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USE OF SHAPE PREFERENCE INFORMATION IN PRODUCT DESIGN

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ABSTRACT
A common trade-off in product design is form versus function. While function is typically analyzed and understood quite well, user preferences for the visual shape of a form are not. Product shape has become an increasingly important market differentiator, and so the need for better shape preference analysis has also increased. Conjoint analysis and PREFMAP are preference assessment techniques that can facilitate the inclusion of shape in a form-function trade-off analysis. This article presents a study that compares PREFMAP and conjoint analysis models based upon the same descriptive input data. Results show that such techniques must be used with great care, lest they fail to capture an actual description of user preference. Next, a conjoint analysis model for shape preference is linked with engineering models of a cola bottle to explore the trade-offs between the bottle's form and the associated technical functionality.

Keywords: preference models, visual aesthetics, conjoint analysis, PREFMAP, product design, bottle, optimization, multidisciplinary design, discrete choice models

1 INTRODUCTION
In a competitive marketplace, consumer products must be developed with great attention to the wants and needs of consumers. Assessing the subjective tastes of consumers and utilizing that information within the product design process should lead to better product designs. Thus, several investigations of human subjectivity in product design have been undertaken. Kansei engineering utilizes semantic information in products to match user wants and expectations [1]. Liu's 'engineering aesthetics' aim to help designers make better decisions regarding the aesthetic qualities of a product [2]. Assessing and employing preference information is a key element of product design [3-5]. In this paper we examine the modeling and use of visually perceived shape preference information in the creation of products and its use along with more traditional engineering functionality goals.
Given a choice between products that all meet functional expectations, users may make choices based upon visual appearance. A rigorous understanding of user preference with respect to shape can provide designers with valuable insights. Shape preference is influenced by aesthetic (geometric) qualities and perceived usability. Thus the study of shape vs. technical functionality is a study of form vs. function, a classic argument (or trade-off) in design.
A model of user preference for shape expressed as a mathematical function of the product's design variables would put shape preference on the same footing as technical preferences. Conjoint analysis [6] and preference mapping (PREFMAP) [7] are preference elicitation and analytical modeling methods. In this article we show that different models can result from these two methods, and also between the results of each method and the actual model of preference that they are intended to predict. Nevertheless, these methods remain the most effective ones available, and so in the second part of this study, we use a conjoint analysis model to capture shape preferences for a cola bottle's shape. Then we combine this model with engineering considerations into a multiobjective design optimization problem that attempts to capture the interplay between form and function.
In the following, we provide some background on conjoint analysis and PREFMAP, and proceed to study the differences in the resulting preference models and in their ability to capture the actual preferences underlying the data they use. Next, we describe the integration of preference and engineering models in an optimization formulation and the results derived for a cola bottle shape. We conclude with some observations on the value and limitations of such a modeling approach.

2 BACKGROUND

Methods of investigating preference have been studied in psychology, marketing and engineering. There are qualitative and quantitative methods. Here we focus on quantitative methods that allow us to build models linking design variables with a shape's appeal. PREFMAP can be used to understand preferences linked to the quantities of particular products, such as size or sweetness preference [8]. Conjoint analysis is now ubiquitous in understanding people's preferences for product offerings [9]. Both methods have been used in conjunction with engineering decisions for product design [5, 10].

2.1 PREFMAP

PREFMAP relates a stimulus space to preference data and generates an "external" mapping of preference, meaning that it is based on data obtained independently of the preference assessment [7, 11]. For instance, if several samples of light were shown to subjects and the subjects rated their preference for each sample, then we could determine brightness preference by mapping the light samples' preference onto a stimulus space of lumens as the external map.

The evaluated data input to PREFMAP are subjective preference rankings for certain stimuli (variations on a particular design, for example). PREFMAP has four different phases of analysis associated with four different types of mapping. Three of these mappings, Phases I to III, are based on an ideal point preference model, while Phase IV is a vector model of preference. The basic idea behind PREFMAP is that each individual has an ideal point of maximum preference and is capable of ranking different stimuli so that the ideal point is revealed [11]. The distances between an individual's rank and the ideal point are different for each PREFMAP phase. The ideal point assumption appears to be axiomatic, but it seems plausible that ideal points could exist in different regions of a potential design space. For instance, a person may like small sports cars, and large sport utility vehicles, but dislike luxury sedans. Thus, two distinct ideal points, not one, would exist if vehicles were evaluated in a stimulus space that consisted of size and price as variables.

