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DISCRETE DESIGN ADAPTATION WITHIN A DYNAMIC ENVIRONMENT

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ABSTRACT

Very often product development, is seen as a process where designers iterate through an Analyze-Design-Build-Test loop until they converge upon a design that satisfies all of the necessary requirements—design within a single epoch. If one takes the view that products change, i.e. that they evolve, a broader view must be adopted that captures the drivers and results of product changes. This paper offers a framework to capture the dynamics of product evolution for products that compete in highly competitive (mature) markets called the Artisan-Patron (AP) model. The AP model shows why and how the artisan adapts its artifacts to the changing environment (consumer taste, government policy, cost of raw materials, etc.). Contrary to existing qualitative models of evolution, the AP model captures the necessary information mathematically. The utility of the model is demonstrated using an abstract design problem that is representative of design problems faced in reality.

1. INTRODUCTION

To help designers become better innovators, researchers of engineering design strive to ascertain how to make design activities more effective, more efficient, and more manageable through the use of conceptual and/or mathematical models (Whitney 1990). Very often design, or product development, is seen as a process where designers iterate through the Analyze-Design-Build-Test loop until they converge upon a design that satisfies all of the necessary requirements—design iteration within a single epoch. Here design iteration can be defined as "repetition of design tasks due to the arrival or discovery of new information" that comes as a result of tests performed on prototypes, pre-product release consumer acceptance studies, or manufacturing feasibility issues (Smith and Eppinger 1997).

The single epoch design assumption reduces complexity and has lead to advances in design theory on several descriptive and prescriptive levels, such as reducing design churn (Yassine et al. 2003), valuing and selecting the best design alternative (Ulrich and Ellison 1999, Cook and Wu 2001), managing experimentation during product development (Thomke 1998), and axiomatic design principles to manage complexity (Suh 1999) to name just a few. Zeng and Gu (1999a, 1999b) posit the same assumption to developed a mathematical framework to represent the information flows and transformations as it passes through the iterative stages of design as previously defined.

The single epoch design assumption is not always appropriate however (Nelson and Winter 1982, Otto and Wood 1998). Since the beginning of trade, artisans have been forced to continually consider ways to improve their artifacts in order to adapt to evolving consumer preferences, advancing technology and competitive offerings (Petroski 1992, 2003). With this conception of consumer goods, an artifact's design is more accurately viewed as transient than constant over time, where any single artifact is simply a instantiation of a design at the time of production. With a dynamic view, design can be seen as an adaptive endeavor that utilizes feedback and/or feedforward to evolve an artifact in an effort to maintain or increase the artifact's level of fitness relative to other competing alternatives and to provide an economic return to the artisan. Feedback comes to the artisan based on how well his artifact is able to garner economic results. Feedforward comes to the artisan through the act of forecasting, which is seen as a necessary part of design. Simon (1996) makes the same conclusion in *The Sciences of the Artificial*, as he makes the following

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rationalization: Since the consequences of design lie in the future, it would seem that forecasting is an unavoidable part of every design process.

Michalek et al. (2003) is an example of a recent design model that presupposes a static environment and design takes place within a single epoch. In their study of the effects of governmental regulation policies on the design of automobiles, the authors develop a methodology for modeling critical design decisions. A similar single-epoch optimization framework is used within this paper, but the scope is enlarged to study the affects of dynamic design constraints which cause the artifact's design parameters to evolve. As discussed by others (Marzotto et al. 2000, for example), often product design and government policy co-evolve as old problems disappear or are redefined, and new problems are created.

Recognizing that artifacts must adapt and evolve through redesign, Otto and Wood (1998) present a comprehensive multi-step process for reverse engineering and artifact redesign. They make a distinction between three approaches to adapt to a changing environment. First, *original design* "…implies that a major conflict exists between the customer needs and the current product in the market…" thereby requiring "…an entirely new concept." Alternatively, *adaptive design* "…seeks to create alternative solution principles to chosen product subsystems, replace subfunctions of the product, or add new subfunctions." Lastly, *parametric design* "…requires a model of the original product or a model of a new product configuration", which is then recalibrated according to the new design criterion. Although the framework presented here may be used to characterize all three of the aforementioned design strategies, this paper focuses solely upon parametric design. This simplifying assumption allows us to use a mathematical framework to capture the dynamics of product evolution that is characteristic of products that compete in highly competitive (mature) markets[1].

