A Probabilistic Capital Budgeting Model for New Product Development under Stage-Gate Process

Mohammad Sharifzadeh[1] & Azi Sharif

[1] College of Management and Technology, Walden University, Minneapolis, MN 55401, USA

Correspondence: Mohammad Sharifzadeh, College of Management and Technology, Walden University, USA. E-mail: mohammad.sharifzadeh@waldenu.edu

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Abstract

Stage-gate model for new product development (NPD) and for any research and development (R&D) project consists of a series of stages and gates; each stage is a set of research activities and gates are milestones at which decisions are made based on predetermined criteria. In this paper we developed a capital budgeting model for a typical 5-stage, 5-gate process to be used for appraising commercial viability of the NPD at Stage 2 which will serve as one of the decision making criterion at Gate 3. Because in an NPD project, completion costs (capital investments), completion times, and future cash flows are uncertain, we developed the Pert-Beta probability distribution to encounter for the randomness of these variables. Furthermore, we suggested the model can be applied to real case NPD projects with the Monte Carlo Simulation approach. We then verified the workability of the model by applying it to a notional NPD project and demonstrated that all decision variables reach steady state in the Monte Carlo Simulation calculations.

Keywords*:* Stage-gate, New Product Development, Capital Budgeting, Pert-Beta, Monte Carlo Simulation

1. Introduction

Stage-gate model for new product development (NPD) and for any research and development (R&D) project consists of a series of stages and gates; each stage is a set of research activities and gates are milestones at which decisions are made based on predetermined criteria. At one of the gates we must assess if the final outcome of the NPD adds value to the firm, rank alternative technology solutions based on the value adding potential and technological/financial risks, and select the best alternative technology solution to proceed to development. However, given the uncertainties affecting the outcome of an NPD, there is a gap in the literature with regards to modeling these uncertainties and developing appropriate probabilistic evaluation metrics. The purpose in this paper, therefore, is to develop a probabilistic capital budgeting model for a typical 5-stage, 5-gate process to be used for appraising commercial viability of the NPD at Stage 2 which will serve as one of the decision making criterion at Gate 3.

The rest of this paper is organized as follows. We first present a brief description of the stage-gate approach for new product development, followed by review of the literature, and a discussion of PV and NPV analysis in continuous time. We will then develop a capital budgeting model for stage-gate process, followed by a proposed probabilistic model for incorporating uncertainty, and finally we will demonstrate with a notional project how Monte Carlo Simulation method can be used in complicated capital budgeting under uncertainty for NPD projects.

2. Stage-Gate Approach

Stage-gate is an approach in project management which funds a project in a sequence of phases based on a set of defined criteria for each phase and the information obtained. Stage-gate model is particularly useful for new product development (NPD) projects, because NPD projects are inherently risky and funding commitments should initially be small and gradually increase as technical and commercial risks are mitigated. Stage-gate model consists of a series of stages and gates; each stage is a set of research activities and information gathering whereas gates are milestones at which decisions are made based on predetermined criteria.

3. Literature Review

Stage-gate model was originally developed in the 1980s, through study of companies that drove successful new products to the market (Cooper, 2014) and has been widely recognized and implemented by companies as a method that brings order to the highly uncertain investments in research and development and new product development projects. Summarizing the results of the second survey of the Product Development & Management Association's (PDMA's) on companies' new product development best practices, Griffin (1997) reported that 60% of respondents were using some form of stage-gate methodology in their new product development efforts. More recently, in a study conducted for the Institute for Defense Analysis, Atta et al. (2012) interviewed R&D leaders of seven large U.S.-based companies: Applied Materials, The Boeing Company, Exxon Mobil Corporation, General Electric, IBM, Intel, and Proctor & Gamble and found that "leading firms use rigorous, but specifically designed stage-gate processes to manage the *cost* of failure. The objective is not to prevent failure per se, because that implies lack of innovation and exploration of new ideas" (p. v).

As pointed out in Atta *et al*. (2012) the number of stages and gates in the stage-gate model can be customized based on the project or corporate priorities. In this paper for the sake of exposition we give a brief description of the typical stage-gate model as discussed by Cooper (*n.d.*). We give very brief description of the stage-gate details, as our purpose is to provide a capital budgeting model for decision making at a specific gate of the process. The model we present is robust and can be applied to any custom-made stage-gate process. A typical 5-stage, 5-gate process as outlined in Cooper (*n.d.*) is as depicted in Figure (1):

