

Design with Uncertain Technology Evolution

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ABSTRACT

A major decision to make in design projects is the selection of the best technology to provide some needed system functionality. In making this decision, the designer must consider the range of technologies available and the performance of each. During the useful life of the product, the technologies composing the product evolve as research and development efforts continue. The performance evolution rate of one technology may be such that even though it is not initially a preferable technology, it becomes a superior technology after a few years. Quantifying the evolution of these technologies complicates the technology selection decision. The selection of energy storage technology in the design of an electric car is one example of a difficult decision involving evolving technologies. In the first year of production, a particular battery cell technology provides the best vehicle performance; however, a few years later, an alternate battery technology may have evolved to a point that its performance surpasses the previous best battery technology. Designing with technologies whose levels of performance evolve over time is poorly understood. The objective of this research is to create a computational method allowing designers to make decisions with a greater understanding of the impact of the decision on the design. In this research, it is assumed that the performance of a technology develops in the form of an S-curve; slowly at first, quickly during heavy R&D spending, and slowly again as the technology approaches its limits. A key concept in this research is that performance evolution of a technology translates to a shift in the corresponding performance Pareto optimal frontier. The assumed form of technology development allows the designer to apply the uncertainty of technology development directly to the S-curve model rather than applying the uncertainty to the performance thus better reflecting the change in performance over time. A case study of designing a battery pack with evolving battery cell technologies in an electric car powertrain demonstrates this method.

CITATION: Arendt, J., Malak, R. and McAdams, D., "Design with Uncertain Technology Evolution," *SAE Int. J. Passeng. Cars - Mech. Syst.* 5(1):2012, doi:10.4271/2012-01-0912.

INTRODUCTION

Engineering design of systems and components is complex because it involves a large number of design variables, complicated interactions, and uncertain consequences. Generally, it is an iterative process of people working towards the common goal of creating a valuable and high performance product by attempting to optimize the component under their responsibility. Design typically involves the use of models to describe a variety of things like the objective of the design, the behavior of the product being designed, or the preferences of the designer. A large team of engineers engaging in a challenging design can work more effectively by combining their understandings and organizing their goals in a way that drives the design to a solution which best fits the needs of the customer or firm. An integration and analysis tool enabling these activities gives the design team the ability to rapidly perform many iterations of the design process in a virtual environment, thus greatly

reducing design labor, prototyping costs, and more rapidly converging to an optimal design solution.

The complexity and difficulty of the design process is greater when uncertainty is a major factor. Uncertainty in design comes from many sources, such as uncertainty in customer preferences, technology available, and modeling accuracy. This research focuses on uncertainty in how the capabilities of a candidate technology will evolve over time. The evolution of technology over time presents the designer with several important questions when selecting specific technologies. What will the performance of this technology be like in 10 years? How much does that affect the decision? How does uncertainty come into play? The objective of this research is to create a formal and quantitative method that enables designers to make decisions with more complete knowledge of the impact of the technology selection on the design. The method presented here applies to the case where technology evolves over time, making it difficult to quantify what technology performance will be available to the



designer over the horizon of the designed system. This paper presents a decision-based design method that uses models of the technology available, the evolution of technology over the program lifecycle, and models of the physical system to quantify the decision under uncertainty. In the method presented, the design engineers create models of the anticipated technology evolution and apply them to models representing the current technology available.

BACKGROUND

A method to support decision-making of a problem of this complexity relies on a wide set of modeling, simulation, and decision-making techniques and methods. For the method developed here, an S-curve model is used to represent how technology evolves in time. Pareto frontiers are used to help designers understand rational tradeoffs of potential technology performance at an instant in time. A Monte Carlo simulation is used to simulate the uncertainty of multiple variables. A general framework for decision-based design uses simulations of the product being designed. In the framework, utility theory expresses the value of the product in the form of utility. These basic techniques and methods are briefly presented here beginning with a discussion of S-curve technology evolution modeling.

As technologies evolve, their performance typically improves. Betz proposed the idea that the performance evolution of a technology follows an S-curve as shown in [Figure 1](#) (1). The Sigmoid curve, or S-curve, was originally applied to model the growth of animal populations. Betz transferred this model to practical engineering application by collecting data of the evolution of the illumination intensity of light bulbs over time. He showed that the performance of the light bulb evolved in time along an S-curve. When incandescent light bulbs were first emerging as a light technology, the performance was low, resulting in the flat bottom of the “S”. As the innovation and research increased, the performance improved rapidly, reflecting the increase in slope at the inflection in the curve. As the innovators approached the physical limitations of the technology, the rapid gains in performance approached full maturity, resulting in 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. S-curve models are typically valid for a specific technology and do not represent the improved performance found when new technologies are introduced that provide the same function such as the transition from incandescent light bulbs to fluorescent light bulbs. These new and superior technologies are called disruptive technologies. Of note, the disruptive technologies performance evolution again follows an S-curve trend. (2).

