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# DESIGN FOR MARKETING MIX: THE PAST, PRESENT, AND FUTURE OF MARKET-DRIVEN PRODUCT DESIGN

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## ABSTRACT
The four Ps of the Marketing Mix are defined as Product, Price, Place and Promotion. The last forty years of engineering design research has seen an increased incorporation of preference into the design process in response to meeting the demands of each 'P'. This incorporation began with surrogates of preference in Design for Product problem formulations where an objective (such as minimizing weight, for example) represented a firm's desire to reduce cost and maximize profit. As our community progressed toward Design for Price problem formulations, we began to represent preferences both of the designer – using decision theory techniques – and of the customer – often in the form of random utility models that then informed models of demand. The Design for Market System special session was created in response to our transition to Design for Place, though much work remains to be done. The objective of this paper is to highlight the advancements of the community through the first two P's (Product and Price) while also highlighting the need, and exciting research opportunities, that exist as we transition to Design for Place and Design for Promotion.

## INTRODUCTION
Over the last four decades, there has been an increased focus on incorporating customer motivation into engineering decisions. Not surprisingly, the methodological development in this area by the engineering design community has followed a trajectory from the product to the customer; i.e., the product is abstracted in terms of its form and function, which in turn may be abstracted in terms of descriptors of customers' propensity to purchase. As will be showcased throughout the paper, research accomplishments have opened multiple avenues for broadening the socioeconomic impact of engineering design as a discipline.

In this paper, we review the research accomplishments in the area of market-based engineering design from the perspective of the Marketing Mix as introduced by McCarthy [1]. These are commonly known as the Four Ps of Marketing: Product, Price, Place, and Promotion. We posit that as the emphasis on integrating the engineering and marketing disciplines has grown over time, the research contributions to this area from the engineering design community have implicitly progressed through the Marketing Mix, beginning with design of the product itself and gradually adding provisions to accommodate price, place, and promotion in engineering design problem formulations. We further intend to demonstrate that explicitly relating available design methodologies to elements of the Marketing Mix serves not only to increase the efficacy of available market-based design methodologies, but also reveals several compelling avenues for future research activity.

## DESIGN FOR PRODUCT
Design for Product is the foundational methodological framework for market-based product design. A Design for Product framework is typically focused on the interaction between system design parameters (x), system attributes (a), the cost of manufacturing and life cycle costs (C), and the exogenous variables (y). While it is often the goal of the firm to maximize the profitability of the product, the research efforts proposed are focused on navigating the tradeoffs that occur at the level of system attributes. In these approaches is often assumed that demand for a product exists in forms such as a procurement contract awarded by the military to design and build an aircraft or set of satisficing specifications have been established in a requirements document [2]. Demand is therefore assumed to be satisfied when requirements are met and corporate preferences drive subsequent design decisions to reduce costs and thereby maximize profit.

In keeping with the iterative nature of design that is well established in the literature, design automation techniques often

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use classical nonlinear optimization principles to create design problems with an objective function that is subject to a set of constraints [3,4]. Research efforts focus either on improving computational efficiency or managing the complexity that is often associated with complex engineered systems. This has led to advancements in the areas of both multiobjective and multidisciplinary optimization techniques.

While the validity of a multiobjective problem formulation has been challenged by a segment of the engineering design community because it does not allow for the selection of a single design configuration, it has been successfully used as a means of exploring the problem's tradespace [5–8] when a proper value function [9,10] cannot be initially created. Navigating this tradespace allows for insights to be generated about the system design (x) configuration that should be adopted [11–13].

Multidisciplinary design optimization (MDO) methods are commonly formulated around the assumption that designers act rationally [14], which aligns philosophically with market-based design in that the objective function is in some sense a surrogate for value. As the system being designed is complex, designers must choose whether to adopt a monolithic or distributed system architecture [15]. Rather than passing information between disciplines, a hierarchical approach can be created where top level design targets are passed to lower levels of the modeling hierarchy [16,17]. The upper level of this hierarchy modifies the passed down targets so that a feasible design can be realized.

Work integrating utility and preference in ***Design for Product*** problem formulations focused on modeling designer's (engineer's) utility for different engineering options [18,19]. However, a limitation of this formulation for market-driven products is that consumer preferences are not explicitly modeled. The behavioral model for demand is a combination of the design's conformance to the requirements document and its performance on corporate preferences embedded in objective function formulation – for example, minimizing weight reduces costs, which in turn leads to a larger potential profit.