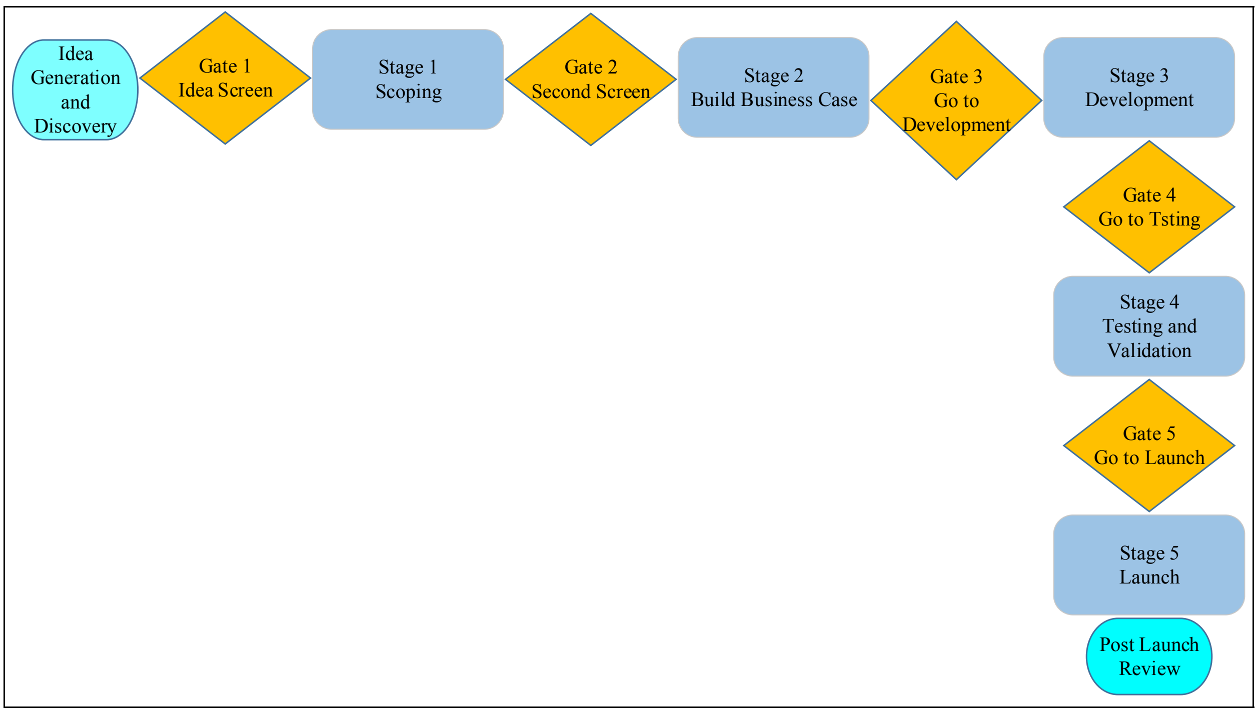

Figure 1. A Typical 5-Stage 5-Gate Process Flow

4. The Authors' Contribution to the Field

At one of the gates we must assess if the final outcome of the NPD adds value to the firm, rank alternative technology solutions based on the value adding potential and technological/financial risks, and select the best alternative technology solution to proceed to development. According to Cooper (*n.d.*) one of the activities in stage 2 which leads to *go to development* in Gate 3 is "a detailed business and financial analysis involving a discounted cash flow approach (NPV and IRR), complete with sensitivity analysis to look at possible downside risks" (p. 6).

Our purpose in this paper is, therefore, to develop a probabilistic capital budgeting model to be used for appraising commercial viability of the NPD at Stage 2 which will serve as one of the decision making criterion at Gate 3. Only capital outlays expected to be incurred after Gate 3 are relevant costs and all costs incurred prior to gate 3 are sunk costs and will not affect the appraisal. A project adds value if it has positive expected net present value NPV and its ranking is based on its expected profitability index. The NPV is the PV of expected free cash flows (FCF) after the new product is launched minus PV of post Gate 3 expected completion costs. The profitability index (PI) defined as the ratio of present value (PV) of future free cash flows divided by present value of capital investments (completion cost) is a metric similar to return on investment with the difference that it considers time value of money as well as financial risk of the project through discounting costs and benefits with a cost of capital commensurate with the risk of the project. In order to develop our model we first give a brief description of present value methodology in continuous time as it relates to capital budgeting models.

5. Present Value Methodology

Present value of a single amount C_t occurring at time t is given by:

$$PV = \frac{C_t}{(1+r)^t} \tag{1}$$

where, r is an appropriate discount rate, also called the cost of capital.
It can easily be demonstrated that in continuous time Equation 1 can be expressed as;

$$PV = C_t e^{-rt} \tag{2}$$

When there are multiple amounts occurring, starting at the beginning of time $t$in the future, and continue occurring at the beginning of consecutive equal time intervals for N periods, the total PV of those amounts would be:

$$PV = \sum_{i=0}^{N-1} C_{t+i} e^{-r(t+i)} \tag{3}$$

Where N is the number of time periods involved.

For the special case where all the future amounts are the same, equal to C, and occur at the beginning of each period Equation 3 can be simplified as:

$$PV = \sum_{i=0}^{N-1} C\, e^{-r(t+i)} = Ce^{-rt} \times \sum_{i=0}^{N-1} e^{-ri} \tag{4}$$

Equation 4 can further be simplified as:

$$PV = Ce^{-rt} \times \frac{1-e^{-rN}}{1-e^{-r}} \tag{5}$$

When we are dealing with unequal amounts occurring in the future, it would be easier for analytical purposes to convert those unequal amounts into a constant *annual equivalent*. That is, to find a constant amount occurring every year for the same period of time as the unequal amount such that the present value of unequal stream is the same as the present value of the equal stream of monies. This can be established through equating the right-hand-side terms of Equation 3 and Equation 5, that is:

$$\sum_{i=0}^{N-1} C_{t+i} e^{-r(t+i)} = Ce^{-rt} \times \frac{1-e^{-rN}}{1-e^{-r}} \tag{6}$$

Solving for C we get:

$$C = [\sum_{i=0}^{N-1} C_{t+i} e^{-r(t+i)}] \times [e^{rt} \times \frac{1-e^{-r}}{1-e^{-rN}}] \tag{7}$$

This means the constant amount C occurring (beginning of the year) every year from year t through year $t+N$ has the same present value as the unequal amounts C_t, C_{t+1}……C_{t+N} occurring (beginning of the year) over the same time period t through $t+N$.

