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Understanding R&D Value Creation with Organizational Simulation

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ABSTRACT

Research and development functions are fundamental drivers of value creation in technology-based enterprises. Successful R&D is a function of invention and R&D management. This paper studies R&D management issues from the perspective of their effect on value creation. The particular issues studied are: (i) How does one attach a value to a particular proposed R&D activity, and (ii) how does one allocate funding over the various stages comprising an R&D value stream? Organizational simulation is used in an experiment to determine the value creation effectiveness of alternative investment policies. Experimental results indicate the superiority of valuation methods (options pricing vs. traditional net present value approaches) and budget allocation strategies under differing conditions and differing value-oriented performance measures. An application of the model to R&D in the forest products industry is presented. © 2007 Wiley Periodicals, Inc. Syst Eng 10: 64–82, 2007

Key words: R&D; value creation; options pricing; budget allocation; organizational simulation

1. INTRODUCTION

Research and development are fundamental drivers of value creation in technology-based enterprises. R&D creates methods, technologies, and prototypes, which may eventually be deployed by the enterprise downstream from the R&D function. Such deployment creates value for the enterprise through future free cash

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flow, in the case of a for-profit enterprise, or through reduced costs or enhanced capabilities to meet the enterprise mission, in the case of other types of enterprises. The purpose of the R&D function, then, is to enable new products, systems, or capabilities that enhance enterprise value when deployed, usually with the twin goals of maximizing value realized and minimizing time until realization. The importance of the R&D function in creating new products that lead to value is illustrated recently in the automotive industry with the rise of Toyota and the faltering of Ford, and has been shown historically by the emergence of Xerox in the 1960s. Ellis [1997] provides a comprehensive set of metrics to evaluate R&D. In this paper, our concern is with value creation measured by free cash flow (revenues minus operating expenses) from deployed R&D.

Here enterprises are considered from a systems perspective, similar to Rouse [2005]. With automated business processes, extensive data collection systems, and increased performance reporting functions, enterprises increasingly are amenable to analysis by the tools and methods used by systems engineers. In particular, the interest here focuses on using such tools to analyze R&D functions within enterprises to enhance their ability to create value.

One tool used extensively in systems engineering is discrete-event simulation. The appeal of simulation lies in its ability to predict system behavior under a wide range of possible scenarios, while incorporating uncertainty, and relaxing assumptions needed to make analytic models tractable. Of interest here are methods from the emerging field of organizational simulation [Rouse and Boff, 2005] to analyze, design, and improve R&D functions within enterprises. Organizational simulation is a computational approach to modeling business processes, individual and team behaviors, and organizational performance under various scenarios. Organizational simulation builds on existing methods of computer simulation, including discrete-event models used to demonstrate behavior and assess performance of workflow systems, continuous models to demonstrate behavior and assess performance of physical and mechanical systems, and Monte Carlo methods used to generate estimates of complex parameters and functions [Law and Kelton, 2000]. Organizational simulation adds an immersive experience to the mix, so that an analyst or other user can more fully experience the future enterprise before committing to that future, or experience many possible futures before committing to a particular one. Thus, organizational simulation may include aspects such as advanced decision logic, multiuser interactivity, rich visualizations, human behavior representations, and model intelligence.

As a first step toward realizing use of organizational simulation to study R&D value creation, this paper discusses a prototype simulation model and initial experiments designed to quantify the effect of various factors on R&D value creation. This model focuses primarily on enterprise decision criteria, rather than the other aspects of organizational simulation such as visualization, model intelligence, or multiuser interactivity, and explores how alternative criteria affect value creation. The experiment studies the effect of investment valuation method and budget allocation across R&D stages, in the context of differing levels of volatility (variability of future free cash flow) and differing initial R&D investment outlooks (probability that an R&D project's initial net present value is negative). The model is applied to an enterprise in the forest products industry to illustrate the model's concepts.

The remainder of this paper is organized as follows: Issues from the research literature are discussed as they impact R&D value creation in Section 2. The discrete-event simulation model used in the study is described in Section 3. Experimental design and results are presented in Section 4. A case study applying the model to the forest products industry is discussed in Section 5. Finally, Section 6 summarizes the results and provides future directions for this research effort.

2. ISSUES IN R&D VALUE CREATION

R&D typically involves a multistage process, with stages corresponding to such categories as basic research, applied research, and advanced development. In creating value, R&D requires a set of investments over these stages, and over time. Roughly speaking, investments take at least two forms. First, in each budget cycle, the enterprise invests a certain percentage of the total R&D budget in each stage. Within each stage, the budget may be further invested into technical area programs. Second, the enterprise invests funding in particular R&D projects. This may occur at several different times during a budget cycle (i.e., if the proposed project review cycle is shorter than budget cycle).

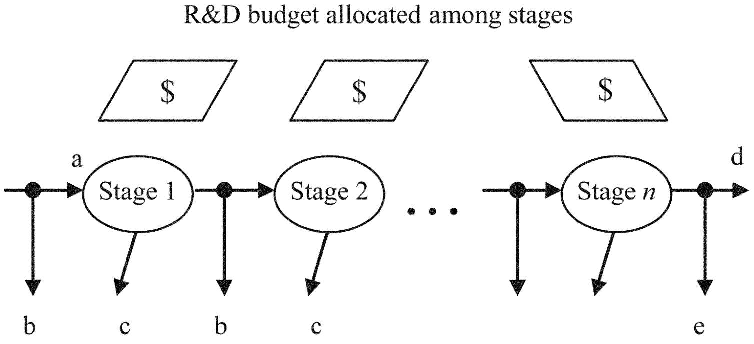
Investments are affected by at least two types of risk: technical risk and market/application risk [Boer, 2000]. Technical risk arises from the probability that a funded project may fail to deliver anticipated results, or may deliver results behind schedule, with attendant market window issues, or over budget. Market or application risk results from changes over time to the estimated future value of the deployed R&D results. Such changes may result, for example, from market conditions (e.g., the market creates a new opportunity for a future product) or enterprise strategy (e.g., enterprise strategy dictates leaving a market or abandoning a mission). The multistage nature of R&D functions helps mitigate both kinds of risks by enabling decisions to discontinue projects between stages if, for example, a project fails on a technical basis or suffers a decline in its estimated market value. Figure 1 shows the nature of the multistage R&D investment problem.

2.1. Determining the Value of an R&D Project

Fundamental to the project selection problem is the ability to attach value to each project. To do this, one must be able to estimate its costs, its contribution to free cash flow after deployment, and the probability of its successful completion. Traditional approaches to R&D use discounted cash flow (DCF) methods to compute a net present value (NPV) for a proposed project. A positive NPV means favorable consideration for funding. Within the past 20 or so years, however, a growing body of research suggests that a real options approach is superior to DCF in capturing the value of managerial flexibility in systems with staged funding, such as R&D [Faulkner, 1996; Herath and Park, 1999; Myers, 1984; Pennings and Lint, 1997; Trigeorgis, 1996].

