AFIT/GOR/ENS/99M-12

PORTFOLIO SELECTION OF INNOVATIVE
TECHNOLOGIES VIA
LIFE CYCLE COST MODELING

THESIS

Scott C. Naylor, 1st Lieutenant, USAF

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THESIS

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Scott C. Naylor, B.S.

1st Lieutenant, USAF

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Scott C. Naylor, B.S., M.S.

1st Lieutenant, USAF

11 Mar 99

Approved:

Dr. Richard F. Deckro Professor of Operations Research Thesis Co-Advisor	15 March 99 Date
Dr. James T. Moore Associate Professor of Operations Research Thesis Co-Advisor	15 Mar 99 Date
LTC Jack M. Kloeber Ph.D. Assistant Professor of Operations Research Committee Member	15 Mar '99 Date

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Above all else, "to Him who is able to keep us from falling and present us before His glorious presence without fault and with great joy, to the only God our Saviour be glory, majesty, power and authority, through Jesus Christ our Lord, before all ages, now and forevermore! Amen" (Jude 1: 24,25).

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Abstract

High technology firms are faced with the dilemma of deciding which products to develop, which generations of technology to pass over, and which products to skip entirely. As competition among these firms increases and the life cycles of technological products shorten, there exists a great deal of pressure to bring products rapidly to the market. As a result, recouping the costs of research and development (R & D) and earning a profit becomes increasingly uncertain. Traditional life cycle cost models do not directly address shortened life cycles, time to market, or learning curve issues; all are critical factors in the development of high technology products.

This thesis allows the investigation of cost estimates involved in the R & D of high technology products. Cost estimations include time to market and learning curve effects. Simulation is used to provide cost and revenue estimates that may then be used to calculate a distribution of potential net present values (NPVs) of a product. Measures of financial risk are also generated. Using the generated expected value and variance of the NPV of each product under consideration, a linear program is built to select the optimal portfolio of products to develop. The method is demonstrated with an illustrative example.

PROGRAM SELECTION OF INNOVATIVE TECHNOLOGIES VIA LIFE CYCLE COST MODELING

Chapter 1: Introduction

Background

Modern day manufacturers are faced with a dilemma in the development of high technology products. As competition among manufacturers increases, the life cycles of technology products shorten, and there exists a great deal of pressure to bring products to the market more rapidly. Such rapidity of production, especially in the high-end technology market, leads to a shortening of the product's life cycle (Von Braun, 1991:43). Shortening of the life cycle of high technology products may not seem like a critical issue, but to producers of these products, it is becoming an increasingly important problem. Time to market, product quality and sales volume must be balanced. It has been shown that a firm is likely to lose market share if it is beat to the market by the competition (Vesey, 1992:72). Von Braun has also shown that this ever-decreasing life cycle may reduce overall sales of the product and may result in a smaller sales volume over a product's life (Von Braun, 1991:43).

When one considers manufacturers that produce more than one product, this dilemma compounds. First, the manufacturer is faced with the negative results of the shortened life cycle in each product's development. A manufacturer must ask if it is possible to stabilize the length of the life cycle and avoid the trap of lost sales and small sales volume. Second, the manufacturer encounters pricing and profit issues. As products are assembled over and over, learning curve effects can result in decreased assembly time.

Consequently, as the time to manufacture products decreases and the volume supplied is reduced, pricing and profits can be affected. The length of time where the learning process positively affects manufacturing is decreased. Finally, because there are limited resources available, the manufacturer faces the decision of which products to develop and which products to pass over. This selection of product line can be thought of as a portfolio optimization. Portfolio Optimization can assist the manufacturer in selecting the products that he or she should introduce to the market in order to earn the highest possible profits.

These issues can be dealt with, in part, using a classic life cycle cost model (LCC). A recently built LCC model (Dereli, 1998) investigates the life cycle cost associated with remediation technologies at the Department of Energy (DOE). While Dereli's model is well suited for the task of evaluating DOE remediation technologies, it is not designed to analyze shortening life cycles, learning curve effects, or the portfolio selection of high technology products.

Problem Statement

The lifeblood of high technology industry is innovation and breakthrough. Throughout the industry, vast amounts of time and money are invested in the research and development of new products. Manufacturers, motivated by profits, must choose the products they will pursue and the products that they will disregard. When selecting new product lines that will yield the highest profit, manufacturers must plan for the risk and uncertainty of the length of the life cycle of each product. This uncertainty, if estimated, can help answer the other question of when to introduce each product into the market.

Length of the life cycle of a product is not the only aspect that is uncertain in the time to market framework. There are other uncertain aspects involved such as length of time it takes to get the product to market (i.e. time to money), cost of material that goes into the assembly of each product, the window of sales opportunity for the product, the costs of personnel to assemble the product, and the time at which the competitors enter the market, to name a few.

Another uncertainty manufacturers face is the cost of production. This uncertain cost includes any learning curve effect. In the manufacturing world, it is often assumed that each time the volume produced doubles, the cumulative average cost declines by a fixed percentage of the previous cumulative average cost (Jordan, 1965:1-2). In the process of estimating costs, the manufacturer should attempt to estimate how the learning curve will impact costs. This estimation, if accurately accomplished, can assist in more accurately estimating profits.

Objective and Scope of the Research

The objective of this research is to develop a generic LCC model, coupled with simulation, to assist the selection and evaluation of a portfolio of products. The generic LCC model gives the user a range of costs for one technology that can then be used to generate a portfolio that will maximize revenue while reducing the risks associated with shorter product life cycles. In this model, net present value calculations are combined with risk assessment techniques to improve portfolio development.

The model is developed for use on a personal computer (PC). The model uses commercially available computing packages to enhance its power and scope. The model runs on Visual Basic for Applications (VBA). Specifically, the model runs using

Microsoft Excel, which is thoroughly integrated with the VBA macro language. Similar to Visual Basic (VB), VBA provides Excel with the means to make more flexible and specific calculations. The user-interface created within VBA is menu driven and is user-friendly to those with life cycle costing experience. In addition, the source code allows those experienced in VBA and Excel to modify the model to suit their needs.

To allow further analysis of risk and cost effects, Crystal Ball (CB) is incorporated in the model. This Excel add-in creates seamless Monte Carlo simulations within an Excel spreadsheet. Crystal Ball also works well with VBA to provide user-friendly interfaces with the data used.

The portfolio optimization phase of this research uses a software package called LINGO 3.0 (student version). The software package is designed to solve linear and non-linear mathematical programs. The output from the Excel model can be manually placed into LINGO to obtain the optimal portfolio of products to pursue.

Chapter 2: Literature Review

Introduction

In today's highly competitive and rapidly changing marketplace, it is crucial to accurately estimate the costs and duration of various research and development projects. If the costs and duration are inaccurately estimated, the wrong products may be produced, or may be produced late in the product life cycle, resulting in losses of market, revenue, and position. In this chapter, time to market and how it relates to new product development and life cycle costs are examined. Literature pertinent to learning curve effects is then investigated. After these two concepts are addressed, the literature that deals with choosing an optimal portfolio of products is reviewed.

Background on Life Cycle Costing

Life cycle costing (LCC) is a fundamental engineering economics concept. To properly evaluate the cost of an acquisition, one must consider not only an item's purchase price, but also its development costs, implementation costs, operations and maintenance costs, as well as any disposal costs and salvage values (Twomey, 1991: 213). In the recent history of this country, LCC was not a readily accepted concept to many people. Its introduction met much opposition. The idea of considering costs other than the purchase price did not initially seem relevant. In fact, until the late 1950s and early 1960s, such considerations rarely took place within the DoD (Gill, 1998: 3).

The first recorded knowledge of the use of some semblance of LCC in federal government acquisitions was in 1933. At that time, the Comptroller General of the U.S. required the inclusion of maintenance costs in the bid procurement price of tractors for government use (Dell'Isola, 1981:4). After World War II and into the early 1950s, materials and labor were in short supply. During this time period, the concept of Value Engineering (VE) was developed (Dell'Isola, 1981:4). Though VE is a much broader concept than LCC, one of its main tenets was the "total cost" concept; that is, the idea of accounting for all costs associated with the development of a product.

In 1965 the office of the Secretary of Defense (OSD) hired the Logistics Management Institute (LMI) to investigate LCC. LMI issued a report that concluded that if total life cycle costs had been considered, many DoD contracts would have been awarded to other than low bidders, at a substantial overall savings to the U.S. government (Dell'Isola, 1981:5). Gill suggests four reasons LCC did not become popular sooner (Gill, 1998:3):

1. Contract regulations of the time period did not mention LCC
2. Political objections to purchasing more expensive systems despite lower LCC
3. Separate congressional funds (procurement, operations, maintenance)
4. Increased contractual detail required if LCC incorporated

Though resistance to LCC was strong within the U.S. government, the tide changed. The DoD decided to embark on pilot programs to see if LCC was truly a worthwhile approach. One such program investigated the purchase of aircraft tires. This study showed that purchasing aircraft tires based on the lowest-cost-per-landing was much more effective than purchasing the tires with the lowest price tag (Gill, 1998:3). In 1971 the DoD issued DODI 5000.1. This acquisition directive established the requirement for life cycle cost and design to cost studies for all major DoD acquisitions. LCC was here to stay.

The current DoD policy requires LCC estimates on all major ($10 million and higher) DoD requests for proposals (RFP) (Gill, 1998:4). However, most models used to estimate life cycle costs do not succeed in capturing all life cycle costs (Gill, 1998:4).

Life Cycle Costing and New Product Development

Introduction

The focus of this research is to address new product development risks for a profit-seeking firm using a life cycle cost model. When a manufacturer makes decisions about developing new products, he must ask himself many questions during the risk analysis process. "When will my competition be ready to go to market with their product?" "How do learning curves affect costs, pricing and ultimately, profit?" "Will the profits from our product offset our R & D, production, and marketing costs and make development worthwhile?" These are just a few questions manufacturers must ask themselves. Life cycle cost modeling is a tool that can assist with answering such risk analysis questions. In particular the life cycle cost model developed in this study incorporates features to answer questions concerning time to market and the effect of learning curves.

Time to Market

Manufacturers face at least one uncertainty that carries a large amount of risk. This uncertainty concerns when they can enter the market with their product. This uncertainty can be a key or a hindrance to the financial success of the product. The introduction of a product(s) to market is commonly referred to as time to market. Time to market becomes a pressing concern when one considers how short the life cycle is for many high technology products. As will be seen shortly, the life cycle of many high technology products is currently relatively short and may become even shorter in the future. Consider the personal computer. Research has shown that the typical life cycle for personal computers is 18 months (Carter and Baker, 1993:26). Let the curve in Figure 1 represent the life cycle of the personal computer market. In this figure, revenue is plotted against time. Let the revenue function be denoted as f (t), a function of time. If the area below f (t) is computed by integrating f (t) from 0 to T (the last point in time the product is sold), the total market revenue (TMR) for that product will be known. This revenue represents the revenue obtained by all corporations that manufacture a common product. An example of such a product is the personal computer (PC) rated at a speed of xxx MHz. Various companies may sell a 400 MHz PC and the combined product revenue for all companies during the life cycle of the product can be found by computing $\int_0^T f(t)$.

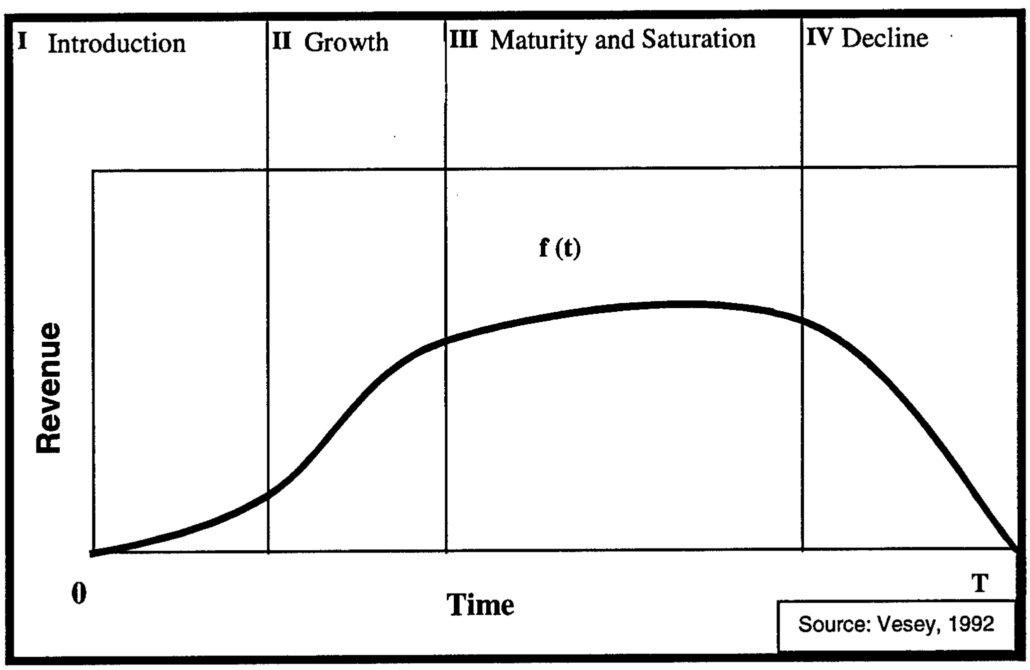


Figure 1: Life Cycle and Revenue

Relating back to Figure 1 above, the sooner one can enter the market with the product, the higher the percentage of revenue that is available to the firm. The opposite is true as well. The later one enters the market, the lower the percentage of revenue that can be earned. In addition, a manufacturer can improve his chances of maximizing revenue by

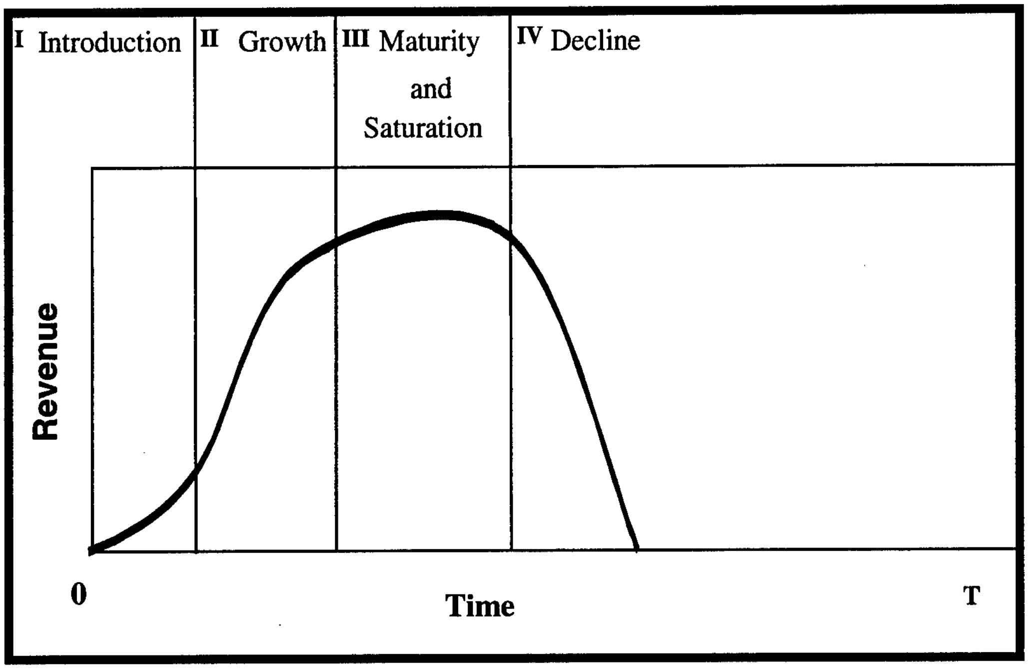


Figure 2: Life Cycle and Revenue Compression

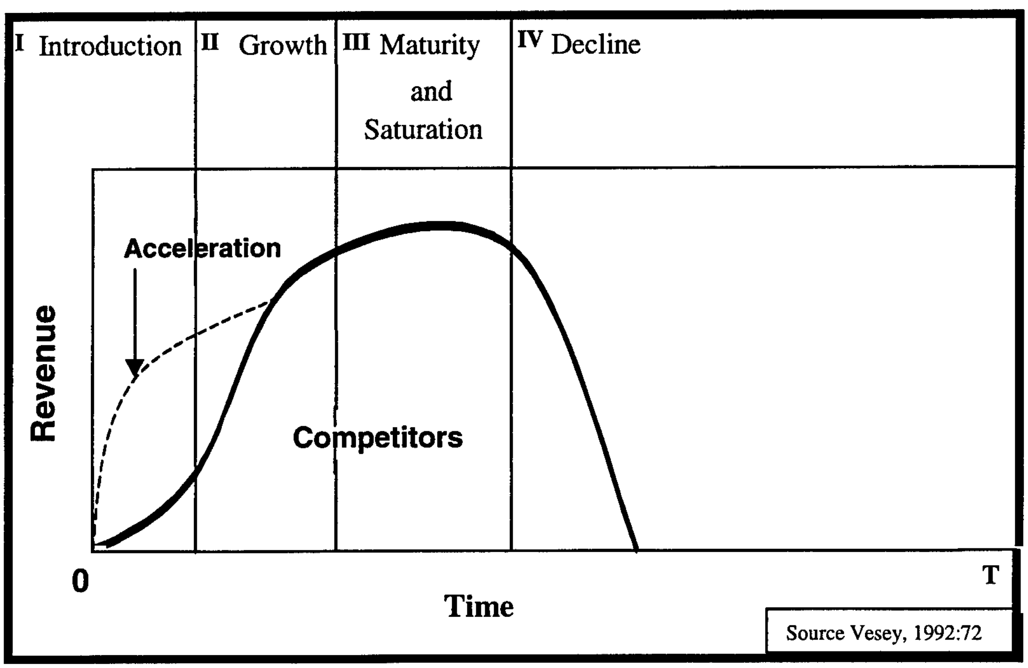


Figure 3: Acceleration of Life Cycle

not only beating all competition to the market $(t = 0)$, but by also introducing a product that is superior to what the competition can offer. Vesey points to a study done by McKinsey & Co. which showed that a high technology product six months late to a market can miss out on up to one-third of its potential revenues over the course of the product's lifetime (Vesey, 1992:72). It should be noted that "late" in the terms of this research means that one has entered after the market cycle has already started. In other studies, it has been shown that companies with fast response times, that is, quick to serve customers, quick to modify products, and quicker to upgrade, are likely to have lower costs and be more innovative than other companies who are not as responsive (Carter and Baker, 1993:27).

There is certainly literature to show there are penalties for entering a market late, but another interesting issue is whether or not the first to market obtains a reward, or extra share of the market. In addressing this issue, the literature is mixed on its findings. For instance, one study looked at the performance of innovations in the metal-oxide semiconductor industry. This study showed that the first manufacturer to produce a design held the largest share of the market (Spital:1983). In another high technology study, however, the share of the first to market was highly correlated to whether or not the first to market was a newly established corporation versus one which was an industry incumbent (Mitchell:1991). Golder and Tellis have further evidence to show that some exaggeration might occur in market share studies. They define a "pioneer" as one who brings a new product into the market. They say that some studies claim that pioneers gain as high as a 30% mean market share, while their own studies point to a much smaller figure of 10% (Golder and Tellis, 1993). Their explanation for this gap is that other studies have based their statistics on limited databases. In the same article Golder and Tellis say that further research should examine advertising, price, promotion, product quality, distribution, and managerial effectiveness and the effects these dimensions have on market share (Golder and Tellis, 1993).

As stated earlier, the life cycle of many technological products, especially high technology products, can be extremely short. For example, Intel Corporation has decreased the life cycle of its microprocessors from as long as four years (486) to as short as two years (Pentium) (Intel Corporation, 1998). It can be seen from historical data that the life cycle of the Intel computer chip is getting shorter and shorter. If other high technology firms feel the pressure to shorten their product life cycles, the result is a shorter length of time in which to sell their products (Vesey, 1992:71). This means that the curve in Figure 1 is compressed leaving a shorter amount of time for all companies to earn revenue and recoup R & D costs. This compression can be seen in Figure 2. With this compression present in a market, it is even more important that one enter the market first, or as close to the beginning of the market as possible. In addition, a firm is further handicapped by entering the market late because the time to "catch up" may have been compressed. This equates to not only a loss of potential revenue, but also equates to the risk of never recovering costs, a net loss to the firm (Vesey, 1992:72).

To demonstrate how detrimental it can be to enter the market late, observe the following equation that illustrates revenue loss.

$$\boxed{\frac{d(3w-d)}{2w^2}}$$

d = Delay to market

w = ½ (Market length)

Equation 1: Revenue Loss (Source: Carter and Baker, 1992:31)

Carter and Baker suggest this equation represents the percentage of revenue that is lost by a delayed entry into the market. In this equation, w represents the length of the market and d represents the delay of the product into the market. For instance, if there is a 12-month market window and the manufacturer is one month late to the market, 12% of the market is lost. Likewise, if a manufacturer is five months late, 54% of the revenue is lost.

Compression of a life cycle translates into a shorter time to earn revenue from sales of a given product. Therefore, the estimate of when one is able to introduce a product into the market becomes increasingly critical. Vesey suggests the answer to this compression is to accelerate one's own perspective of the life cycle. This would suggest accelerating R & D so one's product can be placed in the market before the competition is able to place their product in the market. This concept of compressing the life cycle can be seen in Figure 3. The goal of acceleration is to obtain a larger share of the market so that the additional revenue more than offsets R & D costs.

One must keep in mind that simply accelerating the entry into the market may not be sufficient to offset R & D costs. Suppose the height of the function in Figure 3 does not increase with compression. Suppose instead the height of the revenue function is variable and is not easily predicted. For instance, if the life cycle of a product is compressed and the expected amount of revenue never exceeds the levels of Figure 1, a much lower overall revenue is realized, which has a ripple effect on all competitors within that market. This could result in fewer competitors recovering expensive R & D costs and other costs and losing essential revenue.

Repercussions of Compression and Acceleration

Having discussed the concepts of the life cycle/revenue curve, the compression of such curves, and the acceleration of one's products into the market, it is important to understand the potential repercussions and other risks associated with compression and acceleration. The remainder of this section is devoted to these repercussions and risks.

The phenomenon that is observed in today's world class competitive markets is that the life cycle for high-end technology products is becoming shorter and shorter (as demonstrated by the Intel computer chip). Von Braun has shown that this ever-decreasing life cycle may reduce overall sales of a product and may result in a smaller sales volume over a product's life (Von Braun, 1991:43). To contribute to some of the negative attributes of a shorter life cycle, Fabrycky and Blanchard have shown phaseout and disposal costs of a product to be very costly (Fabrycky and Blanchard, 1991:11). The more compressed the life cycle becomes, the greater the likelihood of dipping into profits to pay for the phaseout and disposal costs. The worse case scenario is to be forced to pay for these phaseout and disposal costs without having earned sufficient revenue. A negative profit margin will occur. If the likelihood of such an outcome is high, a manufacturer may decide to skip a generation of development in favor of the next generation in hopes of recouping phaseout and disposal costs, along with yielding an acceptable margin of profit.

There are at least four risks that affect decisions in the new product development community that should be mentioned. These risks are serious enough in an uncompressed market, but these risks are aggravated in a compressed market. The first risk is to underestimate or overestimate the amount of product one should produce. If one has faulty market research, or if production fails to meet market demands, not only is revenue curtailed, but the loyalty of customers is likely to suffer. On the other hand, if one over estimates the demand for a new product, the product might never sell, which equates to overspending and a potential loss of revenue.

A second risk that affects new product development is the level at which the supplier can provide components or raw material. Manufacturers should not make the assumption that the raw materials and other components will arrive in time for production every time they are needed. If such materials and components do not arrive on time, the product's entry into the market could be delayed. This translates into revenue lost and perhaps long-term losses of market share.

A third risk that affects new product development, given by Rosenthal, has two facets. First, he mentions that a company can be a technology leader without having a commanding market share. Second, he mentions that a company can be a technology leader while holding a large market share. In the first scenario, a company must stay at the technological forefront to gain or maintain the market share it desires. For this competitor, the stakes are high and meeting the projected market window is critical (Rosenthal, 1992:67). In the second scenario, a company that already has a significant share of the market, and has no serious competition, can afford to enter the market late (Rosenthal, 1992:67). He cites Motorola as an example. When Motorola was developing the Keynote pocket pager, the company spent extra time streamlining their product line by retiring older, less cost-effective products. In doing so, they introduced the pager to the market considerably later than promised; yet revenues were relatively unaffected. This means that the risk of entering the market late depends strongly on the position of the company, namely if the company already holds a major share of the market or not.

A fourth risk that affects new product development decisions is the risk of failure. An innovative new product may be a noteworthy product but at the same time may not perform well in the market. If the market does not purchase the product, any hopes of revenue gain or of recouping R & D investments are gone. Martino gives two reasons why a product may not fare well in the marketplace. First, if the needs of the potential users have not been clearly identified and built into the design, the product has a strong probability of failure. Second, if there are more appealing alternatives to the customer, the product could fail (Martino, 1995:131). Perhaps the competitors' product has a lower price. Perhaps the competitors' product is simpler to operate. Finally, perhaps the competitors' product has flaws that are more permissible than the flaws of the proposed product.

With the shortening of product life cycles, there is clearly a need to determine the best time to enter the market with a new product. Entering too early may result in spending resources earlier than is necessary. Entering too late not only cuts into revenues, but can also prevent the recapture of R & D costs. Von Braun identifies three issues that contribute to determining when to enter the market. The first issue he identifies is competition (Von Braun, 1991:47). Manufacturing corporations compete to be the first to market in order to obtain the largest share of the market and ultimately revenue. If a manufacturing corporation does not participate in the competition, it will sacrifice its potential share of the market. However, as corporations strive to be the first to market, creating shorter and shorter life cycles, the product that is currently being used becomes obsolete more rapidly. Von Braun's caution is that customers do not have unlimited purchasing power and cannot keep buying the "latest and greatest" without becoming acquainted with the product they currently use (Von Braun, 1991: 47). At the same time, competition not only outdates products quickly but also can result in a glut of new products. Therefore, competition, though healthy, may actually hurt the competing corporations if change occurs too rapidly, or if entry into the market is poorly planned.