Adaptive design in this paper is seen as a four step process: (1) analysis of new information; (2) update decision models; (3) update design; (4) cascade design changes. We call this framework the Artisan-Patron (AP) model. The AP model structures several kinds of information: (1) the information needed to aid the Artisan in adapting its artifacts to the changing environment (consumer taste, government policy, cost of raw materials, etc.); (2) the design information that results from the adaptation; (3) the veritable product performance; and (4) the consumer response that serves as feedback for the next adaptive iteration.

The remainder of the paper proceeds as follows. Section 2 describes the theories of biological adaptation and evolution and explains why these analogies are inadequate for describing the evolution of artifacts. Next, Section 3 motivates and presents a framework, the AP model, for solving the design adaptation in a dynamic environment problem. Section 4 provides an illustrative example to help demonstrate the method and utility of the framework. The paper concludes with a summary and discussion (Section 5).

[1] Here, mature markets are those where a market has converged upon a dominant design or architecture (Utterback 1996).

2. THE ADAPTATION AND EVOLUTION OF ARTIFACTS

One of the predominant theories for explaining why products evolve is that there is an inherent uncertainty in both technology and consumer taste. Clark (1985) presented three important results that form a partial philosophical basis for this paper. First, he develops the idea that there is a *design process* "behind sequences of innovations in a specific product." Secondly, he argues for a *framework* that considers the evolution of consumer preferences as an additional important aspect of innovation, rather than focusing only on the evolution of technical aspects of the design. Thirdly, he notes that *consumer preferences may evolve* due to the influence of the evolved technological development path. In his own words:

> If a context were well specified so that requirements could be developed with precision and confidence, if the functional implications of alternative design concepts were likewise well known, the design problem at a given point in time would be trivial. One would only have to select the set of components that satisfied the requirements. Moreover, if the context and the set of design concepts remained stable over time, the selected design would persist.

Clark also makes the point that "rival firms and designers" would most likely understand the market in different ways and thus progress along different technological trajectories, which is a stark disconnect from orthodox economic theory where firms posses unbounded rationality.

Evolution is the process in which something passes by degrees to a more advanced or mature stage. Just as biological theory has progressed through a deeper understanding of evolutionary theory as a result of Darwanism, product management, economic, and marketing theorists have been able to better understand their domain by conceptualizing products as evolving entities (Clark 1985, Nelson and Winter 1982, Abernathy and Utterback 1978, Abernathy and Townsend 1985). Evolution has been used widely in marketing to explain gradual improvement of products, but can be defined more precisely by the following four characteristics (Tellis and Crawford 1981): (1) there is a cumulative effect as each change builds on the previous; (2) there are forces that motivate the improvement; (3) products become more complex and diverse; (4) there is an emergent structure of improvements. Therefore, an evolutionary story of a product would describe the temporal relationship of the four aforementioned characteristics.

Indeed, many scholars have used biological analogies to explain economic and technological evolution phenomena. Mokyr (1991), however, makes a cautionary remark to researchers who choose this path:

> Even those who tried their hand at the use of biological metaphors and who used words like ‘evolution’ and ‘natural selection’ left and right have not always studied the literature of evolutionary biology carefully. Had they done so, they would have realized that in fact the theory of evolution is at least as dispute-ridden as economics, which tends to make it interesting but also more hazardous to apply its insights to other fields.

Penrose (1952) expressed a similar point of view to the application of biological analogies to economics:

> The chief danger of carrying sweeping analogies very far is that the problems they are designed to illuminate become framed in such a special way that significant matters are frequently inadvertently obscured.

One of the favorite biological evolution theories used in the realm of product development, for obvious reasons, is that of Darwinism. Darwinian evolution is when, “a population or species changes through the continuous production of new genetic variation and through the elimination of most members of each generation, because they are less successful either in the process of the nonrandom elimination of individuals or in the process of sexual selection (Mayr 2001).” The model has the three important principles of random variation, natural selection, and sexual selection-reproduction. A Darwinian process can therefore be represented as shown in Fig. 1. Some problems with using Darwinian processes to explain product evolution are the following (Massey 1999):

1. Darwinian evolution relies on random generation of variants only, without the use of an adaptive agent (product designer)
2. In economic systems the fitness of the product is determined by a selective agent (the consumer)
3. Darwinian product evolution does not consider customer-needs, which is in conflict with most marketing theory, which strives to full-fill consumer-needs as its major goal
4. Pricing is not random
5. Advertising messages are not random
6. Distribution strategy is not random

For the short-list of reasons offered above, any use of Darwinism to explain technological progress must be taken with a grain of salt.

