Evaluation Method for Strategic Investments

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Evaluation Method for Strategic Investments

By

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A Thesis

Presented to the Faculty of

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Real Options Analysis (ROA) has become a complimentary tool for engineering economics. It has become popular due to the limitations of conventional engineering valuation methods; specifically, the assumptions of uncertainty. Industry is seeking to quantify the value of engineering investments with uncertainty. One problem with conventional tools are that they may assume that cash flows are certain, therefore minimizing the possibility of the uncertainty of future values. Real options analysis provides a solution to this problem, but has been used sparingly by practitioners. This paper seeks to provide a new model, referred to as the Beta Distribution Real Options Pricing Model (BDROP), which addresses these limitations and can be easily used by practitioners. The positive attributes of this new model include unconstrained market assumptions, robust representation of the underlying asset’s uncertainty, and an uncomplicated methodology. This research demonstrates the use of the model to evaluate the use of automation for inventory control.
# Table of Contents

Table of Contents......................................................................................................................... iii

Table of Figures.............................................................................................................................. Error! Bookmark not defined.

CHAPTER 1: INTRODUCTION................................................................................................................. 1
  1.1 Background ................................................................................................................................. 1
  1.2 Motivation of Thesis .................................................................................................................... 2
  1.3 Objectives of Thesis ................................................................................................................... 4
  1.4 Scope of Thesis ............................................................................................................................ 5
  1.6 Structure of the Thesis ............................................................................................................... 6

CHAPTER 2: VALUATION METHODS.................................................................................................... 8
  2.1 Introduction to Valuation ............................................................................................................ 8
  2.2 Valuation Methods ..................................................................................................................... 9
    2.2.1 Profitability Index (Benefit-Cost Ratio) ............................................................................... 9
    2.2.2 Internal Rate of Return ...................................................................................................... 10
    2.2.3 Net Present Value .............................................................................................................. 10
    2.2.4 Decision Tree Analysis ...................................................................................................... 12

CHAPTER 3: REAL OPTIONS ANALYSIS .............................................................................................. 16
  3.1 Options ........................................................................................................................................ 16
  3.2 Real Options .............................................................................................................................. 17
  3.3 Real Option Techniques ............................................................................................................ 23
    3.3.1 Black-Scholes ..................................................................................................................... 24
    3.3.2 Binomial Option Pricing Model .......................................................................................... 26
    3.3.3 Simulation .......................................................................................................................... 27

CHAPTER 4: INTRODUCTION TO THE BDROP MODEL........................................................................... 29
  4.1 BDROP Model Summary .......................................................................................................... 33

CHAPTER 5: BDROP AND BLACK-SCHOLES MODEL COMPARISON ..................................................... 35
  5.1 Mathematical Comparison ......................................................................................................... 35
  5.2 Statistical Comparison .............................................................................................................. 36
    5.2.1 Methodology ..................................................................................................................... 36
    5.2.2 Results ............................................................................................................................. 37
  5.3 Analysis ...................................................................................................................................... 38
TABLE OF FIGURES

<table>
<thead>
<tr>
<th>Figure/Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 2.2.3-1: Net Present Value Example</td>
<td>11</td>
</tr>
<tr>
<td>Figure 2.2.4-1: Decision Tree Analysis Example</td>
<td>13</td>
</tr>
<tr>
<td>Figure 3.2-1: Process of Valuation Methods</td>
<td>19</td>
</tr>
<tr>
<td>Table 3.2-1: Comparison of Decision Rules for Valuation Methods</td>
<td>20</td>
</tr>
<tr>
<td>Figure 3.2-2: Real Options Analysis Example</td>
<td>21</td>
</tr>
<tr>
<td>Table 3.2-2: Real Option Classifications</td>
<td>22</td>
</tr>
<tr>
<td>Figure 3.3-1: Process of Real Option Techniques</td>
<td>23</td>
</tr>
<tr>
<td>Figure 4-1: Old and New Probability Density Functions of the Beta Distribution</td>
<td>32</td>
</tr>
<tr>
<td>Table 5.2.1-1: Input Factors - Comparison of BDROP and Black-Scholes Techniques</td>
<td>37</td>
</tr>
<tr>
<td>Table 5.2.2-1: Test of Correlation Between BDROP and Black-Scholes Techniques</td>
<td>38</td>
</tr>
<tr>
<td>Table 5.2.2-2: Test of Difference Between BDROP and Black-Scholes Techniques</td>
<td>38</td>
</tr>
<tr>
<td>Figure 6.4-1: Dot Project Stages</td>
<td>45</td>
</tr>
<tr>
<td>Table 6.4.1-1 BDROP Model Parameter Values</td>
<td>47</td>
</tr>
<tr>
<td>Table 6.5-1: BDROP Model Values versus Net Present Values</td>
<td>50</td>
</tr>
</tbody>
</table>
CHAPTER 1: INTRODUCTION

1.1 BACKGROUND
Typically, valuation has been conducted using traditional methods such as the discounted payback method (DPM) which uses discounted cash flows to determine the time it takes to recoup the original investment; the internal rate of return (IRR) which uses the condition of when the present value is equal to zero to yield the corresponding discount factor or IRR; and the profitability index (PI), also known as the benefit-cost ratio (BCR), which determines the ratio of discounted benefit cash flows to the project’s costs.

Perhaps the most widely used traditional valuation method is NPV (NPV). The NPV method takes expected future cash flows and discounts them to the current time period. Another valuation method known as decision tree analysis (DTA) uses NPV in its valuation, but also accounts for the details of events in a valuation period such as decisions that include cash flow scenarios. The DTA method determines the expected values of outcomes based on their probability of occurrence given that certain decisions are made over time.

Both the NPV and DTA methods have inherent limitations. The NPV method assumes that decisions are fixed at the time of the valuation therefore reducing flexibility the project might have over its life. The DTA method compensates for this lack of flexibility because of its ability to identify the possible decisions that can be made. This creates strategic insight, but may not be suitable to describe the dynamic decision making possibilities. Due to these limitations, the real option analysis valuation method has become a complimentary tool for these valuation methods. The real options analysis
method determines the value of this flexibility to dynamically make decisions and
because of this provides a useful tool for valuation in strategic investments.

1.2 Motivation of Thesis
Currently, the challenges of real options analysis limit the widespread use of this
methodology by practitioners. One problem associated with real options analysis is
constraints due to assumptions stemming from the original use of these models in the
stock market for valuing stocks which was to value stocks. Option pricing was originally
developed to value stocks and traded securities. Real options are therefore constrained to
a system that may or may not follow an underlying asset (Steffens & Douglas, 2007).

Real options use a portfolio of traded securities that replicate the variation over time
(volatility) of the actual investment excluding any options. The future value of this
replicated portfolio is then modeled based on historic price movements. This assumption
constrains real options valuations to identify stocks that will replicate the unique behavior
of the actual investment. This can prove to be very difficult in many real world instances
that do not have any direct correlation to the stock market. For instance, the airline
industry has been known to hedge using oil securities; however, a company researching
new technology may not have a direct link to any existing stock market securities.

In an attempt to overcome this constraint, Copeland & Antikrov [2001] apply a ‘Market
Asset Disclaimer’ (MAD), where the traditional NPV is used as the value of the
underlying asset. They contend that this value is the best unbiased estimator of the
investment’s value given that it is a value of the investment with no flexibility. While
this may help determine the value of the underlying asset, a problem still persists even
with MAD. The problem is that, even in this approach, the volatility is still allowed to be
modeled based on prices of relevant traded securities. This again introduces the bias of an assumed relationship to the stock market.

Another challenge of current real options analysis techniques is the conventional use of the Lognormal distribution to describe the investment’s cash flows. The problem here is that the Lognormal distribution may be limited in the number of different cash flow distributions it can effectively represent. Other distributions, like the generalized Beta distribution, are more general and flexible than the Lognormal distribution (Chotikapanich, Roa, & Tang, 2007). The Lognormal distribution was originally used to describe the never-negative nature of stock prices. Real options cannot be constrained by this assumption because they inherently may have negative possibilities in their cash flows.

Probably the most compelling problem in the use of real options analysis is the lack of upper management support due to options pricing being viewed as complicated instruments and hard for them to understand. In a recent study, the number one reason for not using real options is the lack of top management support. Further research indicated that top managers of many companies are hesitant to use techniques that they cannot follow step by step (Block, 2007). Rogers [1995] suggests there five attributes of innovation that determine its rate of adoption: Superior Idea, Compatible, Low Complexity, Triability, and Observability. In this case the underlying problem exists in real options analysis’s complexity because upper management does not view it as easy to understand.
Industry is seeking to quantify the value of capital investments that contain the flexibility to dynamically make decisions. Many research articles are citing NPV as inadequate to handle the flexibility of projects. Net present value has been criticized due to its inadequacy dealing with the potential flexibility that comes with investment projects, resulting in changes in the original cash flow pattern (Reyck, Degraeve, & Vandenborre, 2008). Some relatively new real option analysis techniques aim to simplify existing or create a more intuitive methodology.