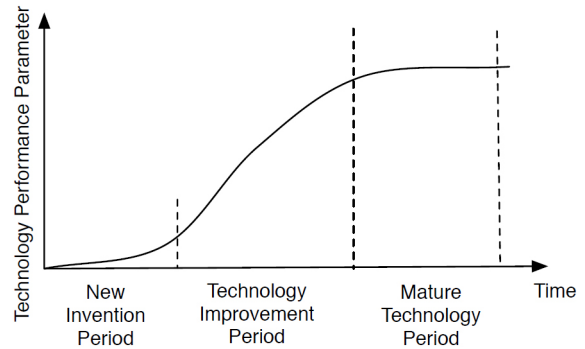


Figure 1. S-curve technology evolution model

Numerous different forms of the S-curve technology evolution model have been introduced since its inception. The forms differ in the number of parameters, mathematical forms, and shapes of the curves. The following forms of the S-curve can be used to model how technology evolves (3).

Nieto and D'Avino have independently concluded that the S-curve model best represents the evolution of technology performance (3, 4). D'Avino specifically recommends the Erto-Lanzotti model based on goodness of fit to multiple sets of data (3). In this research the logistic model will be used because it is more widely accepted than other models. However, the other forms may be substituted depending if the user prefers greater flexibility or does not assume symmetry.

In this research, the performance of a single technology is allowed to have multiple attributes - such as power density and energy density. To allow for the fact that there may be inherent tradeoff in attempting to improve both attributes simultaneously, a Pareto curve is used to represent that rational space of optimal solutions. The points on the frontier are instances of the technology with particular levels of technology. The trade-off curve is a Pareto optimum solution set, or Pareto frontier. The Pareto optimum solution set is defined as a set consisting of feasible solutions in each of which there exist no other feasible solutions that will yield an improvement in one objective without causing degradations in at least one other objective. It is a set of candidate solutions from which the optimum solution is selected (5).

Generally, a Pareto frontier pertains to the alternatives available to the designers at a given point in time. The idea of Pareto frontiers originated in economics but has been adopted for use in engineering design (6, 7). It has also been suggested that a Pareto frontier can move due to the evolution of the underlying technology (8). De Weck quantified a Pareto frontier shift based on satellite performance data as a single new solution entering the Pareto optimal solution set. The result is a local movement of the Pareto frontier. This idea of a moving Pareto frontier can be extended to the idea of the S-curve evolution model by observing that an increase in the performance of a technology as it evolves along an S-curve results in a shift in the Pareto frontier. Here, we introduce the formal addition of S-curve performance evolution to dictate the movement of a Pareto frontier in time.

Table 1. Forms of the technology evolution model

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

The evolution of technology is an uncertain event with uncertain outcomes. Thus, it is logical to apply uncertainty to the location of the Pareto Frontier. Mattson and Messac presented work that applies uncertainty to the position of a Pareto frontier when selecting among concepts with Pareto frontiers existing in the same space (9). However, a Pareto frontier is a deterministic line connecting optimal solutions and is undefined under uncertainty. When considering uncertainty, the attributes of the solutions are uncertain and the Pareto dominance criterion no longer has meaning. A stochastic dominance criterion, which defines solution dominance based on uncertainty, is used instead (10, 11). In this research it is assumed that the Pareto frontier is deterministic at the beginning of the simulation. Since the S-curve that models the evolution of technology is uncertain, the location of the future Pareto frontiers is uncertain as well. Since the S-curve that models the evolution of technology is uncertain, the locations of the future Pareto frontiers are uncertain as well. However, the same uncertainty is applied to all solutions in a set so dominance criteria can be applied. The case study will further illustrate how uncertainty is applied in this context.

The technology selection decision is a critical step in the design process. There are a variety of methods widely used in engineering that support decision-making during design. Common methods for evaluating design decisions include Pugh selection charts and Quality Function Deployment models (12, 13). Methods like these assist engineers in understanding and presenting information about the decision at hand and use subjective weighting factors to determine the value of candidate alternatives. However, they are limited in the usefulness of rigorously evaluating alternatives, so a more formal decision-making framework has been laid out (14). In the specific context of competing technologies, methods have

been developed that include functional modeling, behavioral modeling, and sensitivity analysis to handle both performance and modeling uncertainty (15). However, the developed function based methods do not consider technological performance evolution. In a similar fashion, event and process modeling is used in design (16). Some authors have advocated making engineering design decisions using simulations of the enterprise events and processes (17, 18). Additionally, Pareto frontiers are common tools used in design simulations because they capture the rational set of alternatives the designer should select from (19). There is a selection of tools that designers and decision makers use, including trade-off studies, simulations, utility theory, and statistical simulations. Utility theory builds models of the preferences of the designers, the firm, or the clients, which allows the designers to quantitatively rank one design alternative against another (20, 21). Utility theory has been applied to decision-making in design as well (22). Multi-Attribute Utility theory expands the method giving designers the power to create a design that is balancing multiple interacting but otherwise dissimilar attributes (23).