This limitation motivated researchers in both the marketing and engineering communities to explore the connections between design decisions and consumer preference and utility. The next steps in this avenue of research marked a transition in market-based engineering design research from ***Design for Product*** to ***Design for Price***.

## DESIGN FOR PRICE

Initial investigations linking preference and demand as a means of generating new product solutions trace back to publications in the marketing research community as early as 1974. Shocker and Srinivasan [20] proposed an approach that used consumer product perceptions and preferences for existing alternatives as a means for generating new product ideas. This approach followed four steps:

1) *Identify the relevant product-market*
2) *Represent these brands (products) abstractly*
3) *Provide a behavioral model consistent with user buying choices among existing products – to be used in predicting how potential purchases will react to nonexistent alternatives*
4) *Use the model (3) in implementing search to find or come close to finding that location or set of locations for new products which best achieve objectives specified by the firm*

Customer choice of an alternative was tied to an ideal point-product distance model, and a design problem was formulated to identify a single optimal (or at least improved) product. It should also be noted that Shocker and Srinivasan [20] highlighted the challenges of defining an appropriate set of objectives for the fourth step of their approach, stating that:

> *"Ideally, search should be guided by a criterion such as net present value of incremental profits. . . . The viability of such a criterion depends upon the existence of means for predicting both incremental revenues and costs as functions both of time and of location within feasible regions of the attribute space. Such projections may be difficult to make validly."*

Another early effort extended problem formulation from a single product to a line of products as introduced by Green and Krieger [21]. Rather than using a distance metric to identify the optimal new product they built on previous problem formulations involving buyer's welfare [22] and seller's welfare [23]. The ***Design for Price*** framework is distinguished from the ***Design for Product*** framework by including the product's price in the design problem formulation. It is typically included for use within a market simulation engine that has been integrated into the design framework for estimating product demand and, ultimately, estimating the profit generated by product sales.

The integration of market-demand models in product and product line engineering design problems started with conjoint analysis [24] and linear demand models [25,26]. In the S-model, product demand ($n_j$) is determined using a linear function of the pseudo price elasticity of demand ($K$), the customer-perceived value ($V_j$), and price ($P_j$) as shown in Equation 1.

$$n_j = K(V_j - P_j) \tag{1}$$

Value is quantified by combining a product's baseline value ($V_0$) with non-compensatory ($v_i$) and compensatory ($\Delta V_j$) specifications, as in Equation 2.

$$V = V_0 * \prod_{i=1}^{m} v_i + \sum_{j=1}^{n} \Delta V_j \tag{2}$$

 

However, it is the framework for Decision-Based Design (DBD) [27] proposed by George Hazelrigg that most significantly, and comprehensively, formulated market-driven product design problems in an engineering context [28]. As shown in Figure 1, solution quality corresponds to the alternative with the highest possible value. Value is assigned to each product alternative by a von Neumann-Morgenstern utility [29] so that rational engineering design decisions can be made, and an iterative process is followed to find alternatives with greater value.

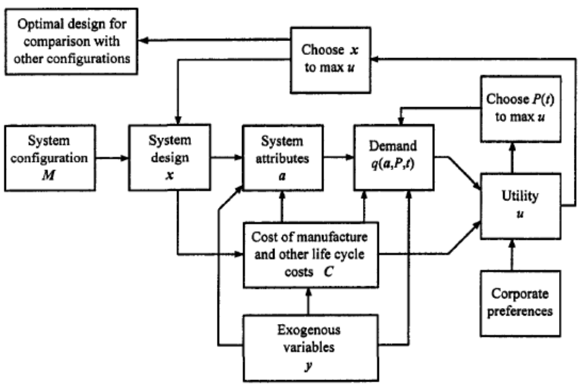


**Figure 1. A framework for decision-based engineering design (from** [28]**)**

In describing his framework, Hazelrigg identifies the *System design (x)* and *Exogenous variables (y)* as having no particular meaning to potential customers. While he acknowledges that these variables do influence manufacturing and life cycle costs, he argues that it is the system attributes that most directly drive demand. Therefore, system attributes (a), product price (P) and time (t) are the key drivers of demand. This creates an iterative sub-optimization process where once the system attributes have been established, price must be determined in such a way that the utility (u) of an alternative is maximized.

