PARAMETRIC DESIGN ADAPTAION FOR COMPETITIVE PRODUCTS

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ABSTRACT

Very often product development is seen as a process where designers iterate through several design cycles until they converge upon a design that satisfies all of the necessary requirements — design within a single generation. If one takes the view that products change (i.e. adapt and evolve), a broader view must be adopted to capture the drivers of design adaptation across multiple product generations. This paper offers a new multi-generation framework of parametric design adaptation for consumer products, called the Artisan-Patron (AP) framework, and a complementary computational model. The AP framework captures the interaction between manufacturers (the Artisan) and consumers (the Patron) by structuring the various relevant information (e.g. consumer taste, government policy, cost of raw materials, etc.). Additionally, the corresponding computational model allows engineers to find the optimal settings for the design variables in this dynamic multi-generation environment. The utility of the framework and the model is demonstrated by considering the parametric design adaptation of the automobile with respect to two design parameters—engine horsepower and weight—based on historical automotive industry data.

Keywords: Product design, parametric design, enterprise modeling, product value, demand and price modeling.

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NOMENCLATURE (OPTIONAL)

J	Set of all competitive products (or manufacturers) competing within a given product segment	$c_{i,t}^{T}$ ($\hat{c}_{i,t}^{T}$)	Total production cost (estimate) for product *i* at time *t*
N	Total number of competitive products (or manufacturers) within a given product segment	$c_{i,t}^{V}$ ($\hat{c}_{i,t}^{V}$)	Variable cost (estimate) for product *i* at time *t*
i	Index denoting product (or manufacturer) *i*. $i \in J$	$c_{i,t}^{I}$ ($\hat{c}_{i,t}^{I}$)	Investment cost (estimate) for product *i* at time *t*
j	Index denoting competition of *i*. $(j \neq i) \in J$	$c_{i,t}^{R}$ ($\hat{c}_{i,t}^{R}$)	Regulation cost (estimate) for product *i* at time *t*
t	Index denoting time period or generation. $t \geq 0$	$\hat{c}_t^{weight}$	Estimated cost as a function of overall automobile weight at time *t* (average for all manufacturers)
fe	Fuel economy	$\hat{c}_t^{engine}$	Estimated cost associated with delivering engine horsepower at time *t* (average for all manufacturers)
at	0-60 mph acceleration time	$\hat{c}_t^{CAFE}$	Estimated CAFE policy penalty formula at time *t* (average for all manufacturers)
sf	Measure of safety which is related to the fatality rate in two-car crashes	V_0	Baseline value (i.e. at reference point)
hp	Vehicle aggregate horsepower	$V_{i,t}$	Value of product *i* at time *t* or average maximum willingness-to-pay for product *i* at time *t*
w	Vehicle weight	$\overline{V}_t$	Average value of all products at time *t*
A	Set of Critical-to-Value Attributes (CVA) in a product	$v\left(\hat{z}_{i,t}^{a}\right)$	Value of a single CVA
a	A single CVA, $a \in A$	$p_{i,t}$ ($\hat{p}_{i,t}$)	Price of product *i* at time *t* (price estimate)
$\mathbf{z}_{i,t}^{A}$	Vector of Critical-to-Value Attributes (CVA) in product *i* at time *t*: $\mathbf{z}_{i,t}^{A} = (z_{i,t}^{1}, \ldots., z_{i,t}^{a}, \ldots)$	p_0	Baseline price (i.e. at reference point)
$\hat{\mathbf{z}}_{i,t}^{A}$	Estimate of $\mathbf{z}_{i,t}^{A}$ – forecasted performance	$\overline{p}_t$	Average price of all products at time *t*
$z^{a,I}$	Ideal attribute setting where the consumer is unwilling to pay for further improvement	$D_{i,t}$	Demand for product *i* at time *t*
$z^{a,C}$	Critical setting for attributes where the consumer is unwilling to purchase the product even if all other attributes are at an ideal setting	$D_{T,t}$	Total market demand (for whole industry) at time *t*
$z^{a,0}$	Baseline attribute settings (i.e. for the baseline product)	$D_{T,0}$	Total market demand (for the whole industry) at the reference state (i.e. baseline total market demand)
$\hat{z}_t^{fe}$	Estimated average fuel economy (*fe*) at time *t*	$\pi_{i,t}$	Profit of a single manufacturer *i* at time *t*
$\hat{z}_t^{at}$	Estimated acceleration time (*at*) at time *t*	Π_t	Profit of the industry (without investment cost) at time *t*
$\hat{z}_t^{sf}$	Estimated safety (*sf*) at time *t*	γ_t^{a}	Measure of attribute '*a*' importance. % time attribute '*a*' is experienced by consumer during product use
z_t^{CAFE}	Sales-weighted (car & truck) adjusted fuel economy standard for the manufacturer's product mix at time *t*	η_0	Price elasticity of demand at the reference state (baseline price elasticity)
$R\left(\mathbf{z}_{i,t}^{A}\right)$	Reward value based on $\mathbf{z}_{i,t}^{A}$	η_t	Price elasticity of demand at time *t*
$\hat{R}\left(\mathbf{z}_{i,t}^{A}\right)$	Estimate of $R\left(\mathbf{z}_{i,t}^{A}\right)$	K_t	Constant - Negative slope of the demand curve for the market segment of interest at time *t*
B	Set of decision/design variables in a product design	ρ_t	Time adjusted CAFE penalty, ($) per mpg below standard
b	A single decision variable, $b \in B$	$\alpha_1^{fe}, \alpha_2^{fe}, \alpha_3^{fe}$	Regression coefficients used for fuel economy (*fe*) transfer function
$\mathbf{x}_{i,t}^{B}$	Vector of design or decision variables for product *i* at time *t*: $\mathbf{x}_{i,t}^{B} = (x_{i,t}^{1}, \ldots., x_{i,t}^{b}, \ldots)$	$\alpha_1^{at}, \alpha_2^{at}, \alpha_3^{at}$	Regression coefficients used for acceleration time (*at*) transfer function
$\mathbf{x}_{i,t}^{B,U}$	Upper bounds on design variables of product *i* at time *t*	$\alpha_1^{sf}, \alpha_2^{sf}, \alpha_3^{sf}$	Regression coefficients used for fuel economy (*sf*) transfer function
$\mathbf{x}_{i,t}^{B,L}$	Lower bounds on design variables of product *i* at time *t*	$\beta_{1,t}$ & $\beta_{2,t}$	Parameters of engine cost
x_t^{hp}	Vehicle aggregate horsepower at time *t*	$\beta_{3,t}$	Cost of automobile raw materials per pound
x_t^{w}	Vehicle weight at time *t*	$\beta_{4,t}$	Multiple to account for economic fluctuation

1 INTRODUCTION

To help designers become better innovators, research in engineering design strives to ascertain how to make design activities more effective, efficient, and manageable through the use of conceptual and/or mathematical models [1]. Very often design (or product development) is seen as a process where designers iterate through several Design-Build-Test cycles until they converge upon a design that satisfies all necessary requirements—design iteration within a single generation [2-3]. Here design iteration is typified by the 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 studies [4-5]. The single generation design assumption reduces complexity and has led to advances in design theory on several descriptive and prescriptive levels, such as reducing design churn [6], valuing and selecting the best design alternative [7], managing experimentation during product development [8], and axiomatic design principles to manage complexity [9].

However, the single generation design assumption is not always appropriate [10]. 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 [11]. With this conception of an economic good, an artifact's design is more accurately viewed as transient than constant over time, where any single artifact is simply an instantiation of a design at the time of production. This multi-generation perspective views design as an adaptive endeavor that utilizes feedback and/or feed-forward information to evolve an artifact in an effort to maintain or increase the artifact's desirability relative to other competing alternatives in the marketplace. Feedback information comes to the artisan based on how well his artifact is able to garner economic results. Feed-forward information comes to the artisan through the acts of market research and forecasting, which is a necessary part of the design process for consumer products.

Two of the predominant explanations behind product redesign (across multiple generations) are technological improvement and consumer taste change. Clark [12] present three important points that form a partial philosophical basis for this paper. First, the idea that there is a *design process* "behind sequences of innovations in a specific product." Secondly, the concept of a *framework* that considers the evolution of consumer preferences as an important aspect of innovation, rather than focusing only on the evolution of technical aspects of the design. Thirdly, *consumer preferences evolve* due to the technological development path. Clark [12] 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.

Recognizing that artifacts must adapt and evolve through redesign, Otto and Wood [10] present a comprehensive multi-step process for reverse engineering an artifact redesign. The authors make a distinction between three approaches to adapt products 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 sub-functions." 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 in this paper may be used to characterize all three of the aforementioned design strategies, the focus is upon parametric design. This simplifying assumption allows us to use a mathematical framework to capture the dynamics of design (or product) adaptation that is characteristic of products that compete in mature markets.[1]

This paper offers a new framework of parametric design adaptation for consumer products is offered called the Artisan-Patron (AP) framework. The Artisan-Patron (AP) framework captures the interaction between manufacturers and consumers by structuring the various relevant 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. As the AP framework brings all the information together, the complementary computational model allows engineers to determine optimal settings for design variables and shows how the variables change from one generation to the next, which gives a historical view of how the design variables were adapted in response to the consumers' perceived requirements and other environmental changes.

The remainder of the paper proceeds as follows. Section 2 provides a quick overview of relevant literature in and around design adaptation and evolution. Next, Section 3 motivates and presents the AP framework for modeling the multi-generation design adaptation problem. Section 4 provides a computational implementation of the AP framework. Section 5 describes an application of the AP framework and the computational model by analyzing the adaptation of two design variables in the automotive industry. The paper concludes in Section 6.

2 LITERATURE REVIEW

Relevant literature spans many research areas ranging from engineering design, product management and marketing[2], economics[3], to biological evolution of natural and man-made systems.[4] However, in this section, we focus on the engineering design literature.

Ullman [13] describes product evolution as the changes in abstraction level throughout the course of design as a refinement of a design from its initial state to its final state --- evolution of product states. That is, representation of specification, function, and behavior becomes more precise as the design evolves. This is similar to Krishnan's et al. [17] notion of "information evolution", which describes design evolution as the process of uncertainty reduction for a design parameter (or the narrowing of a value range) as the design evolves from its initial to its final stage. Thompson and Lu [18] propose a set of methodologies and tools that capture and utilize decision rationale during

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[1] Mature markets are defined as those where the manufacturers have converged upon a dominant design or architecture [14].

[2] Evolution and adaptation of products has been used in product management and marketing literature to explain gradual improvement of products. Tellis and Crawford [15] summarize this literature by the following four observations: (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.

[3] For example, Nelson and Winter [16] present simulation models that strive to mimic how firms adapt their decision routines.

[4] Darwinism and Lamarchism are two popular biological models of adaptation and evolution that is often used as an analogy by those wishing to describe the drivers of product evolution [31-32]. Another potentially useful biological model that was pointed out by one of the anonymous reviewers is the predator-prey model [33].

design in order to build a design evolution information management system. Similarly, Shooter et al. [19] describe an information model of product design which leverages an analogous notion for design evolution. Although our proposed model is similar to the notion of information evolution found in this research stream; however, this paper focuses on multiple generations instead of within a single generation.