Datar and Mathews of Boeing developed a new real options model using Monte Carlo simulation and packaged it as an add-on in spreadsheet software. It is now commonly referred to as the Datar-Mathews method. In this method they create an algorithm that contains real options thinking, but simplifies the complexity of its formulation. It has been shown to converge to the traditional real options analysis solutions under specific assumptions (Mathews, 2009).

1.3 Objectives of Thesis
This study seeks to provide a new model that addresses the challenges of real option analysis techniques. The attributes of this new model encompasses unconstrained market assumptions, robust representation of the underlying asset, and uncomplicated methodology. The new model should take into account market risks, but also should not be constrained to stock market assumptions used in traditional option pricing models. This allows a model that can be expanded to be applied to many more problems; for example, real options analysis using the uncertainty stemming from technological assets or systems. Also, the new model should represent a more diverse group of capital investment distributions; namely, more diverse than the Lognormal distribution used as a
standard of current option pricing models. Lastly, the new model should be easily adoptable by users. The model should be simplified.

Therefore the specific objectives of this research are:

1) to create a new valuation method that addresses the current challenges of real option analysis techniques,

2) to compare this new model against an existing real options analysis technique, and

3) to apply the new model in a case study to demonstrate its applicability to industry.

1.4 SCOPE OF THESIS
Real options analysis valuation is a viable method to account for flexibility of future decisions by focusing on the evolution of a few complex factors over time that determines the value (Walters & Giles, 2000); however, this focus on “dynamic complexity” does not necessarily negate the DTA method. Walters and Giles [2000] explain this by stating that, “it would be foolish to argue that [the] dynamic complexity [described using real options analysis] is generally more important than [the] detail complexity [described using DTA]…but real options can distil your strategic thinking into focusing on a few dynamic processes, where a decision-tree would overflow the largest boardroom whiteboard.” The benefits of the real options analysis method are best served as a complimentary tool to the best practice NPV and DTA methods.

The goal of this thesis is therefore to find a solution to the challenges facing valuation methods and demonstrate its applicability as a complimentary tool in the valuation of strategic investments in industry. In the scope of this thesis, strategic investments are
defined as investments where managers have the flexibility to make decisions along the course of the investment period. This study focuses on strategic investments such as those that might be undertaken by research and development departments. Generalizations to the model are suggested as future research in this work.

1.6 Structure of the Thesis
In Chapter One, a brief background on the state of valuation methods was discussed.

In Chapter Two, valuation will be defined. This includes terms that are used in this thesis. Also, four different types of valuation methods: profitability index, internal rate of return, NPV, and DTA will be described. An example is presented and used in the chapter to describe the methods.

In Chapter Three, real options analysis is introduced. The progression from general options to real options is analyzed and the taxonomy of these real options are identified. This chapter also describes three real option models: Black-Scholes, Binomial Option Pricing, and the Datar-Mathews. These models are illustrated using the example of chapter two and the challenges of them are discussed.

In Chapter Four, an introduction of a solution to the challenges established in chapter three is presented. The solution, a new model called the Beta Distribution Real Option Pricing, is derived and illustrated using the example of chapter two. The new model’s steps are summarized in the conclusion of the chapter.

In Chapter Five, the new model is tested against the Black-Scholes model; a standard in real option pricing models. First a hypothesis is formulated. Then a description of how
the new model would be tested is presented. The results are given and an analysis
conducted on them.

In Chapter Six, a case study of a department of transportation is presented to show the
applicability of the new model. What is special about this study is it uses a reliability
ranking method to describe the stochastic properties of the returns of different radio
frequency identification systems. The BDROP model uses these rankings by mapping
them into monetary values and deriving the necessary model inputs parameters to value
the systems. The results are used in a decision model for choosing a system to use.

Chapter Seven, includes a discussion of the met objectives of this thesis. The new
model’s limitations and contributions to the body of knowledge will be examined.
Possible future research is also explored at the conclusion of this chapter.
CHAPTER 2: VALUATION METHODS

2.1 INTRODUCTION TO VALUATION
Valuation plays an important role when assessing investments. Merrian-Webster [2010] defines valuation as, “the estimated or determined market value of a[n] [investment].” A number of evaluation methods have been created to determine the market value of an investment. In order to appropriately describe these methods the following terminology must be defined: uncertainty, risk, and flexibility.

In this thesis, the term “uncertainty” is defined as, “the lack of complete certainty...the existence of more than one [possibility; meaning,] the true...value is not known,” (Hubbard, 2007). To measure uncertainty, certain probabilities are given to corresponding possibilities. To measure the uncertainty of the returns of an investment, for example, suppose the probability that an investment will yield a positive return is 20%, the probability that an investment will yield a negative return is 30% percent, and the probability that an investment will yield no return is 50% percent.

Hubbard [2007] goes on to define risk as, “a state of uncertainty where some of the possibilities involve a...undesirable outcome.” In the context of this thesis, the “undesirable outcome” will be taken to mean negative returns on an investment. Measuring risk involves defining possibilities with quantified probabilities and quantified losses. For example, recall the aforementioned example of measuring the uncertainty of return from an investment. In this example, the measure of this risk is a 20% probability that the returns on an investment will negative with a value of -$3 million.
This thesis will make reference to two different sources of risk. The first is market risk which refers to factors from the economy such as interest rates. This source of risk is considered systematic because a company valuing the investment cannot affect it (Ollila, 2000). Ollila [2000] continues, contending that because market risk is fully diversifiable, investors are not willing to pay a premium for it. Therefore, this thesis associates market risk with the risk-free rate of interest.

The second source of risk referenced in this thesis is the project, or investment, risk. This risk refers to factors not related to market risk such as uncertainty over costs of development and manufacturing or the actions of competitors (Ollila, 2000). Project risk is therefore considered unsystematic. This thesis associates the project risk with a company’s overall required return on the firm as a whole; the weighted average cost of capital (WACC).

This thesis defines flexibility to be the ability to make decisions about an investment during the course of a valuation of a possible investment opportunity. The decisions can be made at any point during this valuation. In the absence of flexibility, the decisions are made at a predetermined point in the valuation; typically, at the beginning of the valuation.

2.2 Valuation Methods

2.2.1 Profitability Index (Benefit-Cost Ratio)

The profitability index, commonly referred to as the benefit-cost ratio, is a common valuation method. This method determines the ratio of after-tax discounted cash flows to the project’s discounted costs. The decision to invest is based on if the ratio of benefits to
cost is greater than 1; meaning that the present value of the future cash flows of the investment’s returns exceeds the costs.

2.2.2 **INTERNAL RATE OF RETURN**

A valuation method commonly used is the internal rate of return. The internal rate of return can be considered the discount rate the when the present value of future cash flows is equal to zero. In this method, the decision to invest is based on when the discount factor, internal rate of return, is greater than the opportunity cost of capital; in many cases, this opportunity cost of capital will be the WACC.

2.2.3 **NET PRESENT VALUE**

Between the profitability index, internal rate of return, and NPV methods, the NPV method is considerably the most popular valuation method currently used. Although taking over two decades to be widely accepted, the NPV method has become the single most widely used tool for large investments made by large corporations (Copeland & Anitkarov, 2001).

Originally used to value bonds, the NPV method discounts the expected future cash flows of an investment’s returns and subtracts the initial investment’s costs. This resulting value is called the NPV. The decision to take on the investment is made based on the maximum value possible when comparing the NPV of the investment if it is undertaken and the NPV of the investment if it is not undertaken yielding a NPV of $0.

To illustrate the NPV method, consider the following example. Suppose an investment opportunity presents itself at \( t=t_0 \) that costs $10 to launch at \( t=t_1 \) and has an expected value of $15 at \( t=t_2 \). Figure 2.2.3-1 illustrates the cash flow diagram for this example.
To calculate the NPV, the future cash flows must be discounted to $t=t_0$ at their appropriate rates to compensate for their associated risk. The launch costs can be discounted at the risk-free rate because there is only market risk associated with it. The expected value of the return, however, is associated with the project risk and therefore must be discounted at the WACC. Given a risk-free annual rate of $r_f=5\%$ and a WACC of 25% annually, both compounded continuously, the NPV can be calculated as:

$$\text{NPV} = -10e^{-0.05\times1} + 15e^{-0.25\times2} = -0.41$$

Since the NPV is less than $0$, the decision will be to forego the investment opportunity.

As illustrated in the example, the NPV method makes a decision at the beginning of the investment period. The NPV method does not take into account the flexibility to make decisions in the future based on information that becomes apparent at those future times.
The NPV method may be only a partial view of the projects actual value because the decision is based only on values that are [given] at the time of the appraisal; therefore, excluding the flexibility of future decisions (Walters & Giles, 2000). There is a need to map out these future decisions and quantify their value, but the NPV method is not a suitable tool for this form of value investigation.

The NPV method also does not explicitly account for the details of uncertain future cash flows. Recall the definition of uncertainty stated in Section 2.1. The NPV method does readily account for more than one possible value for the same future cash flow. The NPV method needs a complimentary tool to account for uncertainty of future cash flows.

