RISK-BASED TECHNOLOGY ASSESSMENT FOR CAPITAL EQUIPMENT ACQUISITION DECISIONS IN SMALL FIRMS

A Dissertation

by

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ABSTRACT

Companies and organizations must make decisions concerning capital budgeting. Capital budgeting is a decision-making process that determines whether a firm should purchase equipment to be used on a long-term basis. The initial investment in the equipment is predicted to be returned through revenue gained by the use of the equipment over its lifetime. However, there is inherent risk associated with these investment decisions. Therefore, potential purchasers must decide whether the risk involved with investing in the equipment is justified.

This dissertation addresses risk-based technology assessment for capital equipment acquisition decisions in small firms. Technology assessment, here, is concerned with understanding the uncertainty associated with assessing the value predicted in the capital budgeting process. When analyzing the risk for a given technology, we assign a probability law to its net present value. Our primary research contribution is providing an analytical framework together with a computational strategy to support capital equipment budgeting in firms where the value of candidate technologies can represent nearly all the firm's value.

Since small firms typically have limited budgets, spending for technology is always a difficult budgeting decision. The organization's administration must decide which, if any, among the available technologies will be best for their operation.

The process for acquiring technology in many small firms can be filled with challenges. Most important among them is that capital budgeting is typically a "one-off" decision. These decisions are difficult since the candidate technologies may not have operational data available. Thus, decision makers need some means to predict how the proposed technology (e.g., equipment or machinery) will be used. Hence, firms should follow techniques

and procedures based on appropriate normative principles and well-established theory. Senior company executives and/or governance boards are often authorized to approve capital equipment purchases. However, these company leaders may not have adequate expertise in the operations of candidate technologies or may lack the understanding necessary to determine how new technologies may impact other company operations. Appropriate financial evaluation measures and selection criteria that incorporate risk are critical to making sound, quantitative acquisition decisions.

The research reported here offers an analytical framework for comparing different technology alternatives in capital budgeting decisions. Comparison is based on the expected net present value and the risk (i.e., probability law on net present value) associated with each decision alternative. To this end, the operational characteristics of each technology alternative are connected to their potential revenue and cost streams. The framework is embedded within a computational architecture that can be customized to account for operations and technologies in specific application scenarios.

One major barrier addressed by this research is overcoming the fact that new technologies typically have no historical operational data. Therefore, characterizing the uncertainty of operations (e.g., distribution of the equipment lifetime) can be very difficult. Discrete-event simulation is used to generate potential revenue and cost estimates.

We demonstrate the tractability and practicality of the analytical framework and computational architecture via a healthcare technology assessment decision. Data extracted from a published journal article detailing a hospital's technology assessment decision are used to find the risk of the medical technology using the computational architecture developed. Widely-available, no-cost software tools are employed. Results of the health care example suggest that the financial analysis in the original technology assessment was inadequate and simplistic. Small firms may find this research particularly beneficial because potential investments can be a significant portion of a small firm's value.

DEDICATION

I dedicate this dissertation to my parents, Vera Merriweather and the late Carl Merriweather.

I would not be who I am or where I am without your love, encouragement, and support throughout my life. I know only a fraction of the numerous sacrifices that you have made for me and my siblings. Thank you.

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Finally, I would like to thank God for His assistance in every aspect of this journey. Thank You for always being there for me. You are faithful.

NOMENCLATURE

AMCC	Academic Medical Center Consortium
ARR	accounting rate of return
BCR	benefit-cost ratio
BEP	break-even point
DCF	discounted cash flow
ECDF	empirical cumulative distribution function
EU	expected utility
FDA	U.S. Food and Drug Administration
IRR	internal rate of return
NPV	net present value
PBP	payback period
SBA	U.S. Small Business Administration
SMH	Strong Memorial Hospital

TABLE OF CONTENTS

Page

LIST OF FIGURES

FIGURE Page

LIST OF TABLES

1. INTRODUCTION

Companies and organizations must make decisions concerning capital budgeting. Capital budgeting is a decision-making process that determines whether a firm should purchase machines and other equipment used on a long-term basis. The capital equipment, it is believed, will improve the value of the organization. The initial investment in the equipment is predicted to be returned through revenue gained by the use of the equipment over its lifetime. However, there is inherent risk associated with these investment decisions. Therefore, potential purchasers must decide whether the risk involved with investing in the equipment is justified.

In its 2009 Annual Capital Expenditures Survey (U.S. Census Bureau, 2011a), the Census Bureau reported that capital expenditures for all businesses with employees and nonemployees in the United States were over $1.09 trillion for the year. Of this $1.09 trillion, nearly $642 billion were allocated for capital equipment expenditures. A further breakdown of equipment purchases showed that over $602 billion was spent by companies with employees, while almost $40 billion was spent by companies without employees. Figure 1.1 gives a breakdown of these equipment expenditures by industry for companies with employees. An alternate breakdown of the same $642 billion yearly equipment expenditure data reveals that nearly $607 billion was spent on new equipment and $35 billion for used equipment (U.S. Census Bureau, 2011b). Figure 1.2 shows the trend of equipment expenditures for companies in the United States with employees. The trend shows a general rise in capital equipment purchases after a dip in 2002-2003. The figure of $602 billion from 2009, suggests another dip in capital equipment expenditures. These dips in capital equipment expenditures correspond roughly to periods immediately following business cycle contractions in the United States economy (National Bureau of Economic

Research, 2010). Despite the periods of decline in expenditures, U.S. companies still purchased hundreds of billions of dollars of new capital equipment.

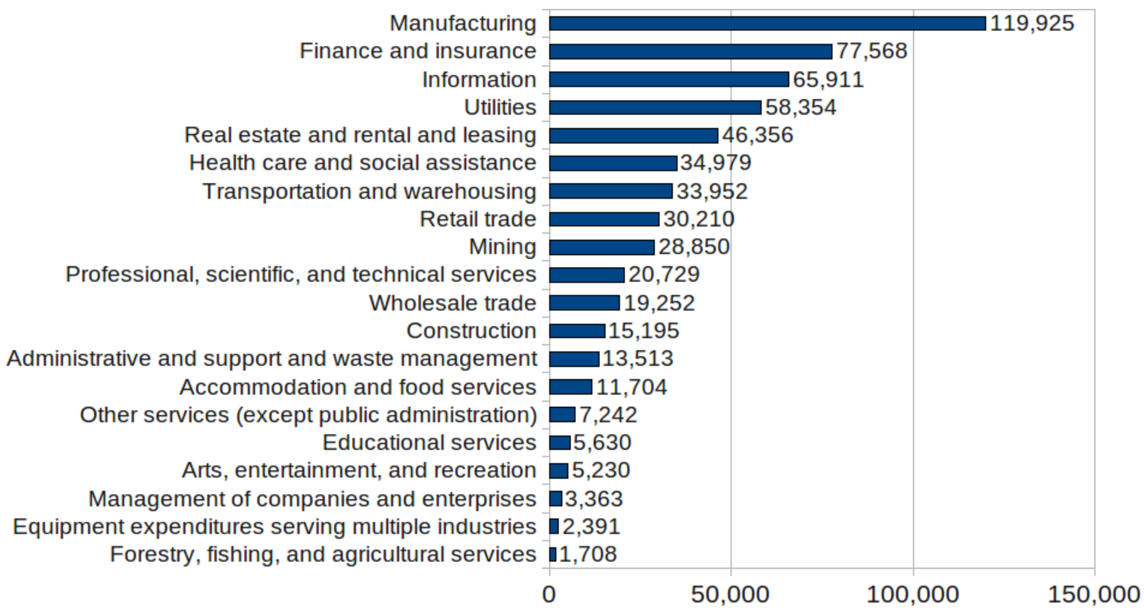

Figure 1.1: 2009 equipment expenditures (millions of dollars) by industry for U.S. companies with employees

Our research focuses on small businesses. The U.S. Small Business Administration (SBA) defines a small business as one with at most 500 employees for most manufacturing and mining industries, and up to $7 million in average annual receipts for most non-manufacturing industries. We shall adopt this definition of small businesses. The Census Bureau estimates that there were over 5.9 million small businesses in the United States in 2008. Small businesses often face capital budgeting decisions that present alternatives where the purchase of capital equipment could require a financial commitment nearly equal to the total value of the business. Hence, the survival of the business can rest upon the selection of appropriate alternatives. Here, the decision to purchase a technology

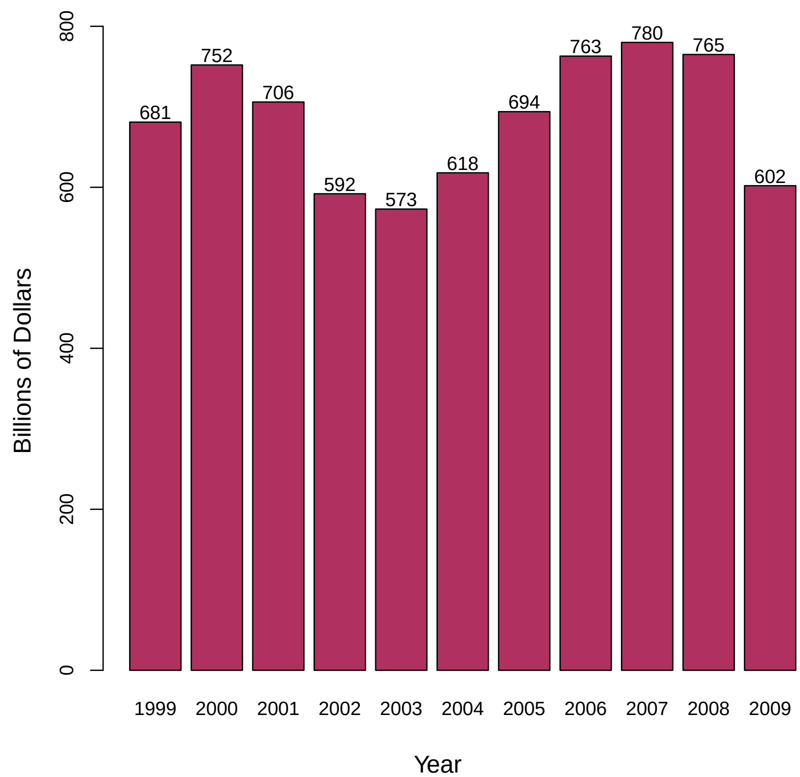

Figure 1.2: Capital equipment expenditures (billions of dollars) for U.S. companies with employees from 1999-2009

can be characterized as one-off bets, i.e., the business has only one chance to purchase an investment or not. The organization's administration must decide which technologies, if any, among those available will be best for the value of their business.

The process for acquiring technology presents difficult challenges in many small firms. Almost always the greatest challenge is quantifying the risk (i.e., uncertainty) associated with predicting the value of capital budgeting alternatives. There are many capital budgeting methods and procedures that are employed in practice. Firms should employ techniques and procedures based on appropriate, established theory in engineering, finance, and economics when making decisions. Decision analysis is founded on "a normative theory of individual decision-making," (Bickel, 2006). Normative theory explains how decisions should be made by "rational" individuals (Bell et al., 1988). An individual is "rational" in that he or she adheres to axioms which delineate how the individual consistently chooses amongst potential preferences (Clemen and Reilly, 2001). Preferences are ranked according to an individual's utility function. This utility function models an "individual's attitude toward risk" (Clemen and Reilly, 2001). In the presence of uncertainty with technology assessments, we propose that small firms appeal to tenets of utility theory for consistent, rational decisions.

Historically, companies have shunned more sophisticated capital budgeting techniques, e.g., net present value (NPV) and internal rate of return (IRR), in favor of more simplistic methods, e.g., payback period (PBP) and benefit-cost ratio (BCR). The benefit-cost ratio is computed by finding the proportion over some time period of the sum of benefits to the sum of costs for an investment. The sums of benefits and costs need not be discounted. A drawback to the BCR is that some benefits and costs may not be expressed monetarily. Payback period or break-even point (BEP) calculates how long it takes until an investment reaches an overall positive amount. A disadvantage for the PBP or BEP method is that it does not take into account what happens to cash flows that occur after the point when net revenues exceed the initial investment cost (Bierman and Smidt, 2007). The NPV is calculated by discounting an investment's future projected costs and revenues to time 0, the time of the initial investment. IRR computes the rate at which the NPV equals zero for an investment, i.e., the rate at which discounted revenues equals discounted costs. Although PBP and BCR are computationally simpler than NPV and IRR, these methods are not in rigorous agreement with utility theory and lead to incorrect value assessments of new technology. For example, PBP fails to take account for the cash flows that occur after the first time cash outflows equal cash inflows. BCR has been utilized more prominently in justifying capital expenditures in the public sector for the general welfare. Small firms and businesses usually operate on a for-profit basis. One reason that NPV and IRR have been shunned is that the amount of data required to employ the measures can be cumbersome.

Leadership culture within a small company may pose other challenges in the technology acquisition process. Senior company executives and/or governance boards are often authorized to approve capital equipment purchases (Deber et al., 1994, 1995). However, these company leaders may not have adequate expertise in financial affairs. Without requisite training and background in economic matters, company leaders may make decisions for the firm that are premised on erroneous logic and/or simplistic methodologies. Although financial measures like PBP or return on investment may be easier to understand (Weingart, 1993), they can be inconsistent (Bierman and Smidt, 2007) which can lead to incorrect decisions. Leaders may not grasp the importance of making new technology decisions based on the financial viability of the technology. As noted in (Weingart, 1993), financial analyses may be merely a hurdle to purchasing, as opposed to the means to justify the decision. Also, some executives may lack understanding on how new technologies will be used or how the purchase would affect company operations.

The principle capital budgeting challenge facing small firms is adequately addressing risk associated with the technology. A deterministic technology assessment does not acknowledge the inherent uncertainty involved with the investment. Appropriate financial evaluation measures and selection criteria that incorporate risk are critical to making sound, quantitative acquisition decisions. Compounding the difficulty of these decisions is the likelihood that the candidate technologies may not have operational data available. Thus, decision makers need some means to predict how the prospective equipment or machinery will be used.

This dissertation addresses risk-based technology assessment for capital equipment acquisition decisions in small firms. Technology assessment focuses on assessing the value of technologies that might be acquired in the capital budgeting process. When analyzing the value of risk of a given technology, a probability law is assigned to the value of the new technologies. The uncertainty of value is functionally related to the uncertainty arising in the predicted operational dynamics of candidate technologies. The primary research contributions are an analytical framework and computational architecture where the uncertainty in predicted operational behavior of candidate technologies is incorporated into the characterization of those technologies at the times of capital budgeting acquisition decisions.

Our analytical framework is built upon stochastic processes which model cash flows of prospective technologies. The projected cash flow trajectories are modeled as marked point processes. When comparing technology alternatives, the expected net present value and the risk (i.e., cumulative distribution function of the net present value) associated with the alternatives, are used. The risk provides decision makers with more information in order to make consistent decisions. This research relies on the axioms of utility theory which provide the foundation for decision makers to make consistent, rational decisions. Various computational tools are employed to allow small firms to effectively approach risk-based technology assessments.

The computational approach developed and presented in this research includes a modular computational architecture for comparing different technology alternatives in investment decisions. The modularity of the architecture allows for customizable software tools appropriate for the specific technology alternatives considered. One important tool embedded in the computational architecture is discrete-event simulation. Simulation allows for the exploration of value uncertainty, due to operational uncertainty, in the reality of ambiguous probability law. To this end, the operational characteristics of each technology alternative are connected to their potential revenue and cost streams. The computational architecture presented in this work utilizes software tools to support the decision-making process. These tools can be customized to account for predicted operational behavior and technologies that are specific to various company needs. Sensitivity analyses can be easily performed to probe ranges of values for investments. Open source software tools have been used in modeling and analyzing technologies. This open source approach for software use bolsters the argument that appropriate technology assessment decisions are practical and affordable to small firms.

The principle barrier that this research seeks to overcome is the fact that with newly acquired technologies, operational characteristics of the technology are rarely available. Therefore, probability laws that characterize operations (e.g., distribution of the equipment lifetime) will not be accessible. Nonetheless, capital budgeting decisions must be executed. The research results reported here offer a computational approach for exploring the consequences of predicted operational uncertainty on the value of risk of candidate budgeting alternatives when acquiring expensive technologies.

This research contributes to the literature through providing an analytical framework and computational decision support architecture for risk-based technology assessments. The design of the architecture purposefully connects the uncertainty associated with technology investment decisions to the technology's potential operations by employing probability models and discrete-event simulation. Small firms may find this research particularly beneficial because possible investments can be a significant portion of a small firm's value. As a rule-of-thumb, Ron Howard, considered the father of decision analysis, advocates spending at least 1% of the investment value to perform a decision analysis (Howard, 1966). Although this is an arbitrary and conservative rule, it amplifies that there is inherent value in correctly assessing decisions to purchase new technologies. Capital budgeting is essentially a one-off gambling process and should be treated as such analytically. We employ a rigorous analytical approach which depends on the expected utility (EU). EU relies on the tenets of utility theory. A characterization of probability on value (i.e., risk) is required to employ the expected utility theorem. Specifying a probability law on value (i.e., risk) is very difficult because it requires characterizing prediction uncertainty about technical operations. Simulation offers a opportunity to accommodate sensitivity analysis through exploring various scenarios computationally. The research presented here has developed a computational architecture that accomplishes risk-based technology assessment using expected utility theory. Although there are many areas where this risk-based technology assessment approach may be useful, this research uses healthcare technology assessment decisions to demonstrate the research approach.

This dissertation is structured as follows: Section 2 details a review of the literature related to various aspects of this research. In particular, technology assessment, capital budgeting, and discrete-event simulation literature sources are summarized. Section 3 presents the background information used in the analytical framework and computational architecture developed to address risk-based technology assessment decisions. Section 4 contains the results from a healthcare example which illustrates practical application of the framework and architecture. The healthcare example uses data from a published technology assessment case study. Section 5 gives conclusions for the dissertation and highlights potential future research directions.

2. LITERATURE REVIEW

The literature on capital budgeting is vast. We do not attempt to review all of it. However, we review literature related to various aspects of the issues faced when making technology assessment decisions. We have found very few published papers that specifically address the risk associated with acquiring new technologies in small firms. Several of the papers reviewed touch on specific aspects of the capital budgeting process. There were papers and books that addressed risk and sensitivity analysis. None of the reviewed literature develop a computational architecture which addresses the methodology of how to make risk-based technology assessment decisions. None of the reviewed papers focus on connecting the technology investment decision to its operational data using probability models. We begin our review with papers that focused on small firm capital budgeting techniques in section 2.1 . We note references that spotlight the problems of relying on non-discount methods for capital budgeting. After that, we expand the focus on capital budgeting methods used by businesses of all sizes in section 2.2. Section 2.2.1 highlights capital budgeting within the public sector. Literature related to health care technology assessment is reviewed in section 2.3. The use of risk and sensitivity analyses and simulation in capital budgeting decisions is also reviewed in section 2.4. Finally, in section 2.5, we summarize the unique contributions of our research in the context of capital budgeting and technology assessment.

2.1 Small Firm Capital Budgeting

Most of the papers address capital budgeting in small firms focus on the financial techniques and methods that the firms employ. Sources such as Block (1997), Runyon (1983), Filbeck and Lee (2000), and Luoma (1967) chronicle the decision-making process for small firms. Questionnaires and other surveys are used to ascertain which techniques are popular with small firms. Below we highlight the results from these sources.

One of the most recent papers that specifically focus on small firm capital budgeting techniques is Block (1997). Block highlights the varied methods and financial measures that small business firms in the 1990s use to make capital budgeting decisions and compares the use of those financial measures with the measures reported in prior studies. Block defines small firms as businesses with less than $5 million in sales and fewer than 1,000 employees. The author uses a questionnaire survey to poll the small manufacturing businesses targeted and bases the analysis in the paper on the 232 usable questionnaires out of 850 total. Payback period (PBP), accounting rate of return (ARR), internal rate of return (IRR), and net present value (NPV), in this order of preference, are the most popular methods used by the small firms in Block's study. Payback period, also known as break-even point (BEP), refers to the length of time in which a firm would want to recoup any costs of investment. The accounting rate of return is a ratio of the average net income to the average investment. The internal rate of return refers to the interest rate at which the cost of an investment would be equal to the benefits gained from the investment. The net present value takes the future revenues and costs of an investment and discounts them to the present time through a discount rate. The author attributes the wide use of PBP in small firms to its ease, its emphasis on recovering initial investment amounts, and pressures from lending agencies. For the firms in the study, the median PBP is 2 years, and the mean PBP is 2.81 years. However, the mean useful life of small firms' investments is 7.09 years. Block states the mean PBP roughly implies a 35.59% required return rate using the payback period reciprocal method, found by taking the reciprocal of the payback period. In comparison to previous studies, the author observes that there is a larger percentage of small businesses using more sophisticated discounted cash flow (DCF) methods (IRR and NPV).

Figure 2.1 illustrates the percentage of small firms which use various capital budgeting

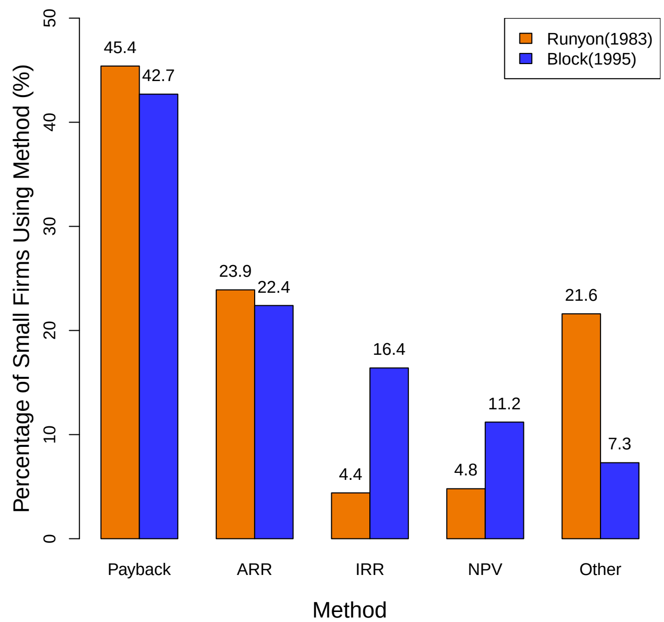

Figure 2.1: A barplot representing the percentage of small firms using various capital budgeting methods. The data are from two studies.

methods. The data are from two studies: Block (1997) and Runyon (1983). Block's 1997 study shows 27.6% of respondents employ IRR and/or NPV for capital budgeting. This percentage is up from 9.2% of small businesses employing IRR and/or NPV in 1983 from the study in Runyon (1983). However, the use of non-discounted cash flow methods including PBP and ARR, seems to be just slightly down over the studies. In Runyon's survey, 45.4% of small firms employ PBP, while 42.7% of firms employ PBP in Block's survey. The percentage of small firms employing ARR is 23.9% and 22.4% in Runyon and Block, respectively. Block notes that more time may be needed before small firms discontinue use of less sophisticated methods such as PBP and ARR.

Although Block (1997) cites an increasing number of firms using discounted cash flow techniques, many of the firms use simple ways to determine the discount rate. Block finds that, of the small firms which employ DCF techniques, a majority (53.1%) of those firms use the discount rate associated with funding a particular project. Another 20.3% of the firms which use DCF methods choose arbitrary discount rates. Block appears to advocate use of the weighted average cost of capital (WACC) for the discount rate. However, only 14.1% of DCF-employing firms use the WACC to discount. Bierman and Smidt (2007) define WACC as "the sum of the weighted cost of debt and equity capital where the weights are the relative importance of each in the firm's capital structure and the [debt and equity capital] costs are the expected returns required by investors as an inducement to commit funds." According to the authors, the weighted average cost of capital for a company can be computed by multiplying the cost of each type of capital the company holds by "the ratio of the market value of the securities representing that source of capital to the market value of all securities issued by the company." Bierman and Smidt (2007) notes that some companies choose to use the book values of securities instead of their market values. Now, Block (1997) states that calculating the cost of equity capital can be harder for small firms. Therefore, firms use WACC less often.

