DESIGN WITH UNCERTAIN TECHNOLOGY EVOLUTION

A Thesis

by

JONATHAN LEE ARENDT

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

August 2012

Major Subject: Mechanical Engineering

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Approved by:

Co-Chairs of Committee,	Daniel A. McAdams
	Richard J. Malak
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ABSTRACT

Design with Uncertain Technology Evolution. (August 2012)

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Design is an uncertain human activity involving decisions with uncertain outcomes. Sources of uncertainty in product design include uncertainty in modeling methods, market preferences, and performance levels of subsystem technologies, among many others. The performance of a technology evolves over time exhibiting improving performance as research and development efforts continue. As the performance of a technology in the future is uncertain, quantifying the evolution of these technologies poses a challenge in making design decisions. Designing systems involving evolving technologies is a poorly understood problem. The objective of this research is to create a computational method allowing designers to make decisions encompassing the evolution of technology. Techniques for modeling evolution of a technology that has multiple performance attributes are developed. An S-curve technology evolution model is used. The performance of a technology develops slowly at first, quickly during heavy R&D effort, and slowly again as the performance approaches its limits. Pareto frontiers represent the set of optimal solutions that the decision maker can select from. As the performance of a technology develops, the Pareto frontier shifts to a new location. The assumed S-curve form of technology development allows the designer to apply the uncertainty of technology development directly to the S-curve evolution model rather than applying the uncertainty to the performance, giving a more focused application of uncertainty in the problem. Monte Carlo simulations are used to the propagate uncertainty through the decision. The decision-making methods give designers greater insight when making long-term decisions regarding evolving technologies. The scenario of an automotive manufacturing firm entering the electric vehicle market deciding which battery technology to include in their new line of electric cars is used to demonstrate the decision-making method. Another scenario of a wind turbine energy company deciding which technology to invest in demonstrates a more sophisticated technology evolution modeling technique and the decision making under uncertainty method.

ACKNOWLEDGMENTS

I would like to thank my co-advisors Dr. Daniel McAdams and Dr. Richard Malak for their guidance and support throughout the course of this research.

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1. INTRODUCTION

Engineering organizations often face decisions with outcomes that unfold over long periods of time and that affect the options available in subsequent decisions. For example, a company might invest millions of dollars in a particular type of manufacturing technology, which effectively constrains future design decisions to use that technology. Similar situations occur when organizations make decisions about investments in product platforms, research and development strategies, and long-term supplier or subcontracting relationships.

Uncertainty is a crucially important consideration in long-term decisions. Long-term decisions are impacted by uncertainties about the final form of an engineered system; the system's operating environment, and system behavior. However, unlike other engineering decisions, long-term decisions are also impacted by the evolution of the underlying technologies. The nature of technology evolution is that it is highly uncertain. For example, suppose a producer of passenger cars seeks to invest in an electric storage technology for its new line of hybrid vehicles. Although lithium-ion batteries may be the best technology initially, fuel cells may have a high likelihood of overtaking the batteries as fuel cell designs improve over the anticipated lifetime of the new line of vehicles. Despite the challenges of forecasting how a technology will evolve, the automaker should consider how this evolution will impact the value of each

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This thesis follows the style of Journal of Mechanical Design.

course of action. It is quite possible that the alternative that is less profitable in the short term will yield the greatest long-term expected profits.

Although many uncertainties exist in how the performance characteristics of a technology will evolve, some common trends are evident. The performance of a technology generally improves over time, as it is refined initially through research and development and later through refinements in design and manufacturing. Empirical evidence shows that most technologies follow an S-curve evolutionary path—performance is poor at its inception, improves rapidly during heavy research and development activity, and finally matures as the performance saturates near the physical limits or boundaries [1].

This thesis presents new methods for supporting engineering decisions where there is uncertainty about how technological alternatives will evolve over time. The first set of methods deals with selecting between competing technologies to achieve the greatest benefit over an extended period of time. The technology selection method answers the question: Given our uncertain expectation of the evolution of competing technologies, which one should we choose? A second method, building upon the first method, answers the question: What evolution profile is needed for a technology to be more preferable than another competing technology? The method to support this decision uses a parametric study over the parameters that describe evolution. This thesis presents an approach to technology evolution modeling which can vary from simplified to sophisticated. The technology evolution modeling will be applied in both the technology selection method and the parametric study method.

The technology performance development model is based on an S-curve technology evolution model with uncertain parameters defining the shape of the S-curves. The S-curve parameters include maximum evolution rate, inflection time, and other parameters depending on the type of S-curve used. Under this proposed model, one assumes that the evolution of a technology follows an S-curve, and the current technology performance available to the designer lies on a Pareto frontier. The Pareto frontier representing technology available at a certain time shifts in time, showing the evolution of the technology. The technology modeling presented here applies the S-curve evolution model to the Pareto frontiers through a discrete simulation of time passing. Over time periods in the S-curve where technology evolves slowly, the Pareto frontier shifts slowly as well. When the S-curve shows great increase in performance, the Pareto frontier shifts rapidly. Section 3 presents simplified and sophisticated techniques for modeling the evolution of technology through time.

The first method supports selecting between competing technologies. Under the proposed technology selection method, one assumes a technology's performance metrics follow an S-curve evolution trend, but the parameters that define the shape of each S-curve are uncertain and represented using probability distributions. Decision makers determine these distributions based on data about the technology in question, the histories of similar technologies, and their own beliefs. At the outset of decision-making, decision makers model the current state of technology as a Pareto frontier in the space of technology performance characteristics.

Modeling with S-curves and Pareto frontiers captures the full scope of desirable implementations of the technology in terms of the performance characteristics that are important for a decision. As simulated time progresses, the Pareto frontier moves following the underlying S-curves. Using this technology evolution model together with a Monte Carlo simulation, decision makers can generate projections about an uncertain future and make rational decisions based on their beliefs about evolving technologies.

The second method allows the user to see what evolution needs to occur so that one technology is preferred over another. The method uses a parametric study building upon the technology selection method. A parametric search is performed over the parameters defining the evolution S-curves. The parametric study will show the user what evolutionary paths will make one technology preferable to another. It also shows which parameters have the greatest effect on the decision and how much.

The technology selection method using simplified evolution modeling is demonstrated with the design an electric vehicle platform. Electric vehicles are slowly emerging onto the maintain market at the current time. Much of electric vehicle technology is in its infancy. Of particular importance is the development of battery technology for use in electric vehicle applications, with battery development previously coming primarily from the portable electronics market. As the interest and incentive to switch from gasoline to electric vehicles increases, the research and development efforts will increase, causing the performance of battery technologies to evolve. In this demonstration, a car design and manufacturing company is making a decision of which competing battery chemistry to select for use in a future line of consumer electric cars. The cars will be designed in the current year and updated every model year with the best battery cell available. The cost of initial tooling and capital investments, and partnerships and contracts with battery cell manufacturers make it impractical to change from one battery cell technology to another in the lifespan of the project.

The technology selection method using the sophisticated evolution modeling technique is demonstrated with the design of a wind power generation system. This problem is of interest due to the current importance of renewable energy as a replacement or supplement to current coal and petroleum energy sources. Additionally, wind turbines have been evolving in performance and will continue to evolve into the near future. In this design decision demonstration, a hypothetical startup energy company is making the decision of whether to install wind turbines on land or offshore. Once the firm commits to the core technology of either offshore or land-based wind turbines, the firm will acquire, design, and develop related elements of an array such as installation equipment, transformers, etc.

Over the next decade, the firm expects to expand and install new arrays of the selected technology. Every year, and with every new installation, the firm selects the best wind turbines available at the time. Because the offshore and land-based technologies are evolving at different rates, the rational choice is not necessarily the technology with the highest performance at the outset of the project. The firm finds that land-based wind turbine technology to be superior initially, but suspects that, due to evolving performance, offshore wind turbines will be preferable over the long run. To gain insight into the decision problem, the firm uses the method developed here to answer the question: Given our expectation of the evolution of land-based wind turbine performance, how does offshore wind turbine technology need to evolve such that it is preferable to land-based? The demonstration applies the proposed method enabling designers to make such a determination based on their uncertain knowledge of how each technology will evolve.

The wind turbine design scenario from the technology selection method is continued for the demonstration of the parametric study method. The parametric study method tells the firm what evolution needs to occur for offshore wind turbine technology to be preferable to land-based. The analysis can give the firm greater insight into the existence of an opportunity to shift the evolution sooner to their favor or to increase the evolution rate through earlier and more research and development effort. Additionally, the analysis shows the firm the risk in going for offshore technology.

This thesis consists of six sections. The next section is the background describing the fundamentals of decision-making, technology evolution models, Monte Carlo simulations, and utility theory. Section 3 presents technology evolution modeling with S-curves and Pareto frontiers. A simplified method using one S-curve to describe the overall performance of a technology is presented, followed by a sophisticated model using an S-curve to describe the evolution of each dimension of the Pareto frontier independently. Section 4 details the technology selection and parametric study methods. Section 5 provides demonstrations of technology selection using simplified and sophisticated evolution modeling as well as the parametric study method. The thesis ends with the future work, summary, and conclusions of the research.

2. BACKGROUND

This section presents the fundamentals and concepts that will be used throughout the thesis. The background describes the basics of decision-making, technology evolution models, Monte Carlo simulations, and utility theory.

2.1. Decision Making

The engineering design literature contains several reports of methods for decision making under uncertainty. However, these provide no specific and formal guidance on how designers can incorporate into their decisions uncertain knowledge about technology evolution. Researchers have demonstrated real options-based methods for designing flexibility or upgradability into systems, but these methods focus on uncertain events external to the system and assume a technology that does not evolve [2-4]. Others advocate using comprehensive business enterprise simulations to evaluate the broad implications of engineering decisions on downstream activities such as manufacturing or distribution, but this approach pertains to the interplay between engineering decisions and business processes rather than the impact one engineering decision has on future engineering problems [4, 5]. In principle, designers can use their understanding of technology evolution when rating decision alternatives in informal methods, such as Pugh selection charts, the Analytical Hierarchy Process (AHP), and Quality Function Deployment (QFD) [5-7]. However, using these methods is a general reflection of designer estimations and judgment without any explicit or formal consideration for technology evolution.

2.2. Technology Evolution Models

As technologies evolve, their performance typically improves. Betz proposed the idea that the performance evolution of a technology follows a Sigmoid curve, a form of an S-curve, as shown in Figure 1 [1, 8]. Using empirical data, Betz demonstrated that this model accurately captures the evolution of illumination intensity of light bulbs. When incandescent light bulbs emerged as a light technology, the performance was low, resulting in the flat bottom of the "S," as shown in Figure 1. As the innovation research and development increased, the performance improved rapidly, reflecting the increase in slope at the inflection in the curve. As development approached the physical limitations of the technology, the rapid gains in performance approached full maturity, reflecting the flattening at the top of the S-curve. The idea that an S-curve models the evolution of the performance of light bulbs can be extended to other technologies. For the purposes of this research, it is assumed that technology evolves following the S-curve model

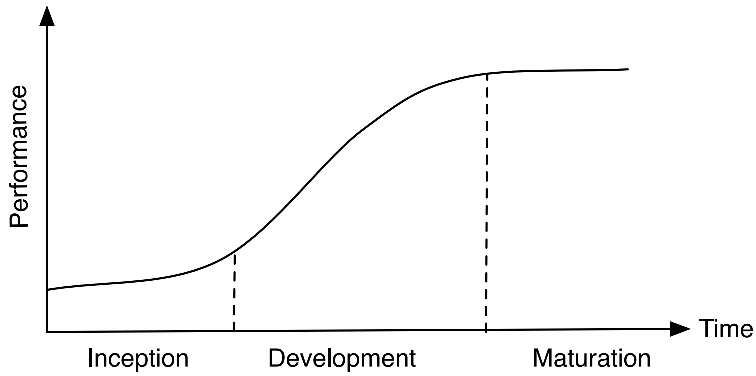

Figure 1. S-Curve Evolution Model

There are limitations to the S-curve assumption, such as the introduction of disruptive technologies. An example is the emergence of fluorescent light bulbs that had a much higher intensity than incandescent bulbs when they were first introduced. Including disruptive technologies into this decision framework goes beyond the scope of the work presented here. Of note, fluorescent bulbs exhibited a performance evolution along an S-curve similar to incandescent bulbs [8]. Also of note, not all technologies appear to follow the S-curve evolution model. According to Moore's law, processor speed evolves linearly instead of along an S-curve [9]. Although one can argue that Moore's law only captures the development stage of the S-curve, and the maturation stage is yet to come.

Since the inception of the S-curve technology evolution model there have been numerous forms introduced, as shown in Table 1 [10]. The forms differ in the number of parameters, mathematical formula, and shapes of the curves. The modeler can use whichever form best suits his or her needs for the given application.

Table 1. Forms of Technology Evolution S-Curves

Model	*Formula*	*Parameters*
Logistic	$P(t) = \dfrac{P_{lim}}{1 + e^{\propto - kt}}$	$\propto, k$
Gompertz	$P(t) = P_{lim} e^{-e^{\alpha - kt}}$	$\propto, k$
Log-Logistic	$P(t) = \dfrac{P_{lim}}{1 + e^{\alpha - k \ln t}}$	$\propto, k$
Erto-Lanzotti	$P(t) = P_0 + \left(1 - e^{-kt^s}\right)(P_{lim} - P_o)$	k, s
Richards	$P(t) = \dfrac{P_{lim}}{(1 + e^{\alpha - kt})^{\frac{1}{s}}}$	$\propto, k, s$
Weibull	$P(t) = P_{lim} - \alpha e^{-kt^s}$	$\propto, k, s$
$P(t) = performance; P_{lim} = \max P;\ P_o = initial\ P; \propto, k, s = shape\ parameters$		

The formulas in Table 1 are in the form of performance as a function of time, *t*. Performance is used here as a term measuring some important attribute, such as power of an engine, speed of a processor, or even cost of a product. The formulas are made of some or all of the parameters, P_{lim}, P_0, α, *k*, and *s*. The Parameter P_{lim} is the maximum performance that the technology will ever reach in the future through evolution. The limit is generally tied to a physical or theoretical performance limit, such as the he thermodynamic efficiency of the Brayton cycle for a turbine engine. The parameter P_0 is the initial performance of a technology. The parameters, k, s, and α dictate the shape, slope, and inflection point of the S-curve, but behave differently in each different S-curve form. These three parameters are difficult to elicit from a designer based on his or her experience, judgment, and expert knowledge. Thus, they will be derived indirectly from more intuitive parameters. The parameters used to define the S-curves depend on what type of S-curve is used.

The forms of technology evolution in Table 1 differ in their shape, symmetry, flexibility and inflection point location. The logistic and Gompertz models are symmetric about the inflection point, which is the point where there is no curvature and the 2^{nd} derivative equals zero. The Richards, Weibull, and Erto-Lanzotti equations are the most flexible, meaning that they are not constrained by assuming symmetry or location of the inflection point [10]. In this thesis, the Logistic and Erto-Lanzotti equations will be used and they will be discussed further in the Technology Evolution Modeling Section.

2.3. Pareto Frontiers

A Pareto frontier is a concept often used to describe preferences in an economic setting. More recently Pareto frontiers have been applied to decision-making in engineering [11-14]. The concept is applied in this research to represent the performance levels of multiple attributes available to a designer. The Pareto frontier is a line, in two dimensions, or hypersurface in more than two dimensions, connecting the points contained in the Pareto optimal set. The Pareto optimal set is the set of non-dominated points or solutions existing in the same space. A point in the space is dominated if there exists another point in the space that is preferable in every attribute [15]. The non-dominated points belong in the Pareto optimal set, also called the Pareto efficient set. Figure 2 shows the Pareto frontier applied to a set of points. In the engineering context, a point is a particular model, product, or realization of technology where the coordinates of the point are the attributes.