2.2.4 Decision Tree Analysis
Decision tree analysis is another form of valuation method, but unlike the NPV method, DTA explicitly accounts for the details of uncertain future cash flows. It assigns probabilities to the corresponding possible outcomes of future cash flows. To analyze the decision tree, the alternative with the greatest value at each decision node is chosen. An alternative’s value is calculated using the probabilities of the possible outcomes and their associated value.

The decision to take on the investment is made based on the alternative with the maximum value at the final decision node. At this node, the costs are subtracted from the expected value of the future cash flows of the investment’s returns. This value is then compared to the other alternatives at the same node and the decision is made to invest in the alternative that yields the greatest value.
To illustrate the DTA method, recall the example of 2.2.3. Suppose at t=t₂, the investment opportunity has uncertain future cash flows of 50% for the probability of a $20 value outcome and a 50% for the probability of a $10 value outcome. Figure 2.2.4-1 illustrates the decision tree for this example.

<table>
<thead>
<tr>
<th>Decision Tree Analysis</th>
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<tbody>
<tr>
<td><img src="image" alt="Decision Tree Diagram" /></td>
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</tbody>
</table>

**Figure 2.2.4-1: Decision Tree Analysis Example**

To calculate the value of the decision tree, first the expected value at t=t₂ must be calculated as:

\[
\text{Expected Value (at t=t₂)} = 0.5 \times \$20 + 0.5 \times \$10 = \$15
\]

Then, the resulting future cash flow and the future cash flow of the cost must be discounted to t=t₀ at their appropriate rates to compensate for their associated risk.
Again, the launch costs can be discounted at the risk-free rate because there is only market risk associated with it and the expected value of the return, associated with the project risk, must be discounted at the WACC. Given the same risk-free annual rate of $r_f=5\%$ and a WACC of 25% annually and still both compounded continuously, the DTA value can be calculated as:

$$\text{NPV} = -10e^{-0.05\times1} + 15e^{-0.25\times2} = -$0.41$$

Similar to the NPV method the decision will be to forego the investment opportunity with a value of $0$ because it is the greatest alternative value of the decision tree final node.

Contrary to the NPV method the DTA method maps out the possible decisions that can be made during the life of the investment. Although the DTA method may account for the details of uncertain future cash flows, it still has other limitations. The DTA method identifies the flexibility in great detail by mapping out every decision to be made during the valuation; however, the DTA method is still limited in that it does little to account for the dynamic complexity of that detail (Walters & Giles, 2000). What this is suggesting is that at each decision it maps out, the DTA method can determine the best alternative; however, this presents a problem because the decision made at that time may change if the same decision is moved to a later time when more the future cash flows were less uncertain. In the DTA method, the final decision to invest or not invest remains at the last node or in other words the beginning of the valuation. The DTA method assumes decisions are static and does not account for the manager’s flexibility in when to make the decision. Simply put, the DTA method identifies the flexibility of managers but does not take into account the value of that flexibility.
CHAPTER 3: REAL OPTIONS ANALYSIS

3.1 OPTIONS
An option is the right, but not the obligation to trade an asset under specified terms (Luenberger, 1998). As an example, consider an opportunity to buy a share of XYZ stock anytime within one year when the option expires (matures) after time=T for a strike price (X) of $20 regardless of when in that year it is purchased and regardless of how much the value of the stock has changed. This opportunity would be considered an option, but not an obligation, to buy a share XYZ stock.

The value of having this option is apparent in situations where the value of the stock increases over the year. For example, suppose the current price (S) of the XYZ stock is $15 and increases to $25 at the end of the option year. This means if the option was held until that time, XYZ stock could be purchased for the strike price of $20 and right away be sold for a profit of $5. This $5 is the return of the option if exercised at maturity and its value is considered to be “in the money”. On the other hand, if the value of stock XYZ is only $18 at the end of the year the return of the option if exercised is -$2 and considered to be “out of the money”.

Recall the definition of an option; giving the right, but not the obligation, to exercise the option. This means that if the return of the option is out of the money, then it should not be exercised. The value of this option (C) at expiration is then calculated as:

\[ C = \max \left( \text{return if do not exercise, return if exercise} \right) = \max \left( 0, S - X \right) \]

This algorithm states that the value of the option is the maximum value that can be obtained between not exercising the option when out of the money, which has a return of
$0, and exercising the option when in the money, which has a return of the value of the stock (S) minus strike price (X).

Holders of an option are not certain of the future value of the stock. As illustrated in the example, there is value in being able to wait until the value of the stock is less uncertain. Intuitively, the value of the option can be considered the value of the ability to wait to see if the stock value will be in the money and therefore purchase the stock (or exercise the option). Given the definition of flexibility in this thesis, it is concluded that an option value is the value of flexibility.

3.2 Real Options
Real options are options that value real assets other than stocks. For example, the option to launch a new product can be considered a real option. As previously concluded the option value is the value of flexibility. In this case the flexibility would be when to decide if the new product should be launched.

Like traditional options, real options have similar parameters to the stock value (S), the strike price (X), the time to maturity (T), and the option value (C). In real options these parameters have a slightly different meaning. The stock value in real options is the price of the asset. In the example used in chapter 2, the asset value would be the present value of the returns from the investment. Continuing with the same example, the real option strike price would be the cost of asset or the launch costs. The time to maturity is how much time is allotted before a decision has to be made about whether to launch the project. Together, these parameters determine the value of the real option, which is to wait on making the decision to launch.
The decision to launch is based on the present value of the returns from the investment minus the costs to launch. If this value is in the money, meaning the present value of the returns is larger than the launch costs, then the decision is to launch. If the value is out of the money, meaning the present value of returns is less than the launch costs, then the decision is to not launch. The real option value is then calculated as:

\[ C = \max (\text{return if do not launch}, \text{return if launch}) = \max (0, S - X). \]

This algorithm is identical to the traditional option algorithm. This is because this algorithm represents the real options thinking of the valuation process.

All valuation methods have four general parts to their process: inputs, model, decision, and output. The inputs are the parameters gathered for the particular valuation method and the outputs are the values resulting from using a particular valuation method. The model is the part of the valuation process where the uncertainty of future cash flows is modeled to fit the valuation method. The decision is the part of the valuation process that contains the algorithm that determines whether or not to take on the investment. The process is depicted in Figure 3.2-1.
Figure 3.2-1: Process of Valuation Methods

Compared to the NPV method, which is mathematically the maximum of expectations, the real options analysis method is the expectation of maximums (Copeland & Anitkarov, 2001). Intuitively this illustrates how the real options analysis method includes the manager’s flexibility in decision making at a later time when more information is known. In the context of this thesis, the DTA method follows the same rule as the NPV method because DTA takes the maximum of alternatives that are calculated as expected values. The NPV and the real options analysis methods rules are listed in Table 3.2-1.
Table 3.2-1: Comparison of Decision Rules for Valuation Methods

<table>
<thead>
<tr>
<th>Valuation Method Decision Algorithm</th>
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<tbody>
<tr>
<td><strong>Valuation Method</strong></td>
</tr>
<tr>
<td>Net Present Value Rule:</td>
</tr>
<tr>
<td>Real Option Analysis Rule:</td>
</tr>
</tbody>
</table>

Source: (Copeland & Antikarov, 2001)

To illustrate the difference in algorithms, consider a reworked version of the example in Section 2.2.3. In this original example, the decision is at $t=t_0$; however, if the real options analysis method was used, this decision could be moved to $t=t_1$. This would allow the manager to decide at that time whether to launch based on better information at that time versus at $t=t_0$. In the event that analysis at $t=t_1$ suggests a value $\$0$ or less (out of the money), then the manager would not invest in the project and accept a $\$0$ dollar value. On the other hand, if it is determined that a value greater than $\$0$ is obtainable (in the money), then the manager would invest and obtain a value of $S_{t_1}-X$. This is illustrated in Figure 3.2-2.
This value of $S_{t_1} - X$ is not the true value of the option. This is because there is risk associated with the value; specifically, a 50% probability that you will not obtain the $20.

To compensate for this risk, the “in the money” values must be adjusted by their corresponding probabilities. This is achieved by the expected value term in the real option formula. Given the same values as the original example, the real options value at time = $t_1$ can then be calculated as:

$$C_{t_1} = E_{t_1} \left[ \max ( S_{t_1} - X , 0 ) \right] = 0.5 \times ( 20e^{-0.25} - 10 ) + 0.5 \times 0 = 2.13$$
Notice in the example that the decision of the real options method is made at maturity; whereas in the NPV method, the decision is made at t=0. This demonstrates how the real options analysis method allows flexibility in decision making. The primary function of the real option analysis method is to quantify this value of flexibility to make future decisions; therefore aiding in dynamic strategic management. This option to change course as information is accumulated is inherently valuable. The real options analysis method is able to capture how much more valuable a project is due to management’s ability to be flexible (Mathews, 2009). Generally, these option values are classified by the primary type of flexibility they offer (Copeland & Anitkarov, 2001). These types of flexibility are summarized in Table 3.2-2.