Another phenomenon Block (1997) studies is the inclusion of risk in small firm capital budgeting. Block discovers that 46.3% of the small firms which account for risk do so by increasing the required return rate in their capital budgeting analyses. Another thirty percent use conservative cash flow projections to adjust for risk. Slightly over 20% of the risk-adjusting small firms use other subjective, non-quantitative risk considerations. Around three percent (3%) of the firms which account for risk use probability distributions in their analyses.

Luoma (1967) details how financial accounting coupled with other information can aid managers of small and medium-sized manufacturing firms in decision making. Luoma studies the firms' operations and compares them to "theoretically acceptable considerations and practices."

In the next section, we expand our focus to literature on capital budgeting practices of companies in general. Nonetheless, similar issues involving method selection and risk analysis are seen in companies of all sizes.

2.2 Capital Budgeting

Several papers in the literature address capital budgeting and its use in alternative selection. Again, we focus on literature sources that relate to similar approaches in terms of the use of financial evaluation methods (i.e., net present value) and the utilization of risk and sensitivity analyses and discrete-event simulation in capital budgeting.

The 1987 survey paper by Mukherjee and Henderson reviews over fifty research papers on capital budgeting. The authors' goal is to discover how and why the practice of capital budgeting differs from the theory associated with it. The authors approach their study by reviewing survey papers in the area and using a four-stage framework to classify the elements of those survey papers. The stages are (1) identifying investment opportunities, (2) developing initial proposals, (3) selecting a project, and (4) controlling/assessing forecast accuracy. The selection stage is the emphasis of the reviewed survey papers. Firms identify capital investment ideas by various means. Ideas usually flow from lower levels of the firm to higher levels. During the development stage of ideas, many firms prematurely screen ideas before developing adequate analysis of the ideas. Therefore, firms could mistakenly reject viable ideas through this pre-screening process. During the selection stage, the research papers reveal that the most frequently studied aspects of capital budgeting are the techniques used, risk analysis, capital rationing and cost of capital methods. Mukherjee and Henderson (1987) notes that many of the firms use discounting cash flow techniques to evaluate the investments. Internal rate of return is the most popular listed technique with net present value as the second most popular technique. Payback period and accounting rate of return are also techniques that firms use to analyze the investments. Many companies require formal committee approval for investment selection. Many firms also conduct post-selection audits using accounting measures (e.g., return on assets, profit and loss, and return on investment) to assess project success.

Mukherjee and Henderson state that the firm's goal should be to maximize shareholders' wealth. However, the authors show that there is a gap between theory and practice in all four stages of capital budgeting. In the pre-selection stages, some projects are rejected for noneconomic reasons. These noneconomic rejections may result in costly mistakes. Another finding in the pre-selection stages is that all firms do not use cash flows to characterize the candidate projects. If firms do use cash flows, sometimes important cash flow components are not included in the analysis. The authors note many gaps between theory and practice during the selection phase of capital budgeting. Among the gaps in this phase are the following:

1. Internal rate of return being used over the theoretically preferred net present value
2. Payback period being used despite its lowered status in theory
3. Risk analysis models not being widely used.

The authors suggest that the gap between theory and practice in the paper they review may be due to shortcomings in the theory. Mukherjee and Henderson summarize some limitations of theoretical models. One limit is an ineffectiveness of models to include organizational behavior attitudes towards risk and decision making. Although existing theory assumes that capital budgeting decisions are made on a strict economic basis, business practices do not rely exclusively on project economics. Politics, intuition, and ineffective communication play a role in practical capital budgeting decisions. Mukherjee and Henderson (1987) notes that in one reviewed paper, organizational behavior partially explains why the internal rate of return method is preferred to net present value. Although theory assumes symmetric risk preferences, the authors find that projects with higher risks of negative returns are eliminated although those same projects may have larger expected net present values. Another limit is the difficulty in applying models due to data availability. Practitioners deem the cost of obtaining accurate data as expensive. Methods, e.g., net present value, that rely heavily on accurate data are shunned for ones, such as payback period, with less onerous gathering cost. Data requirements also affect the use of risk analysis models. In practice, companies tend to choose simplistic techniques to address the risk associated with candidate projects. The authors view net present value as the preferred method. They state, "Although NPV and IRR are both effective, NPV is considered superior because (1) it conforms to the value-additivity principle, (2) its assumed reinvestment rate is consistent with valuation theory and uniform across projects, and (3) it avoids multiple answers for a single project which sometimes result from using IRR." In conclusion, the authors suggest that new capital budgeting models incorporate organizational behavior theory, not just the economics of cash flows.

The survey paper on discounted cash flow analysis by Carmichael and Balatbat (2008) lists capital budgeting papers that use some form of probability distributions to characterize the uncertainty of making a decision to invest in capital equipment. Many of the papers that Carmichael and Balatbat (2008) review estimate risk by constructing a distribution on the net present value or other discounted cash flow methods (e.g., future worth, internal rate of return, and payback period). Their study classifies financial papers by the type of method used. The authors chronicle the history of each method's use. The equations and assumptions for each method's calculation is given in the paper. The authors propose more empirical studies to guide decision makers about parameters for these theoretical discounted cash flow methods.

White et al. (2010) dedicate an entire chapter to supplementary analyses in capital budgeting. The three types of supplementary analyses the authors detail are break-even analysis, sensitivity analysis, and risk analysis. Break-even analysis involves finding the break-even point (BEP) or payback period (PBP) (see section 2.1). Sensitivity analysis studies how changes in various parameters affect the overall economic measure. Risk analysis assigns some probabilistic statement about the economic value of the investment. The authors demonstrate the use of Monte Carlo and Latin hypercube simulations with risk analysis in the capital budgeting framework. Microsoft Excel spreadsheets are used throughout the book to model various calculations. The risk analyses in White et al. (2010) do not include modeling the system operations of new technologies.

2.2.1 Capital Budgeting within the Public Sector

Several papers detail how public sector organizations and government entities use capital budgeting techniques to purchase resources. In the papers below, we focus primarily on the methods companies employ for financial evaluations.

Kee et al. (1987) survey 200 city finance officers in the United States about their city's capital budgeting procedures. The authors construct a survey questionnaire that addresses the policies that municipal leaders use in determining how their city acquires capital equipment and invests in capital projects. The authors consider cities with populations of 50,000 or more. The authors base their analysis on the ninety-seven complete questionnaires of the 200 total, a response rate of 48.5%. Although the methods of internal rate of return (IRR) and net present value (NPV) are considered to be "more sophisticated," there is not broad implementation of these two models in the cities. The authors find that only 4% of cities use these models as a primary method in capital budgeting. Cities opt to use the benefit-cost ratio (BCR) and the payback period (PBP) as primary capital budgeting methods with 40% and 13%, respectively. Approximately 33% of the city financial officers respond that they use no quantitative methods to conduct capital budgeting. However, it seems that the cities conduct some type of risk analysis in their capital budgeting processes. From the survey, Kee, et al. (1987) find that thirty-nine percent of cities use nonquantitative techniques to analyze risk in capital budgeting decisions. Thirty-two percent use conservative cash flow estimates to address risk considerations for their investment decisions. Other risk analysis methods include shortening the PBP (10%), increasing the required rate of return (7%), determining cash flow probability distributions (5%), and conducting sensitivity analysis and simulation techniques (5%). Overall, the authors summarize "the less sophisticated capital budgeting methods and nonquantitative assessments are the most popular approaches" that cities use in capital budgeting. The authors attribute the use of the less sophisticated methods to the fact that the majority of city investments do not consider the bases of saving costs or generating revenues. Political and social influences also factor into city investments.

In their 1991 paper, Kee and Robbins survey 400 government finance officials (200 city finance officers and 200 county financial managers) about capital budgeting techniques at the city or county level. Of the 400 total surveys, 169 questionnaires are usable, indicating a 42% response rate. The respondents' annual budgets range from under \$500,000 to over \$30,000,000. The authors discover that over two-thirds of respondents do not use different techniques when analyses are conducted for non-profit investments versus for-profit investments. Kee and Robbins (1991) concludes that "financial considerations appear to play a relatively minor role in most municipal and county investments. Even in instances where the primary motive of a proposed investment is the generation of revenues or cost savings, financial considerations have little impact upon the selection or use of capital-budgeting techniques in local government." The results of the survey suggest that many governments with larger budgets still rely on less sophisticated techniques such as ARR, PBP and BCR to perform capital budgeting.

Sekwat (1996) surveys how county governments in the United States use various models and techniques in purchase decisions. Sekwat uses three factors to categorize how counties use capital budgeting techniques and incorporate risk in purchase decisions. The three factors are (1) the form of government for the counties, (2) how urbanized the counties are, and (3) the size of county capital investment. The survey targets four hundred county financial officers or other officials. The author focuses on counties with populations greater than 10,000 residents. The author assumes counties with smaller populaces would not have the capacity to undergo systematic capital budgeting. With 214 valid questionnaires, the response rate is 53.5%. Sekwat finds that counties use benefit-cost ratio (BCR) and payback period (PBP) [also known as break-even point (BEP)] as the two most popular capital budgeting decision models. Other models the counties employ include the accounting rate of return (ARR), net present value (NPV), and internal rate of return (IRR). Counties also use other undocumented decision models. The benefit-cost ratio gives the ratio between the sum of benefits to the sum of costs for investments. The sums of benefits and costs may not be discounted. A drawback to the BCR is that some benefits and costs may not be expressed monetarily. Payback period or break-even point calculates how long it takes until the initial cost of an investment is recovered through revenues. A disadvantage for the PBP or BEP method is that it does not take into account cash flows that occur after the investment reaches the zero point. The accounting rate of return gives the ratio of the average returns to the average net cost for an investment. Average returns are the sum of the revenue divided by the expected life of the investment. The average net cost is the average of an investment's initial cost and its salvage value. The ARR's downfall is that it does not take into account the time value of money. The NPV calculates an investment's value by discounting future projected costs and revenues to time 0, the time of the initial investment. IRR computes the rate at which the NPV equals zero for an investment, i.e., the rate at which the discounted revenues equal the discounted costs. A drawback for the NPV and IRR methods is the need for data to estimate the projected costs and revenues throughout the time horizon for an investment.

Less than 7% of the counties use NPV or IRR as a primary decision model for capital budgeting. Over half of the counties use BCR or PBP as primary methods for capital budgeting. Nearly 31% of counties use NPV or IRR as secondary tools for capital budgeting, while 44% of the counties use BCR or PBP as secondary methods. Survey respondents also note that qualitative factors influence their decisions. These qualitative factors include political, legal, and equity considerations. Sekwat summarizes that "with the exception of the BCR and PBP, NPV, IRR, and ARR decision tools have limited application" in the surveyed counties. Another result from Sekwat is that 41% of counties actually account for risk in their decision models.

In the next section, we review papers that address technology assessment acquisition decisions. Technology assessment focuses on determining the value of technologies that companies may acquire in the capital budgeting process. Many of these papers focus on health care technologies. However, there is not a specific focus on small firms within the health care industry. We highlight the departure in approach from risk-based decision making in these health care technology assessments.

2.3 Health Technology Assessment

Deber et al. (1994) and Deber et al. (1995) address technology acquisition in Canadian hospitals. These papers detail a 1990 nationwide survey of Canadian hospital technology decision makers. The hospital technology decision makers were asked to provide information on how the organizations went about deciding when and how to purchase or replace technology within their hospitals. The authors of the paper focus on the hospitals' budgets for technology assessment, and the process and information hospitals use to make a purchase decision. The hospitals report their overall operating budgets and the portion for capital expenditures. The papers thoroughly address the composition and functional roles of the team (e.g., administrators, board members, medical and nursing staff) that decides to purchase new technologies. In addition, the surveys list the different sources of information that are reviewed before making the investment decisions. These sources of information include staff presentations, equipment manufacturers, request forms, and internal and external written technology assessment reports. The authors conclude that more analysis is necessary to make the increasingly difficult decisions on new technology. As a result, the decision makers at the hospitals should seek the right people and information to help in making these technology assessment decisions. However, these papers do not focus on connecting the operational use of the technologies to the purchase of the technology, how the technologies affect the cost and revenue streams of the hospitals, or the risk associated with acquiring the technologies.

In Watts et al. (1993), the authors present a case study of how the Hamilton Civic Hospitals in Ontario, Canada, use technology assessment. The case study highlights a technology assessment which aided hospital administrators in deciding when to purchase new equipment or when to repair aging equipment in the hospital system. A detailed accounting of the states of the current equipment is given along with a future equipment purchase list for the hospitals. Findings from doctor and medical staff interviews help in evaluating the state of the current medical equipment used by the hospital. Cost estimates for the new equipment and an allocation of the costs over a five-year period are illustrated in Watts et al. (1993). Priority rankings for purchasing new equipment are given based on the condition of the current equipment and the urgency of need for the new equipment. The authors conclude that their approach to identifying current equipment states and ranking the priority of proposed equipment acquisitions allows hospital decision makers to determine what equipment to purchase each year. Although there is a financial analysis, it does not address the operational aspects of the new technologies with their purchase. The financial viability of the new technologies seems to be based on the budget allocated for each year and not explicitly on how profitable the technologies will be for the clinic.

Other papers that had a health care technology assessment focus describe the process of how actual equipment purchase, budgeting, and other decisions are made by the board of directors at the health care facility. Uphoff and Krane (1998) describe the motivations of why technology assessment should be made in hospital settings. The authors argue that technology assessment can be an effective tool to deliver information when making a decision to acquire new or maintain existing technology. They further stress that safety, effectiveness and affordability are all important factors when evaluating medical technologies. Uphoff and Krane detail essential questions that hospital-based technology assessments should address. These questions are compiled from several papers and studies on hospital technology assessment. The questions relate to the operation, safety, and cost of the technology and its potential impact on the hospital and patient communities. The paper also includes an operational model, summarized by a flow chart, that describes the steps that hospitals can take to plan and implement a technology assessment.

Lettieri et al. (2008) discusses a benchmarking study of the proposal forms used by four Italian hospitals to conduct technology assessment. The authors conduct a literature review to determine the criteria used in decision making for hospitals. The criteria, grouped into five perspectives, are as follows: technology, patient, organization, economics, and level of evidence. The technology perspective relates to a description of the technology and how critical the technology is to the hospital's operations. The patient perspective describes how the technology will be used to benefit patient health and satisfaction. The organization perspective gives information about how the adoption of the technology will impact the hospital's operations. The economics perspective addresses the expected costs and revenues of the new technology. Finally, the level of evidence perspective relates to the weight given to each source of information used to make the purchase decision. The authors analyze proposal form question from the study hospitals to ascertain how well the questionnaires adhered to these five main perspectives. The hospital forms seem to cover the technology perspective well. However, there are some limitations in the other four perspectives. The authors conclude that more research is needed to address these limitations. A particular note on this paper is that the economics perspective of the hospital questionnaires did not include sensitivity analysis for the costs and revenues of the new technology.

Weingart (1993) describes the results from a survey of twelve major medical centers. Decision makers at the Academic Medical Center Consortium (AMCC) member centers are asked to detail their decision making processes and criteria for acquiring technology. Medical centers at Johns Hopkins, the Mayo Clinic, and UCLA are among the member institutions. Weingart finds that responsibility for technology assessment to be fragmented, i.e., there is no single individual or office responsible for technology assessment. Another finding is that acquisition decisions are deemed somewhat "political," "informal," or "ad hoc" by the decision makers. Incoming faculty request new equipment as part of their compensation package, and established, well-regarded researchers submit proposals for new equipment. Although respondents say that the rationale for acquiring technology is motivated by the capital budgeting process, for many of the twelve survey institutions, the capital budgeting process is largely passive. Proposals for new equipment are conglomerated and presented to senior administrators and board members for approval subject to budget constraints. Weingart discovers that decision makers at the AMCC institutions do not use precise or explicit criteria to assess the proposed technologies. Although the institutions consider quality of care, quality of clinical care, research and teaching, these criteria have no definitive role in assessments. In contrast, all twelve institutions consistently perform financial analyses. However, the medical centers use payback period and return on investment methods for financial analyses. Respondents note that although the net present value method is seen as better than payback period and return on investment, physicians have a harder time understanding and using net present value computations.

The author concludes that an organized, rational approach to technology assessment helps in identifying and justifying technology acquisitions. The amount of time and the systems requirements necessary to make technology assessment work properly are drawbacks to the process.

Now Weingart (1995) chronicles the decision-making process for acquiring expensive medical technology at Strong Memorial Hospital (SMH), the teaching hospital of the University of Rochester School of Medicine and Dentistry. Hospital officials at SMH contemplate the purchase of a biliary lithotripter, medical equipment which shatters gallstones and/or kidney stones. Weingart categorizes the literature on acquiring technology into seven broad criteria. These criteria are the following:

1. Efficacy and effectiveness of the technology
2. Safety
3. Profitability
4. Social costs and benefits of acquiring the technology
5. Feasibility of implementing the technology
6. Strategic focus of acquiring the technology
7. Risk associated with acquiring the technology

In the first criterion, Weingart states that *efficacy* relates to the "probability of benefit to appropriately selected patients if a technology is used under 'ideal' conditions," and *effectiveness* relates to the "likely benefit of the therapy under the 'average' conditions of actual practice settings."

The second criterion, *safety*, pertains to the balance between the risk of harm of a technology to its expected benefit to patients. As Weingart says, "a technology must be safe."

The third criterion of *profitability* is important in acquiring new technology. Weingart states that although financial analysts use net present value to evaluate new technology investments, the calculation of an investment's NPV "can be difficult and uncertain, since it depends on accurate estimates of reimbursement rates, U.S. Food and Drug Adminstration approval dates, and anticipated demand for services."

Although a new technology's profitability is important, the *social costs and benefits of acquiring the technology* are also taken into account when making the decision to purchase it. Administrators are encouraged to favor "broader considerations about the impact of a new technology ... on a patient's quality of life, or his or her ability to give informed consent, on the cost of treatment, or on access to care."

Weingart states that the dominant criterion in acquiring expensive medical technology is *feasibility of implementing the technology*. Practical considerations on the investment's timeline to be implemented, space needs, infrastructure requirements, and personnel needs are all weighed for this criterion.

How a newly acquired technology fits within a health care institution's *strategic focus* is another criterion that is evaluated during the purchase decision. The new investment may play a role in the health care facility's market share, reputation, or long-term vision.

The last criterion of the *risk associated with acquiring the technology* addresses what happens if the new technology does not work as planned. Litigation, competition from other health facilities, obsolescence, and regulators' approval process are all considerations for the riskiness of a new technology.

In the Strong Memorial Hospital case, management needed to decide whether to acquire new biliary lithotripsy technology. Lithotripsy technology entails a patient immersed in a tub of water while sonic waves are emitted to burst gallstones into small fragments. The smaller fragments are expelled through a patient's urine. Administrators at Strong

Memorial authorized a task force to study the candidate technology. The task force members sought out information about the technology. Strong Memorial Hospital had been very successful in implementing renal (kidney) lithotripsy, a similar technology to biliary lithotripsy. Task force members gathered information from clinical trials conducted in Europe. These trials suggested that the technology was effective and widely successful in gallstone treatment. Manufacturers of biliary lithotripters presented information to the task force members as well. The task force decided to recommend one manufacturer because of its technology was deemed superior due to patient safety, convenience, and cost. This manufacturer's equipment could be used to treat gallstones and kidney stones. The chosen lithotripter manufacturer also had available investigational sites which allowed Strong Memorial to apply for discounted equipment pricing. Instead of the $1.2 million retail price tag, Strong Memorial paid only $650,000 for its lithotripter. The financial analysis for the proposed technology supported the decision to purchase. With allocations for additional labor, capital, and other expenses, task force members projected a net revenue of over $550,000 after three years. Despite the promising projections, the biliary lithotripsy technology was considered a disaster. The lithotripter suffered many mechanical breakdowns. Patients considered the shock treatment painful. Technicians lowered the power of the shock waves to accommodate patients' concerns. However, the lowered power reduced the effectiveness of stone fragmentation. As a result, patients required additional treatments. Strong Memorial realized less than 15% of its projected demand for the lithotripter. Weingart concludes that in the Strong Memorial case, decision makers did not fully evaluate the strategic implications of the decision to purchase the biliary lithotripter. The culture at the hospital was more a second-wave technology adopter. The investigational option with biliary lithotripsy was counter to the prevailing culture. The author also notes that the financial analysis could have included best-case and worst-case scenarios, net present value, or rate of return calculations to better assess the risk of the candidate technology. Weingart states that "task force members' satisfaction with the estimates may reflect a lack of expertise among the clinical chiefs in this area or a viewpoint that financial considerations are more of a hurdle to be jumped than a tool for decision making."

Bishai et al. (2003) evaluate three alternative treatment strategies for women in rural Georgia, USA. The women seek doctors to perform a colposcopy, a cervical examination. Alternatives for colposcopy given in the paper are (1) using trained local practitioners, (2) using trained local practitioners with telemedicine consultation from a distant expert, or (3) having patients travel to a referral expert practitioner. The authors perform detailed cost and sensitivity analyses on several cost model parameters. The authors evaluate each of the three alternatives using its respective estimated costs. The paper lists baseline costs associated with the colposcopy procedure. For sensitivity analyses, ranges for the baseline cost parameters are also listed in the paper. An annualized average cost per patient is determined for each alternative. Bishai et al. (2003) conclude that the cost of the telemedicine option outweighs its benefit to the patients. The least cost option for the study participants is to see local practitioners. The authors also note that the costs associated with telemedicine may decrease and that the telemedicine technology may be a more viable option with reduced costs.

2.4 Simulation

Several references explain the difficulty with determining input probability distributions when data are unavailable. To employ discrete-event simulation, there must be some information (whether known or estimated) available to use for input parameters and distributions. In this section, we review sources that address simulation under situations with little or no operational data available. We also focus on a subset of sources that use discrete-event simulation in the context of risk analysis.

Banks et al. (1996) notes that for new non-existent systems, experts may be needed to make educated guesses and assumptions about model parameters and operations. The authors also cite that the uniform, triangular, and beta distributions can be applied when data for a system are incomplete or limited. Law (2007) describes ways to select input probability distributions when data are unavailable for collection or when collection of data is undesirable. Techniques and approaches that use triangular, uniform, and beta distributions are detailed. Law also gives an example that depicted how use of approximating distributions when data are available results in output errors. Pegden et al. (1995) also describe the process of determining input probability distributions when data are unavailable. As in (Law, 2007), Pegden et al. (1995) detail use of different distributions when certain data are available. The authors provide guidance for when only the mean value is available, when only a range (smallest and largest) of values is available, and when the range and most likely value are available. Guidelines are given for when the exponential, triangular, uniform, and beta distributions can be used to approximate simulation input distributions. When only the mean value is available, the authors highlight through a small example that the triangular distribution produces the smallest amount of variance compared to using the uniform or exponential distributions with similar mean values. Pegden et al. (1995) favor employing the triangular distribution in cases when the range is available or the range and most likely value are available.

Both Smith (1994) and White et al. (2010) incorporate risk analysis and simulation in the context of capital budgeting. Both of these literature sources use Microsoft Excel® to generate cost and revenue parameters that are uncertain. The authors use normal distributions to vary the parameters. These two sources employ Monte Carlo simulation techniques to show how different cost or revenue parameters can be changed over potential ranges. These ranges allow model builders to explore how sensitive the overall investment decision is to those parameter changes. Clemen and Reilly (2001) utilize simulation in the context of risk analysis. The software suite DecisionTools® including RISK software is used in conjunction with Microsoft Excel® to analyze various investment decisions through sensitivity analyses. The software suite has many graphical options to visualize parameter sensitivity including tornado graphs and spider graphs.

