns, risk tolerances, and so forth, portfolio optimization takes into account all these to create an optimal portfolio mix. The analysis will provide the optimal allocation of investments across multiple projects.

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[8] See "Real Options Analysis, Second Edition: Tools and Techniques," (Wiley 2005) by Dr. Johnathan Mun for more technical details on framing and solving real options problems.

[9] See Chapters 10 and 11 of "Modeling Risk," (Wiley 2006) by Dr. Johnathan Mun for details on using Risk Simulator to perform portfolio optimization.

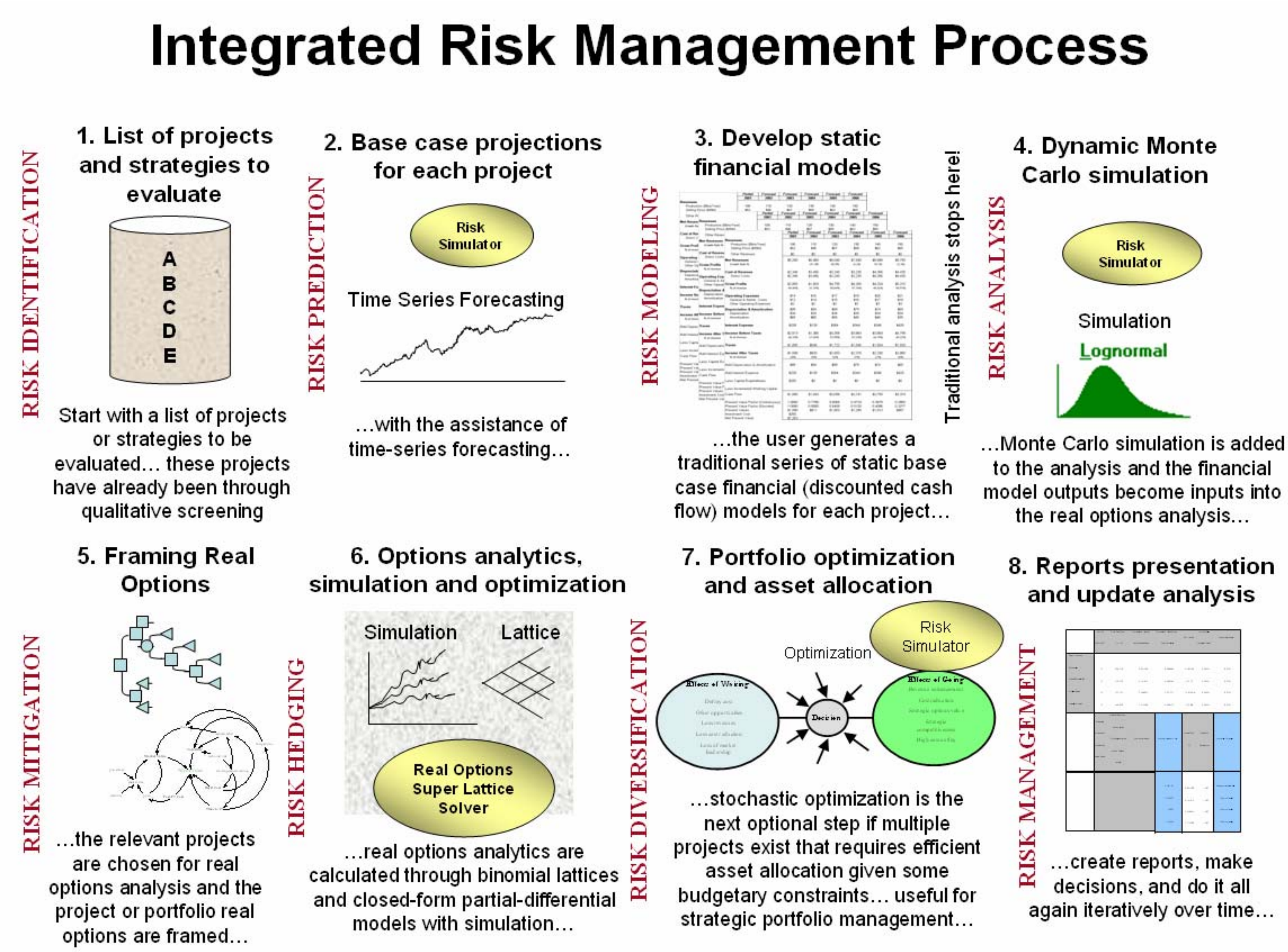

Figure 9 – Integrated Risk Management Process

8. Reporting and Update Analysis

The analysis is not complete until reports can be generated. Not only are results presented, but the process should also be shown. Clear, concise, and precise explanations transform a difficult black-box set of analytics into transparent steps. Decision makers will never accept results coming from black boxes if they do not understand where the assumptions or data originate and what types of mathematical or analytical massaging takes place. Risk analysis assumes that the future is uncertain and that decision makers have the right to make midcourse corrections when these uncertainties become resolved or risks become known; the analysis is usually done ahead of time and thus, ahead of such uncertainty and risks. Therefore, when these risks become known over the passage of time, actions, and events, the analysis should be revisited to incorporate the decisions made or revising any input assumptions. Sometimes, for long-horizon projects, several iterations of the real options analysis should be performed, where future iterations are updated with the latest data and assumptions. Understanding the steps required to undertake an integrated risk analysis is important because it provides insight not only into the methodology itself but also into how it evolves from traditional analyses, showing where the traditional approach ends and where the new analytics start. In this phase, management dashboards, balanced scorecards, and other reporting mechanisms can be created from the outputs of the previous seven phases.