Table 3.2-2: Real Option Classifications

<table>
<thead>
<tr>
<th>Real Option Type</th>
<th>Real Option Type Description</th>
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<tbody>
<tr>
<td>Option to Defer</td>
<td>American call option found in most projects where one has the right to delay the start of the project.</td>
</tr>
<tr>
<td>Option to Abandon</td>
<td>American put option giving the right to abandon a project for a fixed price.</td>
</tr>
<tr>
<td>Option to Expand</td>
<td>American call option where you have the right to scale up the operations.</td>
</tr>
<tr>
<td>Option to Switch</td>
<td>American call and put options allowing their owner to switch at a fixed cost between two modes of operation</td>
</tr>
<tr>
<td>Compound Options</td>
<td>A combination of options that is contingent on the earlier exercise of other options. Most commonly realized in phased investments.</td>
</tr>
<tr>
<td>Rainbow Options</td>
<td>Options that are driven by multiple sources of uncertainty.</td>
</tr>
</tbody>
</table>

Source: (Copeland & Anitkarov, 2001)
3.3 **Real Option Techniques**

In this thesis, three basic techniques of the real options analysis method are discussed: the Black-Scholes, the Binomial Option Pricing Model, and the Simulation techniques. In addition to these, this thesis derives one other technique and names it the Beta Distribution Real Option Pricing model. Recall the valuation process of Figure 3.2-1.

The process of each of the techniques in this thesis is the same, but assumes that the decision algorithm is based on real options thinking. The difference of these techniques differs in the way they model uncertainty. Figure 3.3-1 illustrates the process for these techniques.

![Process of Real Option Techniques](image)

**Figure 3.3-1: Process of Real Option Techniques**
3.3.1 BLACK-SCHOLES
A number of methods have been formulized to value options in the stock market. Many methods used in real options analysis have been adapted from them. One such method is the Black-Scholes equation. Derivation of the Black-Scholes equation was motivated by prior warrant pricing research. It has become arguably the most popular method for valuing European call options (Kremer & Roenfeldt, 1992). Assuming that stock price follows a geometric Brownian motion, the starting point for the derivation of the Black-Scholes partial derivative equation is:

\[
\frac{dS_t}{S_t} = \mu dt + \sigma dW_t;
\]

where, \( \mu \) is the expected return rate, \( \sigma \) is volatility, and \( dW_t \) is the standard Brownian motion (Yang, Liu, & Wang, 2007). Given Ito’s lemma for two variables,

\[
dV = \left( \mu S \frac{dV}{dS} + \frac{dV}{dt} + \frac{\sigma^2 S^2}{2} \frac{d^2 V}{dS^2} \right) dt + \sigma S \frac{dV}{dS} dW,
\]

and a trading strategy where the return will be risk free, called a delta-hedge portfolio (\( \Pi \)) given by

\[
dV_t - \Delta S_t = \Pi_t dt = r(V_t - \Delta S_t) dt,
\]

the Black-Scholes partial derivative equation can be derived as (Yang, Liu, & Wang, 2007)

\[
\frac{dV}{dt} + \frac{1}{2} \sigma^2 S^2 \frac{d^2 V}{dS^2} + rS \frac{dV}{dS} rV = 0.
\]
Its creators, Fischer Black and Myron Scholes, derived a differential equation that is related to any non-dividend paying stock derivative price (Yang, Liu, & Wang, 2007). The solution to this partial differential equation is stated in Equation (3.3.1-1).

\[(3.3.1-1) \quad C_0 = S_0 N(d_1) - X e^{-rT} N(d_2)\]

where,
\[N = \text{cumulative distribution},\]
\[d_1 = \frac{\ln(S) + rT}{\sigma \sqrt{T}} + \frac{1}{2\sigma \sqrt{T}},\]
\[d_2 = d_1 - \sigma \sqrt{T},\]
\[rf = \text{risk free rate},\]
\[T = \text{time to maturity},\]
\[X = \text{exercise price},\]
\[S = \text{price of underlying},\]
\[\sigma = \text{volatility of underlying}.\]

The “\(N(d_1)\)” and “\(N(d_2)\)” terms are the probabilities that the option will expire in the money under the risk neutral probability measure. The formula applies these probabilities to the underlying asset and strike price and then discounts the resulting values back to time zero using the risk free rate of return. Originally formulated for options pricing, where it is not possible to realize negative values of the asset, the Black-Scholes method assumes that cash flows follow a Lognormal distribution. Due to these stock market assumptions, the Black-Scholes method may be limited in its ability to represent the stochastic properties of the asset’s return.

Another problem with this method is its complicated derivation. This formula is derived using Ito calculus. This is because of the assumption that the underlying follows a Brownian motion. Again this assumption was made because of the behavior of stocks on the open market. This particular assumption was made to describe how stocks fluctuate
in a manner that is not differentiable at any point causing traditional integration to be difficult. To handle this, the methods of standard calculus must be extended; Ito calculus plays this role.

### 3.3.2 Binomial Option Pricing Model

Unlike the Black-Scholes method that can only evaluate European options, the Binomial Option Pricing Model (BOPM) is primarily used to value American options. Essentially, the BOPM maps out the potential intervals at which the option could be exercised before expiration. The BOPM assumes that at each interval the underlying asset price will move up or down by an amount determined using the inputs of volatility and remaining time until expiration, producing a recombining tree of prices (also called a lattice). Assuming that there are no dividends paid at these intervals, the BOPM tree created has been shown to approximate the Black-Scholes value when the lengths of these intervals approach the minimum limit.

A number of different versions of the BOPM provide proof that their models converge to the Black-Scholes model. In fact, one version suggests that any probability other than zero or one will lead to convergence (Chance, 2008). The advantage of BOPM over the Black-Scholes model is that it allows for early exercise (American options), but valuing an American option with a large number of intervals creates a limitation for the model due to the time it would take to determine all the prices.

Due to similarities of BOPM to DTA’s lattice it makes for a more intuitive model to derive. Despite this, BOPM suffers from other limitations shared with Black-Scholes method.
3.3.3 Simulation

The Datar-Mathews method (DM method), a relatively new real option pricing model developed at Boeing, contends that it is algebraically equivalent to the Black-Scholes equation, but is simple and transparent (Mathews, Datar, & Johnson, 2007). Based on real options thinking, this method is most easily understood as an extension of the NPV multi-scenario Monte Carlo model with an adjustment for risk-aversion and economic decision making (Mathews, 2009). The most advantageous feature of this method is its ability to use information available from the standard NPV analysis that is normally used by companies (Datar & Mathews, 2004).

Using the inputs normally used for NPV, this technique simulates possible outcomes that the NPV could take on given the uncertainty of the cash flows. The real options thinking is that if a project is not profitable at maturity there is the option not to give the project the “green light” and therefore mitigate any losses. Using this thinking, the D-M method creates a new distribution which chooses the maximum value between 0 and the NPV (operating costs – launch costs). This algorithm essentially means that at maturity only positive NPVs will remain and the rest of the scenarios will be considered $0 because if it is not positive, managers would choose not to proceed with the project and therefore collect a $0 NPV. From this new distribution of $0 and positive NPVs, the mean value is calculated. This value is then discounted with a rate that accounts for the risk associated with those cash flows. This risk is the probability of obtaining a NPV greater than $0. The discounted mean value is considered the value of the real option.

The D-M method is based on simulation. Using a simulation technique allows real option models to be able to represent different distributions other than the Lognormal
used in the Black-Scholes method. Simulation can be used to solve complex problems because it can handle multiple sources of uncertainty; however, for less complex problems simulation may become the bottleneck of valuation as it can be very time consuming to use.
CHAPTER 4: INTRODUCTION TO THE BDROP MODEL

The Beta Distribution Real Options Pricing (BDROP) model utilizes real options thinking in a similar manner to the D-M method. It is based on the expected value of the maximums obtained from the cash flows of returns minus the investment costs. The BDROP aims to simplify the process of the D-M method by using a specific distribution, namely the Beta distribution of cash flows. The reason for doing this is to eliminate the need for simulation that may take too much time for certain applications. Using the properties of the Beta distribution, a real option value may be realized in the same manner as the Black-Scholes technique in that the value can be calculated from an equation. Unlike the Black-Scholes, the BDROP model using the Beta distribution allows for more flexibility in describing distributions of uncertainty in cash flows, moreover because it allows for negative values to be used; the Lognormal distribution of cash flows does not allow negative values. The generalized probability density function of the Beta distribution is given in Equation 4-1.

\[
(4-1) \quad f(x) = \frac{(x - a)^{\alpha - 1} \cdot (b - x)^{\beta - 1}}{B(\alpha, \beta) \cdot (b - a)^{\alpha + \beta - 1}}
\]

where,
B(\alpha, \beta) = the Beta function,
\alpha & \beta = the Beta distribution shape parameters and
a & b = the upper and lower bounds of the Beta distribution respectively.

For adoptability of the model for practitioners and upper management, BDROP can use commonly used inputs of the popular NPV method such as multi-scenario approach’s pessimistic, optimistic, and most likely values or the expected value and standard deviation. These inputs are used to approximate a Beta distribution that represents the
cash flow distribution. This is done by using parameter estimate equations derived from the Beta distribution. For example, if given the cash flow distribution expected and standard deviation values, the parameters of the Beta distribution would be found using the estimate equations.