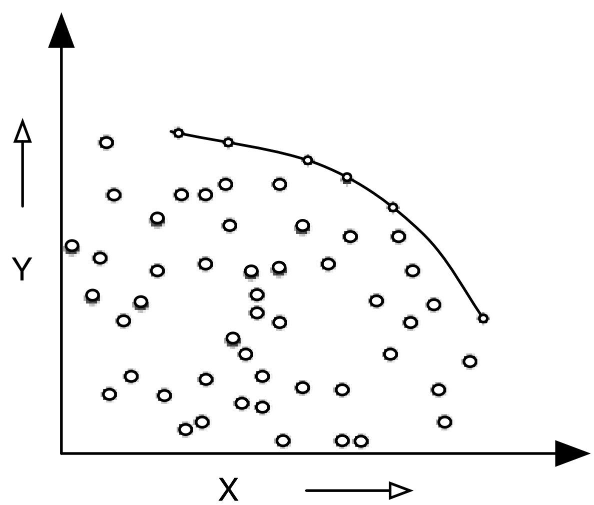

Figure 2. ***Pareto Frontier***

In figure 2, a decision maker wants to maximize two attributes, X and Y, for example, mobile phone screen size and battery life. The attribute space is populated with points representing cell phone models available on the market. The coordinates of each point are the screen size and battery life of the mobile phone model. The Pareto optimal set is the collection of points of non-dominated points, those that are more preferable in every attribute. The Pareto frontier is the boundary line connecting those points. The person selecting a cell phone based on the attributes of screen size and battery life should only choose a cell phone shown by the points on the Pareto frontier. The dominated points are suboptimal and can be ignored. He or she must consider the performance trade-offs that exist along the Pareto curve and make a final decision of which cell phone to select. The trade-offs reflect giving up some of one attribute, battery life, in exchange for more of another attribute, screen size. The Pareto frontier concept will be used extensively to represent the performance of a technology with multiple attributes.

The Pareto frontier in Figure 2 is deterministic and there is no uncertainty involved. If there is uncertainty involved in the coordinates of a point in the attribute space, it is unclear if one point dominates another. The location of one point relative to another is uncertain, so stochastic dominance is used [15]. In this thesis there is uncertainty involved in the Pareto frontier, but at any point in time it is deterministic, a so simple dominance criterion applies.

As described earlier, the performance of a technology increases over time. As a Pareto frontier describes the performance of a technology in multiple attributes, it follows that a Pareto frontier shifts in time as the technology evolves. De Weck proposed that a Pareto frontier moves due to the evolution of the underlying technology by quantifying a Pareto frontier shift based on satellite performance data as new solutions enter the Pareto optimal solution set [16]. As newer and better solutions enter the space, they dominate some of the older points, resulting in local movements of the Pareto frontier. Figure 3 shows the shift in a Pareto frontier from one time point to another time point in the future.

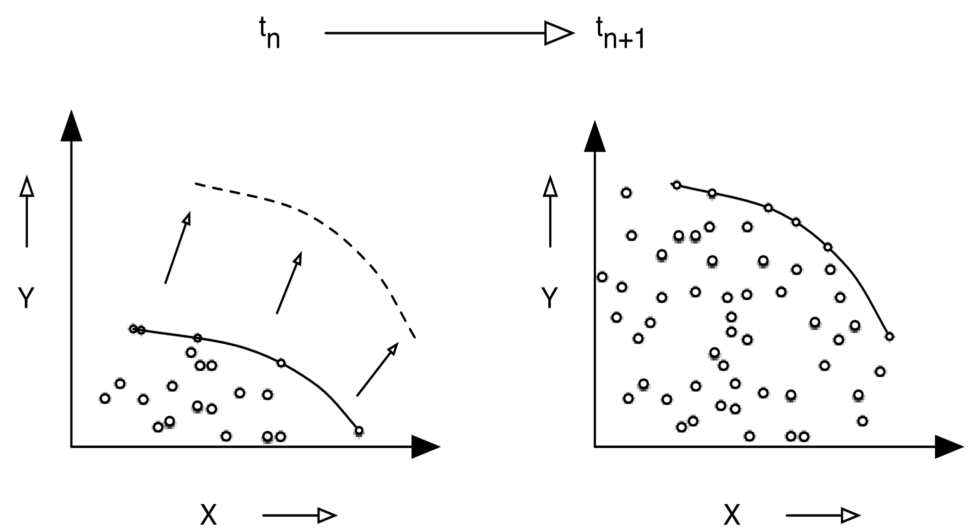

Figure 3. Pareto Frontier Shifting

As time passes and new models or iterations of a technology enter the market, more points are added to the attribute space. When new points that dominate older points are added, the Pareto frontier shifts outward, in the case of Figure 3. The concept of Pareto frontier shifting will be used extensively in this thesis.

2.4. Monte Carlo Simulations

Monte Caro simulations are used in this research to analyze the effects of uncertainty in technology evolution. Monte Carlo simulation is a computational technique to deal with randomness in a mathematical analysis [17, 18]. A Monte Carlo simulation tests a very large number of random events, such as the random draw of a card in a game of Blackjack. In a similar ways a random S-curve is sampled and the events following the S-curve unfold over time. The result is a distribution of the results due to the series of random events.

The major disadvantage to using Monte Carlo simulations in uncertainty analysis is the significant computational burden. A great number of samples, 10,000 or more, are needed for statistical significance. The computational burden increases when evaluating complex simulations or sampling in multiple dimensions. A Monte Carlo simulation can be used when more than one variable is uncertain. The user creates a distribution for each uncertain random variable. A number is sampled from each of the distributions and the simulation is run. Figure 4 illustrates a Monte Carlo simulation with multiple uncertain variables. The uncertain variables are X_1, X_2, to X_n, each represented by a distribution in the figure. To begin a Monte Carlo run, realizations, x_1, x_2, to x_n, are sampled from the probability distributions of random variables. The realizations are tested in a simulation or model that maps the realizations to an outcome. The process of sampling the distributions and testing the realizations repeats a great number of times. The result is a distribution, or many distributions, of outcomes occurring as a result of the random inputs.

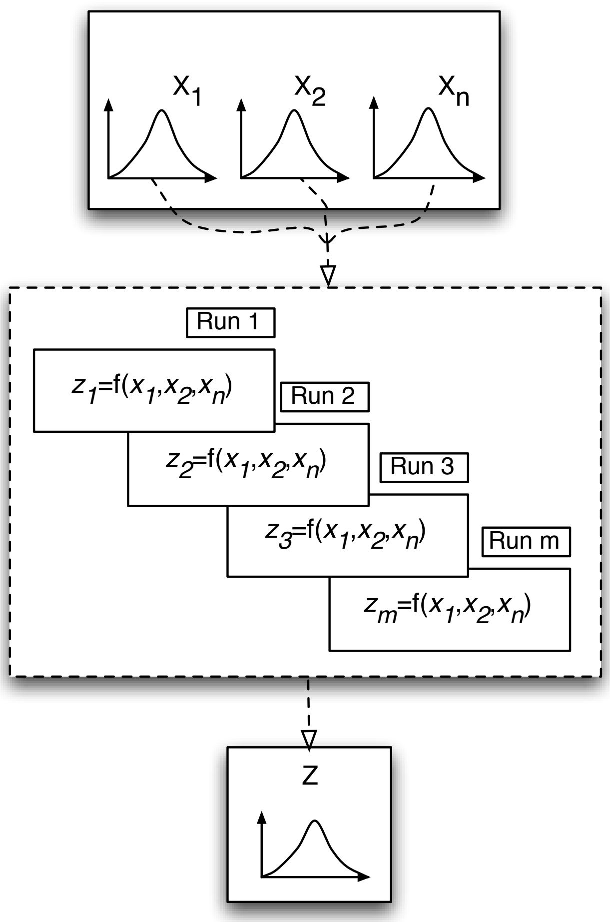

Figure 4. ***Monte Carlo Simulation***

One can sample numbers from the distributions at random or use a sophisticated sampling technique. Latin hypercube sampling technique samples the distributions in a manner to minimize the total number of samples needed to give equivalent results. Latin hypercube sampling is advantageous compared to random sampling when dealing with larger numbers of dimensions, or a larger number of uncertain variables [19]. When analyzing uncertainty in this research, random distributions of the parameters that make up the S-curves are sampled. Realizations from each of the parameter distributions are combined to create an S-curve.

2.5. Utility Theory

Utility theory is a mathematically rigorous foundation for decision making under uncertainty [20, 21] that has received much study and application in the design community [22-29]. Utility theory provides a way to make rational decisions rationally, but it does not address making decision based on uncertain knowledge about how a technology will evolve. To select between two or more competing technologies, there must be a common measure or metric between them. Utility provides a common measure between alternatives in a deterministic case, expressing the preferences of the decision maker about multiple independent or unrelated attributes. In an uncertain case, expected utility provides a scalar measure that incorporates the decision makers' preferences for multiple attributes as well as his or her risk attitude, or preference for uncertainty. Expected utility maps a distribution of utility values to a scalar value encompassing preference and risk attitude.

3. TECHNOLOGY EVOLUTION MODELING

This section discusses the technology evolution modeling techniques employed in the decision methods. An S-curve models the evolution of technology that has only one attribute, but typically technologies have multiple attributes significant to the designer [30]. Novel techniques for modeling the evolution of multiple attributes of a technology are presented in the following subsections. Technology evolution modeling in multiple attributes follows a general framework where Pareto frontiers model the current performance and S-curves describe the evolutionary paths. This thesis presents two different implementations of the generalized framework. A simplified technique to model evolution in multiple attributes uses one S-curve to describe the movement of the Pareto frontier as a whole, while a more sophisticated technique uses multiple S-curves to describe the evolution of each attribute on the Pareto frontier.

As the underlying technology evolves, the performance improves, thus changing the Pareto frontier. Under the general framework, the movement in the Pareto frontier is modeled as the movement of the points belonging to the Pareto efficient set, as shown in figure 5. The points move through the X and Y directions much like a particle moves through the spatial coordinates X and Y.

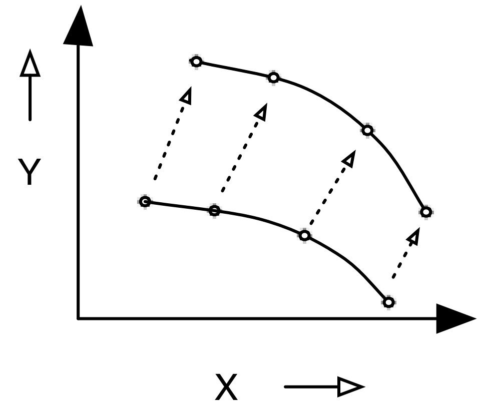

Figure 5. Shifting Of Pareto Efficient Set Points

As the performance evolves, the points in the Pareto optimal set move to a new location in the attribute space and define a new Pareto frontier. The specifics of how points on the Pareto frontier move through time and attribute space are not defined explicitly under the general framework. As the evolution of technology is uncertain, the movement of any point on the Pareto frontier through time is also uncertain. Every point can follow its own independent path through time. The modeler can apply any one of a number of different implementations of this framework, depending on his or her assumptions and desired modeling sophistication.

Two implementations of the framework sharing some common concepts are presented in the following subsections. In both modeling techniques, a point on the Pareto frontier follows a set of equations describing its movement through attribute space. The passing of time is simulated as discrete series of time steps, so the equations,

$$X_{t_{n+1}} = X_{t_n} + v_{X_n}\Delta t + \frac{1}{2} a_{x_n}\Delta t^2 \text{ and,} \tag{1}$$

$$Y_{t_{n+1}} = Y_{t_n} + v_{Y_n}\Delta t + \frac{1}{2} a_{Y_n}\Delta t^2 \tag{2}$$

describe the motion of a point existing in a space defined by attributes X and Y. Equations 1 and 2 are discretized equations that describe the motion as a linear approximation of the motion over the time step. The approximations are the summation of a number of the terms of a Taylor Series expansion approximating the functions *x(t)* and *y(t)*. As the equations are approximations, error is inherent. The approximation is applicable when the time step is sufficiently small. Additionally, reducing the step size reduces the error. For the purposes of modeling the evolution of time, three-term equations of motion demonstrate an implementation of Pareto frontier point movement. In the three term equations of motion, higher order terms, such as jerk, are assumed constant over time. Adding additional terms will reduce the approximation error. Ultimately, the implementation of point movement through attribute space is up the modeler.

In equations 1 and 2, the coefficients v_{X_n} and a_{x_n} are the X components of velocity and acceleration in the attribute space, respectively, at time point *n*. The S-curve model describes the motion of the Pareto frontier via equations 1 and 2. The velocity and acceleration components at time *t* are proportional to, or the same as, the 1st and 2nd derivatives of the S-curve at time *t*. In technology evolution modeling, the S-curve can describe the evolution of the performance of a technology in different ways. The technology evolution modeling techniques in the following subsections connect the S-curve model to the Pareto frontier. The techniques, one simple and one more sophisticated, differ in exactly how the S-curve describes the movement of the Pareto frontier.

There are a number of assumptions that the modeler can make, including similarity, shape change, and convergence. It is cumbersome and difficult to describe the motion of every point on the Pareto frontier independently, so the modeler may assume that the points move similarly along each axes of the Pareto frontier or that all points move identically in all axes. In certain circumstances the curvature of the Pareto frontier is tied to a physical phenomena or constraint. For example, the Pareto frontier of a spherical water tank with attributes of volume and diameter has curvature tied to geometric relationships between volume and diameter. In similar circumstances, the modeler assumes that the curvature of the Pareto frontier does not change. The modeler can also assume that the Pareto frontier points do not converge to a utopia point.

3.1. Simple Technology Evolution Modeling

The simple technology evolution modeling technique uses one S-curve to describe the evolution of a Pareto frontier as a whole. The simple technique is less cumbersome and computationally intensive than the more sophisticated technique because it requires fewer S-curves, thus has fewer uncertain parameters. A Pareto frontier has two or more independent attributes, which are described simultaneously by a single S-curve.

In general, the designer is free to use any S-curve from Table 1 or any other technology evolution model that he or she sees fit, but the logistic model is the simplest form of the S-curve because it has the fewest number of parameters and is symmetric. Since the logistic form of the S-curve has the fewest parameters, less information needs to be elicited from the user. The simple technology evolution modeling technique will use the logistic model from here. The general equation of the logistic S curve is

$$P(t) = \frac{P_{lim}}{1+e^{\alpha - kt}}, \tag{3}$$

with performance, P, dependent on the independent variable time, t, with parameters P_{lim}, k, and α. The equation will be rewritten to make it easier for the modeler to manipulate and to better fit the technique. A single S-curve written as performance as a function of time describes the evolution of only one performance attribute. In this implementation of the general framework, Equation 3 is rewritten with maturity as a function of time rather than performance so that the equation can describe the evolution of multiple attributes. Maturity measures how much the performance has matured from its initial performance, at a maturity of zero, to its maximum possible performance when maturity equals 1. The equation is rewritten as

$$M(t) = \frac{1}{1+e^{\alpha - kt}} \tag{4}$$

replacing P_{lim} with the limit 1 for maturity. The remaining parameters, k and α, are difficult to elicit, as they are not tied directly to any significant phenomena. Instead, the parameters slope constant, C, and initial technology maturity, M_o, are introduced. The slope constant is the slope of the curve at the inflection point where the curvature is zero and the slope is maximum. The initial maturity is the level of maturity that a technology has already reached as viewed from the current time. At some point in the past, the maturity was zero, and at some point in the future the technology will mature to one. At the current time, the maturity is between zero and one. The initial maturity is inserted into equation 4 through the substitution

$$t_{M_0} = ln\left(\frac{1}{M_0} - 1\right) \tag{5}$$

to get the final equation

$$M = \frac{1}{1+e^{-\left(t*c-t_{M_0}\right)}}. \tag{6}$$

Figure 6 shows a logistic S-curve with the parameters labeled.