In the next section we use Equation 5 and Equation 7 to formulate PV of costs at each stage following Gate 3 and, therefore, will formulate PV of completion costs.

6. Completion Cost and NPV Model

Total completion costs valued at Gate 3 (investment) is the sum of present values of all the investment outlays expected to occur at Stage 3, Stage 4, and Stage 5, That is:

$$CapitalInvestment = PV(CompletionCosts) = PV(Stage3Cost) + PV(Stage4Costs) + PV(Stage5Costs) \tag{8}$$

and,

$$NPV = PV(FreeCashFlows) - PV(CompletionCosts) \tag{9}$$

Free cash flows (FCC) occur during the new product's life cycle (from launch to withdrawal).

We are not including post launch review costs as part of completion costs, because those costs occur in the commercialization phase and will be included in the FCF of the year they occur. To express Equations8and 9 into their constituent components we define the following notations:

C_1 = Annual equivalent costs during Stage 3

N_1 = Stage 3 completion time

C_2 = Annual equivalent costs during Stage 4

N_2 = Stage 4 completion time

C_3 = Annual equivalent costs during Stage 5

N_3 = Stage 5 completion time

FCF = Annual equivalent free cash flows during new product's life cycle

N_4 = New product's life cycle

whereC_1, C_2,C_3, and ***FCF*** are calculated using Equation 7. Now using the above notations and applying Equation 5 to each component of ***Completion Costs*** in Equation 8and to $PV(FreeCashFlows)$ in Equation 9we get:

$$PV(Stage3Costs) = C_1 \times \frac{1-e^{-rN_1}}{1-e^{-r}} \tag{10}$$

$$PV(Stage4Costs)) = C_2 e^{-rN_1} \times \frac{1-e^{-rN_2}}{1-e^{-r}} \tag{11}$$

$$PV(Stage5Costs) = C_3 e^{-r(N_1+N_2)} \times \frac{1-e^{-rN_3}}{1-e^{-r}} \tag{12}$$

$$PV(FreeCashFlows) = FCFe^{-r(N_1+N_2+N_3)} \times \frac{1-e^{-rN_4}}{1-e^{-r}} \tag{13}$$

and, therefore:

$$PV(CompletionCosts) = C_1 \times \frac{1-e^{-rN_1}}{1-e^{-r}} + C_2 e^{-rN_1} \times \frac{1-e^{-rN_2}}{1-e^{-r}} + C_3 e^{-r(N_1+N_2)} \times \frac{1-e^{-rN_3}}{1-e^{-r}} \tag{14}$$

$$NPV = FCFe^{-r(N_1+N_2+N_3)} \times \frac{1-e^{-rN_4}}{1-e^{-r}} - \left\{ C_1 \times \frac{1-e^{-rN_1}}{1-e^{-r}} + C_2 e^{-rN_1} \times \frac{1-e^{-rN_2}}{1-e^{-r}} + C_3 e^{-r(N_1+N_2)} \times \frac{1-e^{-rN_3}}{1-e^{-r}} \right\} \tag{15}$$

and,

$$PI = \frac{PV(FreeCashFlows)}{PV(CompletionCosts)} \tag{16}$$

Equation 14 expresses PV of completion costs (capital expenditures) as a function of three annual equivalent costs, three completion times (schedules), and the cost of capital, Equation 15 expresses NPV as a function of annual equivalent free cash flows, life of the new product (from launch to withdrawal), and the variables contained in the completion costs equation, and Equation 16 expresses PI as a function of variables contained in PV of free cash flows and PV of completion costs equations. However, as the empirical evidence indicates, actual costs, schedules, and benefits (free cash flows) almost always deviate from initial estimates. Therefore, a realistic approach is to treat costs, completion times, and FCFs as random variables and determine their probability distribution functions. But, because in the case of new product development we do not have a multitude of similar historical data to develop frequencies and histograms and estimate expected values, it is not really possible to estimate probability distributions from historical data. Therefore, we have to treat each alternative technology solution for a NPD project as a unique case and propose a probability distribution function for it. In this paper, we develop the Pert-Beta approach to estimate probability distribution functions for costs and completion times. But, because the relationships expressed in

Equations 14, 15,, and 16 are not linear, we can not determine the probability distributions of **PV of *Completion Costs***, ***NPV,*** and ***PI*** even if we know the probability distributions of costs and completion times at each Stage of the NPD process and the probability distribution of FCFs during the new product's life cycle. Therefore, we need to resort to methods such as Monte Carlo Simulation to study the combined effects of uncertainties at each Stage and for the evaluation metrics expressed in Equations 14 through 16 and conduct risk analysis. In section 7 we will develop the Pert-beta probability distribution function and apply it to costs, completion times, and FCFs estimation and in section 8 we will demonstrate application of Monte Carlo Simulation for probabilistic completion costs, completion time, NPV, and PI analysis in the context of a notional case study.