The pre-Darwinian ideas of biological evolution are grouped into what has become known as Lamarkism. A Lamarckian process is based on the idea that organisms can adapt during their lifetimes and transmit the acquired traits to their offspring, who pick up where their parents left off. Further, organisms will lose non-used traits through disuse. So the principles of this theory are, first, ‘use-it-or-lose-it”, and second, inheritance of used traits. Lamarkism presuposes the ability to first identify positive (used) traits and also some means to incorporate this information into the next generation (something like an adaptive agent) and therefore can be represented as a process (Figure 1). This evolution analogy, with a little imagination, can be used to describe how marketing researchers (the analysis agent) analyze market information and provide suggestive modifications of the future product (organism) to the product designers (adaptive agent) (Nelson and Winter 1982, Massey 1999).

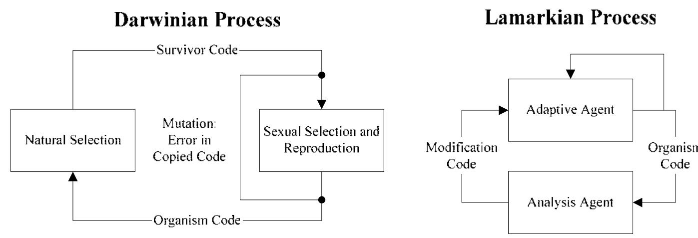

Figure 1: Darwinian and Lamarkian Processes of Evolution

In spite of its seemingly attractive features, there are also some problems with using Lamarckism to explain product evolution. Namely, the theory lacks an agent that takes on the role of the consumer who selects ‘fit’ products. Also, clearly there is some type of “survival of the fittest” phenomenon at work in economic systems that is related to, but not completely explained by “survival through use”.

What becomes clear is that although adaptation and evolution take place in both natural and artificial systems, the mechanisms and processes are markedly different. Therefore, we will not pursue biological analogies for their own sake, but we will use words and ideas from a biological context if it helps to make concepts more clear.

Sterman (2000) discusses at length the intricacies of modeling artificial (man-made) dynamic systems. One of the key notions he develops is that of the double-loop learning cycle, which describes how both mental models and decisions change as new information is received from the real world. Sterman (2000) lists the following barriers to learning and good decision making within these systems: dynamic complexity, limited information, confounding variables, bounded rationality, flawed cognitive maps, erroneous inferences about dynamics, judgmental errors and biases, defensive routines, and implementation failure. In spite of these barriers, humans must make decisions in these types of systems. Indeed, for learning to occur, the loops must be cycled quickly relative to the rate of change in the environment, or knowledge becomes obsolete.

Recognizing that industries, markets, and economies evolve as a result of technological innovation and changes in environmental factors, Nelson and Winter (1982) described simulation models that can mimic how firms adapt their decision routines. The authors discuss at length how many of the simplifying assumptions of "orthodox" economic theory can not be used to explain how economies evolve as a result of learning either through internal development or through imitation of successful competitors. The difference between the evolutionary theory of economic change line of research and the present work is that the former focuses upon *descriptive* techniques to model the evolution of economic systems. The model presented here strives to help structure information to make normative decisions regarding the evolution of products.

To aid decision making, analysts create models to test the validity and impact of possible actions and decisions as experimenting with real systems is often too costly, time-consuming, and difficult to learn from. In addition, the model conditions can be manipulated and scenarios can be tested that may be considered controversial or unethical. Regardless of the modeling technique, simplifying assumptions must be made about the real world, which introduce ambiguity, bias, and error. In the end, the old adage holds: All models are wrong…, but some are useful.

3. THE ARTISAN-PATRON MODEL

As discussed earlier, an artifact's design evolves and adapts as a result of improvements in technology or changes in external factors such as consumer taste, governmental policy, cost of ownership, or costs of raw materials. Faced with shocks that make old designs sub-optimal, artisans are forced to redesign their artifact based on incomplete information, such as future market conditions, material costs, and Patron preferences (Nelson and Winter 1982).