Real options valuation is analogous to financial options valuation, except that the underlying asset is a system or product to be deployed in the future, rather than a financial instrument. In staged funding systems, the decision to fund a particular stage of R&D can be treated as purchase of a call option, where exercise of that option involves funding a later stage or stages (including deployment). Financial options have been widely studied since the development of methods to compute their value. Black and Scholes [1973] pioneered analysis of European call and put options, with the assumption that market risk is represented as a random walk process for asset value over time (i.e., volatility). This method has been extended with the notion of compound options (i.e., an option on an option), which can be used to analyze multistage decision systems such as R&D [Cassimon et al., 2004; Geske, 1979; Herath and Park, 2002]. A discrete-time version assumes a binomial probability of asset price increase or decrease each period, as opposed to the continuous random walk process [Cox, Ross, and Rubinstein, 1979]. Other research efforts incorporate the concept of stochastic jump processes to model sudden asset price swings [Martzoukos and Trigeorgis, 2002; Pennings and Lint, 1997].

Borrowing from this foundation, real options have been used in analyzing a variety of corporate domains, including intellectual capital [Sudarsanam, Sorwar, and Marr, 2004], pharmaceutical R&D [Bowman and Moskowitz, 2001; Cassimon et al., 2004], consumer product R&D [Herath and Park, 1999], product life cycles [Bollen, 1999], outsourcing [Nembhard, Aktan, and Shi, 2001], manufacturing supply chain flexibility [Nembhard, Shi, and Aktan, 2002], bank expansion [Panayi and Trigeorgis, 1998], petroleum exploration [Boer, 2000] electronic banking network expansion [Benaroch and Kauffman, 2000], and e-commerce [Jensen and Warren, 2001], as well as public-sector domains, including NASA [Shishko, Ebbeler, and Fox, 2004], satellite servicing [Saleh et al., 2003], transportation infrastructure [Saphores and Boarnet, 2004] and state monopoly information technology development [Panayi and Trigeorgis, 1998]. Trigeorgis [1996] pre-



a – Project funded for next stage
b – Project not funded for next stage
c – Project fails at current stage (technical failure)
d – Results deployed (e.g., new technology)
e – Project shelved (not deployed)

Figure 1. Investments in R&D stages.

sents a comprehensive discussion of a real options framework in relation to capital budgeting of projects. Real options include not only the ability to exercise a future purchase, but also include the ability to defer, to expand or contract, to sell, or to switch inputs (e.g., convert to a new technology). Many of these efforts use valuation models derived from the fundamental analytic Black-Scholes and binomial methods. Others adapt numerical techniques such as Monte Carlo simulation [Boyle, Broadie, and Glasserman, 1997].

The analogy with financial options is not precise, though. Lander and Pinches [1998] discuss its limitations, which include the following:

1. Future asset values and other parameters may not be known (or knowable).
2. Real options may not satisfy the assumptions on the underlying asset used for valuating financial options (e.g., complete markets and no arbitrage).
3. A random walk process may not be reasonable for modeling asset value variability.
4. Analysis may focus only on one real option, when others are present and have an interaction effect with the first.
5. Exercise may not be instantaneous (e.g., time needed to build a plant).
6. Options analysis is mathematically complex. Corporate and other managers may not have the background for full understanding and buy-in.

Limitation (1) can be addressed with sensitivity analysis [Rouse and Boff, 2004], with Bayesian analysis [Herath and Park, 2001], or via specialized methods (e.g., volatility estimation [Cobb and Charnes, 2004; Herath and Park, 2002]). Limitation (2) can be addressed by tying the non-traded asset to a tradable twin security (i.e., cash flow) [Trigeorgis, 1993]. Typically, this results in a shortfall in return expected from the asset as compared to the twin security [Trigeorgis, 1996]. Since this shortfall is difficult to estimate, sensitivity analysis can be used to assess its effect [Benaroch and Kauffman, 2000]. Limitation (3) is addressed by research in stochastic jump processes [Martzoukos and Trigeorgis, 2002; Pennings and Lint, 1997]. Trigeorgis [1993, 1996] presents a set of examples that illustrate how to address limitation (4). Nembhard, Shi, and Aktan [2002] use Monte Carlo methods to valuate implementation delays, i.e., limitation (5). Limitation (6) must be addressed via education and user-friendly software. For limitations (2), (3), and (5), while there is little research in this regard, the effects of these limitations on "system performance" (i.e., value creation) can be addressed through the use of discrete-event simulation. Here, simulation models can be used to determine the effectiveness, for example, of options-based valuation methods vs. other approaches under conditions in which assumptions for the options approach are not met.

2.2. Budgeting and Portfolio Management

In contrast to the project valuation problem, the budget allocation problem operates at a more strategic level. Hansen, Weiss, and Kwak [1999] suggest allocating budget across R&D stages in a manner conceptually similar to line-balancing, whereby allocations are proportioned according to the expected project budget requests at each stage, factoring in the effect of technical failure. However, this approach does not account for the potential effect of market or application risk.

In a more general sense, investment decisions can be framed in the context of R&D portfolio management and optimization, which accounts for valuation and risk. In portfolio optimization, the decision problem can be formulated as minimize risk subject to ensuring a certain expected return, or maximize return subject to a limit on the amount of risk exposure. Quantitative methods include simulation-optimization frameworks [Better and Glover, 2006; Cobb and Charnes, 2003; Lockett and Gear, 1973], efficient frontier analysis using risk-reward [Graves, Ringuest, and Case, 2000; Lawson and Finkelstein, 2002], screening by stochastic risk-reward dominance [Ringuest, Graves, and Case, 2004], data envelopment analysis [Linton, Walsh, and Morabito, 2002], dynamic programming [Childs and Triantis, 1999], and strategic percentage allocation among differing levels of market risk vs. technical risk [MacMillan and McGrath, 2002]. Portfolio management must account for interactions between value streams [Chien, 2002; Childs and Triantis, 1999]. Hazelrigg and Huband [1985] present an approach to manage a large-scale R&D program with such interactions, through use of Monte Carlo simulation.

Portfolio management also must include management preferences (e.g., preference of one technical area or product line over others). Management preference may not be easily quantified in a scientific sense. One approach is to provide tools for what-if analysis based on portfolio management methods. Such tools must be intuitive, as Henriksen and Traynor [1999] note that managers typically do not use methods prescribed in the research literature due to the complexity of the methods. MacMillan and McGrath [2002] and Graves, Ringuest, and Case [2000], in particular, create methods to appeal to managers in this sense. Rouse and Boff [2004] expand on managerial strategy and enumerate a number of principles in this regard, in particular arguing that an enterprise's R&D function is to create a portfolio of technology options, which can then be exercised or not by the enterprise downstream.

2.3. R&D Enterprise Design

R&D enterprise design has a major impact on value creation. DeSanctis, Glass, and Ensing [2002] study organization design for corporate R&D, particularly the conflict between centralized and decentralized R&D. Based on empirical studies, they categorize the conditions under which various organizational designs promote the best value creation. For instance, a decentralized R&D approach, where R&D units are tied closely to individual business units, is advantageous for short-term focus on customer needs and for improving existing products (i.e., a "defender" business model), but not for enterprise-focused R&D. A networked R&D approach links central R&D with business units, business units with outside companies, or both central R&D and business units with outside research agencies. This organization is found more effective for new product and technology development (i.e., a "prospector" model). Finally, a networked model that combines these two approaches, e.g., through cross-functional teams that link business units to teams from central R&D, allows the enterprise to pursue both kinds of R&D initiatives (i.e., an "analyzer" model).