Some assumptions are made in the creation of this model because of the use of the Beta distribution. One assumption made is that the maximum and minimum limits bound the range of values that the cash flow can take on. Also, shape parameters (α, β) are assumed to be greater than 1. When this is true for those parameters the Beta distribution takes on a uni-modal shape. This is important because, for instance, the inputs from the multi-scenario approach only specify one most likely, or mode, value. In addition to being greater than 1, the shape parameters are assumed to be integers. This allows for simpler calculations of the moments for the distribution because of the use of the gamma distribution.

The relationship between the shape parameters and the most likely value (mode) is given in Equation (4-2). Given the mode and the range it is given within, the relationship between α and β can be pre-determined as a linear relationship. This implicitly suggests that the three NPV (at t = T) inputs; pessimistic, optimistic, and most likely, can characterize the general shape of the Beta distribution. This relationship is given in Equation (4-3).

\[
\text{mode}_{\text{Beta}} = \left(\frac{\alpha - 1}{\alpha + \beta - 2}\right) \ast (b - a) + a
\]
Once the Beta distribution is created the real options value can be formulated. The BDROP model uses the real options analysis rule to manipulate the Beta distribution. All S-X values that are less than zero are given zero values and all positive S-X values are left the same. This represents the flexibility of managers to exercise the right not to launch the project if the operating profits do not exceed the launch costs at the time of maturity. An example of this change of distribution is depicted in Figure 4-1. Using the new probability density function that includes only maximum payoffs, the real option value is understood to be the expected value of this distribution.

\[
\beta = \frac{a - b(\alpha - 1) - \text{mode}_{\text{beta}}(\alpha - 2)}{\text{mode}_{\text{beta}} - a}
\]
Figure 4-1: Old and New Probability Density Functions of the Beta Distribution

The function describing the Beta distribution can be thought of as a function with four parameters: \( F(x; \alpha, \beta, a, b) \). The real option value given by the BDROP model is depicted in Equation (4-4). Referring back to the real option rule,

\[
C = E_0 \left[ \max(S_T - X, 0) \right]
\]

where, the maximum of \((S_T - X)\) is represented by \( f_{ROA}(x) \) depicted in Figure 4-1. \( E_0 \) is the expected value of the distribution at time \( t=0 \). This is just the expected value at \( t = T \) (\( E_{Tadj} \)) discounted at the risk-free rate (\( r \)); where \( E_{Tadj} \) is the expected value adjusted for the risk associated obtaining the positive payouts. In terms of \( f_{ROA}(x) \), this value is:

\[
E_{Tadj} = \int x * f_{ROA}(x) \, dx
\]

Because \( f_{ROA}(x) \) is a piecewise function given by:

\[
f_{ROA}(x) = \begin{cases} 
S_T - X, & \text{if } S_T - X > 0 \\
0, & \text{if } S_T - X \leq 0
\end{cases}
\]

Therefore the risk adjusted expected value is simply:

\[
(4-4) \quad E_{Tadj} = \int_{X}^{b} x * f_{ROA}(x) \, dx
\]

where, the integral is evaluated from launch cost (X), to the upper limit of the distribution (b); the maximum possible value in the distribution.
Given the risk adjusted expected value, the real option value (C) is then calculated with the formula given in Equation (4-5).

\[
C = e^{-rT} \int_{X}^{b} x \cdot f_{ROA}(x) \, dx
\]

where, the \(e^{-rT}\) term represents the option value being discounted at the risk free rate over \(t = T\).

### 4.1 BDROP Model Summary

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Model the System</td>
<td>Model the system’s uncertainty using the Beta distribution. For example, using multi scenario inputs (pessimistic, optimistic, and most likely), derive a pdf for a 4 parameter Beta distribution: (f(x;\alpha,\beta,a,b))</td>
</tr>
<tr>
<td>2. Filter the Distribution</td>
<td>Create a new modified pdf, (f_{ROA}(x)), by filtering the current pdf using the real options analysis rule: (\max(0, S_t - X))</td>
</tr>
<tr>
<td>3. Evaluate the Filtered Distribution</td>
<td>Use statistical software to evaluate the risk adjusted expected value of (x) at (t=T): (E_{Tadj} = \int_{X}^{b} x \cdot f_{ROA}(x) , dx).</td>
</tr>
<tr>
<td>4. Discount Value to (t=0)</td>
<td>Discount this value, using the risk free rate ((r)) over the time period (t=0) to (t=T), to find the expected value at (t=0): (C = e^{-rT} \int_{X}^{b} x \cdot f_{ROA}(x) , dx)</td>
</tr>
</tbody>
</table>
CHAPTER 5: BDROP AND BLACK-SCHOLES MODEL COMPARISON

The Black-Scholes technique is widely accepted as the standard of option pricing. Real options follow the same premise when comparing a new or existing technique. This is not to suggest that the Black-Scholes is the most accurate in the valuation of real options. Black-Scholes is regarded the standard benchmark because of its wide scale use to value options of financial derivatives and real assets or investments.

5.1 MATHEMATICAL COMPARISON
To begin the comparison of the BDROP model to the Black-Scholes, it is important to first compare the two techniques mathematically. This yields an applicable starting point to investigate the possible statistical testing that is appropriate to compare the models.

The mathematics of both the Black-Scholes and the BDROP techniques has been previously addressed. This section serves as a subjective comparison leading to the more objective comparisons of the statistical comparisons in Section 5.2.

From a macro perspective, these techniques have similar mathematical meaning. They both use the real options thinking in their formulation of the real option value. They both use a specific statistical distribution to model the uncertainty of future cash flows. The choice of a distribution, however, is also where they diverge. The Black-Scholes, as explained in Section 3.3.1, uses the Lognormal distribution of cash flows. This is due to its original ties to pricing stock market derivatives that could never obtain a less than $0 value. The BDROP model uses the Beta distribution to model the uncertainty of future cash flows. This is to aid the BDROP technique in its ability to model a more diverse population of possible distributions, including distributions that include negative values.
The use of different statistical distributions may cause some deviation between the values obtained by the two techniques. Ricciardi, Pinder and Belitz [2005] state that the Lognormal distribution is generally heavy tailed. This means that the Beta distribution is most likely converging to zero faster than the Lognormal and differences in values may arise in these tail areas of the two distributions even if they share the same inputs, such as the mean, that describes their shape. Despite these differences, the Beta distribution is a viable alternative to the Lognormal distribution to characterize uncertainty (Ricciardi, Pinder, & Belitz, 2005).

5.2 Statistical Comparison

5.2.1 Methodology
In this Section, a more objective approach is used to compare the BDROP and the Black-Scholes techniques. This statistical study first establishes whether there is a statistical relationship between the output values the techniques would yield. Then the study goes on to compare the means of these outputs, given the same inputs.

There were five input factors varied to observe outputs from the different techniques: expected value of S (E[S]), volatility (v), time to maturity (T), risk-free rate (r_f), and strike price (X). These factors are the five input factors needed to evaluate the Black-Scholes equation. Table 5.2.1-1 describes the ranges of the input data.
Table 5.2.1-1: Input Factors - Comparison of BDROP and Black-Scholes Techniques

<table>
<thead>
<tr>
<th>Inputs Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>E[S]</td>
</tr>
<tr>
<td>Low: 4375</td>
</tr>
<tr>
<td>High: 13450</td>
</tr>
</tbody>
</table>

5.2.2 Results
The first test conducted was to observe the strength (rho) of the two technique’s relationship. To conduct this test, Pearson’s correlation coefficient was used. If this coefficient is a 1, the models are perfectly positive correlated. If the coefficient is a -1, the models have a perfectly negative correlation. A value of 0 for this coefficient means there is no correlation between the models. The level of confidence in this test was 95%. This test rejected the null hypothesis in favor of the alternative hypothesis that there is a statistically significant relationship between the two technique’s output values. Table 5.2.2-1 summarizes the test results.
Table 5.2.2-1: Test of Correlation between BDROP and Black-Scholes Techniques

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Statistic Value</th>
<th>P-Value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0$: $\rho = 0$</td>
<td>$\rho = 0.859$</td>
<td>$p = 0.000$</td>
<td>Reject $H_0$</td>
</tr>
<tr>
<td>$H_1$: $\rho \neq 0$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The second test conducted was to observe the difference (D) between the two technique outputs. To conduct this test, the $t$ statistic was used. The level of confidence in this test was 95%. This test rejected the null hypothesis in favor of the alternative hypothesis that there is a difference in mean across the two techniques’ output values. Table 5.2.2-2 summarizes the test results.

Table 5.2.2-2: Test of Difference between BDROP and Black-Scholes Techniques

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Statistic Value</th>
<th>P-Value</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>$H_0$: $D = 0$</td>
<td>$t = -24.40$</td>
<td>$p = 0.000$</td>
<td>Reject $H_0$</td>
</tr>
<tr>
<td>$H_1$: $D \neq 0$</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

5.3 Analysis
These results show a strong positive relationship between the Black-Scholes and the BDROP techniques. This contends that with 95% confidence the two techniques are
statistically related. The results also show that although they are related, it can be shown with 95% confidence that they do not closely approximate each other’s output values. The reasoning for this is not certain; however, as it was suggested in the mathematical comparison of Section 5.1, the tails of these distributions may not converge and as a result may be contributing to the differences. Figure 5.3-1 illustrates this issue.

