

A DESIGN SCIENCE APPROACH TO ANALYTICAL PRODUCT DESIGN

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ABSTRACT

Product design involves many diverse disciplines and is often treated as an experience-based skill following an apprenticeship learning process. While this is a valuable approach, it can be greatly enhanced by analysis capabilities derived from the diversity of disciplines that contribute to design, including engineering, economics, marketing, and psychology. Quantitative models from these disciplines can be integrated into a design decision model framework. Analytical product design is an exemplar of Design Science, and serves as a basis for teaching product design and for designing products taking into account market and policy environments along with the usual engineering requirements. This article describes the basic ideas in constructing the design decision model framework and provides examples of its use in education, industry and policy.

Keywords: design science, product design, perceptual attributes, design optimization, analytical decision making

1 INTRODUCTION

Design Science studies the creation of artifacts and their embedding in our physical, psychological, economic, and social environment. Traditional science studies the world as we found it; design science studies the world as we make it. In an increasingly designed world, good design is the means to improving this world through innovative, sustainable products and services, creating value, and reducing or eliminating the negative unintended consequences of technology deployment [1]. In the Design Science context, product design can be approached in a quantitative and analytical manner drawing from the knowledge of the various disciplines that contribute to successful product design. Indeed, the very definition of “successful” may be the first step in an analytical product design process. Successful can be defined as something that works well; something that provides pleasure and satisfaction to its users; something that people buy a lot; something that monetarily enriches the designer or the producer; something that is environmentally sustainable; something that advances a social or political agenda. Accepting any of these definitions of success establishes a metric to evaluate a proposed product concept, even create a new concept. An iterative process then can be set up: Create an alternative, evaluate its expected success, and create a new improved one, if possible. This model of design as a decision-making process is the basis for mathematical optimization formalisms to do design, see e.g., [2].

An optimization framework is limited by our ability to model analytically the relevant decisions. For example, some success metrics above may be possible to quantify using engineering or marketing science methods. Others, such as perceptions of pleasure and satisfaction, can be elusive; below we will provide some ideas on modeling perceptual attributes. Analytical approaches are also limited in their ability to generate new concepts or configurations. Although progress has been made in this direction, e.g., [3, 4], in our present discussion we simplify matters by assuming that a basic configuration for the design has been determined.

Design optimization as a basis for engineering design decisions has been well established and used, driven by the availability of robust computational methods for evaluating functionality, for example, kinematic and dynamic analysis, stress and thermal analysis, or ergonomic analysis. In recent years, there has been a significant effort to expand optimization modeling to include decisions based on analysis capabilities derived from other disciplines. We briefly outline some of these developments, not as a proper literature review but rather as a description of the evolution that led to the particular

framework described in the present article. Thus referencing is not inclusive of other similar research efforts that have grown significantly in recent years, see e.g., [5].

In some of the earliest work, Georgiopoulos et al. introduced the idea of explicitly linking engineering design decisions with economic decisions of the producing firm [6-11]. Economic decisions were inserted into a design optimization formulation by establishing profit maximization as the objective function, and the basic model was set up as:

$$\begin{array}{ll} \text{maximize} & \text{(expected net present value)} \\ \text{with respect to} & \text{(engineering variables, investment variables)} \\ \text{subject to} & \text{(engineering constraints, enterprise constraints)}. \end{array} \quad (1)$$

The objective includes revenues and expenditures resulting from asset allocation and the engineering performance of these assets; the enterprise constraints include production constraints, such as production capacity or government regulations. The key new element here is that revenues, expenditures, and enterprise constraints are functions of design variables that appear also in the engineering functions. For example, the typical linear microeconomic model of demand as a function of price is now extended to make demand a function of price and design variables—price being itself an independent variable. Thus, market demand participates directly in determining the values of design variables. Cooper extended this formulation to include simple market penetration models for new products and to examine how valuation of new technology can affect the actual designs likely to appear in the market [11, 12]. A problem of particular interest in this context is how to set high-level enterprise targets and translate them into detailed product targets using analytical target setting and target cascading processes [e.g., 8, 13, 14]. The limitations of microeconomic demand models led Michalek et al. to the implementation of more sophisticated demand models within this framework, derived using discrete choice conjoint analysis and spline functions to create continuous models suitable for optimization and for target cascading [15-20]. This earlier work forms the instructional framework presented in Section 2 below. Market (Nash) equilibrium models were also included to capture how competition affects design decisions [15].