Recognizing that design decisions need to be tied to broader issues that are important to the firm, Papalambros [20] introduces '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. [21] defined the enterprise-wide design decision model as:

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

The crux of this solution method relies on the ability to link product parameters (e.g. engine type and size) to product performance attributes (e.g. fuel economy and acceleration). This linking is accomplished by defining transfer functions that allow forecasting of performance attributes as design variables change [22]. Our proposed model builds on the notion of enterprise-wide models and transfer functions, as described in the next section. Along these lines, Michalek et al. [23] propose a single-generation design optimization model that studies the effects of governmental regulation policies on the design of automobiles. A similar single-generation optimization framework is used within this paper, but the scope is enlarged to study the effects of dynamic environmental variables that cause the artifact's design parameters to change from one generation to the next.

Another related stream of research is the engineering change management literature [24-25]. This literature presents the problems and processes associated with design changes (mainly within a single product generation). It also looks at the causes, effects, and costs of an engineering design change [25]. Fricke and Schulz [26] recognize the importance of Design for Changeability (DfC), suggesting that flexibility, agility, robustness, and adaptability are four key aspects of changeability and discuss incorporating changeability into a system's architecture. Engel and Browning [27] describe a method (called design for adaptability) to assess whether a system can be upgraded easily and economically based on its architecture and show that this adaptability results in an increase in a system's lifetime value.

More recently, research into flexible, reconfigurable, and evolvable systems design is also relevant to our paper (e.g., [28-30]). Flexible and reconfigurable systems are capable of undergoing changes in order to meet new objectives, function effectively in varying operating environments, and deliver value in dynamic market conditions. However, these studies primarily focus on the cost of building flexibility (in anticipation of future changes in demand and before the actual need for switching arise) compared to future unplanned switching costs should future needs necessitate the change. Additionally, these designs are usually shorter term, platform-based approaches which allow some flexing in the design parameters (and corresponding performance attributes) within a reasonable range to accommodate varying customer tastes and needs [34]. Although this research stream could be relevant in identifying the proper design parameters and performance attributes, but does not provide the proper modeling paradigm required for design evolution and adaptation. It is more of a proactive approach to potential (anticipated) changes to mitigate the costs and risks of switching to another configuration instead of a reactive evolutionary approach that mimics design adaptation.

3 THE ARTISAN-PATRON (AP) FRAMEWORK

In this paper, the design problem is viewed as a multi-generation adaptation 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 other 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. 1), the Artisan-Patron (AP) framework is created, which captures the information flow required to adapt the design within each generation. When the information flows are encoded, this will create a computational model of multi-generational design adaptation (described in Section 4) that aids the Artisan in determining the best settings for what he can control—design variables. The rest of this section provides details for each of the tasks.

The Analysis Task

If an artifact is described by a finite vector of critical-to-value attributes (CVAs), $\mathbf{z}$, it is easy to see that although the actual reward value, R, flowing from the Patron to the Artisan is observable (see Fig. 1), the reward function, $R(\mathbf{z})$, of the Patron is not. The Artisan must therefore create a reward forecasting function, $\hat{R}(\mathbf{z})$, whose parameters are adjusted from one time period to the next to forecast the veritable reward based upon beliefs about how the Patron makes trade-offs. The task of modeling and adjusting the $\hat{R}(\mathbf{z})$ parameters is one of the Artisan's primary challenges in the analysis task because it is necessary for the Artisan to evaluate the competitiveness of his artifact to that of competing artifacts available to the Patron.

Estimating reward functions has traditionally been performed by the marketing arm of the firm. Mathematical psychology researchers (e.g., [35-36]) developed the foundation for discrete choice analysis (DCA), which strives to generate a probability that an alternative is chosen based upon its relative merit. Popular methods for capturing merit, or willingness-to-pay, functions of consumers has been conjoint analysis [37-38] and the direct value method (DVM) [7,39].

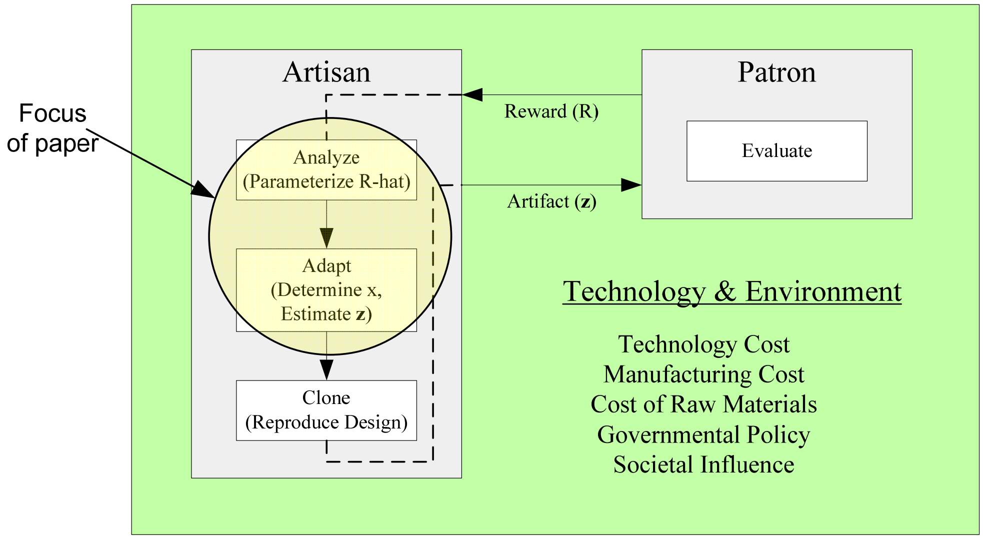

Figure 1: The Artisan-Patron (AP) Model

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. Technological factors include advances in materials and architectural knowledge as well as advances in manufacturing processes. Environmental factors include cost of raw materials, changes in relevant government policy, and changes that influence the cost of owning the artifact (fuel prices, maintenance, storage, etc.). If all the exogenous variables (reward function, technological innovation, and the environment factors) were static, the Artisan would be able to discern the true analytic 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 how the Patron makes decisions and the design adaptation task, consequently, would become unstable. Therefore, the proposed model focuses on design problems where the critical exogenous variables are unknowable, yet somewhat predictable or stable, as is the case with many consumer products such as automobiles or household appliances. The analysis task is complete when all of the exogenous variable relationships have been estimated to the extent that they are able to provide guidance to the artisan throughout the adaptation task.

The Adaptation Task

With $\hat{R}(\mathbf{z})$, the Artisan is able to forecast the commercial feasibility of new designs. The Artisan's design adaptation task proceeds by searching and evaluating the feasible design space for satisficing settings of the design variables (DV's), $\mathbf{x}$, which maximize the posited reward function. As designs are evaluated based on their CVA's and not their DV's, the Artisan must create models that map $\mathbf{x} \to \hat{\mathbf{z}}$, called transfer functions. These transfer functions are either created through 'bottom-up' approaches such as Computer Aided Engineering (CAE) models (e.g., [40-41]) or through 'top-down' statistical approaches such as design of experiments (DOEs) or regression from test data (e.g., [39,42]). The Artisan's design adaptation task is complete when $\mathbf{x}$ and $\hat{\mathbf{z}}$ have been determined.

The Cloning Task

When artifacts are produced, manufacturing variation is introduced which results in artifacts that do not always perform as intended (i.e., by design). The Patron often determines the reward based on actual performance and not the designed performance. If the artifact's forecasted performance is summarized by a vector $\hat{\mathbf{z}}$, then the veritable performance vector, $\mathbf{z}_k$, has the same number of elements and describes how an individual artifact k actually performs. The cloning task captures how actual performance deviates from designed performance in the form of a statistical distribution.[5]

The Evaluation Task

The evaluation task describes how consumers determine which artifact to purchase and how much to pay. The two classical frameworks offered by consumer behavior researchers are the hierarchy of effects model and the consumer information processing model [43]. While the first model describes the mental stages that consumers go through as they ponder the purchase decision, the second model makes a more detailed analysis of the consumer's mind. Although this research domain has demonstrated to be useful in the design of advertising and media campaigns, it is unclear how the results could be captured mathematically and included in our proposed model for use in engineering design decision making regarding product design parameters. For this reason, a detailed analysis of the purchase decision process is not included in this paper, but remains open for future research.

4 THE PARAMETRIC DESIGN ADAPTATION MODEL

The proposed model is based on the analysis and adaptation portion of the above framework. As described earlier, the analysis task requires the determination of all CVAs and linking them to a value model in order to make necessary trade-offs between the considered design variables. Then during the adaptation task, the Artisan first links design variables to CVAs, and second, determines the best balance between patron value, cost incurred to produce the artifact, and other constraints imposed by the environment. In the rest of this section we describe the approach used to determine the value model, the cost model, the transfer functions used in the engineering model, the demand model, the price model, the profit model, and then integrating all these sub-models into a complete formulation for the parametric design adaptation model.

Figure 2 shows the proposed parametric design adaptation model. The boxes with bold borders designate the transient environmental factors that must be considered during each design cycle. The boxes within the shaded area show where sub-models need to be created. Overall, the model is very similar to the one used by Michalek et al. [23], except price is removed as a decision variable and replaced by a pricing equation that takes value, cost, and number of competitors as inputs. The objective is to find the optimal settings for the design variable, $\mathbf{x}$, to maximize profit.

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[5] The philosophy that artifacts should be manufactured to reliably perform as designed is a guiding doctrine of Six Sigma [22,44].