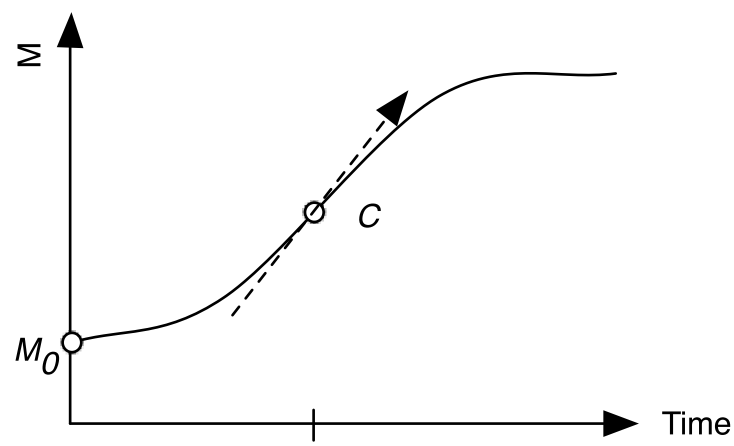

Figure 6. Logistic S-Curve

As discussed in section 3, the Pareto frontier moves discretely through time following the equation that approximate the motion of a point in attribute space, equations 1 and 2.

The two equations pertain to the two independent axes of the Pareto frontier, each one describing a performance attribute. In the simple technology evolution modeling technique, the velocity and acceleration terms, v and a, are the 1st and 2nd derivatives of the S-curve with respect to time.

$$\frac{d}{dt}M(t) = \frac{ce^{\left(t_{M_O}-ct\right)}}{\left(e^{\left(t_{M_O}-ct\right)}\right)^2} \tag{7}$$

$$\frac{d^2}{dt^2}M(t) = \frac{2c^2e^{\left(2t_{M_O}-2ct\right)}}{\left(e^{\left(t_{M_O}-ct\right)}+1\right)^3} - \frac{c^2e^{\left(t_{M_O}-ct\right)}}{\left(e^{\left(t_{M_O}-ct\right)}+1\right)^2} \tag{8}$$

The evolution of a technology as a shift in the Pareto frontier is simulated discretely over time using the equations 1 and 2 and an S-curve. Figure 7 shows the discrete model of a Pareto frontier moving through time.

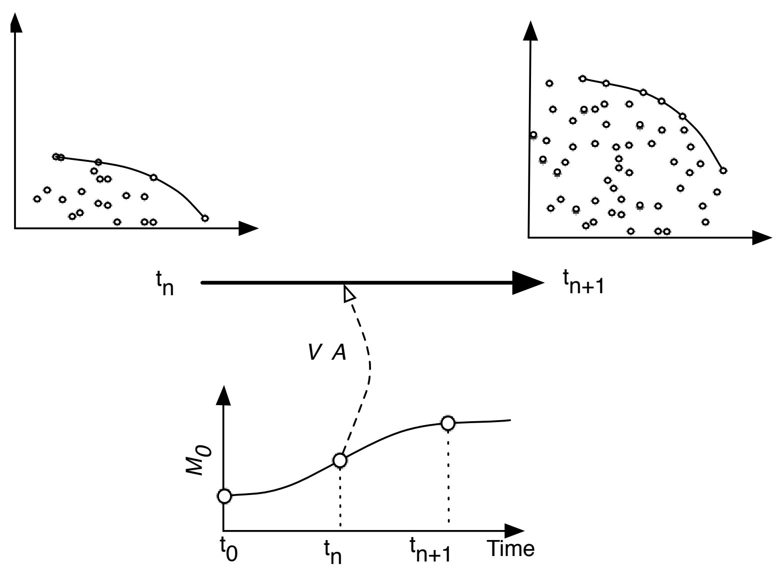

Figure 7. Pareto Frontier Shifting under Simple Model

At time t_0, the 1st and 2nd derivatives are calculated from equations 7 and 8. The derivatives are substituted into equations 1 and 2. This implies that a point on the Pareto frontier has the same velocity in the X direction as it does in the Y direction. Applying equations 1 and 2 to every point on the Pareto frontier gives the locations of the points on the Pareto frontier at time t_1. The process repeats, iterating in time to define the Pareto frontiers at every time step.

The advantages to the simple technology modeling technique are that there are only two uncertain parameters, and Pareto frontier motion is simplified by applying the same motion to all axes of the Pareto frontier. This simplification is applicable in certain circumstances requiring speed or when extensive evolution information is lacking. If the modeler does not wish to assume that the Pareto frontier moves identically in each attribute, he or she can apply the more sophisticated method presented in the next subsection.

There are some implicit assumptions in the simple evolution modeling technique. The technique explicitly assumes that a single S-curve describes evolution in multiple attributes. Because of this, the Pareto frontier translates through the attribute space. Since the Pareto only translates, it does not change shape or curvature. Since the curvature is maintained, the Pareto frontier points do not converge to a Utopia point. These assumptions do not perfectly reflect what one would expect to occur as a technology evolves. While these assumptions limit the sophistication of the modeling, they enable the user to provide less initial information. The sophisticated evolution modeling technique presented in the next subsection has less implicit assumption at the expense of requiring more initial information from the user.

3.2. Sophisticated Technology Evolution Modeling

The sophisticated technology evolution modeling technique follows the simple technique with a few modifications. In this technique, a number of S-curves describe the motion of the Pareto frontier rather than a single S-curve describing the evolution as a whole. Instead, each S-curve independently describes the motion of the Pareto Optimal set along one axis in the attribute space. This is a more powerful and more complete method because it gives the modeler greater flexibility in manipulating the evolution of the performance of a technology across multiple attributes.

There are more flexible S-curves available than the logistic curve used in the simple modeling technique. The Erto-Lanzotti equation is used here for the sophisticated modeling technique because of its flexibility while having less parameters than other flexible S-curves. Additionally, Nieto and D'Avino have concluded that the Erto-Lanzotti S-curve model best represents the evolution of technology performance [10, 30]. D'Avino specifically recommends the Erto-Lanzotti model based on goodness of fit to multiple sets of data for evolving technologies including turbine and piston aircraft engines, and digital signal processors [10].

While other S-curves were created for reasons like describing the growth of population or through statistics, the Erto-Lanzotti equation was formulated for the purpose of describing the evolution of technology. The general form of the Erto-Lanzotti equation is

$$P(t) = P_0 + \left(1 - e^{-kt^s}\right)(P_{lim} - P_o). \tag{9}$$

The performance of one attribute is a function of time. The parameters are P_{lim}, P_o, k, and s. The parameters P_o and P_{lim} are the initial and final limit of performance of an attribute of a technology. The initial performance is the current performance as viewed from the current point in time. The performance limit is the maximum limit that the performance can ever achieve, which is generally tied to a physical or theoretical limit. The remaining parameters, k and s, are not connected to any significant phenomena. Thus, they are difficult to elicit from a user.

To aid in eliciting the parameters of the Erto-Lanzotti equation, the parameter, t^*, inflection point time is introduced. The inflection point time is the time where the curvature of the S-curve is zero and the derivative is maximum. In addition, the performance when the technology reaches its inflection, P_{t^*}, is another parameter. The Erto-Lanzotti S-curve is fully defined by four parameters; P_{lim}, P_o, t^*, and P_{t^*}. The performance at the inflection point is

$$P_{t^*} = P(t^*) = P_0 + \left(1 - e^{\frac{1-S}{S}}\right)(P_{lim} - P_o). \tag{10}$$

Which is solved for S,

$$S = \frac{1}{\ln\left(\frac{P_{t^*} - P_{lim}}{P_o - P_{lim}}\right) + 1}. \tag{11}$$

The parameter *S* is substituted into

$$k = \frac{S-1}{St^{*S}} \tag{12}$$

to find k. The parameters *k* and *s*, now in terms of t^* and P_{t^*}, are substituted into equation 9. Figure 8 illustrates the Erto-Lanzotti S-curve and its parameters.

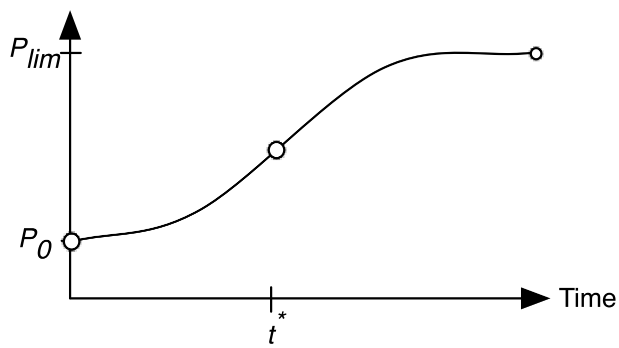

Figure 8. ***Erto-Lanzotti S-Curve***

In the decision making process, the evolution of technology is simulated discretely through time. The sophisticated technology evolution modeling technique uses multiple S-curves to describe points on the Pareto frontier moving along each axis independently. If the Pareto has two attributes, thus two independent axes, there are two S-curves. The Pareto frontier moves following equations 1 and 2. The derivatives, in terms of *k* and *s*, of an Erto-Lanzotti S-curve are

$$\frac{dP}{dt} = (P_{lim} - P_0)\frac{kst^{s-1}}{e^{kt^s}} \tag{13}$$

$$\frac{d^2P}{dt^2} = \frac{(P_{lim}-P_0)}{e^{kt^s}}\left((s-1)kst^{s-2} - k^2s^2t^{2s-2}\right). \tag{14}$$

To move the Pareto frontier, the modeler first takes the 1st and 2nd derivatives of each S-curve at time t_0. The 1st and 2nd derivatives of the S-curve describing the motion of the Pareto frontier along the X direction are a_{xn} and v_{xn}, the velocity and acceleration of a point in the X direction. Similarly, taking the 1st and 2nd derivatives of the S-curve describing motion in the Y direction gives the velocity and acceleration in the Y direction. The derivatives from equations 13 and 14 are applied in equations 1 and 2 to every point on the Pareto frontier to find the locations at time t_1. The simulation iterates over time giving the location of the Pareto frontier at every time step.

Figure 9 shows the movement of a Pareto frontier with two attributes moving from time t_n to time t_o. The S-curve on the left of figure 9 controls movement of the Pareto frontier in the X direction while the S-curve on the right controls the movement of the Pareto frontier in the Y direction. The derivatives of the two curves define the movement through the equations 1 and which approximate movement through attribute space.

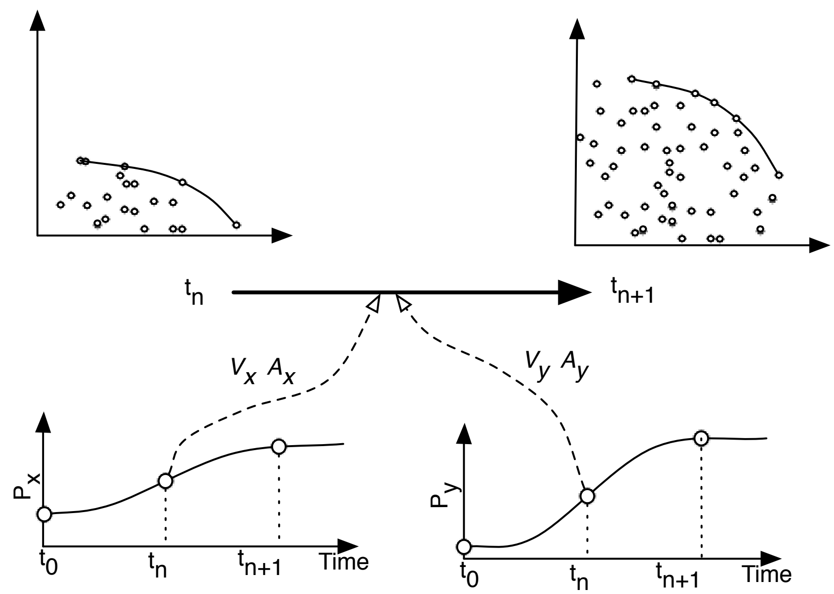

Figure 9. Pareto Frontier Shifting under Sophisticated Model

The sophisticated technology modeling technique differs from the simplified technique in the number of S-curves required and the type of S-curve. If one were to replace the Erto-Lanzotti S-curve with the logistic S-curve and create identical S-curves for each axis, the two techniques would be identical. The simplified modeling technique is a special case of the sophisticated technique.

The advantage of using a more powerful S-curve and using multiple S-curves is that the user has greater control over the model. Since no symmetry between dimensions is assumed, the Pareto frontier can flatten, stretch, or dilate as it evolves. One disadvantage is in the greater number of uncertain parameters required. The sophisticated technique requires four parameters per dimension, rather than two total for the simple technique. The increase in the number of parameters leads to much greater computational burden when applied to decision-making under uncertainty.

The sophisticated evolution modeling technique makes a few implicit assumptions. The explicit assumption is that one S-curve describes the motion of all points on the Pareto frontier in one direction. There is one S-curve for each independent axis of the Pareto frontier, or one for each independent performance attribute. It is assumed that all points move in the X direction with the same velocity and acceleration. Similarly the points on the Pareto frontier move in the Y direction with the same velocity and acceleration. However, the points do not necessarily have the same velocity and acceleration in X direction as they do in the Y direction. Moving identically in all directions is an implicit assumption of the simple evolution modeling technique, but not of the sophisticated technique. This means that the Pareto frontier translates in attribute space, but moves with different velocity and acceleration in each direction. Since the Pareto frontier only translates, the curvature and shape is preserved. Since shape is maintained, the points do not migrate to a utopia point. While these assumptions limit evolution modeling, they reduce the amount of information that user provides to define the evolution. The user is free to make modeling assumptions under the general depending on how much the user chooses to take on.

4. METHODOLOGY

The methods presented here involve technology evolution modeling using S-curves and Pareto frontiers in combination with a Monte Carlo simulation and models or simulations of the item being designed. A Monte Carlo simulation provides a method to analyze the effects of uncertainty in the technology evolution modeling process. The decision-making process proceeds as a simulation of the events that unfold over time as the technology or technologies evolve. The decision is made on the basis of expected utility.

Two distinct decision making methods, operating similarly but supporting decision making in different ways, are presented in this section. In the first method, the decision maker selects between two or more simultaneously evolving technologies. It is difficult to select between two simultaneously evolving technologies because the future performance levels are highly uncertain. The first method presented in this section support making a decision under uncertainty. In the second method, the decision maker uses a parametric study to explore what evolutionary behavior is required for one technology to be preferable to another. Demonstrations of the methods will follow in the next section. This section begins by explain the propagation of uncertainty through the decision making process. The following subsections explain the technology selection decision method and the parametric decision method.

4.1. Analyzing Uncertainty in Technology Evolution

The effects of uncertainty of the evolution of technology in decision-making are analyzed through a Monte Carlo simulation. The decision-making methods use simulations of events unfolding over time based on the uncertain technology evolution models. The user first defines the random distributions of parameters reflecting the uncertain expectations of technology evolution. The Monte Carlo simulation consists of a series of runs, each beginning with S curves defined by a set of parameters. The parameters defining the S-curves are realizations of the probability distributions of the uncertain parameters. Within each run, there is a simulation over time of the movement of the Pareto frontier, the design decisions that occur, and the payout received due to the design. Uncertainty is propagated through the decision process differently for the simple and sophisticated technology evolution modeling techniques. The following subsections will describe the propagation of uncertainty for each technique.

4.1.1. Uncertainty Propagation with Simple Evolution

This subsection describes the propagation of uncertainty built on the simple technology evolution modeling technique. The user first defines the distributions of uncertain parameters. If one uses the simple technology evolution modeling technique, the uncertain parameters are the slope coefficient, c, and the initial maturity, M_o. The user defines a mean and standard deviation for each of the parameters. Since there is one S-curve with two uncertain parameters, there are two distributions. The distributions appear at the top of Figure 10. A point is randomly sampled from each of the distributions and an S-curve is constructed according to equation 6. The distributions are sampled a number of times, and a family of S-curves is produced. The family of S-curves is illustrated in the 2nd box from the top in Figure 10.