Chesbrough [2003] advocates use of the open innovation paradigm for R&D. In this paradigm, an enterprise engages in partnerships and other methods (i) to infuse ideas from outside the enterprise into its R&D, and (ii) to provide an outlet for the enterprise's nondeployed results to be commercialized at a profit to the enterprise, instead of remaining shelved. This paradigm is well suited to today's market conditions of labor mobility, global competition, and accelerated technological change. Other potential enterprise design-related issues include setting the number of R&D stages, defining the programmatic mix of technical areas, and outsourcing of R&D activities.

3. R&D WORLD

Clearly, extensive and important research has been conducted in options valuation, portfolio management, and R&D organizational design. However, other than single case study analysis and empirical studies [e.g., Ramezani, 2003; Tong and Reuer, 2004], little work has addressed the performance of various approaches over time in terms of effectiveness in creating value under various conditions (e.g., different value stream characteristics, volatility, etc.) with constraints on funds. One opportunity to study enterprises in this way involves the use of discrete-event simulation as an experimental platform, allowing for controlled experimentation.

R&D World is a simulation-based environment used to study value creation issues in R&D systems [Bodner, Rouse, and Pennock, 2005]. Currently, it is implemented using the ARENA® discrete-event simulation modeling software (version 7.01) [Kelton, Sadowski, and Sturrock, 2003]. ARENA is widely used for modeling and simulating manufacturing and business process systems. The model focuses on the "enterprise physics" aspect of organizational simulation.

3.1. Model Description

The model fundamentally is based on the conceptualization of R&D as a workflow system. Proposed projects arrive at various stages in the R&D system, where they are queued for a decision on funding. If funded, they proceed to the "work" phase of the stage, during which the particular work of the project is performed. If successful during a stage, a project becomes a proposed project for the next stage, and is sent there for consideration. If a project is not funded or yields unsuccessful results, the project is deactivated. A project successfully completing a stage of R&D creates value, and this value can be transferred to the next stage of R&D to produce further results. After completing R&D, the project's results are deployed. Deployment is treated as a stage, similar to the R&D stages. A project completing deployment captures value through the realization of free cash flow (i.e., revenue minus operating expenses). In this way, the model embodies the notion of value streams, whereby value is created and propagated in a multi-stage process [Rouse and Boff, 2003]. We define the following notation for the model:

n = number of stages, including deployment,
T = time horizon under study in years,
B = annual R&D budget for the enterprise (in \$ millions),
r = risk-free interest rate,
s = discount rate,
v = volatility of estimated free cash flow (standard deviation of the return on the estimated free cash flow asset, expressed here in annualized terms as a percent of the initial estimated asset value),
N_t = number of proposed projects arriving at stage 1 in year t ($t = 1, 2, \ldots, T$),
b_{ij} = budget requested by project i at stage j ($j = 1, 2, \ldots, n$) (in \$ millions),
V_i = estimated post-deployment revenue (or cost savings) for project i, discounted to time of deployment (in \$ millions),

m_i = estimated post-deployment operating costs for project i, discounted to time of deployment (in $ millions),
P_j = percentage of annual R&D budget devoted to stage j ($j = 1, 2, \ldots, n$),
f_j = probability of technical failure at stage j ($j = 1, 2, \ldots, n$),
d_j = duration of stage j in years ($j = 1, 2, \ldots, n$).

Upon arriving at stage j, proposed R&D projects have their value computed, either by a net present value approach or a real options approach using the Black-Scholes method. Then, proposed projects are held until all to be reviewed in a particular budget cycle have arrived. The funding decision is next, and is in the form of a knapsack problem (i.e., select a subset of the available items to maximize the value of the selected items, subject to meeting a budget constraint on the cost of the selected items). Here, the value to be maximized is the summation of the valuations computed for each project. The budget constraint is that the sum of the budget requests of selected projects for stage j must be less than or equal to the R&D budget for that stage (P_jB). A method is executed to solve the knapsack problem and to select the projects to be funded for stage j. Those not funded are abandoned. Those funded proceed to the work stage, where they spend d_j years. If successfully executed after that time (i.e., no technical failure), a funded project becomes a proposed project for stage $j + 1$, or in the case of $j = n$, it is deployed. Figure 2 shows a schematic of this business process.

Note that the flowchart allows the possibility that a project may encounter a time delay between its valuation and the selection procedure, during which its value may change due to market risk. In situations where no time delay is allowed, the flowchart can be adjusted by moving the "hold" block to a position prior to the "compute value" block.

Project budget requests are assumed to be constant over time. That is, once project i is initiated, b_{ij} is known and does not change for any j. However, the free cash flow (i.e., $V_i - m_i$) is assumed to vary over time in accordance with the assumptions underlying the Black-Scholes options pricing method. That is, it varies log-normally with volatility v.

3.2. Assumptions

The model operates on several key assumptions, detailed below.

- The R&D budget is constant each year, and there are no inflation effects. Unspent funds in one year are not carried over to future years.
- Value created from deployed R&D is not directly invested back into the R&D function.
- The budget allocation P_j among stages is static.
- The budget cycle is the same as the review cycle, each lasting one year (i.e., $d_j = 1\ \forall\ j$). In any review cycle and for any stage, the stage's full budget can be expended, but cannot be overspent.
- Deployment is instantaneous (i.e., $d_4 = 0$), and the enterprise receives the discounted cash flow $V_i - m_i$ immediately upon successful deployment of i.
- System parameters, such as rates of technical failure and volatility, are known and constant over the time horizon in question. Volatility is constant over all projects and stages.
- R&D projects are in the form of lines of R&D, which proceed linearly from stage to stage (i.e.,

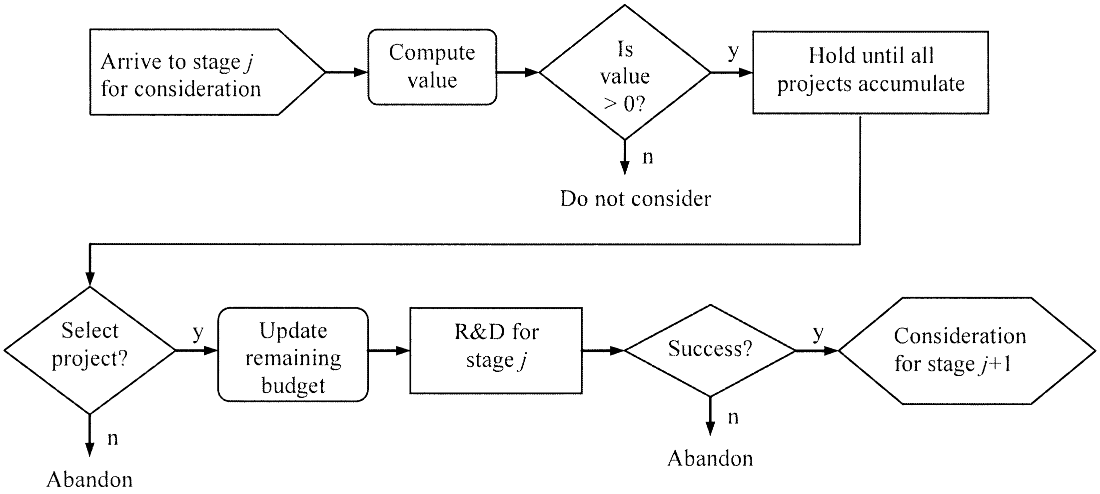


Figure 2. Business process for projects.

no branching), and which are independent of one another.