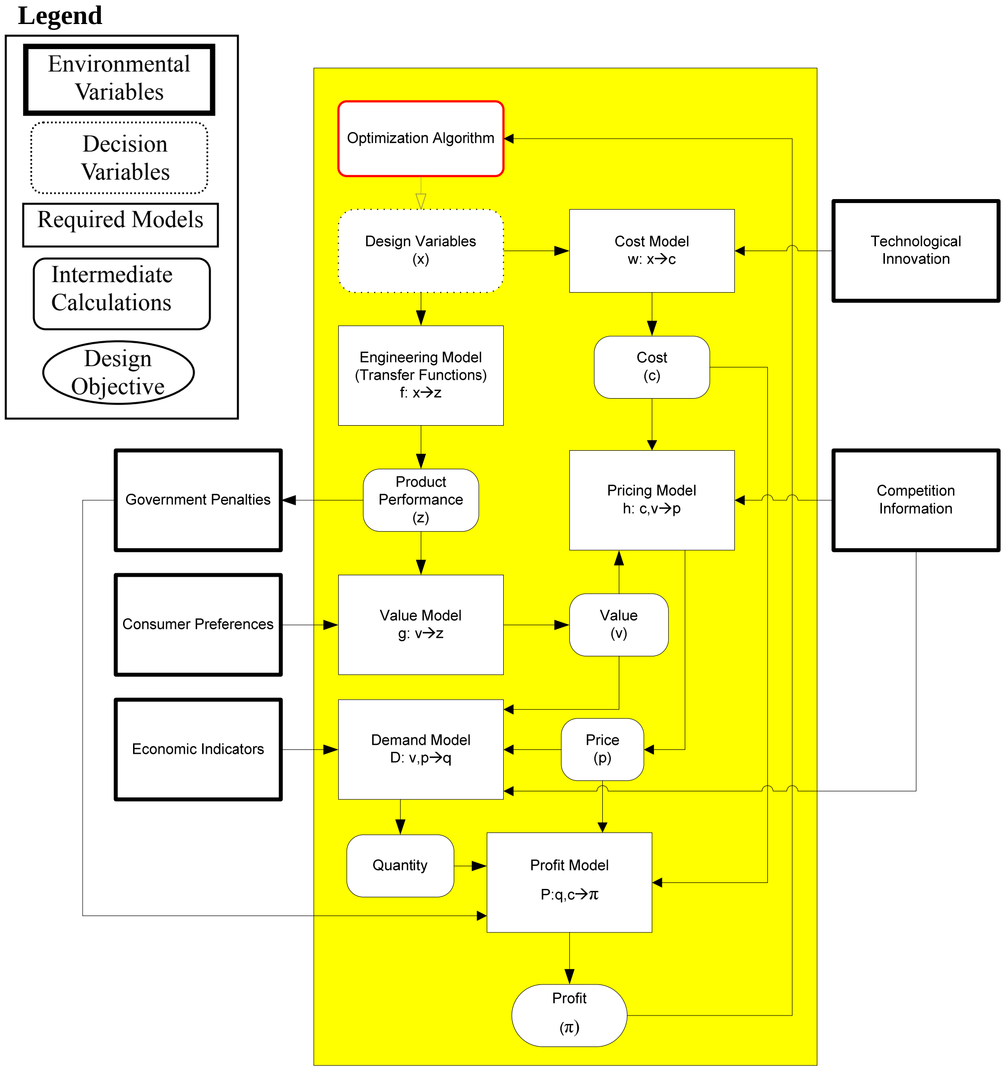

Figure 2: The Proposed Parametric Design Adaptation Model

Starting with the 'design variables' box in Fig. 2, the Artisan's (i.e. manufacturer) choice for the design variables vector (**x**) simultaneously determines the product performance (**z**) through an engineering model that acts as a transfer function mapping **x** to **z**, and the cost of producing the design using a costing model. The performance vector (**z**) (along with a consumer preference profile) is entered into a value model to estimate the value of the designed artifact as perceived by the patron (i.e. consumer). The resultant value is entered into a pricing model (along with the earlier cost estimate and information about the competition) in order to estimate the price to be charged for the product. Collectively, price, value and competition (along with some other economic indicators) will be used in a demand model to estimate demand and ultimately profits. The objective is to maximize these profits with respect to the choice of the design variables and subject to some other constraints. Finally, the arrow connecting the optimization algorithm to the design variables represents design iterations within a single-generation of a product design in order to optimize profits. The successive application of this model generation after generation (as the environmental variables change) constitutes our posited multi-generational model of parametric design adaptation.

4.1 Engineering Model—Transfer Functions

Transfer functions are engineering models used to project how a change is expected to influence one or more CVAs at the full system level. Simply, transfer functions are used to create a link/map between design variables (**x**) and product performance attributes (**z**). The challenge is in accurately modeling how the change in a component or subsystem affects the CVAs of the product. The problem is not trivial, almost always involving non-linear interactions [22].

Although sophisticated analytical tools, such as ADVISOR [45], have been shown to be quite adept engineering models for use in the automotive industry when comparison of alternative engine architectures are of concern, designed experiments or simple regression models from historical data could also be adequate as will be shown in the automotive design case study in Section 5. The generic form of these transfer functions is as follows, where $\mathbf{x}_{i,t}^{B}$ is a vector of design variables for product *i* at time *t* and $\hat{\mathbf{z}}_{i,t}^{A}$ is the corresponding forecasted performance of the proposed design for product *i* at time *t*:

$$f\text{: } \mathbf{x}_{i,t}^{B} \rightarrow \hat{\mathbf{z}}_{i,t}^{A} \tag{1}$$

4.2 Cost Models

It is recognized that manipulating design specifications (or process operating conditions) has consequence not only on product performance, but also on production costs that ultimately establish the profit margin a firm can realize [46]. Generally, three different approaches to cost modeling (i.e. estimation) exist: analogous, parametric and detailed [47]. Analogous models estimate the cost by analogy with an existing similar product. This method requires expert judgment and complete familiarity with the product [48]. It is very good for new products. Parametric cost analysis consists of equations or cost estimation relationships that describe relationships between cost and measurable attributes of systems [49]. This method is not very good for product utilizing new technologies. Finally, the detailed method works by estimating the direct costs of a product or activity using estimates of labor times and rates, material quantities and prices. This method gives the most accurate cost estimates, but is time consuming and costly as it requires detailed knowledge of the product. Activity-based costing (ABC) [47] and process-based costing (PBC) [46] are two popular detailed methods.

Any of these three cost modeling approaches could be used to arrive at a production cost estimate useful in our proposed analysis. However, in this paper, we assume a hybrid approach mainly due to limited availability of detailed data (or experience) required by a particular single cost estimation approach. Therefore, in this paper, we, generally, assume that the cost of production for a particular design is divided into variable ($\mathrm{c}_{i,t}^{V}$) and fixed investment costs ($c^{I}_{i,t}$). Variable costs are those that scale linearly with production volume, such as material, machining, assembly, labor and energy costs. Alternatively, investment costs include those items that do not scale with production volume, such as production machines, tooling, buildings, and overhead costs, to name a few. Sometimes, additional regulatory costs ($c^{R}_{i,t}$) are incurred by the manufacturer (i.e. Artisan) in order to comply with specific requirements such as governmental or environmental regulations (e.g. Fuel efficiency, emissions, and recyclability). It is worth noting again that specialized cost estimation formulations, which pertain to a specific design under investigation, may have to be employed to estimate the three different cost drivers. For example, the costing model employed in the case study formulates the variable and compliance costs based on engine horsepower and weight. So, in general the design decisions are mapped to cost drivers as follows:

$$g\text{: } \mathbf{x}^{B}_{i,t} \rightarrow c^{V}_{i,t}, c^{I}_{i,t}, c^{R}_{i,t} \tag{2}$$

Finally, we will assume that all artisans (i.e. manufacturers) have the same production cost structure. This assumption is appropriate especially for oligopoly analysis [23].

4.3 Value Model

Being able to measure the aggregate value of an economic good is critical to modeling how the market will respond to a design alternative. Cook [39] expresses value as the location where a tangent to the hypothetical demand curve intercepts the price axis when drawn from a demand/price reference state (see Fig. 3 which is discussed in detail in the next section). Moreover, the value of any proposed product i can be calculated by translating all critical-to-value attribute into value coefficients, $v\left(\hat{z}^{a}_{i,t}\right)$, and then multiplying these coefficients by the baseline value of the product, V_0, as shown in Equation (3) [39]:

$$V_{i,t} = V_0 \prod_{a \in A} v\left(\hat{z}^{a}_{i,t}\right) \tag{3}$$

The value of a single CVA within product i $\left(\hat{z}^{a}_{i,t}\right)$ could be estimated by specifying three reference attribute levels as shown in Equation (4), where $z^{a,I}$ is the ideal attribute setting where the consumer is unwilling to pay for further improvement; $z^{a,C}$ is the critical setting where the consumer is unwilling to purchase the product even if all other attributes are at an ideal setting; and $z^{a,0}$ is the attribute setting of the baseline product [39]. Lastly, γ^{a}_{t} can be viewed as a measure of attribute importance that is related to the percentage of time attribute 'a' is experienced by the consumer during product use. As γ^{a}_{t} approaches zero, the value coefficient goes to 1, which means that the attribute will not affect value so long as a critical threshold is maintained.

$$v\left(\hat{z}^{a}_{i,t}\right) = \left[\frac{\left(z^{a,I} - z^{a,C}\right)^2 - \left(z^{a,I} - \hat{z}^{a}_{i,t}\right)^2}{\left(z^{a,I} - z^{a,C}\right)^2 - \left(z^{a,I} - z^{a,0}\right)^2}\right]^{\gamma^{a}_{t}} \tag{4}$$

Finally, the baseline value can be calculated using Equation (5), where η_0 is the baseline price elasticity of demand and p_0 is the baseline price [39].[6] The notion of the baseline reference point is discussed next.

$$V_0 = p_0 \left(\frac{\eta_0 + 1}{\eta_0} \right) \tag{5}$$

4.4 Demand Model

Generally, demand for a product is forecasted by comparing the net values (i.e., value minus price) of products that compete within a given product segment [39]. However, the competitive environment we consider in this paper (i.e. an oligopoly of *N* manufacturers competing within a given product segment and targeting the same customers) generally results in competitive products having similar values and prices (but with some differentiation). In this case, when the net values of the products are similar in magnitude, one can make demand forecasts using a cartel point (where the *N* products are assumed identical) and a linear demand model, as shown in Fig. 3 [39]. The value, price, and demand for the cartel point are constructed by averaging the values, prices, and demands for the *N* products across a reference or baseline state.[7]

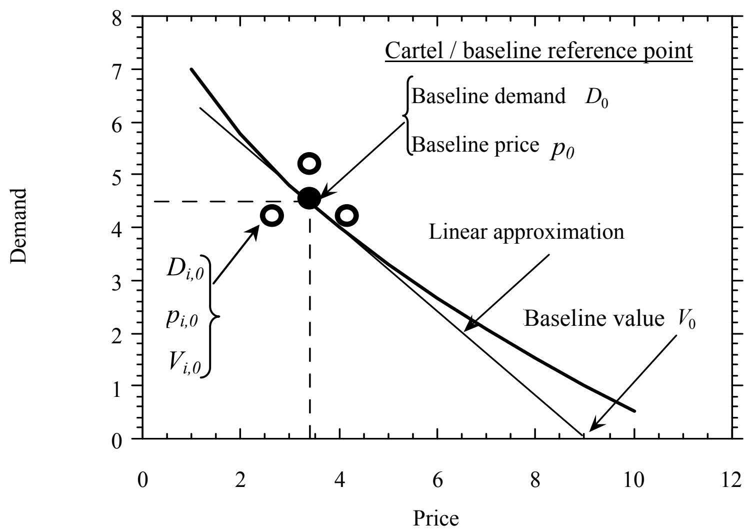

Figure 3: Cartel Point and Linear Approximation to a Non-linear Demand Curve

The linear demand function shown in Fig. 3 is exact in the limit of small departures in price, value and demand, which occurs in highly competitive market segments [39].[8] The fundamental assumption of this linear demand model is that the demand for a product *i* is an analytic function of the values and prices of the *N* competing products that make up a market segment. Equation (6) is a hyper-plane approximation to the actual demand surface for a single competitor *i* among *N* total competitors in the market [39].