In Figure 1, we can visualize the first three phases as elliptical paraboloid models of preference with varying levels of complexity where the maximum (or minimum) point is the ideal point. Phase I presents the most general level of preference and describes the preference space as an elliptical paraboloid that can be rotated within the plane (thus the variables can interact). In Phase II the paraboloid is not rotated (thus variables cannot interact). In Phase III the paraboloid is circular. Phase IV uses a vector model, with the vector pointing in a direction of increasing preference for the attributes associated with the stimulus space [9]; visually, the ideal point predicted in Phase IV is far from the actual stimuli tested and the iso-preference circles become nearly parallel, suggesting a gradient of ascent toward the ideal point.

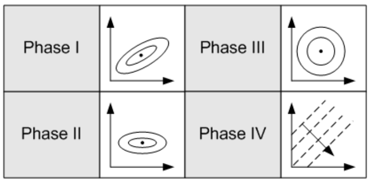

Figure 1. Visual description of the four different phases of PREFMAP.

In this study we look at Phase I analysis. We want to fit user response data (typically averaged over a sample population) to a paraboloid defined by

$$P_{model}(x_1,x_2) = b_0 + b_1x_1 + b_2x_2 + b_3x_1x_2 + b_4x_1^2 + b_5x_2^2 \qquad (1)$$

where $P_{model}(x_1,x_2)$ is the model of preference, x_1 and x_2 are design variables, and $\mathbf{b} = \{b_0, b_1, ..., b_6\}$ are constants determined by minimizing the distance between observed user response data ($P_{avg}(x_1,x_2)$) and $P_{model}(x_1,x_2)$, namely:

$$min\ F(b) = \sqrt{\sum_i \sum_j (P_{avg}(i,j) - P_{avg}(i,j))^2} \qquad (2)$$

From this formulation we can determine the maximum preference point of the user. In this study, the external stimulus space is simply the two design variables weighted on a linear basis.

A variation of PREFMAP was used recently to capture aesthetic preference for a table glass shape described by two variables [5]. Subjects evaluated glass shapes that spanned the entire design space. The resulting linear preference model suggested that users preferred a shape at an extreme corner of the design space, which points to a potential limitation of the approach.

2.2 Conjoint Analysis

Conjoint analysis determines the best combination of feature or attribute values based on the preference response data from a large test group. It is based on the principle that consumers try to maximize their utility when making choices, and has been used for product design, concept evaluation, product positioning, and market segmentation [12].

To collect data, respondents are shown several potential products, images of products, or descriptions of products. Each product is of a similar nature, but levels of product attributes are varied. Respondents are then asked to evaluate the products in some fashion. A popular form of evaluation is through selection of one product amongst a set, referred to as discrete choice analysis. In this case, we assume that utility, u_{iq}, is comprised of a deterministic term, v_{iq}, and a random error term, ε_{ij}, where i and q are the individual and product, respectively [6].

$$u_{iq} = v_{qj} + \varepsilon_{iq} \tag{3}$$

A no-choice alternative is included as well. The error term is assumed randomly distributed and of double-exponential form [6] [13],

$$f(\varepsilon) = exp(-e^{-\varepsilon}) \tag{4}$$

to yield the mathematically tractable multinomial logit model (MNL) [6]. Further, the maximum likelihood estimation (MLE) is used to estimate the choice parameters in the utility model:

$$P_{iq} = exp(V_{iq}) / \sum_{j=1}^{J}(exp(V_{iq})) \tag{5}$$

$$V_{jq} = \sum_{k=1}^{K} \beta_{jk} X_{jkq} \tag{6}$$

Here P_{iq} is the probability that individual q chooses alternative i; V_{jq} is the utility of the jth alternative to individual q composed of attributes X_{jkq} with an associated "part-worth," or alternate-specific constant, β_{jk}, where k is the level of attribute j; see Louviere for a thorough and accessible treatment [6]. In using conjoint analysis care must be taken to avoid violating the MNL model assumptions.

3 EXAMINATION OF DIFFERENCES BETWEEN PREFMAP AND CONJOINT

3.1 Methodology

To illuminate potential differences between the above preference modelling techniques, we used a test function representing the "real" preference. The two methods were then tested in their ability to reproduce this function using only information requested by the querying tool of each technique and subject to that model's own constraints. The goal was not necessarily to ascertain which method is better, but to show that these two techniques yield different results.