In this paper, the design problem is seen as an adaptation and learning process performed by a single entity, called the Artisan. The Artisan has three major tasks during each design iteration: (1) discern how other entities, called Patrons, determine their reward structure for the Artisan's artifacts and how relevant environmental factors will affect design decisions—the *analysis* task; (2) adapt the artifact's design to satisfice between patron value, the cost incurred to produce the artifact, and other constraints imposed by the environment—the *adaptation* task; and (3) reproduce the artifact as designed—the *cloning* task. When the Artisan's tasks are combined with the Patron's task of *evaluation*, (depicted by Fig. 2), a model is created that can be used as a framework for the information flow that accompanies design evolution. The model appears deceptively simple at first glance, but it is quickly enriched as the information flows are encoded to create a mathematical formulation to aid the Artisan in determining the best settings for what he can control—decision variables.

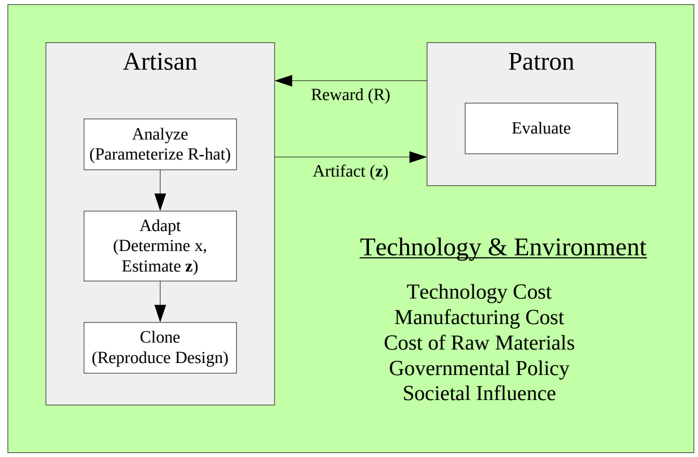

Figure 2: The Relationship between the Artisan, Patron, and Environment

3.1 The Analysis Task

There is a complicating aspect of this model, which makes its analysis especially difficult when compared to other cybernetic systems. When the artifact is described by a finite vector of critical-to-value attributes (CVAs)[2], $\mathbf{z}$; it is easy to see that although the actual reward value, R, flowing from the Patron to the Artisan is observable, the reward function, $R(\mathbf{z})$, of the Patron is not. The Artisan is therefore forced to create a reward estimator function, $\hat{R}(\mathbf{z})$, whose parameters are adjusted from one time period to the next to forecast the veritable reward. The task of modeling and adjusting the $\hat{R}(\mathbf{z})$ parameters is one of the Artisan's primary challenges in the analysis task. $\hat{R}(\mathbf{z})$ is necessary for the Artisan to evaluate the design proposals created to maintain or increase the relative fitness of its artifact to that of alternatives available to the Patron.

In addition to determining the Patron's reward function the Artisan must also determine how the design decision may be affected by changing technological and environmental factors. Environmental factors include, for example: cost of raw materials, changes in relevant government policy, and changes that influence the cost of ownership. The Artisan must also consider how technological innovation has influenced both the expense to manufacture the artifact (process innovation) and the cost of delivering the CVAs.

If all the exogenous variables ($R(\mathbf{z})$, technological innovation, and the environment factors) where static; one can imagine that the Artisan would be able to discern the true parameters over time. This would greatly simplify the Artisan's adaptation task. On the other extreme, if these variables were extremely chaotic, the Artisan may never be able to understand

[2] A popular marketing view is that products are nothing more than a bundle of attributes. This perspective is thought to have been first introduced by Lancaster (1971).

how the Patron makes decisions and the design adaptation task, consequently, would become unstable. Therefore, the model proposed within this paper focuses on the design problem where the critical exogenous variable are unknowable, yet somewhat predictable or stable, as is the case with mature products such as the automobile or household appliances. The analysis task is complete when all of the exogenous variable relationships have been determined to the extent that they are able to provide guidance to the artisan throughout the adaptation task.