Source: (Ricciardi, Pinder, & Belitz, 2005)
Figure 5.3-1: Lognormal versus Beta Distribution Probability Function Approximation
CHAPTER 6: BDROP MODEL APPLICATION

6.1 OVERVIEW
A large Department of Transportation (DOT) in the southwest region of the United States manages approximately 1.1 million acres of land that provide right-of-way (ROW) for approximately 80,000 center miles of state-maintained roads. Management of the ROW involves managing and inventorying a large number of facilities within the state ROW including utility (i.e., gas (liquid or natural), energy, sewer, telecommunications, water) assets, roadway infrastructure (i.e., pavements, bridges, traffic signs), and beautification facilities (i.e., outdoor advertising facilities). It has been a particular challenge to effectively manage the numerous utility installations within the states ROW, among which, a significant proportion of assets are underground.

While data management practices within the utility industry varies, the utility industry has used underground markers for decades to help locate cables, pipes, valves, and other underground assets. These markers typically emanate radio signals in a passive mode with a set range of frequencies. Within this range, each type of asset uses a unique frequency for the purpose of asset differentiation; however, these markers do not store or transmit any identification data, which has severely limited the usability of the markers for data collection, inventory, and inspection purposes.

To address the limitations of underground markers, pioneering researchers and the utility industry have been exploring the use of radio frequency identification (RFID) technology in utility asset management. RFID technology provides the capability to store a unique
identification (ID) number and some basic attribute information. This data can be retrieved wirelessly when the markers detect a radio signal from a remote reader. RFID technology has the potential to offer this DOT a unique opportunity to help optimize the management of utility installations within their state ROW. It could also offer this DOT the opportunity to better address other ROW functions (i.e., outdoor advertising, parcel information), as well as asset inventory and management needs in connection with this DOT's own infrastructure (i.e., communication ducts, cable, boxes, manholes, signs, survey/ROW monuments).

6.2 Research Objectives
The objective of this thesis was to evaluate the use of the BDROP model for evaluating technology assets. The objective of this study was to use the BDROP model to analyze its ability to decide which RFID system, enabling technology, is appropriate for a state Department of Transportation (DOT) Right of Way (ROW) needs. In order to test the BDROP model, data from a previous study was used and a comparison to the results of a Black-Scholes model. The process was used to determine which RFID system implemented in ROW is the most economical. The analysis of this question focuses on acquisition cost for implementing an RFID system for a DOT. This study includes an economic analysis of six different types of RFID systems: RF Code System, 3M System, Smartmark System, Confidex System, Motorola System and Intermec System.

This study formulates a cost analysis of implementing an RFID system that will be used in ROW. The best plan of action is defined by the results of an evaluation of costs of implementing RFID systems. The goal of a new system is to cost the least amount of money and to be the most reliable when using the system in ROW. This RFID system
must be implemented in a certain span of time so as to make managing the facilities easier and more convenience.

**6.3 BACKGROUND**

6.3.1 **Radio Frequency Identification Technology**

Radio Frequency Identification (RFID) is the use of an object applied to or incorporated into a product, animal, or person for the purpose of identification and tracking using radio waves. RFID systems are comprised of interrogators (also known as readers) and tags (also known as labels). There are generally three types of RFID tags: active RFID tags, which contain a battery and can transmit signals autonomously. Other passive RFID tags, which have no battery and require an external source to provoke signal transmission; and battery assisted passive (BAP), which require an external source to wake up, but have significant higher forward link capability providing great read range.

6.3.2 **Real Options of RFID**

RFID projects contain numeric uncertainties or risk factors, including trading-partner RFID adoption, tag costs, technology capabilities, and evolving standards. In this way, RFID projects meet the requirements for using real options analysis. Organization decision makers may intuitively realize the strategic potential from investing in RFID even if initial returns look unfavorable. Decision makers are likely to appreciate the current uncertainty pertaining to the technology and the way it is going to evolve over time, thus making it prudent to wait for more information to arrive before investing in the technology. Further, decision makers might also realize that while investing in RFID is somewhat irreversible, they have the flexibility of structuring the investment project in small incremental steps (Goswami, Teo, & Chan, 2008).
The real option identified in this research is the Learning option, which is the option to learn and gather information and reduce uncertainty through an initial investment (Brach, 2003). In this DOT project, the learning real option model is used to evaluate the different types of RFID systems identified for this project. A decision model is created and used to eventually decide which system would be most beneficial.

6.3.3 Department of Transportation - Right of Way
RFID tags have been used for transportation toll systems since the early 1970s (Jones & Chung, 2008). Transponder, or tag, based radio frequency systems have been utilized for highway weigh-in motion and other transportation enforcement actions over the last several decades with systems such as Pre-Pass and NorPass. The concept of using one RFID based system that can be integrated with RFID toll systems, other transponder based systems, and additional state systems that utilize common information is the foundation for this research. It is envisioned that such a system can be created by having standardized (ISO) RFID tags embedded in license plates that can be scanned or read by a mile marker with a reader. This idea allows states to expand extra scanning capacity in an incremental manner. Existing readers, that interrogate other transponders, could also read the common information due to the systems’ ISO standardization. Multiple aspects of this type of system must be tested for it to be successful. The physical capability of the system is described in this study.

Radio Frequency Identification (RFID) is an emerging technology which has been introduced into the transportation system. Currently, the approach to data capture for inspections is a manual “screening” by enforcement of safety and registration guidelines. Enforcement operations have a critical need to provide a more efficient means of
capturing data for trucking inspection purposes. The automated technology that could be utilized in traffic counts, enforcement data collection, and toll usage information must be accessible and collected in a reliable way. RFID technologies’ ability to work in license plates was studied to find ways to make information collection for CVO more efficient.

One of the largest challenges for the transportation industry is to investigate and test the feasibility of emerging technologies such as RFID. Also determining the economic benefits when comparing the RFID systems to decide which to use proves to be challenging. This study utilizes reliability testing to determine the opportunities and shortcomings of a RFID license plate system. Reliability is the ability for a product or a system to perform consistently over time. In this study quality measurements, such as statistical reliability, were utilized to test the feasibility of a proposed system.

6.4 APPLICATION OF THE BDROP MODEL
The DOT project is comprised of three stages: Phase 1: the preliminary phase, where the initial data is gathered in a laboratory setting to describe the performance of the system; Phase 2: the trial phase, where a limited system kit would be implemented in the true environment to describe the true performance of the system; and Phase 3: the implementation phase, where the full implementation of the RFID system would be completed. The stages are summarized and depicted in Figure 6.4-1.
Using the four steps of the BDROP model, the three stages were analyzed. Reviewing the steps:

Step 1 is to model the system’s stochastic properties as a Beta distribution pdf,

Step 2 is to filter the pdf using real options thinking,

Step 3 is to evaluate the filtered distribution to adjust for risk of the returns, and

Step 4 is to discount the resulting value to time 0.

6.4.1 STEP 1 - MODELING THE SYSTEM
In many projects involving technology, the source of uncertainty comes from the stochastic properties of its reliability; this is especially true in RFID technology applications. In these cases, the diverse environments where the technology is implemented do not allow for the specifications of the performance to always be 100% accurate. This case study examines this situation.

The data from Phase 1 was obtained from research in a laboratory and in the field that modeled the actual environments that the RFID system would encounter. This preliminary research, gives an estimate of the stochastic properties of the technology’s performance. These properties are used as an indicator of uncertain future returns from the investment after implementation.

The performance was quantified using performance measurements of the systems. The reliability of an RFID system is how consistently the tags read. This data was collected and analyzed. Then the data was valued by a ranking system with 0 being the minimum performance (or 0% reads) and 10 being the maximum performance (or 100% reads).
Using these ranks for different environments the expected performance rankings was calculated as well as the standard deviation of the performance.

Next these rankings must be converted into monetary values. It is assumed in this study that each RFID system has a present value of $10,000 at the start of Phase 3. In order to evaluate the value of the option, the units of the parameters must be the same. The launch costs are in dollars; therefore, the rankings were converted to dollars as well. To obtain their monetary value, each ranking were divided by 10 (to change their units to a percentage) and then multiplied by the $10,000 present value. The adjusted present values ($S_T$) are presented in Table 6.4.1-1.