We defined the "exact" preference function as (see also Figure 2)

$$F(x_1,x_2) = \left[(x_1\text{-}2.5)(x_1+3)(x_1+2)\right]^2 + \left[(x_2\text{-}2.5)(x_2+3)(x_2+2)\right]^2 \tag{7}$$

This polynomial surface has ridges and a single maximum (0.86, 0.86) within the intervals [-2, 2] for x_1 and [-2, 2] for x_2. To provide preference information the design space was discretized into a 5 by 5 grid of equally spaced points.

For the PREFMAP query we ranked the 25 design points by scaling the function values at the discrete points to be integers between one and nine, as shown in Table 1. This scale is typical of PREFMAP, where 1 corresponds to least liked and 9 to most liked. This information was then used in Eq. (2) to create a "predicted" model of preference.

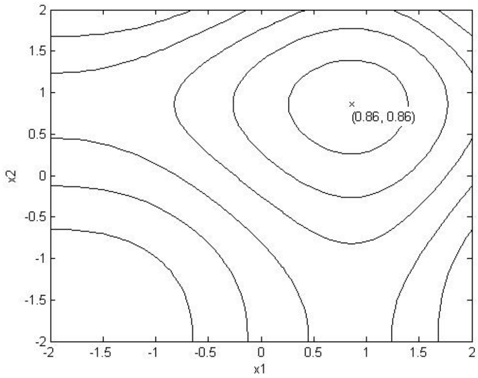

Figure 2. Proposed surface of preference.

Table 1. Values used to answer PREFMAP survey.

$x_1 \backslash x_2$	-2	-1	0	1	2
-2	1	2	4	5	2
-1	2	2	4	6	3
0	4	4	7	8	5
1	5	6	8	9	6
2	2	3	5	6	3

The discrete choice analysis query was formed using Sawtooth Software's Choice Based Conjoint module [14]. Forty "subjects" were agents answering the survey with preferences defined by the function in Eq. (7). Each unique survey consisted of sixteen questions; each question had five options: four were designs selected from the discrete set, and one was the no-choice option. To highlight one assumption of MNL models, we used Eq. (7) to answer these questions in two different ways. First, the agents answered each question using Eq. (7), such that the option presented in the set with the greatest functional value was chosen from the set. Second, each question was answered using Eq. (7) along with an error term having a double exponential distribution. These data were then analyzed with Sawtooth's SMRT module, and the resulting part-worths for each attribute level were analyzed in a MNL model, thus creating an interpretation of the full-factorial marketplace [15]. This marketplace describes how each design option is preferred relative to every other option. We then fit natural cubic splines to these data to obtain a continuous and differentiable model of preference.

3.2 Results and Discussion

PREFMAP yielded an elliptical paraboloid centered at $(x_1,x_2) = (0.46, 0.46)$, Figure 3. The **b** values associated with Eq. (1) are shown in Table 2. Clearly, it would be impossible for a paraboloid model to identify the ridges associated with Eq. (7).

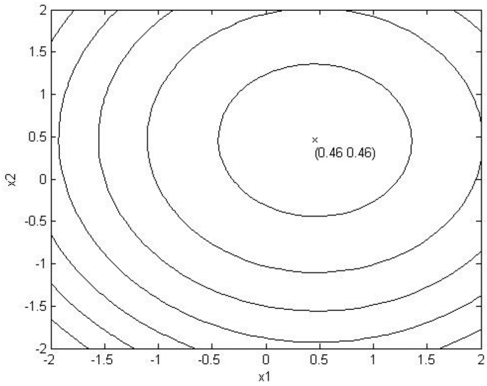

Figure 3. PREFMAP interpretation of proposed preference model.

The MNL model derived from the first set of answers mentioned above is shown in Figure 4 with part-worth values in Table 3. The model is polarized at an optimal value of $(x_1,x_2) = (1.06, 1.06)$ and appears relatively insensitive to the ridges of Eq. (7). The optimal point is located near the discrete choice (1, 1) available in the survey.

Table 2. PREFMAP solution b-values.

b_0	b_1	b_2	b_3	b_4	b_5
6.82	0.54	0.54	-0.01	-0.60	-0.60

Table 3. MNL model part-worths for data without error distribution term.