The second issue Von Braun identifies as important to the time to market decision is what he calls "depth of value added" (Von Braun, 1991:48). Manufacturers must find the resources internally (thus depth) to maintain the expensive (value added) competition of being the first to market, or outsource to a contractor when it cannot find such resources. Reaching internally for such resources may be intractable; yet, Von Braun shows contracting can also be negative. He points out that in high-end technology, profits are on the whole much higher for the manufacturer and seller of the end product rather than for the maker and seller of the components. As life cycles shorten, this discrepancy can only become worse. Contractors may not tolerate this ever-widening disparity (Von Braun, 1991:49).

The last issue Von Braun addresses as being important to the time to market decision is "manufacturer responsibility" (Von Braun, 1991: 49). This responsibility is qualitative. For example, the Japanese customer frequently blames the manufacturer for faulty products, recalls, and accidents when a product has an excessively short life cycle (Von Braun, 1991: 49). This demonstrates that not only must the manufacturer consider life cycle length; the manufacturer must consider the quality of its product.

As described in the previous paragraph, the manufacturer must consider the high quality of its product to be a prime goal. Research has shown that the cost of making changes to a product grows very quickly, depending on which stage of development the manufacturer finds itself (Miller, 1993:6). For example, a change made during the design phase of production could cost $1,000. However, if the same change is made during the test production stage, the cost becomes $1,000,000. This concept is further demonstrated in Figure 4. It is clear from this figure that it is extremely important for manufacturers to correct design errors as soon as possible. A correction at a later stage simply translates into higher development costs. If corrections are made too late, costs could easily outweigh revenue.

Typical cost for each change made during the development of a major electronics product

When changes are made	Cost
During Design	$ 1,000
During Design Testing	$ 10,000
During Process Planning	$ 100,000
During Test Production	$ 1,000,000
During Final Production	$ 10,000,000

Source: Miller, 1993:7

Figure 4: Cost Associated with Design Changes

The concepts of life cycle length, quality, and sales volume are all issues that must be balanced to determine the best time to introduce products to the marketplace. This need for balance led to the development of a model that combines the objectives of "speed to market" and the need for product quality. One manufacturing process that attempts to address these concerns is concurrent engineering. Shina uses the following definition for concurrent engineering:

> "...the earliest possible integration of the overall company's knowledge, resources, and experience in design, development, marketing, manufacturing, and sales into creating successful new products, with high quality and low cost, while meeting customer expectations."
> (Shina, 1991:1)

Not only does concurrent engineering emphasize the manufacture of a quality product, it also emphasizes getting that product to the market before the competition. Though concurrent engineering began in the late 1970s, it really took off in 1982 (Carter and Baker, 1993:1). In 1982, the Defense Advanced Research Projects Agency (DARPA) began to look for ways to manufacture goods in a parallel fashion as opposed to the traditional, "over-the-wall" approach (Carter and Baker, 1993:1). This parallel or simultaneous process keeps the manufacturing process from being compartmentalized and instead keeps everyone in the manufacturing process communicating from cradle to grave. Concurrent engineering also recognizes the importance of the concept phase in the development of a new product. As Figure 5 demonstrates, though the concept stage of the life cycle of a product only costs 3% of the life cycle costs, it affects up to 70% of the life cycle costs. Consequently, before a manufacturer develops a new product, it must be certain that the product will pay for itself. If the manufacturer has stepped beyond the concept stage, design changes become very costly. On the other hand, if the manufacturer performs well in the concept stage of development, costly changes in future stages of development will be avoided as illustrated in Figure 4.

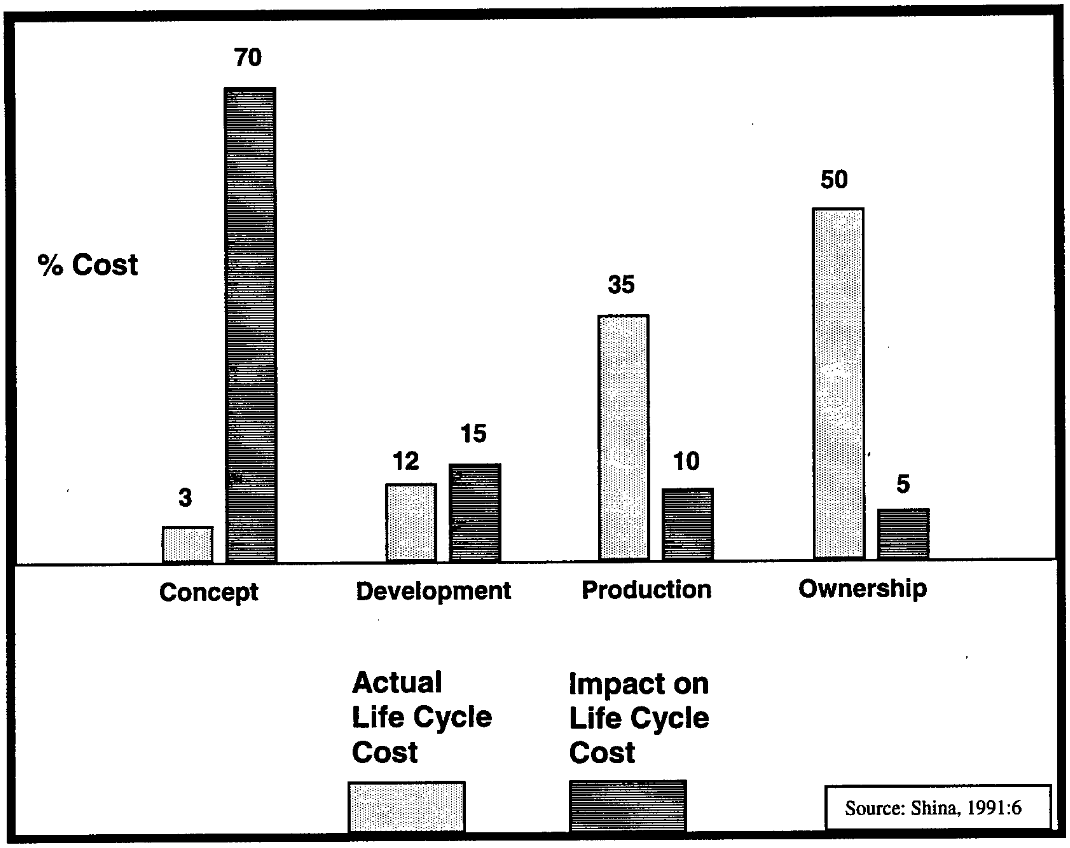


Figure 5: Leveraged Effect of Design Phase

Deckro, Hebert, and Kloeber have investigated an approach for balancing the need for quality products and timely delivery into the market. Their approach takes the form of a mathematical programming model. The model seeks to speed a product to the market without sacrificing quality. As its goal, the program seeks to maximize overall profit. (Deckro, Hebert, and Kloeber, 1998:1).

Learning Curve Effect

The concept of a learning curve is widely utilized in the manufacturing community. The basic tenet of learning curves is that a product can be made better and in a shorter time each time it is produced (i.e. practice makes perfect.). This concept becomes very important when viewed in conjunction with the compression of the life cycle of high technology products. As the life cycle of high technology products compresses, it becomes important to maintain one's share of the market through many means. One of the ways to reduce costs and thus reduce prices so as to maintain one's share is to experience a learning curve effect. A learning curve effect enables a manufacture to lower its production costs. Even if the competition experiences a learning curve effect similar to the one experienced by the first to market, the competition will be at a disadvantage because their learning curve effect will be too late. This disadvantage could be serious if they are unable to gain the share of the market they desire or if they do not recoup their development costs.

As mentioned above, learning curve effects can benefit the first to market and penalize those who come to the market later. If a manufacturer is the first to the market, and if the next competitor does not enter the market for some time, the first to market can charge a premium price for their product (Blackburn, 1991:123). By the time the other competitors arrive to the market, the first to market will already have experienced a learning curve effect. This effect enables the manufacturer to lower production costs because there are fewer labor hours expended on production, there is more efficient use of materials, or the production process has been streamlined in some other way. This lowering of costs enables the first to market to under price the new competition and still make a profit. If the first to market continues to experience a learning curve effect, they could continue to enjoy their share of the market and their substantial profit earnings, while the competition never has the chance to make up for lost time.

Certainly, there is an intuitive appeal to the concept of learning curves, but it is grounded in solid theory. In 1922, T. P. Wright began studying what he called the "variation of cost with quantity." In his studies, he tracked how the cost of producing aircraft for the DoD diminished over time. He identified specific factors that led to this decrease in production costs. Eventually, Wright's research led to his findings in 1936, which proved to be the foundation for modern day learning curve theory (Wright, 1936:122,124).

The learning curve theory states that each time production of a product doubles, the cumulative average cost declines by a fixed percentage of the previous cumulative average (Jordan, 1965:1-2). As workers attain experience in their jobs, the amount of time required producing the same amount of product decreases at a diminishing rate. The common learning curve most often used assumes this percentage of improved efficiency is a constant and is realized each time the production doubles (Dhillon, 1989:112). Dhillon also suggests this efficiency relies on the following factors:

1. Worker/management relationships
2. Lengths of the production runs
3. The nature of the production process
4. The degree of preproduction planning
5. Product design standardization

(Dhillon, 1989:112).

The equation commonly used for the learning curve can be seen in Equation 2 below

$$\boxed{PE = E_f Z^{\beta}}$$

Equation 2: Learning Curve

Where PE = production effort (hours per unit of product Z)
E_f = effort (hours) needed to produce the first unit
Z = cumulative total of units produced

β = Negative slope parameter of the learning curve. This parameter determines the percentage value by which PE diminishes each time the value of Z increases twofold.

In today's marketplace, it is important for manufacturer's to maintain as large a share of the market as possible. The process of assembly "teaches" manufacturers how to assemble a product efficiently and cheaply. As product assembly becomes less expensive, production savings can be passed on to the consumer in the form of lower prices leading to an increased share of the market. This has been true in the case of Texas Instruments (TI) and Digital Equipment (DEC). As these two companies pass on the savings to consumers, they find they are able to obtain a larger share of the market (Kerzner, 1995: 926, 947).

Kerzner points out that the concept of a learning curve is reliable, but only if considering production of more than 100 items. He also gives eight limitations of using the learning curve. They are as follows:

1. Learning curve does not continue forever
2. The knowledge gained on one product may not extend to other products
3. Cost data may not be available to build a meaningful learning curve
4. Quantity discounts can distort the costs and perceived benefits of learning curves
5. Inflation must be expressed in constant dollars; otherwise, the gains realized from experience may be neutralized
6. Learning curves are most useful on long-term horizons (i.e. years)
7. External influences, such as limitations on materials, patents, or even government regulations, can restrict the benefits of learning curves
8. Constant annual production (no growth) may have a limiting effect after a few years

(Kerzner, 1995: 935,936).

The two limitations that should be elaborated on are 6) and 8). In the case of high-end technology, the sixth limitation suggests caution be exercised when trying to incorporate a learning curve effect in an LCC model because of the short life cycles of high-end technologies. The last limitation suggests that as one's competition learns how to produce a product more efficiently, the price to the customer can be lowered. Thus, one must maintain the same level of efficiency as one's competition. In terms of the learning curve, the same percentage must be maintained. If one fails to keep up with the competition, not only could a share of the market be lost, one could be put out of business (Kerzner, 1995: 943).

Most importantly, Kerzner links the concept of learning curves to the concept of scaling. The use of scaling allows cost estimates to be made by scaling future plans according to a known cost. Kerzner illustrates the link between learning curves and scaling by mentioning the six-tenths factor to plan for building a plant with a larger capacity (Kerzner, 1995: 926). The six-tenths factor is used in Equation 3 below.

$$\boxed{C_x = C_k\left(\frac{E_x}{E_k}\right)^n}$$

Equation 3: Six-Tenths Factor

In this equation, C_x (in terms of dollars) is the unknown cost of a piece of equipment E_x and C_k (in terms of dollars) is the known cost of a piece of equipment E_k. The exponent n has an average value of 0.6 for most plants and equipment, but it can vary greatly. This method of estimation is most accurate when the size of the project completed compared to the size of the project to be undertaken has a ratio of 2:1 and should not be used if the ratio is larger than 5:1 (Humphreys, 1996:9). Kerzner goes on to say that in certain industries, mathematical expressions exist that clearly show the link between scaling and learning curves (Kerzner, 1995:926).

In addition to the importance of maintaining the same learning curve percentage as the competition and how closely related scaling is to using a learning curve effect, manufacturers must keep in mind that the learning curve effect adds uncertainty to estimating the net present value of new products under consideration for development. Fields notes that there are at least three uncertainties to keep in mind when analyzing cash flow estimates. These uncertainties are the impact of the variance of the learning rate, the time required to produce the first unit, and the total number of units to be produced (Fields, 1993:166). He adds that it is very important to conduct sensitivity analysis in these three areas because each can affect the accept/reject decision that occurs in the capital budgeting process (Fields, 1993:167).

Optimizing Portfolios of New Products

Introduction

At the beginning of the Life Cycle Costing and New Product Development section, hypothetical questions from a manufacturer's point of view were posed. These questions asked how much revenue could be expected from a proposed product. These questions also asked if the expected revenue could offset R & D expenditures. Finally, these questions asked for a quantity to attach to the risk associated with developing such a product. The life cycle costing model of this research is designed to address such questions. The aforementioned section, however, dealt with whether to pursue product A, B, or C. This section on the other hand, addresses the question, "Given certain budgetary constraints, and given a list of products to develop, which group of products will meet the constraints, maximize revenue, and minimize risk?"

In a world of limited resources, one must make choices all of the time about what to do or not do, what to buy or not buy. This is true of individuals and of firms, but in the industrial community, these choices are made on a much grander scale. In a given year, a manufacturer considers large numbers of products for R & D. The fact remains, however, that each product pursued consumes a portion of the available resources. Resources are limited. There is no way every product can be funded by a particular firm. The manufacturer must therefore choose a product line (portfolio) which is the most valuable for that firm to pursue. This is where the concept of portfolio optimization becomes important. The manufacturer is not simply trying to maximize the potential earnings with an optimal portfolio of products. It is one thing to earn revenue with a product line; it is quite another to earn enough revenue to offset R & D costs. Therefore, the optimal portfolio, besides optimizing revenue, minimizes the risk of failing to recoup the R & D costs involved with new product development.

In the world of finance, portfolio optimization refers to selecting the portfolio of investments that maximize the expected return while minimizing the variance on that return. To the manufacturer considering new product development, the portfolio chosen should maximize the expected revenue earned on the portfolio of products while reducing the risks involved. With new product development, these risks involve the time the product is ready for market, the time at which the competitor introduces a similar product, the demand for the product, and the length of the product life cycle.

Linear Programming Models

A number of models have been proposed to help the decision-maker compose the optimal portfolio. Gear presents various linear models that could be used to pick the most advantageous portfolio. He outlines a model developed by D.C. Bell and a model developed by L. D. Watters (Gear, 1971:66, 68). The Bell model is a linear program that can break future time into more than one planning period. One of the disadvantages of this model is that it assumes the time series of resource requirements are exactly known in advance (Gear, 1974:120).

Watters' model, on the other hand, is an integer program with a budget constraint in each of several time periods. This model allows the inclusion of risk and probabilistic constraint rows and equations that include project dependence and independence. The disadvantage of this model is that it assumes only budget constraints are necessary (Watters, 1967:69). Gear cites difficulties in the use of this model. For example, it may be hard to obtain data that includes the expected value of the costs and returns of projects, as well as the probabilities of exceeding budget constraints (Gear, 1971:68). Despite the limitations cited, this model is used in this research to optimize the portfolio for the sample problem in the methodology and analysis sections of this thesis.

Another approach to choosing the optimal portfolio is referred to in the literature as a conformance approach. Used in the investment community, this method is somewhat qualitative in nature. For instance, some of the factors considered when choosing one stock over another are the company's capitalization, the past performance of that stock, and the quality of the investment (Trippi, 1996:24).

Efficient Frontier

A major breakthrough in the field of portfolio optimization occurred when Markowitz introduced a mean-variance optimization model in 1952 (Markowitz, 1959). This approach seeks to minimize the uncertainty of the variance while achieving a

Minimize $$V_p = \sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij}x_i x_j$$

subject to :

$$\sum_{i=1}^{n} R_i x_i = R_p$$

$$\sum_{i=1}^{n} x_i = 1$$

$$x_i \geq 0, \qquad i = 1,\ldots n,$$

where:

n is the number of available securities.
x_i is the fraction of the portfolio held in security i.
$R_i \equiv E(r_i)$ is the expected value of return on security i.
$R_p \equiv E(r_p)$ is a target level of expected return on the portfolio.
σ_{ij} is the covariance of returns of securities i and j.
V_p is the variance of the portfolio's return.

minimally acceptable expected return. By definition, the model's objective function is quadratic and the model's constraints are linear. When such a model is solved, the solution is called an efficient portfolio. The model's formulation can be seen in Figure 6

Figure 6: Markowitz Mean-Variance Model Formulation—(Trippi, 1996:27)

When this quadratic problem is solved, the result is what is commonly referred to in finance as the efficient frontier. This efficient frontier, Figure 7, is a set of points known as efficient portfolios. Each point on the efficient frontier minimizes the variance of a portfolio's return while obtaining a minimally acceptable expected return. As can be seen from Figure 7 , A is the current portfolio. Because A does not lie on the efficient frontier, it is a portfolio that obtains a certain yield at too high of a risk. In the case of A, the portfolio make-up should be altered in the direction of the X-axis and/or the Y-axis, depending on the desired outcome. If the portfolio moves in the Y-direction, it will obtain a higher expected yield for the current level of risk. If the portfolio moves in the X-direction, it will obtain the same yield it had been obtaining with a lower risk. Trippi and Lee point out that as the number of assets from which the portfolio is chosen increase, the portfolio selection never results in a lower efficient frontier. However, they are just as quick to point out that as investors include new assets whose returns are not positively correlated with the current assets available, the risk-return combinations can be improved (Trippi, 1996:29).

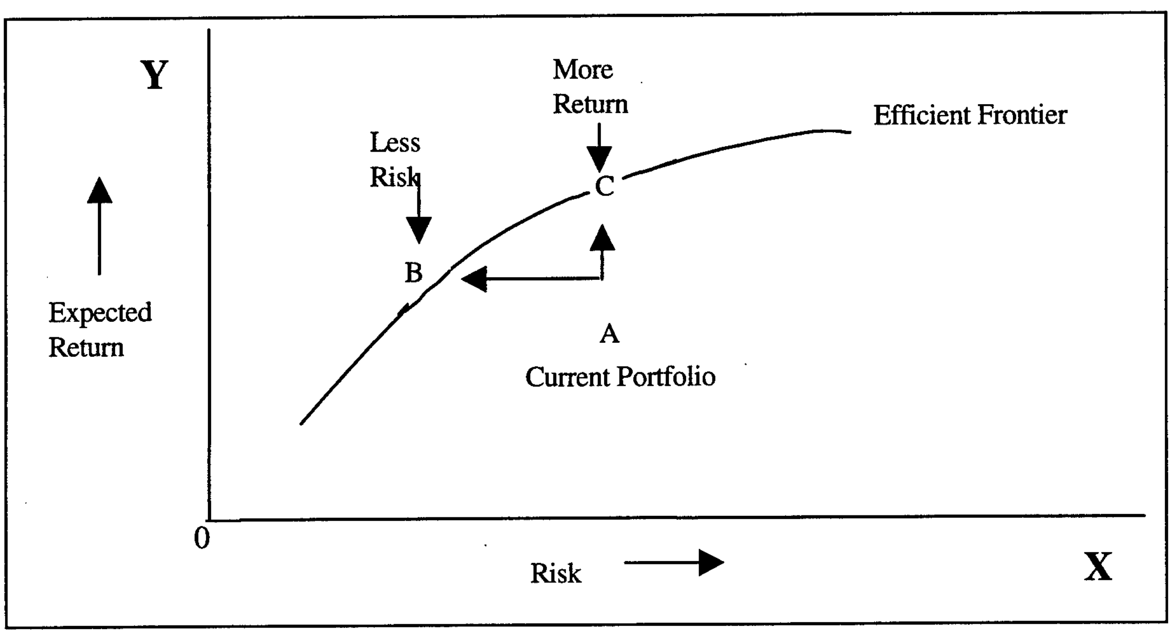


Figure 7: Efficient Frontier

The Markowitz model is elegant, but as the number of available securities to build a portfolio becomes large, determining the ever-increasing values of the covariance matrix becomes unwieldy because the computation uses too much computer memory and time.

Sharpe, however, proposed an answer to this dilemma. He suggested that as long as two factors could be supplied, the covariance matrix involved with the Markowitz model would be derived much more efficiently (Sharpe, 1963:277). The first factor needed is the covariance of each security with the entire market (I). The second factor needed is the responsiveness of the security's return to the return of the entire market (r_I) (the return of the entire market), also referred to as the beta coefficient. This beta coefficient is the slope of the following linear equation (Equation 4 below).

$$\boxed{r_i = \alpha_i + \beta_i r_I}$$

Equation 4: Characteristic Line

In this equation r_i is the return on an individual security, α_i is the component of security i's return that is independent of the market's performance (random variable), and β_i is a constant that measures the expected change in r_i given a change in r_I. This line is also commonly referred to as the characteristic line. If the securities are highly correlated with some index (I) with return variance σ_I^2, then the product $\beta_i \beta_j \sigma_I^2$ provides a good estimate of the covariance σ_{ij} (Trippi, 1996:33). This estimate of the covariance can only be a good estimate of the covariance σ_{ij} if the only source of common variation is the market return. If this is valid, then the Markowitz model has been drastically simplified.

Capital Asset Pricing Model

Another model used in the optimization of investment portfolios is the Capital Asset Pricing Model (CAPM). Sharpe, Lintner, and Mossin each independently developed the CAPM within a year of each other. Briefly, this model shows the relationship between the expected return of an asset and its risk under perfect conditions (market equilibrium). This relationship is also assumed to exist in a market in which all investors undertake optimal portfolio selection using the Markowitz mean-variance framework (Tucker, 1994:209).

The following are assumptions of the CAPM commonly found throughout the literature.

1. All assets are marketable.

2. Capital markets are perfect:
   a. Fractions of assets can be traded.
   b. No one investor can influence the market by buying or selling actions.
   c. Taxes and transaction costs do not affect the investment decision.
   d. Unlimited borrowing and short selling are allowed.
   e. Information is freely available to every investor, and all possess the same information.

3. A risk-free interest rate exists at which all investors can undertake unlimited borrowing or lending.

4. All investors are risk averse and seek to maximize expected utility over one-period horizons.

5. Investors have homogenous expectations:
   a. They possess the same investment horizons, and their estimates of the expected returns, variances, and covariances of risky assets are identical.
   b. They all base their portfolio selection decisions on Markowitz mean-variance optimization.

(Tucker, 1994:209).

The equation (Equation 5) of the CAPM is:

$$\boxed{E(r_i) = r_f + [E(r_M) - r_f]\frac{COV(r_i, r_M)}{\sigma_M^2}}$$

Equation 5: CAPM

where r_i is the return on any risk asset i, r_f is the risk-free rate, r_M is the market risk premium, and σ_M^2 is the variance of the market.

Often, this is simplified,

$$E(r_i) = r_f + [E(r_M) - r_f]B_i$$

$$\text{where } B_i = \frac{COV(r_i, r_M)}{\sigma_M^2}$$

This equation states that the equilibrium expected return on any risky asset ($E(r_i)$) consists of the risk-free rate (r_f) plus a risk premium (the second term). The risk-free rate is given as the rate of U.S. Treasury Bills. Treasury Bills are used because their prices are relatively insensitive to changes in the financial world, and because they are backed by the U.S. government, they are considered stable (Levary and Seitz, 1990:43). The second term depends on the covariance of the asset's return with that of the market portfolio. The market portfolio is the portfolio that consists of all securities within the entire market.

It should be noted that the expected market risk premium and the variance of the market portfolio return are the same for any risky asset we wish to estimate. Therefore, the term (B_i) is unique to each risky asset (i). B_i is referred to as the market beta of asset i, and is a measure of the covariance risk of asset i (Tucker, 1994:213).

In the CAPM, expected return of a portfolio is related to risk in a linear fashion. This line is referred to as the security market line (SML). This SML depicts the expected return-risk relationship for any asset or portfolio i, which need not be on the efficient frontier (Tucker, 1994:214). If the market beta (B_M) is equal to one, this means M has perfect positive correlation with the market portfolio. If this is true, the expected return for that asset is that of the market portfolio. Therefore, an asset or portfolio with a beta < 1 will have an expected return proportionately less than the market portfolio. Alternatively, a beta > 1 indicates an expected return proportionately greater than the return of the market portfolio.

The beauty of the CAPM is that the result is identical to the Markowitz model, but with a much greater efficiency of computation. However, there has been controversy concerning the CAPM. Statistical analysis has been performed using this model and the results are inconclusive as to its validity. Tucker attributes these mixed reviews to the complexity of the capital market. He also says that in the "real" world, many of the assumptions of the CAPM can be violated (Tucker, 1994:219).

LCC Models

Though most models do not attempt to capture all life cycle costs, Dereli developed a model that does seek to capture as many costs as possible in a remediation process. To enable the model to be specifically used by the DoE, Dereli developed the model so the DoE could input their Work Breakdown Schedule (WBS). The model supports the DoE in making decisions about alternative remediation technologies that could be used to clean sites contaminated with hazardous materials. Dereli's model incorporated cost scaling methods to improve the traditional LCC modeling techniques (Dereli, 1998:vii). Cost scaling methods help to estimate costs based on past expenses. For example, if a corporation was trying to estimate the costs of building a new facility, it might estimate based on the costs of a facility built in the past. He also investigated and incorporated inflation factors into the model in order to make better cost estimates to use in evaluating which technologies to pursue and which technologies not to pursue.