2.5 Summary of Literature Review

The work presented in this dissertation differs from the work cited above chiefly because our approach aims at evaluating a new technology investment decision through connecting the operation of the new technology with its cash flows (i.e., revenues and costs) generated by use of the technology. As cash flows for new technology investments are uncertain, we treat their capital budgeting process as a one-off (only one chance to invest) gambling process. We appeal to tenets of expected utility to ensure optimality in one-off bets. Employing the expected utility theorem requires a characterization of probability on the value (i.e., risk) of a new technology. It is very difficult to specify a probability law on a new technology's value, i.e. risk, due to uncertainty about the technology's operations. The risk associated with each candidate technology is assessed using net present value, a consistent financial evaluation method. This research is further distinguished from the reviewed health technology assessment and capital budgeting literature by use of discrete-event simulation to generate cash flows through modeling proposed operations with the new technology. Simulation provides a computational paradigm to construct a probability law on risk for new technologies and accommodates sensitivity analysis to address value uncertainty.

3. ANALYTICAL MODEL FOR RISK-BASED TECHNOLOGY ASSESSMENT AND COMPUTATIONAL ARCHITECTURE

In this Section we present our analytical model for risk-based technology assessment. We start by providing background information about the axioms that underlie normative utility theory and the expected utility theorem in section 3.1. Next, we connect the expected utility theory to the capital budgeting decision of a technology as a one-off bet or gamble. We compare the utility of the technology one-off bet to an alternative bet which has the utility of a zero-valued investment. Section 3.2 details the analytical model we use to connect value with the operational aspects of new technologies. The stochastic process that describes the random elements of the analytical model is given. In section 3.4 we detail our computational architecture developed to explore risk. The embedded simulation structure and each element of the architecture are described. Finally we give example models that can be used to construct a risk-based technology assessment in section 3.5.

3.1 Utility Theory and the Expected Utility Theorem

When evaluating candidate technologies, we appeal to the tenets of utility theory. Von Neumann and Morgenstern (1953) describe a "rationally" acting individual who wants to maximize his or her utility or satisfaction. The authors describe the aim of the "rational" individual as follows:

> We shall therefore assume that the aim of all participants in the economic system, consumers as well as entrepreneurs, is money, or equivalently divisible and substitutable, freely transferable and identical, even in the quantitative sense, with whatever 'satisfaction' or 'utility' is desired by each participant.

Since the goal of an individual is to maximize utility, there has to be a mechanism for the individual to express his or her preference between possible alternatives. The axioms below encapsulate the manner in which a rational individual would choose preferences. These axioms are taken from Clemen and Reilly (2001) and Schoemaker (1982).

- *Order*: Alternatives can be ordered according to the decision maker's preference for the alternatives. Assume there are two alternatives, A_1 and A_2. Then there are three orderings the decision maker can have for those two alternatives:

  1. A_1 is preferred to A_2 ($A_1 \succ A_2$)
  2. A_2 is preferred to A_1 ($A_2 \succ A_1$)
  3. A_1 is indifferent from A_2 ($A_1 = A_2$)

- *Transitivity*: Given three alternatives, A_1, A_2, and A_3, if $A_1 \succ A_2$ and $A_2 \succ A_3$, then $A_1 \succ A_3$.

- *Finiteness*: There are no infinite payoffs, negative or positive.

- *Continuity*: Given alternatives A_1, A_2, and A_3, with $A_1 \succ A_2 \succ A_3$, then there is a gamble that can be constructed with some *preference probability*, p, where $0 < p < 1$, that makes the alternative A_2 indifferent from the gamble. The gamble involves receiving alternative A_1 with probability p and alternative A_3 with probability $1 - p$. A_2 is called the *certainty equivalent* of the gamble involving A_1 and A_3.

- *Substitutability*: A decision maker is indifferent to a given alternative A and its certainty equivalent (see *Continuity* axiom directly above). The decision maker can substitute an alternative for its certainty equivalent.

- *Monotonicity*: Given two gambles with the same possible outcomes, then the decision maker must choose the gamble with the higher probability of winning the most preferred outcome.

- *Invariance*: A decision maker's preferences for uncertain events can be determined by the events' payoffs and corresponding probabilities.

- *Reduction of Compound Uncertain Events* A decision maker is indifferent between a compound uncertain event (a mixture of gambles) and a simple uncertain event which is produced by reduction using standard probability. The assumption suggests that we can perform the reduction without affecting the decision maker's preferences.

The individual that adheres to the axioms in 3.1 has a preference that can be expressed by a utility function. The rational decision maker whose behavior is consistent with these axioms will choose gambles that maximize his or her expected utility Goodwin and Wright (2004). The next section details the mathematical models that describe the stochastic process for the random cash flows associated with the new technology.

3.2 Evaluating Technologies

Consider a technology, i.e., equipment, that is put into operation. Based on the operational characteristics of the equipment, random amounts of cash flows occur at random points in time. Let T_j denote the time of the j^{th} value change epoch and X_j denote the amount of j^{th} value change for $j \geq 1$. Each time a revenue or cost producing activity occurs, the time of the activity $\left(T_j \geq 0, T_j \in \mathbb{R}_+\right)$ and the amount of value change initiated by this activity $(X_j \in [\alpha_j, \beta_j], \alpha_j \leq 0 \leq \beta_j, \alpha_j, \beta_j \in \mathbb{R})$ is marked or recorded. Consider the marked point process $(T, X) = \left\{(T_j, X_j), j \in \mathbb{Z}_+\right\}$ (Last and Brandt, 1995). Then, the net present value of a technology can be expressed as follows:

$$V = \sum_j f\left(T_j, X_j\right) \tag{3.1}$$

where f is some discount function that takes (T,X) from $\mathbb{R}\times\mathbb{R}_+$ to $\mathbb{R}$ (Park, 2008). The sum in equation 3.1 can be assumed to be finite. Figure 3.1 gives a possible representation of the random cash flows for a technology. The horizontal axis represents time and the vertical axis represents the magnitude of value changes. Arrows in Figure 3.1 that point upward from the horizontal time axis represent positive cash flows. The arrows pointing downward from the time axis denote negative cash flow values. Discounting these cash flows to time $t=0$ using some function would give the net present value for the technology.

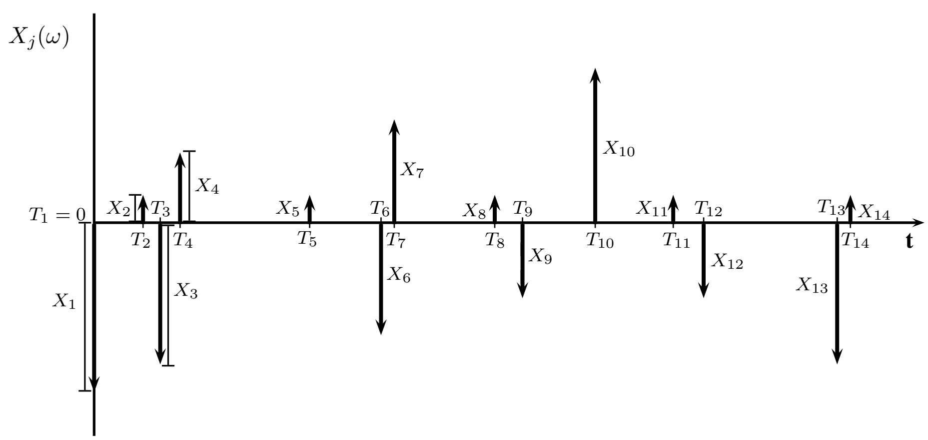

Figure 3.1: A sample path that shows the realizations of random cash flows for a technology

In order to compute the cumulative distribution function (CDF) of the net present value, i.e., risk, of an investment, multiple replications of the marked point process (T,X) described above are simulated. The NPVs from all replications are then arranged according to the value of the NPV, smallest to largest. A histogram of the NPVs is constructed to illustrate the values simulated. The risk of an investment is produced by using the empirical cumulative distribution function (ECDF) within the statistical program R (R Development Core Team, 2011). The ECDF procedure in R takes in a vector of NPV observations and produces a CDF based on the number and values of observations.

Suppose that a set of alternative technologies, denoted by A, must be evaluated. Identifying the technology with the highest expected utility is the goal. Let i be a particular alternative with $i \in A$ and random elements defined on probability triple $(\Omega_i, \mathcal{F}_i, \mathbb{P}_i)$ (Williams, 1991). Define the cumulative distribution of the net present value of technology i by

$$F_{V_i}(v) = P(V_i \leq v), i \in A \tag{3.2}$$

where V_i is the random variable that denotes the net present value of technology i. Then, the expected utility of technology i is computed as follows:

$$E[U(V_i)] = \int_{[a,b]} U(v) \mathrm{d}F_{V_i}(v) \qquad i \in A \tag{3.3}$$

where $V_i \in [a,b]$. As a result, the technology with the highest expected utility is given by:

$$\underset{i \in A}{\operatorname{argmax}}\, E[U(V_i)]. \tag{3.4}$$

Note, again, that the Finiteness property implies that the utility function is bounded on a compact set (see (Bartle, 1976) for more information about compact sets), i.e., there is no infinite utility, negative or positive.

Determining which utility function to use can be a significant issue for small firms. The next section explores different techniques firms can employ to assess utility and develop utility functions.

3.3 Assessing Utility and Developing Utility Functions

Decision makers need to assess their risk attitudes to determine their individual utility functions. Clemen and Reilly (2001) and Goodwin and Wright (2004) both show two techniques to elicit utility. One technique is assessing utility by certainty equivalents. The second technique is to assess utility using probabilities.

Eliciting an decision maker's utility by certainty equivalents involves the decision maker assessing at what value the decision maker would be indifferent to a two-option gamble. The value options for the gamble are commonly taken from the range of the investment under consideration. For example, suppose a decision maker is presented with an uncertain technology investment that, after a certain time frame, could result in a net present value anywhere in the following range: (-\$1.5 million, \$8.5 million). The endpoints for the investment's net present value range can be used as the initial endpoints of the utility function. So, using $U(v)$ to denote the utility of some value, v, then U(-\$1,500,000) $= 0$ and U(\$8,500,000) $= 1$. These two utilities represent the worst and best outcomes for the investment. Other points for the utility function can be found by eliciting utilities by using two-option gambles. Suppose the decision maker is offered a gamble, say $G1$, as follows:

$$\begin{array}{rl} \text{Win } \$8,500,000 & \text{with probability } 0.5 \\ \text{Lose } \$1,500,000 & \text{with probability } 0.5. \end{array} \tag{G1}$$

The amount of money at which the decision maker is indifferent to taking $G1$ or pocketing the money would be the certainty equivalent for the gamble $G1$. This certainty equivalent could be used to obtain another point on the decision maker's utility function. Suppose the decision maker is indifferent to taking the gamble $G1$ and receiving \$5.0 million. Then the utility of \$5.0 million is equivalent to the expected utility of the gamble (Clemen and Reilly, 2001) and (Goodwin and Wright, 2004). The new point on the decision maker's utility function can be found as following, where $p(v)$ is the probability of v:

$$\begin{aligned} U(\$5,000,000) = \quad & U(-\$1,500,000) * p(-\$1,500,000) \\ & +U(\$8,500,000) * p(\$8,500,000) \qquad \text{(G1 utility)} \\ = \quad & 0 * (0.5) + 1 * (0.5) \\ = \quad & 0.5. \end{aligned}$$

Let $G2$ be another gamble as follows:

$$\begin{aligned} &\text{Win } \$8,500,000 \quad \text{with probability } 0.5 \\ &\text{Win } \$5,000,000 \quad \text{with probability } 0.5. \qquad \text{(G2)} \end{aligned}$$

Suppose the decision maker's certainty equivalent for gamble $G2$ is \$6.0 million. Then the utility of \$6.0 million is the following:

$$\begin{aligned} U(\$6,000,000) = \quad & U(\$5,000,000) * p(\$5,000,000) \\ & +U(\$8,500,000) * p(\$8,500,000) \qquad \text{(G2 utility)} \\ = \quad & 0.5 * (0.5) + 1 * (0.5) \\ = \quad & 0.75. \end{aligned}$$

One more point on the utility function can be found by another gamble $G3$:

$$\begin{aligned} &\text{Win } \$5,000,000 \quad \text{with probability } 0.5 \\ &\text{Lose } \$1,500,000 \quad \text{with probability } 0.5. \qquad \text{(G3)} \end{aligned}$$

Suppose the decision maker's certain equivalent for gamble $G3$ is \$4.0 million. Then the utility of \$4.0 million is as follows:

$$\begin{aligned} U(\$4,000,000) = & \quad U(\$5,000,000) * p(\$5,000,000) \\ & +U(-\$1,500,000) * p(-\$1,500,000) \qquad \text{(G3 utility)} \\ = & \quad 0.5 * (0.5) + 0 * (0.5) \\ = & \quad 0.25. \end{aligned}$$

Then there are five points which can be plotted to develop the decision maker's utility function.

Another technique used to elicit points for a utility function is the method of assessing utility using probabilities. Assessments by probabilities use a gamble that is set by choosing a probability that will make the decision maker indifferent in taking the bet. Suppose a decision maker is presented with the previous uncertain technology investment that results in a net present value anywhere in the following range: (-\$1.5 million, \$8.5 million). As stated before, the endpoints for the investment's net present value range can be used as the initial endpoints of the utility function, i.e., U(-\$1,500,000) = 0 and U(\$8,500,000) = 1. Now assume that the decision maker wants to assess his utility for \$3.0 million. Instead of guessing through interpolation based on the other points assessed using the certainty-equivalence procedure, consider the following gamble, $G4$: Let $G4$ be another gamble as follows:

$$\begin{aligned} &\text{Win } \$8,500,000 \quad \text{with probability } p \\ &\text{Lose } \$1,500,000 \quad \text{with probability } (1-p). \qquad \text{(G4)} \end{aligned}$$

The decision maker would adjust the value of probability p in gamble $G4$ until he is indifferent in this lottery and taking \$3.0 million. The utility of \$3.0 million is as follows:

$$\begin{aligned} U(\$3,000,000) &= U(\$8,500,000) * p + U(-\$1,500,000) * (1-p) \qquad \text{(G4 utility)} \\ &= 1 * p + 0 * (1-p) \\ &= p. \end{aligned}$$

Observe that the probability that makes the decision maker indifferent in the case of $G4$ is the utility for \$3.0 million due to the setup of the gamble using the endpoints of the utility function. The endpoints have utility values of 0 and 1 which simplifies the calculation for U(\$3,000,000).

The next section details the computational architecture developed for this research. The architecture provides a guide on how technology assessment decisions can be modeled using computer software and decomposing the operational activities that affect revenues and costs for new technologies.

3.4 Computational Architecture

Breaking down the projected revenue and cost streams associated with a new technology is an important part of connecting the use of new technologies to those revenues and costs associated with the new technologies. We take a systems engineering perspective to approach the decomposition of the constituent elements of small firms' operations related to revenue and cost trajectories. Several software tools were employed to construct the computational architecture developed for this research. The following section details the computational architecture and provides a guide on how technology assessment decisions can be modeled.

Figure 3.2 gives a schematic view of the distinct levels involved in assessment decisions and how data from one level flow to another level. Each level in Figure 3.2 represents

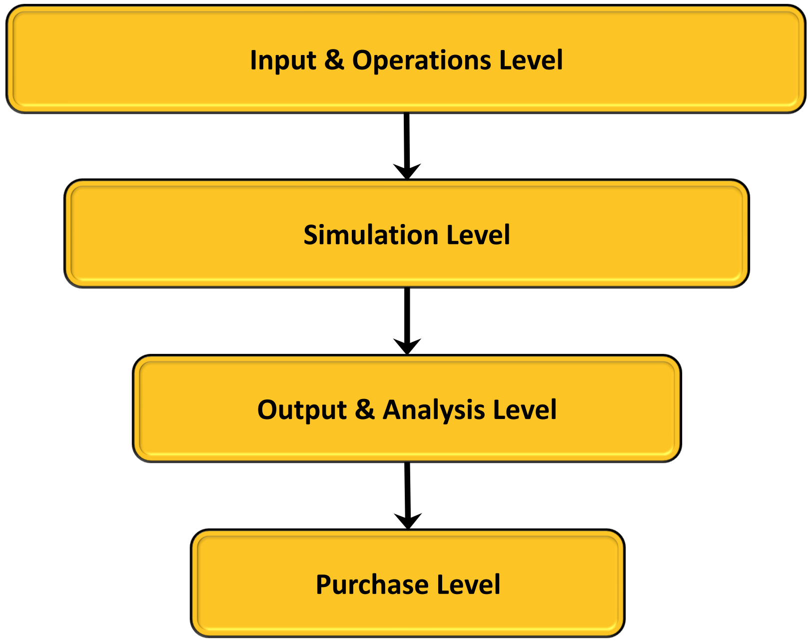

Figure 3.2: The levels within the computational architecture

the various elements and activities that occur at that level. The arrows in this figure show the direction of information flow between the levels. In particular, elements that are directly related to the operations of the firms are grouped separately from the elements in the simulation model. The links in Figure 3.2 between the simulation level (labeled ***Simulation Level***) and the operations elements (labeled ***Input & Operations Level***) show how the operations of a firm can be connected to the simulation model. Simulation results and data undergo further processing and analysis in the level labeled ***Output & Analysis Level***. After the analysis is conducted, the information influences the overall decision to purchase at the ***Purchase Level***. Other input data, parameters, and information are given in the ***Input & Operations Level***. Descriptions and details of the elements and activities for each architecture level are given in Figure 3.3 below.

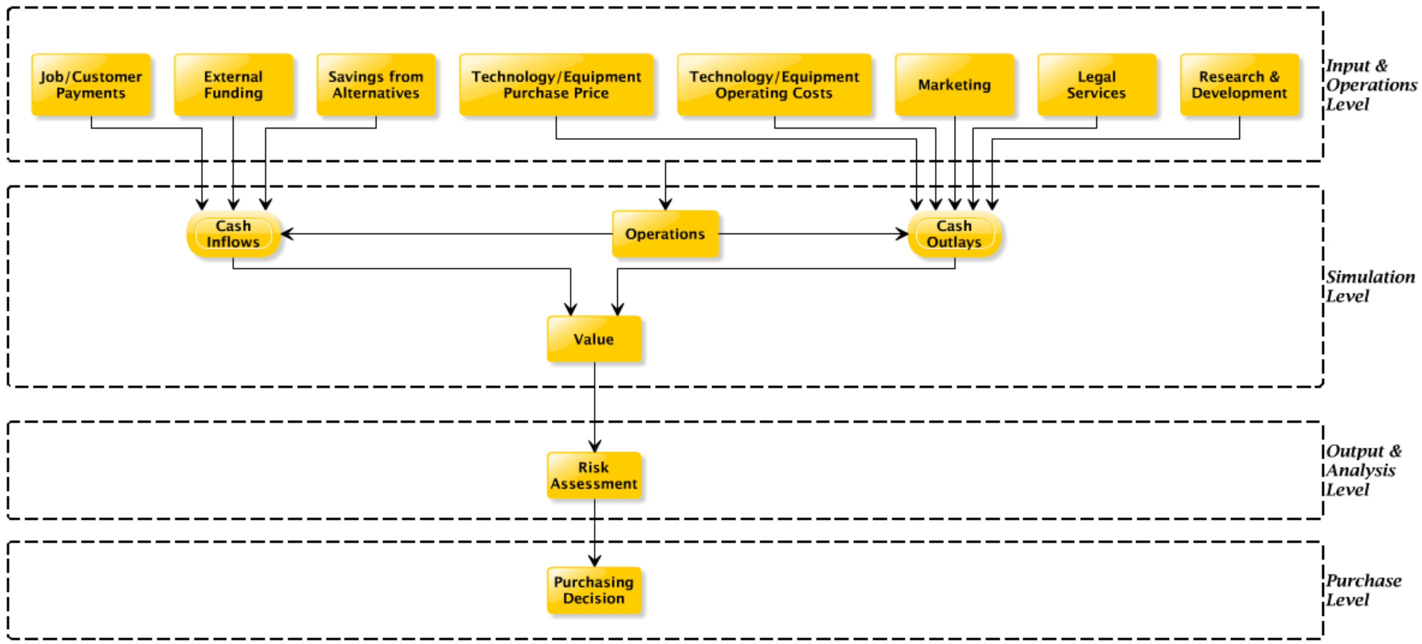

Figure 3.3: A schematic diagram of the computational architecture

3.4.1 Input & Operations Level

The ***Input & Operations Level*** represents the level where the operations activities and input data needed for the simulation model are determined. Any activities that affect the small firm's cash flows can be modeled. The arrow from the bottom of the ***Input & Operations Level*** box (denote by a dotted line) to the *Operations* element in the ***Simulation Level*** box depicts that any activities that affect operations are included in the simulation model.

3.4.1.1 Cash Inflows

When simulating the revenue or cash inflows, there may be several possible revenue streams for the small firm. Each of these streams can be included as a cash inflow module. The *Cash Inflows* element in Figure 3.3 shows some possible activities and information sources which can be used to simulate the revenue streams for a small firm.

The *External Funding* element represents the cash flows that can be obtained from any grant proposals or other sources of external funding that the firm has sought. Small firms may apply for grants from government agencies, private philanthropic foundations or other organizations. Generally grants are gifts that the firm must use for particular projects or specified purposes. If awarded a grant or other external funding, a firm can use the awarded proposal or application as an estimate of any funds related to acquiring, maintaining, or using the potential technologies. Any awarded amounts and/or payment schedules can be included in the overall cash inflow module.

The *Savings from Alternatives* element incorporates any cost savings from updated technology. If a firm is using a current technology that will be replaced by the proposed new technology, then the difference in price for any materials or other costs may be a factor in the proposed operations. These savings data can be modeled in the simulation. The small firm could use data from the current technology operations to estimate the potential savings with the new technology.

The *Job/Customer Payments* element represents the information related to the firm's revenue-producing arrival streams. The rate at which jobs and/or customers arrive to be processed can be included in this module. This arrival rate can be varied to see the effect arrivals have on the potential value of the new technology. The amount of payment per completed job or customer is important information for this module, too. Different customer types with various payment projections can be addressed in the simulation models.

3.4.1.2 Cash Outlays

Costs associated with the candidate technology or equipment can be modeled using simulation. Each cost stream connected with the use of the proposed technology can be included as a cash outlay module. The *Cash Outlays* element in Figure 3.3 depicts possible activities and information sources which can be used to simulate the cost streams for a small firm.

The *Technology/Equipment Purchase Price* element represents the investment price of the candidate technology or equipment. Firms can solicit vendors and/or manufacturers of the new technology or equipment to obtain cost estimates. Other costs related to installation of the new technology, i.e., building renovations or shipping, can be modeled in this module. The discount rate used in investment calculations is important in determining its profitability.

Any costs related to the operations of the new technology or equipment can be modeled in the *Technology/Equipment Operating Costs* module. Each operating cost that may have its own characteristic cost stream and/or schedule can be included as a separate submodule. Maintenance costs, salaries, utilities, transportation costs, insurance payments, and/or monthly service fees may all be modeled as submodules. For instance, in the maintenance submodule, equipment or technology breakdowns can be modeled. Figure 3.4 shows a

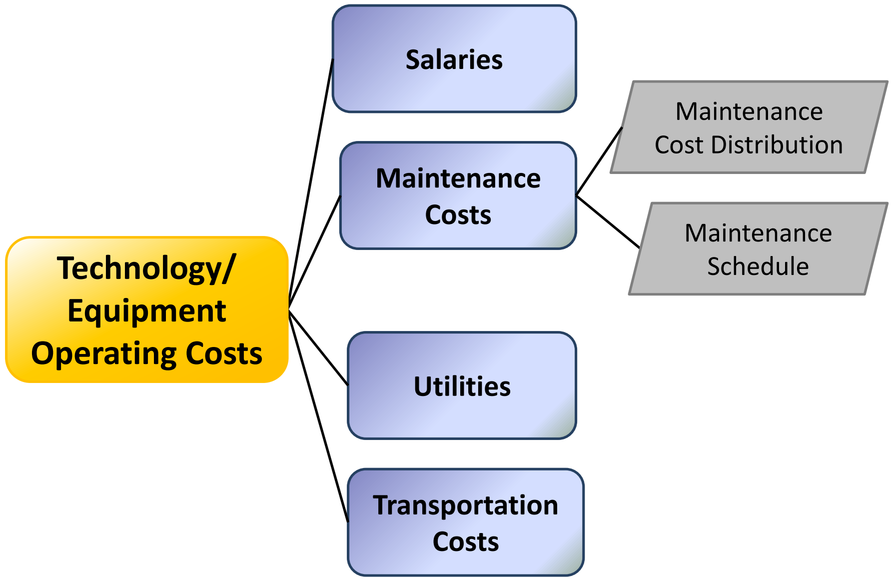

Figure 3.4: A depiction of the Technology Equipment Operating Costs submodules in the Input & Operations Level of the computational architecture

possible depiction of several *Technology/Equipment Operating Costs* submodules. *Maintenance Costs*, *Salaries*, *Utilities*, and *Transportation Costs* are just a few of the costs that are encapsulated in the *Technology/Equipment Operating Costs* module. The *Maintenance Costs* submodule is detailed further in Figure 3.4. The boxes *Maintenance Schedule* and *Maintenance Cost Distribution* symbolize the information needed to generate maintenance costs for the *Maintenance Costs* submodule. Different breakdown profiles can be modeled and studied for different simulation models. Operational characteristics of the maintenance schedule and costs can be included in the models. Another cost can be attributed to any workers or technicians that are needed to operate the equipment. Operator salaries and work schedules can be included in the simulation models. Other operator characteristics that may contribute to system costs may be added to the models. For example, if an operator is required for the equipment to work properly, then that behavior and any costs incurred by the system when the operator is unavailable, can be studied. Special customer or job handling rules can be modeled in the simulations. Rework, multiple service encounters, and lost customers can be included in simulations if appropriate for the proposed technology's operations.