β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	
-45.75	-28.31	25.52	60.04	-11.50	
β_{21}	β_{22}	β_{23}	β_{24}	β_{25}	β_0
-45.50	-28.50	25.63	59.90	-11.53	-36.05

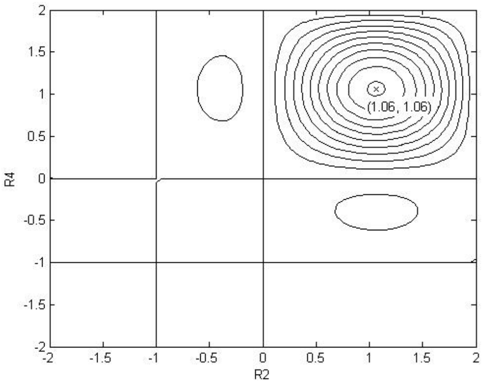

Figure 4. PREFMAP interpretation of proposed preference model.

Figure 5 presents the MNL model results using the second set of answers that included the random error term, with part-worth values in Table 4. This model, while not fully able to recreate the original model, is much more successful. The ideal point coincides with a design option and the contours are less polarized.

Table 4. MNL model part-worths for data with error distribution term.

β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	
-1.59	-0.82	0.85	1.86	-0.31	
β_{21}	β_{22}	β_{23}	β_{24}	β_{25}	β_0
-1.32	-1.037	0.90	1.82	-0.36	-17.14

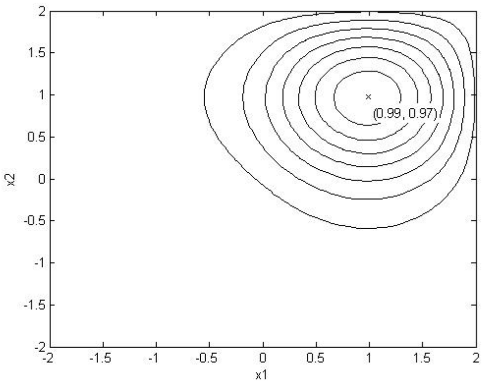

Figure 5. PREFMAP interpretation of proposed preference model.

Indeed, the error term is an important assumption of discrete choice analysis. Using "perfect" preference data without an error term, the MNL model quickly identifies the most preferred option and defines the design space so that the most preferred option takes outstanding preference over all other options. At the extreme, using survey information from a large number of respondents answering perfectly according to a specified preference model, the MNL model will specify precisely the most preferred option, but will obscure the slopes and curvatures of the surrounding design space. Thus, if the most preferred design was technically infeasible, which might occur in a marketing survey, then identifying acceptable alternative designs would be very difficult.

4 COMBINING PREFERENCE AND ENGINEERING FUNCTIONALITY

4.1 Methodology

To investigate the interplay between shape preference and engineering objectives, we formulated a problem that focuses on the design of a plastic cola bottle. We used conjoint analysis to obtain the aesthetic preference information of a sample population. From the engineering standpoint, the bottle was analyzed using finite element analysis (FEA) to examine its stress characteristics. We then used the resulting models to compute the Pareto set associated with maximizing shape preference and minimizing material volume, two potentially competing objectives.

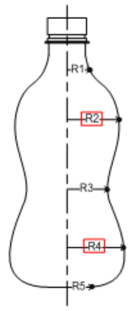

Figure 6. Parameterized bottle shape

Branding through shape is important to the beverage industry. Much effort is put forth in creating unique and appealing bottle designs [16-18]. The bottle shape used for this study was defined by a spline fit through five points, and subjected to prescribed end conditions. Two of the five points were considered variable, points *R2* and *R4* in Figure 6, and provided sufficient shape differentiation. Values for *R2* and *R4* were constrained between 25mm and 50mm. The other three points were fixed parameters during optimization. Point *R1* was set for a perfectly vertical end condition, while *R5* was set with an end condition to create an angle of 20º with the horizontal. In the engineering analysis the variables were continuous. In the conjoint analysis we discretized the design space with five possible values for *R2* and *R4*, spaced at an increment of 6.25mm, thus creating a design space with 25 different designs.