- The duration of each stage is known, with no extensions provided, and success is judged as a binary process, without any middle ground.
- Project budget requests b_{ij} increase with increasing j, while technical failure rates f_j decrease with increasing j.
- The real options framework here uses the European call format, implying that at the end of an R&D stage, the project "option" must be exercised or lost (i.e., no shelving of project results). An underlying assumption with this framework is that the return of the real asset is comparable to the return of the matched asset in the investment portfolio.
- Competition is not modeled, nor is the resulting effect of early option exercise [Smit and Trigeorgis, 2004].
- The R&D environment does not suffer from cultural issues (e.g., questions of whether R&D should have value and of whether someone else can specify the objectives of a particular R&D effort).

Previous work has validated the usefulness of options pricing as applied to R&D investment decisions through numerous case studies [Rouse and Boff, 2004]. This particular R&D investment/payoff model has been discussed with R&D staff from the forest products industry and from the Air Force Research Laboratory. These discussions have provided face validity for the model. Additional validation was performed by applying the model to a company in the forest products industry (Section 5). Extensions of R&D World to move beyond some of the assumptions above are discussed below.

3.3. Simulation Implementation

ARENA is based primarily on the process-interaction simulation paradigm, in which a set of entities or transactions travels through a set of blocks, to represent the dynamic behavior of a system. Here, projects are modeled as ARENA entities, which travel through a set of ARENA blocks, representing the business processes of the R&D system. Project entities have attributes that specify the characteristics of the project in question. Attributes include b_{ij}, V_i, and m_i. Attributes are also defined for intermediate values needed for computations, as well as estimated free cash flow ($V_i - m_i$). Characteristics of the R&D enterprise are represented as global variables, e.g., B, r, s, d_j, P_j, and f_j. While v is assumed fixed over all projects in this paper, it is implemented as an attribute for future work, when projects may have different volatilities. Specific values for these parameters are associated with the simulation experiment, discussed in Section 4.

The simulation model has $n = 4$ stages, with the last stage being deployment. Within each stage, the business processes modeled are described in Table I, in sequential order.

Equation (1) computes the net present value, using discount rate s, for a project, incorporating the probability of technical failure:

$$Q_{ij} = NPV(V_i - m_i)\prod_{k=j}^{n}(1 - f_k) - \sum_{k=j+1}^{n} NPV(b_{ik})\prod_{l=1}^{k-1}(1 - f_l) - b_{ij}. \qquad (1)$$

Equation (2) uses the Black-Scholes framework for options computation, but it addresses a multistage option, rather than a simple option. It treats b_{ij} as purchase of the option, hence subtracting b_{ij} from the Black-Scholes option value to obtain the net option value. ρ is the continuous time version of the risk-free rate r, needed for Eq. (2). Stages $j + 1$ to n are treated as exercise of the option, and thus E (exercise price) is the NPV of the budget requests from $j + 1$ to n, discounted to the decision time of stage $j + 1$, and factoring in the probabilities of technical failure. τ is the time until this decision time (i.e., $\tau = 1$). D_1 and D_2 are functions from the Black-Scholes equation. Since the normal distribution function Φ has no closed form expression, it is implemented as a Visual Basic® approximation [Abramowitz and Stegun, 1964] called by ARENA.

$$R_{ij} = (V_i - m_i)\Phi(D_1) - Ee^{-\rho\tau}\Phi(D_2) - b_{ij}. \qquad (2)$$

Neither Eq. (1) nor Eq. (2) factor in the probabilities that a project may not be selected in future stages due to budgetary reasons.

Because the project entities are created together, they travel through the blocks together. Thus, there is no delay between valuation and project selection in this implementation. In addition to the modeling of the R&D processes themselves, separate modules are implemented to model the budget renewal process and the review process for each stage. In these modules, entities travel in a loop in which they are delayed for a year to represent the cycle. At the beginning of the next year, the budget entity re-initializes the budget, and the review entities signal that proposed projects can be released for selection.

Table I. ARENA Modeling of R&D Business Processes

Process	Model Implementation
Project arrival to stage 1	Projects are generated, all at the same time, using random number generators for the number of projects arriving each year (N_t), the project budget requests (b_{ij}), and the estimated free cash flow ($V_i - m_i$). It is assumed that $b_{i,j+1} = 2\ b_{ij}\ \forall\ i$ and $j = 1, 2, 3$ (i.e., project budget requests double with each successive stage).
Project valuation	An ASSIGN block computes either a net present value Q_{ij} (Eq. 1) or a net options value R_{ij} (Eq. 2) for the project.
Project grouping	All projects to be judged in a particular budget cycle are collected in a HOLD block. A separate module releases the projects once the beginning of the budget year is reached, using a SIGNAL block.
Project selection	Projects are ordered in the QUEUE embedded in the HOLD block by descending ratio of estimated value to project budget request for the current stage. Thus, projects are considered for funding in that order. A project is selected if the stage has enough remaining R&D budget to fund the project's budget request. If not, the project is not selected and is discarded. This implements a well-known heuristic for solving the knapsack problem.
Budget adjustment	The project budget request is deducted from the remaining R&D budget for the stage, before the next project is judged.
Project work	Project work is modeled as a PROCESS block with simple delay behavior. In this model, the delay $d_j = 1$ year for $j = 1, 2, 3$ and $d_4 = 0$.
Technical failure	Upon completion of the PROCESS block, project entities encounter a BRANCH block that randomly discards a project with probability f_j.
Modification to free cash flow value	The free cash flow value is modified in an ASSIGN block, which modifies the value according to a lognormal distribution with volatility v.
Moving to next stage	If the current stage is not deployment, projects not discarded are sent to the valuation process for the next stage. If the current stage is deployment, the free cash flow value from the project is captured.

3.4. Extensions

The model used in this paper is fairly simple and is designed to illustrate fundamental behavior for R&D systems. More advanced versions of the model, most also implemented in ARENA, include the following characteristics of R&D systems:

- Multiple funding cycles per budget year. Here, a key issue is management of the R&D budget within each stage, e.g., to prevent overspending in the early part of the year from denying promising projects proposed later in the year.
- Unfunded priorities. Projects not funded during the regular funding cycle are held for potential funding using end-of-year funds. End-of-year funds may be whatever is left of the R&D budget, or may be an amount specifically designated for unfunded priorities.
- Multiyear stages with out-year budget commitments. Many R&D projects require multiple years per stage, necessitating that out-year budget commitments be managed to balance the needs of currently funded projects and those to be funded in the future with out-year funds.
- Value network structure for R&D. Instead of simple R&D lines, R&D projects often constitute a value network, whereby one R&D result enables two or more downstream results, or whereby two results must be combined to yield one downstream result. This representation has been implemented using Microsoft® Access, integrated with ARENA [Bodner, Rouse, and Pennock, 2005].

- Compound options computations and integer programming support for the knapsack problem optimal solution. A version of R&D World has been implemented using DSOL, an open-source, Java™-based simulation platform [Jacobs, Lang, and Verbraeck, 2002]. This version has been integrated with Matlab® for compound options computations using the formulation of Geske [1979], and with CPLEX® optimization software to provide an optimal integer programming solution to the knapsack problem for project selection.