The small firm may have to spend money to market the new service or technology. The *Marketing* module incorporates the costs associated with building the customer base for the new technology. Marketing budget projections and timing of outlays can be included in this module.

The *Research & Development* module accounts for any research-related costs to produce or develop a product or service. Projected research outlays and schedules can be included in this module.

The *Legal Services* module represents any legal costs that may be directed related to the acquisition or operations of the new technology or equipment.

3.4.2 Simulation Level

The ***Simulation Level*** represents the level where the value for the new technology is computed based on projected cash flows from the technology. Stochastic processes that are higher in the hierarchy of the architecture depend on lower level stochastic processes. This level depends on information from the operations of the new technology. The simulation models generate random variables for the cash flows experienced for the firm. These random variables represent values that the cash flows could realize when the candidate technology is in place. The box (denoted with a dotted line) labeled ***Simulation Level*** in Figure 3.3 depicts the elements that are generated by the simulation model. The box labeled *Value* represents the simulation module that calculates the value measure, e.g., net present value, for each candidate technology. The value for an alternative is generated through simulating the revenue and cost cash flow streams of the system when that alternative is utilized. All operations and activities that affect the cash flows are simulated in the models and are incorporated in the module labeled *Operations*. This module is vast and can be broken into several submodules accounting for each aspect of operations. Figure 3.5 shows a few of the submodules of the *Operations* module that can be modeled in the simulation. There may be many more submodules than the ones depicted in Figure 3.5. The *Equipment Reliability* submodule is highlighted in the figure. This submodule can be broken down into its constituent elements. In Figure 3.5, there are several elements that are shown which describe the information needed for the *Equipment Reliability* submodule. This information includes *Breakdown Distribution*, *Breakdown Costs*, *Repair Time Distribution*, and *Repair Costs*. The stochastic processes related to the new technology's activities that contribute to company revenue are included in the module labeled *Cash Inflows*. The *Cash Outlays* box represents those stochastic processes related to the new technology's cost-producing activities. The activities that produce the cash inflows and outlays are included in the operations level.

3.4.3 Output & Analysis Level

The ***Output & Analysis Level*** represents the level where the risk for each technology alternative is determined. An alternative's risk assessment is comprised of the cumulative distribution of the net present value for the alternative. The element in Figure 3.3 labeled *Risk Assessment* depicts where the risk is evaluated for each candidate technology. As discussed in Section 3.2, the risk is found through replications of discrete-event simulation models of the underlying system operations with the new technology alternative in place. Each replication of the simulation outputs a value of the equipment and/or technology. The outputs are used to construct the cumulative distribution function. Figure 3.6 shows the output of the risk for the *Risk Assessment* module. The probability that each alternative will return a value less than or equal to a certain amount (see equation 3.2 above) is determined

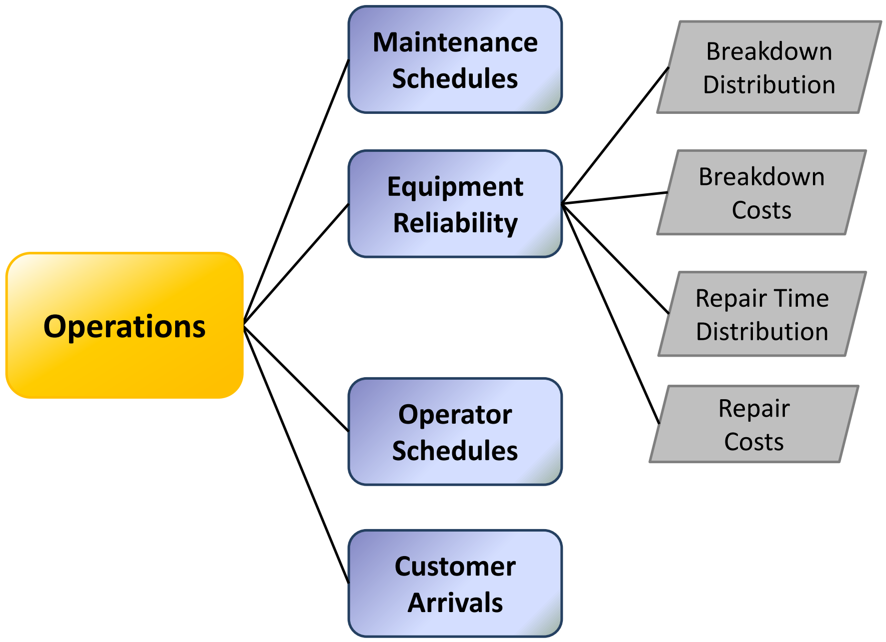

Figure 3.5: A depiction of the Operations submodules from the Simulation Level of the computational architecture

using this distribution function. The *Risk Assessment* element is based on the information obtained from the simulation models.

3.4.4 Purchase Level

The ***Purchase Level*** in Figure 3.3 represents the level where the decision whether to purchase a technology is made. At this level, the box labeled *Purchasing Decision* represents the choice to purchase a technology or not. This decision is based on the risk assessment of the different alternatives evaluated. Figure 3.7 gives a depiction of the decision at this level. Assuming the purchase is a one-off bet, then there is only one opportunity to accept or decline the purchase. Also, if multiple alternative technologies are available, alternatives are ranked and the one-off bet is made on the one alternative that maximizes the expected utility. This box relies on the risk assessment from each alternative. The risk assessment is provided from the ***Output & Analysis Level***.

Figure 3.6: A depiction of the Risk Assessment output at the Output & Analysis Level of the computational architecture

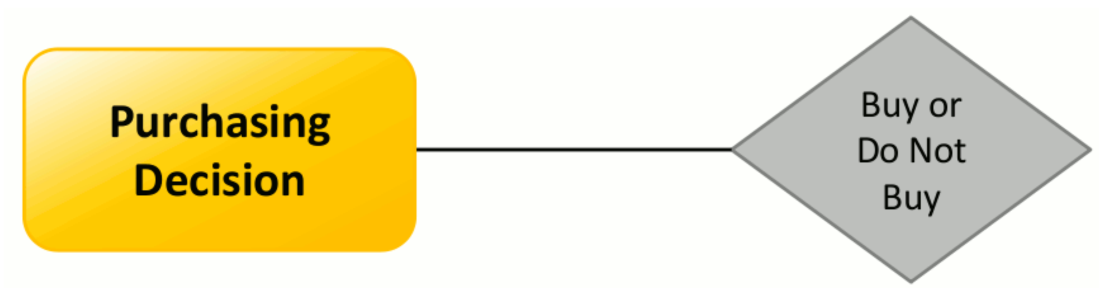

Figure 3.7: A depiction of the Purchasing Decision output at the Purchase Level of the computational architecture

The computational approach includes using a discrete-event simulation package to model the component modules. Each module can be designed so that it can be easily added, deleted, or modified to fit specific needs for each firm. Python and SimPy have been used to develop simulation models. Python is an object-oriented programming language. SimPy is a discrete-event simulation software package that "is written in, and called from, Python" (Matloff, 2008). All input data needed for each of the modules have been stored in text files. Output data could be saved to text files or to a common database computer software package such as SQLite. Data can be queried from the database and used for appropriate component modules and system analysis. Analysis of net present value data may be performed using other statistical analysis packages, e.g., R (R Development Core Team, 2011). The statistical package R also allows for construction of charts, tables, and figures related to the data generated. SimPy also has several options to produce graphs and figures based on the random variables or other attributes generated by a simulation model. Other open source technologies and software are available to use in risk-based technology assessment decisions.

The next section describes example models that give a possible representation of the relationship between a firm's capital equipment operations and the revenues and costs associated with the equipment. These cash flows can be triggered by state changes when the technology is used. There could be multiple states for the technology. One way to connect the cash flows with the operational information of such a technology is through the reliability and/or availability of the technology. Examples of this relationship between the operations and cash flows is given in the Example Models section (Section 3.5) that follows.

3.5 Example Models

We deploy simple queueing models to show the interaction between a firm's capital equipment operations and the revenues and costs associated with the equipment. The first model in Section 3.5.1 connects the operation of a single machine system with the revenue and cost streams associated with use of the machine. The second model described in Section 3.5.2 simulates a system that requires an operator to be available to process jobs or orders on a machine. Graphs included in this section show the relationship between revenues and costs corresponding to different states for each of the systems modeled.

3.5.1 *Single Machine Model*

One model that could be considered is a system with one machine. Suppose that a firm has a machine that operates for a random amount of time and then fails. Once the machine fails, it gets repaired and becomes as good as new. The repair time is also random. The machine continually cycles between the operational (up) state and the failed (down) state.

Define $M(t)$ as the state of the machine at time t. $M(t)$ is defined by:

$$M(t) = \begin{cases} 1 & \text{if the machine is in the up state at time } t \\ 0 & \text{otherwise.} \end{cases}$$

Consider the following reward and cost structure for the system. Let $r(t)$ be defined as the rate (\$/unit time) at which revenue is earned at time t and $c(t)$ as the rate (\$/unit time) at which costs are incurred at time t. Revenues and costs are continuous. So $r(t)$ is defined as:

$$r(t) = \begin{cases} r & \text{if the machine is in the up state at time } t \\ 0 & \text{otherwise ;} \end{cases}$$

and $c(t)$ as

$$c(t) = \begin{cases} c_o & \text{if the machine is in the up state at time } t \text{ (operating cost),} \\ c_r & \text{if the machine is in the down state at time } t \text{ (repair cost)} \end{cases}$$

for $t \geq 0$.

Let U_n denote the n^{th} up time of the machine and D_n denote the n^{th} down time of the machine. Figure 3.8 depicts a possible system sample path and the corresponding revenue and cost rates. The first graph in Figure 3.8 displays a sample path of the machine states with respect to time. The machine alternates between the up and down states. As the state of the machine changes, so do the revenues and costs associated with the system. The

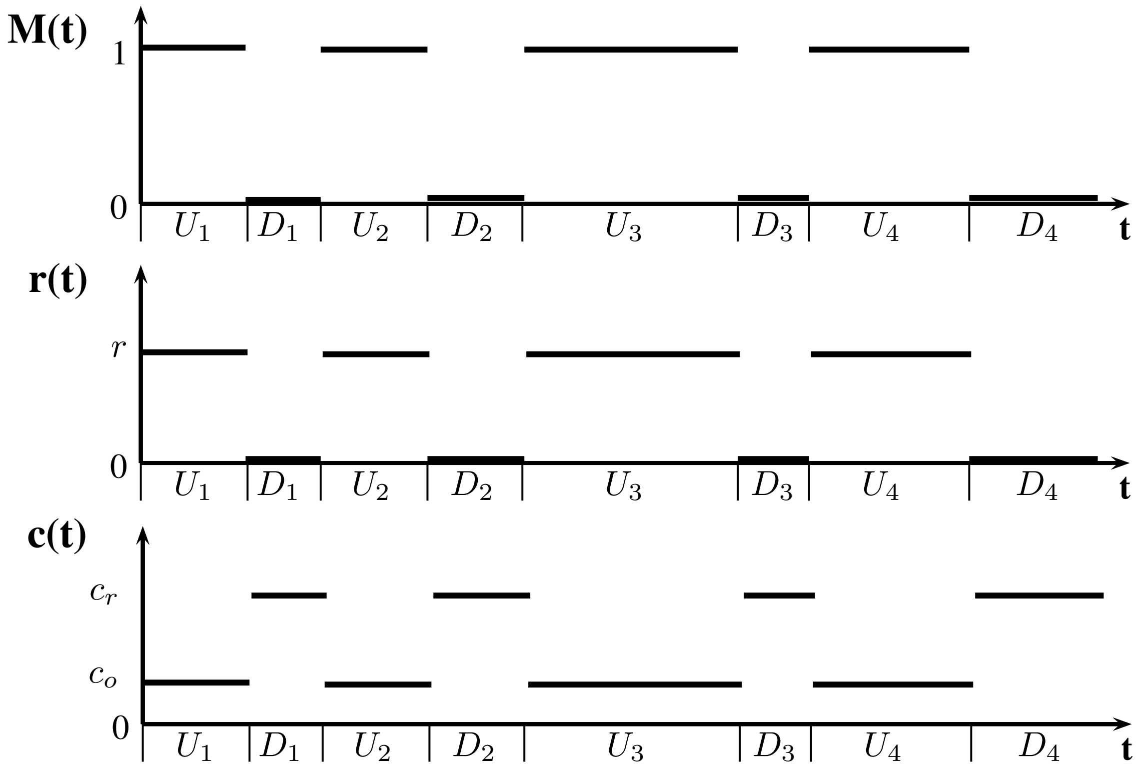

Figure 3.8: One sample path of machine availability and corresponding revenues and costs

second and third graphs in the figure give the corresponding revenue and cost rates for the system, respectively. The graph for revenues shows the system gaining revenue of r when the machine is up and 0 when the machine is down. The cost graph reflects that when the machine is in the up state, the system incurs a cost of c_o. When the machine is in the down state, the cost of c_r is incurred. Firms want to compute the net present value of the system through time t. Let $V(t)$ denote the net present value of the system through time t. $V(t)$ can be expressed with discrete random variables. Using discrete random variables for the net present value gives a better representation of how the discrete event simulation program generates random variables. To express $V(t)$ using discrete random variables, assume that the system starts at time $t = 0$ with the machine in the up state.

To compute $V(t)$, the total amount of time the machine has spent in the each of the up and down states until time t is needed. Define $U_n + D_n$ as the length of the n^{th} operation cycle, $n = 1,2,\ldots$. Let N represent the number of operation cycles completed up to time t. Then, N can be expressed as follows:

$$N = \max\left\{n : \sum_{k=1}^{n} (U_k + D_k) \leq t\right\}. \tag{3.5}$$

Let F_n denote the time of the n^{th} failure and R_n denote the time of the n^{th} repair for $n = 1,2,\ldots$. The variables F_n and R_n can be expressed in terms of random variables U_i and D_i, $i = 1,2,\ldots,n$, as follows:

$$\begin{aligned} F_1 &= U_1, && (3.6)\\ F_n &= \sum_{i=1}^{n-1} (U_i + D_i) + U_n, \quad n \geq 2 && (3.7)\\ R_n &= \sum_{i=1}^{n} (U_i + D_i), \quad \forall n. && (3.8) \end{aligned}$$

If time t occurs during the down time of a cycle, we assume that a complete operation cycle occurs. That is, $D_n = t - F_n$ when t falls during a cycle's down time. Then $V(t)$ can be computed using the following equation:

$$\begin{aligned} V(t) &= (r - c_o)\sum_{i=1}^{N} U_i - c_r \sum_{i=1}^{N} D_i \\ &\quad + (r - c_o)\left[t - R_N\right] 1\left(F_{N+1} \geq t\right) \\ &\quad + \left[(r - c_o)U_{N+1} - c_r(t - F_{N+1})\right] 1\left(F_{N+1} < t\right). \end{aligned} \tag{3.9}$$

where the first term in equation 3.9 represents the total profit for the operation cycles completed up to time t, the second term represents the profit if t occurs in the uptime of the $(N+1)^{\text{st}}$ operation cycle, and the third term represents the profit if t falls in the downtime of the $(N+1)^{\text{st}}$ operation cycle. Note that $1(A)$ is an indicator function such that:

$$1(A) = \begin{cases} 1 & \text{if A occurs} \\ 0 & \text{otherwise.} \end{cases}$$

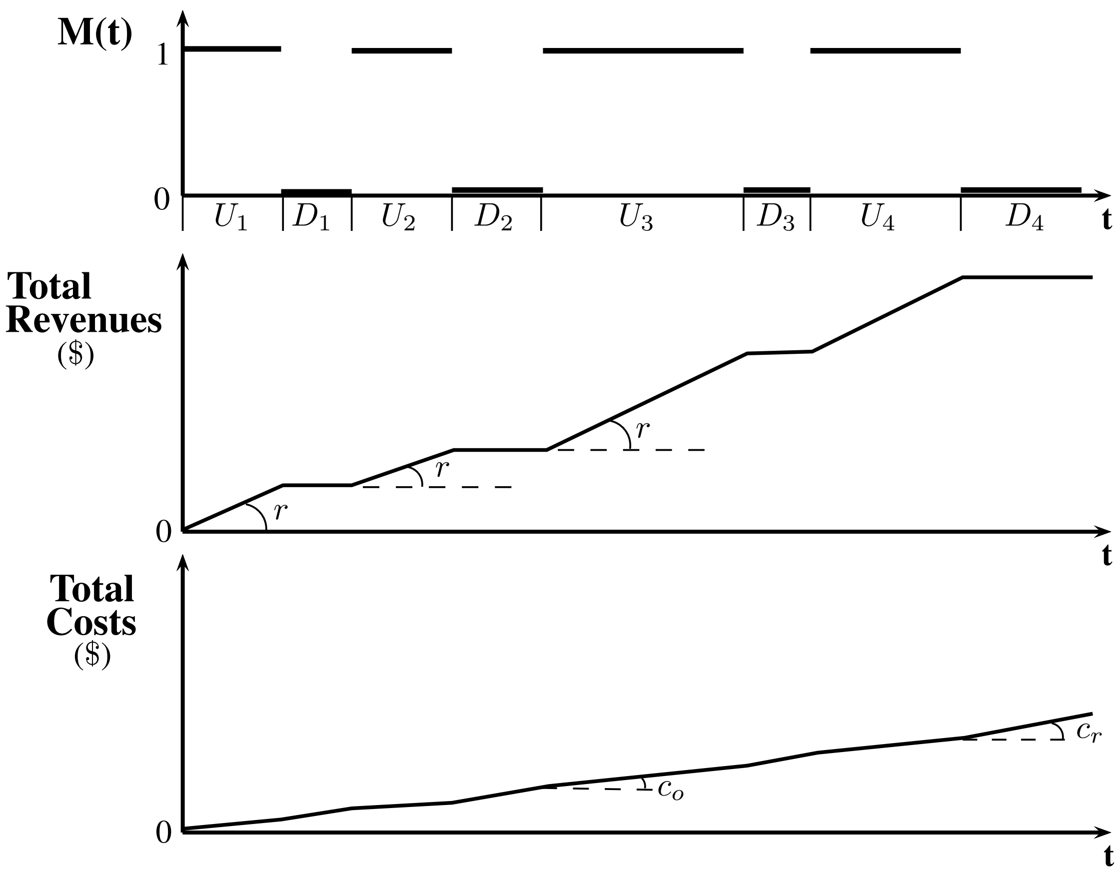

Figure 3.9: One sample path of machine availability and corresponding total revenues and total costs

Figure 3.9 gives an illustration of a possible system sample path. The first graph in Figure 3.9 shows a sample path of the machine availability with respect to time. The machine alternates between the up and down states. As the state of the machine changes, so do the revenues and costs associated with the system. The second and third graphs in the figure give the corresponding revenues and costs for the system, respectively. The graph for revenues has slope of r when the machine is up and no slope when the machine is down. The slope of the cost graph corresponds to c_o when the machine is in the up state and c_r when the machine is in the down state.

3.5.2 Single Machine, Single Operator Model

Now consider the single-machine system described above. Assume that an operator must be available for the machine to function properly. The operator works for a period of time before becoming unavailable for an amount of time. The operator cycles between these states of availability and unavailability. When the machine is in the up state and the operator is available, the system is gaining revenue, r, and incurring an operating cost, c_o. If the machine is in the up state but the operator is unavailable, the system incurs a lost sales cost, c_l, in addition to the operating cost, c_o. When the machine is down, the system incurs a repair cost, c_r. If the operator is available when the machine is down, the system still incurs the operating cost, c_o. However, if the machine is in the down state and the operator is unavailable, the system does not incur the operating cost. Instead, only the cost of repair is incurred. These changes need to be adjusted in the net present value calculations.

Let $O(t)$ denote the availability of the operator at time t. Define $O(t)$ as follows:

$$O(t) = \begin{cases} 1 & \text{if the operator is available at time } t \\ 0 & \text{otherwise.} \end{cases}$$

Since both the machine state and operator availability determine the amount of revenue or cost accrued in the system, the portion of time when the machine is up and the operator is available and the portion of time when the machine is up and the operator is unavailable must be marked or recorded. Likewise, the portion of time that the operator is available and unavailable when the machine is down has to be tracked.

In the example given in Section 3.5.1, $V(t)$ can be expressed with discrete random variables. To express $V(t)$ using discrete random variables, assume that the system starts at time $t = 0$ with the machine in the up state and the operator available. Let U_n and D_n denote the n^{th} up time of the machine and the n^{th} down time of the machine, respectively. Let W_n denote the n^{th} time that the operator is available and Y_n denote the n^{th} time that the operator is unavailable. Now define $Z(t)$ as follows:

$$Z(t) = M(t) * O(t), \tag{3.10}$$

where $M(t)$ is the machine state at time t and $O(t)$ is the operator availability at time t. When the machine is up and the operator is available, $Z(t) = 1$. Let Z_i denote the successive, corresponding time periods when $Z(t) = 1$, with $i = 1, 2, \ldots$. Time intervals when $Z(t) = 1$ occur only during up periods of the machine. Exploiting this fact assists in finding out the times of operator unavailability. Consider the i^{th} up period, U_i. There may be multiple times when the operator is available and unavailable during this single up period. Summing the total amount of time that $Z(t) = 1$ during an interval U_i, i.e., $\sum Z_j$, where $Z_j \in [R_{i-1}, F_i]$, gives the time epochs when the system can gain revenue during the up state. The amount of time that the operator is unavailable during an up period can be found by taking the difference between U_i and the sum of the times when $Z(t) = 1$ on U_i, i.e., $U_i - \sum_{Z_j \in [R_{i-1}, F_i]} Z_j$. This procedure is repeated for all U_i's on interval $[0, t]$.

A similar process can be done with the down periods (D_i's). Let $Q(t)$ be defined as follows:

$$Q(t) = 1\big((M(t)=0)(O(t)=0)\big) = \begin{cases} 1 & \text{if } M(t)=0 \text{ and } O(t)=0 \\ 0 & \text{otherwise.} \end{cases}$$

Then $Q(t)$ indicates the time epochs when the machine is in the down state and the operator is unavailable. Let Q_j denote the corresponding time periods when $Q(t)=1$, with $i = 1,2,\ldots$. Since $Q(t)$ only takes the value of one during machine down times, this fact can be used to express the amount of time when the operator is available during a machine down time. Consider the i^{th} down period, D_i. The total time that the operator is unavailable during this down period can be expressed as follows: $\sum_{Q_j \in [F_i,R_i]} Q_j$. The amount of time that the operator is available during the i^{th} down period can be expressed as follows: $D_i - \sum_{Q_j \in [F_i,R_i]} Q_j$. This procedure is repeated for all down periods D_i on interval $[0,t]$. Figure 3.10 displays a sample path representation for the system and functions $Z(t)$ and $Q(t)$. The first graph in Figure 3.10 shows a sample path of the machine availability with respect to time. The machine alternates between the up and down states. The second graph in Figure 3.10 depicts a sample path of the operator availability with respect to time. $O(t)$ takes the value one when the operator is available and takes the value zero when the operator is unavailable. The third graph shows the function $Z(t)$ that corresponds to the first two graphs in Figure 3.10. When $M(t)=1$ and $O(t)=1$, then $Z(t)=1$. If $M(t)=0$ or $O(t)=0$, then $Z(t)=0$. The last graph in Figure 3.10 displays the function $Q(t)$, where $Q(t)=1$ if $M(t)=0$ and $O(t)=0$.