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[6] Products with high elasticities ($\eta_0 > 1$) are often called luxuries, whereas those with small elasticities ($\eta_0 < 1$) are called necessities [50].
[7] For example, during the planning of a new product (e.g. to be produced in four years), the baseline state is constructed from the values, prices, and demands for the *N* products in the current year [22].

$$D_{i,t} = K_t\left[V_{i,t} - p_{i,t} - \frac{1}{N}\sum_{j\neq i}\left(V_{j,t} - p_{j,t}\right)\right] = K_t\left[V_{i,t} - p_{i,t} - \frac{(N-1)}{N}\left(\overline{V}_{j,t} - \overline{p}_{j,t}\right)\right] = K_t\left[\frac{N+1}{N}\left(V_{i,t} - p_{i,t}\right) - \left(\overline{V}_t - \overline{p}_t\right)\right] \quad (6)$$

$V_{i,t}$ and $p_{i,t}$ are the value and price, respectively, of product *i* at time *t*, which are near but assumed away from the value and price of the cartel point. Similarly, $V_{j,t}$ and $p_{j,t}$ are the values and prices of the (*N*-1) competitive products, at time *t*. $\overline{V}_{j,t}$ and $\overline{p}_{j,t}$ are the average value and price of the (*N*-1) competitive products at time *t*. $\overline{V}_t$ and $\overline{p}_t$ are the average value and average price, respectively, for the *N* competing products at time *t*. Finally, the constant K_t is the negative slope of demand with price at the cartel point and estimated from the baseline state as:

$$K_t = \frac{\eta_t D_{T,t}}{\overline{p}_t} \quad (7)$$

Where η_t is the price elasticity of demand at time *t*, and $D_{T,t}$ is the aggregate demand of the entire market, which can be obtained from Equation (6):

$$D_{T,t} = \sum_{i=1}^{N} D_{i,t} = K_t\left(\overline{V}_t - \overline{p}_t\right) \quad (8)$$

A market share estimate, for product *i* at time *t*, could be obtained by combining Equations (6) and (8). It is straightforward to see that one can use the choice probability as a surrogate for market share and multiply it by a fixed market size to arrive at the demand for each competitor in the market.

4.5 Price and Profit Models

The pricing model is used to forecast the manufacture's pricing strategy (e.g., MSRP) to aid in cash-flow projections. There are numerous applicable pricing strategies that may be feasible given a particular market environment and structure. Nevertheless, the feasible price range for a competitor's good is ultimately dictated by that competitor's cost and product value. We present, first, the profit equation for a single-product firm as:

$$\pi_{i,t} = D_{i,t}\left[p_{i,t} - c_{i,t}^{V}\right] - c_{i,t}^{I} \quad (9)$$

Taking the first-order condition for product *i*'s profit maximization problem produces the following result when solved for p_i:

$$p_{i,t} = \frac{V_{i,t} + c_{i,t}^{V}}{2} - \frac{(N-1)\left(\overline{V}_{j,t} - \overline{p}_{j,t}\right)}{2N} \quad (10)$$

where $\overline{p}_{j,t}$ is the average of the prices set by the competition (at time *t*) as they go through the same process.

Equation (10) is more useful when reduced to a closed form solution coming from the resulting set of *N* simultaneous equations [52]:

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[8] Alternatively, when the net values are markedly different, the non-linear logit model may provide a better fit [51].

$$p_{i,t} = \frac{\gamma_1 c_{i,t}^V + \gamma_2 V_{i,t} + \gamma_3 \left(\overline{c}_{j,t}^V - \overline{V}_{j,t}\right)}{\gamma_4} \tag{11}$$

where $\gamma_1 = N^2 + 2N$, $\gamma_2 = N^2 + N + 1$, $\gamma_3 = N^2 - N$, and $\gamma_4 = 2N^2 + 3N + 1$.

Careful inspection of Equation (11) reveals three interesting special cases. First, Equation (11) simplifies to $p_t = (V_t + c_t^V)/2$ for a monopoly, which agrees with common knowledge. Alternatively, when the number of competitors becomes large, Equation (11) approaches $\lim_{N\to\infty} p_{i,t} = (V_{i,t} + c_{i,t}^V - \overline{V}_{j,t} + \overline{c}_{j,t})/2$. Third, when a homogeneous market assumption is made ($V_i = V$) with the same cost model ($c_i^V = c^V$), Equation (12) simplifies to the well known result of a Cournot game amongst homogeneous competitors in value and cost [53]:

$$\hat{p}_t = \frac{\overline{V}_t + N\hat{c}_t^V}{N+1} \tag{12}$$

4.6 Complete Formulation of Optimization Model

When integrating the above sub-models together, the result is a complete model of parametric design adaptation. This model, in its entirety, links profit to the design variables and yields a discontinuous, non-linear solution space. The solution space is discontinuous due to the value-coefficient functions that force value to zero when a critical attribute level has been breached (which forces profit to zero). However, when the solution space is constrained to feasible design variable settings, the solution space is convex, which means any constrained non-linear optimization technique can find the optimum solution to this system of equations. The complete mathematical model is as follows, where $\mathbf{x}_{i,t}^{B,U}$ and $\mathbf{x}_{i,t}^{B,L}$ are the upper and lower bounds on the design variables, respectively:

Maximize: $\pi_{i,t} = D_{i,t}\left[p_{i,t} - c_{i,t}^V\right] - c_{i,t}^I$

With respect to: $\mathbf{x}_{i,t}^B$

Subject to:

$$\begin{aligned}
&\mathbf{x}_{i,t}^{B,L} \le \mathbf{x}_{i,t} \le \mathbf{x}_{i,t}^{B,U} \\
&c_{i,t}^V = f\left(\mathbf{x}_{i,t}^B\right) \\
&D_{i,t} = K_t\left[V_{i,t} - p_{i,t} - \frac{(N-1)}{N}\left(\overline{V}_{j,t} - \overline{p}_{j,t}\right)\right] \\
&K_t = \frac{\eta_t D_{T,t}}{\overline{p}_t} \\
&V_{i,t} = V_0 \prod_{a\in A} v\left(\hat{z}_{i,t}^a\right) \\
&p_{i,t} = \frac{V_{i,t} + c_{i,t}^V}{2} - \frac{(N-1)\left(\overline{V}_{j,t} - \overline{p}_{j,t}\right)}{2N}
\end{aligned} \tag{13}$$

5 AUTOMOBILE PARAMETRIC DESIGN ADAPTATION CASE STUDY

Although several simplifying assumptions must be made, the parametric adaptation of the aggregate automotive design (in terms of horsepower and weight) as a result of several environmental factors such as the CAFE policy, price of gasoline, and the cost of steel can be modeled using the AP framework. The important feature that makes this possible is that the automobile's power plant has been dominated by the spark ignition (SI) engine. Although there are many different designs of SI engines and the automobile has had many architectural changes throughout its many subsystems, historical data suggests that vehicle aggregate horsepower and weight can be used to predict both aggregate fuel economy and the time it takes to accelerate the vehicle from rest to 60 miles/hr (mph). As weight negatively influences fuel economy and acceleration time, an attribute to "keep weight in" was sought. This was done by finding a relation between vehicle weight and safety. All other ideas for "keeping weight in", such as additional styling, features and/or options, introduced other confounding attributes. Therefore, the analysis proceeds under the assumption that automotive consumers base their purchase decisions on three CVAs: fuel economy (*fe*), 0-60 mph acceleration time (*at*), and a measure of safety which is related to the fatality rate in two-car crashes (*sf*).

Furthermore, we assume that the design decisions were influenced by only a few external variables: price of steel, price of fuel at the pump, unemployment rate, CAFE policy, and inflation. Simplifying assumptions were also made regarding market structure, namely that entire automotive industry can be represented by six manufacturers who compete with homogeneous products.[9] This level of aggregation was thought appropriate because the interest was in understanding how the automotive industry as a whole reacted to changes in the environment versus the reactions of a single player. Therefore, in all subsequent equations in this case study, we suppress the product index '*i*', which means that all variables in the case study reflect averages in cost, price and value for the *N* competing products. Finally, many of the "orthodox" economic theory assumptions, such as unbounded rationality, profit maximization, and the notion of equilibrium (transient) were also posited.

5.1 The Analysis Task

During the analysis task, the Artisan attempts to discern how Patrons determine their reward structure for the Artisan's artifacts and how relevant environmental factors will affect design decisions. The following sub-sections describe the consumer value model used, the critical to value attributes posited, and factors influencing vehicle cost.

5.1.1 Critical-to-Value Attributes and Design Variables

In this case study, two design variables were used to forecast fuel economy (*fe*): horsepower (x^{hp}) and weight (x^{w}). Changing the weight and horsepower, however, also influences the acceleration and top speed performance of the automobile. For all three attributes, more horsepower and less weight improve performance. We chose to use the time to accelerate from 0 to 60 mph as the representative attribute for all types of acceleration metrics as top speed is rarely experienced.

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[9] A possible argument for 6 players is that this may be the limit of how many alternatives a consumer may be able to consider at a given moment. The actual limit found through psychological studies is usually thought to be 7 +/- 2 [54].

The amount of horsepower that can be put into an automobile is limited by the increasing cost of doing so (technological constraints) in spite of its positive influence to fuel economy and acceleration and therefore has a built-in constraint to limit it. Weight, however, is not "kept-in" in the same manner as cost decreases (assuming all else equal) and value increases as weight goes down. Because weight is not something directly experienced by consumers as in the case of laptop computers, mp3 players, or cell phones for example; weight cannot be a CVA in and of itself. Therefore, there must be at least one CVA that explains why weight might be desired. After much consideration, it was decided that fatality rate in two car collisions would be the best way to make the connection.[10]

Table 1 summarizes the value coefficients (Equation (4)) for the aforementioned CVAs. The acceleration time parameters came from a study conducted by McConville and Cook [55]. The critical level for fuel economy was found using a mind exercise that assumed that the average fuel tank volume was 15 gallons and that one must drive 7.5 miles on average to find a gas station.[11] The safety factor critical value was chosen based on an informal survey administered to several faculty and staff at the University. The baseline vehicle for this study is the average vehicle of 1995 (car and truck). The baseline value (at the cartel point) can be calculated using Equation (5).[12]

Table 1: Value Curve Parameters for the CVAs[13]

Attribute (a)	*Baseline*	*Ideal*	*Critical*	γ_t^a
fe(mpg)	21.9	∞	0.5	γ_t^{fe}
at(sec.)	11.3	1.5	40	0.17
sf (deaths per mil. Vehicles)	47	0	150	γ_t^{sf}

5.1.2 Vehicle Cost Model

Total variable cost, for this case study, is decomposed into two components: cost as a function of overall automobile weight and cost associated with delivering engine horsepower. The general form for the cost function associated with providing horsepower comes from previously published results that studied the wholesale price of engines as a function of engine power [23]: $\hat{c}_t^{engine} = \beta_{1,t} e^{\beta_{2,t} x_t^{hp}}$. The cost as a function of weight is based on the assumption that the vast majority of the automobile is constructed from steel[14] and that the assembled vehicle cost can be modeled as a multiple of the yearly price of steel.[15] The multiples used within our model give results that are consistent with a comparative study conducted by the Argonne National Laboratory [56]. The variable cost of an automobile as a function of weight is assumed to adhere to the following relationship: $\hat{c}_t^{weight} = \beta_{3,t} x_t^w$. The

[10] This conclusion was made after consideration of several reports and papers in the literature that provide evidence that automobile weight is related to fatality rates in two car collisions (e.g., [57-58]).
[11] These assumptions could be adjusted to reflect the decision maker's beliefs. An alternative method to assess the value of fuel economy would be to create an economic value calculation as described in [22].
[12] Donndelinger and Cook [50] determined that η_0 was approximately unity for automobiles. We determined that a value of $\eta_0 = 1.2$ gave the best fit at the baseline year (see also Table A.1 in Appendix A).
[13] γ_t^{fe} and γ_t^{sf} are discussed thoroughly in Table A.1 in Appendix A.
[14] As an illustration, consider the weight distribution in the Ford Taurus [59].
[15] A historical overview of the average yearly price of steel can be found in the in Appendix B, Fig. B.1.

assumptions that are fed into the current model regarding engine cost are summarized in Table A.1 in Appendix A. The total variable cost to manufacture an automobile is therefore assumed to be estimated by:

$$\hat{c}_t^{V} = \hat{c}_t^{weight} + \hat{c}_t^{engine} \tag{14}$$

The regulatory or compliance cost is estimated from the CAFE policy penalty formula, c_t^{CAFE}, which is multiplied by the total sales of the manufacturer, has remained unchanged since its inception in 1978 and is calculated as follows:[16]

$$c_t^{CAFE} = \max\left[0,\ \rho_t\left(z_t^{CAFE} - \hat{z}_t^{fe}\right)\right] \tag{15}$$

where ρ_t is the time-adjusted CAFE penalty per mpg below standard (see Table A.1 in the Appendix A); z_t^{CAFE} is the sales-weighted (car and truck) adjusted fuel economy standard for the manufacturer's product line mix at time *t* [60]; and $\hat{z}_t^{fe}$ is the average fuel economy for an auto maker's fleet [61].