Three other models that have been used extensively are the Parametric Review of Information for Costing and Evaluating model family (PRICE), the Modular Life Cycle Cost model (MLCC), and the Cost Analysis and Strategy Assessment (CASA) model. The PRICE family of models was developed and extensively used by General Electric and consists of six different program modules that perform specific functions (Twomey, 1991:136). Data results from each of the modules can be fed into the other modules as the need arises. The module of most interest is the PRICE M (Electronic Module and Microcircuit) module. This module is able to provide quick and reliable development and production costs, and to produce schedule estimates for electronic modules (Twomey, 1991:138).

Similar to the PRICE model is the MLCC model. Gruman developed this model for use by the USAF (Twomey, 1991:154). Both the PRICE and MLCC models are quite similar because they were created to estimate life cycles costs using R & D, acquisition, and operation and support data. Neither model takes product disposal into account when computing life cycle costs and neither model takes advantage of simulation to analyze uncertainties.

The CASA model, however, does allow simulation inabling risk assessment to be performed. However, in similar fashion to the PRICE and MLCC models, the CASA model does not allow for disposal cost data to be entered into the model (Twomey, 1991:213).

None of the three models just mentioned (PRICE, MLCC, and CASA), introduces a learning curve effect or uses simulation to investigate a time to market feature. These features offer a strong contribution to the field of life cycle costing and are available in this research's model. In addition, this research's model runs on a PC platform, can be freely distributed, and does not take numerous analysts to run. In contrast, the PRICE model is a time-share model and is expensive to run. PRICE, MLCC, and CASA require numerous analysts to accomplish the task of life cycle costing.

More recently, another life cycle costing model that has been used commercially is LifeCast Pro, marketed by Hunter Technologies Group, Inc. This model is designed for small, medium, and large firms that produce new products or services on a regular basis. The model is designed to forecast the success of new products by using time series forecasting and is based on the diffusion theory that was developed by Bass in the late 1960s (Hunter Technologies, 1998). The model is written in Visual Basic and runs on a PC platform. Though the model is user-friendly and is designed for the product manager and marketer, the model relies on the knowledge of the user or historical data. For example, it assumes that the market size and life cycle is known. It also assumes the foreknowledge of the entry of the competition. This research's model, however, is more flexible in that the market size and length of life cycle are not deterministic. Finally, this research's model treats the entry of the competition stochastically rather than deterministically.

Chapter 3: Methodology

Introduction

The bottom line for any company is the amount of profit that is expected from its operations. In the field of new product development, this bottom line is very uncertain and, thus, very difficult to estimate. Because companies rely on new products for upwards of 1/4 to 1/3 of their annual revenue, the estimates of profit from new products becomes even more important, despite its volatility (Thomas, 1993:17). The objective of this research is to develop a model that provides high technology companies a means to select those new products to pursue and those to pass over. To accomplish this objective, cost and revenue estimates must be accurate so that the expected value of profit may be more accurately estimated. To reach this research objective, a series of milestones have been met along the way. First, this model provides a means of estimating new product R & D costs. Second, this model provides a means of estimating revenues from new product development. Third, and most important, this model utilizes portfolio analysis to select those new products or projects that should be pursued and those that should be passed over. Those projects or products that are selected are expected to accomplish the goal of maximizing the expected value of profit and minimize the uncertainty, or variance of this expected value.

This chapter outlines the methods and rationale that were used to accomplish the goals established in developing the model. The ramifications of linking learning curve effects to cost estimating are discussed. In addition, time of entry into the market is investigated and how this entry impacts profit estimation is studied. Finally, a zero-one integer program is discussed, and its use in portfolio analysis is discussed. After discussing the methodology behind the development of the model, the chapter concludes with the presentation of a sample problem analyzed with the model.

Based on the literature reviewed in Chapter 2, a life cycle cost (LCC) model for new product development was developed. In the remaining sections of this chapter, the following topics are discussed: work breakdown structure, learning curve effects, time to market, portfolio optimization, risk analysis, sensitivity analysis, and a specific application of the LCC model.

PPSM Model

The Product Portfolio Selection Model (PPSM) has been developed in Microsoft Excel 97 with Visual Basic for Applications (VBA) as its programming language. The other two components of the PPSM environment are Crystal Ball (CB), a risk analysis tool, and LINGO, an optimizing software package. PPSM is menu driven and is user friendly for individuals who have limited programming background. The macros, written in VBA, are menu-driven and guide the user through the steps of creating a PPSM based upon a product work breakdown structure. CB uses Monte Carlo simulation to place distributions on variable and cost element values. It also permits the use of what it defines as forecasting to determine a risk profile for cash outflows and inflows, as well as net profit. The expected value of the net present value (NPV) and the variance of the NPV for each product is then placed into a mathematical program format that is evaluated by LINGO. The VBA programming code, in its entirety, is commented and can be located in the Visual Basic editor within the Excel model.

The structure of PPSM is illustrated in Figure 8. CB and VBA interact directly with Excel during the model setup, data modification, and simulation. Once these stages are complete, the simulation results are input into an optimizer package, LINGO, and a portfolio is selected.

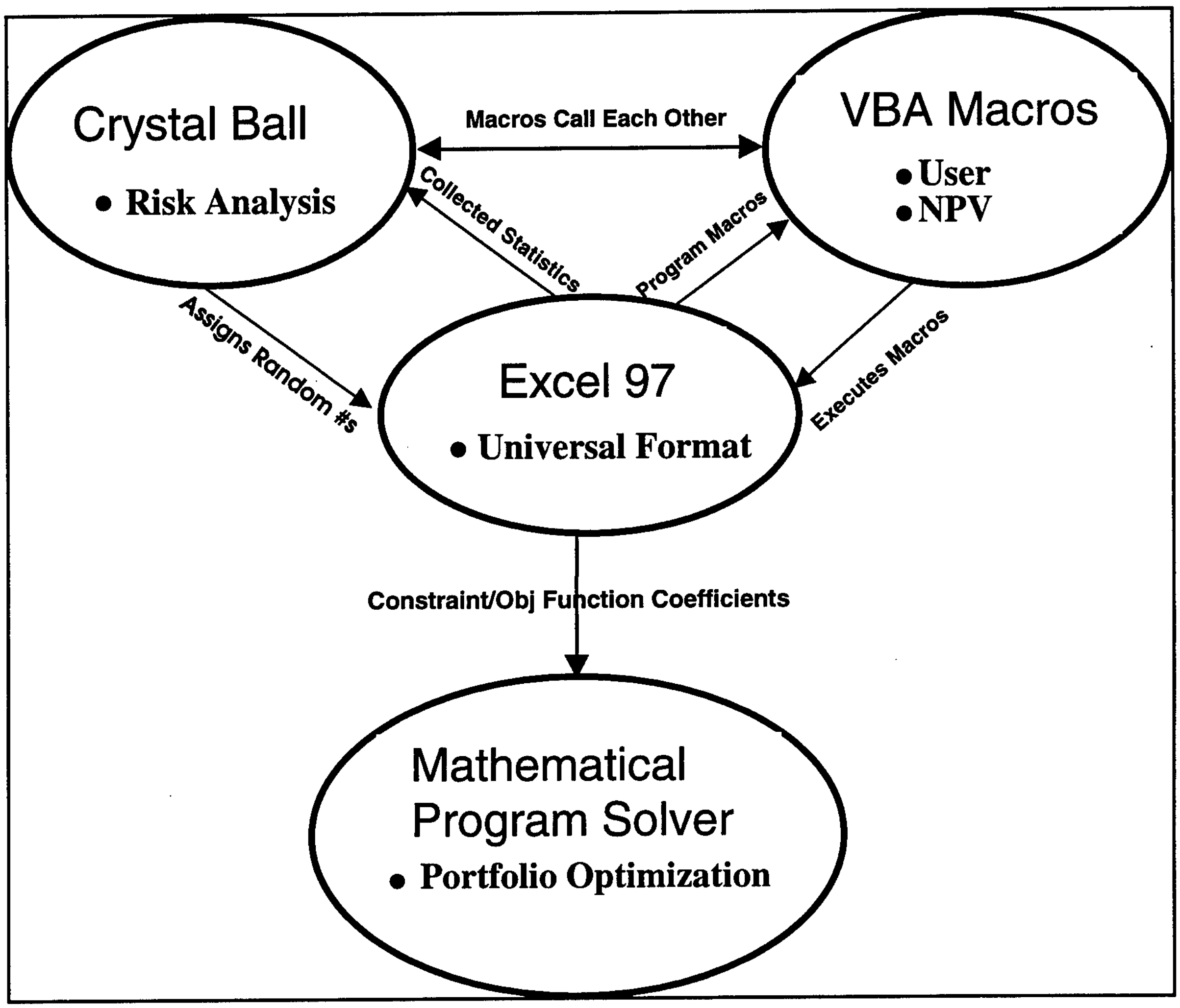


Figure 8: PPSM Framework

Figure 8 is designed to provide a very broad overview of the interactions of the major building blocks of the model. For a more detailed look please refer to Figure 9.

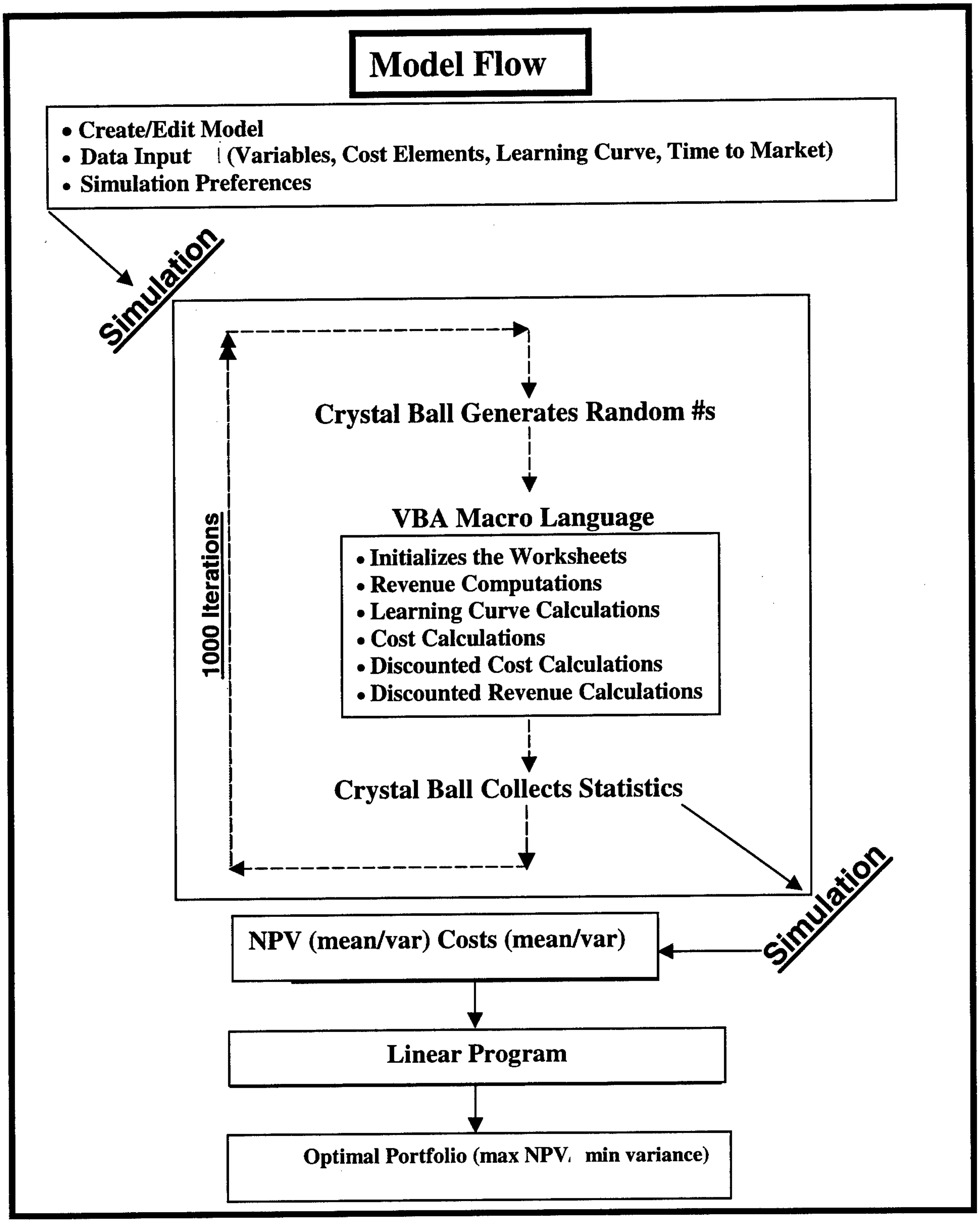


Figure 9: Product Portfolio Selection Model (PPSM)

Work Breakdown Structure

As mentioned in the introduction of this chapter, it is extremely important that the developers of new products estimate the costs associated with R & D as accurately as possible. To assist in making these estimates, all the work required to manufacture a product must be specified in detail. This is accomplished by means of a framework called a work breakdown structure (WBS). The purpose of a WBS is to assure that all key cost elements from idea conception to phaseout can be accounted for (Dereli, 1998:11). With the WBS in hand, the user can enter cost elements, and the variables upon which they rely, into the model. The user creates a new model and inputs this data specific to his needs.

Learning Curve Effect

In addition to the work breakdown structure, another feature available in the model that can be used for better cost estimation is a learning curve effect feature. As defined in the literature review, a learning curve represents the concept that as a product is manufactured over and over, costs involved in the production process can decrease as a result of learning more efficient ways to produce. This can translate into fewer labor hours, less material, higher quality, or in general more efficient production strategies.

The model offers the use of the arithmetic learning curve or the logarithmic learning curve, also referred to in the literature as the Crawford learning curve (Fields, 1993). Though both are available in the model, the example problem utilizes the Crawford curve. Throughout the literature, the Crawford learning curve appears to be used most often. The logarithmic-based learning curve captures diminishing returns to scale in a more reasonable fashion than does an arithmetic curve.

Recall, that the learning curve formula is as follows:

$$PE = E_f Z^{\beta}$$

PE = production effort (hours per unit of product Z)
E_f = effort (hours) needed to produce the first unit
Z = cumulative total of units produced
β = negative slope parameter of the learning curve

In the formula for the learning curve, the question often becomes an issue of determining β. Given, $PE_1 = E_f Z_1^{\beta}$ and $PE_2 = E_f Z_2^{\beta}$, where PE_1 is the amount of time required to produce the first unit, and PE_2 is the amount of time required to produce the second unit. Also, Z_i, i = 1,2 is the cumulative number of units produced (i.e. one and two in this development). With this substitution, dividing the first equation by the second yields:

$$\frac{PE_2}{PE_1} = 2^{\beta}$$

To determine β, take the natural log of both sides and divide both sides by the ln(2). For example, if the reader wanted to estimate β when the learning curve is 75 %, the equation becomes:

$$0.75 = 2^{\beta}$$

Taking the natural log of both sides:

$$\ln(.75) = \ln\left(2^{\beta}\right)$$

Simplifying further

$$\beta = \frac{\ln(.75)}{\ln(2)}$$

so,

$$\beta = -0.3219$$

In general, β can be computed using the following formula:

$$\beta = \frac{\ln(\textbf{Learning Rate})}{\ln(2)}$$

The prompts within the PPSM suggests the user pick a percentage that lies between 0.70 and 0.95 because this is the common range that can be found in literature pertaining to the manufacturing community. The range however, is not limited to (0.70, 0.95). The user can input any number ($0 < x \leq 1$).

In the PPSM, learning curve effects can be placed upon variables or cost elements. A variable is defined as an element within the model that is a constant or formula that links to the net present cost (NPC) calculations within the model. For example, a user might need to incorporate *Wages* as a variable. In this case *Wages* could be tied in to the cash outflow each period that links to labor costs. Cost elements, on the other hand, are directly linked to the NPC calculations and can be a constant or formula. Three types of cost elements are provided within the PPSM. Those three types are recurring, trapezoidal, or percentage. Recurring cost elements are specified as occurring for a given number of periods. Trapezoidal cost elements are based on a trapezoidal equation which takes into account a starting period, a phase-in period, a constant period, and a phase-out period. Percentage cost elements occur for a specified number of periods with a percentage (also specified by the user) of the cost element flowing out each of the specified periods. An example of a recurring cost element is *LaborCost*. *LaborCost* could refer to the amount of cash outflows that occur each period to pay the workers. As the model calculates period costs and revenues, any variable or cost element that is influenced by a learning curve effect is updated according to the percentage set by the user. In addition, if the initial value of the variable or cost element contains uncertainty, CB can be utilized to place distributions upon such uncertainties.

Market Uncertainty

Up to this point of the chapter, cost estimation features that enhance accuracy have been discussed. In new product development, it is just as important to estimate the revenue from product sales as it is to accurately estimate cost elements. This section and the following section of the chapter describe how the estimation of revenue is improved. First, dynamics of the market are discussed. Then entry into the market is described.

There are three main aspects of the market that are important in the revenue estimation process. These three aspects are market length, market size, and market distribution (Deckro, Hebert, and Kloeber, 1998). Length of market describes the period of time in which a product is sold and yields revenue. This becomes important to manufacturers because there is a limited window of opportunity to become not only leaders in the field, but to earn enough money to recoup R & D expenses for the product. The shorter the length of the market, the less time there is to earn money. In the example problem of this thesis, the length of market ranges from 12 months to 24 months. These restrictions are consistent with the literature that demonstrates a short life cycle for high technology products.

The size of the market is also very important in revenue estimation. The size of the market refers to the amount of revenue available to all that enter the market to sell an equivalent product. The risk with the size of the market is that the amount of revenue for the entire market may not cover the R & D costs of one or more entrants.

Finally, the distribution of the market is important to revenue estimation. The market may very well support more than one competitor, but if the highest level of sales occurs near or at the beginning of the market, one who enters late may lose out on potential revenue and may risk total loss. Therefore, the shape of the market distribution becomes very important and is a source for risk.

The model incorporates CB to handle the uncertainty of the market length and size. CB allows distributions to be set on the market length. During each run of the simulation, random numbers are used to estimate the length of the market. CB handles the size of the market in a similar fashion. Each run of the simulation yields a different market size. Table 1 lists the distributions available within CB.

Table 1: CB Distributions

Crystal Ball Distributions
• Beta • Binomial • Custom • Exponential • Extreme Value • Gamma • Geometric • Hypergeometric • Logistic • Lognormal • Negative Binomial • Normal • Pareto • Poisson • Triangular • Uniform • Weibull

Though distributions of the market length and size are set by CB, the distribution of the market is set through the PPSM. Within the model Excel/VBA user-interface, four distributions are available to the user. These four distributions are Beta, LogNormal, Normal, and Gamma. The Beta distribution is available in the model because of its flexibility to represent variability over a fixed range and to predict the random behavior of percentages (Sargent and Wainwright, 1996: 79). The LogNormal distribution is available in the model because, as mentioned earlier, the uncertain variable cannot fall below zero and it is positively skewed toward the lower limit. The Normal distribution is available in the model because of two underlying conditions: the mean value of the uncertain variable is known, and though the uncertain variable is equally likely to fall above or below the mean, most values fall within three standard deviations of the mean (Sargent and Wainwright, 1996:61). When one uses the Gamma distribution, he/she assumes there can be an unlimited number of customers and that these customers make purchases independent of one another (Sargent and Wainwright, 1996:92). In reality though, there is a limited number of customers, and there may be some correlation of purchase, but in some cases, these assumptions may be relaxed and retain validity. Beside the fact that the available market distributions have been included to match market assumptions, they are built into Excel and are readily accessed from VBA. The user determines this aspect of the model when he/she builds or modifies the model. The user is assumed to have some reasonable idea of the shape of the market distribution, determined by historical data, expert opinion, or some other market research technique.

Time to Market

The literature review demonstrates the need to enter the market in a timely fashion because of the uncertainty of the market length, size, and distribution. It has also been shown that the time at which a company enters the market directly influences the percentage of the market share it is able to obtain. How can one be certain to enter the market before the competition? The answer is that one cannot be absolutely certain. The market data the company collects may have been collected in a nearly flawless manner, but that same company cannot be absolutely certain of the accuracy of the data. This demonstrates the need for the model to allow uncertainty for not only one's own market entry, but also the entry of one's competitors.

The model is designed for the user to determine the number of competitors that are expected to enter the market. Though the model has been programmed to allow between one and four competitors to make analysis more tractable, slight alterations in the programming would allow more competitors to be modeled. Though the number of competitors is deterministic, the model allows the user to make competitor entry (including oneself) deterministic or stochastic (distributions established through Crystal Ball).

Thus far, this chapter has discussed how the model can be used to handle the number of competitors and the entry point for each. One might wonder at this point if the first one to enter the market has any advantage over entrants who enter the market after him/her, and if so, can the model estimate this advantage? If there was no advantage, one would assume that as each competitor enters the market, the remaining revenue is divided equally. For example, if there are two competitors entering the market at the same time, they each have a 1/2 share of the revenue until the third competitor enters, at which point they each have a 1/3 share of the revenue. The model is set, by default, to handle competitor share of the market in this manner. In the sample problem, however, the first to market is given a higher weight than just the standard $\frac{1}{n}$ share. The sample problem has been set up to add a weight to the first entrant ranging from 1/10 to 3/10, distributed uniformly. As the literature points out, though the findings for such weights are not conclusive, evidence does exist to point to an advantage for the first to enter the market. Other factors may be key players in determining extra shares of market to the first entry such as advertising, price, promotion, product quality, distribution, and managerial effectiveness. These are noted, but in limiting the scope of this research to examine only entry into the market, such aspects are assumed to be equal among all competitors who enter the market. Though the example problem rewards the first competitor to enter the market, the user has the option of neglecting or altering the weights based on their knowledge of the market. All other competitors share the remaining portion of the market, once the first to market share is removed, equally.

Monte Carlo Simulation

The methodology description to this point has included variable, cost element, and learning curve element input. It has also discussed the dynamics of the market and the ramifications of entry into the market for oneself and for one's competitors. The next step of the PPSM is to perform a simulation so that an expected value for profit can be estimated, including a variance on this point estimator. Before discussing simulation, however, the methods for establishing distributions and forecasts must be discussed.

Variables, cost elements, learning curve elements acting as variables or cost elements, market length, market size, and time to market data all have something in common. Each of these has the potential to be stochastic. As such, a tool is needed to estimate their values and the variance surrounding those value estimations. Monte Carlo simulation is well suited to the task of estimating expected values and establishing variances around expected values. In this model, Crystal Ball is used to set distributions on the uncertain model elements. CB is also used to forecast distributions on critical output. In this model an example of critical output is the expected NPV and variance of NPV for a new product being considered for development. When called from the VBA interface, CB uses Monte Carlo simulation to act on the set distributions so that the required forecasts may be obtained. Sensitivity analysis must then be performed to determine the elements that are key influences on the forecasts.

Portfolio Runs

At this point of the methodology the researcher presupposes that all simulation runs have taken place. In other words, all variables and costs elements have been placed in the model, all market information has been input, and time to market data has been established. An additional assumption is that all simulation runs with sensitivity analysis have been performed and the user has a point estimator (with variance) of net profit (in terms of net present value) for each product that is evaluated using this model.

With this information in hand, portfolio optimization can now be accomplished. In the financial world, portfolio optimization depends on a mathematical program, such as the linear or quadratic programs presented in the literature review. Quadratic programs, such as the Markowitz or CAPM models, are designed to pick the portfolio with the greatest expected value for a given level of risk. In the financial world, this optimal portfolio consists of a mix of securities, which means that a portfolio may consist of percentages of securities. In the case of this research, though, it is assumed that an optimal portfolio cannot consist of percentages of the available products. Either the product is, or is not, selected to join the portfolio. The optimal portfolio in new product development, therefore, becomes a zero-one integer problem. To this end, a model developed by Watters has been selected (Watters, 1967). This model has been adapted to select the optimal portfolio of products and results in the required binary solution format. Figure 10 presents the modified formulation.

The objective function of Watters' linear program is:

$$\textbf{Maximize E[U(R)]} = \sum_{j=1}^{N} \left(\mu_j - A \cdot \sigma_j^2 \right) x_j \quad (1)$$

The objective function consists of the summation of the expected NPVs of each product less the risk aversion factor multiplied by the variance of the expected NPV. The decision variables in the objective function are binary so that if the variable equals 1, the product enters the portfolio, otherwise the variable equals 0.

The first constraint of the formulation is:

$$-\sum_{j=1}^{N} \left(z_i^2 \cdot \sigma_{c,i,j}^2 + 2B_i \cdot c_{i,j} - c_{i,j}^2 \right) x_j + 2\sum_{j=1}^{N-1} \sum_{k=j+1}^{N} c_{i,j} \cdot c_{i,k} \cdot x_{j,k} \geq -B_i^2 \qquad (i = 1,2,\ldots,M) \quad (2)$$

This is the budget constraint that keeps the selected portfolio from exceeding a certain percentage. This cap relates to the standardized random variable associated with the desired probability.

The second constraint of the formulation is:

$$\sum_{j=1}^{N} c_{i,j} \cdot x_j \leq B_i \qquad (i = 1,2,\ldots,M) \quad (3)$$

This constraint ensures the expected costs of the portfolio not exceed the budget for a given period. In the sample problem of this thesis, there is only one budget period, thus only one budget constraint.

The third set of constraints of the formulation are:

$$\begin{Bmatrix} x_j + x_k - x_{j,k} \leq 1, \\ -\frac{1}{2}\left(x_j + x_k\right) + x_{j,k} \leq 0, \\ x_j, x_k, x_{j,k} = 0 \textbf{ or } 1, \end{Bmatrix} \qquad (j = 1,2,\ldots,N-1; \quad k = j+1, j+2,\ldots,N) \quad (4)$$

This set of constraints transforms quadratic interaction terms (as a result of multiple budget periods) into linear terms. The variables and parameters are defined in Figure 10.