As in equation 3.5, let N represent the number of operation cycles completed up to

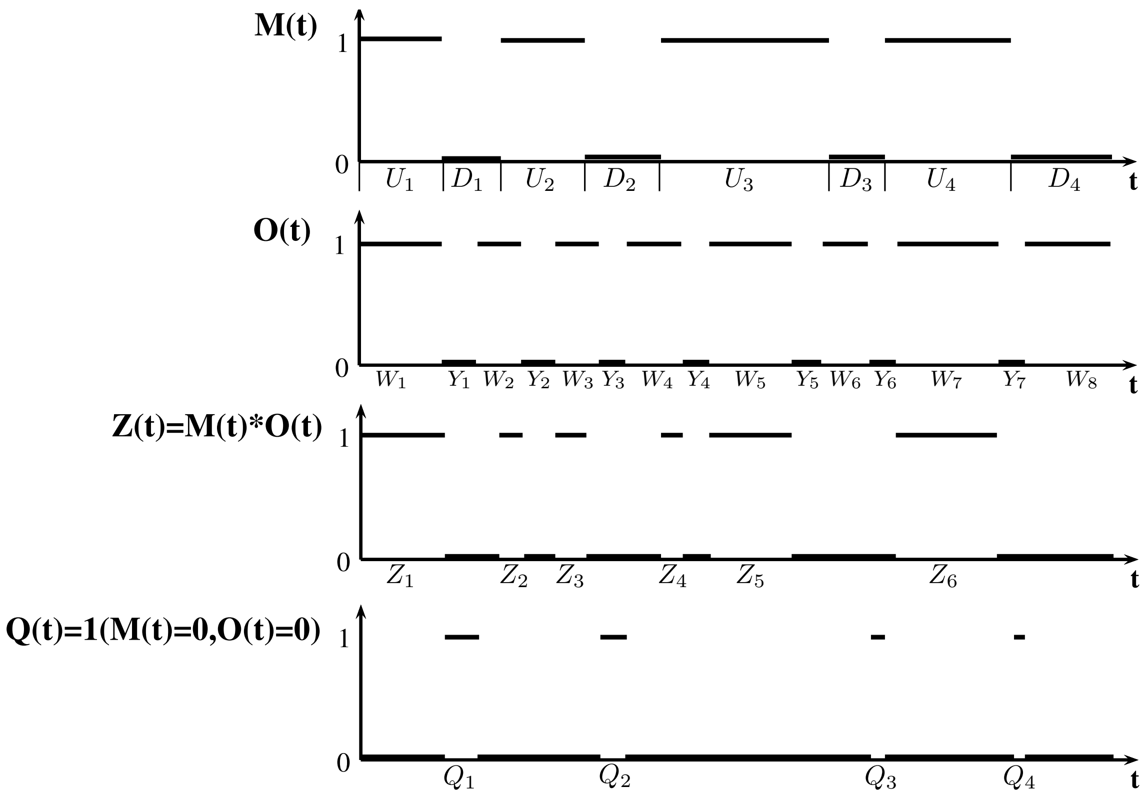

Figure 3.10: A sample path representation of a system with a machine and an operator and the corresponding graphs for functions Z(t) and Q(t)

time t. We also define the following terms:

$$A = \sum Z_i, \text{ where } Z_i \in [0,t] \tag{3.11}$$

$$B_i = U_i - \sum Z_j, \text{ where } Z_j \in [R_{i-1}, F_i] \tag{3.12}$$

$$G = \sum Q_i, \text{ where } Q_i \in [0,t] \tag{3.13}$$

$$H_i = D_i - \sum Q_j, \text{ where } Q_j \in [F_i, R_i] \tag{3.14}$$

Then the net present value can be expressed as follows:

$$V(t) = f\left[(r-c_o)A - (c_o+c_l)\sum_{i=1}^{N} B_i - c_r(G) - (c_r+c_o)\sum_{i=1}^{N} H_i\right]. \tag{3.15}$$

The function f in equation 3.15 denotes the discount function for the net present value calculation. The four terms of the equation deal with the different system states. The first term in equation 3.15 calculates the profit gained in the system over all the times that the machine is up and the operator is available during the N complete operation cycles. The second term accrues the cost associated with any lost sales in the system. Lost sales occur when the machine is up but the operator is unavailable. The third term of the equation determines the cost to the system when the machine is down but the operator is available. The fourth term accounts for the total repair cost of the system when the machine is down and the operator is unavailable. If time t falls during an up period, then the $N+1^{st}$ failure (F_{N+1}) has not occurred. For purposes of calculating $V(t)$, we assume that time t corresponds with the time of the $(N+1)^{st}$ failure, i.e., $F_{N+1} = t$. Now, if time t falls during a down period of a cycle, then we assume that time t corresponds with the time of the N^{th} repair, i.e., $R_N = t$.

Figure 3.11 gives an illustration of a possible system sample path. The first graph in Figure 3.11 shows a sample path of the machine availability with respect to time. The machine alternates between the up and down states. The second graph in Figure 3.11 depicts a sample path of the operator availability with respect to time. When the machine and operator states change over time, so do the revenues and costs associated with the system. The third and fourth graphs in the figure show the corresponding revenues and costs for the system sample paths shown in the first two graphs of Figure 3.11. The graph for revenues has slope of r when the machine is up and the operator is available and has slope of zero when the machine is down. The slope of the cost graph corresponds to c_o

when the machine is in the up state and the operator is available. When the machine is up but the operator is unavailable, the system incurs cost $c_l + c_o$ depicted with slope $c_l + c_o$ on the fourth graph of Figure 3.11. When the machine and operator are unavailable, the slope c_r is shown in the cost graph. The slope $c_r + c_o$ corresponds to the times when the machine is down but the operator is available.

Different operations have various triggers for the costs and revenues associated with the system. In the next Section, we apply the example in this section (3.5.2) to a real-life healthcare technology assessment decision.

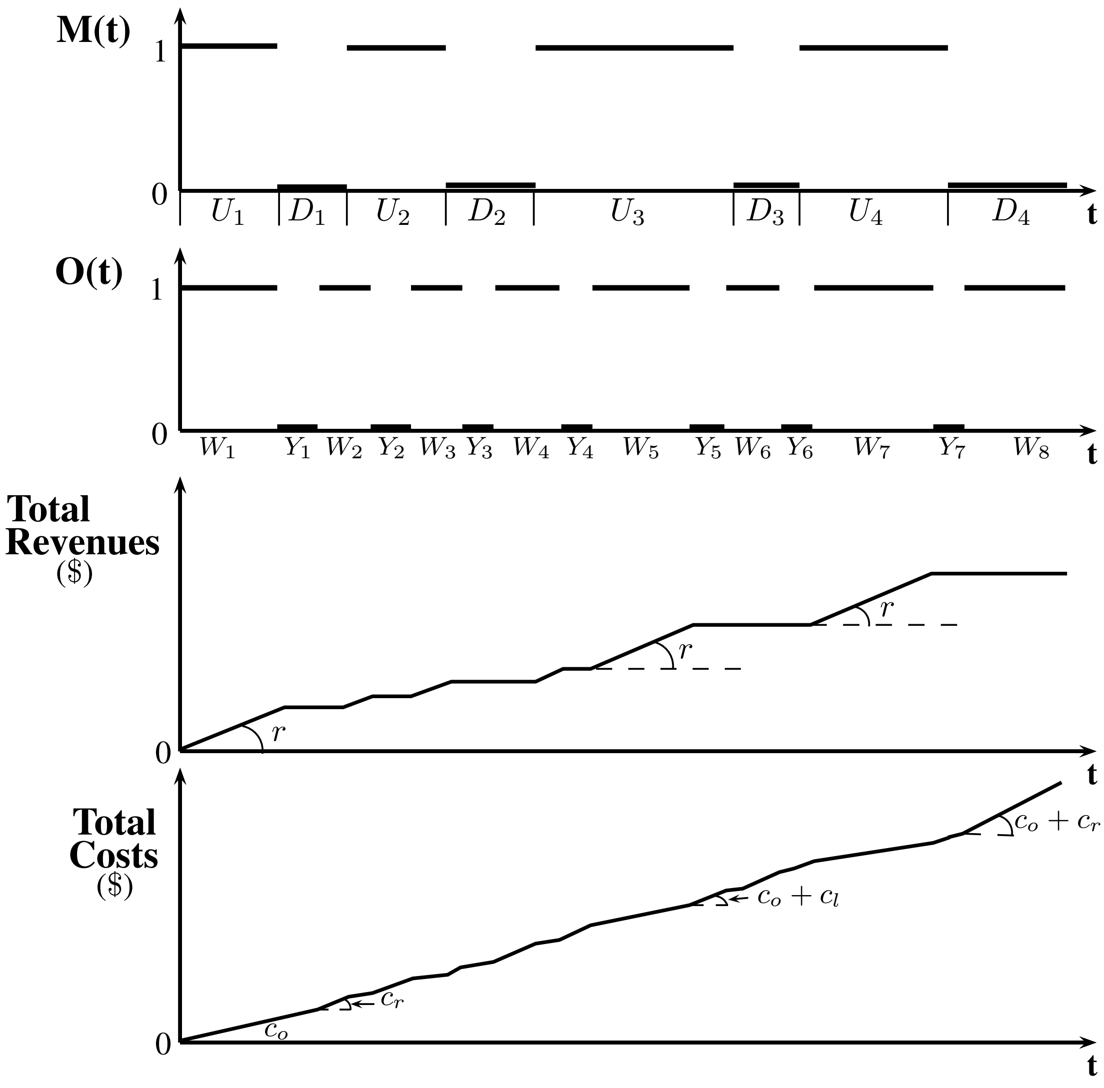

Figure 3.11: A sample path representation of a system with a machine and an operator and corresponding revenues and costs

4. APPLYING RISK-BASED TECHNOLOGY ASSESSMENT*

This section details the use of our computational architecture to assess new technology. We summarize some of the various ways in the literature that do not properly account for risk and highlight them in section 4.1. Section 4.2 summarizes a real-life application of technology assessment in the healthcare industry. A journal paper (Weingart, 1995) highlighted in this section is unique in that the author expounds on several failures made in the Strong Memorial Hospital (SMH) technology assessment decision. The paper gives a case study on how the decision to purchase the new technology was made. We illustrate how incorrect methods were applied in the SMH case. We use data from the paper to demonstrate our computational architecture and systematic approach for risk-based technology assessment. Section 4.3 expounds on the operations for the lithotripter. Subsequent subsections of 4.3 detail various aspects of the discrete-event simulation models employed in constructing the risk. Section 4.3.1 discusses how patient arrivals are generated in the simulation models. Rationalization for the distributions used in generating patients into the hospital is given as well. Section 4.3.2 explains the various cash flows for SMH and how they are modeled in the simulations. The specific elements of the hospital computational architecture are detailed in section 4.3.3. Details of using SimPy for the simulation models are given in section 4.3.4. Results from the base simulation model are given in section 4.3.5. Section 4.3.6 explores how different financial measures would influence the SMH technology assessment decision. Sensitivity analyses occupy the next several sections. Section 4.3.7 explores how sensitive valuations for the SMH technology are to changes in discount rate. Section 4.3.8 details how re-entering patient flows impact the technology

*Part of the data reported in this chapter is reprinted with permission from "Deciding to Buy Expensive Technology: The Case of Biliary Lithotripsy." by Saul N. Weingart, 1995. *International Journal of Technology Assessment in Health Care*, 11(2), 301-315, Copyright [1995] by Cambridge University Press.

assessment for SMH. Finally, we conclude the Section by discussing how other possible scenarios for operations can be explored through simulation in section 4.3.9.

4.1 Literature Summary Highlighting Technology Assessment Inadequacies

This section summarizes the inadequacies we found in the literature of risk-based technology assessment.

One issue with the literature we reviewed in Section 2 was that many companies used inconsistent techniques to model the value of the technology involved. Kee et al. (1987), Kee and Robbins (1991), and Sekwat (1996) highlight the percentage of government entities that used simplistic methods such as break-even point (BEP) and benefit-cost ratio (BCR) to make capital budgeting decisions. Bierman and Smidt (2007) advocate using net present value (NPV) or internal rate of return (IRR) as they are consistent evaluation methods. Mukherjee and Henderson (1987) and Goodwin and Wright (2004) also deem NPV as a technique that is consistent with properties of expected utility theory.

Another concern with technology assessment is not accounting properly for risk. As Smith (1994) and Amirkhalili (1997) argue, relying only on one point estimate without incorporating uncertainty in capital budgeting models can lead to an erroneous decision. The Weingart (1995) case study illustrated this failure to adequately assess risk in purchasing new technology. Both Smith (1994) and Amirkhalili (1997) use spreadsheets to conduct simulations of the various costs and revenues for new investments. These sources develop distributions on the net present value, i.e., risk, for the investments.

Although many reviewed sources account for risk and give methods and techniques to incorporate risk in the capital budgeting decision process [(Smith, 1994), (White et al., 2010), (Amirkhalili, 1997)], none of the sources reviewed simulated the new technology through connecting its operations to its projected cash flow trajectories. Simulation is used or listed as a method to generate potential cost and revenue estimates in several sources

However, none of the literature sources cite modeling the operations of the system studied with the new technology.

The case highlighted in the next section, Section 4.2, illustrates how using estimates for a technology's value without considering uncertainty can lead to incorrect decisions. The purpose of the example is to demonstrate how one would use an axiomatically valid approach to risk-based technology assessment instead of the ineffective method explained in the reported case study.

4.2 Healthcare Technology Assessment Example: Strong Memorial Hospital

Weingart (1995) details the decision-making process for acquiring expensive medical technology at Strong Memorial Hospital (SMH), the teaching hospital of the University of Rochester School of Medicine and Dentistry. Hospital officials contemplated the purchase of a dual purpose biliary lithotripter, medical equipment used to shatter gallstones and/or kidney stones. The paper reflects on the learnings SMH administrators gleaned from the acquisition process. The task force assigned to gather information about the acquisition decision applied an incorrect method during the technology assessment. According to Weingart (1995), the task force members did not properly account for the role of risk in their decision to purchase the lithotripter. The task force appears to have relied on point estimates which did not account for risk when assessing the financial viability of the technology. As stated in the paper,

> The staff could have prepared estimates based upon alternate assumptions (e.g., best-case and worst-case scenarios) or they could have used net present value or rate of return calculations to make comparisons between lithotripsy and other acquisitions. Task force members' satisfaction with the estimates may reflect a lack of expertise among the clinical chiefs in this area or a viewpoint that financial considerations are more of a hurdle to be jumped than a

tool for decision making.

Lithotripsy technology entailed a patient immersed in a tub of water while sonic waves were emitted to burst gallstones into small fragments. The smaller fragments were expelled through a patient's urine. Administrators at Strong Memorial authorized a task force to study the candidate technology. The task force members sought out information about the technology. SMH had been very successful in implementing renal (kidney) lithotripsy, a similar technology to biliary lithotripsy. They gathered information from clinical trials conducted in Europe. These trials suggested that the technology was effective and widely successful in gallstone treatment. Manufacturers of biliary lithotripters presented information to the task force members as well. The task force decided to recommend one manufacturer because its technology was deemed superior due to patient safety, convenience, and cost. This manufacturer's equipment could be used to treat gallstones and kidney stones. The chosen lithotripter manufacturer also had available investigational sites which allowed Strong Memorial to apply for discounted equipment pricing. Instead of the $1.2 million retail price tag, Strong Memorial would pay only $650,000 for its lithotripter. An additional $100,000 was needed for space renovations. There was a projected yearly savings of over $133,000 from consumable materials factored in use of the biliary lithotripter instead of the previous equipment used exclusively for kidney stones. Task force members estimated that a demand of ninety-two biliary lithotripsy patients would bring in over $218,000 for each of the first two years, with a reimbursement rate of $2,308 per patient. Pending approval of the technology by the Food and Drug Administration (FDA), task force members projected a yearly net revenue of over $550,000 for the technology, with allocations for labor and other expenses, after the first two years. Income from Medicare was projected to account for over $461,000 of the net revenue after FDA approval.

Despite the promising projections, the biliary lithotripsy technology was considered a disaster. The lithotripter suffered many mechanical breakdowns. Patients considered the shock treatment painful. Technicians lowered the power of the shock waves to accommodate patients' concerns. However, the lowered power reduced the effectiveness of stone fragmentation. As a result, patients required additional treatments. Strong Memorial realized less than 0.15 of its projected demand for the lithotripter.

In the next section, we model the Strong Memorial operations with the lithotripter using our computational architecture. We demonstrate how incorporating risk and uncertainty into the assessment decision would have equipped the decision makers at Strong Memorial to make a more informed decision regarding purchasing the biliary lithotripter.

4.3 Modeling the Strong Memorial Lithotripter Operations

It seems that the task force members failed to recognize the impact that uncertainty had on the project's financial success. The projected yearly demand of ninety-two patients was an educated estimate based on seemingly reasonable ailment patterns and market analysis. However, the Weingart (1995) paper suggests that the SMH lithotripter task force did not account for the risk associated with the uncertain number of patients. The revenue for the hospital's proposed new technology was directly related to the number of patients treated at the facility. Any variances in the projected patient demand could vastly impact the financial viability of the technology. Another consideration that task force members seemed to overlook in assessing the lithotripter technology is the reliability of the technology. Task force members appeared to rely on the success of the European trials for the technology. SMH officials did not account for the risk associated with the lithotripter reliability. There was no risk analysis based on whether the lithotripter would operate properly or whether patients would adopt the new technology. Task force members apparently assumed that the operation of the lithotripter would be highly successful.

More information can be gained about the financial risk associated with Strong Memorial's technology assessment decision by modeling the hospital's operations with the biliary lithotripter. Use of the lithotripter technology is connected to the costs and revenues associated with its use. Assume that the equipment can be in one of two states, up and down. Suppose that the equipment operates for a random amount of time and then fails. Once the equipment fails, it gets repaired and becomes as good as new. The repair time is also random. The equipment continually cycles between the operational (up) state and the failed (down) state. Assume that an operator must be available for the equipment to function properly. The operator works for a period of time before becoming unavailable for an amount of time. The operator cycles between these states of availability and unavailability. The operations of the biliary lithotripter base model are similar to the example system detailed in Section 3 (section 3.5.2).

The base model assumes that patients enter the system at some given arrival rate. Patients are served when they enter the system if both the operator is available and the equipment is in the up state. If either of the resources (operator or equipment) is unavailable when a patient arrives for service, then the patient waits until the resource becomes available. Assuming a ten hour workday, twenty-five days per month and twelve months per year, there are 3,000 hours per year for the simulation model. Since Weingart (1995) did not specify a discount rate, 0% is assumed for the base model. Ramifications of the discount rate on the overall risk are explored using sensitivity analysis later. The financial data detailed in the paper (Weingart, 1995) were used as guides in setting parameter values within the simulation model. The next section details how we model the patient arrival process for the SMH system.

4.3.1 Modeling Patient Arrivals

One prominent variable in the SMH case was the number of patients that would use biliary lithotripsy. The task force studying the viability of the new technology did not seem to account for the uncertainty associated with the number of patients that would use this technology. One instance of the base simulation model generates the inter-arrival times between patients arriving to the system as exponentially distributed. The mean of the exponential distribution accounts for the mean time between arrivals. Each year is modeled in the simulation as 3000 hours. A patient arrival rate of 92 patients per year (the estimate given in Weingart (1995)) would then imply a mean interarrival time of approximately 32.6 hours between patients. To reflect a range of possible patient arrival patterns, the mean parameters for the arrival distribution were set to various levels. There were 261 experiments constructed that reflect the different levels for the patient arrivals to the hospital for lithotripsy treatments. The experiments include patient arrival rates that vary from an average of one patient per year to an average of 300 patients per year. The parameters for the experiments are given in Appendix A. Varying the patient interarrival times is important in modeling so that worst-case and best-case scenarios can be reflected in the overall technology assessment. Some traditional capital budgeting estimates rely only on one projection of the net present value for the new technology. The approach that accounts for risk in the arrival patterns gives a wider range of possible projections for the net present value used in the technology assessment. The base model assumptions for the lithotripter are given in Table 4.1.

Table 4.1: Base model assumptions

Simulation Run Time Duration	15,000 hours (Five years @ 3,000 hours per year)
Number of Experiments	261
Number of Replications per Experiment	1000
Interest Rate	0% effective, compounded yearly

Since the case does not list a particular discount rate, we assume a rate of 0% for the base case. Zero percent would be a best-case scenario regarding discount rate. Most capital equipment acquisitions would require a non-zero discount rate. We explore how discount rate changes affect the overall risk in section 4.3.7 below. In the following section, we explain how cash flows for the SMH lithotripter system and how technology lifetimes and repair times are generated and modeled in the simulation.

4.3.2 Modeling Projected Lithotripter Cash Flows and Technology Lifetimes

Cost and revenue parameters were modeled using the normal distribution. Estimated values for each cost or revenue given in Weingart (1995) were used as the mean of a normal distribution for each cost or revenue parameter modeled in the simulation. The standard deviation of each of these cost or revenue parameters was assumed to be five percent of their means. For example, the maintenance cost for the lithotripter was estimated at $75,000 per year. In the simulation, this cost is modeled as a normal distribution with a mean of 75000 and a standard deviation of 3750. The five percent assumption for the standard deviations is made to give some variation to the parameter estimates. Cost parameter values are summarized in Table 4.2, and revenue and cost savings parameter values are summarized in Table 4.3. There are two parameter values for the revenue gained from patient reimbursements. During the first two years of operating the lithotripter system, Strong Memorial Hospital expected to be reimbursed at a lower rate since the FDA had only approved of the lithotripter for trials. The hospital estimated that it could receive revenue of $2,380 per patient during years 1-2 using the biliary lithotripsy. Years three through five have higher reimbursement rates due to predicting the full FDA approval of the lithotripter and Medicare reimbursement. The Weingart (1995) case did not break down the additional reimbursement rate by patient, nor did the case project any changes in the number of lithotripsy patients seen each year. As a result, the estimated patient rate per year was unchanged. The reimbursement rate during years 3-5 was assumed to be $7,398 per patient. The patient reimbursement rate of $7,398 was computed by dividing the hospital's yearly projected Medicare reimbursement income of $461,652 by the expected yearly arrival rate (92 patients per year). This quotient, approximately $5,018, was added to the $2,380 projected revenue per patient from using biliary lithotripsy.