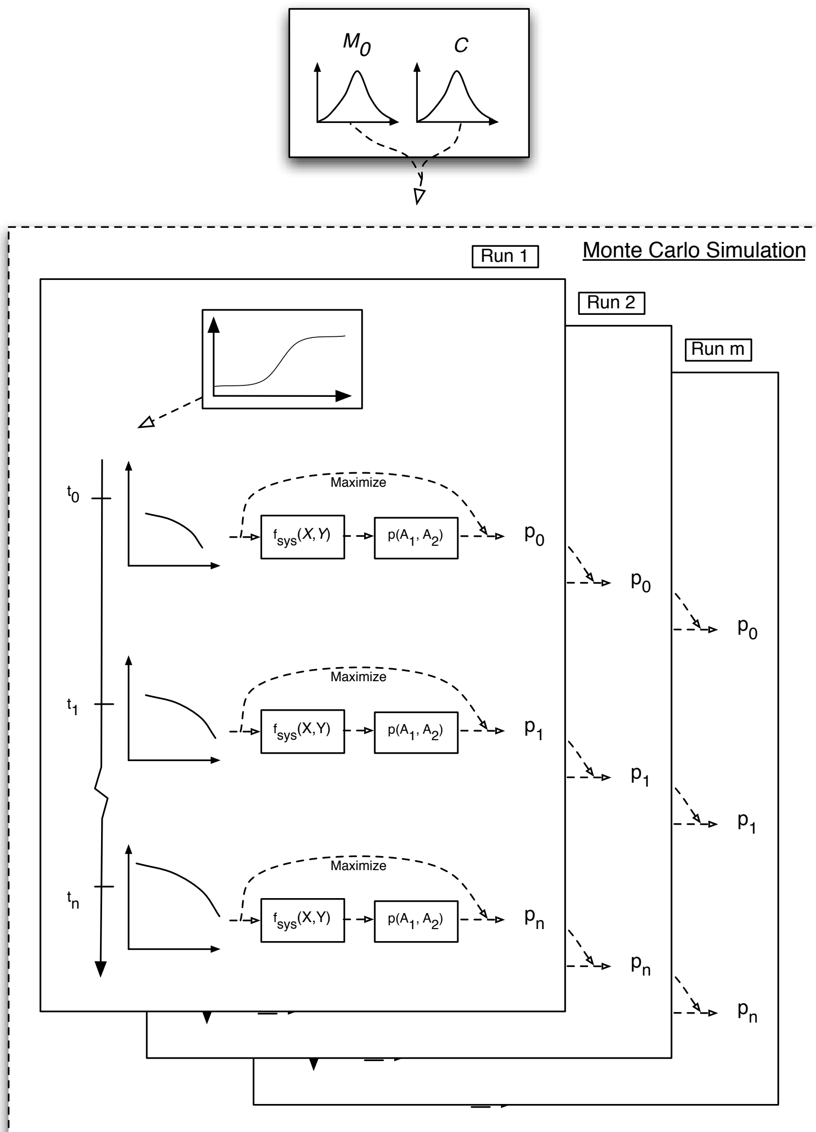

Figure 10. Propagation of Uncertainty- Simple Evolution

The Monte Carlo simulation proceeds as a series of identical runs each seeded with one of the S-curves from the family. Within each run the series of events, such as the technology evolving, designing the product, and receiving a payout, is simulated through time. One run of the Monte Carlo simulation takes place for each unique S-curve in the S-curve family.

At the beginning of a Monte Carlo run, one S-curve is taken from the family of S-curves. At every time step, the designer or firm selects among the points on the Pareto frontier. The designer selects the point on the Pareto frontier that maximizes the payout that will be given to the firm as a result of designing and producing a product using that instance of the technology. Using this instance of the technology under consideration and its associated performance taken from the Pareto frontier, a simulation or model maps the design variables to the system-level attributes. Based on the system-level attributes, the payout function gives the payout received by the firm based on the design. These steps are consistent with a rational design decision-making process.

The time simulation iterates to the next time step, a new Pareto frontier is determined, and the process is repeated. The result is a series of chronological payouts that resulted from the events occurring due to the evolution of technology dictated by the S-curve. The Monte Carlo runs repeat, each seeded by a new S-curve taken from the family of S-curves until all have been tested. The end result of the Monte Carlo simulation is a chronological series of payout for each Monte Carlo run. As the Monte Carlo simulation produces a very large array of data, it is not in a form that allows the user to easily make a decision by comparison to another technology. Section 4.2 outlines how a decision is made using the payout series that come out of the Monte Carlo simulation.

4.1.2. Uncertainty Propagation with Sophisticated Evolution

The propagation of uncertainty through the decision process using the sophisticated technology evolution modeling technique is similar to propagation of uncertainty with the simple technique. The key difference is in how the S-curves seed the Monte Carlo simulations. The differences between the simple and sophisticated technology evolution modeling techniques are in the number of S-curves used, how they control the movement of the Pareto frontier, modeling underlying the S-curve behavior. The sophisticated technique has one S-curve per dimension of the Pareto frontier. Figure 11 shows the propagation of uncertainty in decision-making using the sophisticated technology evolution technique for a Pareto frontier that has two dimensions. Thus is has two S-curves.

The Erto-Lanzotti S-curve is in terms of performance of an attribute as a function of time. It has four parameters, P_{lim}, P_o, t^*, and P_{t*}, of which P_{lim}, P_o, and t^* are uncertain. The user creates the three distributions of uncertain parameters for each S-curve, as shown at the top of Figure 11. The parameter initial performance, P_o, is known directly from the Pareto frontier at the first year. The initial performance is the maximum value of an attribute from any point. For example, looking at the Pareto frontier in Figure 2, more of both attributes X and Y are preferred. The initial performance parameter, P_0, for the S-curve in the X direction is the greatest value of X that any point holds, which is the same as the X coordinate of the farthest right point on the frontier. Similarly the initial performance parameter, P_0, for the S-curve in the Y direction is the greatest value in the Y that any point holds, which is the same as the Y coordinate of the highest point on the Pareto frontier.

To begin the decision-making, the user creates the Pareto frontier at the current time, t_o. The user then assigns mean and standard deviation value for each of the three uncertain parameters for each of the S-curves. The Pareto frontier appearing next to the timeline within each run in Figure 11 has 2 dimensions, X and Y, thus there are two S-curves, each with three uncertain parameters. The user assigns the mean and standard deviation for each of the six total unknown parameters, as shown at the top of Figure 10.

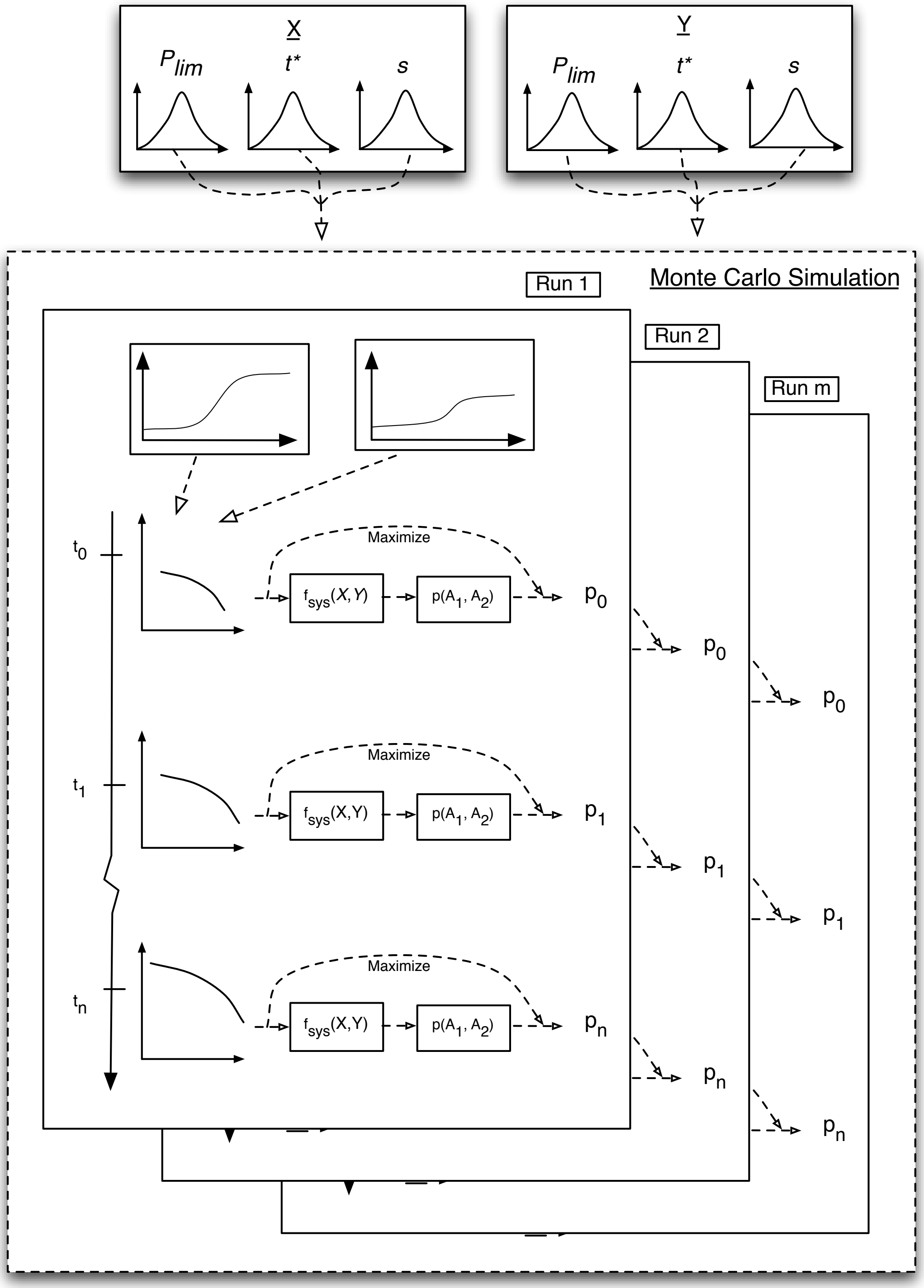

Figure 11. Propagation of Uncertainty- Sophisticated Evolution

The distributions for one S-curve are sampled, taking a parameter value from each of the distributions. An S-curve is created according to equation 10. The distributions for the other dimension are sampled, and an S-curve is created. The sampling is repeated, creating a large family of S-curves for each dimension of the Pareto frontier. From there, the Monte Carlo simulation consisting of a series of identical runs seeded with the randomly generated S-curves begins. Every Monte Carlo run begins with the S-curves taken from the families of S-curves and the Pareto frontier at the current time. Within a Monte Carlo run, a time-based simulation occurring at fixed time intervals simulates the evolution of technology, the design process, and the payout received. The time-based simulation and design process involving selecting a point on the Pareto frontier to maximize payout occurs the same as with the simple technology evolution modeling. The evolution of technology follows the sophisticated technique where each S-curve describes the motion of points along one axis of the Pareto frontier. The result of the time simulation is a series of chronological payouts. The result of the Monte Carlo simulation is collection of payout series.

4.2. Selecting Alternatives from a Monte Carlo Simulation

This subsection details the first method, selecting between two or more mutually exclusive technologies. This method builds on the propagation of uncertainty as described in the previous subsection. When dealing with technologies that evolve, it is very difficult to decide between technologies due to the greater uncertainty in the future performance. The method presented here allows the decision-maker to directly compare alternatives given the means and standard deviation that define the S-curve parameters. The decision maker selects the alternative with the greatest expected utility.

Figure 12 shows the process of finding the expected utility of a technology from the set of payout series resulting from the Monte Carlo simulation. The payout series appearing within each Monte Carlo run in Figure 12 are taken from the Monte Carlo runs shown in Figures 10 or 11, depending on the modeling technique used. The value of payout to the decision maker is not necessarily equal at all times. For example, if the payout is in monetary units, a decision maker typically will account for the time value of money through use of a discount factor [31, 32].

Within one run of the Monte Carlo simulation having a series of payout, the discount function converts all payout values to a common time base at the first year. Since the payouts are all now equivalent, they can be average to find a payout that that represents the mean effective payout of that Monte Carlo run. The process of applying the discount function and finding the average payout repeats for every Monte Carlo run. Moving up in Figure 12, the average payout from every Monte Carlo run is aggregated into a single payout distribution. The Payout distribution has one point for every Monte Carlo run.

A utility function, which expresses the users risk attitude and preference for payout, maps the payout to a utility distribution. The expected utility, which is the average of the distribution, is a scalar number expressing the worthiness of the alternative in the decision.

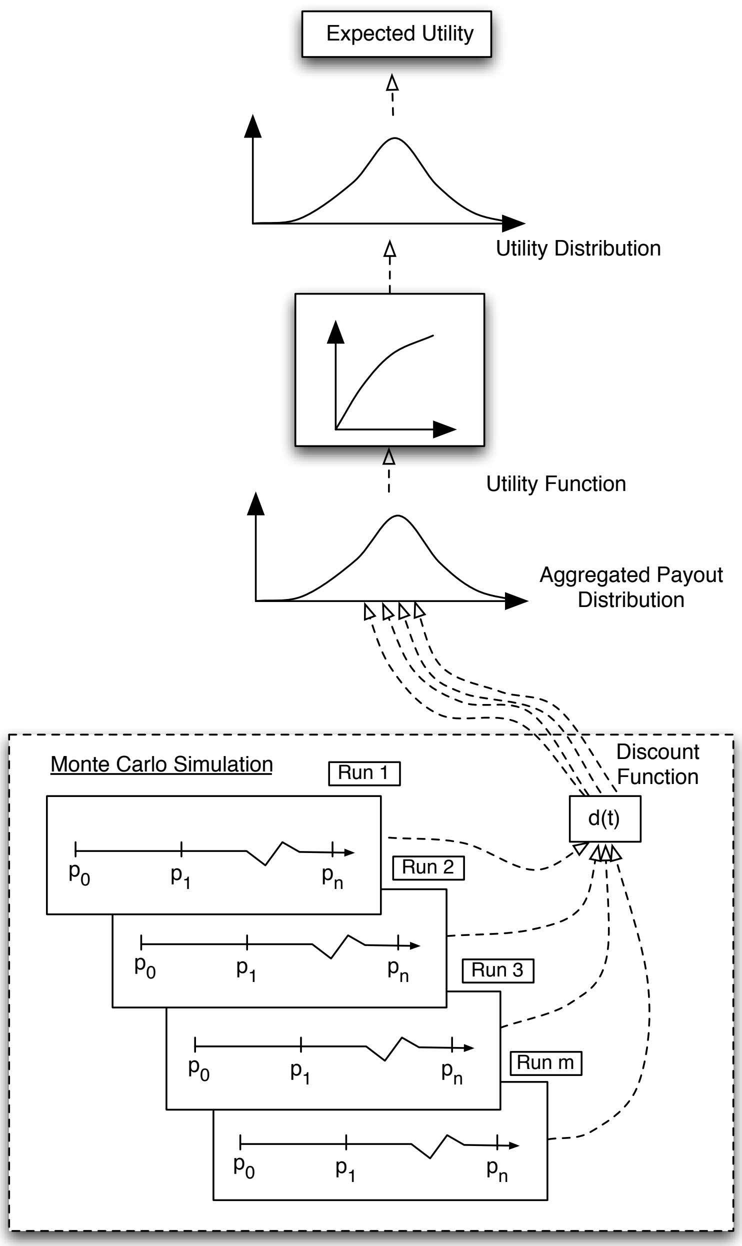

Figure 12. Finding Expected Utility of Payout

Expected utility is a scalar that allows the decision maker to compare alternatives with uncertain consequences due to evolution on a common scale. Figure 13 illustrates the final decision process for the case of two technological alternatives. The decision maker selects the technology that delivers the greatest expected utility under the specified conditions. The outcome of the decision is dependent on the S-curve parameters and standard deviations applied at the beginning of the analysis.