7. Pert-Beta Probability Distribution Function for Costs and Schedules

To develop the *Pert-Beta* probability distribution we combine the Program Evaluation and Review Technique (PERT) approach of project management, originally developed in 1958 by the U.S. Navy for risk analysis in activity duration analysis in the POLARIS missile program, with the well-known *beta probability distribution*. Since its inception the Pert approach has been widely used in probabilistic modeling of projects' activity times as well as project's cost modeling (Cooper et al., 2005).

The *beta probability distribution* is appropriate for a continuous random variable whose values are bounded between finite limits ***a*** (minimum) and ***b*** (maximum). The density function of such a probability distribution is written as:

$$f(x) = \frac{1}{B(q,r)} \times \frac{(x-a)^{q-1}(b-x)^{r-1}}{(b-a)^{q+r-1}}, \tag{17}$$

for $a \leq x \leq b$ and = 0 elsewhere.

Where ***q*** and ***r*** are the shape parameters and can take different values giving rise to different shapes of the beta distribution and ***B(q,r)*** is the *beta function* defined as:

$$B(q,r) = \int_0^1 z^{q-1}(1-z)^{r-1}dz \tag{18}$$

The mean and variance of the beta distribution are as follows (Ang & Tang 1975):

$$\text{Mean: } \mu = a + \frac{q}{q+r}(b-a) \tag{19}$$

and

$$\text{Variance: } \sigma^2 = \frac{qr}{(q+r)^2(q+r+1)}(b-a)^2 \tag{20}$$

In the special case where the boundary values are ***a = 0*** and ***b = 1***, the distribution is called *standard beta distribution*.

The main advantage of beta distribution for practical applications is that it does not have any predetermined shape, as the bell shape of the normal distribution does. In many real life applications, including in issues like completion time and cost estimates in project management, we do not have prior knowledge of the shape of the distribution of the random variable, and thus as Taylor [2011] indicated the Beta distribution gives us the flexibility of adjusting the shape of probability distribution to different unique circumstances.

In the Excel environment ***q*** and ***r*** are called Alpha and Beta respectively and ***a*** and ***b*** are denoted by ***A*** and ***B***. The function to get random values belonging to the beta distribution is ***=BETAINV(rand(),alpha,beta,A,B)*** and the function to get cumulative probabilities for a given value of the beta random variable ***x*** is ***=BETADIST(x,alpha,beta,A,B).*** We will be using these Excel functions later in this paper to generate random numbers for costs and schedules for each Stage of the NPD process and will use them for the Monte Carlo Simulation analysis.

The Pert-Beta distribution is a special case of beta distribution in which the mean and variance are forced to be expressed independent of the shape parameters ***q*** and ***r***. This is done by incorporating the PERT technique of estimating mean and variance of a random variable into the beta probability distribution. Consequently, the mean and variance of Pert-Beta distribution are defined as:

$$\text{Mean: } \mu = \frac{a+4m+b}{6}, \tag{21}$$

and,

$$\text{Variance: } \sigma^2 = \frac{(b-a)^2}{36} \tag{22}$$

Where ***a, b***, and ***m*** are subject matter experts' (SME's) estimates of the minimum, the maximum, and the most likely (***m***) values of the random variable ***x***. The Pert-Beta distribution is similar to the Triangular distribution in the sense that it is based on SME's estimates of the same three parameters. However, the Pert-Beta distribution is more suitable than the Triangular distribution for reflecting probabilities based on SME's three parameter estimates because of the following:

- The expected value (mean) of the Triangular distribution is equal to the simple average of the lowest, the highest, and the most likely estimate, and thus carries equal weights (1/3) for all the three parameters. But, in the Pert-Beta distribution the mode is given four times more weight than the lowest and the highest estimates in order to arrive at an expected value (mean). This is because estimators can usually provide a more confident guess for the mode than they do for the minimum or maximum. Thus, the expected value in the Pert-Beta distribution places less emphasis on the lowest and the highest estimates
- The standard deviation (square root of variance) of Pert-Beta distribution is 1/6 of the range (maximum less minimum).
- Unlike the triangular distribution, the Pert-Beta distribution constructs a smooth curve, which places progressively more emphasis on values around the most likely value.