A major part of the analysis task is traditionally performed by the marketing arm of the firm. Much has been written regarding how to translate the "voice of the customer" (Griffin and Hauser 1993) into product specifications, such as Quality Function Deployment (QFD) (Hauser and Clausing 1988). Determining actual consumer response has proven to be very elusive however. Theoretically, the artisan should be able to gauge consumer acceptance based on the reward he is able to garner from the patron. Ascertaining what design changes are responsible for changes in reward is a very tricky and involved learning problem. Reinforcement learning is "the problem faced by an agent that must learn behavior through trial-and-error interactions with a dynamic environment (Kaelbling et al. 1996)." The two main strategies for parameterization of these models has either been through evolutionary computation (Schmidhuber 1996) or through statistical and dynamic programming techniques (Kaelbling et al. 1996, Bell 2001). The application of reinforcement learning to the parameterization of consumer preference models seems to a natural application of this theory. Nevertheless, discerning consumer preferences directly from sales data is a daunting, if not impossible task given the existing state of knowledge. This learning problem is further complicated with the addition of influential dynamic environmental variables into design decisions.

Most frequently, survey methods are used in conjunction with subjective interpretation of sales results for estimating a future artifact's acceptance. The most popular methods for capturing the value (willingness-to-pay) function of consumers have been conjoint analysis (Kohli and Mahajan 1991, Jedidi and Zhang 2002) and the direct value method (DVM)(Donndelinger and Cook 1997, Cook 1997, Cook and Wu 2001). In spite of the strategic and managerial importance of understanding product value functions, the methods and tools are still in their theoretic infancy.

3.2 The Adaptation Task

With $\hat{R}(\mathbf{z})$, the Artisan is able to estimate how new designs will bring more and/or better rewards. The Artisan's design adaptation task is completed by searching and evaluating the feasible design space for satisficing settings of the decision variables (DVs), $\mathbf{x}$, which maximize the posited reward function. As designs are evaluated based on their CVAs and not their DVs, the Artisan must create models that map $\mathbf{x} \to \hat{\mathbf{z}}$. An obvious biological metaphor for the DVs and CVAs is therefore genotype and phenotype, respectively.

We name the DV/CVA map a transfer function. These transfer functions can either be created through 'bottom-up' approaches such as mathematical and computer simulation (i.e. Computer Aided Engineering) models[3] or through 'top-down' statistical approaches such as design of experiments[4] (DOEs).

But how are the optimal setting for the DVs found? Recognizing that design decisions need to be tied to broader issues that are important to the firm, Papalambros (2002) introduced the conception of 'Enterprise-wide Design', which strives to consider more than just technological performance while designing new products. In an effort to link engineering design decisions to product portfolio valuation, Georgiopoulos et al. (2002) defined the enterprise-wide decision model as:

$$\left\{\begin{array}{l}\text{Maximize (expected net present value)}\\ \text{With respect to (investment and engineering variables, price)}\\ \text{Subject to (investment and engineering constraints).}\end{array}\right.$$

The crux of this solution method posits that the aforementioned transfer functions are available and ready for use and that decisions are made discretely. The decisions need to be made discretely because the optimization scheme requires one to assume a temporary equilibrium condition. Being that nearly all the parameters of the model are estimates, and therefore uncertain, the results can not be seen as optimum per se, but rather a satisficing solution.

3.3 The Cloning Task

When $\mathbf{x}$ and $\hat{\mathbf{z}}$ have been determined, the Artisan's design adaptation task is complete and the cloning task begins. The cloning task, which is likened to manufacturing, represents the observation that artifacts do not always perform as they were designed. As the Patron determines the reward based on actual performance and not the forecasted design performance, this aspect must be included in the model.

The Cloning task within this framework is the simplest to model. The cloning task takes the design's theoretical performance and perturbates each CVA according to a predetermined theoretical statistical distribution. If the artifact's forecasted performance is summarized, as described earlier, by a vector $\hat{\mathbf{z}}$, then the veritable performance vector, $\mathbf{z}$, has the same number of elements and describes how the artifact actually performs. The cloning task can therefore be represented as follows

$$\hat{\mathbf{z}} \underset{cloning}{\Rightarrow} \mathbf{z}$$

Viewed in this manner, cloning is much akin to the phenomenon of mutation in biology.

The philosophy that artifacts should be manufactured to reliably perform as they were designed is a guiding doctrine of

[3] The reader is referred to Mills et al. (2002) and Pontikakis and Stamatelos (2001).