Table 6.4.1-1 BDROP Model Parameter Values

<table>
<thead>
<tr>
<th>BDROP Model Parameters and Option Values</th>
<th>S_T</th>
<th>X</th>
<th>C_0</th>
</tr>
</thead>
<tbody>
<tr>
<td>RFID Systems</td>
<td>$9000</td>
<td>$21793</td>
<td>$0</td>
</tr>
<tr>
<td>RF Code</td>
<td>$8100</td>
<td>$10520</td>
<td>$0</td>
</tr>
<tr>
<td>3M</td>
<td>$2175</td>
<td>$6500</td>
<td>$0.93</td>
</tr>
<tr>
<td>Motorola</td>
<td>$1500</td>
<td>$3740</td>
<td>$10.11</td>
</tr>
<tr>
<td>Smartmark</td>
<td>$1500</td>
<td>$2825</td>
<td>$45.36</td>
</tr>
<tr>
<td>Confidex</td>
<td>$1200</td>
<td>$2070</td>
<td>$55.70</td>
</tr>
<tr>
<td>Intermec</td>
<td>$1200</td>
<td>$2070</td>
<td>$55.70</td>
</tr>
</tbody>
</table>
To create a Beta distribution from this data, the shape parameters need to be estimated. The shape parameter ratio can be estimated using the relationships in the following formulas:

\[
\alpha = \bar{x}(\frac{\bar{x}(1-\bar{x})}{v} - 1) \quad \text{and} \\
\beta = (1 - \bar{x})(\frac{\bar{x}(1-\bar{x})}{v} - 1)
\]

where, \( \bar{x} = \frac{\mu - a}{b - a} \); \( \mu \) is this case is sample mean. In the formulas, \( v \) is estimated to be 27\% for all RFID systems being compared. For example in the 3M RFID system case, \( \mu = $8,100 \) and \( \sigma = 27\% \). The range \([a, b]\) of the distribution is assumed to have a lower bound \( a \) of $0 and an upper bound \( b \) of $10,000. Using the estimated shape parameters, the corresponding probability density function is created.

6.4.2 STEP 2 - FILTER THE DISTRIBUTION
During Phase 2, a trial period is to be completed with the system to determine the actual performance of the system under actual conditions. It is in this stage that the uncertainties described by Phase 1 will become certain enough for managers to make an informed decision on whether to enter Phase 3, meaning, if they will implement the system. The decision the managers will be making is based upon the returns accrued versus the costs to launch a full scale implementation. Full scale implementation costs include the cost of the RFID reader and tags. The costs \( X \) associated with launching each RFID system are also included in Table 6.4.1-1.

To filter the probability density function to represent the new distribution, \( f_{\text{ROA}}(x) \), recall the real options rule; max \([0, S_T - X]\). In this project, \( S_T \) represents the returns of the
project and X represents the implementation costs. This means that if there is a positive cash flow generated from the return of the system minus the implementation costs, then the managers will decide to proceed with Phase 3 yielding a net value of $S_t - X$ dollars. If there is not a positive cash flow, then the managers will not continue to Phase 3, yielding a net value of $0$.

6.4.3 STEP 3 - EVALUATE THE FILTERED DISTRIBUTION
Although some of these values may be greater than zero, they are not a true representation of the value because of the risk associated with obtaining them. To adjust for this, the values are multiplied by their likelihood of occurrence. In mathematical terms, this is the expected value of the distribution. The expected value is evaluated using Matlab software. The results are the options values.

6.4.4 STEP 4 - DISCOUNT THE VALUES
Since the present value was used in the calculations, the number of years to discount by is 0; therefore, Step 4 is not necessary. The BDROP model option values ($C_0$) are listed in Table 6.4.1-1.

6.5 RESULTS
Using the 4-Step process of the BDROP model, real option values were calculated for each system. Each system had unique data inputs for Step 1, so in Step 3, each system’s expected value was individually evaluated. The expected value could have been evaluated with any statistical software; however, in this project, Matlab software was used to calculate the expected value. The code is listed in Appendix A.

There are only two systems that do not realize an option value greater than $0$. These systems are the RF code and the 3M. All other systems contain some value in waiting for
more information. The NPV method, however, will decide to forego all RFID systems. This is because the expected values of the returns for each system are less than the intended implementation costs. Table 6.5-1 compares the option values to the NPVs ($S_T - X$) using the same data.

Table 6.5-1: BDROP Model Values versus Net Present Values

<table>
<thead>
<tr>
<th></th>
<th>Option Values versus Net Present Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant Parameters</td>
<td>$\sigma = 27%$, $r_f = 6%$, $T = 6$ years</td>
</tr>
<tr>
<td>RFID Systems</td>
<td>RF Code</td>
</tr>
<tr>
<td>$S_T$</td>
<td>$9000$</td>
</tr>
<tr>
<td>$X$</td>
<td>$21793$</td>
</tr>
<tr>
<td>$S_T - X$</td>
<td>-$12793$</td>
</tr>
<tr>
<td>$C_0$</td>
<td>$0$</td>
</tr>
</tbody>
</table>

6.6 Conclusions and Recommendations

In order to analyze real options, it is important to remember what its value means. Its value is not a value of the system explicitly. The real options value is the measure of how valuable waiting for more information is. The four systems that have a real option value are the Confidex, Motorola, Smartmark, and the Intermec systems. This means there is value in doing more research on these systems in the trial phase. At the end of Phase 2 when the system’s reliability is more certain, a decision can be made on whether to fully implement the system or scrap it. Currently, the most valuable option is held by the Intermec system. This system should be the one chosen to continue during the trial phase, if only one system is to be chosen.
CHAPTER 7: GENERAL DISCUSSION

7.1 MET OBJECTIVES
This thesis set out to create a new model that addresses the current challenges of real options analysis. This objective was met by addressing the challenge that real option analysis techniques were constrained market assumptions. The BDROP model combines methodologies of Copeland and Antikarov’s [2001] market asset disclaimer and Datar, Mathews, and Blake’s [2007] simplification of real options thinking to create an unconstrained formulation of the options value. Also, the BDROP model can easily manipulate input data to quickly value the option.

This thesis met its second objective to compare this new model to an existing one by comparing it to the Black-Scholes technique. In comparing models, the BDROP was found to not significantly follow or approximate the same value as the Black-Scholes. This deviation was speculated as a result of how the uncertainty of the future cash flows was modeled; specifically, which statistical distribution was used.

The third objective of this thesis was to apply the new model to a real world situation. This was accomplished by valuing the options of RFID system in a case study of a transportation department. The model was used effectively decide whether conducting more research on a particular RFID system would have any potential benefit. The completion of this objective solidified the success of meeting all three objectives of this thesis.
7.2 LIMITATIONS
This model is limited to the assumptions made during its development. The model only applies to uni-modal distributions that can be defined by a Beta distribution. This was derived from the assumption of only using shape parameters, alpha and Beta, greater than one. Also this model assumes that the shape parameters are integers. This limits the flexibility of the parameters to create the most accurate shape of the distribution.

Furthermore, specifically using the Beta distribution may limit how robust the model is. There may be other stochastic systems that more closely follow another distribution. Future research may involve expanding the BDROP model to solve this problem. The generalized model (properly named the Net Present Value-DROP model) would entail the same thinking used to derive the BDROP model but would be able to insert any distribution’s probability density function for the Beta distribution.

Due to the simplified derivation of integral using a large number of discrete intervals, rather than solving it directly, may be a source of more error. Further test may need to be conducted to determine the impact these assumptions have made on the model’s accuracy. Lastly, in any model that represents a real system there is the inherent errors that yield from subjective data given by the managers. These inexact estimations allow the values obtained from the BDROP model to only be approximations at best.

7.3 CONTRIBUTIONS TO THE BODY OF KNOWLEDGE
The research conducted for this thesis contributes to the body of knowledge of engineering economics; specifically ROA. This new model provides a simplified technique to value investments with inherent uncertainty. This model, is intuitive for users to understand and able to represent more distributions than traditional models like
the Black-Scholes and the BOPM. It is also not limited to the assumptions and restrictions based on the stock market. One obvious benefit to this point is the ability to represent distributions that contain negative values. Lastly, the applications of this model can be expanded to represent strategic decisions based on reliability of systems that a company will be choosing to invest in.

A model like this is a significant contribution to research because it connects the theories of the academic world with the practicality of the business world. This model brings these two worlds closer together. Future research into this topic may prove an even closer relationship can be obtained, allowing more intuitive and more accurate tools for practitioners to use in industry.
APPENDIX A: BDROP MODEL CODE

%BDROP MODEL compared to the Black Scholes Model

%Building Model Comparison Tables

modeltable = zeros(88,105);

modeltable(1:44,1) = 4375;     % low expected value
modeltable(45:88,1) = 43750;    % high expected value
modeltable(1:22,2) = 1345;     % low volatility
modeltable(23:44,2) = 13450;    % high volatility
modeltable(45:66,2) = 13450;    % low volatility
modeltable(67:88,2) = 134500;   % high volatility
modeltable(1:11,3) = 0.055;    % risk free rate = 5.5%
modeltable(12:22,3) = 0.09;    % risk free rate = 9.0%
modeltable(23:33,3) = 0.055;    % risk free rate = 5.5%
modeltable(34:44,3) = 0.09;    % risk free rate = 9.0%
modeltable(45:55,3) = 0.055;    % risk free rate = 5.5%
modeltable(56:66,3) = 0.09;    % risk free rate = 9.0%
modeltable(67:77,3) = 0.055;    % risk free rate = 5.5%
modeltable(78:88,3) = 0.09;    % risk free rate = 9.0%