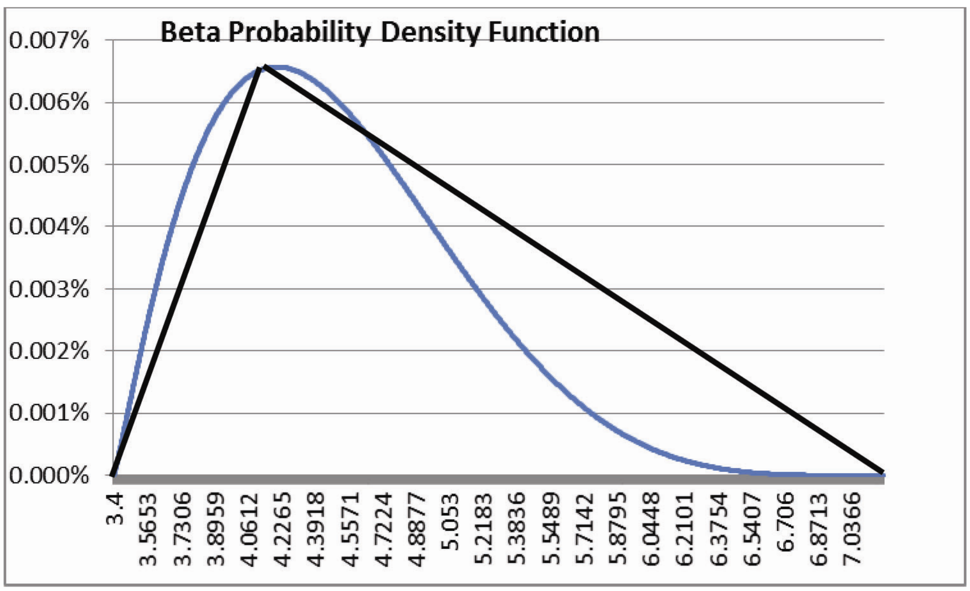

Figure 2. Comparison of Pert-Beta and Triangular Distributions

Because traditionally the PERT approach is applied to activity analysis, project management texts and academic papers about the PERT approach go as far as applying the *central limit theorem* to the sample mean and construct 95% confidence interval for the mean of beta distribution for activity time. However, for the central limit theorem to be valid a large number of instances is required, which is not always the case. Moreover, the literature does not discuss how the expert estimates and the PERT mean and variance in Equations 21 and 22 can be incorporated into the beta probability distribution for risk analysis and probability statements. In what follows we will explain how PERT mean and variance equations can be used to define a unique beta distribution function so that we can conduct risk analysis without resorting to central limit theorem.

Pert-Beta distribution can be simulated in Excel, even though Excel does not have a specific function for Pert-Beta distribution. The fact that mean and variance of pert-beta are predetermined leads to single and unique values for the shape parameters ***q*** and ***r*** in terms of ***a***, **b**, and ***m***. By substituting mean and variance defined in Equation 21 and Equation 22 into Equation 19 and Equation 20 respectively we can express ***q*** and ***r*** in terms of ***a***, ***b***, and ***m***. We can then input these values of ***q*** and ***r*** into Excel beta distribution function as the ***alpha*** and ***beta*** arguments and use Excel beta distribution function to generate Pert-Beta random numbers or make probability statements about specific values of the variable. Solving Equations 19 through Equation 22 for ***q*** and ***r*** in terms of ***a***, ***b***, and ***m*** we get:

$$q = Alpha = \lambda [\frac{4m + b - 5a}{6(b - a)}] , \tag{23}$$

and

$$r = Beta = \lambda [\frac{5b - a - 4m}{6(b - a)}] , \tag{24}$$

where,

$$\lambda = q + r = \frac{(4m + b - 5a)(5b - a - 4m)}{(b - a)^2} - 1 \tag{25}$$

Depending on whether ***m*** is close to ***a***, or close to ***b***, or in the middle of the two, the Pert-Beta distribution could be left skewed, right skewed, or symmetrical. In particular when ***m = (a+b)/2*** then the mean and the mode become equal and we get a symmetrical distribution with ***q=r=4.***

8. Case Study with Monte Carlo Simulation

In the traditional NPV approach, uncertainty is treated by including a risk premium in the cost of capital commensurate with the riskiness of the project. This reduces the NPV of projects with higher risks and thus makes them less desirable. Therefore, the compounding effect of the risk premium in the traditional approach penalizes investments with longer life and thus leads to favoring investment projects with short life spans (Carmichael & Balatbat, 2008). Moreover, when there are multiple risk factors with different degrees of uncertainty involved in affecting the NPV, it is not obvious which risk factors are reflected in the assigned cost of capital. Monte Carlo Simulation is an approach that resolves these shortcomings.

Monte Carlo simulation has been successfully applied in fields related to modeling complex systems in biological research, engineering, geophysics, meteorology, computer applications, public health studies, and finance. Since the original article published by Metropolis and Ulam (1949) on application of the Monte Carlo Method in mathematical physics, researchers have applied the Monte Carlo method to a wide range of nonequilibrium and equilibrium processes and to a variety of complex problems (Amar, 2006). Kawk and Ingall (2007) explored the applications of Monte Carlo simulation for managing project risks and uncertainties. They reported that researchers in project management currently apply the Monte Carlo Simulation primarily in the areas of cost and time management to quantify the risk level of a project's budget or planned completion date as well as for better understanding of project budget and estimating final budget at completion. Williams (2003) discussed advantages of Monte Carlo Simulation compared to other methods in addressing uncertainty in project management. He particularly emphasized that the problem with other analytical methods is that "the restrictive assumptions that they all require, making them unusable in any practical situations" (p.3).

In Monte Carlo simulation we know a dependent variable is affected by some independent random variables, we know the mathematical formula that defines the dependent variable as a function of the independent variables, and we know the probability distribution of each independent random variable. However, we don't know the probability distribution of the dependent variable. By making many draws from the probability distribution of each independent variable and calculating the values of the dependent variable, we can get an idea about the probability distribution of the dependent variable, graph the probability density function and the cumulative distribution function, and make probability statements. In other words, we have the random variable ***y*** being a function of some random variables x_i as defined in Equation 26

$$y = f(x_1, x_2, \ldots x_n) \tag{26}$$

where, each x_i is a random variable with known probability density function. We randomly draw one number from the probability distribution of each x_i and then calculate the value of ***y***. We then repeat the process many times, and then organize the values of ***y*** in a relative frequency histogram and a cumulative relative frequency polygon. The resulting cumulative relative frequencies can then be used to make probability statements about the value of ***y*** falling below, or above, or between some thresholds of interest. Moreover, the mean and the standard deviation of the calculated ***y'***s give us an estimate of the expected value and the expected volatility (uncertainty) of the dependent variable ***y*** (Taylor, 2011). Commercial software for Monte Carlo Simulation recommend at least10000 trials in a Monte Carlo Simulation. However, validation of a Monte Carlo Simulation requires repeating the trials until a steady state is reached, where the expected value (mean) of the results stays constant and does not changes with further repetition of the trials (Taylor, 2011). In a capital budgeting problem, the dependent variable is the NPV, or other metrics discussed in this paper, and the independent variables are completion costs (capital outlays), future FCFs, completion times (schedules), and the cost of capital.