Maximize (Portfolio Expected Return - A $\cdot$ (Portfolio Variance))

$\rightarrow$

Maximize E[U(R)] $= \sum_{j=1}^{N} \left(\mu_j - A \cdot \sigma_j^2\right) x_j$

μ_j --Expected NPV from sales of Product j

σ_j^2 --Variance of the expected NPV from sales of Product j

x_j = 0 or 1; 1 if Product j is selected, 0 if Product j is not selected

A --Risk Aversion (i.e. The amount of risk the decision-maker is willing to take)

Subject to:

Budget Constraint:

$$\sum_{j=1}^{N} -\left(z_i^2 \cdot \sigma_{c,i,j}^2 + 2B_i \cdot c_{i,j} - c_{i,j}^2\right)x_j - 2\sum_{j=1}^{N-1} \sum_{k=j+1}^{N} c_{i,j} \cdot c_{i,k} \cdot x_{j,k} \geq -B_i^2 \qquad (i = 1,2,\ldots, M)$$

z_i^2 --Represents the standardized random variable corresponding to the stipulated probability α_i (Ensures the budget for period i does not exceed desired percentage; eg. $z_i = 1.28$ keeps the budget for period i from being exceeded by 10 %).

$c_{i,j/k}$ --Cost of product (j,k) for period i

$\sigma_{c,i,j}^2$ --Variance of the cost for period i, product j

B_i --The budget for period i

$$\sum_{j=1}^{N} c_{i,j} \cdot x_j \leq B_i \qquad (i = 1,2,\ldots, M) \text{ (Ensures the costs do not exceed the budget each period)}$$

$$\left\{\begin{array}{l} x_j + x_k - x_{j,k} \leq 1, \\ -\frac{1}{2}\left(x_j + x_k\right) + x_{j,k} \leq 0, \\ x_j, x_k, x_{j,k} = 0 \text{ or } 1, \end{array}\right\} \qquad (j = 1,2,\ldots, N-1; \quad k = j+1, j+2,\ldots, N)$$

$x_{j,k}$ --Linear terms transformed from quadratic terms of original formulation

Figure 10: Watters' Linear Portfolio Selection Formulation

Watters' integer program is designed to pick the optimal portfolio for multiple periods. The sample problem, however, examines a market cycle with only one budget period. This makes the (i) index in the model unneeded since it is equal to one, but future research could examine multiple budget periods while investigating new versions of the same product. The objective function of this linear program is to maximize the expected profit less (A*variance of the profit). In this formulation, "A" refers to the risk aversion the decision-maker is willing to take. The value of "A" can range from 0.00 to 1. The closer to 0.00 "A" becomes, the more risk neutral the resulting answers become. If, for instance, the decision-maker allowed A = 0.00, he/she is acts as if immune to such a large amount of variance. On the other hand if the value of "A" approaches 1, the expected profit approaches 0 because large values of "A" assume the decision-maker is not willing to take any risk. A visual representation of various choices of "A" can be seen in Figure 11. As the value of "A" decreases, the less effect on the variance of the NPV, and the lower the greatest expected value of the NPV. When A = 0.00 for example, the decision-maker is not concerned with risk at all and the mean value of NPV is $1,300,000 yet the probability of falling far from the mean are great. In contrast, as the value of "A" increases, the lower the probability of falling far from the expected NPV.

The budget constraint allows the user to set a limit on the percentage the budget is exceeded. For example, if $z_i = 1.28$, the user does not want to pick a portfolio that is allowed to exceed the budget by 10%. In this constraint, it is assumed the user knows the allotted amount for each budget period. It is also assumed the user knows the costs for each product (j) in period (i). Finally, the user is assumed to have an estimate on the variance of those costs. In the model developed within the context of this research, the costs, and their variances can be estimated using the Crystal Ball forecast feature. The third constraint keeps a portfolio from being selected that exceeds the budget in any given period (i).

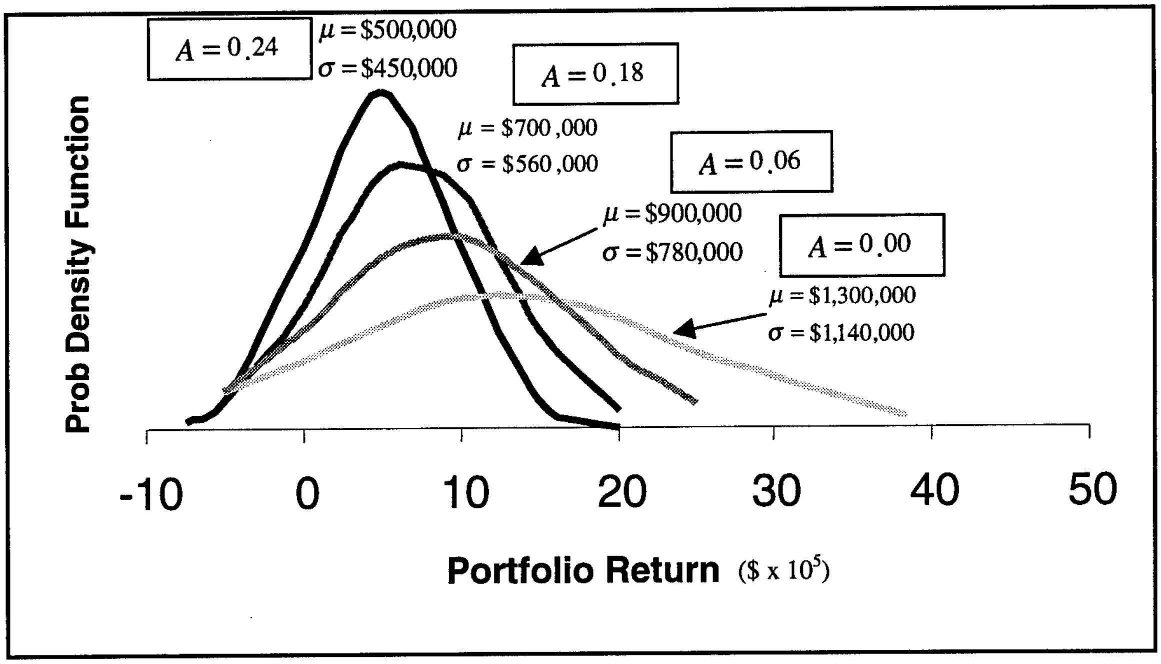


Figure 11: Risk Aversion (A) and Expected NPV (Watters, 1967)

The fourth set of constraints is the result of a transformation Watters performed from his original formulation. His original formulation involved quadratic terms because of the multi-period nature of the problem. His transformation turns the quadratic terms of the original formulation into linear and binary variables that can then be used in his linear programming formulation. More information concerning this transformation can be found in Watters' dissertation (Watters, 1967:71).

Once the formulation is set up, the next step is to place the formulation into a solver in the correct manner. In the case of the sample problem, LINGO 3.0 was selected to be the solver. For the binary variables, a value of "1" is interpreted as, the product is included, and a value of "0" means the product is not included in the portfolio.

Sample Problem: Input Device

This section of the chapter describes the sample data used, and the experiments that have been investigated within the model. First, the work breakdown structure of the problem is discussed. Second, the various variables and cost elements are explained. Third, the distributions, or assumptions as Crystal Ball refers to them are defined for the various model elements. Finally, the design of the experiments and the assumptions required to justify them are presented. It should be noted, however, that the PPSM can accept any WBS inputted by the user. If the proper cost estimates are available for the level of fidelity desired, any of structure can be accepted.

The data that has been used and modified has been derived from an example used at a conference sponsored by Digital Corporation on the topic of integrated product development for cycle time reduction. Other supplemental data was derived from a product design textbook by Ulrich and Eppinger (Ulrich and Eppinger, 1995: 267). The product line investigated represents a fictitious corporation that produces high technology products including input devices for computers. The focus of this product line is the mouse, a particular input device used with desktop computers and workstations.

The work breakdown structure (WBS) for the sample problem is located in Appendix A. The WBS is a key feature of the model. It allows the user to obtain as detailed a view of all aspects of a project or product that relate to a timeline. In the case of the model, it also allows cost to be broken into as many sub-components as desired to achieve an even more accurate estimate of costs associated with the product. As can be seen from the WBS for making an input device, most of the information is related to the assembly of the mouse. There are, however, items within this WBS that relate to gearing up for production. For example, there is an assortment of tooling costs, and there are R & D details which describe the activities that lead up to the manufacture of the product.

The parameters and their formulas/values, used in the development of the input device portfolio problem, are shown in Table 2. The first parameter is *Interest Rate*. This variable drives the net present value calculations. Had this variable been set at zero, the time value of money would not enter into the discussion of the analysis. For all simulation runs, this value remained constant. The second parameter, *Wages_Unit*, represents the labor costs for each input device produced. For the baseline data, each item in the WBS that had an associated assembly time was aggregated to obtain a total production time, in terms of hours, for each unit produced. Such an aggregation may risk over-simplification of the system because it assumes there is no concurrent production. Though the risk is noted, for analytical purposes and because of the scope of this research, the aggregation holds. The *Unit_Price* is the consumer price for this particular input device. *Demand*, the fourth parameter, drives the cost calculations that relate to production. In this system of production, there is an assumed level of defects due to machinery or human error; thus the fifth parameter *Defects* is included in the model. Associated with many items in the WBS were costs associated with parts, therefore the justification for the sixth parameter, *Parts_Cost_Unit*. *Wages*, the seventh parameter, is an average wage/hour among all labor involved in the production of the input device. The eighth parameter, *Total_Cost_Per_Period,* is an aggregation of parameters 9 and 10. Parameter 9, *Cost_Good_Units*, is the cost per unit of each input device that is of good enough quality to enter the market for consumer sales. Parameter 10, *Cost_Bad_Units,* on the other hand, accounts for the cost of producing input devices that do not have a high enough quality to be sold in the marketplace. The eleventh parameter, *Time_Unit*, is utilized by the second parameter, and represents an aggregation of the time it takes to produce one input device.

Table 2: Input Device Parameters

1. InterestRate	0.01
2. Wages_Unit	=Time_Unit*Wages
3. Unit_Price	$40.00
4. Demand	=RevenuePer/Unit_Price
5. Defects	0.05872
6. Parts_Cost_Unit	$19.90
7. Wages	$20.62
8. Total_Cost_Per_Period	=(Cost_Good_Units+Cost_Bad_Unit
9. Cost_Good_Units	=Demand*(Parts_Cost_Unit+Wages_Unit)
10. Cost_Bad_Units	= Demand*Defects*(Parts_Cost_Unit+Wages_Unit)
11. Time_Unit	0.237265064

The cost elements that were used in the development of the input device are shown in Table 3. Each cost element in this table has been input from the WBS shown in Appendix A. With the exception of *Production_Cost*, each cost element holds a direct monetary value. *Production_Cost* is the sum of all production costs for each period, so it contains a formula that allows it to change each period. This formula, tied in with the VBA calculation routines of the program, computes the cost per period so NPV is taken into account. The first column in Table 3 contains the name of each cost element used. The second column contains the amount of cash outflow associated with the cost element. The third column is the period the cash outflow occurs. The fourth column is the number of payments that will take place. The fifth column is the skip-factor, available in the case where cash flows may occur sporadically throughout the life cycle of the product. The sixth column contains the category associated with the cost element. At this point a major assumption should be explained. The start period for each of the cost elements in the example runs, with the exception of *Production_Cost*, is period 0. This start period does not mean that the R & D of the product took 0 time. It does assume, however, that the manufacturer has already discounted all R & D and capital costs to forward to period 0. The importance of this assumption and extensions to this research are noted in Chapter 5 of this thesis.

Table 3: Input Device Cost Elements

Name	Value	Start	Payments	Skip	Category
Base_To_Fixture_Tool	$22,460.22	0	1	0	Capital_Cost
Label_Hold_Tool	$1,539.82	0	1	0	Capital_Cost
Wear_Pads_Tool	$700.00	0	1	0	Capital_Cost
Cable_Tool	$600.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,465.16	0	1	0	Capital_Cost
Microprocessor_Tool	$11,646.84	0	1	0	Capital_Cost
Electrical_Test_Tool	$2,339.99	0	1	0	Capital_Cost
Buttons_Tool	$500.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.74	0	1	0	Capital_Cost
Hatch_Door_Tool	$737.94	0	1	0	Capital_Cost
Box_Tool	$1,000.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,001.27	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$1,999.28	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$2,067.41	0	1	0	Capital_Cost
Shaft_Tool	$12,000.09	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$3,700.00	0	1	0	Capital_Cost
Roller_Tool	$6,200.24	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,381.52	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$1,100.00	0	1	0	R&D_Cost
Consultants	$750.00	0	1	0	R&D_Cost
Receive_Accept_Specification:	$3,999.88	0	1	0	R&D_Cost
ConceptGeneralization	$10,092.99	0	1	0	R&D_Cost
DetailDesign	$29,560.25	0	1	0	R&D_Cost
TestBetaPrototype	$2.67	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.84	0	1	0	R&D_Cost
DesignMolds	$16,094.21	0	1	0	R&D_Cost
DesignToolings	$8,007.33	0	1	0	R&D_Cost
FabricateMolds	$21,000.00	0	1	0	R&D_Cost
DebugMolds	$20,003.85	0	1	0	R&D_Cost
CertifyDesign	$7,999.06	0	1	0	R&D_Cost
InitialProductionRun	$5,000.00	0	1	0	R&D_Cost
Ball_Tool	$12,999.78	0	1	0	Capital_Cost

The discussion of the sample problem has set forth the parameters and cost elements that lay the groundwork for the input. If Crystal Ball distributions were not established at this point, the model would simply be deterministic. The premise of this research, however, is that many elements of high technology and new product development are uncertain. In particular market length, market size, entry into the market, and the advantage of being first to the market are highly variable. Because there are elements of the model that are variable, introducing randomness based on known distributions and running simulations with Crystal Ball transforms the model into a stochastic model. The distributions for the stochastic elements of the input device sample problem are displayed in Table 4.

Table 4: Random Variables for Input Device Sample Problem

Entry of YourFirm	LOGNORM(3,1.5)--Min of 1
Entry of Competitor1	LOGNORM(3,1.5)--Min of 1
Entry of Competitor2	LOGNORM(3,1.5)--Min of 1
FirstAdvantage	UNIF(10 %, 30 %)

The distribution of the market size is not shown in the table because this distribution was changed for each product simulation. Market length is not shown in this table for the same reason. The justification for using the lognormal distribution for market entry is two-fold. First, the uncertain variable cannot fall below zero; second, the uncertain variable is positively skewed with most of the values near the lower limit (Sargent and Wainwright, 1996:74). The *FirstAdvantage* variable signifies the market-share advantage given to the one who enters the market first. The literature is inconclusive as to the level of advantage, but there are indications that the share is given additional weight between 0.10 and 0.30. This justifies using the uniform distribution for this variable.

Portfolio Selection

The central goal of this thesis is to provide a tool by which a decision-maker can accomplish several objectives. First, it helps the decision-maker accurately estimate the costs and revenues of a given number of products under consideration for R & D. Second, it employs simulation to obtain an expected value and variance for the profit of those products. Finally, the results can be used to optimize the portfolio that satisfies the goals of the corporation, namely maximum NPV with minimum risk. Minimum risk in this context refers to minimizing the amount of variance associated with maximum NPV.

To present a sample design that would demonstrate these three goals, this section introduced a sample product, the input device, commonly known as a mouse. The fictional company that designs these input devices has eight designs under consideration for research and development. The parameters, cost elements, and their distributions have been defined. A complete list of all R & D and capital cost elements can be found in Appendix C.

Table 5: Portfolio Variables and Cost Elements

Variable : Cost Element	Product							
	1	2	3	4	5	6	7	8
Unit_Price	$40	$45	$50	$55	$60	$65	$70	$75
Defects	0.0578	0.0587	0.0587	0.0587	0.04713	0.054	0.0443	0.04439
Parts_Cost_Unit	19.898	19.898	19.898	19.898	16.8422	16.1386	15.3873	15.3873
Wages	20.615	20.615	20.615	20.615	21.4176	23.0491	21.1019	23.746
Time_Unit	0.2372	0.2372	0.2372	0.2372	0.2972	0.3787	0.2613	0.3727
All R & D Cost Elements All Capital Cost Elements	See Appendix C							

Product data for the eight products, and some distributions had to be changed for each product to obtain a different expected value for NPV, and for each product to have a different variance on that expected value. The elements that were altered can be seen in Table 5. All R & D and capital cost elements were generated with random numbers. Some of the values in Table 5 were generated with the help of random numbers; other values were selected to vary the expected value for NPV as well as its variance.

The distributions of market length, market size, market distribution, entry into the market by all competitors, and the advantage of being first to the market can be found in

Table 6. These distributions were the main drivers in compiling a set of NPV profiles that could then be utilized to meet the portfolio optimization analysis of this research.

Table 6: Portfolio Distributions

Distributions	Product 1	Product 2	Product 3	Product 4
Market Length	Norm(48,6) Min24/Max48	Tri(24,36,48)	Tri(24,36,48)	Tri(24,36,48)
Market Size	Norm($4M,$3K)	Norm($4M,$3K)	Norm($4M,$3K)	Norm($5M,$300K)
Market Distribution	Norm(5,1)	LogNorm(5,1)	Norm(5,1)	Beta(2,2)
Entry of YourFirm	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1
Entry of Competitor1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1
Entry of Competitor2	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1
AdvantageShare	Unif(.10,.30)	Unif(.10,.30)	Unif(.10,.30)	Unif(.10,.30)
Distributions	**Product 5**	**Product 6**	**Product 7**	**Product 8**
Market Length	Tri(24,36,48)	Tri(24,36,48)	Tri(24,36,48)	Tri(24,36,48)
Market Size	Norm($5M,$400K)	Norm($5.5M,$750K)	Norm($6M,$1.2M)	Norm($6.5M,$1.5M)
Market Distribution	Beta(2,2)	Beta(2,2)	Beta(2,2)	Beta(2,2)
Entry of YourFirm	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1
Entry of Competitor1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1
Entry of Competitor2	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1	LogNorm(3,1.5) Min1
AdvantageShare	Unif(.10,.30)	Unif(.10,.30)	Unif(.10,.30)	Unif(.10,.30)

The explanation and ramification of the assumptions of this example problem are now presented. One assumption is that the company producing these input devices can meet the demand in any given period. This is not an unreasonable assumption because in the manufacturing community, one must expect to build inventories to handle periods with higher than projected demand. Tied in very closely to this assumption is that all products that are not defective are sold. This does demonstrate that the model is not taking into account a disposal cost. However, this cost could be established within the context of this model. It is also assumed that the price for each product remains constant throughout the market cycle.

One important feature of the Watters' linear program to solve portfolio optimization assumes that all products being considered are independent of one another. It is assumed that all the input devices chosen by the optimal portfolios will compete in different market segments, with immaterial cross over between segments.

One key feature of the model is to allow the user to determine distributions for entry to the market. These distributions affect one's own entry as well as one's competitors. In addition, an advantage weight can be added for being first to the market. The natural question is what might happen if more than one competitor, including oneself, is picked by the random number generator of Crystal Ball as the first to enter? The answer is in the assumption on breaking ties. A tie that includes oneself, or *YourFirm,* results in *YourFirm* gaining the extra weight for being first to the market.

In the literature search it was noted that the higher the quality of the marketing, the greater the possibility one has in gaining a larger share of the available market. Marketing, however, does not come cheaply; therefore, marketing costs are a prime candidate for estimation. In this model, though, marketing costs are assumed to be constant throughout the calculations of each cost and revenue period and have not been incorporated as an individual cost element. Further, each firm is assumed to have a comparable marketing program. It is worth noting however, that marketing may be explicitly included as a cost element within the PPSM.

To summarize this experiment, the goal is to take each of the eight products with their individual differences, including differences in parameters, cost elements, and key distributions, and run them through a series of Monte Carlo simulation runs. These runs are designed to obtain key statistics on costs, revenue, and ultimately NPV for each product run. The statistics on the NPV yield an expected value for the NPV and a variance that can then be used to obtain the optimal portfolio of products based on various levels of risk aversion.

Learning Curve Effect

During the course of this research endeavor, it became important to investigate learning curves. In particular, it was important to determine the effects learning curves have on estimating the costs and NPV of a product. In the runs of the sample problem, learning curve effects were not introduced because it was assumed that products developed by the same company would have similar learning curve effects. Thus to negate them from the model would not influence the results. The literature review of this research reflected the need to maintain an equivalent or improved learning curve compared to one's competition. Accomplishing this, Kerzner pointed out, is critical in maintaining or gaining shares of the market (Kerzner, 1995: 943). This was motivation to introduce a learning curve capability into the model. To analyze learning curve effects on product development, one of the input devices from the sample problem was utilized. For the portfolio runs, no learning curve was introduced. Product 1 was then run and a learning curve effect of 0.95 was placed upon the time to produce Product 1. The results of this experiment are discussed in the analysis section.

Early to Market

Another premise upon which this research rests is that entering the market early or late can greatly influence the amount of revenue that can be gained, or forfeited. To this end, an experiment was performed to investigate the effect entering early has on the revenue gained. Similar to the learning curve experiment, the early to market experiment uses the same data for Product 1, except for the distribution of *YourFirm*. In the portfolio runs, *YourFirm* was modeled with a log normal distribution with a mean of 3.0 and a standard deviation of 1.5 for the time to enter the market. In this early to market experiment, a LogNorm(1, 0.5) was used. The entry distribution of both competitors remained LogNorm(3, 1.5) as in the portfolio runs. The results of this experiment are compared in the analysis section. If a statistically significant effect can be established, such information can be used in future research to analyze R & D project planning, scheduling, and budgeting.

Late to a Compressed Market

The final experiment run was based on *YourFirm* entering a market that was compressed with entering based on late-entry. As in the early and late to market experiments, the data from Product 1 is used and is held constant except for the distributions of the entrants to market, and in this case the market length. The competitors maintained the LogNorm(3, 1.5) distribution and *YourFirm* took on a LogNorm(8, .5) distribution. To model a semblance of market compression, the revenue mean was increased from $4M to $5M. The results for this experiment are compared in the analysis sections.

Summary

This chapter has focussed on the methodology of using a life cycle cost model to investigate high technology markets that have compressed markets. In particular, the model developed, the Product Portfolio Selection Model (PPSM) is designed to allow a user to estimate all costs associated with developing a new product in a high technology market. This is accomplished through a work breakdown structure that can be input into the PPSM.

Next the importance of incorporating time to market factors into the PPSM was discussed. This chapter addressed the issue of gaining a market share advantage by being first to the market with a product and how the PPSM models the time to market factor. This chapter also discussed how the PPSM can be used to place a distribution on the time each competitor enters the market.

Monte Carlo simulation is the vehicle by which the PPSM estimates all costs of developing a high technology product as well as the revenues earned by that product. In addition, this type of simulation allows a risk profile to be placed on each product that is simulated. This risk profile consists of estimating the NPV of the product and the variance surrounding that estimate.

The method of portfolio optimization was also discussed in this chapter. Once the risk profiles of all products being considered for development are generated by the PPSM, portfolio optimization can be addressed. A formulation developed by Watters is presented, along with the rationale behind using this model for portfolio analysis. The reason for choosing this formulation over one of the available quadratic formulations was to hold to the assumption that a product can either be selected or passed over. One of the major tenets of the quadratic formulation is that partial products can be selected to enter the optimal portfolio.

Finally this chapter concluded with information specific to the sample problem. Namely, data was generated to spawn a line of high technology products (input devices/mice) proposed by a fictitious firm. The parameters and cost elements were described, along with the distributions placed on various parameters and elements of the PPSM. The various experiments were also described briefly. The experiments to be conducted involved portfolio selection involving the eight generated products, learning curve effect analysis, and time to market analysis.

Chapter 4: Analysis

Hardware and Software Utilized

Various hardware and software platforms were used to perform the runs and analysis of the sample data used as a proof of concepts for this thesis.

The PPSM is written for Excel 97 with Visual Basic for Applications (VBA). The simulation interface is Crystal Ball 4.0c. The optimizer package used to analyze the portfolio problem was LINGO 3.0, from the LINDO Suite (Student Edition).

Most of the simulations were run on a ZENITH, Pentium 133MHz desktop PC with 32 MB of RAM. Other simulations were run on PCs with CPU speeds of up to 300MHz. Some runs were performed on various hardware platforms to reduce the time spent performing runs. The length of the simulations depends on various factors. First, the number of distributions placed on the parameters and variables within the PPSM increases simulation times. Second, simulation times are further increased by the number of forecasts required from the simulation. A third factor that increases the time of simulation runs is whether or not learning curve calculations take place within the PPSM model. The speed of the CPU used to process the simulation runs is the fourth factor.

To give a more concrete idea of the time, given the four factors mentioned, a simulation with 1000 runs takes approximately 1.5 hours on a PC with a 133MHz CPU processor. This includes distributions on market length, market size, and entry of three competitors into the market, and an advantage for being first to the market. Forecasts included in this scenario are market length, market size, discounted cost/revenue, and NPV. Finally in this scenario the learning curve calculations were utilized for the length of time to produce one unit of product. Obviously changing any of the four factors will change the processing times.