It is rare that all the input variables to a decision, as well as the outputs of all the underlying models and assumptions result in a deterministic problem. Decision based design can be extended to include uncertainty through simulating the effects of uncertainty in the alternatives or evaluation of a design by using a Monte Carlo simulation (24). A Monte Carlo simulation in decision based design applications generally generates a random input variable to the simulation of the decision and delivers a resulting value of the random variable (25). This process of finding a result based on a random input is repeated until a statistically significant distribution is produced showing the probability of a particular result occurring, allowing designers to better

understand the expected value of a decision alternative and to assess it in terms of risk and uncertainty. Latin Hypercube sampling creates sets of random variables sampled evenly in orthogonal dimensions, minimizing the number of samples needed to have a significant multivariable Monte Carlo simulation (26). The framework for decision based design with uncertainty, utility theory, trade-off studies, Pareto frontiers, and decision simulations have been applied to design of complex systems (11, 27).

EXAMPLE SCENARIO

To better motivate and explain the methods developed here, a hypothetical scenario is presented. In this scenario, a global vehicle design and manufacturing firm has decided to enter into the electric vehicle market and is about to begin its first design cycle for this market. At this time, the firm is investigating which competing battery technology to invest in for the long-term production. It is vital to select the proper battery technology immediately because the firm must invest in specialized manufacturing and handling equipment, find suitable suppliers, and design the vehicles to use a specific battery technology. In this scenario, the firm must select and commit to battery technology early in the design process for the future line of vehicles that will be developed. However, the firm can perform minor design modifications periodically. For example, on an annual basis, the firm can update the design of the vehicle by making visual changes, resizing the battery pack, or using the highest performance batteries available within the technology selected early. Since the battery technology evolves over the program lifecycle, it is advantageous to select the battery technology that will maximize the future wealth of the firm over the production run of vehicles. In this hypothetical scenario, the firm is selecting among three competing lithium-ion battery technologies with similar, but not identical performance. The firm expects that some of the technologies will develop more rapidly than others and that some have already developed further than others.

The firm faces a great number of challenges in formulating this decision. They must decide among multiple battery technologies that currently exhibit similar performance. These competing battery technologies are all expected to evolve through research and development within the program lifecycle that this decision is considering. The challenge is to effectively model and quantify the effects of the evolution of the technologies. Additionally, the uncertainty in how different technologies develop provides another challenge. The firm must consider the system performance of the vehicle due to the selection and implementation of a battery technology, as well as the customers' preference for vehicle performance and how the firm values the performance. These challenges combine into a complex problem with numerous consequences that depend on numerous factors. Here, we present a new method to quantify important elements of the technology selection while

considering technology evolution and the associated uncertainty.

METHOD

Quantifying the technology selection decision requires a vast set of modeling, analysis, and decision-making techniques. The approach to solving the problem in this research is to create a mathematical simulation of the pertinent factors of the decision, such as the performance of the vehicle, the evolution of the competing technologies, the preferences of the customers and the firm, and the uncertainty. The method presented here includes the use of Pareto frontiers to model the technology performance, S-curves to model technology evolution, utility theory to support making the decision, probability theory for uncertainty modeling, and a Monte Carlo simulation for uncertainty propagation. The company applies their uncertainty about the evolution directly to the S-curve. The simulation of time-evolving performance supports the firm in making a decision by giving them an expectation of the utility of each battery technology alternative. The subjective value of the decision-making tool depends on the users' judgment of firm and customer preference and expected evolution.

A meaningful model of technology evolution that the user can manipulate effectively is critical for decision making with uncertain technology evolution. Decision makers can select from any number of curves that he or she sees suitable and meaningful. Here, we use the logistic type S-curve as shown in Figure 2. The basic mathematical form of the logistic S-curve appears in Table 1. Since this method assumes that the technology evolution curve is an S-curve, the two terms will be synonymous for the remainder of this paper.

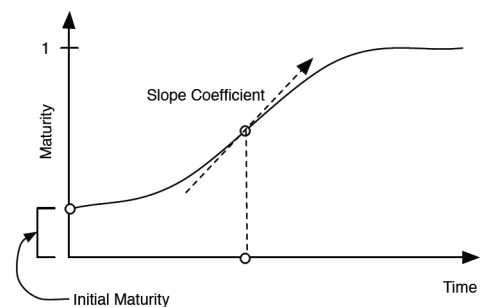


Figure 2. Technology evolution curve

The parameterization of the S-curve allows the decision-maker to manipulate the shape of the curve. Typically, the S-curve represents the evolution of a single performance attribute. In the classic light bulb example, the performance attribute of the S-curve is illumination intensity. Many technologies designers use with have multiple performance attributes, such as illumination intensity as well as efficiency in the case of light bulbs. The single performance attribute S-curve does not describe the evolution of multiple attributes. Instead of displaying a single performance attribute, maturity is used allowing the S-curve to describe the evolution of