While aggregate demand models, such as those derived from discrete choice conjoint analysis, are widely used in marketing, they offer little insight into why people express the preferences they do, and indeed why they behave in apparently inconsistent ways in their product preferences. In addition, perceptual attributes, such as luxury, safety or sustainability, have strong influence on people's product choices but are highly resistant to quantification, in part because they are difficult to express as computable functions of the design variables that are under the control of the designer or engineer. An example perceptual attribute is craftsmanship, the property that gives a product the appeal of being well made and well functioning at its very early interaction with the customer. Product market analysts evaluate craftsmanship assiduously, but an explicit functional linking of user perceptions and specific design attributes of craftsmanship is challenging; some limited success can be achieved using methods from the behavioral sciences [21-24]. Kansei Engineering is also a possible modelling avenue [25, 46]. Another perceptual attribute is beauty, under the proportionality principles prevalent in the ancient and renaissance times [26, 27], and still used extensively today. Product semantics can be also included successfully into a design optimization framework, for example, in wine portfolio optimization [28]. An altogether different approach is to elicit preferences by engaging the users directly in product selection, and use their preferences for generating alternative designs that embody these preferences through interactive genetic algorithms [29-32]. Finally, there is a major challenge in capturing user preferences and addressing inherent inconsistencies in such preferences in a way that can be included in the aforementioned decision framework [33-36].

Section 2 describes how a relatively simple design decision model has been used for design instruction. Perceptual attribute modelling is discussed in Section 3. An expanded framework that integrates perceptual attributes, and examples in instructional use, industrial decision making, and policy analysis are given in Section 4. We offer some conclusions in Section 5.

2 DESIGN DECISION MODEL

The work described above has led to the formal framework in Figure 1. The framework includes quantitative models representing the product, the consumer, the firm, and its competitors. Product attributes, producer cost, consumer demand, and producer profit are expressed as functions of producer decisions or variables. We describe the use of the framework as a pedagogical tool in an

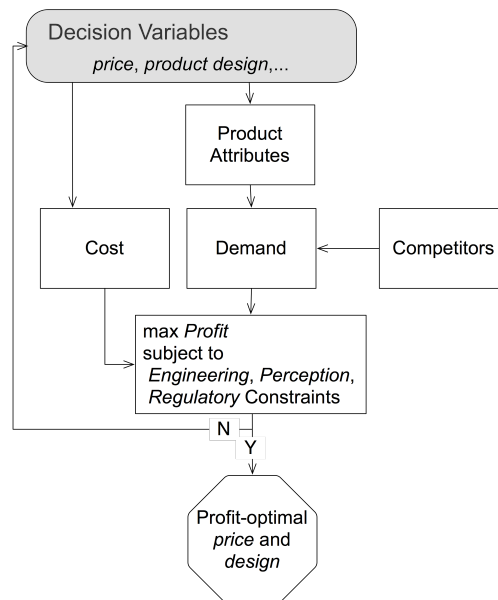


Figure 1. Design decision model schematic

Analytical Product Design (APD) course over the past six years [37], which has served as a test bed to gain practical experience with this framework in addition to its research-oriented use.

The APD course addresses seniors in mechanical engineering and art & design, and graduate engineering, design science, information science, economics, business, and architecture students, who worked in mixed teams on projects proposed by the teams. Typical class and team sizes are 35-40 and 3-4, respectively. Project work includes: Information gathering; concept development and selection; development of mathematical models representing the product, the business interest, and the consumer, including the use of engineering analysis tools and software, spreadsheet-based cost and investment analysis, user surveys and conjoint analysis via statistical packages to support user preference modeling; prototype construction and testing; and business plan development. There is a three-generation prototype construction to test design concepts prior to finalizing the design.