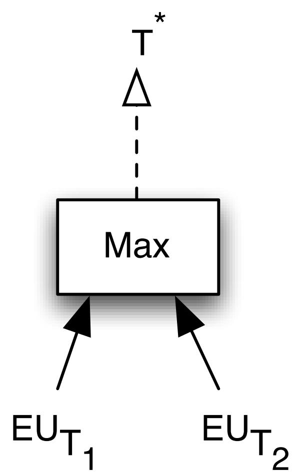

Figure 13. Selecting Among Alternatives

4.3. Parametric Study Method

The method technology selection method is useful for directly comparing alternatives when the user fully defines all the needed S-curve parameters. However, it can be informative to "invert" the decision in order to develop a better understanding of the problem. For example, instead of asking "Which technology, A or B, is preferred?"

given certain information or beliefs about how the technologies are likely to evolve, one could ask “What evolution of Technology A leads to it being more preferred than Technology B?” Using this reformulation of the problem, decision makers can explore how different probability distributions for the various S-curve parameters impact the decision problem. The results of this study can be useful for guiding information-gathering efforts. Organizations can direct their limited resources toward understanding or affecting the S-curve parameters that matter most in their decision problem. A key motivation for conducting a parameter study is to help determine whether it would be worthwhile to gather more information about one or more of the S-curve parameters for a particular technology.

The parametric study method holds the parameters of one technology’s S-curve fixed while the search is performed over the probability distribution parameters for the S-curve of the alternative technology. If the distributions for the S-curve properties have two parameters, mean and standard deviation, the resulting parametric study is defined over a six-dimensional search space. One divides this space into a sample grid and evaluates the expected utility of the technology at each sample vector using a method described in 4.1.1 or 4.1.2.

5. DEMONSTRATION OF METHODS

This section provides demonstrations of the methods presented in section 4, applying the evolution modeling techniques in section 3. The demonstrations show how the methods are applied in real world scenarios involving technologies that are currently evolving. The first scenario is that of an automotive company wishing to enter the electric vehicle market. The hypothetical firm is deciding which of three battery technologies to commit to for use in their future line of electric vehicles. This scenario demonstrates the technology selection method with simple technology evolution modeling. The second scenario is that of a startup utility company investigating wind turbine technology. To demonstrate the technology selection method using sophisticated evolution modeling, the company investigates weather to invest in land based or offshore wind turbines. To demonstrate the parametric study, the firm investigates what evolution needs to occur for offshore wind turbines to be preferable to land based.

5.1. Selecting Automotive Batteries with Simple Evolution Modeling

The selection of batteries for use in the design of a line of electric vehicles demonstrates the methods presented in section 4.1.1 and 4.2. In this scenario, an automotive firm is investigating three candidate battery technologies with similar current performance, denoted battery technologies 1, 2, and 3, for use in their future line of electric cars. The firm is a major automotive manufacturer entering into the electric vehicle market for the first time. They are designing their first electric vehicle model, which will be updated annually with new batteries as they are released. Due to the battery supplier contracts, and tooling expenses, the firm must select one battery technology at the outset of the project and continue with it for the duration. At the current time, one battery technology is most preferred, but over the lifetime of the vehicle line, one battery technology may surpass the others.

5.1.1. Scenario Background

The firm uses the simple technology evolution modeling approach to support the battery technology selection decision. The simple technique is preferred due to the greater number of alternatives evaluated and the large computational burden associated with evaluated the electric vehicle model. Since there are few uncertain parameters associated with using a simpler S-curve, the computational burden is also reduced. There are a few questions to answer regarding the technology selection. What is the best battery technology to select over right now, over a 5-year horizon, over a 15-year horizon? How much advantage is there in choosing one battery technology over another? For how many more years will the currently leading technology remain the leader?

The hypothetical Pareto frontiers of the candidate battery technologies available when this decision is being analyzed are presented in Figure 14. The firm is deciding between three similar batteries with slightly different chemistries, packaging design, and safety features that affect the performance of the battery. The batteries are manufactured by competing companies, but have similar performance at the current time. The performance attributes of concern to the designers are power density and energy density. There are a great number of other important battery performance characteristics including safety, life cycle, and thermal properties, but those are secondary to energy and power requirements and not included in this demonstration. Examining Figure 14, it is clear that battery type 2 is the current best technology. However, the firm anticipates that battery type 2 will be surpassed by one of the other types at an unknown point in the future.

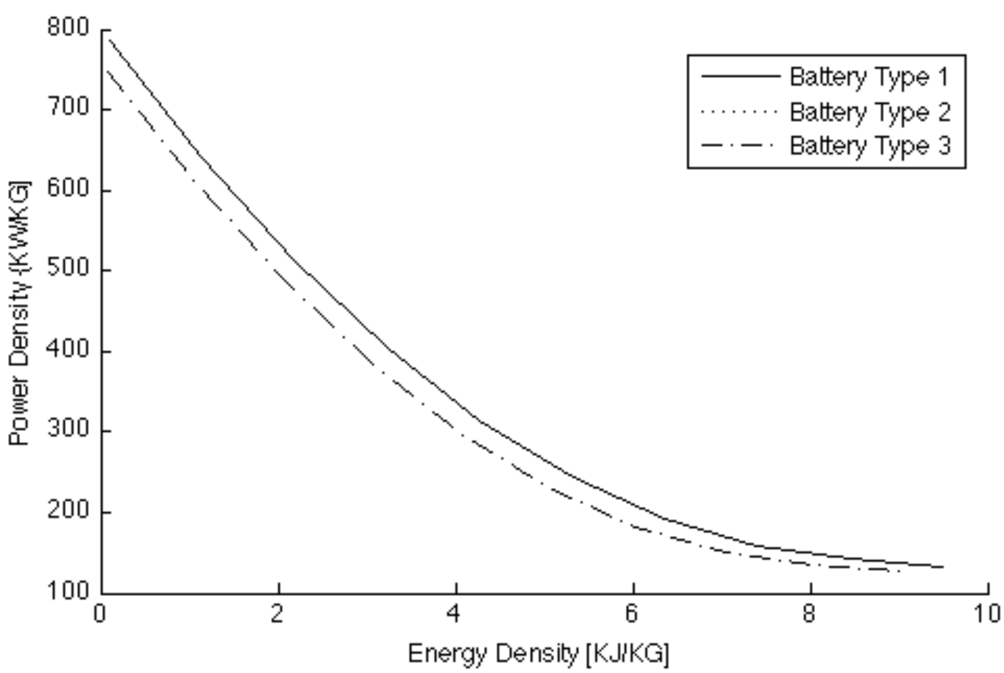

Figure 14. Pareto Frontiers of Electric Vehicle Scenario

5.1.2. Demonstration of Method

The parameters and uncertainty values in Table 2 describe the firm's beliefs about the evolution of the candidate technologies. A set of randomly distributed variables is created using Latin Hypercube sampling. A pair of random slope coefficient and initial maturity variables is used in equations 5 and 6 to create a random S-curve. The resulting nominal S-curves, those created from the mean values, are shown in Figure 15. The figure shows only the portion of the S-curve that lies within the planning period, so the tails are clipped. Looking at Figure 15, it is intuitive that either battery type 2 or battery type 3 will surpass the current leader. However, it is difficult to intuitively know when or by how much the new leader will surpass the old without a simulation of the events. Consequently, a best decision is not clear either.

Table 2. Electric Vehicle Scenario S-Curve Parameters

Battery Type:		*1*	*2*	*3*
Slope Coefficient	μ	1.00	1.00	0.70
	σ	0.15	0.15	0.15
Initial Maturity	μ	0.90	0.20	0.20
	σ	0.05	0.05	0.05

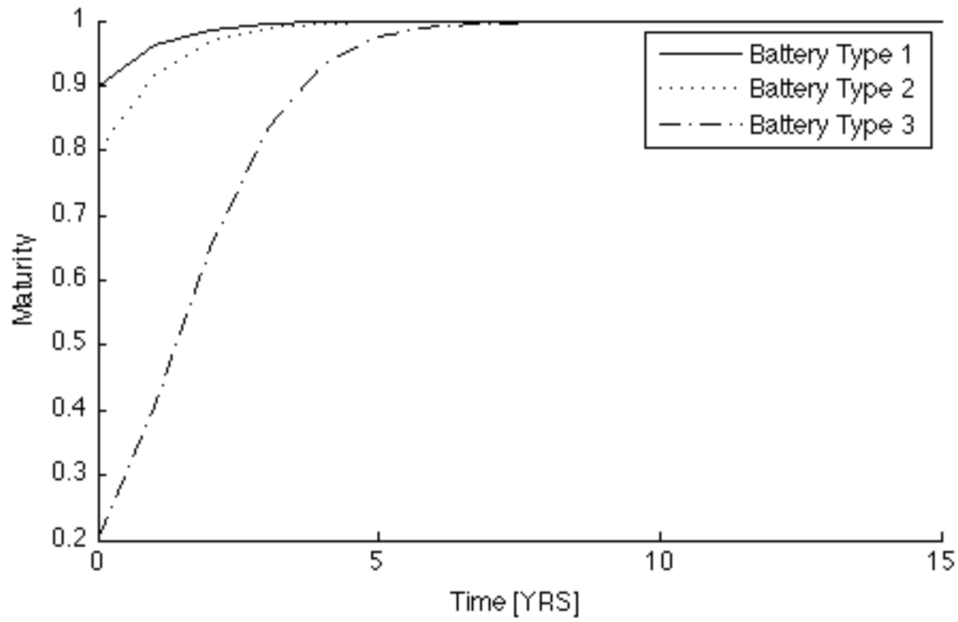

Figure 15. Electric Vehicle Scenario S-Curves

A behavioral model of the electric vehicle is used to determine the performance attributes from the design variables. In this behavioral model, the design variables are the battery power, energy, mass, and cost. Additional constants, such as motor efficiency, regenerative braking efficiency, base vehicle mass and cost, rolling resistance, drag coefficient, and more are used. The design variables are generated by selecting a point on the Pareto frontier and a battery mass. Figure 16 details how the behavioral model uses the design variables to create the vehicle attributes. The behavioral model delivers the performance attributes: range, cost, acceleration time, and top speed. In the behavioral model, the car drives the Environmental Agency (EPA) highway and City driving cycles once each [33, 34]. The range in each event is extrapolated from the change in energy during the event assuming that the battery is depleted at 20% state of charge. The reported range is the average of highway and city range. The vehicle also does full power acceleration from a stand still for 1 minute. The acceleration time is the time it takes to reach 100 km/hr and the top speed is the speed at the end of the test. The cost of the vehicle is the cost of the base vehicle plus the additional cost of the battery pack, which depends on the optimum battery pack mass. The variables battery pack mass and cost, while generally desirable quantities, are not included in the Pareto frontier because decreasing them may lead to a low power or low range car which is less desirable than a high power, faster one. The design variables are optimized to find the design with the most valuable performance attributes. The behavioral model in Figure 16 is function, $f_{sys}(x,y)$ in Figure 10, where X and Y are the design variables energy density and power density. The simulation of the system is similar to a Pareto frontier based design decision study of personal electric vehicles [35].

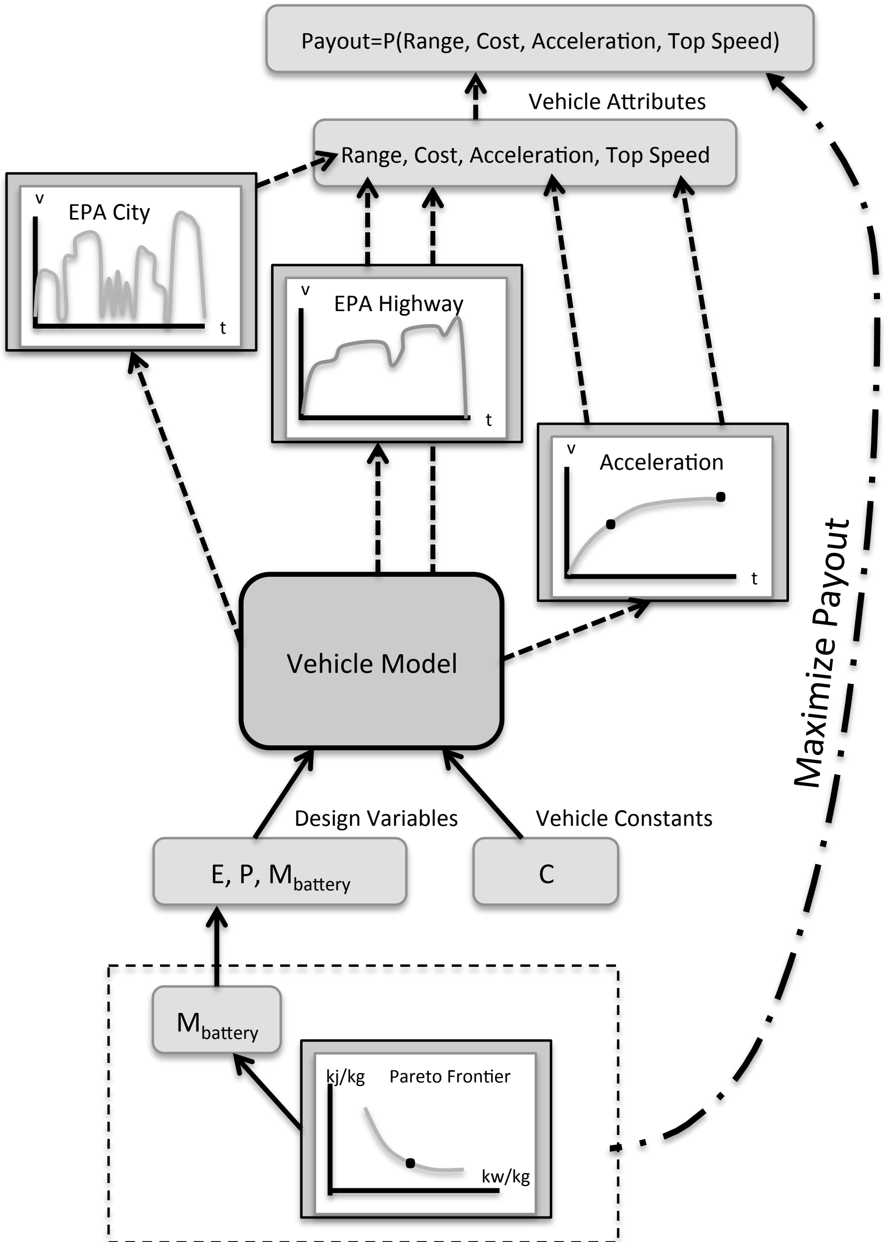

Figure 16. ***Electric Vehicle Simulation***

Building on the initial Pareto frontiers of current battery technology, the S-curve parameters, and the behavioral model, designers follow the methods presented in 4.1.2

and 4.2 to support the decision of which battery technology to choose. A step-by step explanation of the process follows.

Using the S-curve parameters listed in Table 2, a set of randomly sampled variables is created using Latin hypercube. A Monte Carlo simulation is started. Each Monte Carlo run tests one S-curve that is generated by a pair of parameters: slope coefficient and initial maturity.

At the first time period, the company designs the car using the batteries that are available to them; a point on the Pareto frontier. The payout is maximized by selecting the point on the trade off curve that, in combination with the constant vehicle parameters and the mass variable, gives the greatest payout. The behavioral model evaluates the vehicle attributes due to the design variables. A payout function transforms the vehicle attributes into a payout that the company receives at that time period. This process follows Figure 16. The payout is the value, monetary or otherwise, that the company receives for the design at that year. In general, the company receives the most payout for designing and delivering a vehicle that best meets the preferences of the customers and the company. In Figure 10, this is the payout, P_o, due to the design at time t_1.

The payout function used in this example is a simple expression giving an arbitrary measure of how much payout the company gets from the attributes. Equation 15 is the payout function used in this case study. The vehicle attributes are top speed, 0-100 km/hr acceleration time, driving range, and cost in units of m/s, seconds, kilometers, and dollars. The expression gives a payout of 1 for a very high performance car and 0 for a car that provides no payout at all. Minimizing acceleration time and maximizing the other vehicle attributes increases payout.

$$P = \frac{1}{4}\left(\frac{top\_speed}{55.5} + \frac{33 - accel\_time}{30} + \frac{range}{100} + \frac{40000 - cost}{40000}\right) \qquad (15)$$

The process repeats, moving ahead one year. At time t_2, the company does a minor redesign of the vehicle, selecting the optimal battery pack mass and optimal point on the Pareto frontier. However, over the year that has passed, the performance of the batteries has evolved, shifting the Pareto frontier. Using the S-curve and equations 1, 2, 7 and 8 the Pareto frontier is shifted as shown in Figure 2. The batteries available for use in the design are present on the new Pareto frontier. Again, the design is optimized and the company receives a payout as shown in Figure 16. This process of shifting the frontier, optimizing the design, and receiving a payout is repeated annually for the length of the program life.