5.2 The Adaptation Task

With all the analysis complete, the Artisan now has all the information needed to make trade-off's in the design. During the adaptation task, the Artisan must first link design decision variables to CVAs, and second, determines the best balance between product value, cost incurred to produce it, and other constraints imposed by the environment.

5.2.1 Transfer Functions

Transfer Functions are created to link design variables to product performance attributes. Although sophisticated analytical tools can be used (e.g., [45]), two simple regression models from historical data proved to be adequate for forecasting fuel economy (*fe*) and 0-60 acceleration time (*at*) from horsepower (x^{hp}) and weight (x^{w}). The data came from an annual published report by the Environmental Protection Agency (EPA) that summarizes key industry-wide automobile performance measures [62]. The transfer functions for fuel economy and 0-60 acceleration time respectively (the coefficients are listed in Table 2) are:

$$\hat{z}_t^{fe} = \alpha_1^{fe} + \alpha_2^{fe} x_t^{hp} + \alpha_3^{fe} x_t^{w} \tag{16}$$

$$\hat{z}_t^{at} = \alpha_1^{at} + \alpha_2^{at} x_t^{hp} + \alpha_3^{at} x_t^{w} \tag{17}$$

The transfer functions are assumed to remain valid so long as the SI engine is the dominant architecture, which is true for the time period under analysis in this case study.

The model used to link weight to fatality rate comes from a report produced by the *Insurance Institute for Highway Safety* [57] that links automobile weight to passenger fatality rates in two car collisions (*sf*). The aggregation of car, truck and van data yielded the following transfer function, where the values of the coefficients are also summarized in Table 2:

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[16] See (http://www.nhtsa.gov/cars/rules/CAFE/index.htm) for more information and details.

$$\hat{z}_t^{sf} = \alpha_1^{sf} + \alpha_2^{sf} x_t^w + \alpha_3^{sf} \left(x_t^w\right)^2 \quad (18)$$

Table 2: Attribute Forecasting Parameters

	$a_1 = fe$	$a_2 = at$	$a_3 = sf$
$\alpha_1^{a_i}$	51.35326	12.0636	339.059
$\alpha_2^{a_i}$	0.107276	-0.0649	-0.13184
$\alpha_3^{a_i}$	-0.01292	0.002694716	1.42479 x 10^{-5}
R^2	0.949	0.978	0.943

5.2.2 Demand, Pricing and Profit Models

The demand, profit, and price models of Equations (8), (10), and (12) are used directly for this case study. Once again, if the overall industry is being considered and not a single competitor, the analysis can be made using the industry average value and cost. Note that the profit of interest is that of the industry without investment cost.

5.2.3 Design Optimization

Bringing the historical data together with the mathematical models presented earlier in this section, we now have a framework to model the parametric adaptation of the automobile as a result of transient environmental variables influencing the automotive industry. This framework, in its entirety, links profit to the design variables and yields a discontinuous, non-linear solution space (Fig. 4 shows the solution space for 1995). The solution space is discontinuous due to the value-coefficient functions that force value to zero when a critical attribute level has been breached (which forces profit to zero). However, when the solution space is constrained to feasible design variable settings, the solution space is convex, which means any constrained non-linear optimization technique such as genetic algorithms or even Solver in Excel can find the optimum solution to this system of equations. The complete mathematical model is:[17]

Maximize: $\Pi_t = \hat{D}_{T,t}\left(\hat{p}_t - \hat{c}_t^V - \hat{c}_t^{CAFE}\right)$

With respect to: $\mathbf{x}_t = \left\langle x_t^{hp}, x_t^w \right\rangle$

Subject to:

$$0 \le x_t^{hp} \le 400$$

$$1000 \le x_t^w \le 6000$$

$$\hat{D}_{T,t} = K_t\left(\overline{V}_t - \overline{p}_t\right)$$

$$K_t = \frac{D_{T,0}\hat{\eta}_t}{p_0}$$

$$\hat{\eta}_t = \beta_{4,t}\eta_0, \; \eta_0 = 1.2 \text{ for base year 1995} \quad (19)$$

$$\hat{p}_t = \frac{\overline{V}_t + N\hat{c}_t^V}{N+1}$$

$$\overline{V}_t = V_0 v_t^{fe} v_t^{at} v_t^{sf}$$

[17] Explanation of β's is offered in Table A.1 in Appendix A.

$$v\left(\hat{z}_t^{fe}\right)=\left[\frac{\left(1-\frac{\left(z^{fe,C}\right)^2}{\left(\hat{z}_t^{fe}\right)^2}\right)}{\left(1-\frac{\left(z^{fe,C}\right)^2}{\left(z^{fe,0}\right)^2}\right)}\right]^{\gamma_t^{fe}}$$

$$v\left(\hat{z}_t^{at}\right)=\left[\frac{\left(z^{at,I}-z^{at,C}\right)^2-\left(z^{at,I}-\hat{z}_t^{at}\right)^2}{\left(z^{at,I}-z^{at,C}\right)^2-\left(z^{at,I}-z^{at,0}\right)^2}\right]^{\gamma_t^{at}}$$

$$v\left(\hat{z}_t^{sf}\right)=\left[\frac{\left(z^{sf,C}\right)^2-\left(\hat{z}_t^{fe}\right)^2}{\left(z^{sf,C}\right)^2-\left(z^{sf,0}\right)^2}\right]^{\gamma_t^{sf}}$$

$$\hat{z}_t^{fe}=\alpha_1^{fe}+\alpha_2^{fe}x_t^{hp}+\alpha_3^{fe}x_t^{w}$$

$$\hat{z}_t^{at}=\alpha_1^{at}+\alpha_2^{at}x_t^{hp}+\alpha_3^{at}x_t^{w}$$

$$\hat{z}_t^{sf}=\alpha_1^{sf}+\alpha_2^{sf}x_t^{hp}+\alpha_3^{sf}\left(x_t^{w}\right)^2$$

$$\hat{c}_t^{V}=\hat{c}_t^{weight}+\hat{c}_t^{engine}$$

$$\hat{c}_t^{engine}=\beta_{1,t}e^{\beta_{2,t}x_t^{hp}}$$

$$\hat{c}_t^{weight}=\beta_{3,t}x_t^{w}$$

$$c_t^{CAFE}=\max\left[0,\ \rho_t\left(z_t^{CAFE}-\hat{z}_t^{fe}\right)\right]$$

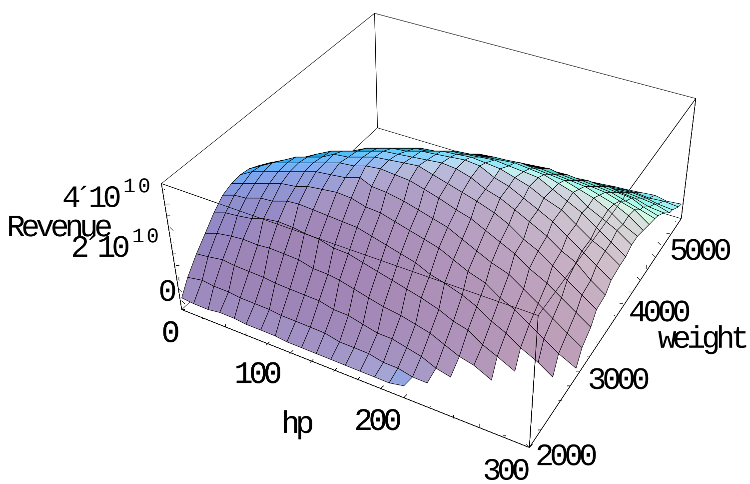

Figure 4: 1995 Solution Space

Two parameters of the model were used to tune the model outputs to match historical data: the exponential parameter in engine cost ($\beta_{2,t}$) and the gamma associated with safety (γ_t^{sf}). Although these parameters can be estimated based on industry reports and consumer surveys, respectively, for all future analysis; this data was not available for the model as formulated in this paper. The process of tuning the parameters began by finding the best settings to mimic the reported average horsepower and weight for each of the years considered in the study (results shown in Fig. 5). For example, these settings were found to be 6.5 x 10^{-3} and 0.82 for $\beta_{2,1975}$ and γ^{sf}_{1975} , respectively, for year 1975. This procedure was repeated for the remaining years.

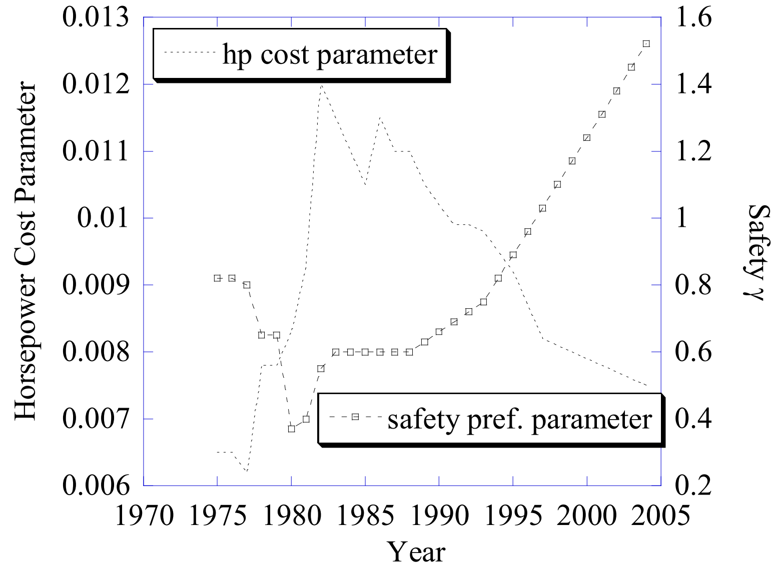

Figure 5: Model Tuning Parameter Results

The path of the horsepower parameter agrees with intuition as the cost of providing horsepower became more expensive due to emission legislation, but decreases over time in a sigmoidal way. The preference for safety (confounded with vehicle size) shows how the consumers preferred small automobiles when fuel prices shot up during the years of the oil embargo (1973-1974). The path of the parameter suggests that after the initial shock of gas prices wore off, consumers began to prefer larger vehicles year after year.