The conjoint analysis survey was administered to 39 college-age individuals from the Ecole Centrale de Nantes, France. Each respondent answered a survey consisting of sixteen questions, and each question offered the respondent four shapes and the no-choice option to choose from, as shown in Figure 7. Each individual received a unique survey, thus creating an efficient survey design. The data were analyzed using Sawtooth Software to obtain part-worths for each variable and level of the two design variables. Equations (8) and (9) below are simplifications of Eq. (5) and (6). Eq. (8) states that each individual bottle design (*i*), has a particular probability of being selected based upon the summation of its variable, or attribute, part-worths compared against all other design offerings.

$$P_i = exp(V_i) / \sum_{i=1}^{I} exp(V_i)_i \tag{8}$$

$$V_i = \sum_j \sum_k \beta_{jk} \delta_{ijk} \tag{9}$$

Note that V_i is a linear combination of part-worth coefficients, β_{jk}, and a binary dummy variable, δ_{ijk}, such that δ_{ijk}=1 when alternative *i* possesses attribute *j* at level *k*.

This formulation can only account for main effects and not interaction effects. The main effects are influenced by each attribute independent of each other attribute. Eq. (10) accounts for interaction terms, which link one attribute to another.

$$V_i = \sum_j \sum_k \left(\beta_{jk} \delta_{ijk} + \sum_l \sum_m \beta_{jklm} \delta_{ijklm} \right) \tag{10}$$

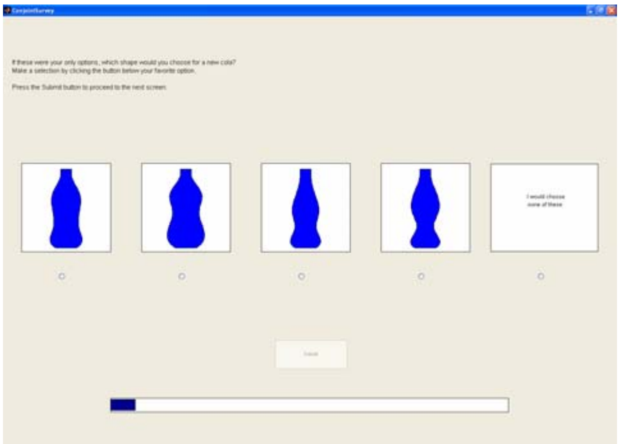

Figure 7. Screenshot of survey tool

Now, δ_{ijklm}=1 when alternative i possesses attributes j and l at levels k and m, respectively. Their inclusion in an analysis is warranted in situations, such as shape or aesthetic preference, where it is likely that one attribute is not independent of the other; consider, for example, proportionality aesthetics. We therefore created the MNL model while accounting for interaction. This discrete model of preference was then made continuous by fitting a cubic spline through the design points [10]. Doing this allows us to use the design space to locate an optimally preferred bottle shape.

From an engineering viewpoint, we desire the bottle shape that uses the least amount of material to hold the desired amount of fluid and to resist the internal pressure without plastic deformation. The internal gauge pressure for this experiment was chosen to be 300 kPa (60 psi). The analysis model was built using the finite element package ANSYS [19]. An axisymmetric solid model was created with a spline shape as previously described. This spline shape was given a uniform wall thickness treated as a design variable. The cap section was given a double wall thickness to prevent a high level of stress in that area [20]. The bottle's bottom section was designed according to an available patent since this is typically the critically stressed location of bottle designs [21]; the wall thickness here was also increased slightly to accommodate increased stress. While this bottom section of the bottle is not flat, it is axisymmetric; so it appears flat to the user in a side view and is therefore consistent with the figures shown to respondents in the conjoint survey. The maximum von Mises stress within the bottle was calculated to ensure that the bottle would avoid exceeding the material tensile strength. Cola bottles are typically manufactured from polyethylene (PET), therefore, PET was selected in this design problem. Its material properties are shown in Table 5.

A simple, linear multiobjective formulation was used.

$$
\begin{aligned}
&\min f(R2,R4) = w_1 * f_1(R2,R4) + (1-w_1) * f_2(R2,R4)\\
&\text{subject to} \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (10)\\
&\quad f_3(R2,R4) - 25MPa \le 0\\
&\quad (25,25) \le (R2,R4) \le (50,50)
\end{aligned}
$$

Here w_1 is an objective weighting, f_1 is the shape preference function (scaled by 500), f_2 is the material volume calculation (scaled by 10^6), f_3 is the maximum von Mises stress in the bottle, and $R2$ and $R4$ are the shape variables. In this problem wall thickness was fixed at 1 mm to simplify the calculation and to make the trade-offs between the two objective functions clearer. The Pareto set was calculated by varying w_1 between zero and one.

Table 5. Material properties of PET cola bottle.