4. BASE MODEL EXPERIMENT

4.1. Experimental Design

The simulation experiment examines the effect on value creation of two decision factors and two enterprise parameters. A decision factor is distinguished from an enterprise parameter in that it is viewed to be subject to manipulation in the real enterprise. While an enterprise parameter may not be subject to change, it is instructive to know the interaction effect between it and the various decision factors. The decision factors are the following:

- Valuation method. In selecting projects for funding, the valuation method factor refers to using net present value based on discounted cash flow analysis (NPV) vs. net option value using real options analysis (NOV).
- Budget allocation across stages. In the "line-balancing" approach to budget allocation across stages, shown by Eq. (3) (derived from [Hansen, Weiss, and Kwak, 1999]), P_j is proportional to the expected budget request at stage j, and inversely proportional to the success rate of current/future stages. The average budget request at stage j is b_j. The first alternative is set to be the application of this method. Letting $\boldsymbol{P} = [P_1, P_2, P_3, P_4]$, this yields $\boldsymbol{P} = [0.132, 0.1584, 0.2534, 0.4562]$ from Eq. (3). Since market risk is modeled, we want to test the effect of shifting funding either upstream or downstream. Initial experiments demonstrate that shifting funds downstream performs poorly in terms of value creation (i.e., not enough projects are funded in early stages, resulting in starvation of later stages) [Bodner and Rouse, 2005]. Therefore, the alternative to be tested is shifting funds upstream. This is accomplished by increasing P_1 by 50%, increasing P_2 by 25% of P_1, decreasing P_3 by 25% of P_1, and decreasing P_4 by 50% of P_1. The alternative (high) $\boldsymbol{P} = [0.198, 0.1914, 0.2204, 0.3902]$.

$$P_j = \left(b_j / \prod_{k=j}^{n} (1 - f_k) \right) \Big/ \sum_{l=1}^{n} \left(b_l / \prod_{m=l}^{n} (1 - f_m) \right). \tag{3}$$

The enterprise parameters studied are the following, which are assumed to be beyond control:

- Investment outlook. This is represented by the probability that initial NPV of a new project is negative. Often, R&D and other projects have a negative NPV when first proposed, while a real options valuation is positive. Past studies in which this occurs include the Gillette Mach 3 razor [Herath and Park, 1999], information technology infrastructure investment and multinational bank expansion [Panayi and Trigeorgis, 1999], and optical tape recording R&D [Pennings and Lint, 1997]. The probabilities studied here are 33% (low) and 50% (high). This NPV is a function of two parameters (b_{i1} and $V_i - m_i$). These parameters are set probabilistically in the simulation, with $b_{i1} \sim$ Uniform (1.5, 4.5) and ($V_i - m_i$) ~ Uniform ($0.5C$, $1.5C$). C is the parameter set in the simulation such that the NPV probabilities equal the desired level. Using a convolution of the b_{i1} and $V_i - m_i$ for the NPV probability, we obtain that $C = 71.96$ corresponds to the 33% level, and $C = 59.86$ corresponds to the 50% level.
- Volatility. Volatility captures the variability of the free cash flow value over time. Two levels are explored: $v = 20\%$ (low) vs. 60% (high). Within each experimental scenario studied, volatility, or the amount of variability, remains constant at either 20% or 60%.

Finally, we study two different metrics for value creation. The first is total value created over the time horizon T from deployed R&D, or total deployed value (TDV). This is the summation of the free cash flow value realized by successfully deployed projects during the time horizon. The second is yield (Y), or the ratio of total deployed value to total R&D budget expended during the time horizon.

This results in two 2^4 factorial experimental designs, one for each performance measure. For each experimental run, ten replications were conducted to ensure statistical significance. In each replication, the simulation model was run for a five-year warm-up period to reach steady-state behavior, after which statistics were reinitialized. Then the model was run for a time horizon $T = 25$ years, over which statistics were collected. This time horizon represents enterprise performance over an extended period of time. Letting $\boldsymbol{f} = (f_1, f_2, f_3, f_4)$, values

Table II. Summary Experimental Results*

Run	Val.	Outlook	Vol.	Alloc.	TDV	Yield	% Budget Expended
1	NPV	L	L	L	21,084.67	1.91	88.4
2	NPV	L	L	H	20,501.59	1.77	92.8
3	NPV	L	H	L	20,662.09	2.24	73.6
4	NPV	L	H	H	24,214.06	2.21	87.5
5	NPV	H	L	L	17,162.43	1.63	84.1
6	NPV	H	L	H	16,149.03	1.53	84.4
7	NPV	H	H	L	15,155.27	1.92	62.8
8	NPV	H	H	H	16,799.31	1.93	69.6
9	NOV	L	L	L	21,092.44	1.92	88.1
10	NOV	L	L	H	20,099.98	1.72	93.6
11	NOV	L	H	L	20,045.68	2.15	74.5
12	NOV	L	H	H	24,430.80	2.16	90.3
13	NOV	H	L	L	17,518.85	1.64	85.6
14	NOV	H	L	H	16,622.20	1.53	86.8
15	NOV	H	H	L	16,783.27	1.92	69.6
16	NOV	H	H	H	19,050.93	1.79	85.2

* "NPV" refers to net present value. "NOV" refers to net option value. "L" refers to the low alternative for the factor, while "H" refers to the high alternative.

and/or distributions for remaining parameters are listed below.

$B = 500$,
$r = 0.08$,
$s = 0.08$,
$N_t \sim$ Triangular (30, 60, 90),
$f = [0.4, 0.2, 0.1, 0.05]$.

4.2. Analysis and Results

Table II reports summary results from the experiment, showing total deployed value, yield and percent budget expended over the 25-year time horizon for each experimental run (different combination of factors). In each run, the data have been averaged over the 10 replications, so that each of the last three columns represents this average.

Minitab® 14 software is used for the statistical analysis. The analysis of variance for the experiment using total deployed value as the response variable is shown in Table III. The analysis of variance is used to compute the effect of each of the main factors, as well as the effects of interactions between them. For additional information on analysis of variance and designed experiments, see Rekab and Shaikh [2005]. Third-order interaction effects are included only if level of significance $p < 0.10$.

Based on the analysis of variance, both decision factors have a significant effect ($p < 0.10$), with allocation having the stronger effect. While the environment factors are significant, as should be expected, we are more interested in their interactions with the decision factors. The following conclusions can be drawn from these results for the TDV response variable.

- In general, using options as a valuation method outperforms using traditional DCF. However, the interaction effect between valuation method and investment outlook (A * B) shows this occurs mainly in environments when NPV has a high probability of being negative.
- The allocation effect is significant, and demonstrates that shifting funds upstream leads to improved total value deployed over the line-balancing approach. However, the interaction effect with volatility (C * D) shows that this effect is due to high levels of volatility. When volatility is low, the line-balancing approach is actually better. As market risk, represented by volatility, increases, it becomes much better to invest funds so as to create an upstream portfolio of possibilities that may create further value downstream. In downstream stages, the promising ones can be kept, while the ones that lose value can be culled.
- Although the A * C interaction is not strong, it does provide some evidence that using options

Table III. Analysis of Variance for Total Deployed Value

Source	DF	SS	MS	*F*	*p*
Valuation method (A)	1	9,583,039	9,583,039	3.35	0.069
Outlook (B)	1	850,546,261	850,546,261	297.43	0.000
Volatility (C)	1	29,844,117	29,844,117	10.44	0.002
Allocation (D)	1	43,714,488	43,714,488	15.29	0.000
A*B	1	18,924,955	18,924,955	6.62	0.011
A*C	1	5,791,963	5,791,963	2.03	0.157
A*D	1	846,993	846,993	0.30	0.587
B*C	1	24,317,907	24,317,907	8.50	0.004
B*D	1	11,880,499	11,880,499	4.15	0.043
C*D	1	146,964,391	146,964,391	51.39	0.000
B*C*D	1	8,514,094	8,514,094	2.98	0.087
Error	148	423,227,004	2,859,642		

increasingly outperforms DCF as volatility increases.