5.3 Results & Discussion

Although the goal was to analyze the implications of transient environmental variables and consumer preferences on the parametric adaptation of the two design variables x^{hp} and x^{w}, we believe that the model should not only be able to forecast the design parameters, but also give reasonable forecasts of the intermediate variables. Figures 6a and 6b show the results of horsepower and weight forecasts, respectively. The fit is almost perfect, which is expected as these were the data that the tuning variables were used to fit. Figure 7a shows the forecasted versus historical values for fuel economy and 0-60 acceleration time. There is only a small amount of disparity in the forecasted data, which is primarily due to fit error in the estimated transfer functions.

Although motor vehicle fatality data is published by the Fatality Analysis Reporting System [63], it is not measured in the same way as the metric derived through the proposed vehicle weight regression model. So, direct comparison may be somewhat problematic unless few added assumptions and transformations are made to the

FARS raw data.[18] Figure 7b shows the transformed FARS fatality data with the forecasted fatality rate. The fit here is not as good, but fit problems could be attributed for several reasons. First, we did not account for innovation in safety, but rather assumed that the technology was the same for all years as it was in 1995 (baseline year where regression was performed).[19] Second, we did not account for legislation changes that may have influenced technology.[20] Lastly, as mentioned earlier, safety is not the only attribute that "puts weight in vehicles" (for example, consumers may like roomier vehicles that seat more passengers).

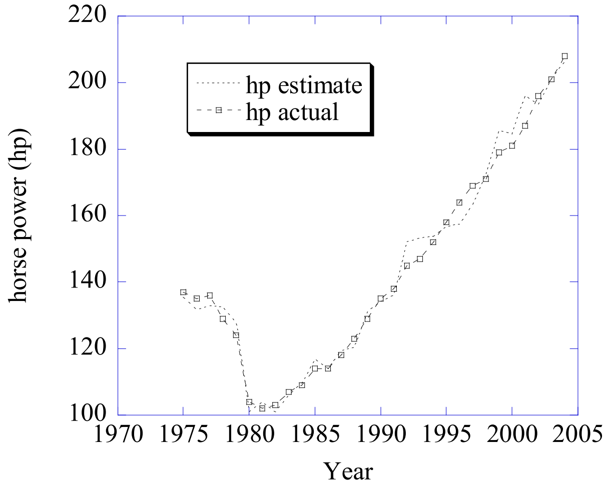

Figure 6a: Forecasted vs. Historical Horsepower (R^2=93%)

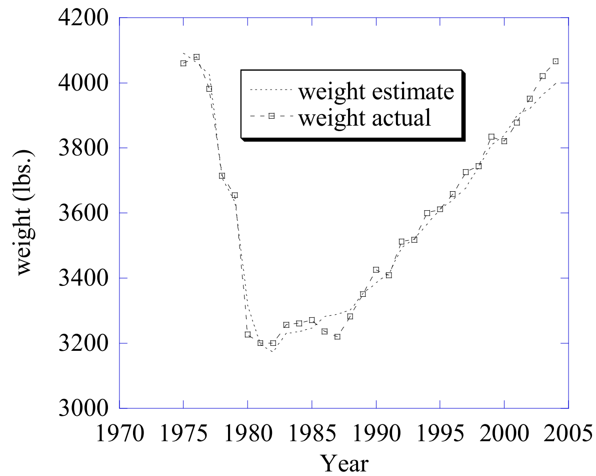

Figure 6b: Forecasted vs. Historical Weight (R^2=95%)

Figures 8a and 8b show the forecasted versus historical demand and price, respectively. The fit here is not as good either, but inspection shows that the forecasts mimic the trends. Looking at demand and price equations reveal that small errors in the input variables may be the cause for this disparity. The large spike in forecasted demand is a result of the very low unemployment rate (used as an economic indicator in the model) during that period. This observation points out that unemployment rate is not a perfect indicator because many of the consumers already owned a vehicle. One also notes that the model's price is overly optimistic after 1995. The price could have been corrected (brought down) by increasing *N*, the number of competitors. With the gaining popularity of the Internet to aid the consumer in gathering information, it may be possible that the assumption that the consumer only considers six alternatives for all time periods may have been too simplistic.

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[18] FARS reports total number of fatal crashes from 1994-2006 only and lumps single and two car crashes, which include passenger cars, light trucks (SUVs), large trucks, motorcycles, buses, and others. However, FARS reports that about 60% of total crashes involved only one vehicle (FARS 2008). So, to calculate the death rate per million, we divided the total number of crashes reported in FARS by the total number of registered vehicles for that year. Then, we multiplied this quantity by 40% to account for two car crashes only. Finally, we multiplied this result further by 60% to account for deaths in passenger cars and SUVs only.

[19] For example, the addition of Electronic Stability Control (ESC) and Anti-Lock Brake Systems (ABS) on more recent vehicles.

[20] Indeed, upon investigation, it was found that airbag legislation was introduced by the Carter presidential administration, revoked by the Regan administration, and reinstated by the first Bush administration.

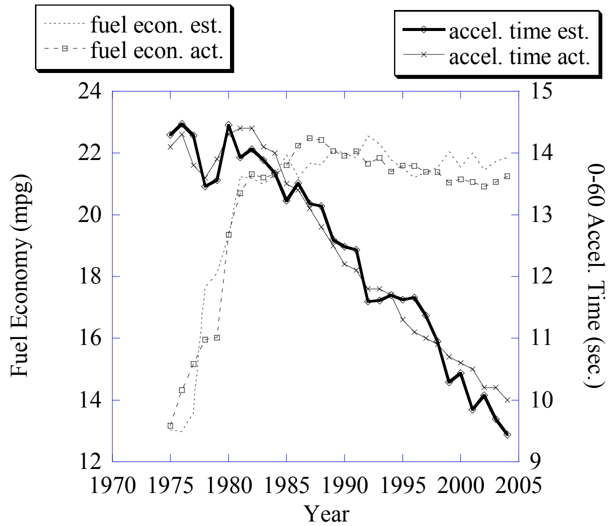

Figure 7a: Forecasted vs. Historical Fuel Economy and Acceleration Time (R^2_{fe}=95%, R^2_{at} =98%)

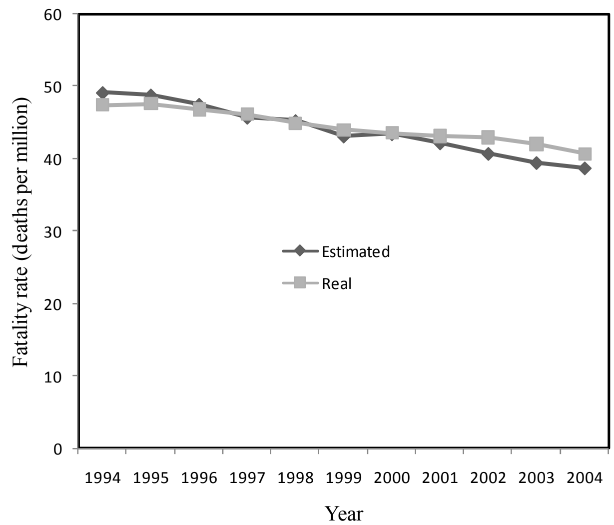

Figure 7b: Forecasted vs. Historical Safety Data (R^2_{sf} =82%)

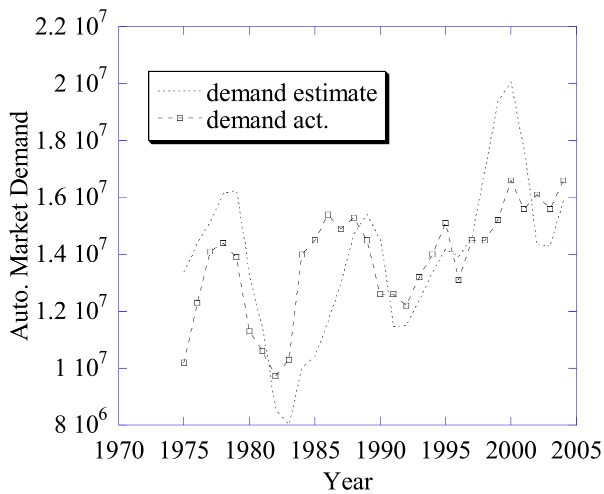

Figure 8a: Forecasted vs. Historical Demand (R^2=30%)

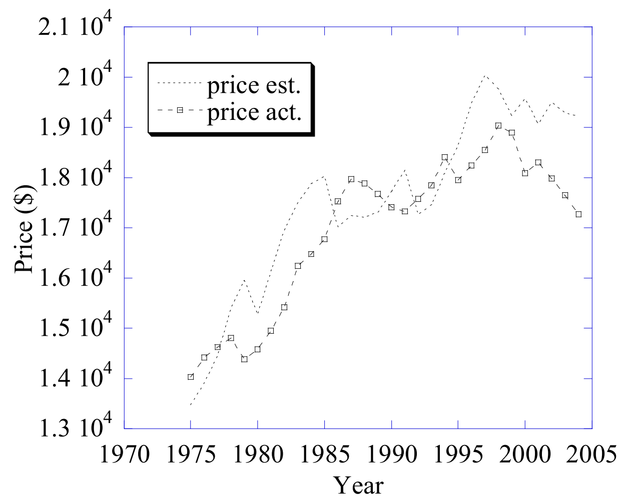

Figure 8b: Forecasted vs. Historical Price (R^2=60%)

The forecasted automotive industry revenue (Fig. 9) fits the historical data reasonably well considering the disparity in the input variables (demand and price). The large forecast error during the late 90's is largely due to overly optimistic demand and price forecasts. The model's forecasts of CAFE penalties paid to the government were severely inflated, which can be explained by the following three points: (1) automobile manufacturers receive credits for outperforming the standard that can be used to offset future penalties; (2) there are caps upon the yearly penalty that must be paid; and (3) manufacturers may petition to have the penalties waved if it can be shown that they will force them out of business.