Young's Modulus	Tensile Strength	Poison's Ratio
1.25 GPa	25 MPa	.3

4.2 Results and Discussion

The preference model, obtained through survey data, is presented in Figure 8 along with the optimal shape. A MNL model that included interaction effects was used, along with splines fit to a discrete set

of potential bottle designs, to generate this contour plot. The values of the main effect and interaction effect part-worths are in Table 6. Interaction terms were considered significant according to the "2 log likelihood test" [21] and included in the model. The optimal design was (*R2*, *R4*) = (32.16, 31.61).
The shape is similar to that of cola and other soda bottles in the market. The results of the conjoint study suggest that individuals gravitate toward a shape that they are familiar with. In fact, from the standpoint of semantics (i.e., the message conveyed by the shape), the result suggests that subjects may prefer this particular shape for a cola bottle specifically because they have encountered it as a cola bottle shape so often previously: This shape means "cola bottle" to these respondents. This supports the notion that we tend to prefer what we are familiar with.
Of course, the empirical evidence here is quite thin. Given a greater level of context for this particular bottle it is possible that a different shape would be preferred. For instance, if we tasked users with selecting the shape that would pour a fluid most easily or if we could find users unfamiliar with cola bottles (arguably difficult), then we may have gotten different results. The goal here was to examine a notion of raw preference, but shape preference was possibly based on familiarity: A cola bottle "should" look like that.

Table 6. MNL model part-worths for preference survey, with main and interaction effects.

β_{11}	β_{12}	β_{13}	β_{14}	β_{15}	
-0.15	0.47	0.44	-0.04	-0.73	
β_{21}	β_{22}	β_{23}	β_{24}	β_{25}	β_0
0.11	0.51	0.28	-0.14	-0.76	-0.82

	β_{jk11}	β_{jk12}	β_{jk13}	β_{jk14}	β_{jk15}
β_{11lm}	0.66	0.84	0.41	-0.43	-1.48
β_{12lm}	-0.07	0.44	0.15	-0.34	-0.19
β_{13lm}	-0.43	0.23	0.32	-0.02	-0.11
β_{14lm}	-0.27	-0.78	-0.06	0.24	0.86
β_{15lm}	0.11	-0.74	-0.82	0.54	0.91

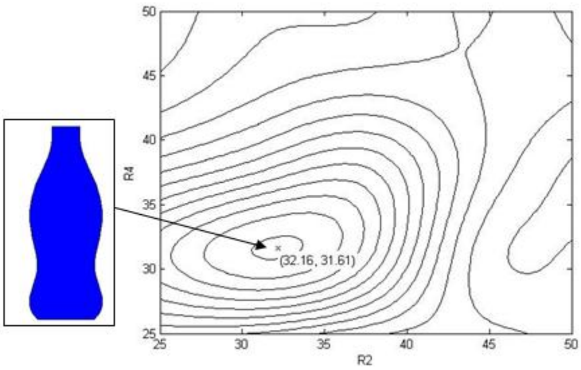

Figure 8. MNL model describing preference for bottle shape, and most preferred shape.

From the engineering perspective the wall thickness should be as small as possible to reduce material volume, subject to the stress constraint. Further, the values of *R2* and *R4* will be minimized to further reduce the amount of material used to make the bottle. This is shown in Figure 9, which shows monotonic decrease toward (*R2*, *R4*) = (25, 25). Note that this figure is presented with a wall thickness of 1mm to show the general trend. The optimal bottle design has (*R2*, *R4*) = (25, 25), and a wall thickness of 0.98mm. The maximum von Mises stress for the bottles occurred in roughly the same location on the bottle's bottom. More importantly, no bottle design will fail with a wall thickness of 1mm. Therefore, the constant wall thickness assumption is reasonable for the multiobjective optimization study.
The Pareto solutions are shown in Figure 10 and are also plotted on the individual objective surfaces in Figure 11 to visualize the trade-off between maximizing preference and minimizing material volume. Figure 10 shows how these two objectives compete. It shows that as we increase shape preference, by adjusting *R2* and *R4*, we also increase the amount of material used. Thus, the design is worse from an engineering perspective. Figure 11 shows the Pareto solutions from Figure 10 on the

shape preference plot presented in Figure 8, and the engineering functionality plot presented in Figure 9. These show how the different Pareto optimal designs perform for the two different objectives. On the left, as we reduce the mass of the bottle we see that the bottle's shape preference is reduced; but, on the right, as we increase the shape preference we increase the amount of material needed to create the bottle. Optimization can inform the decision maker of the best bottle shape for a given objective. We see that different objectives may not always have collocated optimality points. In this instance, if the producer chooses to use the least amount of material, then she will likely save on manufacturing costs, but it will come at the expense of shape preference, and hence market share. So, the producer must balance manufacturing costs with the bottle shape's marketability. The presented data show that by changing the design variables to perform better on one objective, the bottle will perform worse on the other.