Table 4.2: Base model cost and expense parameters

Initial Equipment Cost ($)	Normal(650000, 37500)
Renovation Cost ($)	Normal(100000, 5000)
Equipment Maintenance Cost ($/year)	Normal(75000, 3750)
Employee Salaries ($/year)	Normal(80073, 4003.65)
Lithotripter Consumables Cost ($/year)	Normal(7050, 352.5)
Lost Cholecystectomy Revenue ($/year)	Normal(96864, 4843.2)

Table 4.3: Base model revenue and savings parameters

Patient Reimbursements (years 1-2)($/patient)	Normal(2380, 119)
Patient Reimbursements (years 3-5)($/patient)	Normal(7398, 369.9)
Consumables Savings ($/year)	Normal(133286, 6664.3)

For this base model, equipment lifetimes and repair times and operator available and unavailable times were all assumed to have uniform distributions. Equipment lifetimes were assumed to be in the range of 1 day (10 hours) to 1 year (3000 hours). Equipment repair times were also assumed to be in the range of 1 day to 1 year. The range of 1 day to 1 year incorporates uncertainty with the equipment. From the Strong Memorial Hospital case study, there were some years with no patients. The range on the equipment repair times allows for the equipment to break down for up to a year. This simulates the equipment being unavailable for up to a year. The equipment cycled between the states of working and in repair as illustrated in the example model given in section 3.5.2 and summarized above in section 4.3. The values for these time parameters are given in Table 4.4. The amount of time a patient would spend in service was modeled as a triangular distribution with mode of 50 minutes (0.8333 hours). The customer service time could range from 40-75 minutes (0.6666-1.25 hours). Patient service time data were based on estimated times from Lee et al. (1990) and Nealon et al. (1991) with similar lithotripter technologies. Operator available and unavailable times were assumed based on a reasonable work schedule for a simulated day. The operator would be available for some amount of time and have periodic breaks throughout the day. In the model, we assumed the operator was available from 9-11 hours. After each generated available time, the operator would be unavailable from 0.75-1.25 hours. Upon completion of an unavailable time, the operator would be available to work. The operator's availability and unavailability cycled back and forth between these two states. More detailed operator work procedures can be modeled if necessary.

Table 4.4: Lithotripter model equipment, operator, and service time assumptions

Equipment Lifetimes (hours)	Uniform(10, 3000)
Equipment Repair Times (hours)	Uniform(10, 3000)
Operator Available Times (hours)	Uniform(9, 11)
Operator Unavailable Times (hours)	Uniform(0.75, 1.25)
Patient Service Times (hours)	Triangular(0.8333, 0.6666, 1.25)

In the next section, we give a depiction of the computational architecture for the Strong Memorial Hospital. We describe the different modules and elements of the architecture in detail and explain how the elements influence the risk for the lithotripter.

4.3.3 Strong Memorial Lithotripter Computational Architecture

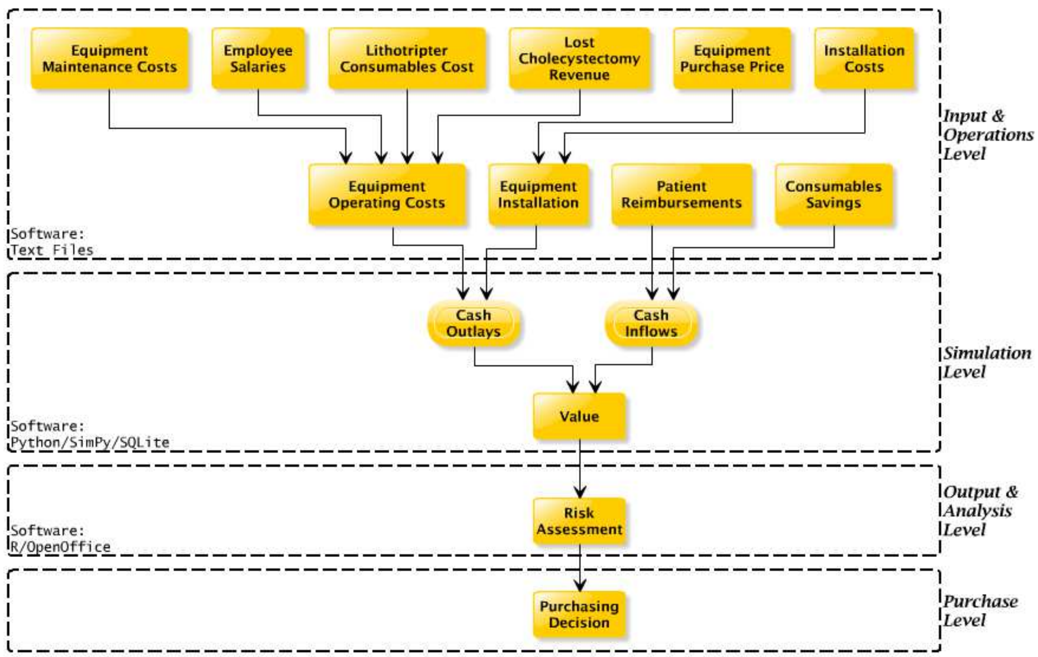

Figure 4.1: Computational architecture for the biliary lithotripter technology assessment at Strong Memorial Hospital

The computational architecture for the Strong Memorial Hospital lithotripter technology assessment is given in Figure 4.1. The expected SMH cash flows and activities related to those flows are reflected in the modules. The SMH computational architecture has four different levels similar to the generic architecture given in Figures 3.2 and 3.3. At the ***Input & Operations Level*** for the lithotripter technology assessment, there are four main cash flows–two cash inflows and two cash outlays. The two main cash inflows are the *Patient*

Reimbursements and the *Consumables Savings* from the current kidney stone equipment. The two main cash outlays are the *Equipment Installation* and *Equipment Operating Costs*. The two main cash outlays for Strong Memorial can be broken down to smaller, distinct outlay streams. The *Equipment Installation* can be divided into two outlays, *Equipment Purchase Price* and *Renovation Costs*. The *Equipment Operating Costs* can be divided into several other separate cash flow streams: *Equipment Maintenance Costs*, *Employee Salaries*, *Lithotripter Consumables Costs*, and *Lost Cholecystectomy Revenue*. Each of these projected cash flow streams were modeled in the simulation based on their projected schedule of occurring in the actual system. For example, the *Equipment Purchase Price* of $650,000 was modeled using a normal distribution with mean of 650000 and standard deviation of 32500. Since the initial equipment price is a one-time occurrence, this cash flow is generated only once for each simulation replication (i.e., run). Likewise, the *Renovation Costs* of $100,000 were modeled following a Normal(100000, 5000). Since Strong Memorial projected each of the operating costs to occur yearly, those costs were generated in the simulation on a yearly basis. The *Equipment Maintenance Costs* of $75,000 were generated at the beginning of each year. Since the simulation run time was for 5 years, these yearly costs were modeled at the beginning of the simulation run (time 0) and at the beginning of years 2-5. The other yearly costs and revenues for Strong Memorial include the following: *Employee Salaries*, *Lithotripter Consumables Costs*, *Lost Cholecystectomy Revenue*, and *Consumables Savings*.

Reimbursement cash flows are generated in the simulation as the patients finish lithotripter treatments. As explained in Section 4.3.2 above, the *Patient Reimbursements* module has a two-tiered structure. When patients complete service in the simulation, a patient revenue is generated based on the two-tiered structure. Patients treated throughout years 1 and 2 of the simulation produce revenue distributed as Normal(2380, 119) for the hospital. Patient reimbursements in years 3-5 are distributed as Normal(7398, 369.9).

Another piece of information at each level in Figure 4.1 is the software used to model the Strong Memorial technology assessment decision. At the ***Input & Operations Level***, text files were used to organize data from each of the modules presented in this level. The software used is listed in the bottom left portion of the dashed box denoted ***Input & Operations Level*** in Figure 4.1.

At the ***Simulation Level***, the information and data from the modules from the ***Input & Operations Level*** are incorporated in the *Cash Outlays* and *Cash Inflows* modules. The *Value* module represents the value put on the equipment. In the Strong Memorial simulations, net present value is used to measure the value of the equipment. In the simulation models, calculations are computed to obtain the net present value associated with each replication or run. The software packages used at this level include Python programming language, SimPy simulation package, and SQLite database package. Additional output to text files were used as well.

At the ***Output & Analysis Level***, the risk for the equipment is constructed. An empirical cumulative distribution function to characterize the risk is generated from the net present values input from the ***Simulation Level***. Charts, graphs, and other results are produced based on the output from simulation models. Statistical analysis is also done at this output level. The R statistical package and OpenOffice applications are employed to analyze the output at this level. These software tools are denoted at the ***Output & Analysis Level*** on Figure 4.1.

Finally, at the ***Purchase Level***, the decision is made to purchase the equipment or not. In the Strong Memorial Hospital context, the administrators would have to make the *Purchase Decision* regarding the biliary lithotripter.

After gathering all the data and information relating to the operations of the lithotripter, the information was used to model the operations for the lithotripter. Simulation was chosen to investigate the value and operational uncertainty of the lithotripter. The operational behavior for the lithotripter is connected to its potential revenue and cost projections in the simulation models. The open source discrete-event simulation software SimPy was used to model the operations for the Strong Memorial Hospital lithotripter system. The next section details the simulation modeling process using SimPy.

4.3.4 Simulation of the Strong Memorial Lithotripter Operations Using Python and SimPy

For the 261 experiments, 1000 replications of each experiment were run using SimPy, an open source, discrete-event simulation package (SimPy Developer Team). The same 1000 seeds were used in each of the experiments to seed the random number generator for the simulation package. Keeping the same seeds across the experiments insured that any differences in the outcomes were not due to randomness from the random number generator. This approach ensures sensitivity analyses focus on how sensitive the net present values are to changes in the different parameters. Each replication of an experiment produced a net present value for the proposed lithotripter. These net present values represent how much the investment in the biliary lithotripter would be worth using the parameters and assumed costs and revenues stated in the simulation model. The risk associated with the biliary lithotripter was found by using the empirical cumulative distribution function within the R statistical package.

There are several sections of the SimPy simulation models which are used to model the operations of the Strong Memorial Hospital lithotripter. These sections include the global data, model components, experiment data, and the model/experiment itself.

4.3.4.1 Global Data Section

The global data section includes information and variables that may be used in several model components. The advantage to using the global data is that multiple components can access to the data from global variables when changes or modifications of the global variables are made throughout the simulation run. One such global variable in the Strong Memorial Hospital lithotripter base model is a connection variable. The connection variable allows access to the databases that store output data generated throughout the simulation runs. Multiple instances of the connection variable are used in various places in the simulation model.

4.3.4.2 Model Components Section

The model components section includes the classes and functions that control the behavior of the entities in the simulation model. One important process method is the `Source` process. The `Source` process generates entities (customers, arrivals, etc.) randomly into the simulation system. The probability distribution used to generate entities is defined in a function under `Source` to propagate entities in the model until the simulation ends. One SimPy defined function in the `Source` process is the `activate`. SimPy's `activate` function instantiates each entity that is generated in the `Source` process. The `activate` function "gives life" to the entity. During the instantiation of the entity, `activate` calls a function from the process that governs the behavior of the entity. For example, in the SMH base model, customers (i.e., patients) arrive into the system and are "given life" by the `activate` function under the `Source` process. The `activate` function calls the function `use` under the `Customer` process.

Process `Customer` contains all the functions which controls any type of behavior that customers exhibit in the simulation model. The SMH base model `Customer` process contains the `use` function. This function models how customers use the SMH lithotripter system. When customer entities arrive into the system, they must grab access to both the operator and the lithotripter machine. If either resource is not available when the customer entity arrives into the system, then the customer must wait until both resources are available to proceed into processing. When both the machine and operator resources are available, then the customer is processed using them. The processing time is according to the patient service times distribution listed in Table 4.4. After a customer is processed then both resources are released to process other customers. When customers complete processing, the system accrues a random amount of revenue according to the simulation time and the reimbursement rates as listed in Table 4.3.

Another process in the SMH base model is the `Equipment` process. This process handles the breakdown and repair behavior for the lithotripter. When a machine instance is instantiated in the SMH model, the `operate` function under the `Equipment` process is called and activated. The `breakdown` function first generates an uptime for the machine according to the Equipment Lifetimes distribution listed in Table 4.4. The machine resource stays in the up state for this generated time. After the uptime has elapsed, the `breakdown` function then generates a downtime for the machine according to the Equipment Repair Times distribution also listed in Table 4.4. When the downtime for the machine has expired, the function then generates another uptime for the machine. The cycle of uptimes and downtimes continues until the simulation ends.

The `Operator` process in the SMH base model governs the behavior of the operator assigned to assist lithotripter patients. When an operator entity is instantiated in the SMH system model, the function `work` within the `Operator` process is activated. This function generates an available time for the operator entity according to the Operator Available Times distribution listed in Table 4.4. Throughout the available time, the operator is able to process any customer entities that arrive into the system. When the duration of the available time ends, the `work` function then is prompted to generate an unavailable time. The operator entity then changes state from available to unavailable for the length of the generated unavailable time variable. The unavailable time variables are generated according to the Operator Unavailable Times distribution listed in Table 4.4. The `Operator` process continues generating the cycles of available and unavailable times until the simulation ends.

The `YearlyCosts` and `YearlyRevenues` processes generate yearly cash flows for various costs and revenues, respectively, in the SMH base simulation model. The `YearlyCosts` process takes in parameter values from all of the recurring yearly costs. Strong Memorial Hospital provided yearly cost estimates for the operator salary, equipment maintenance, consumable materials to operate the lithotripter, and lost revenue from cessation of cholecystectomies. These parameter values are used to generate cost estimates according to a normal distribution. Since the estimates are yearly, at the end of each year, the function `generateCosts` generates a new value for each of the yearly costs according to each estimate's distribution. For example, the yearly equipment maintenance cost was estimated to be $75,000. Recall that a year of simulation time is equivalent to 3000 hours of system operation. Beginning at 3000 hours of simulated time in the model, the `generateCosts` function generates a yearly equipment maintenance cost for the lithotripter using a normal distribution with mean of 75000 and standard deviation of 3750. At successive multiples of 3000 hours (i.e., 6000, 9000, 12000, and 15000 hours) this function generates another estimate of the maintenance cost for those years. The process stops at the end of the simulation run (5 years = 15000 hours). The `generateCosts` process generates cost estimates for all yearly costs at the end of each year. When a cost estimate is generated, the overall net present value estimate is updated by subtracting the appropriately discounted yearly cost estimate. Readers may refer to Table 4.2 for a summary of all yearly cost distributions and parameters.

The `YearlyRevenues` process receives parameter values from the only recurring yearly revenues for the Strong Memorial Hospital, the savings for discontinuance of the Dornier renal lithotripter. Beginning at 3000 hours and at successive multiples of 3000 hours, the `generateRevenues` function under the `YearlyRevenues` process generates a yearly revenue estimate for consumables savings. The savings are modeled as a normal distribution with mean of 133286 and standard deviation of 6664.3 for the SMH base case simulation. After the yearly revenue estimates are generated, the overall net present value estimate is updated by adding the discounted yearly revenue estimate. Table 4.3 summarizes the yearly revenue distributions and for Strong Memorial.

4.3.4.3 Experimental Data Section

The experimental data section of a SimPy simulation model includes data for use in the various parts of a simulation model. In the case of the SMH simulation models, data were read in from text files for further use in the simulation models. All parameters and data for the various costs, revenues, operator, equipment and service times, and customer arrival information were included in this section. For example, for each of the 261 experiments for the SMH simulation model, this section reads in the mean time between customer arrivals from a text file containing the mean times.

4.3.4.4 Model/Experiment Section

The model/experiment section of a SimPy simulation model initializes the simulation model and model components. This section also defines the length of the simulation model run. The model portion governs the behavior of the simulation run. In the case of the SMH simulation models, the model/experiment section includes logic for the handling of all 261 experiments used in the simulation. One thousand replications or runs of the experiment are performed. Output data from each of the 1000 runs are gathered in database and/or text files for further analysis and processing. Between each run of an experiment, global variables are refreshed and initial model parameters and values are restored. A new seed is used with each experiment to randomize the generated values for the various costs, revenues, and times used in the simulation model. Across all 261 experiments, the same 1000 seeds are used to allow comparison of the results for those experiments. By using the same seeds, randomness from the generation of model parameters is avoided and distinctions between experiments are assured to be a result of differences between the variables that are changed and not because of randomly generated parameter values.

Results for the base simulation model are given in the next section. The results include a comparison using some of the data in Weingart (1995). We also compare the results from the base model to results gained from using incorrect assessment methods.

4.3.5 Base Model Results

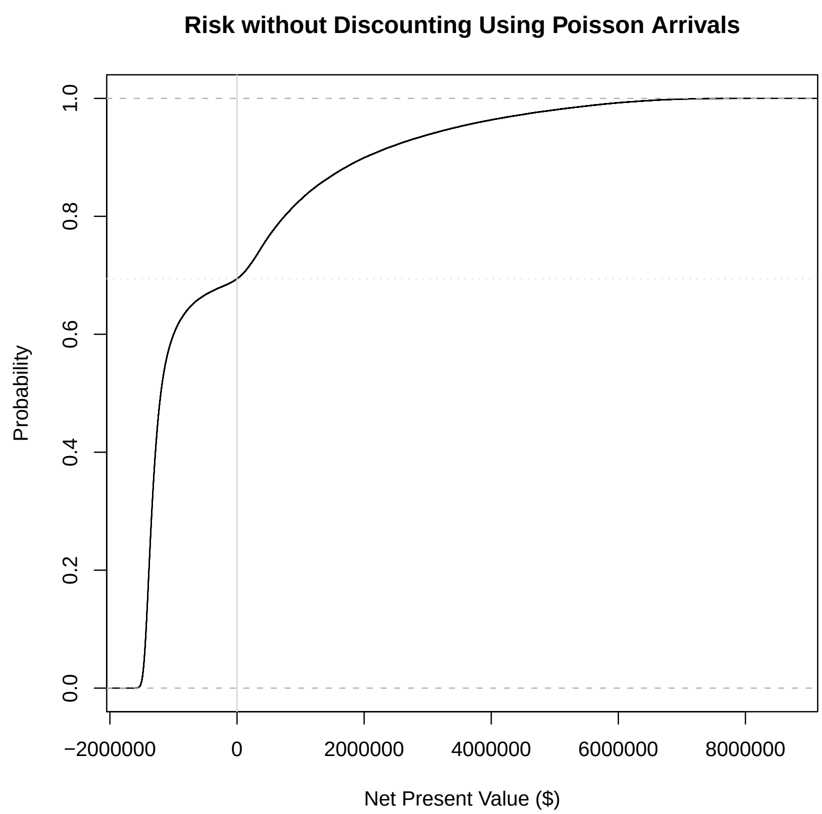

Figure 4.2: Risk associated with purchasing the biliary lithotripter without discounting

Figure 4.2 gives the risk associated with purchasing the biliary lithotripter (i.e., cumulative distribution function of the NPV) using the assumptions and parameters summarized in Tables 4.1, 4.2, 4.3, and 4.4. Note that using the set of parameters and assumptions made with this particular model, the lithotripter seems far less profitable than the analysis presented in the Strong Memorial Hospital case. There is a probability of 0.69 that the simulated net present values for the lithotripter are negative after a five-year horizon. Including the initial cost of $650,000 for the purchase of the lithotripter and the $100,000 building upgrades, Strong Memorial's projection for the net present value of the lithotripter would be about $1,101,251, after five years of operation. There is a probability of about 0.84 that the investment will be less than or equal to the projected value of $1,101,251. The next section details how different financial measures might have influenced the Strong Memorial decision to purchase the lithotripter if different measures had been used.

4.3.6 Exploring Financial Measures

As discussed earlier in the literature review section, many companies use different financial measures to make capital budgeting decisions. However, many of these measures are not consistent with normative axioms. We use the Strong Memorial Hospital data to illustrate that using these measures can lead to erroneous decisions.

Previous surveys including Block (1997) and Runyon (1983) note that several small firms used break-even point analysis to determine their capital budgeting needs. If Strong Memorial had calculated the payback period (PBP) or break-even point (BEP) for the investment using the base model assumptions without accounting for risk or variation in the revenue, cost, or parameter estimates (i.e., only using the mean values), then the BEP would be approximately 3.09 years. However, when computing the BEPs for each of the 261,000 NPV point estimates, the probability that point estimates completed the entire five-year simulation run horizon without breaking-even is 0.68. The net present value for these point estimates stayed negative throughout the length of the simulation. Using 5 years as the break-even point for these negative point estimates, the mean BEP is just over 4.36 years for the investment to reach a value of zero. However, this mean BEP is not accurate because the point estimates that remained negative were encoded as breaking even after 5 years. Excluding the five-year point estimates, the average BEP was just over 2.98 years. However, the average BEP that excludes the five-year point estimates is optimistic, too, as 600 of the data points in Figure 4.2 are generated from experiments where average patient arrival rates are over twice the average of 92 patients per year that Strong Memorial projected it would treat. Since more patient arrivals directly translate to more revenue, then the higher the yearly arrival rate, the higher the revenue will be, when all other parameters are held at the same levels. The high patient arrival rate may not be realistic to the number of patients Strong Memorial expected to treat using the lithotripter.

Another financial measure highlighted in the literature is the accounting rate of return (ARR). The ARR takes the ratio of the average net income to the average investment as shown in (4.1).

$$\text{ARR} = \text{Average net income}/\text{Average investment} \tag{4.1}$$

There are several variations on ARR computations. We use the definition of average net income as the average profit, i.e., the average revenue less the average cost. The average investment is defined as the average of the sum of the book value of an investment at the beginning of year 1 and the book value of the investment at the end of its useful life, i.e.,

$$\text{Average Investment} = (\text{Book Value in Year } 1 + \text{Book Value at End of Life})/2 \tag{4.2}$$

For the average profit, we use the estimated profit that Weingart (1995) cited for the Strong Memorial Hospital case. The lithotripter task force members expected the technology to net an average of \$93,259 for the first two years of operations. In successive years, the lithotripter would bring in approximately \$554,911 after FDA approval. We assume the lithotripter purchase price of \$650,000 to be the book value for the investment in the first year. In the Strong Memorial Hospital case there was no indication of the salvage value of the lithotripter after 5 years. We calculate the ARR using two extremes for the book value at the end of useful life for the lithotripter: the original book value in year 1 of \$650,000, and a \$0 salvage value. Then for a time period of five years, we calculated the accounting rate of return. When the end of useful life is \$650,000, we have the following:

$$
\begin{aligned}
\text{ARR} &= \frac{\text{Average Profit}}{\text{Average Investment}} && (4.3)\\
&= \frac{\sum_{i=1}^{5} P_i}{\frac{BV_0+BV_5}{2}} && (4.4)\\
&= \frac{2(93,529)+3(554,911)}{\frac{650,000+650,000}{2}} && (4.5)\\
&= 2.85 && (4.6)
\end{aligned}
$$

where P_i represents the average profit in year i and where BV_0 and BV_5 denote the book value of the investment at the *beginning* of the first year and the *end* of the fifth year, respectively. The ARR is 2.85 for this system.

If a zero salvage value is used instead to compute the end of useful life, then the ARR is 5.70:

$$
\begin{aligned}
\text{ARR} &= \frac{\text{Average Profit}}{\text{Average Investment}} && (4.7)\\
&= \frac{\sum_{i=1}^{5} P_i}{\frac{BV_0+BV_5}{2}} && (4.8)\\
&= \frac{2(93,529)+3(554,911)}{\frac{650,000+0}{2}} && (4.9)\\
&= 5.70 && (4.10)
\end{aligned}
$$

These ARR values imply that for every dollar invested in the lithotripter, Strong Memorial can expect to return anywhere from \$2.85 to \$5.70, depending on the salvage value of the lithotripter. Relying on this measure would give a very optimistic viewpoint on the lithotripter investment, giving an impression that the company can make almost 3-6 times the initial investment in the technology.