[4] The reader is referred to Cook (1997) and Montgomery (2000)

Six Sigma (Pande et al. 2000). Whereas Six Sigma has often been thought of and portrayed as a method to better meet customer requirements, the argument is easily made with a small bit of circumspection that it is actually a method to steer processes and products to *perform as designed*. Upon moving the philosophy upstream into design, one stumbles upon the emerging and still developing doctrine of Design for Six Sigma (Cook 2005). Here, statistical techniques and tools are used to reduce variance in product and process performance, as well as determine parameter targets during product and process design with the ultimate goal of improving the metrics which increase the fitness of the firm—bottom-line metrics such as cash flow, market share, etc.

3.4 The Evaluation Task

Consumer behavior models of the evaluation and purchase decisions are a research domain on its own, so the reader is referred to Solomon (2003) for a more comprehensive view. Within this framework, the simplified evaluation task begins with the Patron determining the value of each of the artifacts under consideration for purchase based that individual's own set of salient CVAs. Value is the price at which the Patron would be indifferent between owning each artifact and retaining the money equal to the price. The Patron's value naturally takes into consideration the individual's wealth position and all other germane factors.

After a value has been determined for each artifact, the perfectly rational Patron would choose the artifact with the largest difference between value and price (the normative theory). Being that humans do not always act rationally, mathematical psychology researchers (Thurstone 1927, Luce 1959, Tversky 1972) developed the foundation for discrete choice analysis (DCA), which generates a probability that each artifact is chosen (the descriptive theory). DCA assigns higher probability to those options with the larger difference between value and price.

Regardless of the modeling technique, a decision is made and a payment results if the Patron decides to exchange capital for the right to own the artifact. The Artisan's reward is therefore the difference between the Patron's payment and the total cost incurred by the Artisan to yield the artifact.

4. ILLUSTRATIVE EXAMPLE

Suppose a market for regular polygons exists. Through years of experience in this market, the polygon artisan has determined that the patron only considers purchasing polygons that fit within a circle with a radius of unity. Furthermore, the patron seems to measure the value of the polygon based on how close its perimeter matches that of a circle. Figure 3 shows two candidate designs, a pentagon and a decagon, where the decagon would be preferred as its perimeter more closely matches that of the encompassing circle.

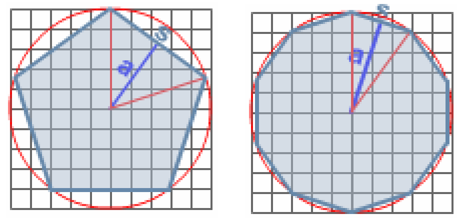

Figure 3: Two Regular Polygon Design Candidates Bound by a Unit Circle—Pentagon (n=5) and Decagon (n=10)

The perimeter of a pentagon whose vertices intersect with a circle with a radius of unity is $p(n) = 2n\sin\left(\pi/n\right)$, which for this example is the artisan's sole critical-to-value attribute, z.[5] The number of sides, n, is therefore the Artisan's design variable. If the z for this example is taken to be a larger-is-better (LIB) attribute, then the following value (willingness-to-pay) function can be posited (Cook 1997):

$$V(n) = V_0\left[\frac{1-\left(p(3)/p(n)\right)^2}{1-\left(p(3)/p(10)\right)^2}\right]^{\gamma_t} \tag{1}$$

where γ_t is a measure of preference and must be estimated by the artisan each time-period based upon either feedback from past sales or by using survey techniques. Larger values of γ_t indicate more curvature in the value function, which results in a higher overall value at the ideal[6]. For this example an arbitrary baseline value, V_0, is set at \$8, which corresponds to the value of a decagon. Any shape with less sides than a triangle is obviously of no value, so $p(3)$ is the critical value for the attribute that forces Eq. (1) to zero if n < 3.

Of course, manufacturing polygons is not free. There is a fixed cost, c^F = \$1, for the raw material and a variable cost that is related to the number of sides as described by Eq. 2.

$$c_t^V = (\alpha_t n)^4, \tag{2}$$

where α_t is a learning parameter.