In the APD course, the teams assume the position of a firm or a group within a larger firm. The objective function is typically profit although other producer objectives are possible. Students are guided to identify requirements and attribute relationships, with a QFD study as a starting point for identifying relationship and optimization tradeoff opportunities. They also identify the use environment for the product (fixed parameters) and the set of decisions to be made by the designer (optimization variables). This entire effort exposes the students to the expanded opportunities for quantitative modeling, its significant limitations, and the multitude of model validity assumptions. Complete reports can be found in the cited source [37].

Each team develops three primary models that correspond to the three blocks Product Attributes, Cost, and Demand, in Figure 1. The *Eco-core Snowboard* team illustrates a typical scope of work [38]. The team designed and prototyped a new snowboard that replaced existing foam core material with a hemp fiber-based composite. They modeled the product attributes: board responsiveness (related to stiffness), percent environmentally friendly materials (related to hemp fiber content), and weight of the snowboard; computed the board stiffness factor based on five different board-loading conditions; and tested material properties based on actual samples provided by a vendor. The team assumed they represented an existing manufacturer launching a new product and developed estimates for production costs based on fixed cost assumptions and variable costs based on material volumes. They developed a choice-based conjoint survey using Sawtooth software [39] that was administered to members of the class as well as the 200-member Michigan snowboarding club. From the survey data they estimated parameters for a simple logit model of consumer choice based on a linear model of consumer utility of the form

$$u_{ij} = \beta(\text{price}) + \beta(\text{stiffness}) + \beta(\text{eco-materials}) + \beta(\text{weight}) + \varepsilon_{ij} \quad (2)$$

for consumer i and product j . Figure 2 shows the β -values, or part-worths estimated for the attributes.

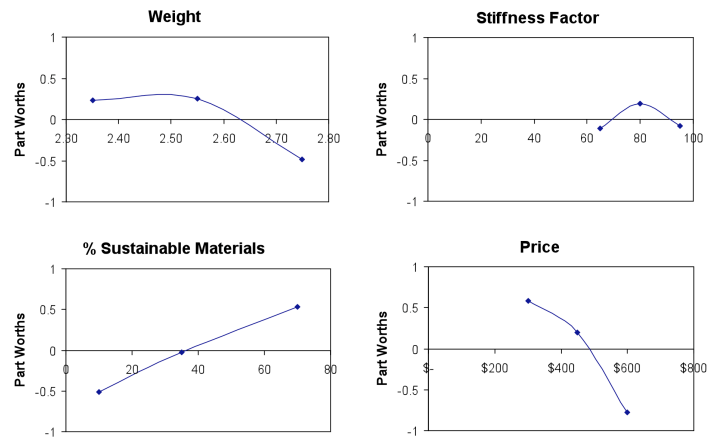


Figure 2: Estimated part-worths for snowboard attributes based on choice-based conjoint survey analysis

The part-worths represent the relative importance of the given attribute to the consumer’s utility for the product. The logit model predicts product choice share under specific assumptions. The product of estimated market size by choice share is taken to be the market demand for a specific product. The product attribute, cost, and demand models were integrated in a spreadsheet, and product price and design variables were optimized to maximize profit subject to constraints on board dimensions and loading. The team made projections for their accessible market size over a three-year period based on their production and distribution strategy. Applying the profit formula at each year they developed a three-year pro forma cash flow and corresponding net present value projection shown in Figure 3. Finally, they developed a business plan based on the work above.

Figure 4 illustrates the flow of the course at each phase. Following the design decision model concept, quantitative models are brought into other areas of the design process. More activities and techniques are introduced in the course than can be implemented by any given team. Some of these activities inform the attribute, cost, and demand models directly, and others are considered when making final design recommendations. The students are continuously challenged to decide what they should include in their work, beyond the basic required design analyses and model building, since there is a wide range of considerations that they can undertake but not enough time to do them all well.