- The B * D interaction effect shows that, while the upstream allocation approach outperforms line-balancing in general, this effect is more pronounced when initial probability of NPV negativity is low.
- A mild three-way interaction exists between B * C * D. If the upstream allocation is used, an R&D system with high volatility will outperform one with low volatility, with this effect being more pronounced when initial probability of NPV negativity is low. The opposite is true for the line-balancing allocation, although the volatility effect is small.

Table IV shows the analysis of variance for the experiment with yield as the response variable. Three-factor interactions are not included, since none is significant at $p \leq 0.10$. Here, quite interestingly, different conclusions are drawn for the yield response variable than for TDV.

- Using DCF outperforms using options, with $p = 0.094$. This is an interesting contrast with the analysis from total deployed value. Fundamentally, DCF appears more conservative than options. Options seem to facilitate total deployed value in the face of an R&D budget constraint, while DCF seems better suited to emphasizing return on R&D investment. This conservatism is further reinforced with analysis of the percent of R&D budget expended (shown in Table II). Under options, the average budget expended percentage across eight runs (ten replications each) is 84.2%. Under DCF, the average percent is

Table IV. Analysis of Variance for Yield

Source	DF	SS	MS	*F*	*p*
Valuation method (A)	1	0.06182	0.06182	2.84	0.094
Outlook (B)	1	2.99373	2.99373	137.58	0.000
Volatility (C)	1	4.53471	4.53471	208.40	0.000
Allocation (D)	1	0.30566	0.30566	14.05	0.000
A*B	1	0.00124	0.00124	0.06	0.811
A*C	1	0.03538	0.03538	1.63	0.204
A*D	1	0.01570	0.01570	0.72	0.397
B*C	1	0.03573	0.03573	1.64	0.202
B*D	1	0.00024	0.00024	0.01	0.917
C*D	1	0.09617	0.09617	4.42	0.037
Error	149	3.24219	0.02176		

80.4%. Using a paired t-test, the difference between the two is statistically significant with $p \approx 0.00$.

- The line-balancing allocation alternative outperforms shifting funds upstream, as well ($p \approx 0.00$). This is explained by the C * D interaction effect. With high levels of volatility, there is little difference between the two allocations. However, with low volatility, line-balancing is more appropriate.

4.3. Analysis of Individual Project Outcomes

One question raised by the experiment is whether an options-based valuation method is better at picking R&D "winners" than traditional net present value methods. Here, we review this issue at the level of individual project selection. In particular, the focus is on projects that are selected by the real options approach at any of the R&D stages (not including deployment), but with a negative NPV. Hence, these projects would be rejected by the NPV method of project valuation.

Using the set of experimental runs conducted for Section 4.2 that use only NOV as the valuation method, we identify and compute two measures of interest for this set of projects:

- Let w equal the ratio of total deployed value from these "NPV-negative" projects to total deployed value from all projects (TDV). Thus, w measures the percent of value created from considering these projects.
- Consider the cost associated with these projects. This cost includes not only the cost of those actually deployed, but also the cost of those in this set that are rejected in a later stage by the options-based approach and the cost of those that fail from technical problems. Let y equal the ratio of total deployed value from the NPV-negative projects to the sum of these three costs. Thus, y represents the yield from this set of projects.

Table V. Summary Results for NPV-Negative Projects

Run	Outlook	Vol.	Alloc.	w	y
9	L	L	L	0.000	0.27 *
10	L	L	H	0.006	0.83
11	L	H	L	0.025	1.23
12	L	H	H	0.037	1.02
13	H	L	L	0.011	0.98
14	H	L	H	0.016	0.70
15	H	H	L	0.077	1.24
16	H	H	H	0.133	1.27

* In run 9, only four of the ten observations of y are valid. For the remaining six, the divisor (total cost) is zero, since for those replications there are no NPV-negative projects.

Table V presents summary data for this experimental analysis, with w and y being averaged over the 10 replications for each run. The run numbers correspond to the runs in Table II (i.e., those runs using the options valuation method). Clearly, the yield for this set of projects is less than the yield for the full set of projects (i.e., y is less than the yield for the full set of projects in each case, as shown in the corresponding rows from Table II). However, these projects still provide value to the R&D enterprise, the amount of which depends on the three factors. From a t-test, the mean of w is 0.0383, with a 95% confidence interval of (0.028200, 0.048313) over all observations. We are therefore confident that it is greater than zero. The yield y, on the other hand, averages 0.996 over all observations, using the same t-test, with a 95% confidence interval of (0.887780, 1.104936). Therefore, we cannot conclude that it is not equal to one. These results are consistent with the earlier findings about the overall performance of options valuation methods vis-à-vis net present value for TDV and total yield.

To examine the dependence on factors, an analysis of variance is conducted for each of the dependent variables w and y, and the results are shown in Tables VI and VII, respectively. In the ANOVA for y, an

Table VI. Analysis of Variance for w

Source	DF	SS	MS	F	P
Outlook (B)	1	0.03532	0.03532	141.03	0.000
Volatility (C)	1	0.071002	0.071002	283.5	0.000
Allocation (D)	1	0.007975	0.007975	31.84	0.000
B*C	1	0.020135	0.020135	80.4	0.000
B*D	1	0.002342	0.002342	9.35	0.003
C*D	1	0.004124	0.004124	16.47	0.000
B*C*D	1	0.0024	0.0024	9.58	0.003
Error	72	0.018032	0.00025		

Table VII. Analysis of Variance for *y*

Source	DF	Seq SS	Adj SS	MS	*F*	*p*
Outlook (B)	1	0.2164	0.3736	0.3736	2.12	0.150
Volatility (C)	1	3.4717	3.3891	3.3891	19.25	0.00
Allocation (D)	1	0.0196	0.0196	0.0196	0.11	0.740
Error	70	12.3256	12.3256	0.1761		

unbalanced ANOVA is used, since not all runs have the same number of replications (run 9 has four replications, while the others have 10). Higher-order interaction effects are included only if they are significant at $p \leq 0.10$.

For the dependent variable w, all main effects and interaction effects are significant. The percentage of TDV due to the NPV-negative projects is higher when initial outlook is more negative, when volatility is high, and when the budget allocation shifts funds upstream. For each two-factor interaction, the effect on w is magnified when both factors are at the high level (e.g., high volatility and shifting funds upstream results in higher w than either of those conditions alone). The three way interaction effect (B * C * D) here is consistent with that in the experiment using TDV as the response ($p = 0.087$). For the dependent variable y, the volatility effect is significant, while the outlook effect is mild at best. This coincides with the A * C effect ($p = 0.204$). In this case, though, the volatility effect on y from the NPV-negative projects is not strong enough to affect overall yield strongly. For the most part, these results are consistent with the results from studying overall value creation and demonstrate that the options valuation approach is able to select "R&D winners" that the NPV method does not.