Monte Carlo Simulation

When conducting a simulation, one must determine the number of runs or samplings the simulation makes to determine the validity of the results (Lewis and Smith, 1979:193). In determining the number of runs, one must make this estimate based on a sample run. Two different runs were made to determine a suitable sample size. The first sample simulation was made for 100 runs; the second sample simulation was made for 250 runs. The following formula was used for determining the expected sample size (Lewis and Smith, 1979:195). In the following equation, $\bar{n}$ represents the estimated sample size. z_α is the standardized normal variate based on the desired α-level. The standardized normal variate is squared in this formula because the confidence interval is two-sided. σ^2 is the sample variance, and d is the accepted amount of error on either side of the estimate μ_j, the mean value of the NPV for Product (j). The assumption

$$\boxed{\bar{n} = \frac{z_\alpha^2 \sigma^2}{d^2}}$$

Equation 6: Sample Size (n) for Portfolio Runs

is that the Central Limit Theorem has taken effect beyond $\bar{n} = 30$, allowing the assumption of normality. In this example $\alpha = 0.025$ and the value of $d = \$20{,}000$. The tabulated results for the simulations of runs of length 100 and 250 can be seen in (Table 7). As displayed, the sample size $\bar{n}$ lies between 627 and 739. However, all runs within this research effort were set at $\bar{n} = 1000$ because 1) a tighter confidence interval would be

Table 7: Sample Size (n)

Trials	$\bar{n}$	σ^2	d^2	$z^2_{\alpha=.025}$
100	739.3495	76983496681	400000000	3.8416
250	626.8239	65266964676	400000000	3.8416

experienced (with error on either side of the mean projected between 15,850 for the trial size of 250 and 17,500 for the trial size of 100 and 2) processing time for these simulation runs was relatively inexpensive.

Product Risk

The reason to run the simulations 1,000 times comes from the fact that a tighter variance on the NPV estimates is important. In the engineering economics field of study, the NPV of a project is assumed to be a point estimator without any variance associated with it. This assumption is built upon another assumption that discounted revenue and discounted costs are deterministic. The community of high technology new product development (NPD) is highly volatile though, and revenue and costs are not deterministic. Discounted revenue and discounted costs are therefore, random variables. Because they are random variables, the estimate of the NPV of a product is also a random variable.

As an illustration of the importance of utilizing the variance of the expected value of the NPV of a product, observe Figure 12. The expected value of this generic product's NPV is $119,612.07. The traditional engineering economics approach would be to make decisions with the assumption that $119,612.07 will be the return on the product, with 100% certainty. However, cost and revenue in the high technology community carry much uncertainty. From the figure, notice that the probability of the NPV lying between $0.00 and $ 600,000 is only 62.2% certain. This means that 38.8% of the time, one can

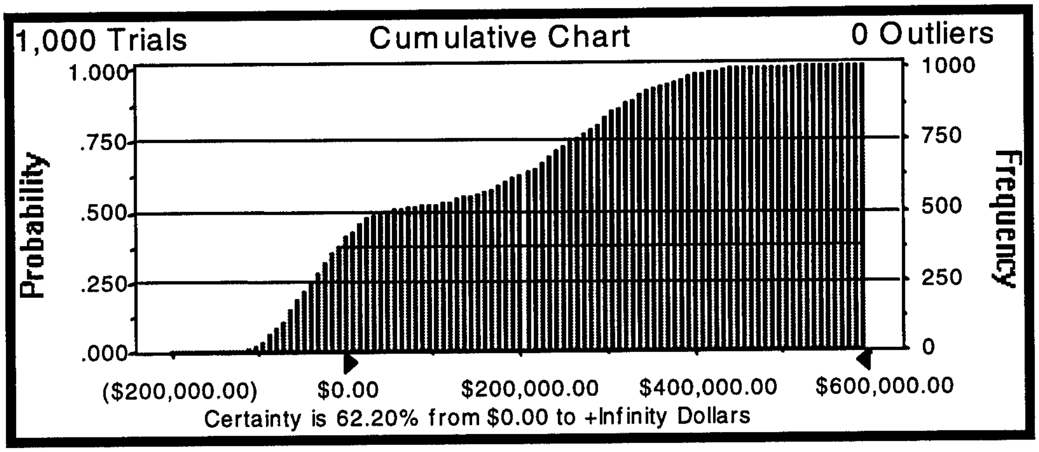


Figure 12: NPV of Generic Product

expect the NPV to be below $0.00. This demonstrates the naiveté of making decisions based on the assumption of a deterministic NPV. This also demonstrates the need to include uncertainty when making decisions concerning the R & D of a high technology product(s).

Portfolio Selection

Independence of Product Sales

In the methodology section, the assumption was made that the products (input devices) being considered for the optimal portfolio of products were designed for markets that were independent of one another. In the Watters formulation and conceptually, this is a critical assumption if one does not incorporate covariance in the model. As will be seen in the risk aversion and sensitivity analysis section, this assumption may be relaxed under certain dependency assumptions. For the baseline portfolio analysis though, the assumption was not relaxed. In addition, the mean expected value for the NPV for each product is assumed to be normally distributed with the given variance.

Simulation Results

To select the optimal portfolio with the Watters' formulation, the expected NPV and its variance are required for each product. In addition, the estimated cost of each product and the variance of that cost is needed. Finally, a budget must be established for the model to function properly. To obtain these estimates, each product was simulated for 1,000 runs. The NPV/variance estimates were obtained from risk profiles produced by Crystal Ball by randomly generating revenues and cost estimates for the net present NPV calculations. The costs for each product were obtained in a similar fashion by profiling the net present cost calculations. The budget was estimated in the following manner. Eight uniformly distributed random numbers from the interval (0.40, 0.65) were generated, one for each cost estimate of each product. This range was selected in order that no portfolio could contain all products. These random numbers were multiplied by the cost estimates of each product and the results were summed for a budget (B_i) estimate for the portfolio for the one period being examined. All required values can be located in Table 8. The complete formulation of the linear program can be found in Appendix D.

Table 8: LCC Output/Portfolio Model Inputs

Product	μ_j Expected Profit ($ x 10^5)	σ_j^2 Variance ($ x 10^{10})	c_j Expected Cost ($ x 10^5)	$\sigma_{c,j}^2$ Variance ($ x 10^{10})
1	2.0	3.8	11.8	15.7
2	3.0	5.5	10.6	12.2
3	3.8	7.4	9.8	10.0
4	5.6	12.6	11.6	15.1
5	6.7	18.3	10.0	9.2
6	7.2	25.1	11.7	12.4
7	10.3	46.3	10.0	10.0
8	11.2	51.2	11.3	14.1

Risk Aversion and Sensitivity Analysis

The key to solving the given portfolio optimization problem is in the variable Watters refers to as the risk aversion factor, or A (Watters, 1967). As described in the methodology section, this factor can vary from 0.00 to 1.00. Recall that low values of A represent a low aversion to risk on the part of the decision-maker. On the other hand, the higher the value of A, the more the decision-maker avoids taking risks. Eventually the value of A becomes so high that no portfolio is selected because no risk adverse project has adequate return to be funded. Of course, if the estimated NPVs of all the products were negative, there might be a need to analyze a portfolio, since a company might want to include the product as a loss leader or for diversity of investment. The approach to the analysis of this section is two-fold. First, various values of A are examined to determine various portfolios and their associated risk. Second, the concept of dependent projects is investigated and the ramifications of this dependency assumption are also investigated.

In Table 9 a range for the value of A is presented, and the products that are selected, are displayed. As A increases, notice which of the products fall out of the portfolios. The example is further restricted in that it only examines one budget period. Had this problem contained two, three, or more budget periods, the number of binary variables would have grown considerably.

Table 9: Portfolio Analysis Results n = 1000 (Independent Products)

A Coefficient of Risk Aversion	Expected Rate of Return on Budgeted Funds (%)	Expected Return of Portfolio($ x 10^5)	Variance of Portfolio ($ x 10^{10})	Funds Budgeted ($ x 10^5)	Expected Funds Required ($ x 10^5)	Products Selected
0.00	0.61	44.8	160.9	74.0	64.4	3,4,5,6,7,8
0.20	0.38	28.3	72.7	74.0	65.5	1,2,3,4,5,6
0.30	0.29	21.1	47.6	74.0	53.8	1,2,3,4,5
0.40	0.19	14.4	29.3	74.0	43.8	1,2,3,4
0.45	0.12	8.8	16.7	74.0	32.2	1,2,3
0.52	0.07	5.0	9.3	74.0	22.4	1,2
0.53	0.04	3.0	5.5	74.0	10.6	2
0.55	0.00	0.0	0.0	74.0	0.0	None

In this one period example, it can easily be explained why the portfolio changes as A varies. The key lies in the objective function and the fact that, because there is only one period, the problem becomes a one-constraint knapsack problem. When a problem such as this entails more than one period, the other constraints become active and the problem is then no longer a knapsack problem. Recall the objective function with the single budget constraint is:

Maximize $(2 - A\sigma_1^2)\,x1 + (3 - A\sigma_2^2)\,x2 + (3.8 - A\sigma_3^2)\,x3 + (5.6 - A\sigma_4^2)\,x4 + (6.7 - A\sigma_5^2)\,x5 + (7.2 - A\sigma_6^2)\,x6 + (10.3 - A\sigma_7^2)\,x7 + (11.2 - A\sigma_8^2)\,x8.$

Subject To: 11.8x1 + 10.6x2 + 9.8x3 + 11.6x4 + 10x5 + 11.7x6 + 10x7 + 11.3x8 <= 74;

When $A = 0.00$ the objective function becomes:

2x1 + 3x2 + 3.8x3 + 5.6x4 + 6.7x5 + 7.2x6 + 10.3x7 + 11.2x8. This function can be maximized by inspection. This portfolio is the optimum for this function. For $A = 0$ this portfolio consists of variables/products 3, 4, 5, 6, 7, 8. When $A = 0.20$, the coefficients for variables x7 and x8 become negative and therefore these variables do not enter the

As A increases in value, the portfolio mix changes. As the portfolio mix changes, so does the total expected NPV and the total variance accounted for in the objective function. This is demonstrated graphically in Figure 13, where a probability density plot of the expected NPV of each portfolio, along with its standard deviation is shown. Each portfolio is centered above its expected NPV and the plot shows the range of that expected NPV. As seen from the figure, the only portfolios that contain the risk of falling below zero occur when $A = .52$ and $A = .53$. The portfolios associated with $A = .52$ contains Products 1 and 2. The portfolio associated with $A = .53$ only contains Product 2. Two observations should be made at this point. First, because the data used to create this eight-product sample problem was in some respects "artificially" created, the percentiles for the individual expected NPVs are "too good to be true" in some respects. This can be seen by observing the individual NPVs for each product in Appendix E. The second observation ties in closely with the first observation. Notice in Figure 13 how the extremely good profiles of each product is reflected in each portfolio selected. Only three of the portfolios have a chance of dropping below a zero expected NPV. This dilemma is answered in a two-part response. First, real data and multiple budget periods would change the product and portfolio profiles substantially. The second part of the response pertains to the variability of the various portfolios. The portfolio with the highest expected NPV occurs when $A = 0.00$ (risk neutral). Even though the interval of risk does not drop below zero, it does cover a large interval (≈\$1.5M, \$7.5M). If the decision-maker relies on the expected NPV of this portfolio for future planning and the actual result is closer to \$1.5M than to the expected NPV of \$4.48M, though R & D costs will be recouped, other losses might occur. Because of such possibilities, it is important to build a table of information

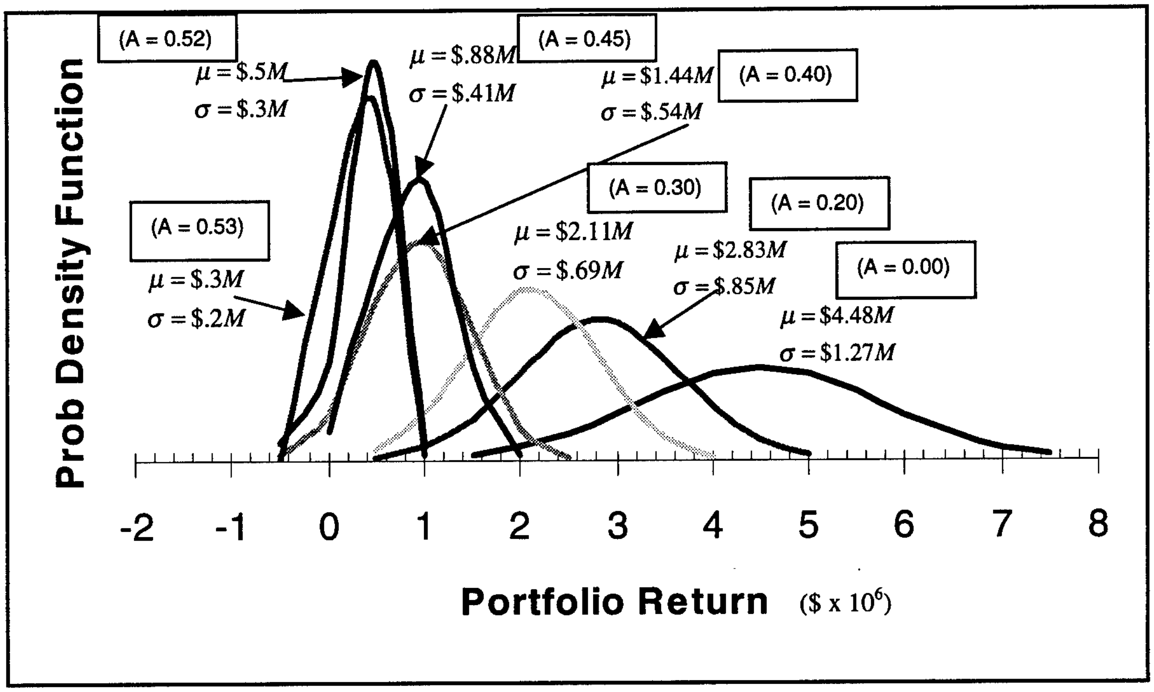


Figure 13: Risk Aversion (A) and Expected Portfolio NPV

that reflects portfolio risk. A table of information that reflects portfolio risk is a tool by which the management of the company building a portfolio of R & D products might obtain a "feel" for the riskiness of each portfolio (Watters, 1967:57). Such a table of risks for the example problem is presented in Table 10. The probabilities of return that are of most concern are those that fall below the expected NPV of the portfolio. As noted previously, except for portfolios 5, 6, and 7, the expected NPV of the portfolios does not fall below zero, but the variance on portfolios 1, 2, 3, and 4 is great enough to present the table as a tool for the decision-maker. For example if the decision-maker is considering choosing portfolio 2 and cannot afford the 16.5% probability of falling below an NPV of \$2.83M, another portfolio would probably be a better choice. Many such scenarios can be addressed with the portfolio risk information table.

Table 10: Portfolio Risk Information

Portfolio	1	2	3	4	5	6	7
Expected Return ($ x 10^5)	44.8	28.3	21.1	14.4	8.8	5	3
Variance ($2 x 10^{10})	160.9	72.7	47.6	29.3	16.7	9.3	5.5
Standard Deviation ($ x 10^5)	12.68	8.53	6.90	5.41	4.09	3.05	2.35
P{return < $4,000,000}	0.353	> .5	> .5	> .5	> .5	> .5	> .5
P{return < $3,000,000}	0.122	> .5	> .5	> .5	> .5	> .5	> .5
P{return < $2,000,000}	0.025	0.165	0.437	> .5	> .5	> .5	> .5
P{return < $1,000,000}	0	0.016	0.054	0.208	> .5	> .5	> .5
P{return < $900,000}	0	0.012	0.040	0.159	> .5	> .5	> .5
P{return < $750,000}	0	0	0.024	0.101	0.375	> .5	> .5
P{return < $500,000}	0	0	0	0.041	0.176	0.500	> .5
P{return < $250,000}	0	0	0	0.014	0.062	0.206	0.416
P{return < $0}	0	0	0	0	0.016	0.051	0.100
P{return < -$250,000}	0	0	0	0	0	0.007	0.010
P{return < -$500,000}	0	0	0	0	0	0	0

Another interesting facet of this problem is when the independent assumption of the products is relaxed in some manner. Assume for instance that Products 6, 7, and 8 are mutually exclusive. In other words, at most one of these products can be selected. The constraint that needs to be added to the formulation is ($x_6 + x_7 + x_8 \leq 1$). A company may find itself in a situation, where perhaps there are three variations of the same product that are being proposed and at most one can be produced. Table 11 shows the portfolio selection results when the constraint $x_6 + x_7 + x_8 \leq 1$ is added to the formulation. Notice that the results are identical to the results before the constraint was added except for $A = 0.00$. When $A = 0.00$ in the problem with the added constraint, the products selected are 1, 2, 3, 4, 5, 8 as compared to products 3, 4, 5, 6, 7, 8 in the problem without the additional constraint. This occurs because the variance of NPV has not changed for each of the products. When the extra constraint is added, the integer program is forced to pick a portfolio mix that might have more variance than a portfolio selected when the constraint was absent.

Table 11: Portfolio Analysis (Add constraint $x_6 + x_7 + x_8 \leq 1$)

A Coefficient of Risk Aversion	Expected Rate of Return on Budgeted Funds (%)	Expected Return of Portfolio($ x 10^5)	Variance of Portfolio ($ x 10^{10})	Funds Budgeted ($ x 10^5)	Expected Funds Required ($ x 10^5)	Products Selected
0.00	0.44	32.3	98.8	74.0	65.1	1,2,3,4,5,8
0.20	0.38	28.3	72.7	74.0	65.5	1,2,3,4,5,6
0.30	0.29	21.1	47.6	74.0	53.8	1,2,3,4,5
0.40	0.19	14.4	29.3	74.0	43.8	1,2,3,4
0.45	0.12	8.8	16.7	74.0	32.2	1,2,3
0.52	0.07	5.0	9.3	74.0	22.4	1,2
0.53	0.04	3.0	5.5	74.0	10.6	2
0.55	0.00	0.0	0.0	74.0	0.0	None

This example was added to show the flexibility of this technique. A given corporation might have more than eight products that are competing for development funds. The corporation is also likely to have additional constraints which make the problem more challenging to formulate and solve. Perhaps more than one version of the same product is under consideration. Another possible constraint might consider bundles of products. For example if Product 1 and Product 3 are selected, Product 6 and Product 8 will not be developed. The list of possibilities is large, but the necessary constraints may be added to the formulation.

Learning Curve Effect

When compiling the data for the portfolio optimization of the various products (input devices), no learning curve effect was introduced. We will now examine the effect of learning on the expected cost and expected NPV of a product.

The product data that was used for this portion of the research can be found in Appendix F. This is the baseline data for the learning curve experiment, the early to market experiment, and the late-to-a-compressed-market experiment. In the learning curve experiment, the only change to the baseline model was the addition of a learning curve. The learning curve effect was placed upon the amount of time to produce one input device. A logarithmic 95% curve was used. The reason for using this element is because it directly affects the labor costs each period and it indirectly affects the total cost of production computed each period. The percentage for the curve is rather large compared to values discussed in the literature, but the goal was to examine the effect of a minimal learning curve.

Table 12: Baseline vs. Learning Curve--Costs

Profile: Costs Discounted (With Learning Curve)		Profile: Costs Discounted (Without Learning Curve)	
Statistic	**Value**	**Statistic**	**Value**
Trials	1,000	Trials	1,000
Mean	$1,277,134.20	Mean	$1,394,122.54
Standard Deviation	$438,476.46	Standard Deviation	$494,415.00
Range Minimum	$563,273.72	Range Minimum	$532,155.22
Range Maximum	$2,195,195.04	Range Maximum	$2,460,204.31
Range Width	$1,631,921.31	Range Width	$1,928,049.09

As can be seen from Table 12, there is an 8% decrease in the discounted cost when the learning curve effect is incorporated. A large-sample α-level hypothesis test was conducted to determine if the mean of discounted costs for learning curve included is statistically different from the mean of discounted costs when the learning curve is not included (Wackerly, Mendenhall, and Scheaffer, 1996:421). This test is used in comparing the means of two large samples of data. If the test is statistically significant, this would suggest the need to include some type of learning curve in the model if a learning curve is believed to occur in some aspect of the product life cycle. The hypothesis test is seen in Figure 14 and tests if the mean of costs when the learning curve is included is statistically significantly lower than the mean for costs without the application of the learning curve effect. Because the z-statistic, - 5.598 is less than $-z_{\frac{\alpha}{2}} = -2.576$, it therefore falls into the rejection region. Hence, at the $\alpha = .01$ level, the conclusion is that sufficient evidence exists to permit the conclusion that the mean costs with the learning curve is lower than the mean costs without the learning curve. Since there is strong evidence to support the alternative hypothesis, a learning curve effect, if present, should be included in the model.

$$H_0 : \mu_{\textbf{With Learning Curve}} = \mu_{\textbf{Without Learning Curve}}$$
$$H_a : \mu_{\textbf{With Learning Curve}} < \mu_{\textbf{Without Learning Curve}}$$
$$\alpha\textbf{ - Level} = .005$$
$$\textbf{Test Statistic: } Z = \text{-}5.598$$
$$\textbf{Rejection Region: } \quad z < -z_{.005}$$
$$\Rightarrow \quad -5.598 < -2.576$$

Figure 14: Hypothesis Test for Learning Curve Costs

Table 13: Baseline vs. Learning Curve--NPV

Profile: NPV (With Learning Curve) Statistic	Value	Profile: NPV (Without Learning Curve) Statistic	Value
Trials	1,000	Trials	1,000
Mean	$435,056.46	Mean	$315,242.05
Standard Deviation	$299,311.52	Standard Deviation	$240,302.25
Range Minimum	$20,282.91	Range Minimum	-$30,135.41
Range Maximum	$1,080,631.73	Range Maximum	$852,044.23
Range Width	$1,060,348.82	Range Width	$882,179.64

In Table 13, notice the difference in the mean value for NPV of the product when the learning curve effect is introduced. As can be seen, an approximate 38% increase in the average NPV is realized when the learning curve effect is included in the model. A hypothesis test, similar to the one conducted for the means of costs is now conducted for the means of NPV of the sample data run with and without a learning curve effect.

$$H_0 : \mu_{\textbf{Without Learning Curve}} = \mu_{\textbf{With Learning Curve}}$$
$$H_a : \mu_{\textbf{Without Learning Curve}} < \mu_{\textbf{With Learning Curve}}$$
α **- Level = .005**

Test Statistic : $Z = -9.870$

Rejection Region : $z < -z_{.005}$

$\Rightarrow$ **:** $-9.870 < -2.576$

Figure 15: Hypothesis Test for Learning Curve NPV

As seen by the hypothesis test in Figure 15, the null hypothesis is rejected and the alternative hypothesis is accepted. In other words, when the learning curve effect is introduced to the model significant evidence supports the hypothesis that NPV will be larger in magnitude than if the learning curve effect is not introduced. With the learning curve effect incorporated, the mix of products that enter the portfolio might be affected.

Early to Market

Similar in nature to the learning curve experiment, the baseline data of Appendix F was utilized to compare early entry to the market vs. entry at, or shortly after the beginning of the market cycle. All information was held constant except for the distribution of *YourFirm*'s entry into the market. Instead of using a LogNorm(3, 1.5), a LogNorm (1.0, .5) was used so that early entry to the market could be modeled. The market share weight awarded to the first to market remained a uniform distribution on the range (0.10, 0.30). The goal is to observe the difference in the NPV of the product where entry is early, compared to when its entry is on equal footing with that of competitors. If any significant difference is noticed, such results may convince a company to utilize resources to be first to the market. The results of the simulation can be seen in Table 14.

The average NPV increases 72.4% when the entry of *YourFirm* is changed from a LogNorm (3, 1.5) to a LogNorm (1.0, .5).

Table 14: Baseline vs. Early to Market--NPV

Profile: NPV (Early to Market)		Profile: NPV (Baseline)	
Statistic	**Value**	**Statistic**	**Value**
Trials	1,000	Trials	1,000
Mean	$543,335.97	Mean	$315,242.05
Standard Deviation	$132,864.55	Standard Deviation	$240,302.25
Range Minimum	-$8,140.27	Range Minimum	-$30,135.41
Range Maximum	$866,772.36	Range Maximum	$852,044.23
Range Width	$874,912.64	Range Width	$882,179.64

A hypothesis test is conducted to determine if there is a statistically significant difference in means between NPV for one who enters early to the market and one who enters on time. In this scenario, "on time" is taken as the baseline model. Notice the hypothesis test in Figure 16. As seen in the hypothesis test, there is significant statistical evidence to support the claim that being early to the market improves one's chances for deriving a larger share of the revenue within that particular market. The importance to decision-makers is that it may be extremely beneficial to be first to the market.

$$H_0 : \mu_{\textbf{Baseline}} = \mu_{\textbf{Early to Market}}$$
$$H_a : \mu_{\textbf{Baseline}} < \mu_{\textbf{Early to Market}}$$
$$\alpha\textbf{ - Level} = .005$$
$$\textbf{Test Statistic : } Z = \text{-}26.268$$
$$\textbf{Rejection Region :} \qquad z < -z_{.005}$$
$$\Rightarrow \qquad : \; \text{-}26.268 < -2.576$$

Figure 16: Hypothesis Test for Early to Market NPV

Late to a Compressed Market (Market Revenue Unaltered)

In this experiment the baseline data found in Appendix F was again used as the baseline for comparison. Two changes altered the baseline data to simulate a compressed market that is entered late by *YourFirm*. The first change was to change the distribution on *YourFirm* from the baseline distribution of LogNorm(3, 1.5) to LogNorm(8.0, .5). The second change was to compress the market, or make the distribution tighter. Instead of the Tri(24, 36, 48) distribution, Tri(24, 30, 36) was used. At this point, one could also alter the distribution on the market revenue; however, this change was not used. The assumption here is that the revenue is unchanged, but that entry is the more important variable to observe. It is noted, however, that another interesting aspect of this issue would be to change the distribution of market revenue. This can be followed up in future research.

The results of this experiment can be seen in Table 15. Similar to the results of being late to an uncompressed market, the baseline average NPV is approximately 45.9% greater than the average NPV for one who arrives late to a compressed market. A hypothesis test is conducted to see if there is a statistically significant difference between the mean NPV of the baseline model and the model of coming late to a compressed market.