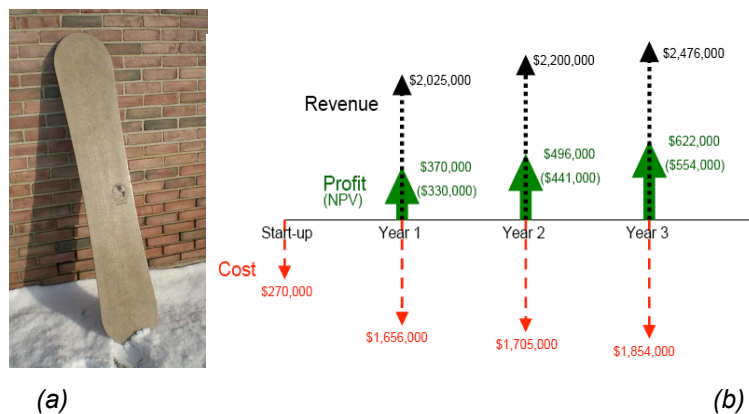


Figure 3: (a) Eco-core board prototype; (b) three-year cash flow and net present value projection for new snowboard introduction

3 PERCEPTUAL ATTRIBUTES

A unique aspect of this framework is the quantification and inclusion of perceptual attributes in the design process. Perceptual attributes are design characteristics that influence people’s judgments about objective qualities such as safety and weight. They influence the product’s ‘image’ to the user and are often critical factors in user choices. While traditional engineers have few skills for such considerations, psychology and marketing have developed a number of rigorous and empirically valid approaches for systematically quantifying perceptual attributes, thus making them good candidates to include along with engineering models.

ANALYTICAL PRODUCT DESIGN SCHEDULE FALL 2008		
AS OF 10/14/2008 (SUBJECT TO CHANGE)		
wk	Date	Lecture/Activity
1	T Sep. 02, 2008	Designing in the Designed World+BusPlan
	TH Sep. 04, 2008	Design process models+DSM
2	T Sep. 09, 2008	Understanding the User+QFD
	TH Sep. 11, 2008	Concept generation + Pugh Charts
3	T Sep. 16, 2008	Survey design
	TH Sep. 18, 2008	Conjoint Analysis: Using Sawtooth
4	T Sep. 23, 2008	Quick prototyping+CAE Tools
	TH Sep. 25, 2008	Reverse engineering
5	T Sep. 30, 2008	Proposals/First Design Review
	TH Oct. 02, 2008	Design optimization modeling
6	T Oct. 07, 2008	Ergonomics and human factors
	TH Oct. 09, 2008	Producer modeling/Microeconomics
7	T Oct. 14, 2008	Cost Benefit Analysis + Cost Modeling
	TH Oct. 16, 2008	Integrating engineering and economics
8	T Oct. 21, 2008	NO CLASS (Fall Recess)
	TH Oct. 23, 2008	Sustainable design
9	T Oct 28, 2008	Preference models and IGA
	TH Oct. 30, 2008	Emotional and aesthetic design
10	T Nov. 04, 2008	Progress/Second Design Review
	TH Nov. 06, 2008	*NSF Design Science Workshop
11	T Nov. 11, 2008	Marketing demand models I
	TH Nov. 13, 2008	Marketing demand models II
12	T Nov. 18, 2008	Integrating design decisions
	TH Nov. 20, 2000	Guest Lecture: Dwight Carlson, CEO Coherix
13	T Nov. 25, 2008	Guest Lecture: TBD
	TH Nov. 27, 2008	NO CLASS (Thanksgiving)
14	T Dec. 02, 2008	Bus. Plan Presentations
15	TH Dec. 04, 2008	Design Expo
	T Dec. 09, 2008	Bus. Plan Presentations+Review+Evaluations

Figure 4: Example of timeline and design activities for a project team in the Analytical Product Design course

The importance of quantifying subjective attributes and preferences in the product design process has been well established. Product designers tend to focus on functionality and usability of products, both of which are necessary but not sufficient because as product variety increases or products mature in the marketplace, the remaining product differentiators are the subjective responses to the product experienced by the customer [40]. Consumers expect more from the products they purchase. Recent trends indicate that consumers show an inclination toward objects that inspire, enhance their lives, and help in triggering emotions [41, 42]. People want more than just a product; they want an experience [43, 44]. A number of methods have been used to assess subjective attributes. Some specific ones include semantic differential methods [45], Kansei Engineering [25, 46], or the Kano method [47]; see [48] for a review. These methods are typically based on the appropriate selection of words and word-pairs to describe subjective attributes and the consumers' ability to interpret and apply their meaning to the products in question.