In Tables 1 and 2 we have the data for completion costs, FCFs, and completions times for a notional new product development project based on subject matter experts' estimates. All investment costs, free cash flows, and completion times are random variables and follow Pert-Beta probability distributions.

Table 1. SME's Estimates of Minimum, Maximum, and Most Likely costs and FCFs of a Notional New Product (All costs are in in Million Constant Dollars

	Minimum (a)	***Maximum(b)***	***Most likely(m)***
Stage 3 Costs *(C_1)*	640.00	960.00	672.00
Stage 4 Costs *(C_2)*	139.69	174.61	153.66
Stage 5 Costs *(C_3)*	10.75	18.50	12.36
Life Cycle Benefits *(FCF)*	605.15	812.12	785.25

Table 2. SME's Estimates of Minimum, Maximum, and Most Likely completion times of a Notional New Product (All completion times are in years)

	Minimum (a)	***Maximum(b)***	***Most likely(m)***
Stage 3 Completion Time *(N_1)*	1.25	2.25	1.75
Stage 4 Completion Time *(N_2)*	0.5	0.75	0.67
Stage 5 Completion Time *(N_3)*	0.33	0.5	0.38
New Product Life Cycle *(N_4)*	4	7	6.00

Applying the information in Tables 1 and Table 2 to Equations 23 through Equation 25 we find estimates of Pert-Beta shape parameters ***q*** and ***r***, respectively. From Equation 21 and Equation 22 we estimate expected values (means) and standard deviations of the random variables. The results are shown in Table 4 and Table 5.

Table 4. Pert Beta Probability Distribution Parameters of Completion Costs and Free Cash Flows (annual Equivalents in constant $million)

	Minimum (a)	***Maximum(b)***	***Most likely(m)***	***Expected value (m)***	***Standard Deviation(s)***	***Shape parameter (q)***	***Shape parameter (r)***
Stage 3 Costs *(C_1)*	640.00	960.00	672.00	714.67	53.33	1.27	2.17
Stage 4 Costs *(C_2)*	139.69	174.61	153.66	154.82	5.82	3.40	4.44
Stage 5 Costs *(C_3)*	10.75	18.50	12.36	13.12	1.29	2.03	4.61
Life Cycle Benefits *(FCF)*	605.15	812.12	785.25	759.71	34.50	4.34	1.47

Table 5. Pert Beta Probability Distribution Parameters of Completion Times and Life Cycle (in Years)

	Minimum (a)	***Maximum(b)***	***Most likely(m)***	***Expected value (m)***	***Standard Deviation(s)***	***Shape parameter (q)***	***Shape parameter (r)***
Stage 3 Completion Time *(N_1)*	1.250	2.25	1.75	1.75	0.167	4.00	4.00
Stage 4 Completion Time *(N_2)*	0.500	0.75	0.67	0.66	0.042	4.64	2.84
Stage 5 Completion Time *(N_3)*	0.330	0.50	0.38	0.39	0.028	2.63	4.67
New Product Life Cycle *(N_4)*	4	7	6.00	5.83	0.500	4.62	2.94

The information in Table 4 and Table 5 provide us with estimates of the parameters (***a, b, q, r***) that define probability density functions of the components of Completion Cost (Equation 14), PV of FCFs (Equation 13), NPV (Equation 15), and PI (Equation 16). We now apply the Monte Carlo Simulation approach to estimate probability distributions for Completion Cost, PV of FCFs, NPV, and PI and find their expected values and standard deviations. To do so we apply the Excel function ***=BETAINV(rand(),alpha,beta,A,B)*** to generate random numbers for $\boldsymbol{C_1}$, $\boldsymbol{C_2}$, $\boldsymbol{C_3}$, $\boldsymbol{N_1}$, $\boldsymbol{N_2}$, $\boldsymbol{N_3}$, ***FCF***, and $\boldsymbol{N_4}$ and then plug the resulted random numbers into equations 13 through 16 to generate random numbers for Completion Cost, PV of FCFs, NPV, and PI. We then repeat the process many times until we reach steady states where the expected values of these outcomes do not change as we repeat the iterations. Table 6 shows a portion of the Monet Carlo Simulation calculations with 10,000 trials.