Table 15: Baseline vs. Late and Compressed Market

Profile: NPV (Late and Compressed)		**Profile: NPV (Baseline)**	
Statistic	**Value**	**Statistic**	**Value**
Trials	1,000	Trials	1,000
Mean	$216,054.80	Mean	$315,242.05
Standard Deviation	$79,228.08	Standard Deviation	$240,302.25
Range Minimum	$13,317.76	Range Minimum	-$30,135.41
Range Maximum	$575,201.37	Range Maximum	$852,044.23
Range Width	$561,883.61	Range Width	$882,179.64

$$
\begin{array}{|ll|}
\hline
H_0 : \mu_{\textbf{Late to Compressed Market}} = \mu_{\textbf{Baseline}} & \\
H_a : \mu_{\textbf{Late to Compressed Market}} < \mu_{\textbf{Baseline}} & \\
\alpha \textbf{ - Level} = .005 & \\
\textbf{Test Statistic}: Z = -12.396 & \\
\textbf{Rejection Region}: & z < -z_{.005} \\
\quad \Rightarrow & : \ -12.396 < -2.576 \\
\hline
\end{array}
$$

Figure 17: Hypothesis Test Late to Compressed Market

As seen by the hypothesis test in Figure 17, the alternative hypothesis is selected signifying that coming late to a compressed market in this experiment has significant effects on the NPV of the given product.

Summary of Analysis

In this chapter, a variety of topics that made up the analysis of this thesis were discussed. The hardware and software platforms used to conduct the analysis, and their speed ramifications were discussed. In addition, the number of runs needed to conduct the Monte Carlo simulation was addressed.

The next phase was to conduct analysis of the optimal portfolios of products. This data, as discussed in Chapter 3, does not reflect real-life information, but is a compilation of sample real-life data. In the portfolio analysis section of this chapter, using results of the simulation runs was discussed and the way in which the portfolio integer program used those results. At this point, the risk aversion factor A was addressed, and the role it plays in the portfolio selection model was examined. In this sample problem, it was demonstrated that with one budget period, the problem became a knapsack problem.

Finally, the various optimal portfolios were discussed and the risk profiles they each contained were addressed.

The last phase of this analysis was to look at learning curve effects, early to market arrival, and late arrival to a compressed market and how each of these compared to a baseline model. The results were clear in the sample problem that incorporating a learning curve effect lowered costs and increased the NPV of the product. The results were also clear that arriving early to market in this example improved the NPV of the product, and likewise, that arriving late to a compressed market significantly reduced the NPV of the product.

Chapter 5: Conclusions

The goal of this research was to take a look at new product development and to develop a tool that could be used to evaluate the costs and revenues associated with new products being considered for development. The research began with a life cycle costing model that provided the framework upon which to build.

The life cycle costing model lacked a means to incorporate learning curve effects. It also lacked a means by which market size, distribution, and length could be accounted for within the same model. These incorporated features (learning curve and market information) now allow a user to simulate the life cycle of a product to determine its NPV and the risk profile associated with that NPV.

With the model in place the user can evaluate more than one product to establish a profile, including the expected NPV and its variance for each product. Such a user might have numerous products that are in the concept stage. Though many might be successful in the market, the budget might limit the number funded. The output from the model (the expected NPV and its variance) can then be used in a binary program to determine the optimal mix of products. A range of portfolios can be investigated, each with a different level of risk and NPV associated with it. The decision-maker can decide which portfolio to select given the risk tolerance and desired return.

Learning curves were also investigated and the effects on NPV/cost estimates evaluated. Along with learning curve effects, the short-lifespan of innovative technologies was investigated. Finally the issue of market entry was addressed. From the literature review it is clear that early market entry is important, though the literature is inconclusive as to the extent market share is affected. The model however, does allow the user to investigate this matter.

Future Research

The topic of new product development is broad. This research, though profitable, barely scratches the surface of the analysis of new product development. There are, therefore, numerous suggestions for future research that can be accomplished in this arena. This section only endeavors to describe a few of those areas.

Accounting for Costs Prior to Period 0

In this research, one assumption was that all cash outflows prior to the start of the market occur during period zero. This assumes that the user has discounted all costs up until that time and already has good estimates on those costs. The key concept is that the amounts of the cash flows and when they occur are accurate estimates. What happens if the market actually begins before a certain company is ready to enter the market? This risk is not taken into account within the context of this research, but the model can easily handle this modification, so it is worth investigating in future research.

First to Market Advantage

In this thesis effort the advantage of being first to the market was investigated. The literature, as pointed out, is still inconclusive as to how much, if any, the extent of the advantage of being first to the market with a given product. Though some research has shown that there can be long-term advantages in relation to market share, other research has shown that in the long-term it may be more profitable to not be the "pioneer." For example, one who is able to observe the first to market may find ways to lower their own production costs and therefore lower prices. This may, indeed, take away market share from the one who entered first.

Market Cycles Cut Short

Though this research did not address the risk of product failure, new product development is full of failure statistics. Many good ideas are in the conceptual stage, few of those ever make it to the market, and of those, a large percentage fail. To intensify this scenario, what happens during a market cycle if a new product is introduced which makes obsolete all those products present in the current market cycle? Such risks could be investigated.

Portfolio Extension

This research investigated one type of portfolio optimization. That is, only portfolio optimization that considered one budget period and binary variables was examined. The problem becomes much more complex and interesting when multiple budget periods and non-binary variables are examined. In relation to non-binary variables, formulations, such as the Markowitz model or the CAPM, model product efficient frontiers that include continuous information. In those models, for example, only a percentage of funds may be dedicated to a given product. If this is permitted, how does one go about defining a partial product? The answer lies in scaling back the product, or achieving the same results with a smaller budget.

Military Application

The application of product selection can be moved into the arena of the United States Air Force (USAF) or other branches of the military. The key driver for business application of this research is NPV; however, the key military driver could be viewed as combat effectiveness. Instead of trying to make money, the USAF could use this tool to gather a risk profile on a certain high technology projects. The projects or weapons that maximize combat effectiveness with some level of risk can be evaluated with this research tool to gather information for the portfolio optimization of those projects or weapons.

Many of the challenges that the Department of Defense (DoD) faces are analogous to the ones that are encountered in the manufacturing community. The technology portfolio problem of competition, though not motivated by profits, still faces the DoD. The competition, in this case, is striving to be the world's technology leader. Uncertainties, such as the length of the life cycle face the U.S., yet aerospace doctrine dictates that the U.S. must win the defense technological race every time (Gansler, 1998).

A secondary objective is to look beyond commercial factors where profit is a driver, and extend the model to include specific DoD considerations. Particularly, the DoD goals engendered in the concept of Full Spectrum Dominance mandate that the DoD choose its technology portfolios wisely (Gansler, 1998). These goals, in conjunction with a measure of combat effectiveness, can be incorporated in this model.

Appendix A: Work Breakdown Structure

Mouse_Lev1
- Plug_Connector
- Reorientation
- Screws
- Ball
- Hatch_Door
- Electrical_Test_M
- Pack_Assembly
- Box
- Foam_Pack_Bottom
- Place_Finish_Units
- Foam_Pack_Top
- Instruction_Sheet
- Close_Box
- Finishing_Area
- Base
- Label
- Self_Stick
- Wear_Pads
- Reorientation
- Foam_Strip
- Cable
- Cable_SnapFit
- Thread_Wire
- Module_Assembly

PCB_Assembly_Lev2
- Place_Fixture
- Circuit_Board
- Capacitor
- Diode
- Reistor
- Microprocessor
- Crystal
- 92s
- Connector
- Burgeaa_Switch
- Leds
- Receptors
- Resistors
- Wave_Reflow_Solder
- Inspect_Parts
- Electrical_Test

Ball_Cage_Assembly_Lev2

Top_Enclosure_Lev2
- Top_Cover
- Buttons
- Hex_Screws
- Adjust_Semicomp

Ball_Cage_Frame_Lev3
- Special_Screws
- Electrical_Test_BC
- Adjust_Led
- Light_Emitter_Bar
- Shaft
- Fit_Shaft
- Encoder_Wheel
- Roller
- Fit_Roller
- Reorientation_BC

Idler_Housing_Snap_Lev4
- Idler_Housing
- Roller_Idler
- Short_Shaft
- Spring
- Spring_Fit
- Check_Gap
- Adjust_Gap
- Inspect_Parts_Idler

Miscellaneous
- Production_Cost
- Defect_Cost
- Wage_Cost

Tooling_Costs
- Base_To_Fixture_Tool
- Label_Hold_Tool
- Wear_Pads_Tool
- Cable_Tool
- Circuit_Board_Tool
- Microprocessor_Tool
- Electrical_Test_Tool
- Buttons_Tool
- Top_Cover_Tool
- Ball_Tool
- Hatch_Door_Tool
- Box_Tool
- Foam_Pack_Bottom_Tool
- Ball_Cage_Frame_Tool
- Light_Emitter_Bar_Tool
- Shaft_Tool
- Encoder_Wheel_Tool
- Roller_Tool
- Idler_Housing_Tool

R_and_D_Costs
- Prototype_Molds
- Consultants
- Receive_Accept_Specifications
- ConceptGeneralization
- DetailDesign
- TestBetaPrototype
- DesignProductionTypes
- DesignMolds
- DesignToolings
- FabricateMolds
- DebugMolds
- CertifyDesign
- InitialProductionRun

Appendix B: PPSM User's Manual

PPSM is a life cycle cost model which combines the power of Excel, Visual Basic for Applications (VBA) and Crystal Ball (Monte Carlo simulation) to generate a net present value (NPV) for an individual new product. If a group of products is used with this model, the NPV information can be fed into a linear program solver to determine the optimal selections of products to fund. Other information generated with this model is an estimate on costs and revenues for a product market cycle.

1. Minimum System Requirements

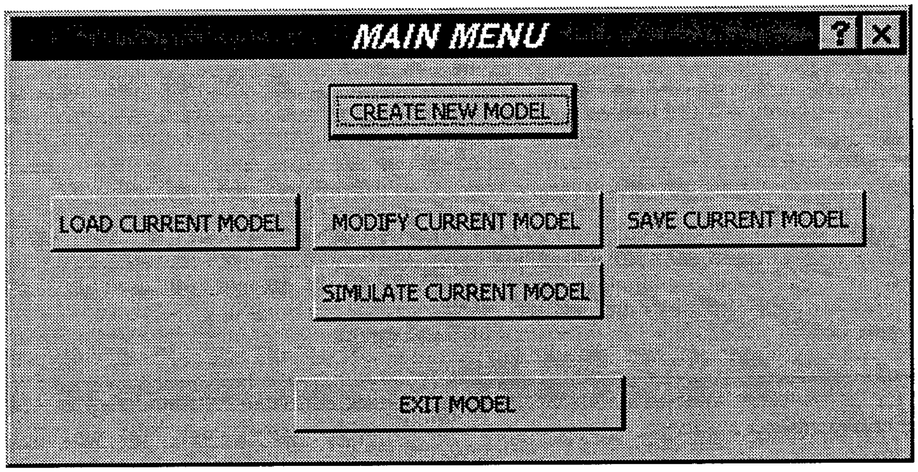
- Windows 95
- Excel 97
- Crystal Ball 4.0/4.0c
- LINGO (or another linear program solver)

2. Installation

The program is an Excel file (PPSM.xls). The only additional installation requirement is to install Crystal Ball. Install Crystal Ball on the hard drive according to Crystal Ball user Manual. When installing Crystal Ball do not choose automatic start option. Activate Crystal Ball using Tools, "Add-In" function of Excel.

3. Running the Program.

Click the "Main Menu" button in the "Main" sheet. The opening screen should be main, otherwise click on Main Tab. ***MAIN MENU*** has six choices as seen below:



A. CREATE NEW MODEL—As the name implies, this button begins the process of creating a new Product model. A series of prompts that create the shell for the new model will be displayed when it is pushed.

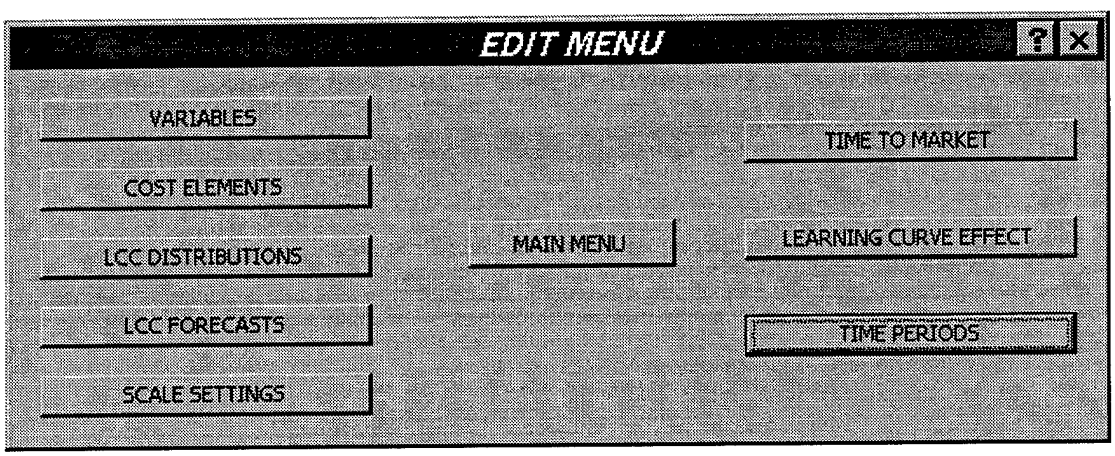
1. R & D Project Name
   Name of R & D Project (optional, however, if O.K. is entered without an entry, or the cancel button is pressed, the model still assumes you wish to continue with the evaluation of the project, it will just do so as a nameless project.
2. Market Length
   Establishes an initial value for the length of the product's market cycle. This can be modified (See MODIFY CURRENT MODEL \ EDIT MENU \ Time Periods). It can also be assigned a distribution with Crystal Ball (See B. MODIFY CURRENT MODEL \ TIME TO MARKET \ Modify Market Data)
3. Interest Rate
   Sets a value for interest rate, or the rate at which all cost and revenue calculations will be discounted.
4. Inflation Rate
   Sets a value for inflation rate, or the rate at which the market is inflating or deflating.
5. Unit Price
   Used to set a value for the price at which the product will be sold for when the product market's cycle begins.
6. Manufacturing time for first unit
   Sets the amount of time to produce the very first unit of production. Used for learning curve calculations. If the user wishes to use the learning curve effect, a cost element or variable can include this (time for first unit). If the user does not wish to use it, it remains as a dummy variable, having no influence whatsoever on

the calculations. If the user does choose to use this variable, it is named *ManufactureTime.*

7. Learning curve percentage
   Establishes a logarithmic or arithmetic learning curve for the variable *ManufactureTime* (see above at estimated time to manufacture the first unit). In the literature the range normally used is (0.70, 0.95), but the user should have knowledge of this percentage before using this feature.
8. Learning curve type
   Logarithmic or arithmetic learning curve for *ManufactureTime*
9. Save model
   The user is warned to rename the file to a name other than PPSM.xls or else the original program could possibly become unstable. The ***EDIT MENU*** appears after saving the model (see B. *MODIFY CURRENT MODEL*\ ***EDIT MENU***) AFTER CREATING A NEW MODEL OR UPDATING THE EXISTING ONE, THE MODEL SHOULD BE LOADED AGAIN FROM THE MAIN MENU.

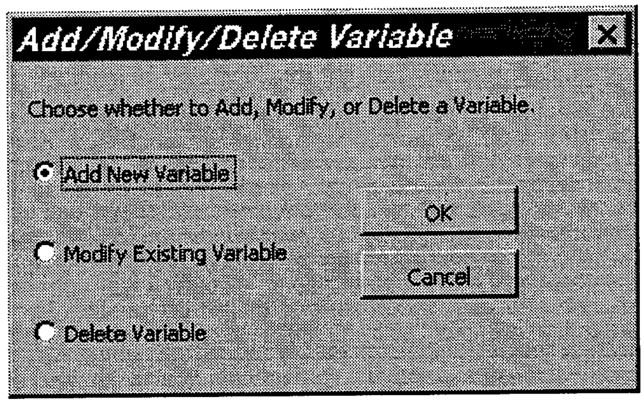
B. LOAD CURRENT MODEL
When an existing model is opened, first use this macro to load the model. This macro copies the defined variable and cost element names to the program lists to reach the names easily during other calculations.

C. MODIFY CURRENT MODEL (Edit Menu)

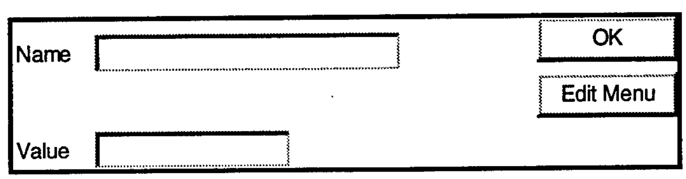


1. EDIT MENU
a. VARIABLES

Add/Modify/Delete Variable

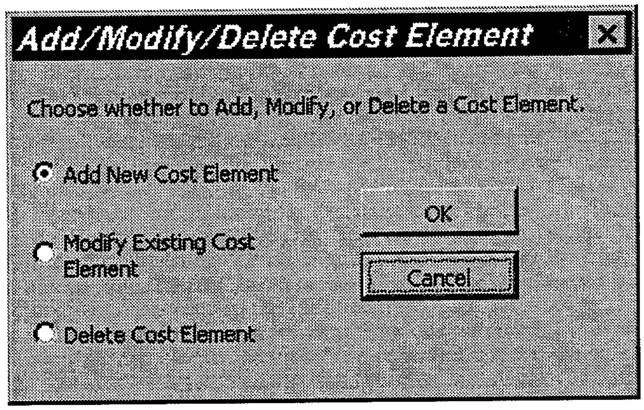


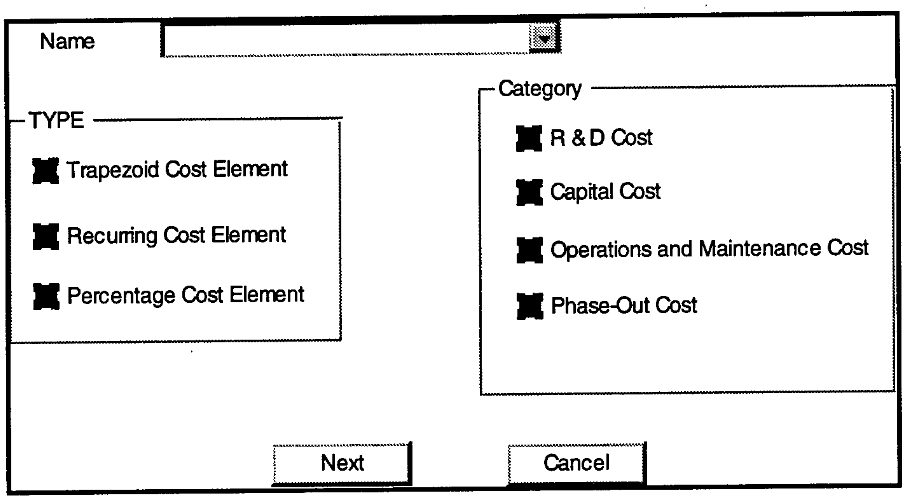
When "Variables" is selected the following window appears. **<u>THE NAME OF THE VARIABLE MUST NOT INCLUDE ANY SPACE. IN ADDITION, A VARIABLE MAY NOT CONTAIN MORE THAN 256 CHARACTERS</u>**. The value assigned to a variable can be a constant, a distribution or a function of other variables. To assign a distribution to the variable, first a value is entered then after defining the variable, Distributions selection in Edit menu is used. Crystal Ball has 17 theoretical distributions available to the user. (See LCC DISTRIBUTIONS(Variable) to set a distribution)



b. COST ELEMENTS
(NOTE: NAME AND CATEGORY OF A COST ELEMENT CANNOT BE CHANGED. THE COST ELEMENT SHOULD BE DELETED AND DEFINED AGAIN IF NAME OR CATEGORY OF THE COST ELEMENT IS TO BE UPDATED.)

Add/Modify/Delete Cost Element

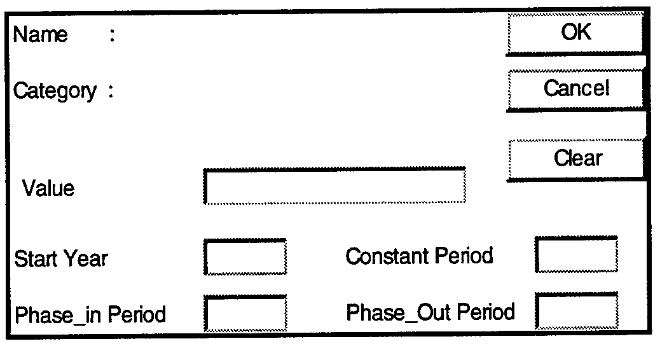




Cost elements can be defined using the <u>Cost Element Input Menu</u>. In the menu there are three types of information requested; Name, Type and Category of cost element. Name of the Cost element can be entered by the user or can be selected from the WBS that is placed to drop down list. An appropriate time phasing method can be chosen from three available cost element types. Cost element categories are also provided to keep track of different cost categories. **<u>NAMES MUST BE ENTERED FOR THE COST ELEMENTS, OTHERWISE ERRORS WILL OCCUR IN THE REMAINDER OF THE PROGRAM.</u>**

According to the type selections above, one of the following windows appears. The window name and category of the cost element are automatically displayed. The user should enter the parameters as requested.

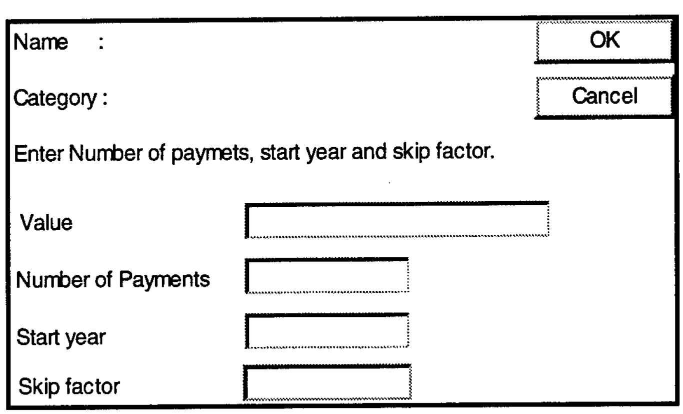
Trapezoid Cost Element



Value: Value refers to constant payment value of the trapezoid cost element. *Value* can be defined as a constant, distribution or function of the variables defined. If the value is a random variable and needs a distribution, any constant value should be defined and Crystal Ball can be used to set its distribution after entering the cost elements. This is done via the ***Distributions*** menu item found on the ***Edit Menu***. If the value is a function of variables first "=" should be entered to model. Excel built-in functions can be used.

Any of four parameters can also be defined as a random variable or function of a variable as well as a constant value.

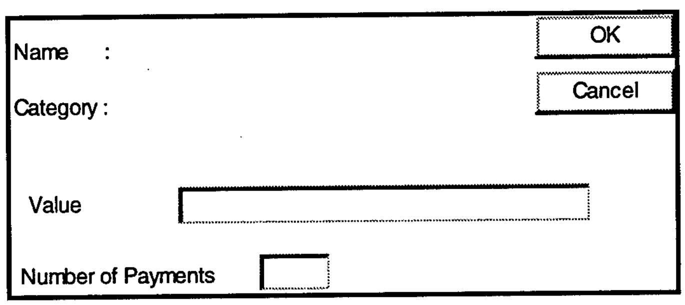
Recurring Cost Element



Value: Value refers to periodic payments for the cost element. *Value* can be defined as a constant, distribution or function of the variables defined. If the value is a random variable and needs a distribution, any constant value should be defined and Crystal Ball can be used to set its distribution after entering the cost elements. This is done via the ***Distributions*** menu item found on the ***Edit Menu.***. If the value is a function of variables first "=" should be entered to model. Excel built-in functions can be used.

Any of four parameters can also be defined as a random variable or function of a variable as well as constant value.

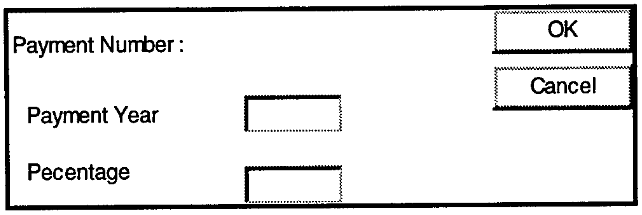
Percentage Cost Element



The ***Percentage Cost Element*** window has two parameters to input. The first one is the value that refers to the total value to be paid. The second is the number of payments.

Value can be defined as a constant, distribution or function of the variables defined. If the value is random variable and needs a distribution, any constant value should be defined and Crystal Ball can be used to set its distribution after entering the cost elements. This is done via the ***Distributions*** menu item found on the ***Edit Menu***. If the value is a function of variables first "=" should be entered to model. Excel built-in functions can be used.

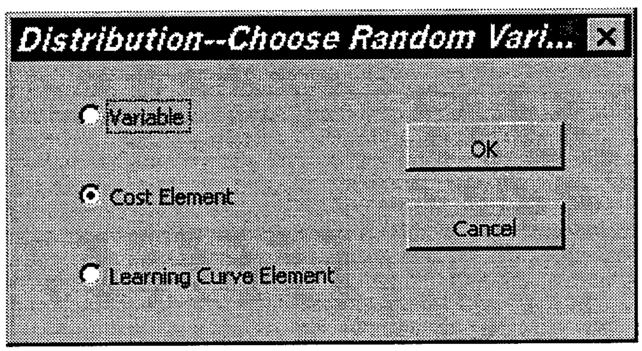
Number of Payments should be an integer number. After entering the parameters, the following window repeats until the value of ***Number of Payments*** is reached.