5. FOREST PRODUCTS R&D APPLICATION

R&D World has been adapted to represent the new product R&D operations of a large forest products corporation. Forest products include a variety of consumer and industrial artifacts such as paper, packaging and building materials. This particular company has six stages ($n = 6$) of R&D. The model is based on summary data and is not an in-depth case study. Nevertheless, it proves useful in illustrating the application of the concepts developed in this paper. The summary data gathered for the model include the following:

- Structure of stages (n),
- Failure rates at each stage (f_j),
- Project approval and stage transition logic (stage-gate process),
- Return of unspent year-end funds to the company (consistent with R&D World assumptions),
- Historical number of projects requesting funding (N_t),
- Annual R&D budget (B),
- Discount rate (s),
- Free cash flow ($V_i - m_i$),
- Average project budget requests by stage (b_{ij}).

Similar to the previous analysis, s and r are assumed equal. Table VIII presents the line-balancing budget allocation and duration for each stage. The allocation is computed using Eq. (3). Two of the stages, opportunity identification and business proposal development, are not budgeted. The durations of the budgeted stages are assumed to be one year for this model, except for the two unbudgeted stages.

Table VIII. Forest Products R&D Stages

Stage Name	Line-Balancing Budget Allocation	Duration
1. Opportunity Identification	0.000	3 months
2. Opportunity Analysis	0.115	1 year
3. Feasibility Analysis	0.195	1 year
4. Feasibility Validation	0.494	1 year
5. Business Proposal Development	0.000	3 months
6. Commercial Implementation	0.196	1 year

The model is parameterized so that the user can modify certain parameters/settings using the ARENA Scenario Analyzer to run experiments quickly. These parameters and settings include the following (most of which are not available from collected data):

- Valuation method (stage-gate vs. NPV vs. options),
- Volatility (v),
- Budget allocation across stages (P_j),
- Budget variability (based on distributional form of b_{ij}),
- Arrival rate variability (based on distributional form of N_t),
- Delay in largest budgeted stage (feasibility validation stage).

The stage-gate selection process is represented probabilistically. The variability for both parameters (N_t and b_{ij}) is set according to a triangular distribution, where the variability factor x ($0 < x < 1$) set by the user yields a distributional form of Triangular $(1 - x)F_{avg}$, F_{avg}, $(1 + x)F_{avg}$, where F_{avg} is the average value of the parameter from the data collected. The delay in the largest budgeted stage is set to be between 0 and 1 year. The volatility, variability, and delay factors are enterprise parameters, in that they likely cannot be controlled. Still, it is interesting and important to see their effect.

Similar to the experiment in Section 4, the model executes for a 5-year warm-up period to reach steady state, after which statistics are reinitialized. Then the model runs for a period of $T = 25$ years, and for each run, it performs 10 replications. The response variables include total deployed value during T (TDV), number of projects deployed successfully (#), the total R&D expenditures during T (RDE), profit (TDV – RDE) and yield (Y = TDV/RDE).

The model was presented to a group of technical R&D managers from the forest products industry, and they were allowed to input parameters into the model to see the effect of different combinations on overall value creation. Table IX presents the results of their input. Row 1 is the baseline case, which has been validated to some extent by comparing its output in number of projects deployed and free cash flow to historical data collected from the company. For validation purposes, these comparisons yield approximate similarity between the simulation output and the data from the real system output.

The results from the user input (rows 2–16) show wide variance in outcomes, based on the combinations of factors selected. Profit ranges from a $254 million loss to a $1732 million profit. Of course, this is not a

Table IX. Forest Products R&D World Results

	Input Factors									Response Variables*				
	Val.	v	Budget Alloc. Across Stages				Variability		Del.	TDV	#	RDE	Profit	Y
			2	3	4	6	b_{ij}	N_t						
1	SG	0.60	0.115	0.195	0.494	0.196	0.10	0.10	0.0	1,788,389	232	703,993	1,084,396	2.54
2	NPV	0.60	0.115	0.195	0.494	0.196	0.10	0.10	0.0	1,861,890	218	667,799	1,194,091	2.79
3	NOV	0.60	0.115	0.195	0.494	0.196	0.10	0.10	0.0	1,815,999	201	659,004	1,156,995	2.76
4	NPV	0.60	0.150	0.220	0.469	0.161	0.10	0.10	0.0	1,878,079	209	747,365	1,130,714	2.51
5	NOV	0.60	0.150	0.220	0.469	0.161	0.10	0.10	0.0	1,961,395	202	743,189	1,218,206	2.64
6	SG	0.60	0.115	0.195	0.494	0.161	0.50	0.10	0.0	1,812,248	207	691,008	1,121,240	2.62
7	NOV	0.60	0.115	0.195	0.494	0.161	0.50	0.10	0.0	1,777,665	192	657,927	1,119,738	2.70
8	SG	0.60	0.115	0.195	0.494	0.161	0.10	0.10	1.0	1,573,172	199	683,581	889,591	2.30
9	SG	0.60	0.150	0.220	0.469	0.161	0.10	0.10	0.0	1,873,276	211	755,908	1,117,368	2.48
10	SG	0.60	0.115	0.195	0.494	0.196	0.10	0.10	0.0	1,788,389	232	703,993	1,084,396	2.54
11	SG	0.60	0.200	0.400	0.300	0.100	0.10	0.10	1.0	1,394,330	114	695,761	698,569	2.00
12	NOV	1.00	0.300	0.150	0.250	0.300	0.90	0.80	0.5	2,134,936	128	586,120	1,548,816	3.64
13	NPV	0.10	0.200	0.200	0.350	0.250	0.10	0.10	0.0	1,439,508	186	679,621	759,887	2.12
14	NOV	1.00	0.200	0.200	0.350	0.250	0.10	0.10	0.0	2,378,322	156	657,506	1,720,816	3.62
15	SG	1.00	0.100	0.400	0.400	0.100	1.00	0.10	0.0	1,555,939	138	582,051	973,888	2.67
16	NOV	0.90	0.400	0.400	0.050	0.150	0.50	0.70	0.0	353,437	22	607,469	(254,032)	0.58

*TDV, RDE and profit are in $1,000s.

designed experiment, and no scientific conclusions can be drawn. Nonetheless, it serves as a powerful demonstration of the importance of selecting not only the right parameters to run the research enterprise, but also the right combination of parameters. The R&D managers who participated in this demonstration found this insight quite compelling. Future work involves developing a more detailed model and conducting more in-depth analysis with this company, which has expressed interest in using the model, as well as with others that have expressed interest.

6. DISCUSSION AND CONCLUSIONS

This paper has presented a model that can be used to study R&D enterprise effectiveness from the perspective of R&D management. The model is primarily aimed at large R&D enterprises and is focused on decision-making rather than on the process of innovation itself. This model uses discrete-event simulation to study system behavior over time, incorporating uncertainty, management decision-making, and the effects of decisions in conjunction with enterprise characteristics that may be difficult to control. This model has been used in a set of experiments to demonstrate the effect of using real options valuation, as opposed to traditional discounted cash flows, and also the effect of different budget allocation methods, under different enterprise conditions.