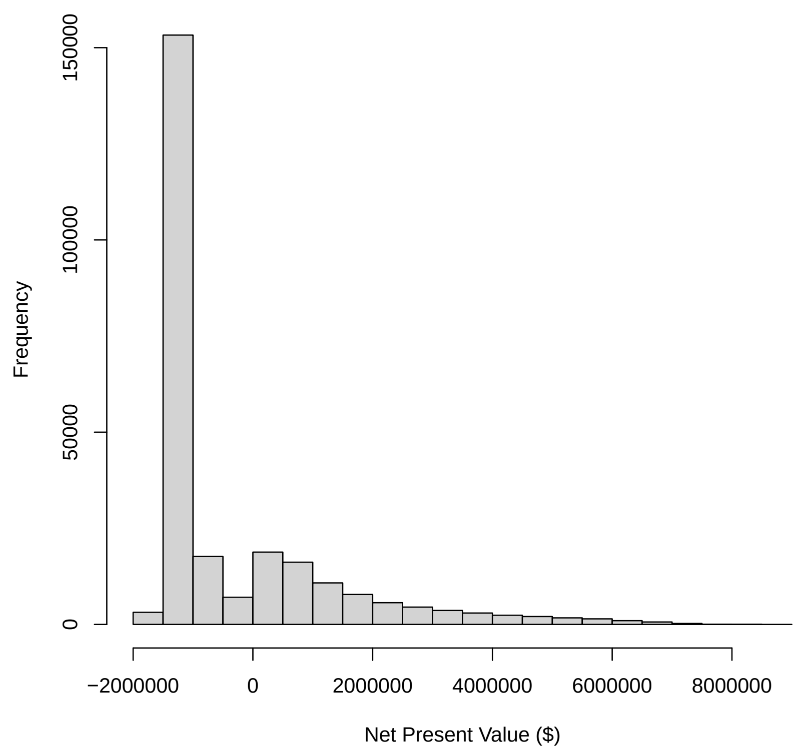

Figure 4.3: Histogram of the net present value point estimates associated with purchasing the biliary lithotripter without discounting

Although the investment seems to be profitable, there is a significant probability for the investment to lose money after a five-year simulation period. The distribution on the net present value ranges from approximately -\$1,636,000 to about \$8,722,000. Figure 4.3

displays a histogram of the net present value point estimates. There are over 153,000 net present value points in the histogram bin range of [-1,500,000, -1,000,000) of Figure 4.3. The probability that a simulated point estimate falls in this bin is 0.58. The steep slope in risk depicted in Figure 4.2 before the net present value reaches the $0 mark is explained by the large number of estimates that populate this bin. Further analysis of the investment reveals that the average net present value is just less than -$310,000. For the 261,000 simulated net present value point estimates, the median value is approximately -$1,199,000. Based on this simulation model, the probability of the simulated NPVs being negative is about 0.69. According to Weingart (1995), Strong Memorial Hospital projected a yearly net revenue of over $550,000 after FDA approval. However, the results from the base simulation model show a different view on projected revenue. Under the base model assumptions, the probability that the lithotripter will *lose* the hospital over $550,000 after five years of operation is over 0.66. The probability that SMH would capture at least the estimated $1,101,251 projection is only around 0.16. Would the Strong Memorial Hospital board approve of the lithotripter if there was a probability of 0.69 of losing the money invested? For example, a risk-neutral decision maker "does not care about risk and can ignore risk aspects of the alternatives that he or she faces" (Clemen and Reilly, 2001). The utility function for a risk-neutral decision maker is linear. Hence, maximizing expected utility is the same as maximizing the expected monetary value of the technology alternative (Clemen and Reilly, 2001). For the SMH biliary lithotripter case, the estimated expected net present value of the technology from the simulated NPVs is a about -$310,500. This implies that the decision to purchase the lithotripter would not have been made for the risk-neutral decision maker. We chose to consider the risk-neutral decision maker because he or she is the least risk-averse decision maker we could have. A more risk-averse decision maker is even more likely to reject this investment. Although this approach does not guarantee firms the best possible *outcome* (which can never be guaranteed for risky capital equipment acquisition decisions), it does guarantee that the best *bet* will be made. It is important that small firms follow a risk-based, prescriptive approach. This type of approach conforms to accepted expected utility theory. Since there is no way to repeat the trials for these one-off bets, there is no way to verify if the decision made is the "right" one. When decision makers choose not to abide by the axioms of expected utility, they expose themselves to decisions that may defeat the purpose of maximizing utility.

The following procedure taken from Law (2007) is used to find point estimates and confidence intervals for the mean of each of the 261 experiments. Assume that n independent replications of a terminating simulation are made. Let X_j be a random variable for the j^{th} replication with $j = 1, 2, \ldots, n$. Further assume that the random variables $X_1, X_2, \ldots, X_n$ are independently and identically distributed with finite population mean and population variance, μ and σ^2, respectively. Let $\bar{X}(n)$ denote the sample mean of the random variables. Then the sample mean is calculated as follows:

$$\bar{X}(n) = \frac{\sum_{i=1}^{n} X_i}{n} \tag{4.11}$$

Let $S^2(n)$ denote the sample variance of the random variables. The sample variance is calculated as the following:

$$S^2(n) = \frac{\sum_{i=1}^{n} \left[X_i - \bar{X}(n)\right]^2}{n-1} \tag{4.12}$$

Estimators $\bar{X}(n)$ and $S^2(n)$ are unbiased estimators of μ and σ^2, respectively, i.e., $E[\bar{X}(n)] = \mu$ and $E[S^2(n)] = \sigma^2$. Using different random generator seeds for each replication allows for independence of the random variable produced during each replication. When $X_j's$ are normal random variables, then a random variable t_n that has a t distribution with $n-1$ degrees of freedom can be defined as follows:

$$t_n = [\bar{X}(n) - \mu] / \sqrt{S^2(n)/n}. \tag{4.13}$$

When the sample size $n \geq 2$, a $100(1-\alpha)$ percent t confidence interval for μ can be constructed using the following equation

$$\bar{X}(n) \pm t_{n-1,1-\alpha/2}\sqrt{\frac{S^2(n)}{n}}. \tag{4.14}$$

The value $t_{n-1,1-\alpha/2}$ represents the upper $1-\alpha/2$ critical value for the t distribution with $n-1$ degrees of freedom. The product added or subtracted from $\bar{X}(n)$ in the t confidence interval is the half-length of the confidence interval.

For the 261 experiments used in the lithotripter base model, fifty replications or runs of each of the experiments were conducted. A different random number generator was used for each replication. During each replication, a net present value was generated. For each experiment the mean NPV of the fifty generated NPVs is found. Confidence intervals are found for each of the mean NPVs by using a 90% t confidence level. Consider the experiment with an average patient interarrival rate of 1 patient every 32.5 hours (Experiment # 45 in Appendix A). This experiment corresponds to a yearly average of 92 patients per year, which is the patient rate SMH considered when assessing its purchase of the biliary lithotripter. The mean NPV of this experiment is -$136293, and the 90% confidence interval is (-$159155, -$113431). Appendix B gives the list of mean NPV values and the lower and upper confidence bounds for each of the 90% confidence intervals for each experiment.

Another thing to consider from the base model is that the operational parameter assumptions are generally optimistic. The assumption that there is no discount rate does not account for the time value of money in these projections. In the Weingart (1995) case, there is an implication that some patients had to come back for subsequent visits due to the treatment efficacy. Patients encountered pain and lithotripter operators had to reduce the intensity of the treatment due alleviate patients. However, gallstones and/or kidney stones were not effectively shattered to allow for safe passage from patients. The reduction of intensity meant that patients had to return for more treatments. This operational phenomenon can be modeled and analyzed through simulation.The system can be stressed by changing these parameters and/or modeling these situations to assess how the net present value would be affected. The next several subsections explore different modifications to the base model. Sensitivity analyses are conducted on several parameters to show how changes to these different parameter levels would affect the risk for the lithotripter. The next section, Section 4.3.7, explores what happens when discount rates are incorporated in the valuation of the investment. In Section 4.3.8, a system where patients have to re-enter the system to complete multiple treatments is studied. The impact of patient re-entry and loss on the risk is shown.

4.3.7 Sensitivity to Discount Rates

One consideration that is not addressed in the case study is the discount rate that is used for the net present value calculations. When the discount rate is not incorporated into computations, the firm can have an unrealistic view on the amount of the risk. Figure 4.4 displays the risk associated with the lithotripter under different discount rates. The same 261 experiments were used from the previous base case model. The varying parameter was the discount rate. Note the difference in the expected net present values and the risk when the discount rates are changed. The risk with no discount rate is displayed along with the risk when the discount rate is 2%, 4%, 6%, 8%, 10%, 12%, 14%, respectively. A vertical reference line at the $0 value delineates the portions of the risk curves where

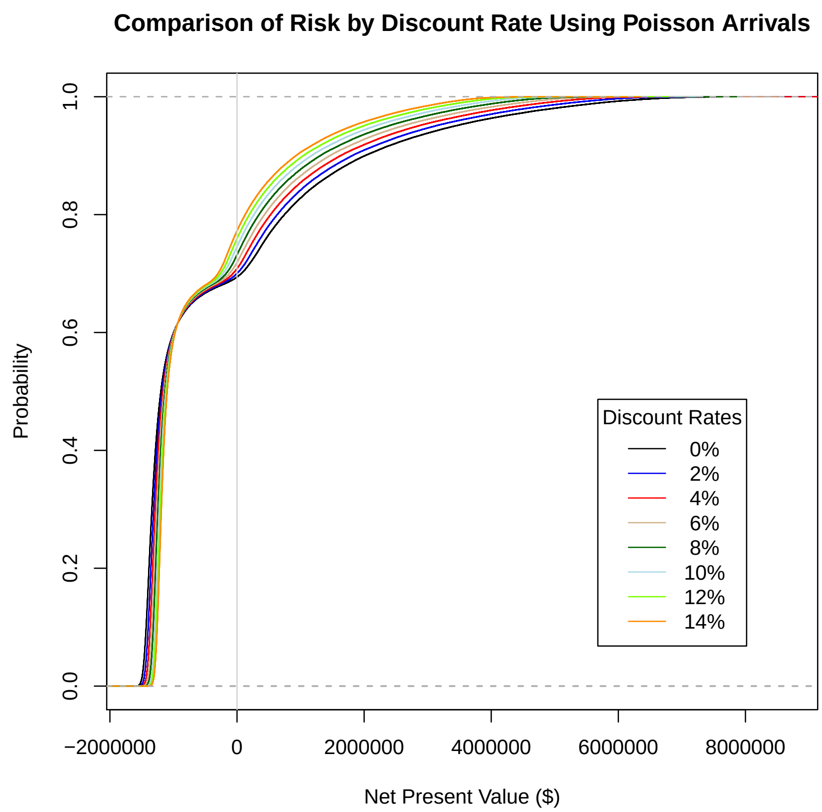

Figure 4.4: Risk associated with purchasing the biliary lithotripter with various discount rates (0%-14%, by 2%)

the investment is negative or positive. The percentage of positive NPVs by discount rate declines as the discount rate increases. Table 4.5 summarizes the average investment net present values and percent of positive net present values by discount rate. The average net present values get more negative as the discount rate increases. The number of net present value point greater than zero decreases with an increase in the discount rate.

Figure 4.5 displays the risk associated with the lithotripter using different discount rates of 0%, 5%, 10%, 15%, 20%, 25%, and 30%. As before, the same 261 experiments were used from the base case model. The probability of negative NPVs ranges from 0.68 when there is no discount rate used to over 0.86 when there is a 30% discount rate for

Table 4.5: Comparison of net present values by discount rate

Discount Rate (%)	Average NPV ($)	Percent(%) NPVs ≥ 0
0	-310,500	30.6
2	-354,200	30.0
4	-393,700	29.2
6	-429,400	28.1
8	-461,800	26.8
10	-491,100	25.5
12	-517,800	24.1
14	-542,200	22.8

the revenues and costs associated with the equipment. Table 4.6 summarizes the average investment net present values and percent of positive net present values by discount rate from Figure 4.5. Again, the general trend for the average net present values holds here as in the comparison in Table 4.5, i.e., as the discount rate increases, the average NPV decreases.

Table 4.6: Summary of discount rates with corresponding average NPVs and percentage of positive NPVs

Discount Rate (%)	Average NPV ($)	Percent(%) NPVs ≥ 0
0	-310,500	30.6
5	-412,000	28.6
10	-491,100	25.5
15	-553,500	22.1
20	-603,300	19.1
25	-643,300	16.5
30	-675,800	14.2

In the next section, we explore the relationship between multiple treatments with the

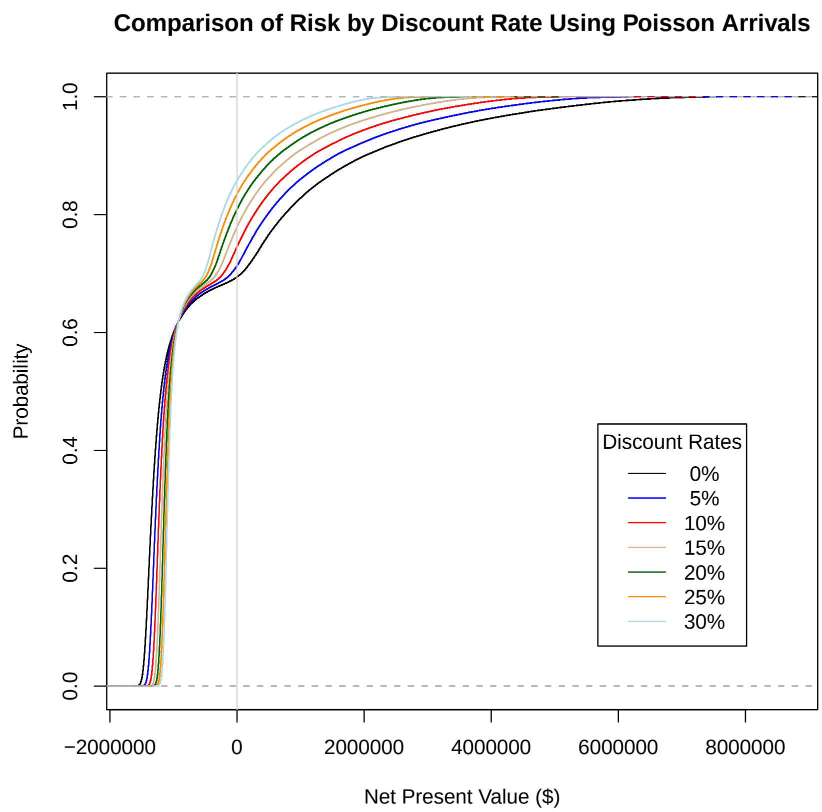

Figure 4.5: Risk associated with purchasing the biliary lithotripter using various discount rates (0%-30%, by 5%)

overall risk for the lithotripter. One of the issues encountered by the Strong Memorial Hospital lithotripter case (Weingart, 1995) was patients who experienced unbearable pain during the shock wave treatments. Lithotripter operators had to decrease the treatment intensities which resulted in incomplete kidney stone or gallstone fragmentation. Therefore, follow-up treatments were required. Re-entering customer flows for SMH and their impact on investment value are approached in the following section.

4.3.8 Sensitivity to Re-entering Flows

One other important concern for the biliary lithotripsy operations was the intensity of the shock waves administered during treatments. Several patient complaints about the pain encountered during treatment led to lowered intensity of the shock waves. The lower intensity levels were less effective in breaking up the kidney stones or gallstones. As a result, patients needed to have more treatments. However, the hospital had trouble getting patients to come back for successive treatments. One way to incorporate this phenomenon into the model is through re-entrant flows. Assume that a certain percentage of patients will have to re-enter the system to undergo additional treatment. When patients complete treatment after the first or second service encounter, then the hospital accrues revenue for these patients. However, if a re-entering patient is selected for a third treatment, then that patient is lost and will not re-enter the system. The hospital gains no revenue for lost patients.

In the re-entering experiments, simulation parameters were set at the base case parameter values. The only factor that was varied in these experiments is the percentage of patients that were lost after each service encounter. It is assumed that each patient would enter at most twice for service. At the end of the first service encounter, there is a probability that the patient will have to re-enter the system again due to ineffective treatment of the gallstone or kidney stone. The re-entering probability is generated randomly using a uniform (0,1) distribution. If the patient must re-enter service, then there is a delay of at least a day before the patient is allowed to be served again. At completion of the second service encounter, patients face a certain probability that the gallstone or kidney stone was not adequately busted. If patients do not complete service after the second service encounter, then those patients are lost. Again, this probability is generated randomly using a uniform (0,1) distribution. Figure 4.6 displays a comparison of the effect that re-entering and/or lost patients have on the risk.

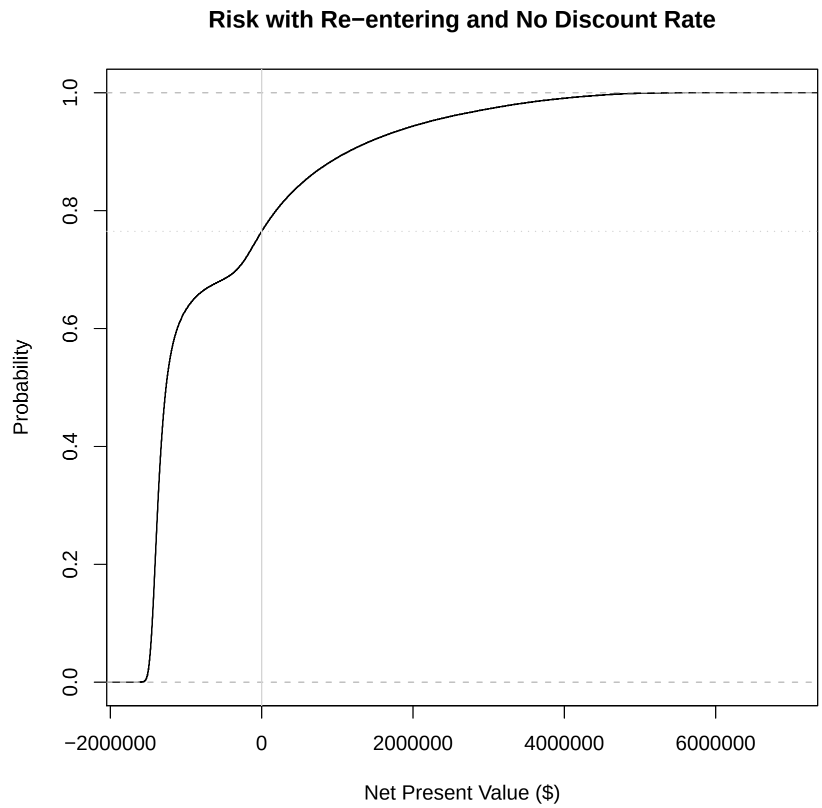

Figure 4.6: Risk associated with purchasing the biliary lithotripter with patient re-entering

The probability of negative NPV points is greater with the re-entering experiments than in the base case simulation experiments. There is a probability of 0.765 that the simulated NPV values for the re-entering system are below \$0. The base case simulation results presented earlier in Section 4.3.5 showed that there is a probability of about 0.69 that simulated NPV values are less than \$0. In the Strong Memorial Hospital lithotripter case study, there was an assumption that the efficacy of the European trials of the lithotripsy technology would be repeatable in the United States. Unfortunately, the technology was apparently uncomfortable for patients in the United States. Simulation models that incorporate potential patient behavior which impacts usage of the technology are beneficial in assessing the affect on the overall risk for the technology.

4.3.9 More Simulation Scenarios

Over the last several sections, the sensitivity analyses were conducted by changing only one parameter at a time to see the effect that change would have on the overall risk. More scenarios can be analyzed by varying more than one parameter at a time to determine the effect on the risk. For instance, if the decision makers at Strong Memorial Hospital decided that the discount rate should be say, 5%, rather than 0% and that they wanted to focus on scenarios with more unreliable equipment and impatient patients, then corresponding parameters could be changed and modeled all at once. The object oriented nature of modeling with SimPy and Python allows for easy customization of possible scenarios for the technology assessment.

5. CONCLUSION AND FUTURE WORK

Small firms and businesses have limited budgets for capital expenditures. This dissertation provides an analytical framework and a computational strategy to support capital equipment budgeting in firms where the value of candidate technologies can represent nearly all the firm's value. The analytical framework employs a straightforward, objective approach that appeals to well established principles in economics, finance and decision making. Our approach relies on utility theory to determine the candidate technology having the most preferred risk. Deficiencies associated with other subjective capital budgeting methods and procedures are explored. Characterizing a technology's value as a function of fixed and operational costs through discrete-event simulation directly ties use of the new technology with the finances of the organization. When analyzing the risk for a given technology, a probability law is assigned to the value of the new technologies. It is this characterization of risk that is required when appealing to the expected utility theorem: the foundational principle underlying our analysis and methods.

The computational strategy for this research employs software and tools that allow highly customizable simulation modeling. The modularity of the computational architecture allows for a straightforward formulation of simulation models. Our approach obviates the need for generic models that do not address the unique operational features that direct technology value for small firms. All of our analyses rely only on free, open source software applications. This shows that small firms need not invest a lot of money in software tools to correctly, effectively and systematically evaluate and assess new technologies.

The analytical framework and computational architecture was applied to a technology assessment at a research hospital. The application used data from a previously published study on the hospital's decision to purchase new equipment to treat gallstones and kidney stones. The objective of the example was to illustrate how small firms could use an axiomatic approach to technology assessment. Projected use of the new equipment with the equipment's expected cash flows was simulated using Python and SimPy software packages. The net present value of the equipment was found using the projected cash flows. Several scenarios were studied for the use of the technology. The risk for the new equipment was found by constructing a distribution on the net present value estimates. With the parameters used in the simulation, there was a probability of 0.69 that the value projections were unprofitable. The probability that the projections met or exceeded the healthcare facility's original financial projections was only 0.16. The application highlighted the danger in relying on only one point estimate for the assessment of new technology. The example also showed that relying on non-discounted cash flow measures, such as the payback period or the accounting rate of return, for determining the profitability of new technology can be erroneous. The impact that machine reliability and customer behavior have on risk were also studied.

Future directions for this research could include the impact that income taxes and depreciation strategies have on the risk of new technologies. Tax implications and different depreciation techniques could influence the cash flows on the small businesses. Investments in insurance can also affect the viability of the new technology. These cash flow impacts can be explored in the simulation models. Studying how valuable technology risk information is to decision makers would be another future research direction.

Although the healthcare example presented in Section 4 focuses on a research hospital, many other types of health care facilities and organizations can benefit from this research when considering the purchase of new technologies. One possible application of risk-based technology assessment in healthcare may be in the adoption of telemedicine and/or home health monitoring equipment. Health care providers can explore the impact these potential technologies would have on revenues and costs associated with their organizations by simulating the use of equipment in patients' homes. In addition to health care providers, governmental health agencies and policymakers would benefit from this research. Results from this research can be used to target proposed legislation and policies to reduce redundant health care costs and make the health care system more efficient.

Health care is only one of several industries that may benefit from this risk-based technology assessment. Alternative energy companies or investors may use this research to evaluate various technologies available to them. One example could be assessing different battery technologies for applications in hybrid or electric vehicles. Electric car manufacturers have to assess the likelihood that various battery technologies would be beneficial to their companies. This research would give a detailed view on evaluating the different battery/energy storage technologies. Wind and solar energy resource companies could also use this research to evaluate potential technologies.

Another important issue in small firm technology assessment is the availability of financing for capital equipment purchases. In Block (1997), the author highlights that "smaller firms have less access to public capital markets and fewer alternatives overall than larger firms." Not only can small business owners benefit in using this computational approach and research, but capital investors would gain insight into the riskiness of their potential investments. In particular, banks and credit unions could enhance their lending practices by exploring the risk of their prospective borrowers' loans. Technology venture capitalists could also use the computational architecture to help identify which investments are appropriate based on the capitalists' utility.

REFERENCES

Reza Amirkhalili. Risk and Capital Budgeting. *AACE International Transactions*, pages 80–83, 1997.

J. Banks, J. S. Carson, and B. L. Nelson. *Discrete-Event System Simulation*. Prentice Hall, Upper Saddle River, NJ, 1996.

Robert G. Bartle. *The Elements of Real Analysis*. John Wiley & Sons, New York, 1976.

David E. Bell, Howard Raiffa, and Amos Tversky. Descriptive, Normative, and Prescriptive Interactions in Decision Making. In D.E. Bell, H. Raiffa, and A. Tversky, editors, *Decision Making: Descriptive, Normative, and Prescriptive Interactions*, chapter 1, pages 9–30. Cambridge University Press, New York, 1988.

J. Eric Bickel. Some Determinants of Corporate Risk Aversion. *Decision Analysis*, 3(4): 233 – 251, 2006.

Harold Bierman, Jr. and Seymour Smidt. *The Capital Budgeting Decision: Economic Analysis of Investment Projects*. Routledge, New York, 2007.

David M. Bishai, Daron G. Ferris, and Mark S. Litaker. What Is the Least Costly Strategy to Evaluate Cervical Abnormalities in Rural Women? Comparing Telemedicine, Local Practitioners, and Expert Physicians. *Medical Decision Making*, 23(6):463–470, 2003.