Once the end of the program lifecycle is reached, the payout received at each time period is transformed by the discount factor and then aggregated. In this simplified example, the discount factor is 1, which means that the present value of a payout is equal to its future value. If the payout were in monetary terms, it is analogous to assuming that the future value is not discounted. Within each Monte Carlo run, the payout over the entire program lifecycle is averaged into a single value, which tells how much payout, in present value, the company anticipates receiving over the planning period from this battery technology following the assumptions made. The average payout values from each Monte Carlo run are aggregated into a payout distribution. In the case where the discount function is 1, the aggregation is simply the sum of all the payouts received. In this simplified example, 50 Monte Carlo runs of the previous process were completed, giving a distribution of the aggregated payout. However, thousands of samples are needed to get a significant distribution. For the purposes of demonstration, 50 samples are sufficient. Continuing vertically in Figure 12, a utility function is applied to the aggregated payout distribution. The utility function expresses the users' attitude toward risk. It is applied to payout from the Monte Carlo simulation expressing the firms' preference for uncertainty in payout.

All of the previous steps are repeated for each candidate technology using their corresponding initial Pareto frontiers and S-curves. The result of performing all the previous steps is a distribution of utility for each candidate battery technology. At this point in the decision making process, there are a number of utility distributions. In order to make a decision, the company needs a better way to compare the technologies. The mathematical expectation of the utility distributions is found. This gives a scalar value that is easy to compare. In this case, the expectation is the average of all the samples in the utility distribution. The decision is to choose the battery technology that has the greatest expected utility, as shown in Figure 13. In this case study, the process of making the decision was repeated over a range of program lifecycles from zero to fifteen years with annual redesign periods. The results of this study follow.

5.1.3. Results and Discussion

The decision is simulated using the presented method. At the beginning of the first time period, when the company is making the first update of the car, the best selection is battery type 2, with an expected utility of 1.59. Battery types 1 and 3 have expected utilities of 1.56 and 1.55. If the company looks only at the present performance of battery technologies, neglecting the anticipated evolution inherent in the decision, battery type 2 is the obvious choice. As shown in Figure 14, the Pareto frontier of battery type 2 dominates the others, leading to the same conclusion. This situation is analogous to a program lifecycle of 1 year. However, if the evolution models are included and the program lifecycle is extended, interesting results arise. Figure 17 shows the expected utility of each battery type as a function of the program lifecycle of the decision. The figure does not show which battery technology is instantaneously better at that point in time.

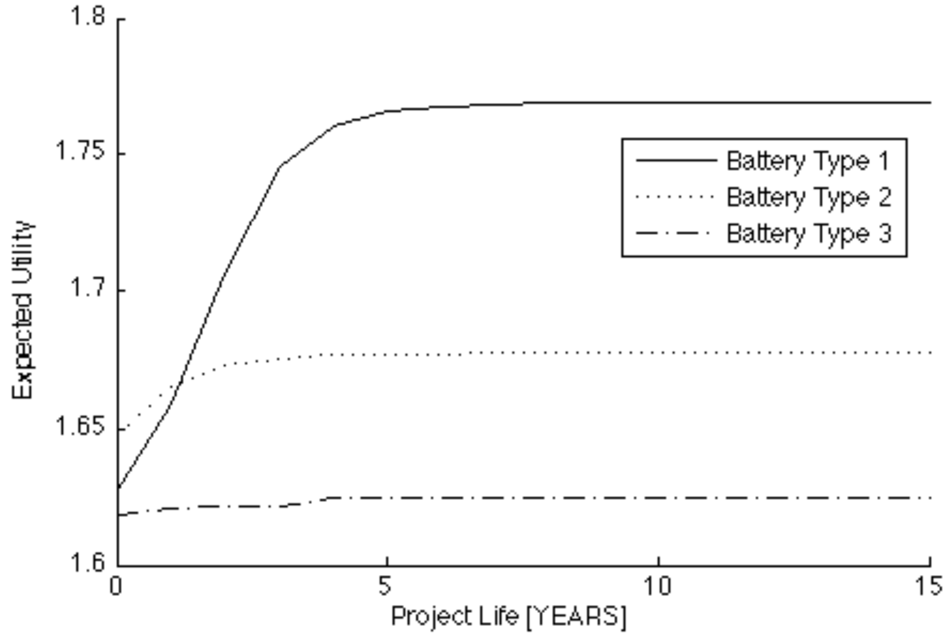

Figure 17. Electric Vehicle Scenario Decision over Time

If the program lifecycle is 15 years, battery type 3 is the best decision. Battery type 3 started with low performance but surpassed the others because it evolved much more. Another noteworthy point is that given a program lifecycle of 1 year, the firm is indifferent between battery types 3 and 1. Similarly, the company is indifferent between battery types 2 and 3 on a 5-year program lifecycle. If the program lifecycle is greater than 15 years, battery type 3 should be chosen. The time when two candidate battery technologies become indifferent is valuable because that information can support the related decision of when to invest or make a technology switch. For example, if the company was already established with battery type 2, this information supports the decision to maintain the current technology and delay switching. The results in figure 17 show that the technology preferred in the short run is not the technology preferred in the long run.

5.2. Selecting Wind Turbines with Sophisticated Evolution Modeling

As a demonstration of the technology selection method technology evolution, we consider a design scenario involving electricity generation from wind power. With the increasing demand for energy as well as increasing awareness about the environmental impact of traditional energy sources like coal or petroleum, wind power generation is becoming an increasingly important topic. Wind turbines can be located either on land or offshore. Due to very different operating conditions and engineering challenges, it is common to consider these as two distinct technologies. Although the United States possesses a great amount of unused offshore wind potential, offshore turbines are used less frequently due in part to greater costs and various engineering challenges [36]. However, wind speed is typically higher offshore, leading to greater energy generation possibilities [37]. As offshore power generation technology evolves relative to onshore technology, it may emerge as the superior alternative. The technology evolution modeling technique in section 3.2 will be applied in the decision method described by sections 4.1.2 and 4.2.

5.2.1. Scenario Background

Consider a hypothetical startup energy company based in Texas that will invest in wind power generation installations either onshore in north Texas or offshore in the Gulf of

Mexico. The firm faces the challenge to choose the type of wind power generation technology that will yield the greatest payoff over their 10 year planning horizon. After choosing whether to build onshore or offshore, they will start with one installation of the chosen type and expand annually. With each expansion, they will install the best equipment available on the market at that time. Thus, they stand to benefit from the evolution of the technology and the relative evolution of the two technologies is an important factor in their decision making process. Due to the limited resources, contract obligations, and great cost and effort to build transmission infrastructure, the firm does not consider choosing both an option. Furthermore, we presume the firm will not switch from one type of generation to the other after sinking cost and accumulating expertise in the type of system chosen at the outset.

Determination of the payout due to a wind turbine array is determined from only a few criteria calculated from the limited data available. The data used in this wind turbine example problem is from a database of 801 wind turbines available on the market including nominal power ratings, diameter, and in some cases, year introduced [38]. The dominant design variables of a power generating array are the nominal power and coefficient of power of the turbines. The firm believes that the performance of land-based and offshore wind turbines is evolving in terms of these two design variables. Figures 18 and 19 show the dominant performances of wind turbines as compiled from the database. Only wind turbines with release year data appear in the figures. The power values are the nominal power ratings coming directly from the database while the coefficient of power values are calculated from

$$C_p = \frac{Electrical\ power\ out}{Wind\ power\ in}. \quad (16)$$

The wind power available for harvesting by a wind turbine is a function of the wind speed, V, and the swept area of the blades, A_{swept}. Air density, ρ, is assumed 1.23 kg/m^3 in all cases. The wind power available to be consumed by a wind turbine is

$$P = \frac{1}{2} * \rho * A_{swept} * V^3. \quad (17)$$

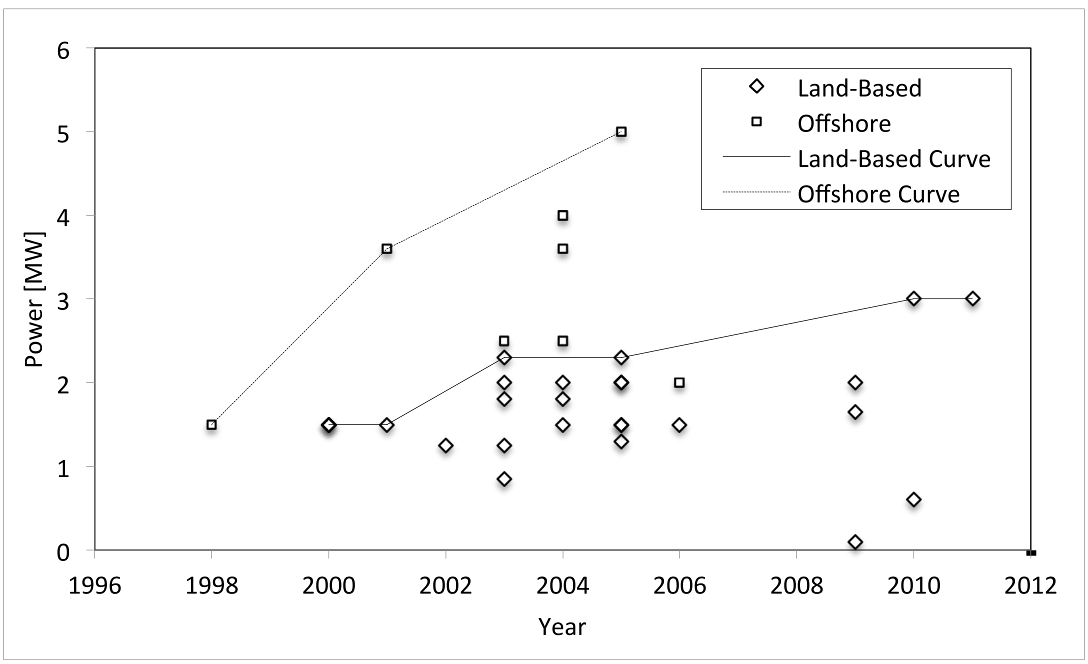

Figure 18. Wind Turbine Power Evolution

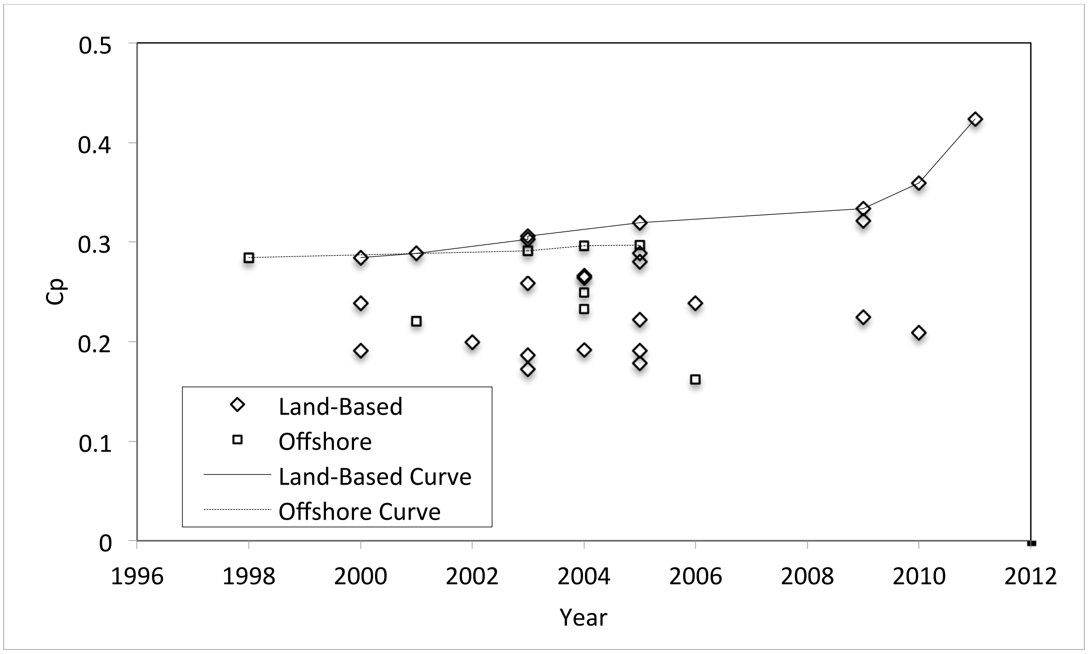

Figure 19. Wind Turbine Coefficient of Power Evolution

Figures 18 and 19 show that the coefficient of power and the nominal turbine power are evolving, and increasing, over time. Since the data is sparse, no strong conclusions can be drawn regarding how well the data fits to the S-curve shape. However, the firm uses the information gathered to assume that offshore wind turbines generally lead land-based in power and they generally have similar evolution in terms of coefficient of power.

To begin, the Pareto frontiers for land-based and offshore wind turbines are created from the database. The firm uses coefficient of power and nominal power as the criteria for selecting a wind turbine. Thus, nominal power and coefficient of power are the independent dimensions of the Pareto frontier. Other factors, such as cost, reliability, or voltage are important to real world decision-making, but are omitted in this demonstration. The points in Figure 20 are wind turbines currently on the market for which sufficient information could be found in the database to calculate coefficient of power and nominal power [38]. Since the designer always prefers more power and greater coefficient of power, the points in the upper right region of the plot are dominant. The Pareto frontier is the boundary line connecting the non-dominated points. The Pareto frontiers are sparse due to limited data. The points tend to be organized into columns arranged at whole and half Megawatt increments, as these are common design size classifications for wind turbines. The Pareto frontiers in Figure 20 are used as the Pareto frontiers at year 0 in the decision analysis.

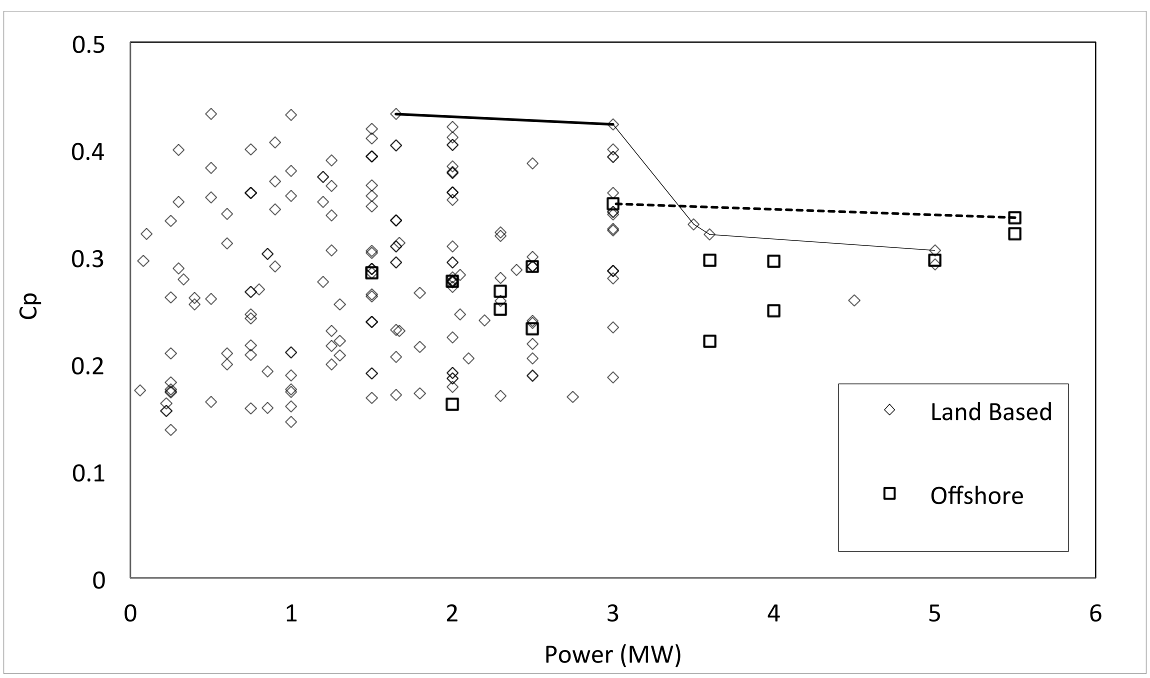

Figure 20. Wind Turbine Pareto Frontiers

5.2.2. Demonstration of Method

The firm chooses to use the sophisticated evolution modeling technique because of its flexibility greater power. Since the evaluation of designs through a simulation or system model is not computationally intensive, the increased computational burden of using the sophisticated technique is acceptable. Based on the current Pareto frontiers and previous evolution trends, the firm creates Table 3, which represents their beliefs about how the two technologies will evolve over time. The table lists the mean and standard deviation values of the parameters that fully define the technology evolution curves for power and coefficient of power. Figures 21 and 22 illustrate the nominal S-curves from Table 3.