Clearly, in order for a transaction to take place, two facts must be true: (1) the price, P, must be less than the Patron's value, V; and (2) P must be greater than the total cost, c^T, as the artisan would be put in a worse economic condition than if he did nothing. For simplicity, we assume there is a single Artisan and a single Patron who share equal bargaining power so that the surplus that results from the transaction ($V - C$) is shared equally. When this is the case, $P = \frac{V+C}{2}$, and the Artisan maximizes its surplus by maximizing total surplus (Cook 1997).

[5] The limit of $p(n)$ as n goes to infinity is 2π (the circumference of a circle with a radius of unity).

[6] Donndelinger and Cook (1997) found that γ_t is roughly the percentage of time the attribute is experienced by the consumer.

Formally, the Artisan's single-epoch design problem is as follows:

max: $V_t - c_t^T$

with respect to: n

such that:

$$V_t(n) = V_0 \left[\frac{1 - \left({p(3)}/{p(n)} \right)^2}{1 - \left({p(3)}/{p(10)} \right)^2} \right]^{\gamma_t}$$

$$c_t^T = c^F + c_t^V$$

$$c_t^V = (\alpha_t n)^4$$

where $V_0 = 8$ and $c^F = 1$. Fig. 4 shows an example of the Artisan's design problem where $\gamma = 1$ and $\alpha = 0.1$. Here, it becomes apparent that the Artisan should produce a polygon having eight sides as this maximizes surplus. Clearly the Artisan's design variable, n, will change as its costs are reduced (α varies) and as consumer preferences change (γ varies) as represented by Fig. 5.

To illustrate the dynamic design problem, let's assume that the period dependent variables follow the schedule of Table 1. Here α_t starts at 0.1 and decreases by 10% per period until $t = 6$ where is decreases by 5% there after, which is consistent with the theory that the rate of technological improvement generally slows as a technology becomes more mature (See Abernathy and Utterback 1978). The preference weight, γ_t, is estimated by the Artisan by observing preference trends and follows a cycle of highs and lows, which is typical of fashion and/or seasonal products. Fig. 6 shows the resulting path of the Artisan's decision variable as the realities of the design environment evolve. The path of the Artisan's decision variable, n, goes up slightly and stays constant at 9 as a result of the decreasing cost (even when γ_t is going down). The number of sides goes up each time period when there is a cost reduction *and* γ_t goes up. Lastly, n stays constant at 12 for several periods as γ_t falls and drops to 11, when the Patron's value can no longer support the higher number of sides.

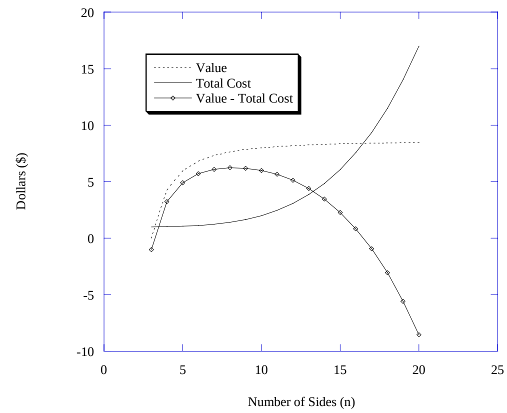

Figure 4: An Instantiation of the Polygon Artisan's Design Problem

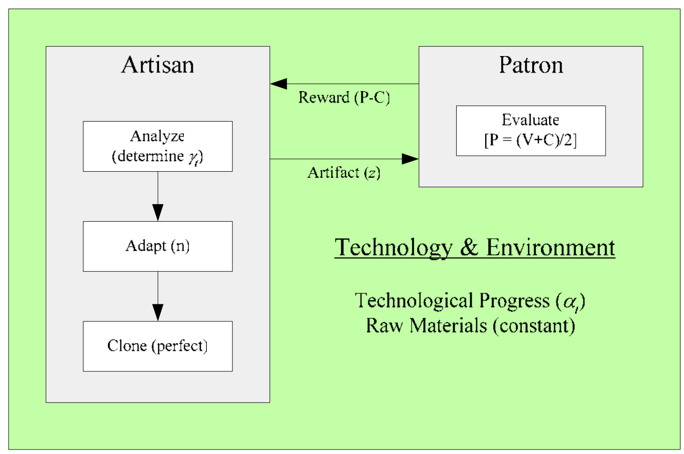

Figure 5: The Dynamic Artisan-Patron Model of Polygon Adaptation

Table 1: Parameter Evolution Schedule

t	α_t	γ_t
1	0.100	1.0
2	0.090	0.8
3	0.081	0.6
4	0.073	0.4
5	0.066	0.6
6	0.062	0.8
7	0.059	1.0
8	0.056	0.8
9	0.053	0.6
10	0.051	0.4