Stanley Block. Capital Budgeting Techniques Used by Small Business Firms in the 1990s. *The Engineering Economist*, 42(4):289–302, 1997.

David G. Carmichael and Maria C. A. Balatbat. Probabilistic DCF Analysis and Capital Budgeting and Investment - a Survey. *Engineering Economist*, 53(1):84 – 102, 2008.

Robert Clemen and Terrence Reilly. *Making Hard Decisions with DecisionTools®*. Duxbury, Pacific Grove, CA, 2001.

Raisa Deber, Mary Wiktorowicz, Peggy Leatt, and François Champagne. Technology Acquisition in Canadian Hospitals: How Is It Done, and Where Is the Information Coming From? *Healthcare Management Forum*, 7(4):18 – 27, 1994.

Raisa Deber, Mary Wiktorowicz, Peggy Leatt, and François Champagne. Technology Acquisition in Canadian Hospitals: How Are We Doing? *Healthcare Management Forum*, 8(2):23 – 28, 1995.

Greg Filbeck and Sharon Lee. Financial Management Techniques in Family Businesses. *Family Business Review*, 13(3):201–216, 2000.

P. Goodwin and G. Wright. *Decision Analysis for Management Judgment*. John Wiley & Sons, West Sussex, England, 2004.

Ronald A. Howard. Decision Analysis: Applied Decision Theory. In D.B. Hertz and J. Melese, editors, *Proceedings of the Fourth International Conference on Operational Research*, pages 55–71. Wiley-Interscience, New York, 1966.

Robert Kee and Walter Robbins. Capital Budgeting in the Public Sector: A Comparative Analysis. *Journal of Managerial Issues*, 3(3):288–302, 1991.

Robert Kee, Walter Robbins, and Nicholas Apostolou. Capital Budgeting Practices of U.S. Cities: A Survey. *The Government Accountant Journal*, 63:16–22, 1987.

Günter Last and Andreas Brandt. *Marked Point Processes on the Real Line: the Dynamic Approach*. Springer-Verlag, New York, 1995.

Averill M. Law. *Simulation Modeling and Analysis*. McGraw-Hill, New York, 2007.

S. H. Lee, J. S. Fache, and H. J. Burhenne. The Value of Extracorporeal Shock-Wave Lithotripsy in the Management of Bile Duct Stones. *American Journal of Roentgenology*, 155(4):775–9, 1990.

Emanuele Lettieri, Cristina Masella, and Umberto Nocco. Budgeting and Health Technology Assessment: First Evidence Obtained from Proposal Forms Used to Submit the Adoption of New Technology. *International Journal of Technology Assessment in Health Care*, 24(4):502–510, 2008.

Gary A. Luoma. *Accounting Information in Managerial Decision-making for Small and Medium Manufacturers*. National Association of Accountants. Research Monograph No. 2. National Association of Accountants, New York, 1967.

Norm Matloff. Introduction to Discrete-Event Simulation and the SimPy Language. 2008. URL `http://heather.cs.ucdavis.edu/~matloff/156/PLN/DESimIntro.pdf`.

Tarun K. Mukherjee and Glenn V. Henderson. The Capital Budgeting Process: Theory and Practice. *Interfaces*, 17(2):78–90, 1987.

National Bureau of Economic Research. US Business Cycle Expansions and Contractions. Technical report, 2010. URL `http://www.nber.org/cycles/US_Business_Cycle_Expansions_and_Contractions_20120423.pdf`. Accessed May 14, 2012.

W. H. Nealon, F. Urrutia, D. Fleming, and J. C. Thompson. The Economic Burden of Gallstone Lithotripsy: Will Cost Determine Its Fate? *Annals of Surgery*, 216(6), 1991.

Jee Hyuk Park. *On the Separation of Preferences among Marked Point Process Wager Alternatives*. PhD thesis, Texas A&M University, College Station, TX, 2008.

C. D. Pegden, R. E. Shannon, and R. P. Sadowski. *Introduction to Simulation Using SIMAN*. McGraw-Hill, New York, 1995.

R Development Core Team. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria, 2011.

L. R. Runyon. Capital Expenditure Decision Making in Small Firms. *Journal of Business Research*, 11(3):389 – 397, 1983.

Paul J. H. Schoemaker. The Expected Utility Model: Its Variants, Purposes, Evidence and Limitations. *Journal of Economic Literature*, 20(2):529–563, 1982.

Alex Sekwat. The Use of Capital Budgeting Decision Models by County Governments: A Survey. *State and Local Government Review*, 28(3):180–192, 1996.

SimPy Developer Team. SimPy Homepage. Accessed April 30, 2009. URL `http://simpy.sourceforge.net/`.

D. J. Smith. Incorporating Risk into Capital Budgeting Decisions Using Simulation. *Management Decision*, 32:20–26, 1994.

Mary Ellen Uphoff and Dale Krane. Hospital-based Technology Assessment: Essential Questions and an Operational Model. *Public Productivity & Management Review*, 22 (1):60–70, 1998.

U.S. Census Bureau. 2009 Annual Capital Expenditures Survey, 2011a. URL `http://www.census.gov/econ/aces/xls/2009/full_report.html`. Accessed July 29, 2011.

U.S. Census Bureau. 2011 Capital Spending Report. Technical report, 2011b. URL `http://www.census.gov/econ/aces/report/2011/capitalspendingreport2011.pdf`. Accessed July 29, 2011.

J. Von Neumann and O. Morgenstern. *Theory of Games and Economic Behavior: 3rd Ed*. Princeton University Press, Princeton, NJ, 1953.

Dave Watts, Donna L. Finney, and Brian Louie. Integrating Technology Assessment into the Capital Budgeting Process. *Healthcare Financial Management*, 47(2):20–4, 26, 28–9, 1993.

Saul N. Weingart. Acquiring Advanced Technology: Decision-making Strategies at Twelve Medical Centers. *International Journal of Technology Assessment in Health Care*, 9(4):530–538, 1993.

Saul N. Weingart. Deciding to Buy Expensive Technology: The Case of Biliary Lithotripsy. *International Journal of Technology Assessment in Health Care*, 11(2): 301–315, 1995.

John A. White, Kenneth E. Case, and David B. Pratt. *Principles of Engineering Economic Analysis*. John Wiley & Sons, New York, 2010.

David Williams. *Probability with Martingales*. Cambridge University Press, Cambridge, UK, 1991.

APPENDIX A

EXPONENTIAL DISTRIBUTION ARRIVAL PARAMETERS

The parameters for the patient arrival distributions in the healthcare example are given in the tables below. Some of the experiments for the healthcare example draw the rate of patients arriving to the system from the exponential distribution (Poisson arrivals). For each of the 261 experiments, the mean for the time between patient arrivals was varied. The experiment number (labeled 'Exp#' in the tables) and the mean (labeled 'Mean' in the tables) interarrival time in hours between patients are listed in the tables below. The experiments include average patient arrival rates that vary from one patient per year to over 285 patients per year.

Exp#	Mean	Exp#	Mean	Exp#	Mean	Exp#	Mean	Exp#	Mean
1	10	37	28	73	46	109	190	145	370
2	10.5	38	28.5	74	46.5	110	195	146	375
3	11	39	29	75	47	111	200	147	380
4	11.5	40	29.5	76	47.5	112	205	148	385
5	12	41	30	77	48	113	210	149	390
6	12.5	42	30.5	78	48.5	114	215	150	395
7	13	43	31	79	49	115	220	151	400
8	13.5	44	31.5	80	49.5	116	225	152	405
9	14	45	32	81	50	117	230	153	410
10	14.5	46	32.5	82	55	118	235	154	415
11	15	47	33	83	60	119	240	155	420
12	15.5	48	33.5	84	65	120	245	156	425
13	16	49	34	85	70	121	250	157	430
14	16.5	50	34.5	86	75	122	255	158	435
15	17	51	35	87	80	123	260	159	440
16	17.5	52	35.5	88	85	124	265	160	445
17	18	53	36	89	90	125	270	161	450
18	18.5	54	36.5	90	95	126	275	162	455
19	19	55	37	91	100	127	280	163	460
20	19.5	56	37.5	92	105	128	285	164	465
21	20	57	38	93	110	129	290	165	470
22	20.5	58	38.5	94	115	130	295	166	475
23	21	59	39	95	120	131	300	167	480
24	21.5	60	39.5	96	125	132	305	168	485
25	22	61	40	97	130	133	310	169	490
26	22.5	62	40.5	98	135	134	315	170	495
27	23	63	41	99	140	135	320	171	500
28	23.5	64	41.5	100	145	136	325	172	510
29	24	65	42	101	150	137	330	173	520
30	24.5	66	42.5	102	155	138	335	174	530
31	25	67	43	103	160	139	340	175	540
32	25.5	68	43.5	104	165	140	345	176	550
33	26	69	44	105	170	141	350	177	560
34	26.5	70	44.5	106	175	142	355	178	570
35	27	71	45	107	180	143	360	179	580
36	27.5	72	45.5	108	185	144	365	180	590

Exp#	Mean	Exp#	Mean	Exp#	Mean
181	600	208	870	235	1700
182	610	209	880	236	1750
183	620	210	890	237	1800
184	630	211	900	238	1850
185	640	212	910	239	1900
186	650	213	920	240	1950
187	660	214	930	241	2000
188	670	215	940	242	2050
189	680	216	950	243	2100
190	690	217	960	244	2150
191	700	218	970	245	2200
192	710	219	980	246	2250
193	720	220	990	247	2300
194	730	221	1000	248	2350
195	740	222	1050	249	2400
196	750	223	1100	250	2450
197	760	224	1150	251	2500
198	770	225	1200	252	2550
199	780	226	1250	253	2600
200	790	227	1300	254	2650
201	800	228	1350	255	2700
202	810	229	1400	256	2750
203	820	230	1450	257	2800
204	830	231	1500	258	2850
205	840	232	1550	259	2900
206	850	233	1600	260	2950
207	860	234	1650	261	3000

APPENDIX B

CONFIDENCE INTERVALS FOR EXPONENTIAL DISTRIBUTION ARRIVAL EXPERIMENTS

The confidence intervals for the experiments from APPENDIX A are listed in the tables below. The parameters for the patient arrival distributions in the healthcare example are given in the tables below. The experiment number (labeled 'Exp#' in the tables) and the mean net present value (labeled 'Mean NPV' in the tables) are given in the tables below. The upper and lower bounds ('Upper Bound' and 'Lower Bound', respectively in the tables) are found for each of the mean NPVs by using a 90% t confidence level.

Exp#	Mean NPV	Lower Bound	Upper Bound
1	6,456,822	6,421,113	6,492,531
2	6,098,384	6,063,156	6,133,613
3	5,731,412	5,698,096	5,764,727
4	5,414,132	5,381,351	5,446,914
5	5,151,080	5,121,290	5,180,871
6	4,880,264	4,850,185	4,910,343
7	4,618,046	4,589,353	4,646,739
8	4,383,919	4,355,610	4,412,228
9	4,218,942	4,191,915	4,245,970
10	3,988,612	3,963,814	4,013,410
11	3,835,051	3,810,161	3,859,941
12	3,665,517	3,642,081	3,688,954
13	3,495,570	3,471,084	3,520,056
14	3,354,175	3,331,866	3,376,484
15	3,191,536	3,169,507	3,213,564
16	3,061,055	3,039,214	3,082,897
17	2,942,419	2,922,292	2,962,545
18	2,840,549	2,820,710	2,860,388
19	2,723,362	2,703,017	2,743,707
20	2,618,842	2,599,533	2,638,151
21	2,491,827	2,472,827	2,510,827
22	2,407,612	2,389,371	2,425,853
23	2,301,099	2,282,941	2,319,258
24	2,216,655	2,199,368	2,233,943
25	2,160,646	2,143,389	2,177,902
26	2,057,531	2,040,863	2,074,200
27	1,979,005	1,962,166	1,995,844
28	1,921,319	1,904,493	1,938,146
29	1,841,009	1,825,480	1,856,538
30	1,772,485	1,757,148	1,787,822
31	1,702,901	1,687,660	1,718,142
32	1,637,930	1,623,036	1,652,824
33	1,585,276	1,570,529	1,600,023
34	1,520,060	1,505,657	1,534,463
35	1,469,327	1,454,532	1,484,123
36	1,413,534	1,399,353	1,427,715
37	1,362,339	1,348,509	1,376,169

Exp#	Mean NPV	Lower Bound	Upper Bound
38	1,316,074	1,302,247	1,329,901
39	1,272,647	1,259,448	1,285,846
40	1,214,391	1,200,988	1,227,795
41	1,164,959	1,151,760	1,178,158
42	1,126,352	1,113,247	1,139,456
43	1,085,576	1,072,898	1,098,253
44	1,046,320	1,033,567	1,059,072
45	1,007,998	995,123	1,020,874
46	963,264	951,344	975,183
47	936,712	924,102	949,323
48	892,145	879,712	904,577
49	859,897	848,101	871,694
50	819,248	807,156	831,339
51	801,359	789,603	813,116
52	775,561	764,084	787,038
53	736,029	724,809	747,249
54	716,882	705,640	728,124
55	671,657	660,447	682,866
56	638,676	627,699	649,652
57	611,337	600,719	621,956
58	586,076	575,361	596,792
59	573,487	563,018	583,955
60	532,768	522,533	543,004
61	514,082	503,591	524,572
62	485,548	474,678	496,418
63	459,756	449,748	469,763
64	446,588	436,249	456,928
65	416,991	407,296	426,686
66	391,652	382,218	401,086
67	371,064	361,029	381,099
68	356,309	346,711	365,906
69	334,654	325,001	344,307
70	305,530	295,981	315,079
71	280,713	270,972	290,454
72	263,031	253,764	272,298
73	249,684	240,347	259,022
74	231,966	222,940	240,993

Exp#	Mean NPV	Lower Bound	Upper Bound
75	223,753	214,926	232,579
76	195,164	185,855	204,473
77	189,199	179,995	198,404
78	158,937	150,000	167,874
79	153,878	145,078	162,679
80	138,946	130,602	147,291
81	115,604	106,848	124,360
82	-31,100	-38,819	-23,381
83	-154,840	-162,311	-147,369
84	-251,634	-258,744	-244,525
85	-335,037	-341,871	-328,203
86	-412,665	-419,296	-406,035
87	-480,801	-487,293	-474,310
88	-537,503	-543,601	-531,406
89	-593,225	-599,155	-587,295
90	-639,101	-644,568	-633,633
91	-678,550	-683,851	-673,249
92	-714,561	-719,760	-709,362
93	-751,540	-756,632	-746,448
94	-782,210	-787,327	-777,094
95	-815,807	-820,428	-811,186
96	-835,373	-840,157	-830,589
97	-864,818	-869,541	-860,095
98	-885,446	-890,012	-880,881
99	-904,443	-909,045	-899,841
100	-923,118	-927,589	-918,648
101	-943,324	-947,483	-939,166
102	-962,663	-966,968	-958,359
103	-977,236	-981,375	-973,097
104	-993,815	-997,959	-989,671
105	-1,007,955	-1,012,064	-1,003,845
106	-1,022,278	-1,026,368	-1,018,187
107	-1,033,233	-1,037,212	-1,029,254
108	-1,048,833	-1,052,848	-1,044,819
109	-1,053,156	-1,057,067	-1,049,246
110	-1,065,429	-1,069,336	-1,061,522
111	-1,075,324	-1,079,177	-1,071,472

Exp#	Mean NPV	Lower Bound	Upper Bound
112	-1,086,926	-1,090,752	-1,083,100
113	-1,092,154	-1,095,947	-1,088,361
114	-1,103,560	-1,107,172	-1,099,947
115	-1,113,161	-1,116,680	-1,109,641
116	-1,121,627	-1,125,261	-1,117,993
117	-1,126,825	-1,130,605	-1,123,045
118	-1,137,326	-1,140,931	-1,133,722
119	-1,144,892	-1,148,512	-1,141,272
120	-1,148,110	-1,151,774	-1,144,447
121	-1,158,094	-1,161,682	-1,154,507
122	-1,159,425	-1,163,087	-1,155,764
123	-1,165,478	-1,169,015	-1,161,940
124	-1,171,948	-1,175,346	-1,168,551
125	-1,178,669	-1,182,171	-1,175,167
126	-1,184,795	-1,188,172	-1,181,418
127	-1,189,784	-1,193,065	-1,186,503
128	-1,198,158	-1,201,430	-1,194,885
129	-1,197,660	-1,200,998	-1,194,323
130	-1,205,979	-1,209,239	-1,202,718
131	-1,210,260	-1,213,570	-1,206,950
132	-1,215,400	-1,218,775	-1,212,024
133	-1,218,306	-1,221,568	-1,215,044
134	-1,217,970	-1,221,303	-1,214,636
135	-1,226,923	-1,230,049	-1,223,797
136	-1,228,371	-1,231,703	-1,225,040
137	-1,231,861	-1,234,997	-1,228,725
138	-1,238,550	-1,241,692	-1,235,408
139	-1,240,784	-1,243,988	-1,237,581
140	-1,244,001	-1,247,105	-1,240,897
141	-1,244,543	-1,247,834	-1,241,251
142	-1,252,301	-1,255,460	-1,249,142
143	-1,253,006	-1,256,081	-1,249,931
144	-1,256,551	-1,259,726	-1,253,375
145	-1,261,249	-1,264,358	-1,258,140
146	-1,263,069	-1,266,168	-1,259,969
147	-1,265,436	-1,268,477	-1,262,394
148	-1,266,588	-1,269,708	-1,263,469

Exp#	Mean NPV	Lower Bound	Upper Bound
149	-1,269,745	-1,272,854	-1,266,635
150	-1,272,475	-1,275,565	-1,269,385
151	-1,273,729	-1,276,744	-1,270,713
152	-1,277,661	-1,280,675	-1,274,647
153	-1,280,002	-1,283,022	-1,276,982
154	-1,283,001	-1,286,050	-1,279,952
155	-1,283,755	-1,286,717	-1,280,792
156	-1,288,707	-1,291,729	-1,285,686
157	-1,286,378	-1,289,377	-1,283,380
158	-1,291,610	-1,294,571	-1,288,648
159	-1,292,329	-1,295,370	-1,289,288
160	-1,294,404	-1,297,397	-1,291,411
161	-1,295,648	-1,298,583	-1,292,713
162	-1,299,175	-1,302,024	-1,296,327
163	-1,298,733	-1,301,645	-1,295,821
164	-1,301,695	-1,304,650	-1,298,740
165	-1,304,270	-1,307,187	-1,301,352
166	-1,304,977	-1,307,872	-1,302,081
167	-1,308,672	-1,311,503	-1,305,841
168	-1,309,366	-1,312,369	-1,306,364
169	-1,311,291	-1,314,149	-1,308,434
170	-1,312,380	-1,315,305	-1,309,456
171	-1,314,150	-1,316,971	-1,311,328
172	-1,318,323	-1,321,134	-1,315,511
173	-1,321,317	-1,324,074	-1,318,559
174	-1,321,130	-1,323,833	-1,318,427
175	-1,325,838	-1,328,535	-1,323,141
176	-1,330,896	-1,333,908	-1,327,884
177	-1,332,318	-1,335,079	-1,329,557
178	-1,333,474	-1,336,270	-1,330,678
179	-1,337,556	-1,340,309	-1,334,803
180	-1,338,610	-1,341,435	-1,335,784
181	-1,341,274	-1,343,910	-1,338,638
182	-1,342,518	-1,345,379	-1,339,657
183	-1,346,007	-1,348,789	-1,343,225
184	-1,348,146	-1,350,827	-1,345,464
185	-1,346,697	-1,349,537	-1,343,857

Exp#	Mean NPV	Lower Bound	Upper Bound
186	-1,351,372	-1,354,015	-1,348,729
187	-1,353,390	-1,356,043	-1,350,737
188	-1,356,750	-1,359,400	-1,354,101
189	-1,357,618	-1,360,340	-1,354,896
190	-1,358,562	-1,361,240	-1,355,884
191	-1,359,040	-1,361,705	-1,356,374
192	-1,363,078	-1,365,744	-1,360,412
193	-1,361,880	-1,364,512	-1,359,249
194	-1,363,508	-1,366,157	-1,360,858
195	-1,365,754	-1,368,375	-1,363,134
196	-1,370,119	-1,372,791	-1,367,447
197	-1,368,307	-1,371,045	-1,365,568
198	-1,370,367	-1,372,983	-1,367,752
199	-1,371,888	-1,374,529	-1,369,248
200	-1,373,295	-1,375,879	-1,370,711
201	-1,373,674	-1,376,389	-1,370,960
202	-1,374,870	-1,377,564	-1,372,176
203	-1,375,225	-1,377,886	-1,372,563
204	-1,379,811	-1,382,405	-1,377,218
205	-1,380,488	-1,383,103	-1,377,873
206	-1,379,489	-1,382,047	-1,376,931
207	-1,380,620	-1,383,134	-1,378,106
208	-1,381,051	-1,383,629	-1,378,474
209	-1,382,624	-1,385,220	-1,380,028
210	-1,384,013	-1,386,649	-1,381,377
211	-1,386,161	-1,388,706	-1,383,616
212	-1,386,583	-1,389,170	-1,383,997
213	-1,386,705	-1,389,247	-1,384,163
214	-1,387,044	-1,389,609	-1,384,479
215	-1,388,566	-1,391,161	-1,385,972
216	-1,388,652	-1,391,169	-1,386,134
217	-1,391,342	-1,394,023	-1,388,660
218	-1,390,670	-1,393,288	-1,388,052
219	-1,393,203	-1,395,746	-1,390,661
220	-1,395,122	-1,397,600	-1,392,644
221	-1,394,356	-1,396,916	-1,391,796
222	-1,399,231	-1,401,728	-1,396,735

Exp#	Mean NPV	Lower Bound	Upper Bound
223	-1,401,310	-1,403,837	-1,398,783
224	-1,404,529	-1,407,069	-1,401,989
225	-1,407,695	-1,410,203	-1,405,188
226	-1,410,271	-1,412,732	-1,407,810
227	-1,412,243	-1,414,700	-1,409,785
228	-1,413,703	-1,416,135	-1,411,272
229	-1,417,032	-1,419,463	-1,414,601
230	-1,418,182	-1,420,625	-1,415,738
231	-1,419,417	-1,421,906	-1,416,928
232	-1,421,476	-1,423,951	-1,419,001
233	-1,424,520	-1,426,860	-1,422,181
234	-1,424,439	-1,426,940	-1,421,937
235	-1,428,163	-1,430,593	-1,425,732
236	-1,426,958	-1,429,453	-1,424,463
237	-1,428,979	-1,431,389	-1,426,568
238	-1,431,511	-1,433,861	-1,429,161
239	-1,429,284	-1,431,749	-1,426,820
240	-1,432,346	-1,434,777	-1,429,915
241	-1,435,638	-1,437,996	-1,433,280
242	-1,435,699	-1,438,050	-1,433,347

Exp#	Mean NPV	Lower Bound	Upper Bound
243	-1,437,283	-1,439,651	-1,434,916
244	-1,436,747	-1,439,138	-1,434,357
245	-1,439,059	-1,441,405	-1,436,713
246	-1,439,263	-1,441,627	-1,436,899
247	-1,440,745	-1,443,046	-1,438,444
248	-1,439,691	-1,442,122	-1,437,259
249	-1,440,100	-1,442,480	-1,437,720
250	-1,442,797	-1,445,091	-1,440,503
251	-1,441,767	-1,444,142	-1,439,393
252	-1,440,231	-1,442,614	-1,437,848
253	-1,444,041	-1,446,374	-1,441,708
254	-1,442,892	-1,445,267	-1,440,517
255	-1,444,301	-1,446,703	-1,441,898
256	-1,444,126	-1,446,553	-1,441,699
257	-1,446,265	-1,448,632	-1,443,898
258	-1,444,749	-1,447,107	-1,442,391
259	-1,446,745	-1,449,062	-1,444,428
260	-1,447,627	-1,449,996	-1,445,258
261	-1,446,634	-1,448,964	-1,444,304