Payment number is displayed automatically. Period of Payment and ***Percentage*** that is paid in that period should be entered. Both of the parameters must be constant and all percentages must add to equal one. If the percentage do not equal one, the user will be asked to begin the process again.

b. LCC DISTRIBUTIONS

The distributions that can be set by Crystal Ball in this section can be placed upon variables, cost elements, and learning curve elements as seen from the following menu. To gain more information on setting the distributions using Crystal Ball, there is a small section of this manual that points out the basics. More detail is found in the Crystal Ball User's Manual.



c. LCC FORECASTS (Crystal Ball)

Crystal Ball refers to its method of collecting statistics on cells as "Forecasting." Specifically, if one wants to collects statistics on a certain cell, Crystal Ball call this a "forecast." From the LCC FORECASTS menu, the following cells can directly be assigned a forecast. For more information on using forecasts within the context of Crystal Ball, consult the Crystal Ball section of this manual for the basics, or the Crystal Ball User's Manual for details.

NetPresentCost is the discount of all cash outflows during a product market cycle.

AnnualCost is the uniform payment that would need to be paid out each period of the product market cycle to be equivalent to *NetPresentCost.*

NPVCapital is the discounted cash outflows for all costs under the category of "Capital Cost."

NPVResDev is the discounted cash outflows for all costs under the category of "Research and Development (R & D)"

NPVOpMain is the discounted cash outflows for all costs under the category of "Operations and Maintenance" (O & M).
NPVPhOut is the discounted cash outflows for all costs under the category "Phase Out."

e. SCALE SETTINGS

Before entering scaling settings, the cost should be calculated by using "Calculate" selection in Run Menu. Scaling parameters can then be entered through the Edit Menu. The steps showed below is followed.

1. Select the scaling variable from the provided list.
2. Select the scaling type,
   Single factor scaling: Scaling is only applied to NPC. There is one factor and cost is escalated.
   Multi-Factor Scaling: Scaling is accomplished in the level of cost elements.
3. If single factor scaling is selected then one of the three scaling factors should only be selected one time.
4. If Multi-Factor scaling is selected for each cost element desired to be scaled the selection from three methods should be repeated.

Scaling Methods

Linear Scaling: For linear scaling, the slope parameter should be entered. The program prompts the user to enter the slope parameter.

$$C_x = C_k * n.\left(\frac{E_x}{E_k}\right)$$

Where,

C_x = Cost of plant and/or equipment item of size E_x
C_k = Known cost of plant and/or equipment item of size E_k
n = Slope parameter

Exponential Scaling: The program prompts the user to enter exponent "n" in the following formula. The scaled value of the cost element is the calculated depending on the value of scaling value.

$$C_x = C_k\left(\frac{E_x}{E_k}\right)^n$$

Where,

C_x = Cost of plant and/or equipment item of size E_x
C_k = Known cost of plant and/or equipment item of size E_k
n = Cost capacity exponent.

Best-Fit Equation Scaling: This method takes the ratio of the two cases of given best-fit equation. The following equation shows the method. The user is prompted to enter a regression model that explains the relation between scaling variable and the cost element.

$$Cost_B = Cost_A x \frac{f(E_B)}{f(E_A)}$$

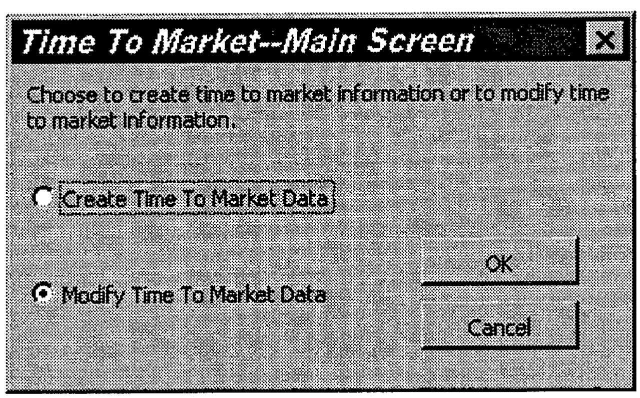
where
$f(E_B)$ = Predicted cost for capacity E_B.
$f(E_A)$ = Predicted cost for capacity E_A.
$Cost_A$ = Actual cost of capacity E_A
$Cost_B$ = Estimated cost of capacity E_B

f. TIME TO MARKET

Time to market is the when each competitor enters the product market cycle, including oneself. If the model has just been created, the proper button to choose in the Time To Market—Main Screen is the "Create Time To Market Data." Otherwise, select the other button , "Modify Time To Market Data."

As pointed out in the thesis related to this model, there is evidence that the first to market obtains an "extra" share of the market. If the user wishes to model this advantage, he/she must accomplish the following steps:

1. End the Macros by closing the Edit Menu dialog box, or the Main Menu dialog box
2. Go to the Worksheet entitled "Revenue", Cell G:32.
3. Place a value in the cell.
4. Use the Crystal Ball menu to set the distribution on that cell, (recommended UNIF(0.10, 0.30).



Create Time To Market Data:

This button will guide the user through setting up the initial time to market data.

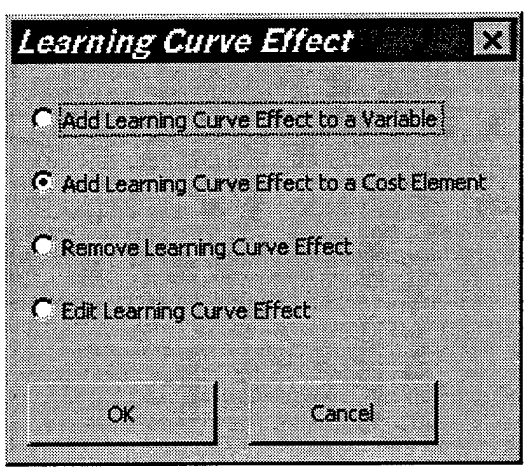
1. Distribution on Entry to Market
   This sets distributions on the entry to market of each competitor. Interfaces with Crystal Ball. See the Crystal Ball section of this manual for the basics, the Crystal Ball User's Manual for details on distributions.

2. Distribution on length of product cycle
   This sets a distribution on the length of the product market cycle.
3. Distribution for Revenue Curve
   This creates a shape for the revenue curve of the product market cycle.
4. Distribution on Market Size (volume)
   This sets a distribution on the volume of the product market cycle, or the amount of revenue all competitors will share during this cycle.

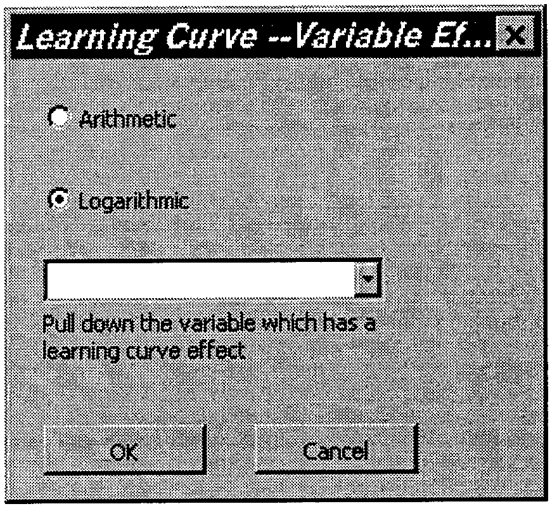
Modify Time To Market Data:
This set of user-menus is for one who is modifying any of the market data created in the "Create Time To Market Data" section.
(IMPORTANT NOTE: IF THE USER IS DECREASING THE NUMBER OF COMPETITORS THAT ENTER THE MARKET, HE/SHE MUST CLEAR THE DISTRIBUTION OF THE COMPETITOR BEING ELIMINATED. THIS IS DONE DIRECTLY ON THE EXCEL WORKSHEET "TIME TO MARKET." TO CLEAR A COMPETITOR, MAKE SURE THERE IS A "0" IN THE RELAVENT CELL (BETWEEN B2:F2), AND SELECT THE CELL AND CLEAR THROUGH THE CRYSTAL BALL MENU)

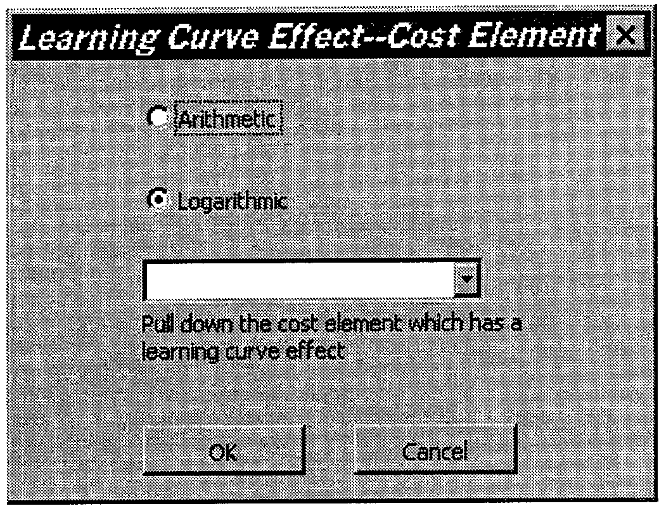
g. LEARNING CURVE EFFECT
This feature is designed to allow the user to model an effect on variables or cost elements that decreases the amount of time/material used as the manufacturing process progresses. As mentioned when creating a new model, the user is asked for such information for a variable called *ManufactureTime.* This variable is already in place if the user wants to link this variable to a cost element that will compute a production cost, or some other cost each time the simulation runs through a product manufacturing cycle.

The first menu asks the user to choose to add a learning curve effect to an existing variable or cost element, or delete or modify a learning curve effect.

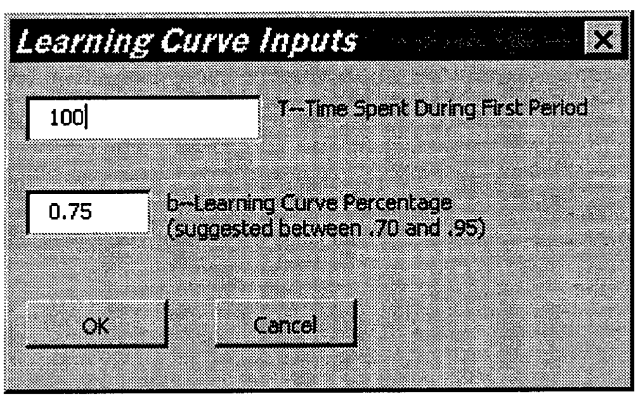


f the user chooses to add an effect to a variable or cost element, the following menu appears asking for the variable/cost element, and the type of curve being placed upon this element.



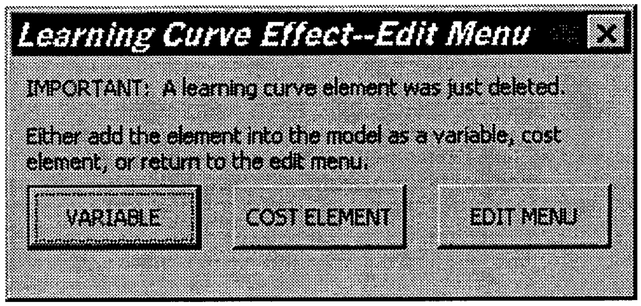


The user is then prompted to place two values in the following menu. The first value (T) is the time spent to manufacture the first product. It can also be a material factor, such as the amount of material in the first product (if there is evidence that material usage follows a learning curve effect). The second input is the percentage of that learning curve.



Modifying a learning curve is very similar to creating one, so similar, in fact, that there is not a need to explain the process.

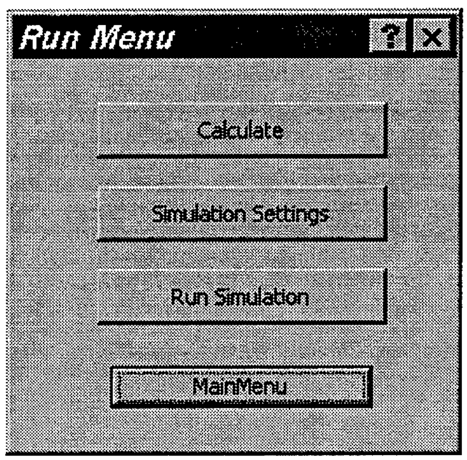
Deleting a learning curve effect is worth mentioning though. Besides deleting a learning curve effect, the user is asked if he/she wants to add the deleted item back into the model as a variable or cost element. If he/she chooses not to, the item is not added back into the model at all. The prompt for this is seen in the following menu item.



h. TIME PERIODS
Edit the length of the product market cycle for a deterministic model.

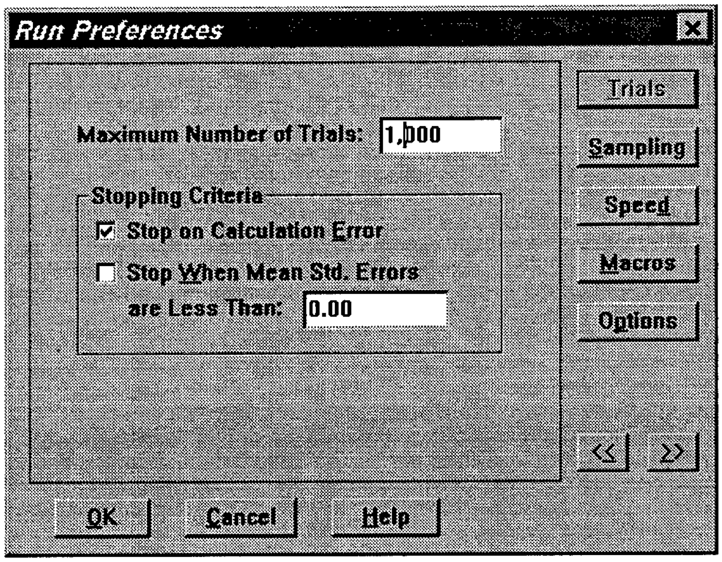
D. SAVE CURRENT MODEL
Saves the model. Another way to save the model is to close the Main Menu and use the Excel menu.

E. SIMULATE CURRENT MODEL
This menu is the most important menu if the user is interested in running a simulation to gain the profile of costs, revenue, and the NPV of the product. The first menu that appears is seen below:

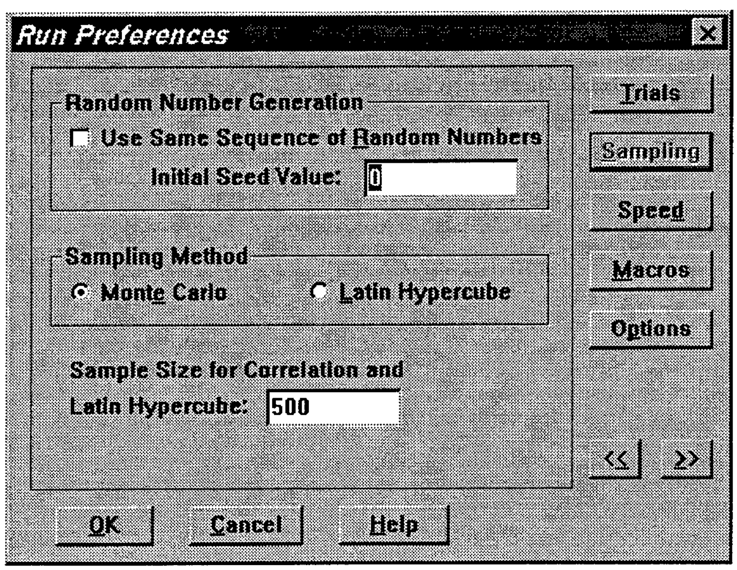


1. Calculate
Deterministically calculates the NPC of the model.

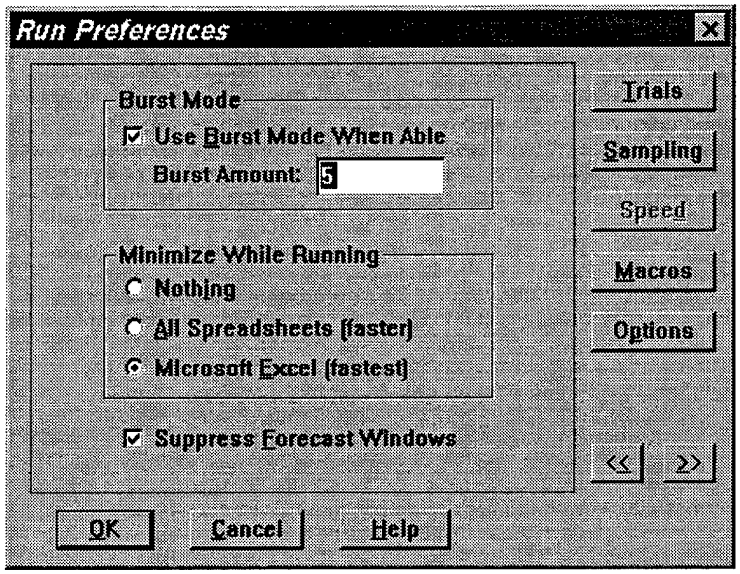
2. Simulation Settings
   Runs the Crystal Ball windows which prompts to specify the simulation settings. Each of the settings tabs is displayed and described in sequence below.



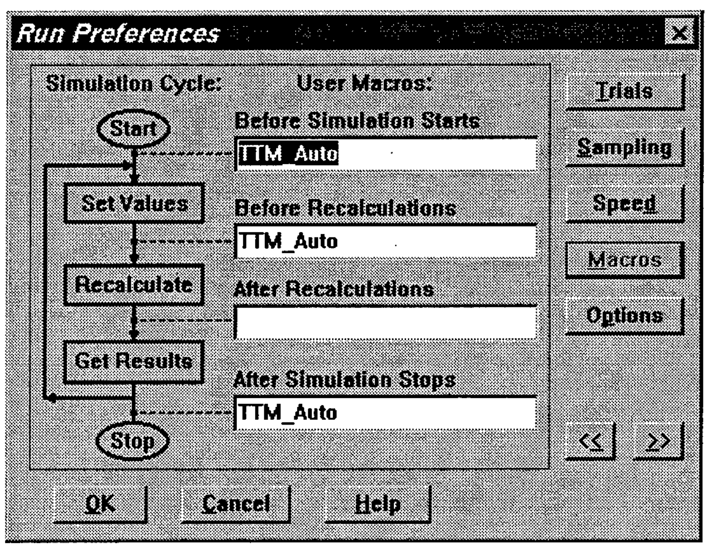
The "Trials" simulation setting dialog box specifies the number of runs to make, and the stopping criteria. The default for Maximum Number of Trials is 10,000. The default for Stopping Criteria is displayed above.



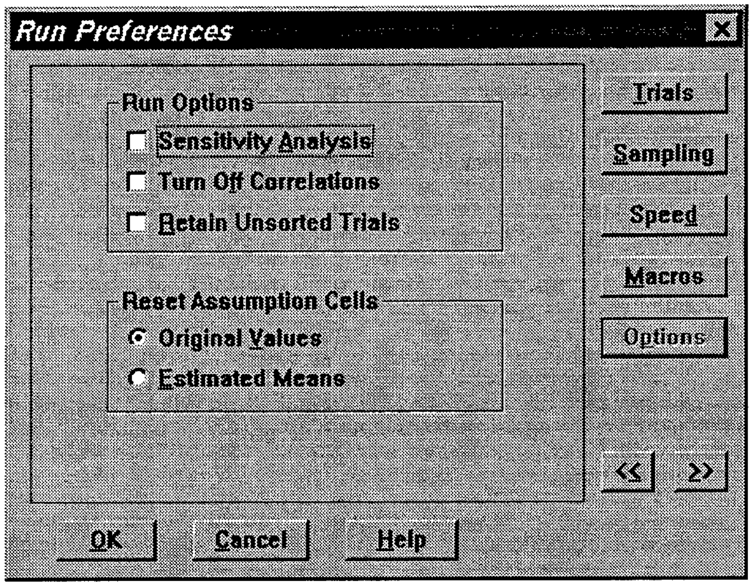
The "Sampling" simulation setting dialog box specifies various simulation options, but the one that drives the PPSM is the Sampling Method (Monte Carlo). The defaults for the entire dialog box are as shown above.



The "Speed" simulation setting dialog box lets the user utilize options that make the simulation span a shorter time. Burst Mode allows the simulation to run in batches as specified in the box. The default value is 5. The Minimize While Running choice lets the user speed up the simulation by minimizing spreadsheets or all of Excel. The Suppress Forecast Windows checkbox allows the Forecasts to be suppressed until the simulation stops running. This increases the speed of the simulation also.



The "Macros" simulation setting dialog box is the most important. It calls the VBA routines that perform the calculations within Excel. They must be specified as shown. The macro is entitled "TTM_Auto" and must be placed in the boxes as shown.



The "Options" simulation setting dialog box enables the user to perform additional statistic gathering functions. When the Run Options are employed, the simulation slows down considerably depending on the number of distributions and forecasts. The Reset Assumption Cells radio buttons allow the user to set the cells with distributions as the original values or the means established through the runs.

3. Run Simulation
   This menu item actually begins the simulation. It prompts the user to close the Main Menu. If the user wants to stop the simulation before it is complete, the Excel window must be maximized, along with the Workbook, and the "Stop Simulation" button must be pressed. It might take several attempts at pressing this button because CB consumes so much CPU time that it might not pick up the initial "press."

4. MainMenu
   Simply returns the user back to the Main Menu

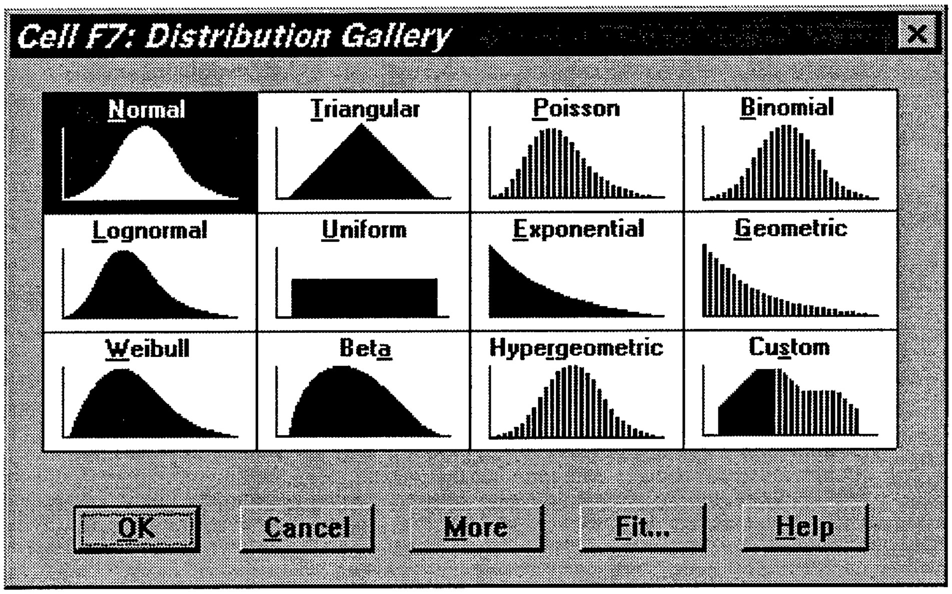
F. EXIT MODEL
   As it says, this option allows the user to exit the model completely. The user is offered the chance to save the model as well.

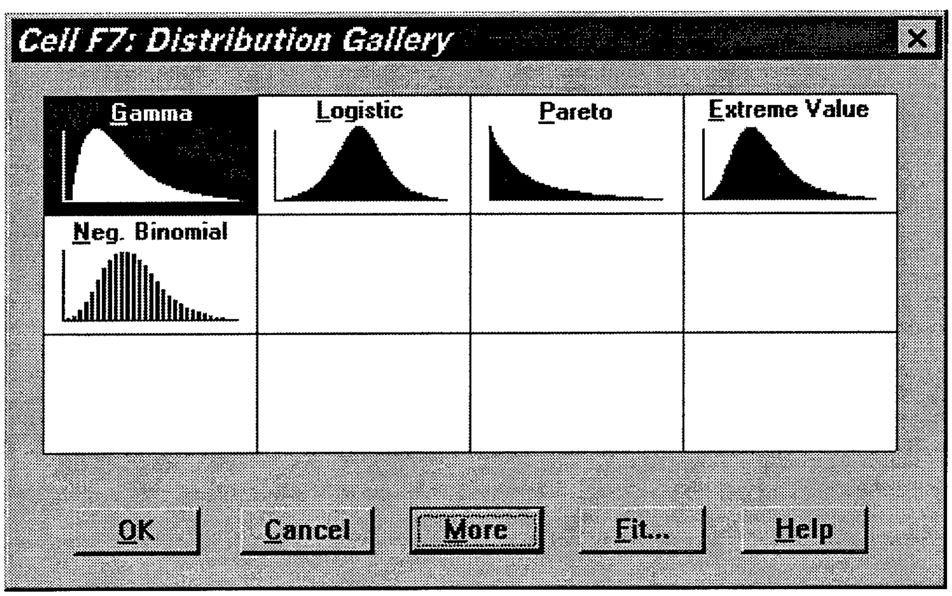
CRYSTAL BALL:

IMPORTANT NOTE: DISTRIBUTIONS AND FORECASTS MUST BE CLEARED MANUALLY ON THE EXCEL WORKSHEET.