%creates the time=T column from t=0 to t=10
for mt1 = 1:11:88
    mtla = mt1-1;
    for mt2 = 1:1:11
        ph1 = mt1+mt2-1;
        modeltable(ph1,4) = mt2-1;
    end
end

%End create the time=T column

BDROPmodeltable = modeltable;
BSmodeltable = modeltable;
BSminusBDROPtable = modeltable;
BDROPpercenterrtable = modeltable;

%End Building Model Comparison Tables

%Enter model results into table
    %This loop completes the model table by iterating through the
different
    %inputs and returning the resulting BS and BDROP models and plugging
them
    %into the table.
for step = 1:1:88
timer = step

% General Input Variables (given from table)

exp_s = modeltable(step,1); % expected value input
vol_s = modeltable(step,2); % volatility value input
var_s = vol_s^2; % variance value calculated input
r_r = modeltable(step,3); % risk free rate of return input
tm = modeltable(step,4); % time to maturity (t) input

% Calculates Model Values given changing Strike Price (X) (or c in this code)
accuracy = 10000; % how many intervals to create. More intervals = More accuracy. default = 10000.
a = 0; % lower bound of the Beta Distribution
b = 7.5*vol_s; % upper bound of the Beta Distribution
wacc = r_r; % weighted average cost of capital or default to risk free rate of return

it = 0;
increment = b/100;

costx = zeros(1,101);
ROV_BS = zeros(1,101);
ROV_BDROPa = zeros(1,101);
% ROV_BDROP = zeros(1,100);
for xtest = 1:1:101
    incr1 = xtest - 1;
    incr2 = incr1*increment;

    c = floor(incr2);
    it = 1+it;
    costx(it) = c;

end

% Black-Scholes Model

% Black-Scholes Inputs
s_0 = exp_s*exp(-wacc*tm);
\[ \theta_2 = \log\left( \frac{\text{var}_s}{(\text{exp}_s^2)} + 1 \right)/\text{tm}; \]

% \theta_2 = .134^2;
\[ \theta = \sqrt{\theta_2}; \]

% \theta = .134;

% End Black-Scholes Inputs

% Equations for Black-Scholes Equation Terms
% Calculates the normal distribution cdf inputs d1 and d2
\[ d_1 = \left( \log(s_0/c) + (r_r + (\theta_2/2)) \text{tm} \right)/\left( \theta \sqrt{\text{tm}} \right); \]
\[ d_2 = d_1 - \left( \theta \sqrt{\text{tm}} \right); \]

% Calculates the normal distribution cdf using matlab erfc function
%(see matlab function description for details of why these
equations used)
\[ n_1 = \frac{1}{2} \text{erfc}\left( \frac{-d_1}{\sqrt{2}} \right); \]
\[ n_2 = \frac{1}{2} \text{erfc}\left( \frac{-d_2}{\sqrt{2}} \right); \]

% End Black Scholes Equation Terms

% Black-Scholes Equation
\[ \text{ROV}_{BS}(it) = \left( s_0 \times n_1 \right) - \left( c \times \exp\left( -r_r \times \text{tm} \right) \times n_2 \right); \]

% End Black Scholes Equation

%-----------------------------------------------END Black-
Scholes Model

%%%%%      %%%%%      %%%%%      %%%%%     %%%%%      %%%%%
%%%%%      %%%%%      %%%%%      %%%%%     %%%%%      %%%%%
%%%%%      %%%%%      %%%%%      %%%%%     %%%%%      %%%%%
%%%%%      %%%%%      %%%%%      %%%%%     %%%%%      %%%%%
%

%-----------------------------------------------BDROP Model

% BDROP Inputs
\%a = 0; \quad \%lower bound
\%b = 7.5*vol_s; \quad \%upper bound
\%xbar = (\text{exp}_s - a)/(b - a); \quad \%parameter estimators
\%vbar = \text{var}_s/((b-a)^2); \quad \%parameter estimators

%-----------------------------------------------END BDROP Model
\[
mx = \left( \frac{(\bar{x} - \bar{x})/vbar}{(1 - \bar{x})/vbar} - 1 \right); \quad \%\text{multiplier term for ease of coding}
\]

\[p = \bar{x} \cdot mx; \quad \%p: \text{alpha beta-dist shape parameter}
\]

\[q = (1 - \bar{x}) \cdot mx; \quad \%q: \text{beta beta-dist shape parameter}
\]

\%END BDROP Inputs

\%Beta Distribution PDF
\%Creates a standard Beta Distribution PDF on the range 0 to 1.

\text{betapdf} = \text{zeros(1,\text{accuracy});}
\text{for r = 1:1:accuracy}
\text{x1} = (r-1)/\text{accuracy};
\text{x2} = x1^{(p-1)};
\text{x3} = 1-x1;
\text{x4} = x3^{(q-1)};
\text{x5} = x2 \cdot x4;
\text{x6} = \text{beta(p,q)};
\text{x7} = x5/x6;
\text{betapdf}(r) = x7;
\text{end}
\%END Beta Distribution PDF

\%Beta Distribution Probability Values
\%PDF's Y axis are in units of probability density, NOT probability.
\%\text{Therefore a conversion to find the approximate probability at that point}
\%is needed. The difference of the upper and lower segment of an interval
\%range is multiplied by the density associated with the lower segment
\%(the lower segment is arbitrarily chosen.) This is approximate
\%because it is most likely not constant over the interval.
\%The limit is the integral of the curve on the interval. Or in this case as the
\%intervals become infinitely small.

\text{interval} = 1/\text{accuracy};
\text{beta rob} = \text{zeros(1,\text{accuracy});}
\text{for j = 1:1:accuracy}
\text{ul} = j-1;
\( u_2 = j \);
\( u_3 = u_1 \times \text{interval} \);
\( u_4 = u_2 \times \text{interval} \);
\( u_5 = \text{interval} \); \hfill \% computing the difference of upper & lower interval
\( u_6 = u_5 \times \text{betapdf}(u_2) \); \hfill \% multiplies it by the lower segment density value

\[
\text{betaprob}(j) = u_6;
\]
\end
\% END Beta Distribution Probability Values

\% PVt Distribution
\% Dividing the range of PVs(@ time=t or maturity) into discrete intervals.
\% As the interval decreases, the distribution reaches the integral limit.

\[
\text{range} = b-a;
\text{inc} = (\text{range}/\text{accuracy});
\text{pvtdist} = \text{zeros}(1,\text{accuracy});
\text{for} \ t = 1:1:\text{accuracy}
\]
\[
v_1 = t-1;
v_2 = v_1 \times \text{inc};
v_3 = v_2 + a;
\]
\[
\text{pvtdist}(t) = v_3;
\]
\end
\% END PVt Distribution

\% Expected Value
\% Calculates the expected value on the range of \( x \) to the upper limit \( b \).

\% this next loop identifies the pointer where npv > cost
\text{mark} = \text{zeros}(1,\text{accuracy});
\text{for} \ e = 1:1:\text{accuracy}
\text{if} \ \text{pvtdist}(e) > c
\text{if} \ \text{pvtdist}(e) \times \exp(-\text{wacc} \times \text{tm}) > c \times \exp(-\text{r}_r \times \text{tm})
\text{mark}(e) = e;
\text{else}
\text{mark}(e) = 0;
\text{end}
\text{end}
\text{adjmark} = \text{find}(\text{mark},1);
\% End pointer identifier

\% Exp Value Distribution Creator
%This next loop first finds the NPV @ t=0 distribution. In the expected value formula $E[X] = \int x f(x) \, dx$, the NPV distribution is used for the "X" values. Then multiplies this value by the probability of "X" occurring, given by betaprob derived from the $f(x)$. This probability represents the NPV adjusted for the risk associated with obtaining that value. What results is a distribution of risk adjusted NPV distribution of pay-offs.

```matlab
%expvaldist = zeros(1,accuracy); expvaldista = zeros(1,accuracy);
for i = adjmark:1:accuracy
  %npv = pvtdist(i) - c;
  npva = pvtdist(i) * exp(-wacc*tm) - c*exp(-r_r*tm);
%finding the risk adjusted npv distribution
  y2 = betaprob(i);
  %y3 = npv*y2;
  y3a = npva*y2;
%multiplying it by the prob of occurrence
  %expvaldist(i) = y3*exp(-wacc*tm);
  expvaldista(i) = y3a;
end
%End Exp Value distribution creator

%expvalx = sum(expvaldist);
expvalxa = sum(expvaldista);

%ROV_BDROP(it) = expvalx;
ROV_BDROPa(it) = expvalxa;
%End Expected Value

%-------------------------------------------------------END
BDROP Model

end
%End Calculations of Model Values given changing Strike Price (X)

BDROPmodeltable(step,5:105) = ROV_BDROPa;
BSmodeltable(step,5:105) = ROV_BS;
BSminusBDROPtable(step,5:105) = ROV_BS - ROV_BDROPa;
BDROPpercenterrtable(step,5:105) = (ROV_BS - ROV_BDROPa)./ROV_BS;
end
%END Enter Model Results into Table
WORKS CITED


BIBLIOGRAPHY