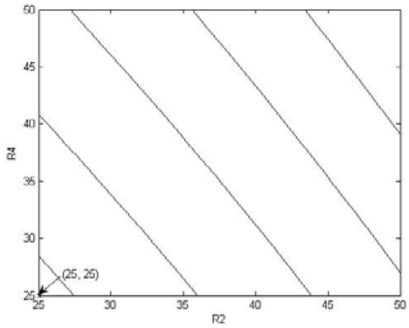

Figure 9. Monotonic surface representing bottle weight,

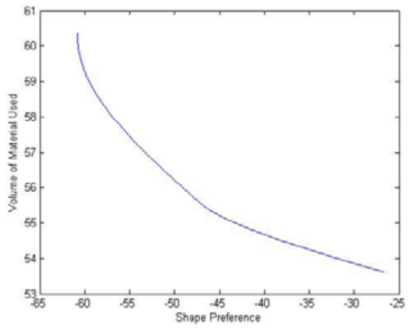

Figure 10. Pareto frontier for multiobjective optimization.

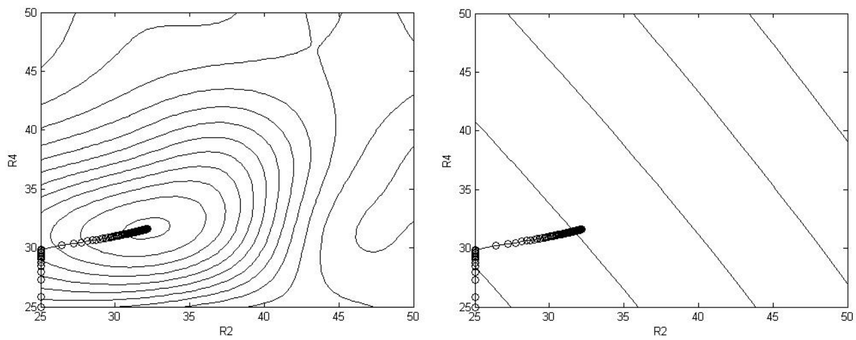

Figure 11. Pareto optimal solutions plotted on preference and engineering models.

One may argue that constraints restricting the interior volume of acceptable bottle designs may change the optimal design. This is true; however, the simplified model we used exposes the asserted quantification of design trade-offs between shape preference and engineering functionality. More refined models are certainly possible. The addition of constraints does not limit the applicability of this approach. For instance, if constraints limited our design space such that the *R2* varied between 35 and 50 mm, instead of 25 and 50 mm, then we would actually see more collocation of optimal designs. In other words, the most preferred shape would also be very near the shape of least mass. This would allow the producer to positively confirm a production decision.

This method does have limitations. It is not yet applicable to designs with discrete features. While discrete-choice analysis can inform producers of the most preferred option among a discrete set, the current approach assumes continuous design variables. For instance, if information existed regarding the preferred number of buttons on a remote control, we could not use a preference map with a continuous design space. If the optimal design in a continuous design space suggested that a remote control have 2.5 buttons, then the producer must still make an intuitive decision regarding the trade-off between too many or too few buttons.

5 CONCLUSIONS

Meaningful quantification of product shape preference is possible using standard methods from psychology and marketing. The methods have limitations, and experiments to elicit preference must be conducted carefully. In the presented study we used two variables (or attributes) to define the variations in a particular product offering. Doing so allowed easy generation and interpretation of results. A more complex design model may describe the product with more variables. In this case, the amount of data needed for statistical validity of the MNL model as used in Section 4 can increase significantly.

A quantification of shape preference allows it to be included along with engineering attributes to explore products that are optimal in a multidisciplinary design sense, specifically exploring trade-offs between form and function. In the study presented, form and function have distinct trade-offs that meaningfully affect each other. Balancing these trade-offs is still a decision that the producer must ultimately make, presumably of quality higher than without the trade-offs quantification.

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