The engineering design literature is familiar with demand, choice and preference models, such as the general class of utility models to represent consumer choice. There is similar literature in psychology and marketing that has developed quantitative models for measuring attitudes, subjective dimensions, and perceptual attributes. These models include factor analysis, multidimensional scaling, and various clustering models, and are good predictors of demand and choice. Methods for relating perceptual attributes to choice include conjoint analysis and preference maps. Several researchers have demonstrated how this can be done. Dagher and Petiot [49] used concepts from Kansei engineering, conjoint analysis and PREFMAP to assess user preference for biomimetically inspired front-end design of cars. They were able to use these techniques to identify the most important factors that influenced preference as well as develop clear categories that characterized the vehicles. Kelly et al. [31] demonstrated the effectiveness of using interactive genetic algorithms (IGAs) to examine and understand visual aesthetic preferences for a variety of shapes. This method allowed users to choose their most preferred shapes from multiple sets and eventually converge to their 'ideal' shape. MacDonald et al. [35] used conjoint analysis and several methods in psychology to identify both crux and sentinel attributes, where crux attributes are those attributes that people actually want but cannot

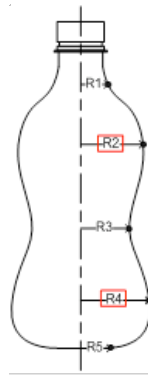


Figure 5: Parameterized bottle shape (after [30]).

readily articulate (e.g., ability of paper towel to absorb water, crashworthiness of a vehicle) and sentinel attributes are those attributes that people perceive will provide the desired crux attribute (e.g., quilt pattern on paper towel, inclusion of airbags in vehicle).

A key aspect of our present approach is to systematically evaluate the perceptual attributes during each stage of the process, which will help with the analysis and interpretation of the data. The steps involved include stimuli creation using design of experiments, data collection, and analysis.

Stimuli creation and design of experiments: This step allows direct identification of factors that have strong influence on the judgments made by the end users. When developing experimental stimuli, it is important to have tight control over the factors that could influence the judgments. This is done by limiting the number of factors, varying only the key factors one wants to study, and taking care not to vary anything else inadvertently. The factors selected should have some relationship to actual engineering attributes. Kelly et al. [29-31] provide an example of systematic variations of stimuli in a cola bottle study, using a spline fit through five points, where the points R2 and R4 were variable and the other three were held fixed, Figure 5. Using a full-factorial design, they generated 25 different designs that people evaluated. In essence, they used a design of experiments (DOE) to guide their stimuli creation. The DOE permits the necessary variations in the stimuli so that main effects and, if possible, interactions, can be detected. Variables R2 and R4 also influence engineering attributes, namely those relating to material use that also impact manufacturing costs.

Data collection via surveys: Use of a survey instrument is a typical way to assess subjective judgments. The survey literature provides ample detail on survey design. At a fundamental level, the following considerations should be incorporated in the survey design process [50]:

- *Clear data collection goals and hypotheses.* What do you hope to learn from doing the survey? What are your hypotheses? What is the experimental design necessary to test your hypotheses?
- *Survey Instructions.* Instructions should carefully provide information about the survey to the subjects without disclosing details explicit to the hypotheses being tested. Researchers have to judge what information to withhold or disclose according to Institute Review Board regulations.
- *Question type.* What type of questions will help collect the information I need: A ranking question, a rating question? Multiple-choice or open-ended questions? A question in the form of a slider?
- *Question wording.* Clear wording is important to reduce noise from ambiguous and heterogeneous interpretations. How can I use everyday language to translate engineering characteristics?

Good surveys use pilot testing and early analyses. Pilot testing ensures the survey is capturing the phenomenon embodied in the research questions [50]; it helps to assess clarity of instructions, average time one takes to complete the study, and whether the survey is boring. It should be done with people who will provide honest feedback (e.g., friends).