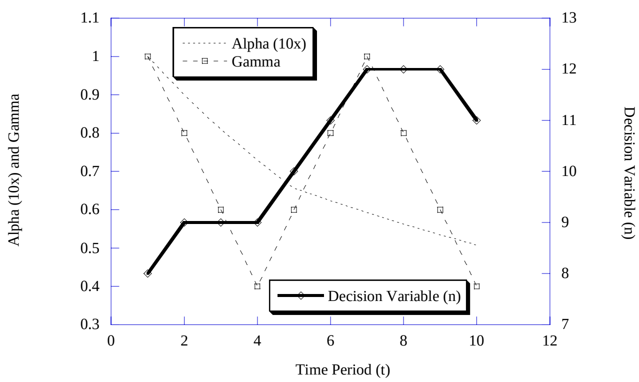

Figure 6: The Evolution of Polygon Design

This simple example helps to illustrate several points. First, if the Patron's value decreases for a particular attribute, the cost of providing that attribute may force the Artisan to move the decision variable in a direction that *reduces* performance. An example of this phenomenon would be the fuel economy in automobiles—the average new car fuel economy of American automobiles has been steadily decreasing ever since 1987 (Hellman and Heavenrich 2004). Second, the evolution of technology most likely follows the Artisan's beliefs about the future world realities and design constraints and not necessarily the real world realities or preferences of the Patron. Third, the evolution of artifacts can be viewed as the juxtaposition of multiple single-epoch design cycles. Lastly, it shows how the evolution of environmental parameters influences the evolution of design decision variables.

5. SUMMARY AND DISCUSSION

The AP model is intended to be a framework for understanding the drivers of artifact change, which can ultimately give artisans a method for managing complexity and making better decisions in highly competitive markets. We showed how design can be viewed as a multi-epoch adaptive effort, which is performed by an Artisan who strives to maximize his reward. The reward is determined by Patrons, who place a value upon the artisan's artifact and choose to purchase based on how that value relates to price. If value is greater than price, the Patron will be induced to make the transaction. The Artisan then uses the reward as feedback to help improve the artifact's future design. The model is based on the notion that artifacts are rarely forged based upon a design that does not evolve as a consequence of a changing environment (Simon 1996, Petroski 1992, 2003).

An abstract, yet representative example was offered to help illustrate how the framework can be used to model the evolution of an artifact as a result of a changing environment. The example had but a single critical-to-value attribute (CVA) (roundness) and a single measure of technical innovation (reduction in cost). This example can be easily extended to represent the evolution of more complex, real-world artifacts with the inclusion of more CVA, more design constraints, and more environmental variables.

The AP model is not intended to be a perfect 'crystal ball' that the Artisan uses to assign values to decision variables with high levels of confidence. Rather, the framework is to be used to help create models that can be used for studying how design parameters might change based on alternative future scenarios. The mathematical representation should also be used with care when analyzing artifacts that are vulnerable to disruptive technology, which fundamentally change the competitive environment. This is a major reason why the scope of the model has focused primarily on parametric redesign as the mode for product adaptation. Future research may relax this assumption to apply the framework to more complex methods of product adaptation such as original or adaptive design as described by Otto and Wood (1998). A standard caveat that accompanies the use of the AP model is that the fidelity of the results and insights are highly dependent upon the quality of data used.

The AP model is currently being used to analyze the evolution of the automotive industry with respect to fuel consumption as influenced by governmental policy (CAFE regulation) and technological innovation. There are several future research opportunities that can use this paper as a foundation. First, the model as presented here is deterministic and therefore one could study how the incorporation of uncertainty influences the artisan's decision making process. Lastly, a new challenging research path, yet seemingly attractive, would be to use the framework presented here to design simple, real-world experiments to test product planning hypothesis and models. Experimental economics, which uses real people and puts them in virtual markets for real cash stakes, has lead to the grounding of many economic theories (Altman 2004). Kagel and Roth (1995) present critical reviews of several studies conducted in this manner ranging from public goods and bargaining experiments to industrial organization and individual decision- making.

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