Looking at Figure 18, the firm estimates that land-based wind turbines typically lead offshore turbines in power by approximately 2 years. They estimate the expected time at which inflection in the technology evolution curves, t^*, will occur at 5 years for offshore power and 3 years for land-based. By examining Figure 19, the coefficient of power evolves the same for both land-based and offshore wind turbine, so the inflection time will be 5 years for both onshore and land-based wind turbines. The performance limit for land-based wind turbines is based on the expected blade diameter limit of 125m due to transportation, installation, and material constraints. Since the current power level of land-based wind turbines is already near the expected limit, there is little expected advancement in power. However, the firm expects the evolution for both land-based and offshore wind turbines to be the same. The firm limits the coefficient of power evolution to 90% of the Betz limit. The initial performance parameters are taken directly from the Pareto frontiers. For example, the land-based coefficient of power, 0.433, is the greatest coefficient of power available in the current year for land-based turbines. The initial performance parameter is calculated directly from the initial Pareto frontiers. The initial performance for offshore power is the greatest power that any wind turbine on the current Pareto frontier has. The remaining initial performance parameters are found in the same manner.

Table 3. Wind Turbine Evolution Parameters

	Land-Based				Offshore			
	Power [MW]		C_p		*Power [MW]*		C_p	
Parameter	μ	σ	μ	σ	μ	σ	μ	σ
P_{lim}	5.75	0.30	0.49	0.02	17.50	0.50	0.49	0.02
P_o	5.00	N/A	0.43	N/A	5.50	N/A	0.35	N/A
P_{t*}	5.35	0.06	0.46	0.005	12.29	0.06	0.42	0.005
$t*$	3	0.1	5	0.25	5	0.25	5	0.25

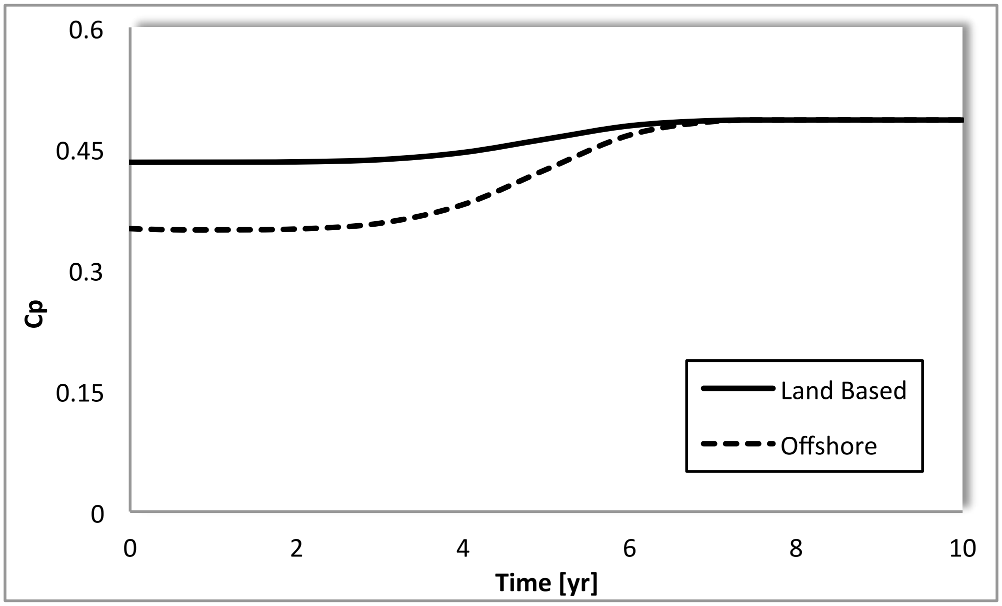

Figure 21. *Wind Turbine Coefficient of Power S-Curves*

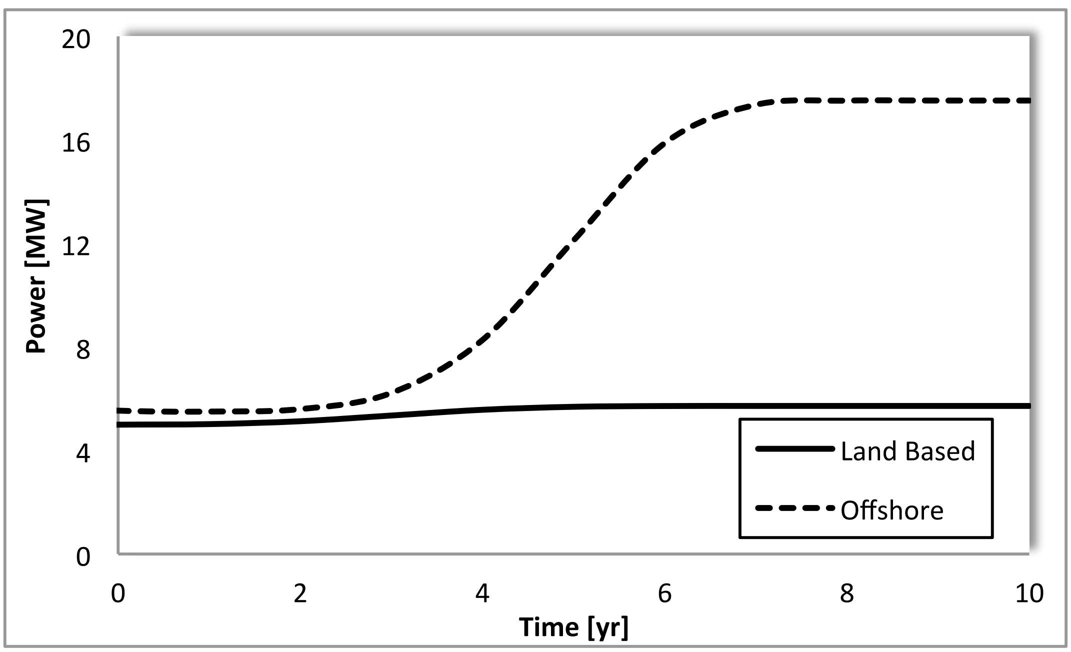

Figure 22. *Nominal Power Evolution Curves*

For the wind turbine example presented here, the system model is evaluated to find the system-level attributes of a complete wind turbine array. The system being designed is a wind turbine array containing equally spaced turbines on a 10km x 10km area. The system's design variables are power and coefficient of power. The significant system-level attributes of concern to the firm are the number of turbines populating the array and the total power produced by the array. Though there are many more attributes to consider in decision-making, the demonstration is limited to these few attributes. The number of wind turbines allowable over a given area is chosen such that only a certain amount of power is removed from the wind. The firm has set the limit that the array may remove 1 watt per square meter of land area. The number of turbines allowable in the array is given by:

$$N = \frac{P_{turbine}}{WPD * A_{array}}. \tag{18}$$

The land area of the array is given by A_{array}. $P_{turbine}$ is the wind power consumed by a single turbine at the average wind speed at the array location, and WPD is the 1 w/m^2 wind power density. Typically wind speeds are higher offshore than on land so the wind turbine power is greater for the same swept area. This term is also the denominator of the coefficient of power equation. The power of one wind turbine is calculated from equations 16 and 17 given the power and coefficient of power of a wind turbine existing on the Pareto frontier. The total power of the array is the nominal power of the turbine times the number of turbines in the array.

The firm desires to maximize the average power of the array in order to produce greater revenue. On the other hand, the firm desires to decrease the number of wind turbines in the array to limit the size of the required power transmission infrastructure and to decrease the number of components in the field requiring maintenance. Additionally, the penalty for the number of turbines in an array is greater offshore due to the greater expenses in constructing the infrastructure and performing repairs. In the analysis, the firm receives a payout each year from the installation of an array. The firm creates payout functions that express their preference for power and number of turbines. More sophisticated payout functions can be created, but for the purpose of providing an example, the following payout functions are used

$$P_{land} = \frac{(45-num)}{44} + \frac{1}{3} * power * 10^{-8} \text{ and} \tag{19}$$

$$P_{offshore} = \frac{(30-num)}{29} + \frac{1}{3} * power * 10^{-8}. \tag{20}$$

The analysis of the decision proceeds with the necessary input parameters and Pareto frontiers, and has created the required system model, payout function, and utility function. The procedure follows the method presented in sections 4.1.2 and 4.2. There is a Pareto frontier for each mutually exclusive alternative, land-based wind turbine technology and offshore wind turbine technology. The Pareto frontiers represent the design variables of the system, with power and coefficient of power as the axes. Thus, there are two technology evolution curves per technology, one for each axes of the frontier. From the mean and standard deviation values listed in Table 3, distributions of the technology evolution curve parameters are created. Illustrations of these distributions appear at the top of Figure 11. The analysis proceeds to find the expected utility of one technology. The process will be repeated to find the expected utility of the alternative technologies and the decision will evaluated by comparing the expected utilities of the alternative technologies.

The Monte Carlo simulation analyzes the effects of uncertainty in the parameters defining the technology evolution curves. Latin hypercube sampling samples the S-curve parameter distributions to create a set of random parameters that will be used to create the families of S-curves in the Monte Carlo simulation. Latin hypercube sampling allows for fewer samples to be generated and still provide statistically significant results when sampling in multiple dimensions [19]. For this example, the Monte Carlo simulation consists of 1,000 runs to demonstrate the method, although 10,000 or more samples would be used for increased statistical significance. Each Monte Carlo simulation run generates a random P_{lim}, P_{t^*}, and t^* for each axes of the Pareto frontier. P_{lim}, P_{t^*}, and t^* are uncertain while the remaining parameters, k and P_0, are calculated directly. To begin a Monte Carlo run a sample P_{lim}, P_{t^*}, and t^* is taken from the Latin Hypercube set. The parameter k is calculated from Equation 12 and P_0 is calculated from the existing Pareto frontier. The S-curve is created from the parameters according to Equation 10.

From randomly sampling the parameter distributions, the Monte Carlo simulation creates a family of S-curves. Each S-curve within a family seeds a Monte Carlo run. The events that unfold within the discrete time simulation depend on the S-curve. Since there are two S-curves in this demonstration problem, one for each attribute of the Pareto frontier, there are two families of S-curves. Figures 23 and 24 show the S-curve families for power and coefficient of power respectively. The figures are histograms depicting families of 10,000 S-curves. They show that the S-curves are very similar in the first year, but show much greater spread as time passes.

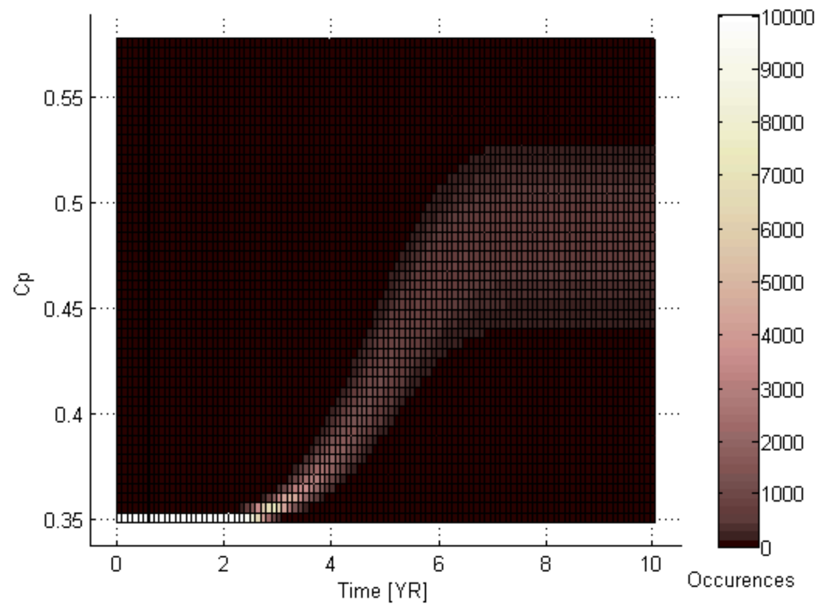

Figure 23. Family of Randomly Sampled Power S-Curves

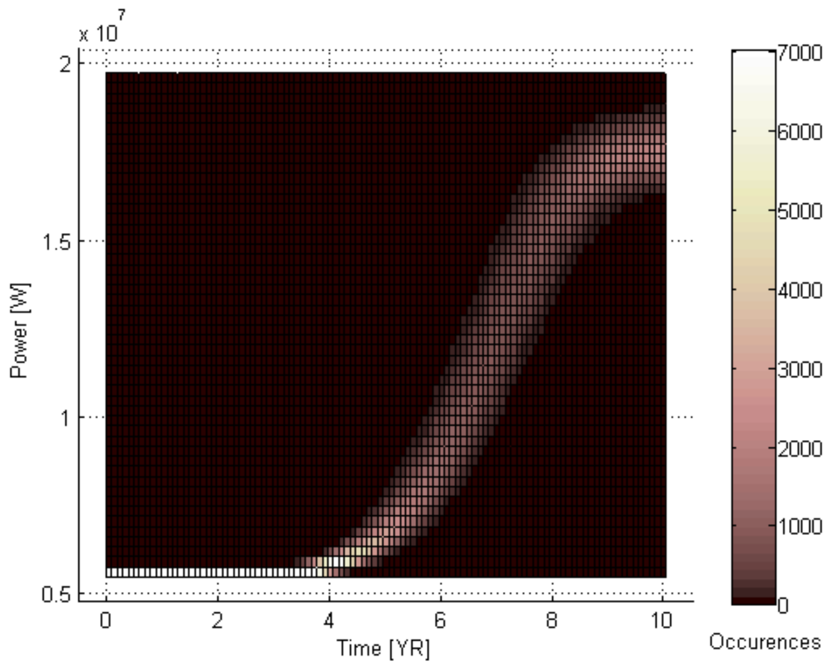

Figure 24. ***Family of Randomly Sampled C_p S-Curves***

Within a Monte Carlo run, the evolution of technology, annual redesign, and the payout received is simulated at annual internals. At year 1, the firm designs the first array of wind turbines that they will install. The firm first makes a decision of which turbine model to install in the array. The range of models, and their performances, is described by the year 1 Pareto frontier. The system model is applied to a point on the Pareto frontier to find the system-level attributes given that point. Equations 16-18 give the number of turbines and total power of the 10km x 10km array given the power and coefficient of power of a turbine. The payout functions, equations 19 and 20, give the payout to the firm from selecting a given wind turbine model. The firm redesigns the array, selecting the point on the Pareto frontier that maximizes the payout in year 1.

Moving down within one Monte Carlo run in Figure 11, the Pareto frontier is shifted from its original location at the first time point to its location at the next time step, one year in the future, according to the technology evolution curve. The first and second local derivatives are calculated at year zero for the power and coefficient of power evolution curves. The values are applied in equations 1 and 2 to move a point on the Pareto frontier to its location in the next year. The result is the Pareto frontier at the next time step. In this demonstration, the firm analyzes the decision at yearly increments for 10 years. The process of finding the derivatives, moving the Pareto frontier, and maximizing payout is repeated, iterating the time step from year 0 to year 10 resulting in a series of annual payouts.