Analysis Procedure: The use of descriptive and inferential statistics should typically be used to analyze survey data. Descriptive statistics provide general data trends and should be reported first [50], whereas inferential statistics assess the main effects and interactions identified on those factors that had the significant influence on the perceptions. These methods include regression models, such as analysis of variance (ANOVA), t-tests and various multivariate tests such as factor analysis. An example is presented by Reid et al where they quantify a perceptual attribute they call 'perceived environmental friendliness' using vehicle silhouettes as a case study [51].

4 EXTENDED DESIGN DECISION MODEL

The set of product attributes can be extended to include perceptual attributes, and the design decision model to include government regulation and a game-theoretic structure for competition between firms, Figure 6. A typical implementation of the expanded framework would assume a limited number of competitors, a set of parameters and constraints describing government regulations, and a Nash equilibrium model of competition.

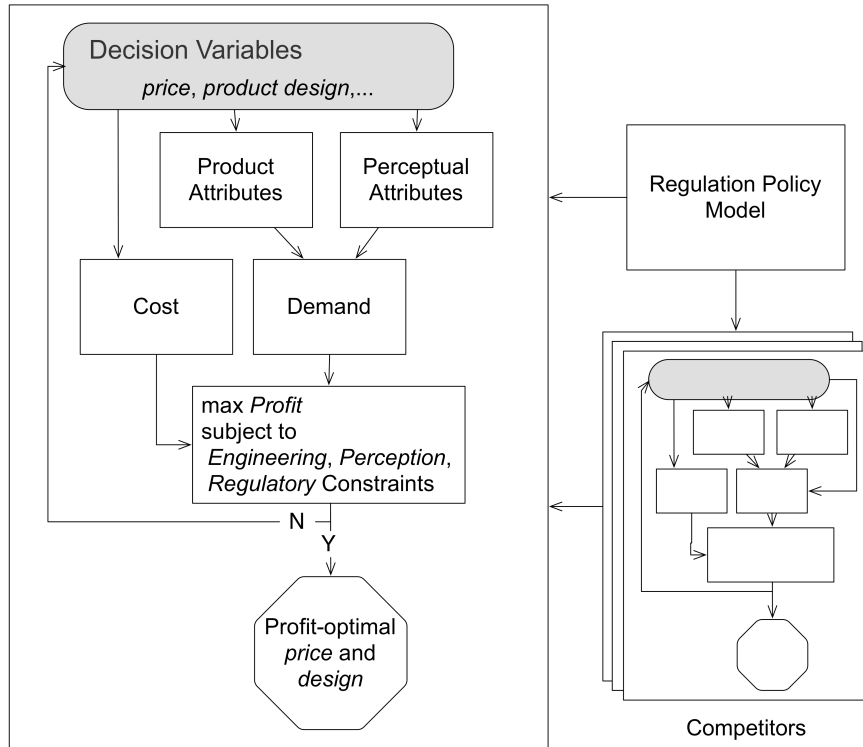


Figure 6: Expanded design decision model schematic

4.1 Application in the APD course

Design decision model implementation in the APD course has paralleled the extensions driven by research work. Class projects exhibit increasing sophistication in product attribute, perceptual attribute, and producer objective modeling. The *Let It Rain Rain Barrels* team [52] demonstrated several enhancements to the basic model. A preliminary survey executed during the information-gathering phase was used to improve attribute modeling. This survey was more open-ended and focused on understanding prospective users and the relative importance of product attributes compared to the choice-based conjoint survey conducted later in the semester that supported a quantitative model of consumer demand. For example, respondent's interest in a foot pump attachment led to including this feature in their design.