Conclusion

Hopefully it has now become evident that the decisions of the future require the use of more advanced analytical procedures for making strategic investment decisions and when managing portfolios of projects. In the past, due to the lack of technological maturity, this would have been extremely difficult, and hence businesses had to resort to experience and managing by gut feel. Nowadays with the assistance of technology and more mature methodologies, there is simply no excuse not to take the analysis a step further. Corporations like 3M, Airbus, Boeing, BP, Chevron, Johnson & Johnson, Motorola, Pfizer, and many others have already been successfully using these techniques for years. The relevant software applications, books, case studies, and public seminars have all been created and proof of concept case studies have already been developed.[10] The only critical barrier to implementation, simply put, is the lack of education or exposure. Many have not seen or even heard of these new concepts and hopefully this primer, if it was successful, serves to open the eyes of the reader to a wealth of analytical techniques and tools out there that can complement what is currently being done.

[10] See www.realoptionsvaluation.com (Download site) for more details on the software applications Risk Simulator and Real Options SLS as well as sample case studies, videos, sample models, and training seminars (e.g., the 4-day Certified Risk Analyst public seminars cover all the methodologies outlined in this primer and more.

Author's Vita

Dr. Johnathan C. Mun is the founder and CEO of Real Options Valuation, Inc., a consulting, training, and software development firm specializing in strategic real options, financial valuation, Monte Carlo simulation, stochastic forecasting, optimization, and risk analysis located in northern California. He is the creator of the *Real Options Super Lattice Solver* software, *Risk Simulator* software, and *Employee Stock Options Valuation* software at the firm, as well as the risk analysis Training DVD and he holds public seminars on risk analysis and Certified Risk Analyst (CRA) programs. He has authored eight books including *Modeling Risk: Applying Monte Carlo Simulation, Real Options, Optimization, and Forecasting,* (Wiley 2006), *Real Options Analysis: Tools and Techniques*, First and Second Editions (Wiley 2003 and 2005), *Real Options Analysis Course: Business Cases* (Wiley 2003), *Applied Risk Analysis: Moving Beyond Uncertainty* (Wiley 2003), *Valuing Employee Stock Options* (Wiley 2004), and others. His books and software are being used at top universities around the world (including the Bern Institute in Germany, Chung-Ang University in South Korea, Georgetown University, ITESM in Mexico, Massachusetts Institute of Technology, Naval Postgraduate School, New York University, Stockholm University in Sweden, University of the Andes in Chile, University of Chile, University of Pennsylvania Wharton School, University of York in the United Kingdom, and Edinburgh University in Scotland, among others).

Dr. Mun is also currently a finance and economics professor and has taught courses in financial management, investments, real options, economics, and statistics at the undergraduate and the graduate M.B.A. levels. He is teaching and has taught at universities all over the world, from the U.S. Naval Postgraduate School (Monterey, California) and University of Applied Sciences (Switzerland and Germany) as full professor, to Golden Gate University (California) and St. Mary's College (California), and has chaired many graduate research thesis committees. He also teaches risk analysis, real options analysis, and risk analysis for managers' public courses where participants can obtain the Certified Risk Analyst (CRA) designation upon completion of the week-long program. He was formerly the Vice President of Analytics at Decisioneering, Inc. where he headed up the development of options and financial analytics software products, analytical consulting, training, and technical support, and where he was the creator of the Real Options Analysis Toolkit software, the older predecessor of the Real Options Super Lattice software. Prior to joining Decisioneering, he was a Consulting Manager and Financial Economist in the Valuation Services and Global Financial Services practice of KPMG Consulting and a Manager with the Economic Consulting Services practice at KPMG LLP. He has extensive experience in econometric modeling, financial analysis, real options, economic analysis, and statistics. During his tenure at Real Options Valuation, Inc., Decisioneering, and at KPMG Consulting, he had taught and consulted on a variety of real options, risk analysis, financial forecasting, project management, and financial valuation issues for over 100 multinational firms (former clients include 3M, Airbus, Boeing, BP, Chevron Texaco, Financial Accounting Standards Board, Fujitsu, GE, Microsoft, Motorola, Pfizer, Timken, U.S. Department of Defense, U.S. Navy, Veritas, and many others). His experience prior to joining KPMG included being Department Head of financial planning and analysis at Viking Inc. of FedEx, performing financial forecasting, economic analysis, and market research. Prior to that, he did financial planning and freelance financial consulting work.

Dr. Mun received his Ph.D. in Finance and Economics from Lehigh University, where his research and academic interests were in the areas of Investment Finance, Econometric Modeling, Financial Options, Corporate Finance, and Microeconomic Theory. He also has an M.B.A. in business administration, an M.S. in management science, and a B.S. in Biology and Physics. He is Certified in Financial Risk Management (FRM), Certified in Financial Consulting (CFC), and is Certified in Risk Analysis (CRA). He is a member of the American Mensa, Phi Beta Kappa Honor Society, and Golden Key Honor Society as well as several other professional organizations, including the Eastern and Southern Finance Associations, American Economic Association, and Global Association of Risk Professionals. Finally, he has written many academic articles published in the *Journal of the Advances in Quantitative Accounting and Finance,* the *Global Finance Journal,* the *International Financial Review,* the *Journal of Financial Analysis,* the *Journal of Applied Financial Economics,* the *Journal of International Financial Markets, Institutions and Money,* the *Financial Engineering News,* and the *Journal of the Society of Petroleum Engineers.*