Moving on to the process outlined in Figure 12, the payout is aggregated and analyzed to find the expected utility of the technology. First, the discount function is applied to the payout series within every Monte Carlo run so that all the entries have values equivalent to time 0. In this demonstration, the firm values all payout in time equally. The average value of the discounted payouts within each Monte Carlo run is taken. The average payout values are aggregated into a payout distribution having one point for each Monte Carlo distribution. The utility function is applied to the payout distribution. The firm is risk neutral so the expected utility is the mean of the aggregated payout distribution. The entire process described is repeated finding the expected utility of the second technology. As shown in Figure 13, the firm should choose the technology with the greatest expected utility.

5.2.3. Results and Discussion

The expected utility of each technology is presented in Figure 25. At year 0, when the firm is investigating the technology selection decision, land-based wind turbines have a greater expected utility. However, over a 10 year lifecycle, offshore wind turbine has a greater expected utility. If the lifecycle is 7 years, the firm is indifferent between selecting land-based or offshore wind turbines given the parameters selected at the beginning of the analysis. From this information the firm can make the decision to select offshore wind turbines over a 10 year project lifecycle.

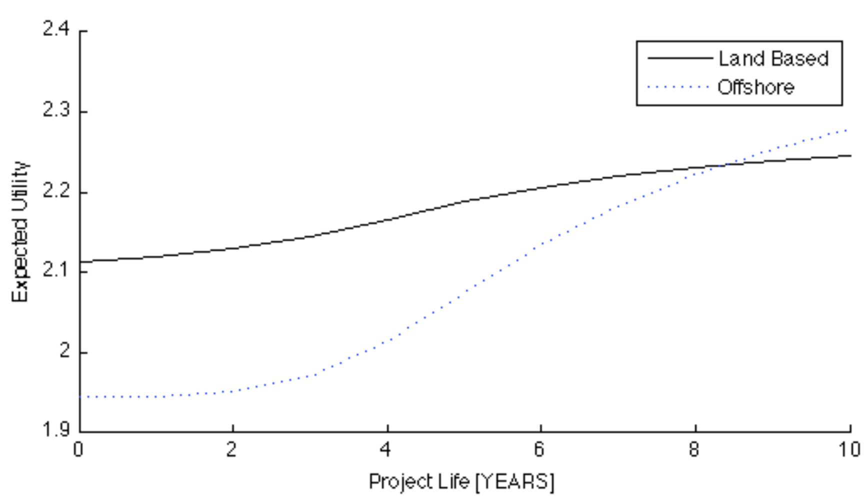

Figure 25. Wind Turbine Technology Comparison

5.3. Wind Turbine Parametric Study

The parametric study method is applied to the wind turbine scenario described in section 5.2. The firm poses the question: Given our expectation of the evolution of land-based wind turbine performance, how does the power of offshore wind turbines need to evolve, and how sure do we need to be, for offshore to be preferable to land based technology? This is looking at the same technology decision from another viewpoint.

5.3.1. Demonstration of Method

The parametric study is performed over a search space of parameters and standard deviations. Since the sophisticated technology modeling technique is used, there are a great number of uncertain parameters in the problem. Each axis of the Pareto frontier has three uncertain parameters and three standard deviations that define the distributions parameter distributions for an S-curve. For this demonstration, the firm focuses specifically on what evolution of power make offshore preferable to land based. The parametric study takes place over the three parameters and standard deviation making up the S-curve for the offshore power. The result is a six dimensional search space that describes where one technology is preferable to another based on expected utility. At each point in search space the method in section 4.2 is repeated using the coordinates of the point at the parameters and standard deviations. At a point within the search space, the preferable technology is the one with the greatest expected utility.

The firm defines a grid search space over the greatest range of the parameters that they anticipate. The expected utility is evaluated using the coordinates of the point as the parameters and standard deviations that define the distributions for the offshore power S-curve. At each point in the search space the best technology is the one with the greatest expected utility.

5.3.2. Results and Discussion

Since a six dimensional space is difficult to visualize, the results are presented in two ways. First, Figure 26 illustrates the trends resulting from searching over the parameters, while Figures 27-29 illustrate the effects of the standard deviation on each parameter. The figures together do not completely describe the 6 dimensional search space. In Figure 26, offshore technology is preferred wherever there is round maker, and land-based wind technology is preferred wherever there is a cross marker. The decision is affected by the mean values of all three parameters. The scenario in presented in section 5.2 uses the coordinates of the point in the center of the search space. One hundred Monte Carlo runs were evaluated at each point within the search space, as this is a demonstration only. The scale of the search grid and the number of Monte Carlo runs is up to those performing the analysis. The plot shows that no single parameter dominates; they are all coupled. The rate has some effect, but is not significant in comparison to others. Thus, it is not greatly advantageous for the firm to affect the slope through rapid development in this scenario. The inflection time has some impact on altering the decision. When the performance limit is very low or very high, the impact of moving the inflection time earlier is minimal. In between those limits, moving the inflection point forward through earlier action in research and development can alter the decision. Since land based technology is evolving alongside offshore, there is less gains to be had by altering the rate or inflection time than evolving to a greater power level.

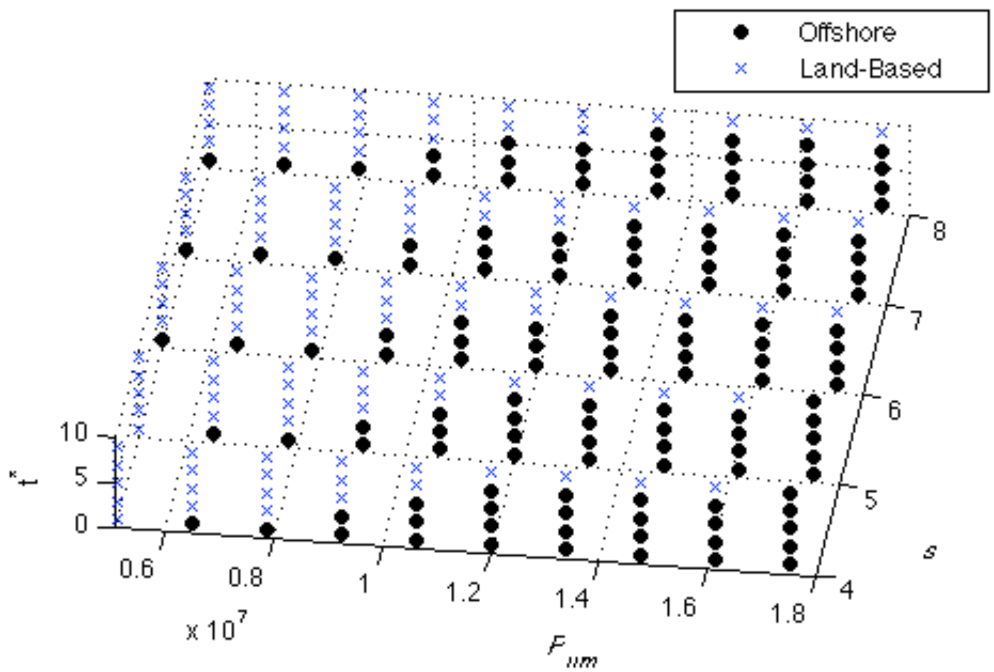

Figure 26. Parametric Study of Wind Turbine Scenario

Figures 26-28 show how each parameters standard deviation affects the decision, using the point in the center of the search space as the baseline. Rather than showing just the results of the decision, as in Figure 26, these figure show the expected utility of both technologies. At a point in the search grid, consisting of a mean and standard deviation, the value along the Z axis is the expected utility of each technology. The technology with the higher point is preferred. The surfaces in this series of figures allow the user to quickly see how the standard deviation of one parameter affects the decision. Since the firm is risk neutral, the standard deviations in Figures 27-29 have minimal effect on the expected utility. In addition, these plots show by how much one technology is preferred to the other.

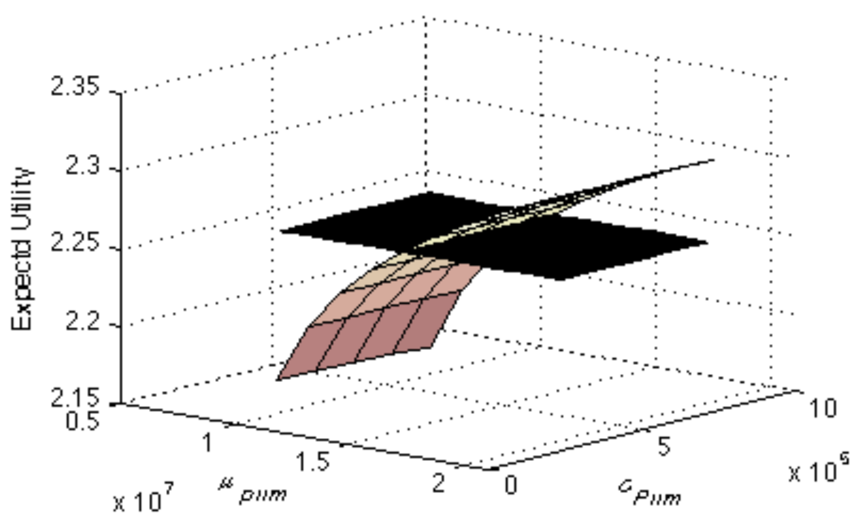

Figure 27. Parametric Study for P_{lim}

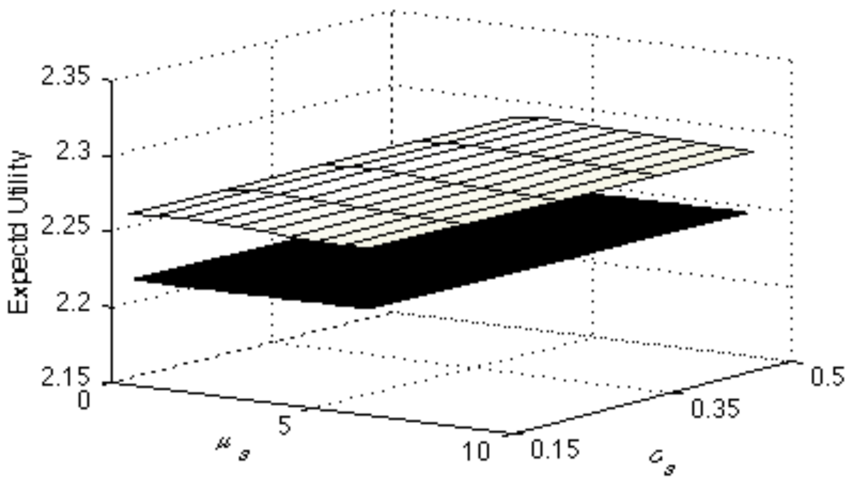

Figure 28. Parametric Study for S

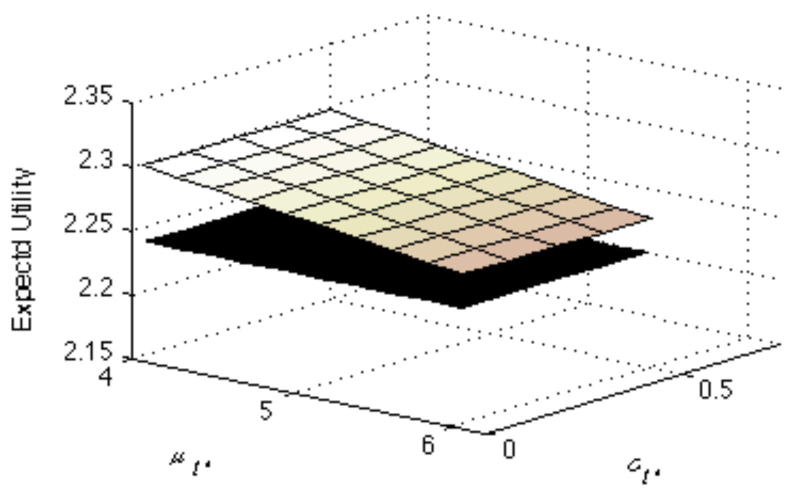

Figure 29. Parametric Study for t^*

The parametric study gives the decision maker valuable insight into the effects that selecting parameters and standard deviation have on the outcome of the decision. To do a truly meaningful parametric study, the user must search over all the uncertain variables for each S-curve. Due to the great number of evaluations and dimensions needed in performing the parametric study, the method described in section 4.1.2, making decision with simple technology evolution, is much faster because it has fewer uncertain parameters to describe an S-curve and only one S-curve.

6. FUTURE WORK, SUMMARY, AND CONCLUSIONS

6.1. Future Work

This research opens up a number of areas and applications for further work. The general framework for modeling the evolution of technology can be applied to support making decision beyond those presented in this thesis. One problem of interest is when is the best time to switch from one technology to another. This problem does not make the earlier assumption that it is not feasible to switch from one technology to another. Another problem that decision makers face is understanding risk. Selecting between competing technologies to use in a project with a long lifespan involves a great deal of risk because the future performance of a technology is unknown. Quantifying the risk associated with choosing one technology in comparison is beneficial when making decisions involving technologies that evolve.

The general framework for modeling evolution of technology allows for many different implementations of modeling techniques depending on the level of sophistication, amount of information about evolution required from the user, and the assumptions made. The implementations of the general framework presented in this thesis make a number of assumptions that do not necessarily apply in all situations. Of particular interest is the implicit assumption that the Pareto frontier does not expand, but only translates. Additionally, the current implementations assume that Pareto frontier maintains its curvature as it evolves, and does not stretch or change shape. This assumption does not apply in all cases. For example, if the performance attributes are truly independent, the Pareto frontier may move differently along each axis. For example, a Pareto frontier of a water container with attributes of cost and volume and cost can change shape because the cost can drop for all water bottles while the volume does not evolve at all, resulting in a shape change.

Some level of error is inherent in modeling. At the current stage of this research, the error has not been quantified. A Taylor series expansion approximates the movement of Pareto frontier points through attribute space. The error of this approximation reduces as the time step decreases and as the number of terms increases. The error due to the number of terms and the step size needs to be quantified. The user needs to know how accurate to make the approximation in order to reduce error to an acceptable level.

One disadvantage of the simulation based decision-making approach is the significant computational burden. The decision–making methods use Monte Carlo simulations to propagate uncertainty. Monte Carlo simulations repeat evaluations of random events a great number of times, which demands great computational resources. Future work includes applying other uncertainty propagation techniques to reduce computation effort. The examples presented here have examined simple problems where there are only two significant attributes. Generally there are numerous performance attributes of interest, but analyzing a problem with many more attributes greatly increases the computational effort required to make the decision. Applying response surface models in place of the model or simulation of the system being designed can reduce the total effort.

6.2. Summary and Conclusions

The performance of technologies evolves over time, posing a challenge in design due to the uncertainties in the future performance. Without the means to account for technology performance evolution, the designer or decision maker can look only at the current technologies available and make educated guesses about how the future affects a current decision. A method for quantifying the effects of evolution is needed to facilitate better understanding and decision-making. This research provides a framework for formally modeling the evolution of technology and making a decision based on a series of uncertain events that will unfold over time. The technology evolution model is a valuable tool to model the evolution of technology performance giving designers and decision makers a way to quantify future performance of multiple attributes of a technology. This research has proposed that a Pareto frontier representing multiple performance attributes moves as the performance of a technology evolves according to S-curves. Additionally, uncertainty can easily be applied to the evolution model and its shape can be easily modified to fit the users' expectations of evolution.

The selection of batteries for use in a line of electric vehicles demonstrates the simple technology modeling technique using a single logistic S-curve to describe the motion of a Pareto frontier. The electric vehicle scenario shows how the decision-making method allows the user to select between multiple competing technologies undergoing different expected evolutionary paths. A scenario of a power generation company deciding between offshore and land-based wind turbines demonstrates the sophisticated evolution modeling technique with multiple independent Erto-Lanzotti S-curves. The parametric study method is applied to this scenario, showing under what distributions of uncertain parameters offshore wind turbine technology is preferred to land-based.

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