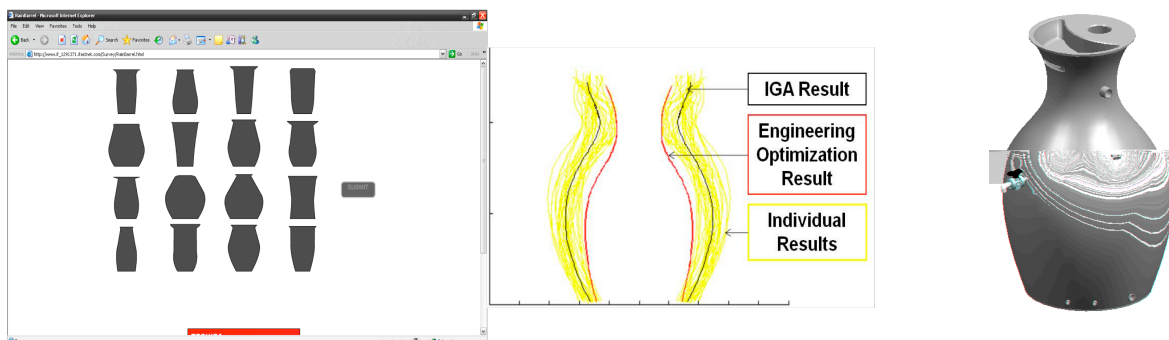


Figure 8: Screen shot of web-based IGA interface (left), respondent's final shape preference superimposed (center), final shape (right)

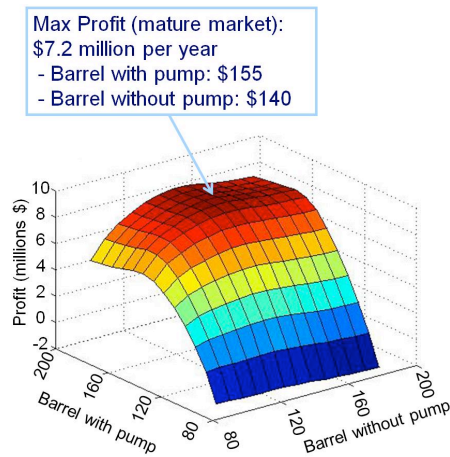


Figure 9: Rain barrel profit as a function of rain barrel price for two product variants

Later in the semester the team conducted a survey that included an interactive genetic algorithm of the rain barrel shape based on work done by Kelly [29] and used it in their final design, see Figure 8. The teams also modified the producer profit objective. The *Let It Rain Rain Barrels* team proposed a portfolio profit maximization problem to maximize total firm profit based on two product variants as seen in Figure 9. Demand estimates for each product variant came from the choice-based conjoint survey where the foot pump option was included as one of the product attributes. We also observed an increasing number of teams formulating their producer objective from the perspective of a non-profit organization.

4.2 Application to automotive design

An application of this extended framework in vehicle design has been performed in collaboration with an industrial partner as shown in Figure 10. The expanded framework was used to study how public and private good objectives can be better aligned in vehicle design [53]. Automotive firms wish to maximize near term profit while meeting strategic objectives, such as sustainability, aligned with public interest through changing consumer preferences, regulation, or public pressure.

Complex vehicle performance simulations were combined with demand models and producer cost models to explore the public vs. private good tradeoffs using Pareto frontiers [53]. Figure 11 shows decision variables, product attributes, and the public/private tradeoff relationship between firm profit and vehicle fuel consumption. Individual Pareto curves represent sets of optimized vehicles and prices under different demand models corresponding to hypothetical differences in consumer preferences. Here sales data were used to inform consumer demand modeling rather than surveys.

4.3 Application in policy analysis

Michalek et al. [15] had proposed implementing the design decision model to examine the tradeoff between consumer and social welfare under various policy regimes for increasing fuel economy. Figure 11 shows sample results from such a study. Ongoing work seeks to include firm design decisions over the vehicle fleet, more realistic models of market demand, and competitive behavior. In one application, the design decision model is embedded inside a larger structure that treats government policy actions as the design variables. In another, the design decision framework is applied to the US automotive vehicle market as a scenario generator for testing hypotheses on alternative vehicle configuration, for example, plug-in hybrids, and then linked with a power grid model to explore how different design configurations will affect power grid operation and vice versa.

5. CONCLUSION

The framework described has proven effective in both instructional and applied research settings. As expansive as this integration may be claimed, it is still capturing a small part of the thinking that goes into designing a product and embedding it into society. The quest for an increased ability to model design in quantitative ways, even if not always successful, helps elucidate the issues at hand and complements well the more intuitive aspects of designing. Designers possess both right and left brains that can be put to good use.