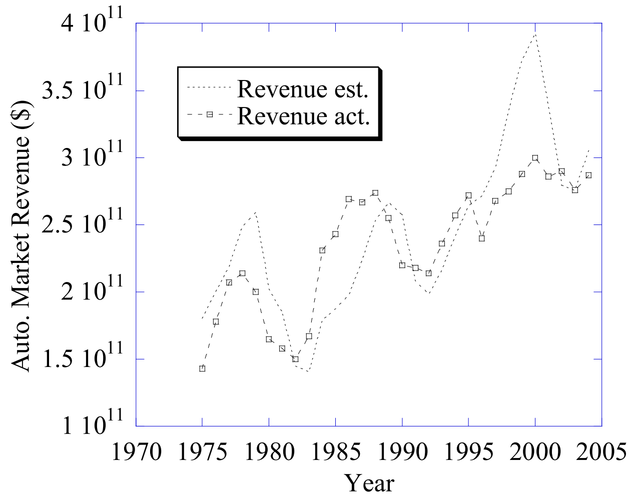

Figure 9: Forecasted vs. Historic Automotive Industry Revenue (R^2=25%)

To investigate the sensitivity of the base case results to uncertainty in model parameters, we performed sensitivity analysis on the optimal results. We focused our analysis on the exponential parameter in engine cost ($\beta_{2,t}$) and the gamma associated with safety (γ_t^{sf}) because both were used to tune the optimal solution (produced by the model) to historical data. For illustration, the sensitivity analysis for t =1975 is shown in Figure 10. The figure shows that model results are insensitive to γ_{1975}^{sf} and somewhat sensitive to $\beta_{2,1975}$ estimates. That is, a 25% change (i.e., increase or decrease) in γ_{1975}^{sf} results in about 3% change in horsepower (hp) and weight. On the other hand, a 20% change in $\beta_{2,1975}$ estimate results in an equivalent percent change in *hp*, but a minimal impact on *weight* (about 2% change). Similar sensitivities were noted for the other years included in the study.

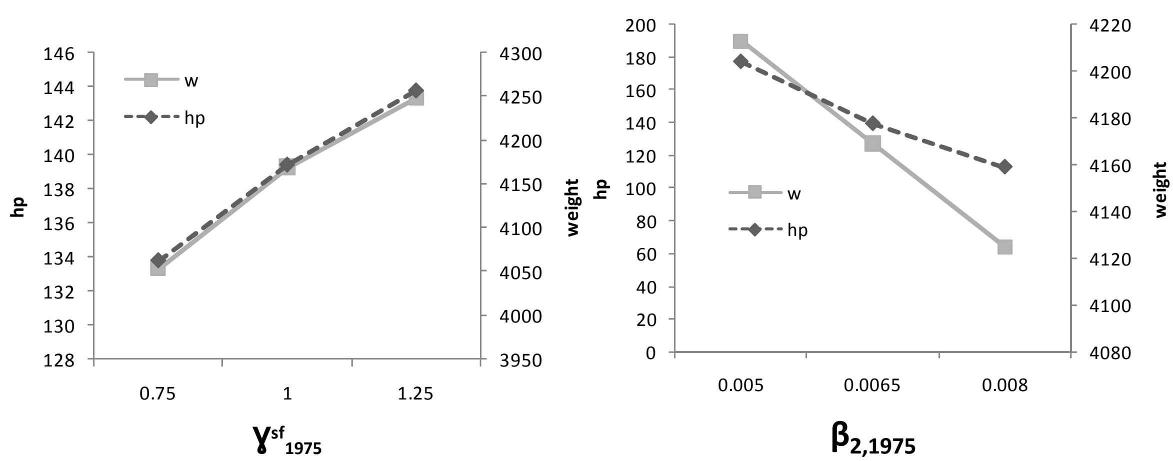

Figure 10: Sensitivity of 1975 solution to γ_{1975}^{sf} and $\beta_{2,1975}$ **estimates** (base values: γ_{1975}^{sf} = 1 & $\beta_{2,1975}$ = 0.0065)

6. SUMMARY AND CONCLUSION

The AP model is intended to be a framework for understanding the drivers of parametric product adaptation, which can ultimately give manufacturers a method for managing complexity and making better decisions in highly competitive markets. We showed how design can be viewed as a multi-generation 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 information as feedback to help adapt (i.e., 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 [11,64].

A detailed case study was offered to help illustrate how the framework can be used to model the parametric adaptation process of an automobile as a result of a changing environment (namely, fuel price, price of steel, and CAFE legislation). The example had three critical-to-value attribute (fuel economy, acceleration, and safety) and two design decisions (engine *hp* and vehicle *weight*). The results indicate that there is a reasonable match between the forecasted and historical data, considering the various simplifying assumptions made. Several gratuitous assumptions were made, the largest being that the death rate in two-car collisions is what keeps weight in the vehicle—obviously simplistic. Nevertheless, it allowed modeling to progress and demonstrated the utility of the proposed AP framework in framing multi-generation adaptive design problems.

The AP model is not intended to be a perfect 'crystal ball' that Artisans use 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 decisions 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 and evolution and improves the model's ability to predict the occurrence of technological changes (rather than mere parametric changes) in response to changing environmental conditions and consumer preferences. In other words, a basic assumption of the proposed model was that the basic automotive architecture, power plant, and technologies were not changed within the period of the case study. Therefore, this model is not about technological changes but about parametric adaptation which could be an indicator of some technological evolution if the value of a particular design variable (predicted by the model) cannot be achieved without a quantum leap or change in technology.

One can see through this model, however, that it is difficult to forecast how a change in any single factor will change industry behavior due to the "gaming" behavior of the Artisans. For example, if gas prices would have stayed constant and high after the OPEC embargo in 1978 it would have influenced the preference for fuel economy for sure, but it would have also influenced the path of technological innovation (the cost for horsepower) and the consumer's willingness-to-pay. Alternatively, if governmental policy would have adjusted the CAFE penalty to account for inflation or made the CAFE standard more stringent over time, it would have also influenced technological innovation, but consumer preferences may have remained unchanged.

Further research is also needed to establish formal methods to build transfer functions to link engineering design variables to performance attributes, and to elicit willingness-to-pay (value) functions from empirical and survey data based on product performance. Within the design task, a self-consistent method for selecting among design alternatives is also needed [65]. Finally, integrating into the model some aspects of uncertainty (e.g., various model parameters and manufacturing information coming from the cloning task to capture how actual product performance deviates from designed performance) could allow for the various analyses to proceed using statistical distributions (rather than point estimates).

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Appendix A: Case Study Data

Table A.1: Time Dependent Model Parameters

Parameter	Description	Assumptions and Comments	Mathematical Formulation
γ_t^{fe}	Preference for fuel economy	The desirability of fuel economy will be related to the price of gas per gallon.	$\beta_{4,t} = \frac{p_{fuel,t}^{real}}{10 * CPI_t^{1995}}$
γ_t^{sf}	Preference for safety and features	This parameter was used to "tune" the safety preference value function.	Discussed in Section 5.2.3
ρ_t	Time adjusted CAFE penalty	The CAFE penalty has been the same since 1978–$55/gal./vehicle—therefore the penalty needs to be adjusted for inflation.	$\rho_t = \frac{\$55}{CPI_t^{1995}}$
$\beta_{1,t}$	Parameter of engine cost	This formulation was used as it was thought that it should relate to the cost of the raw material. Price of steel is per pound.	$\beta_{1,t} = \frac{2000\left(p_{steel,t}^{real}\right)}{CPI_t^{1995}}$
$\beta_{2,t}$	Exponential parameter of engine cost	This parameter was used to "tune" the engine cost function. One can see the jump in cost around 1980, which may symbolize a change in architecture. One can also see an S-curve shape taking place after the jump, which might be interpreted as the pace of innovation over time.	Discussed in Section 5.2.3
$\beta_{3,t}$	Cost of automobile raw materials per lb.	Translates to 10x the real price of steel per pound in year t	$\beta_{3,t} = 10 * (\, p_{steel,t}^{real}\,)$
$\beta_{4,t}$	Multiple to account for economic fluctuation	We assume an inverse relationship between the yearly average unemployment rate (u_t) and aggregate automotive demand (U.S. Department of Labor, Bureau of Labor Statistics). The 6.78 factor makes η_0=1.2 in 1995.	$\beta_{4,t} = \frac{6.78}{u_t}$

Where $p_{steel,t}^{real}$ and $p_{fuel,t}^{real}$ are the real prices of steel and fuel, respectively, for year *t*, (see Figs B.1 and B.2 in Appendix). u_t is the unemployment rate for year *t*, and CPI_t^{1995} is the consumer price index adjusted for 1995.

Appendix B: Cost of Ownership and Raw Materials

The price of steal is an important indicator of vehicle cost; arguably, 75-90% of vehicle's total weight comes from steel components [59]. Except for a small jump in the late 70's, the adjusted price of steel has steadily decreased to nearly half of its record set in 1978 (See Fig. B.1).

There are many aspects of an automobile that affect its cost of ownership, but the factor that traditionally receives the attention and is often in the mind of the consumer during the purchase decision is the cost of fuel consumption [66]. Although fuel prices reached record levels in 2004, they are still lower than the prices of the late 70's when adjusted for inflation (see Fig. B.2).

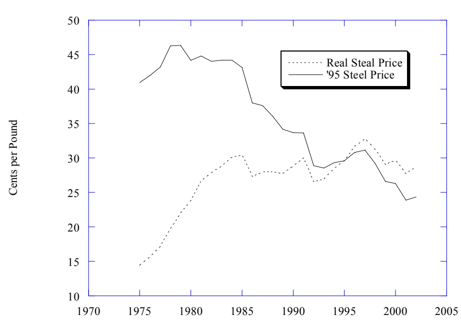

Figure B.1: Real vs. Adjusted Avg. Yearly Steel Price[21]

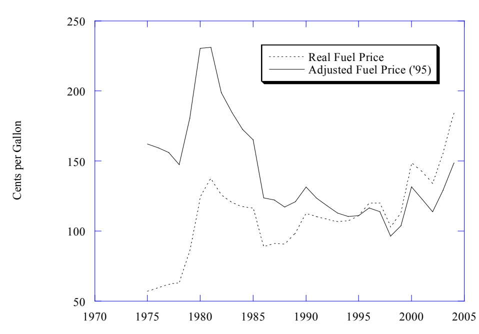

Figure B.2: Real vs. Adjusted Avg. Fuel Price[22]

[21] http://minerals.usgs.gov/minerals/pubs/of01-006/ironandsteel.pdf.

[22] History: Gasoline Prices: Bureau of Labor Statistics (BLS) survey prices: 1919-1979 leaded regular; 1980-1981: unleaded regular; 1982-1994: Energy Information Administration (EIA) data extrapolated using BLS survey data; 1995-current: EIA Survey. Real (inflation adjusted prices) price data is deflated by the Consumer Price Index (CPI), source BLS, where year 1995 = 1. Forecast 2004-2005: Gasoline prices, current Short-Term Energy Outlook (STEO). Forecasted Consumer Price Index, Global Insight.

REFERENCES

[1] Whitney, D.E., 1990, "Designing the Design Process," *Research in Engineering Design*, **2**: 3-13.

[2] Wheelwright, S. C., Clark, K.B., 1994, "Accelerating the Design-build-test Cycle for Effective Product Development," *International Marketing Review*, 11(1):32-46.

[3] Maimon, O., Braha, D., 1996, "On the Complexity of the Design Synthesis Problem," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, 26(1):142-151.

[4] Eppinger, S.D., Nukala, M.V., Whitney, D.E., 1997, "Generalized Models of Design Iteration Using Signal Flow Graphs," *Research in Engineering Design*, 9(2):112-123.

[5] Eppinger, S.D., Whitney, D.E., Smith, R.P., Gebala, D.A., 1994, " A Model-Based Method for Organizing Tasks in Product Development,"*Research in Engineering Design*, 6(1):1-13.