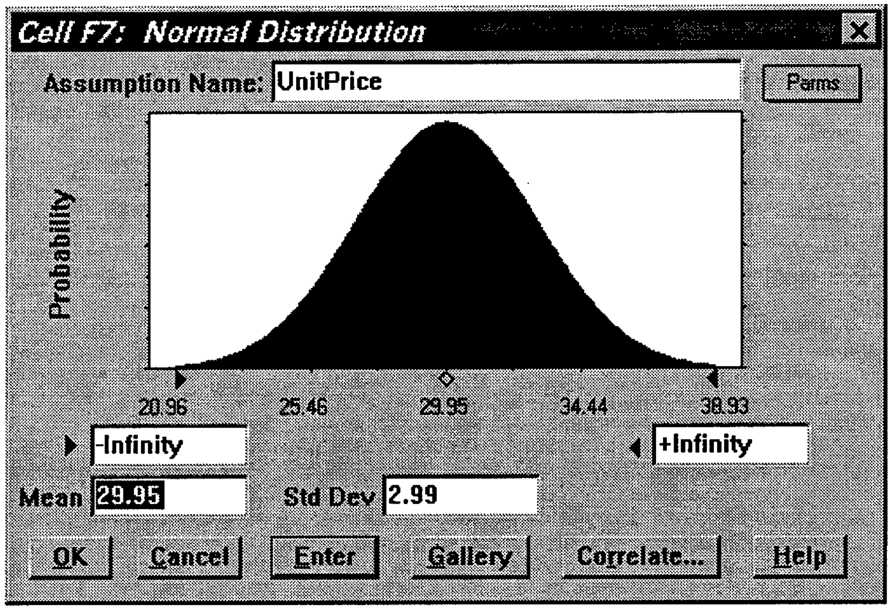
Distributions:

Distributions are set on an individual cell. The cell must already contain a numerical value other than zero. Other stipulations are contained within the Crystal Ball User's Manual. Below are two figures that show the distributions that are available within Crystal Ball.





After the user selects a distribution, Crystal Ball prompts the user to set parameters on the distribution. Below is a sample where the normal distribution has been selected.



Forecasts:

Crystal Ball also contains a feature called "Forecasts." This is the method by which the NPV and the estimates of cost and revenue are determined within the PPSM. Forecasting is basically collecting many statistics and allowing the user to gain information concerning the profile of a certain cell. In the PPSM the use is a risk profile. Just a few of the statistics gathered are the mean, median, min, max, and standard deviation.

Appendix C: R & D and Capital Cost Elements for Portfolio Products

Product 1: R & D and Capital Cost Elements

Name	Value	Start	Payments	Skip	Category
Base_To_Fixture_Tool	$22,460.22	0	1	0	Capital_Cost
Label_Hold_Tool	$1,539.82	0	1	0	Capital_Cost
Wear_Pads_Tool	$700.00	0	1	0	Capital_Cost
Cable_Tool	$600.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,465.16	0	1	0	Capital_Cost
Microprocessor_Tool	$11,646.84	0	1	0	Capital_Cost
Electrical_Test_Tool	$2,339.99	0	1	0	Capital_Cost
Buttons_Tool	$500.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.74	0	1	0	Capital_Cost
Hatch_Door_Tool	$737.94	0	1	0	Capital_Cost
Box_Tool	$1,000.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,001.27	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$1,999.28	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$2,067.41	0	1	0	Capital_Cost
Shaft_Tool	$12,000.09	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$3,700.00	0	1	0	Capital_Cost
Roller_Tool	$6,200.24	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,381.52	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$1,100.00	0	1	0	R&D_Cost
Consultants	$750.00	0	1	0	R&D_Cost
Receive_Accept_Specifications	$3,999.88	0	1	0	R&D_Cost
ConceptGeneralization	$10,092.99	0	1	0	R&D_Cost
DetailDesign	$29,560.25	0	1	0	R&D_Cost
TestBetaPrototype	$2.67	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.84	0	1	0	R&D_Cost
DesignMolds	$16,094.21	0	1	0	R&D_Cost
DesignToolings	$8,007.33	0	1	0	R&D_Cost
FabricateMolds	$21,000.00	0	1	0	R&D_Cost
DebugMolds	$20,003.85	0	1	0	R&D_Cost
CertifyDesign	$7,999.06	0	1	0	R&D_Cost
InitialProductionRun	$5,000.00	0	1	0	R&D_Cost
Ball_Tool	$12,999.78	0	1	0	Capital_Cost

Product 2: R & D and Capital Cost Elements

Base_To_Fixture_Tool	$20,454.84	0	1	0	Capital_Cost
Label_Hold_Tool	$1,591.10	0	1	0	Capital_Cost
Wear_Pads_Tool	$500.00	0	1	0	Capital_Cost
Cable_Tool	$600.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,357.29	0	1	0	Capital_Cost
Microprocessor_Tool	$12,071.15	0	1	0	Capital_Cost
Electrical_Test_Tool	$4,032.70	0	1	0	Capital_Cost
Buttons_Tool	$700.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.95	0	1	0	Capital_Cost
Hatch_Door_Tool	$1,301.13	0	1	0	Capital_Cost
Box_Tool	$900.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,001.17	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$2,000.07	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$1,243.74	0	1	0	Capital_Cost
Shaft_Tool	$12,000.01	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$43.67	0	1	0	Capital_Cost
Roller_Tool	$6,722.04	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,307.72	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$3,500.00	0	1	0	R&D_Cost
Consultants	$2,800.00	0	1	0	R&D_Cost
Receive_Accept_Specifications	$4,270.06	0	1	0	R&D_Cost
ConceptGeneralization	$10,000.00	0	1	0	R&D_Cost
DetailDesign	$27,816.67	0	1	0	R&D_Cost
TestBetaPrototype	$2,500.00	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.86	0	1	0	R&D_Cost
DesignMolds	$15,278.30	0	1	0	R&D_Cost
DesignToolings	$8,497.40	0	1	0	R&D_Cost
FabricateMolds	$7,800.00	0	1	0	R&D_Cost
DebugMolds	$20,001.42	0	1	0	R&D_Cost
CertifyDesign	$8,000.98	0	1	0	R&D_Cost
InitialProductionRun	$6,000.00	0	1	0	R&D_Cost
Ball_Tool	$12,999.84	0	1	0	Capital_Cost

Product 3: R & D and Capital Cost Elements

Base_To_Fixture_Tool	$22,573.79	0	1	0	Capital_Cost
Label_Hold_Tool	$1,450.92	0	1	0	Capital_Cost
Wear_Pads_Tool	$350.00	0	1	0	Capital_Cost
Cable_Tool	$450.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,511.33	0	1	0	Capital_Cost
Microprocessor_Tool	$12,220.84	0	1	0	Capital_Cost
Electrical_Test_Tool	$1,343.06	0	1	0	Capital_Cost
Buttons_Tool	$850.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.72	0	1	0	Capital_Cost
Hatch_Door_Tool	$1,055.09	0	1	0	Capital_Cost
Box_Tool	$740.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,002.41	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$1,998.73	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$1,138.25	0	1	0	Capital_Cost
Shaft_Tool	$12,000.18	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$710.00	0	1	0	Capital_Cost
Roller_Tool	$5,701.69	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,226.85	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$620.00	0	1	0	R&D_Cost
Consultants	$720.00	0	1	0	R&D_Cost
Receive_Accept_Specifications	$3,902.09	0	1	0	R&D_Cost
ConceptGeneralization	$10,394.29	0	1	0	R&D_Cost
DetailDesign	$28,442.18	0	1	0	R&D_Cost
TestBetaPrototype	$780.00	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.36	0	1	0	R&D_Cost
DesignMolds	$16,020.61	0	1	0	R&D_Cost
DesignToolings	$11,068.16	0	1	0	R&D_Cost
FabricateMolds	$8,000.00	0	1	0	R&D_Cost
DebugMolds	$20,002.18	0	1	0	R&D_Cost
CertifyDesign	$8,001.49	0	1	0	R&D_Cost
InitialProductionRun	$5,000.00	0	1	0	R&D_Cost
Ball_Tool	$13,000.92	0	1	0	Capital_Cost

Product 4: R & D and Capital Cost Elements

Base_To_Fixture_Tool	$20,958.34	0	1	0	Capital_Cost
Label_Hold_Tool	$1,465.72	0	1	0	Capital_Cost
Wear_Pads_Tool	$195.00	0	1	0	Capital_Cost
Cable_Tool	$560.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,292.37	0	1	0	Capital_Cost
Microprocessor_Tool	$12,269.35	0	1	0	Capital_Cost
Electrical_Test_Tool	$1,561.20	0	1	0	Capital_Cost
Buttons_Tool	$720.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.93	0	1	0	Capital_Cost
Hatch_Door_Tool	$916.88	0	1	0	Capital_Cost
Box_Tool	$1,300.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,002.28	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$2,001.20	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$1,679.45	0	1	0	Capital_Cost
Shaft_Tool	$12,000.30	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$963.00	0	1	0	Capital_Cost
Roller_Tool	$5,882.27	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,098.41	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$4,500.00	0	1	0	R&D_Cost
Consultants	$2,600.00	0	1	0	R&D_Cost
Receive_Accept_Specification:	$4,379.19	0	1	0	R&D_Cost
ConceptGeneralization	$10,075.58	0	1	0	R&D_Cost
DetailDesign	$43,145.93	0	1	0	R&D_Cost
TestBetaPrototype	$590.00	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.85	0	1	0	R&D_Cost
DesignMolds	$15,865.29	0	1	0	R&D_Cost
DesignToolings	$9,315.32	0	1	0	R&D_Cost
FabricateMolds	$2,600.00	0	1	0	R&D_Cost
DebugMolds	$20,001.33	0	1	0	R&D_Cost
CertifyDesign	$8,000.37	0	1	0	R&D_Cost
InitialProductionRun	$14,000.00	0	1	0	R&D_Cost
Ball_Tool	$13,000.76	0	1	0	Capital_Cost

Product 5: R & D and Capital Cost Elements

Base_To_Fixture_Tool	$21,022.85	0	1	0	Capital_Cost
Label_Hold_Tool	$1,490.41	0	1	0	Capital_Cost
Wear_Pads_Tool	$195.33	0	1	0	Capital_Cost
Cable_Tool	$2,400.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,786.27	0	1	0	Capital_Cost
Microprocessor_Tool	$11,811.42	0	1	0	Capital_Cost
Electrical_Test_Tool	$879.43	0	1	0	Capital_Cost
Buttons_Tool	$5,300.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.66	0	1	0	Capital_Cost
Hatch_Door_Tool	$1,388.93	0	1	0	Capital_Cost
Box_Tool	$2,433.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,002.76	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$1,998.45	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$1,322.01	0	1	0	Capital_Cost
Shaft_Tool	$11,999.86	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$3,800.00	0	1	0	Capital_Cost
Roller_Tool	$5,803.72	0	1	0	Capital_Cost
Idler_Housing_Tool	$7,992.22	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$8,000.00	0	1	0	R&D_Cost
Consultants	$2,400.00	0	1	0	R&D_Cost
Receive_Accept_Specifications	$3,628.52	0	1	0	R&D_Cost
ConceptGeneralization	$9,407.92	0	1	0	R&D_Cost
DetailDesign	$76,049.61	0	1	0	R&D_Cost
TestBetaPrototype	$8,300.00	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.57	0	1	0	R&D_Cost
DesignMolds	$15,619.18	0	1	0	R&D_Cost
DesignToolings	$7,318.46	0	1	0	R&D_Cost
FabricateMolds	$2,600.00	0	1	0	R&D_Cost
DebugMolds	$20,001.66	0	1	0	R&D_Cost
CertifyDesign	$8,001.82	0	1	0	R&D_Cost
InitialProductionRun	$1,790.00	0	1	0	R&D_Cost
Ball_Tool	$12,999.40	0	1	0	Capital_Cost

Product 6: R & D and Capital Cost Elements

Base_To_Fixture_Tool	$20,180.99	0	1	0	Capital_Cost
Label_Hold_Tool	$1,532.53	0	1	0	Capital_Cost
Wear_Pads_Tool	$2,111.00	0	1	0	Capital_Cost
Cable_Tool	$2,133.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,657.40	0	1	0	Capital_Cost
Microprocessor_Tool	$12,579.64	0	1	0	Capital_Cost
Electrical_Test_Tool	$2,211.48	0	1	0	Capital_Cost
Buttons_Tool	$3,333.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.70	0	1	0	Capital_Cost
Hatch_Door_Tool	$981.46	0	1	0	Capital_Cost
Box_Tool	$27,000.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,000.85	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$2,000.81	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$4,244.01	0	1	0	Capital_Cost
Shaft_Tool	$12,001.29	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$5,733.00	0	1	0	Capital_Cost
Roller_Tool	$6,076.47	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,328.52	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$7,333.00	0	1	0	R&D_Cost
Consultants	$26,666.00	0	1	0	R&D_Cost
Receive_Accept_Specifications	$3,820.50	0	1	0	R&D_Cost
ConceptGeneralization	$9,921.70	0	1	0	R&D_Cost
DetailDesign	$67,003.05	0	1	0	R&D_Cost
TestBetaPrototype	$3,333.00	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.42	0	1	0	R&D_Cost
DesignMolds	$15,712.80	0	1	0	R&D_Cost
DesignToolings	$8,711.12	0	1	0	R&D_Cost
FabricateMolds	$25,666.00	0	1	0	R&D_Cost
DebugMolds	$20,001.57	0	1	0	R&D_Cost
CertifyDesign	$7,998.44	0	1	0	R&D_Cost
InitialProductionRun	$23,333.00	0	1	0	R&D_Cost
Ball_Tool	$13,001.03	0	1	0	Capital_Cost

Product 7: R & D and Capital Cost Elements

Base_To_Fixture_Tool	$20,612.12	0	1	0	Capital_Cost
Label_Hold_Tool	$1,482.06	0	1	0	Capital_Cost
Wear_Pads_Tool	$2,043.00	0	1	0	Capital_Cost
Cable_Tool	$2,433.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,667.24	0	1	0	Capital_Cost
Microprocessor_Tool	$11,911.81	0	1	0	Capital_Cost
Electrical_Test_Tool	$4,332.67	0	1	0	Capital_Cost
Buttons_Tool	$46,667.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.77	0	1	0	Capital_Cost
Hatch_Door_Tool	$4,085.00	0	1	0	Capital_Cost
Box_Tool	$2,546.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,002.58	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$1,998.60	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$1,279.51	0	1	0	Capital_Cost
Shaft_Tool	$12,000.53	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$3,966.00	0	1	0	Capital_Cost
Roller_Tool	$5,606.76	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,022.48	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$66,667.00	0	1	0	R&D_Cost
Consultants	$2,600.00	0	1	0	R&D_Cost
Receive_Accept_Specification:	$4,135.54	0	1	0	R&D_Cost
ConceptGeneralization	$10,579.79	0	1	0	R&D_Cost
DetailDesign	$2,646.87	0	1	0	R&D_Cost
TestBetaPrototype	$20,000.00	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.70	0	1	0	R&D_Cost
DesignMolds	$15,365.46	0	1	0	R&D_Cost
DesignToolings	$4,426.67	0	1	0	R&D_Cost
FabricateMolds	$2,633.00	0	1	0	R&D_Cost
DebugMolds	$20,002.99	0	1	0	R&D_Cost
CertifyDesign	$8,000.87	0	1	0	R&D_Cost
InitialProductionRun	$1,417.00	0	1	0	R&D_Cost
Ball_Tool	$13,000.45	0	1	0	Capital_Cost

Product 8: R & D and Capital Cost Elements

Base_To_Fixture_Tool	$23,843.96	0	1	0	Capital_Cost
Label_Hold_Tool	$1,487.54	0	1	0	Capital_Cost
Wear_Pads_Tool	$1,999.00	0	1	0	Capital_Cost
Cable_Tool	$2,433.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,681.53	0	1	0	Capital_Cost
Microprocessor_Tool	$12,285.97	0	1	0	Capital_Cost
Electrical_Test_Tool	$3,678.55	0	1	0	Capital_Cost
Buttons_Tool	$3,333.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.33	0	1	0	Capital_Cost
Hatch_Door_Tool	$1,047.17	0	1	0	Capital_Cost
Box_Tool	$2,733.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,004.56	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$2,000.77	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$1,333.13	0	1	0	Capital_Cost
Shaft_Tool	$12,000.64	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$37,000.00	0	1	0	Capital_Cost
Roller_Tool	$6,056.14	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,218.09	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$10,000.00	0	1	0	R&D_Cost
Consultants	$22.33	0	1	0	R&D_Cost
Receive_Accept_Specification:	$4,041.23	0	1	0	R&D_Cost
ConceptGeneralization	$10,413.07	0	1	0	R&D_Cost
DetailDesign	$52,091.51	0	1	0	R&D_Cost
TestBetaPrototype	$6,667.00	0	1	0	R&D_Cost
DesignProductionTypes	$30,001.00	0	1	0	R&D_Cost
DesignMolds	$15,466.40	0	1	0	R&D_Cost
DesignToolings	$7,239.58	0	1	0	R&D_Cost
FabricateMolds	$25,333.00	0	1	0	R&D_Cost
DebugMolds	$20,002.39	0	1	0	R&D_Cost
CertifyDesign	$7,999.59	0	1	0	R&D_Cost
InitialProductionRun	$16,402.00	0	1	0	R&D_Cost
Ball_Tool	$12,999.59	0	1	0	Capital_Cost

Appendix D: Portfolio Linear Program Formulation

$$[\mathrm{OBJ}]\ \mathrm{MAX} = (2 - A\sigma_1^2)x1 + (3 - A\sigma_2^2)x2 + (3.8 - A\sigma_3^2)x3 + (5.6 - A\sigma_4^2)x4 + (6.7 - A\sigma_5^2)x5 + (7.2 - A\sigma_6^2)x6 + (10.3 - A\sigma_7^2)x7 + (11.2 - A\sigma_8^2)x8;$$

Subject to:

```
-1632.88288*x1 - 1476.42848*x2 - 1370.744*x3 - 1606.97984*x4  -1395.07328*x5 -
        1615.02616*x6 - 1396.384*x7 - 1567.81144*x8  + 250.16*x12 + 231.28*x13 + 207.76*x23
        + 273.76*x14 + 245.92*x24 + 227.36*x34 + 236*x15 + 212*x25 + 196*x35 + 232*x45
        + 276.12*x16 + 248.04*x26 + 229.32*x36 + 271.44*x46 + 234*x56  + 236*x17 + 212*x27
        + 196*x37 + 232*x47 + 200*x57 + 234*x6 + 266.68*x18 + 239.56*x28 + 221.48*x38 +
        262.16*x48 + 226*x58 + 264.42*x68 + 226*x78  >= -5476;

 11.8*x1 + 10.6*x2 + 9.8*x3 + 11.6*x4 + 10*x5 + 11.7*x6 + 10*x7 + 11.3*x8 <= 74;

 x1 + x2 - x12  <= 1;
 x2 + x3 - x23  <= 1;
 x3 + x4 - x34  <= 1;
 x4 + x5 - x45  <= 1;
 x5 + x6 - x56  <= 1;
 x6 + x7 - x67  <= 1;
 x7 + x8 - x78  <= 1;

 -0.5*x1 -0.5*x2 + x12  <= 0;
 -0.5*x2 -0.5*x3 + x23  <= 0;
 -0.5*x3 -0.5*x4 + x34  <= 0;
 -0.5*x4 -0.5*x5 + x45  <= 0;
 -0.5*x5 -0.5*x6 + x56  <= 0;
 -0.5*x6 -0.5*x7 + x67  <= 0;
 -0.5*x7 -0.5*x8 + x78  <= 0;

@BIN(x1);
@BIN(x2);@BIN(x12);
@BIN(x3);@BIN(x13);@BIN(x23);
@BIN(x4);@BIN(x14);@BIN(x24);@BIN(x34);
@BIN(x5);@BIN(x15);@BIN(x25);@BIN(x35);@BIN(x45);
@BIN(x6);@BIN(x16);@BIN(x26);@BIN(x36);   @BIN(x46);
@BIN(x56);@BIN(x7);@BIN(x17);@BIN(x27);@BIN(x37);@BIN(x47); @BIN(x57);
@BIN(x67);@BIN(x8);@BIN(x18);@BIN(x28);@BIN(x38);@BIN(x48); @BIN(x58); @BIN(x68);
@BIN(x78);

END
```

Appendix E: NPV for Individual Products

Percentiles--NPV	Product 1
15%	($10,658.89)
20%	$1,279.56
25%	$15,440.77
40%	$54,810.51
50%	$118,341.84
95.0%	$485,196.14
97.5%	$500,059.41
100.0%	$529,932.51

Percentiles--NPV	Product 2	Product 3	Product 4
0.0%	($683.99)	$43,255.69	$65,253.39
2.5%	$9,316.07	$56,849.29	$121,441.15
5.0%	$19,672.01	$63,063.00	$139,510.54
50.0%	$175,986.40	$228,160.19	$366,605.10
95.0%	$651,327.88	$793,398.88	$1,125,566.61
97.5%	$679,674.23	$813,782.79	$1,153,407.68
100.0%	$724,979.81	$890,376.20	$1,306,292.73

Percentiles--NPV	Product 5	Product 6	Product 7
0.0%	$95,106.15	($42,301.63)	($3,541.35)
2.5%	$163,568.44	$87,499.25	$163,979.22
5.0%	$186,145.88	$118,667.90	$226,379.49
50.0%	$446,927.81	$546,935.72	$795,137.39
95.0%	$1,351,729.51	$1,550,596.88	$2,265,716.54
97.5%	$1,448,421.74	$1,651,848.46	$2,407,397.94
100.0%	$1,741,843.28	$2,079,727.53	$2,962,229.96

Percentiles--NPV	Product 8
0.0%	($8,821.10)
2.5%	$151,326.10
5.0%	$222,649.67
50.0%	$910,304.05
95.0%	$2,423,493.73
97.5%	$2,603,670.27
100.0%	$3,379,894.77

Appendix F: Baseline Data for Learning Curve, Early/Late to Entry, Late and Compressed Market Experiments

Distributions	
Market Length	Tri(24,36,48)
Market Size	Norm($5M,$300K)
Market Distribution	Beta(2,2)
Entry of YourFirm	LogNorm(3,1.5) Min1
Entry of Competitor1	LogNorm(3,1.5) Min1
Entry of Competitor2	LogNorm(3,1.5) Min1
AdvantageShare	Unif(.10,.30)

Capital and R & D Cost Elements:

Base_To_Fixture_Tool	$20,958.34	0	1	0	Capital_Cost
Label_Hold_Tool	$1,465.72	0	1	0	Capital_Cost
Wear_Pads_Tool	$195.00	0	1	0	Capital_Cost
Cable_Tool	$560.00	0	1	0	Capital_Cost
Circuit_Board_Tool	$3,292.37	0	1	0	Capital_Cost
Microprocessor_Tool	$12,269.35	0	1	0	Capital_Cost
Electrical_Test_Tool	$1,561.20	0	1	0	Capital_Cost
Buttons_Tool	$720.00	0	1	0	Capital_Cost
Top_Cover_Tool	$25,000.93	0	1	0	Capital_Cost
Hatch_Door_Tool	$916.88	0	1	0	Capital_Cost
Box_Tool	$1,300.00	0	1	0	Capital_Cost
Foam_Pack_Bottom_Tool	$16,002.28	0	1	0	Capital_Cost
Ball_Cage_Frame_Tool	$2,001.20	0	1	0	Capital_Cost
Light_Emitter_Bar_Tool	$1,679.45	0	1	0	Capital_Cost
Shaft_Tool	$12,000.30	0	1	0	Capital_Cost
Encoder_Wheel_Tool	$963.00	0	1	0	Capital_Cost
Roller_Tool	$5,882.27	0	1	0	Capital_Cost
Idler_Housing_Tool	$8,098.41	0	1	0	Capital_Cost
Production_Cost	Cost_Good_Units + Cost_Bad_Units	YourFirm	Time - YourFirm + 1	0	O & M Cost
Prototype_Molds	$4,500.00	0	1	0	R&D_Cost
Consultants	$2,600.00	0	1	0	R&D_Cost
Receive_Accept_Specification:	$4,379.19	0	1	0	R&D_Cost
ConceptGeneralization	$10,075.58	0	1	0	R&D_Cost
DetailDesign	$43,145.93	0	1	0	R&D_Cost
TestBetaPrototype	$590.00	0	1	0	R&D_Cost
DesignProductionTypes	$30,000.85	0	1	0	R&D_Cost
DesignMolds	$15,865.29	0	1	0	R&D_Cost
DesignToolings	$9,315.32	0	1	0	R&D_Cost
FabricateMolds	$2,600.00	0	1	0	R&D_Cost
DebugMolds	$20,001.33	0	1	0	R&D_Cost
CertifyDesign	$8,000.37	0	1	0	R&D_Cost
InitialProductionRun	$14,000.00	0	1	0	R&D_Cost
Ball_Tool	$13,000.76	0	1	0	Capital_Cost

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Vita

1st Lt Scott C Naylor was born on 13 November 1968 in Houston, Texas. He graduated from Bloomington High School South, Bloomington, Indiana in 1987. In 1994 he graduated with a Bachelor of Science Degree in Secondary Education (Mathematics). After teaching middle-school mathematics for a short stint, he entered the Air Force Officer Training School in March of 1995 and was commissioned in June of 1995. His first assignment was AFIT/RR and AFIT/CI as a personnel officer. In August 1997, he entered the School of Engineering, Operations Research Program, Air Force Institute of Technology, Wright-Patterson Air Force Base, OH. Lt Naylor will be assigned to the Air Force Logistics Management Agency, Gunter AFB AL upon graduation.

Permanent Mailing Address:
AFLMA
501 Ward Street, Bldg 205
Maxwell AFB, Gunter Annex AL 36114-3236

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2950 P Street
WPAFB OH 45433-7765

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13. ABSTRACT *(Maximum 200 words)*
High technology firms are faced with the dilemma of deciding which products to develop, which generations of technology to pass over, and which products to skip entirely. As competition among these firms increases and the life cycles of technological products shorten, there exists a great deal of pressure to bring products rapidly to the market. As a result, recouping the costs of research and development (R & D) and earning a profit becomes increasingly uncertain. Traditional life cycle cost models do not directly address shortened life cycles, time to market, or learning curve issues; all are critical factors in the development of high technology products.

This thesis allows the investigation of cost estimates involved in the R & D of high technology products. Cost estimations include time to market and learning curve effects. Simulation is used to provide cost and revenue estimates that may then be used to calculate a distribution of potential net present values (NPVs) of a product. Measures of financial risk are also generated. Using the generated expected value and variance of the NPV of each product under consideration, a linear program is built to select the optimal portfolio of products to develop. The method is demonstrated with an illustrative example.

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