Table 6. Monte Carlo Simulation Results with 10,000 Iterations

Generating Random Numbers from Probabilty Distributions									Equation 14	Equation 13	Equation 15	Equation 16
Trial	Stage 3 Costs	Stage 3 Completion Time	Stage 4 Costs	Stage 4 Completion Time	Stage 5 Costs	Stage 5 Completion Time	New Product's FCF	New Product's Life Cycle	PV (Completion Costs)	PV(FCFs)	NPV	PI
1	667.9355	2.039462623	154.604	0.639575565	13.9819	0.398459269	757.0634811	5.45266491	1320.19	1651.32	331.13	1.25
2	938.4176	1.800158247	156.281	0.62864999	12.8533	0.382482887	782.678127	6.52333358	1653.44	1979.16	325.72	1.20
3	698.4707	1.661130577	150.126	0.598445416	13.0604	0.373044037	700.5645869	5.6636717	1168.27	1692.47	524.20	1.45
4	835.0331	1.590920231	154.066	0.678835441	12.5282	0.403775406	731.4514199	6.59967848	1346.60	1907.63	561.04	1.42
5	755.3944	1.876809228	148.615	0.637679798	12.5762	0.394443148	770.0520441	5.10849252	1387.73	1665.08	277.35	1.20
6	649.3903	1.637478791	148.873	0.669633153	17.3258	0.348688022	777.4034926	5.51996748	1087.00	1842.62	755.62	1.70
7	646.5171	1.746588565	155.257	0.701518815	13.5798	0.365959757	781.6301572	5.29930374	1143.77	1757.71	613.94	1.54
8	801.2247	1.84611252	158.748	0.681729385	12.2388	0.344989	732.9358221	6.59870099	1457.81	1844.01	386.19	1.26
9	731.1494	1.617040418	155.237	0.673884548	11.741	0.38112453	696.315731	6.12966061	1204.46	1746.16	541.70	1.45
9992	757.1613	1.853578848	161.018	0.721269704	16.7212	0.38132149	783.1702912	5.64465524	1393.44	1781.53	388.10	1.28
9993	925.4455	1.757129826	147.456	0.663899379	12.0052	0.382481629	778.6095192	5.81955417	1599.92	1852.52	252.60	1.16
9994	849.4883	1.398297881	152.758	0.592349989	11.5111	0.368811657	754.5109673	6.5827468	1223.54	2079.44	855.89	1.70
9995	749.8343	1.878506526	150.492	0.711366842	13.1809	0.429861434	801.3458426	5.96360173	1387.97	1859.20	471.23	1.34
9996	804.2747	1.70450701	153.5	0.68827184	14.0661	0.374180384	742.4904645	5.84920988	1373.48	1783.36	409.87	1.30
9997	873.3774	1.493898786	152.948	0.686376059	13.0333	0.392072037	750.1687958	5.9024559	1336.19	1875.58	539.38	1.40
9998	750.8708	1.822146175	158.665	0.681507256	16.8686	0.350303337	737.5580332	5.7368453	1358.68	1724.89	366.20	1.27
9999	722.7146	1.956579619	166.643	0.629519718	13.7373	0.392586358	740.7329361	5.45016898	1382.13	1644.25	262.12	1.19
10000	748.4177	1.857216217	143.951	0.628973735	12.1722	0.348620619	688.2646245	5.82637184	1360.86	1629.44	268.58	1.20

All expected values reached steady states between 8500 to 9500 trials. As an example the graph of NPV's expected value versus the number of trials is exhibited in Figure 3.

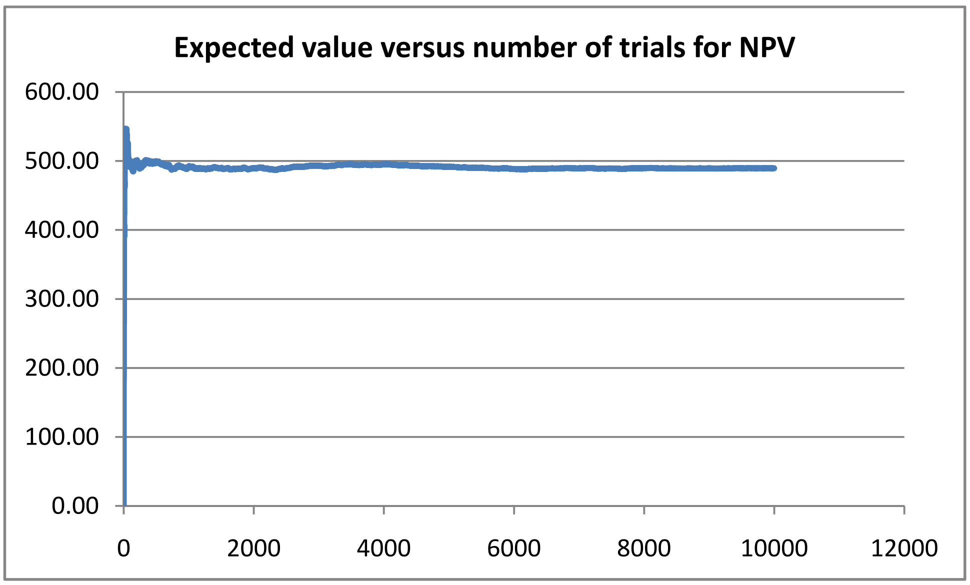

Figure 3. NPV's Expected Value versus Number of Trials in Monte Carlo Simulation

Expected values (means), standard deviation, and other descriptive statistics of PV of cop[letion cost, PV of FCFs, NPV, and PI are reported in Table 7.