From these experiments, the following two main conclusions can be drawn:

- Real options provide a desirable alternative to traditional discounted cash flow methods for determining the value of projects when the objective is to maximize value creation with a given R&D budget. On the other hand, traditional DCF methods are superior when the objective is to maximize the value created per R&D investment. This effect results from DFC's more conservative approach in spending R&D budgets.
- Budget allocation across stages is another key value lever for R&D. In high volatility environments, it makes sense to invest funds in upstream stages so as to provide options for downstream selection, when the objective is to maximize value from a given budget. When considering R&D yield, though, a line-balancing allocation makes sense.

These results raise a key philosophical issue regarding the purpose of R&D. If the goal is to conserve the R&D budget, then DCF does this much better than option-based criteria. If, on the other hand, the goal is to maximize value to the enterprise, then option-based criteria are better. These conclusions have been demonstrated using a simulation study of an abstract R&D enterprise, and need further validation using detailed case studies. The reason for this is that option-based approaches focus on the risk of the next stage, knowing that projects with diminished prospects can be cancelled. DCF models assume execution of all stages, which includes consideration of the risks of all stages. It should be noted that high uncertainty can be assigned to latter stages, effectively meaning nonexecution of those stages.

6.1. Assumptions and Future Research Questions

The current version of R&D World is based on a number of assumptions. The model is designed to illustrate fundamental behaviors and effects in R&D management. Section 3.4 outlines a number of enhancements that already have been implemented. Relaxing the assumptions in the model and using these enhancements can be used to explore other questions, such as:

- What is the best way to manage R&D investments when there are multiple review cycles, unfunded priorities and/or out-year budget commitments, under various enterprise conditions?
- This paper assumes that R&D budgets double with successive stage. Do its findings hold for other budget request ratios? What is the best ratio as a function of other factors?
- What is the best approach to manage various structures of R&D value networks that incorporate relationships between R&D projects? In this paper, it is assumed that R&D projects are independent, and that each R&D project undergoes all stages of R&D. What is the effect of removing these assumptions?
- What is the best way to allocate funding over program areas to yield the most success from R&D?
- How much benefit does using compound options methods provide over the approach used in this paper?
- What is the effect of modeling the return shortfall, and of allowing the enterprise to delay implementation of project results? What are the risks from competition in such delays?
- What is the effect when the assumptions underlying the real options model are not met (e.g., free cash flow does not vary lognormally, etc.)?

In addition, this research has used the Black-Scholes options pricing model. This method is useful, in part, because it has a closed form solution. In more detailed models, though, it likely is appropriate to use more specialized methods. Trigeorgis [1996] discusses the development of such methods. Copeland and Tufano [2004] advocate using spreadsheet tools with an underlying binomial method implementation, specialized to a company's decision tree. We are working to specify and study more specialized models, as well [Pennock, in progress].

Finally, there is a role for intuition to play. Quantitative models are useful when conditions are well understood. However, when underlying conditions change suddenly, quantitative models must be reassessed. For instance, the global liquidity crisis of 1998 caused the collapse of Long Term Capital Management, which operated in the financial markets with much success using the Black-Scholes and related quantitative risk management approaches [Lowenstein, 2000]. Understanding the relationship of quantitative models, intuition and changing conditions is an important area of research.

6.2. Data Requirements

For such an approach to be useful, one must be able to obtain the required input data. Data availability for quantitative management techniques is a real issue. In fact, one of the executives with our forest products company partner expressed such a concern.

Hazelrigg and Huband [1985] expand on the data required for their work, which uses a Monte Carlo simulation model to provide robust R&D decision rules. They suggest that expert opinion often is not an adequate source of accurate data, so they develop an approach whereby data required is disaggregated into sub-project data, value network construction data, and economic/decision-making data, so that experts can validate individual data elements. For their case study in magnetic confinement fusion, they find that data collection requires substantial effort, similar to any substantive management approach, but the costs are insignificant when compared to overall cost of a large-scale program.

The forest products case study presented in this paper illustrates similar findings. The data used did not require extensive effort to gather. Additional data needed may have required significant effort. The case study model, in effect, uses sensitivity analysis for such parameters as volatility and variability. As such, it is a useful tool to study performance under different conditions. In addition to sensitivity analysis, Section 2.1 suggests Bayesian analysis and specialized methods to address data collection difficulties.

While data collection for this type of analysis may not be straightforward and may require extensive effort, even with available tools and techniques, it is a valuable exercise in and of itself.

6.3. Applying the Model

To apply this modeling and analysis approach to an R&D enterprise, the following steps are necessary:

- Formulate the problem and identify goals. For instance, the problem may be business process improvement, which may involve experimental analysis of different alternatives, or it may be transformation, which may involve exploratory what-if analysis.
- Gather data about the enterprise using methods of Section 6.2 if needed. Such data should include the parameters described in Section 3.1. The data should also include business processes, such as budget cycles, project review cycles, project acceptance criteria, etc. Data should also include any information needed to test modifications to the enterprise (e.g., information needed for an options valuation method if one is to be considered).
- The data should be compiled into a conceptual model that can be reviewed with key personnel to determine if it is correct. Note that if different enterprise structures are being evaluated, there may be more than one conceptual model needed.
- The conceptual model(s) must then be implemented as a simulation model(s). The implementation platform can be a simulation package such as ARENA or an open-source library compiled in a high-level programming language such as Java. This step most likely will require someone with expertise in simulation modeling and coding.
- Once coded, the model(s) must be verified and validated. Verification refers to the internal correctness of the model (e.g., does an options pricing method implemented in the simulation yield the correct result). Validation refers to correctness with respect to the system being modeled (e.g., do the output measures of the model match those of the real system).
- To test different alternatives, an experiment must be designed (similar to Section 4.1), and then the simulation model must be run with enough replications to ensure statistical significance. This may require an iterative approach, since the first set of replications may not yield significant results and must be supplemented with additional ones.

- Finally, statistical analysis needs to be performed, and results and conclusions compiled for enterprise decision-makers.

Many of these steps are described in more detail in standard simulation reference books such as Law and Kelton [2000].

6.4. Organizational Simulation

Clearly, the current model addresses mainly the "enterprise physics" aspect of organizational simulation. That is, it models workflows, work transformations via business processes, decision points, entry to and exit from the system, etc. The organizational simulation approach has many other aspects that, when explored, can offer interesting and useful insights into R&D value creation. Three such aspects are the following:

- Human behavior and decision-making. Human decision-making incorporates managerial preferences on such issues as value, risk, and technical area investment. Two approaches that can be used here are interactive simulation, whereby a person interacts with and enters decisions into the simulation model, and artificial intelligence, through which "characters" in the simulation can simulate human decision-makers. Artificial intelligence increasingly is being integrated with gaming environments.
- Gaming. One key motivation for R&D is competition with other enterprises. Game theory and interactive gaming environments are two means of modeling competition. In addition, they can be used to model collaboration, as suggested by Chesbrough [2003]. The current model represents R&D as a push process. A gaming model can represent R&D as a pull process, too, whereby, for instance, competition causes an enterprise to initiate an R&D program.
- Visualization. Visualization techniques can be used to represent data for understanding and for decision-making. Hence, there exist opportunities to use visualization to support human decision-making and gaming.

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