[6] Yassine, A., N. Joglekar, D. Braha, S. Eppinger, Whitney, D., 2003, "Information hiding in product development: the design churn effect," *Research in Engineering Design*, **14**: 145-61.

[7] Cook, H.E., Wu, A., 2001, "On the Valuation of Goods and Selection of the Best Design Alternative," *Research in Engineering Design*, **13**: 42-54.

[8] Thomke, S.H., 1998, "Managing Experimentation in the Design of New Products," *Management Sci.*, **44**(6): 743-62.

[9] Suh, N.P., 1999, "A Theory of Complexity, Periodicity and the Design Axioms," *Res. Eng. Design*, **11**: 116-31.

[10] Otto, K.N., Wood, K.L., 1998, "Product Evolution: Reverse Engineering and Redesign Methodology," *Research in Engineering Design*, 10: 226-43.

[11] Petroski, H., 2003, *Small Things Considered: Why There Is No Perfect Design*, Vintage Books: New York, NY.

[12] Clark, K.B., 1985, "The interaction of design hierarchies and market concepts in technology evolution," *Research Policy*, **14**: 235-251.

[13] Ullman, D. G. , 1993, "Evolution of function and behavior during mechanical design," American Society of Mechanical Engineers, Design Engineering Division (Publication) DE, v 53, Design Theory and Methodology, 1993, p 91-103.

[14] Utterback, J.M., 1996, *Mastering the Dynamics of Innovation*, Harvard Business School Press: Boston, MA.

[15] Tellis, G.J., Crawford, C.M., 1981, "An evolutionary approach to product growth theory," *Journal of Marketing*, **45**(Fall): 125-32.

[16] Nelson, R.R., Winter, S., 1982, *An Evolutionary Theory of Economic Change*, Belknap Press: Cambridge, MA.

[17] Krishnan, V., Eppinger, S., Whitney, D., 1995, "Accelerating Product Development by the Exchange of Preliminary Design Information," *ASME Journal of Mechanical Design*, 117: 491-498.

[18] Thompson, J., Lu, S., 1990, "Design evolution management: A methodology for representing and utilizing design rationale," American Society of Mechanical Engineers, Design Engineering Division (Publication) DE, v 27, Design Theory and Methodology - DTM '90, 1990, p 185-191.

[19] Shooter, S., Keirouz, W., Szykman, S., Fenves, S., 2000. "A Model for the flow of design information in product development." Engineering with Computers, Vol. 16, pp. 178-194.

[20] Papalambros, P.Y. 2002, "The optimization paradigm in engineering design: promises and challenges," *Computer-Aided Design*, **34**: 939-51.

[21] Georgiopoulos, P., M. Johnson, Papalambros, P.Y., 2005, "Linking Optimal Design Decisions the Theory of the Firm: The case of resource allocation," ASME *Journal of Mechanical Design,* **127**(5): 358-366.

[22] Cook, H.E., 2005, *Design for Six Sigma as Strategic Experimentation*, American Society for Quality.

[23] Michalek, J.J., Papalambros, P.Y., Skerlos, S.J., 2004, "A study of emission policy effects on optimal vehicle design decisions," *ASME Journal of Mechanical Design,* **126**(6): 1062-1070.

[24] Wright, I. C., 1997, "A Review of Research into Engineering Change Management: Implications for Product Design," *Design Studies*, 18(1):33-42.

[25] Eckert, C., Clarkson, P.J., Zanker, W., 2004, "Change and Customization in Complex Engineering Domains," *Research in Engineering Design*, Vol. 15, pp. 1-21.

[26] Fricke, Ernst, and Schulz, Armin P., 2005, "Design for changeability (DfC): Principles to enable changes in systems throughout their entire lifecycle," *Systems Engineering*, 8(4):342-359.

[27] Angel, A., Browning, T., 2008, "Designing Systems for Adaptability by Means of Architecture Options," Systems Engineering Journal, Vol. 9, pp. 125-146.

[28] Olewnik, A., Lewis, K., 2006, "A Decision Support Framework for Flexible System Design", *Journal of Engineering Design*, 17(1):75-97.
[29] Ferguson, S., Siddiqi, A., Lewis, K. de Weck, O., 2007, "Flexible and Reconfigurable Systems: Nomenclature and Review," ASME Design Automation Conference, September 4-7, 2007, Las Vegas, Nevada, USA, DETC2007-35745.
[30] Silver, M., de Weck, O., 2007, "Time-Expanded Decision Networks: A Framework for Designing Evolvable Complex Systems," *Systems Engineering Journal*, 10(2):167-186.
[31] Massey, G.R., 1999, "Product evolution: a Darwinian or Lamarckian phenomenon?" *Journal of Product & Brand Management*, **8**(4): 301-18.
[32] Mayr, E., 2001, *What Evolution Is*. Basic Books: New York, NY.
[33] Berryman, A. 1992, "The Origins and Evolution of the Predator-Prey Theory," *Ecology*, 73(5):1530-1535.
[34] Suh, E. de Weck, O., Chang, D., 2007, "Flexible Product Platforms: Framework and Case Study," *Research in Engineering Design*, 18: 67-89.
[35] Thurstone, L., 1927, "A Law of Comparative Judgment," *Psychological Review*, **34**: 273-86.
[36] Luce, R., 1959, *Individual Choice Behavior: A Theoretical Analysis*. Wiley: New York, NY.
[37] Kohli, R., Mahajan, V., 1991, "A reservation-price model for optimal pricing of multi-attribute products in conjoint analysis," *Journal of Marketing Research*, **28**: 347-54.
[38] Jedidi, K., Zhang, Z.J., 2002, "Augmenting Conjoint Analysis to Estimate Consumer Reservation Price," *Management Science*, **48**(10): 1350-68.
[39] Cook, H.E., 1997, *Product Management: Value, Quality, Cost, Price, Profit, and Organization*, Kluwer Academic: Amsterdam.
[40] Mills, V., B. Samuels, Wagner, J., 2002, "Modeling and analysis of automotive antilock brake systems subject to vehicle payload shifting," *Vehicle System Dynamics*, **37**(4): 283-310.
[41] Pontikakis, G., Stamatelos, A., 2001, "Mathematical modeling of catalytic exhaust systems for EURO-3 and EURO-4 emissions standards," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automotive Engineering*, **215**(9): 1005-15.
[42] Montgomery, D.C., 2000, *Design and Analysis of Experiments, 5th ed*. John Wiley & Sons: New York, NY.
[43] Wilke, W.L., 1994, *Consumer Behavior, 3rd edn*. John Wiley & Sons: New York, NY.
[44] Pande, P.S., Neuman, R.P., Cavanagh, R.R., 2000, *The Six Sigma Way: How GE, Motorola, and Other Top Companies Are Honing Their Performance*, McGraw-Hill: New York, NY.
[45] Markel, T., Brooker, A., Hendricks, T., Johnson, V., Kelly, K., Kramer, B., O'Keefe, M., Sprik, S., Wipke, K., 2002, "ADVISOR: a systems analysis tool for advanced vehicle modeling," *Jour. of Power Systems*, **10**(2):255-66.
[46] Kirchain, R. , Field, F.R., 2001, "Process-Based Cost Modeling: Understanding the Economics of Technical Decisions," *Encyclopedia of Materials Science & Engineering*: 1718–1727.
[47] Ben-Arieh, D. Qian, L., 2003, "Activity-Based Cost Management for Design and Development Stage," *International Journal of Production Economics*, **83**: 169-183.
[48] Asiedu, P., Gu P., 1998, " Product life cycle cost analysis: state of the art review," *International Journal of Production Research,* 36:883–908.
[49] Castagne, S., Curran, R., Rothwell, A., Price, M., Benard, E., and S. Raghunathan, 2008, "A Generic Tool for Cost Estimating in Aircraft Design," *Research in Engineering Design*, **18**: 149-162.
[50] Donndelinger, J., Cook, H.E., 1997, "Methods for analyzing the value of vehicles," *SAE Transactions: Journal of Passenger Cars*, **106**: 1263-81.
[51] Ben-Akiva, M, Lerman, S.R. 1985, *Discrete Choice Analysis: Theory and Applications to Travel Demand*, MIT Press, Cambridge, MA.
[52] Monroe, E.M., Silver, R.L., Cook, H.E., 1997, "Value versus price segmentation of family automobiles," *SAE Paper 97076*. Society of Automotive Engineers: Warrendale, PA.
[53] Pepall, L., Richards, D.J., Norman, G., 2002, *Industrial Organization: Contemporary Theory and Practice, 2nd edn*. South-Western: Cincinnati, OH.
[54] Miller, G.A., 1956, "The Magical Number Seven Plus or Minus Two: Some limits on Our Capacity for Processing Information," *Psychological Review*, **63**: 81-97.
[55] McConville, G.P., Cook, H.E., 1996, "Examining the value trade-off between automobile acceleration performance and fuel economy," SAE Paper 960004, Society of Automotive Engineers, Warrendale, PA.

[56] Vyas, A., Santini, D., Cuenca, R., 2000, *Comparison of Indirect Cost Multipliers for Vehicle Manufacturing*, Center for Transportation Research, Argone, IL. (http://msl1.mit.edu/classes/esd123/vyas.pdf)
[57] IIHS- Insurance Institute for Highway Safety, 1998, *New Study of Relationships between Vehicle Weight and Occupant Death Rates Helps Put in Perspective Issue of Crash Compatibility*, Highway Loss Data Institute. (http://www.iihs.org/sr/pdfs/sr3301.pdf).
[58] Ahmad, S., Greene, D., 2005, "Effect of Fuel Economy on Automobile Safety: A Reexamination," Transportation Research Record: Journal of the Transportation Research Board, No. 1941, pp. 1-7.
[59] OTA- Office of Technology Assessment, 1995, *Advanced Automotive Technology: Visions of a Super-Efficient Family Car*, Office of Technology Assessment, OTA-ETI-638: GPO stock #052-003-01440-8. (http://www.princeton.edu/~ota/disk1/1995/9514/951405.PDF).
[60] CBO - Congressional Budget Office, 2002, *Reducing Gasoline Consumption: Three Policy Options*, Congressional Budget Office (CBO) study, November 2002. www.cbo.gov.
[61] Wissmann, L., Yassine, A., 2005, "Design Evolution Using the Artisan-Patron Model - The case of automotive evolution," ASME Design Theory and Methodology conference, Long Beach, CA., 2005.
[62] Hellman, K.H., Heavenrich, R.M., 2004, *Light-Duty Automotive Technology and Fuel Economy Trends: 1975 through 2004*, Office of Transportation and Air Quality—U.S. Environmental Protection Agency (http://www.epa.gov/otaq/fetrends.htm).
[63] FARS - Fatality Analysis Reporting System, 2008, http://www-fars.nhtsa.dot.gov/. Accessed 5 June 2008.
[64] Simon, H.A., 1996, *The Sciences of the Artificial, 3rd edn*. MIT Press: Cambridge, MA.
[65] Hazelrigg, G.A., 2003, "Validation of Engineering Design Alternative Selection Methods," *Engineering Optimization*, **35**(2): 103-20.
[66] Ward's Dealer Business, 2004, High Fuel Prices Show Effects in Showrooms. Sept. 1, p. 9.