Table 7. *Descriptive Statistics of PV of Completion cost, PV of FCFs, NPV, and PI*

	Steady State expected value	Standard deviation	Skewness	Kurtosis
PV(FCFs)	1,809.55	133.64	-0.19	-0.18
PV(Completion Costs)	1,322.32	155.4	0.35	-0.19
NPV	487.24	230.74	-0.12	-0.17
PI	1.39	0.22	0.39	0.04

Histogram of PV of completion cost, PV of FCFs, NPV, and PI are shown in Figure 4

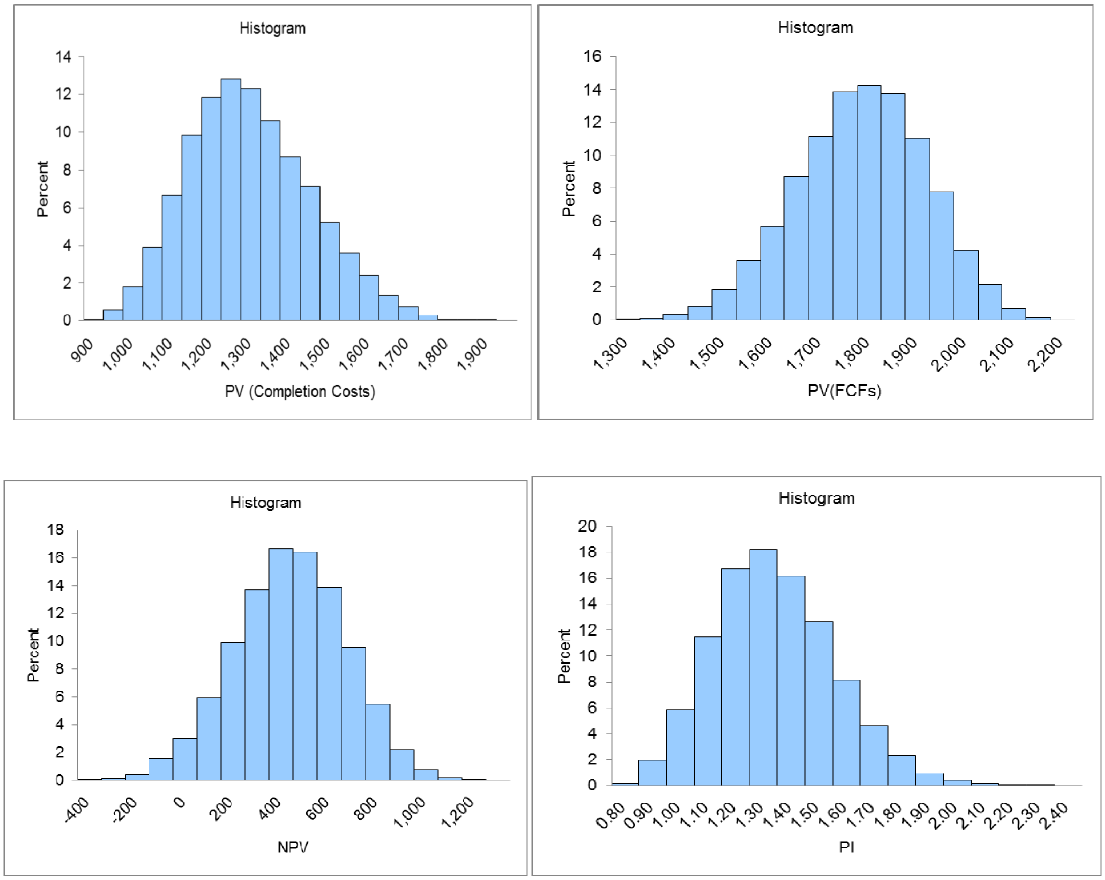

Figure 4. Histograms of Monte Carlo Simulation Results for PV of Completion cost, PV of FCFs, NPV, and PI

9. Conclusion

Stage-gate model for new product development (NPD) and for any research and development (R&D) project consists of a series of stages and gates; each stage is a set of research activities and gates are milestones at which decisions are made based on predetermined criteria. However, given the uncertainties affecting the outcome of an NPD, there is a gap in the literature with regards to modeling these uncertainties and developing appropriate probabilistic evaluation metrics.

In this paper we contributed to the field by developing a probabilistic capital budgeting model for a typical 5-stage, 5-gate process to be used for appraising commercial viability of the NPD at Stage 2 which will serve as one of the decision making criterion at Gate 3. Because in an NPD project, completion costs (capital investments), completion times, and future cash flows are uncertain, we developed the Pert-Beta probability distribution approach to encounter for the randomness of these variables. Furthermore, we suggested the model can be applied to real case NPD projects with the Monte Carlo Simulation approach. We then verified the workability of the model by applying it to a notional NPD project and demonstrated that all decision variables reach steady state in the Monte Carlo Simulation calculations.

The model we developed here is based on the assumption that there are always some SMEs that can provide us with estimates of the required parameters of the model. Therefore, a limitation of this approach is the availability, the willingness, or the ability of SMEs to provide reliable estimates for the specific NPD under review.

One area of further research include extension of the model to include assessment under other Stages after Stage 2 and development of a compound model to incorporate uncertainties removed or added after stage 2 evaluation. Another area for further research is to consider multiple SMEs providing estimates and possibly consider SMEs' estimates of the model parameters as random variables rather than constant values

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