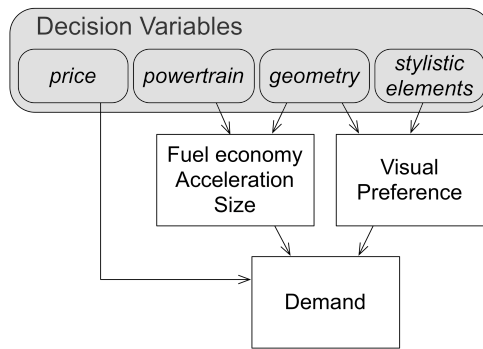


Figure 10: Product and perceptual attribute integration

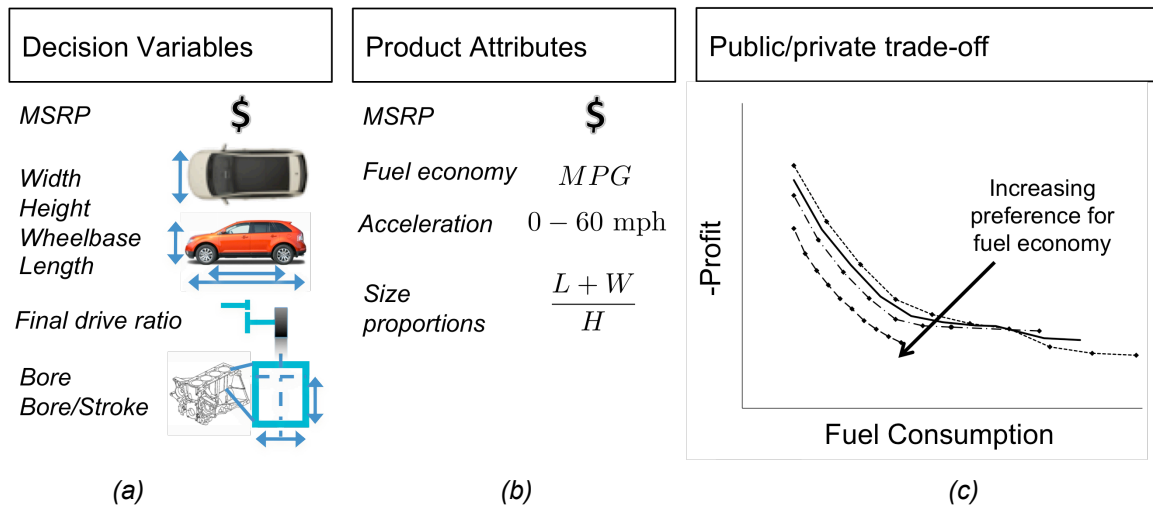


Figure 11: (a) Vehicle design decision variables (b) Vehicle attributes included in demand model (c) Sample results from public/private tradeoff study [53]

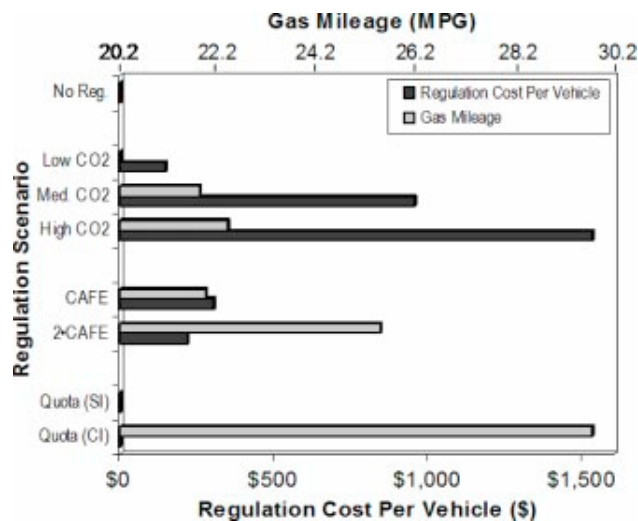


Figure 11: Policy analysis of consumer versus social welfare generated by implementing the design decision model for vehicle design under various policy regimes

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