Hazelrigg's DBD framework spawned at least two distinctly different avenues of research, each defined by the decision on which they focused. The first focused on the designer's decision-making process. Work in this area included exploratory studies of product development decision making [30], exposition on the application of normative decision analysis in the engineering design process [31] and methods for elicitation and application of designer preferences in engineering decision-making [32,33]. Although this was a substantial body of work in itself, the majority of the work occurred in the second avenue in which the customer's decision-making process was the focal point. In this work, models of customer purchase behavior were exercised to estimate products' sales volumes and market-bearing prices. These models, combined with real-time cost estimating models, enabled development of the class of product design frameworks classified in our work as ***Design for Price*** frameworks. Design for Price frameworks are similar in nature to the MDO frameworks created for Design for Product problem formulations, as they include disciplines associated with engineering performance and market simulation, allowing for the estimation of price. When cost models are included, perhaps as another discipline, the framework is extensible beyond Design for Price to Design for Profit.

Mistree and Marston [34] developed one of the earliest ***Design for Price*** frameworks, allowing a product alternative to be improved with respect to the net present value of profit. Li and Azarm [35] furthered this formulation by using conjoint analysis and regression to estimate utility functions at the individual level, and by considering net present values of share and profit.

The framework of Wassenaar and Chen [36] could be considered the archetype for applying a random utility model in a Design for Price framework. Numerous extensions of this framework were then demonstrated, including decomposition of the optimization problem in the engineering domain [37–39] or in the marketing domain [40,41], design of entire product families rather than single products [42–45], and using revealed preference data to estimate the demand model [44–46]. A wide variety of market demand models have been used, including models derived from traditional econometric methods [35,42–44,47,48] and random utility models spanning from multinomial logit [36,38,39,46] through generalized extreme value [41,45] to mixed logit [49,50].

These works further cemented the socioeconomic impact of engineering design as a discipline. Researchers within the engineering design community then began to ask questions about how assumptions regarding choice of model(s) and problem setup influenced engineering design decisions and the validity of the predicted performance outcome of an engineering design activity. In response to this increased interest in Design for Price problems, the *Design for Market Systems* special session was created in 2008 as part of the program fielded by the ASME Design Automation Conference.

## DESIGN FOR PRICE – ACCOMPLISHMENTS WITHIN THE DESIGN FOR MARKET SYSTEMS SESSION

To understand the research progress made in understanding, formulating, and solving Design for Price problems, we collected every paper published under the Design for Market Systems heading from 2008-2016. The research objectives and contribution areas of these papers were then mapped to key elements of Hazelrigg's DBD framework. This was done to identify what assumptions regarding problem formulation were being challenged and to identify which aspects of the framework were receiving greater amounts of research attention. In line with Figure 1, the following categories will be discussed:

- Linking system design (x) and attributes (a) to the demand model (q)
- Cost of manufacture and other life cycle costs (C)
- Form of demand model (q)
- Corporate preferences
- Optimization of product concept
- Exogenous variables (y)

**Linking system design and system attributes to the demand model**

Our review of the literature found that there has been only a small subset of papers that directly address the link between system design variables, system attributes and the demand model. Much of the work surveyed assumes that the technical attributes which define the form and function of the design are well established, and place a more significant concern on the form of the demand model or the type of customer choice/rating information used to estimate the demand model. Two significant topics covered under this heading relate to 1) the challenge of visually representing the form of the product to obtain some type of customer rating, or 2) understanding the relationship between different product attributes so that an appropriate demand model can be constructed.

Visual conjoint analysis has been proposed and fielded in [51–53] to understand the interaction between product form and customer preference. These works explored how a shape can be parameterized and presented to a series of respondents so that preference structure could be estimated using a choice-based conjoint analysis. This represented a significant departure from the standard text-based surveys where product levels represent a feature inclusion or some qualitative/quantitative measure of system performance. An example choice-based question used in [53] is shown in Figure 2. Visual elements of the product were also considered in [54,55] by studying respondent perception of a vehicle's front-end. Conjoint analysis was used rather than choice-based conjoint, and preferences were established from direct ratings on a scale and pairwise comparisons.

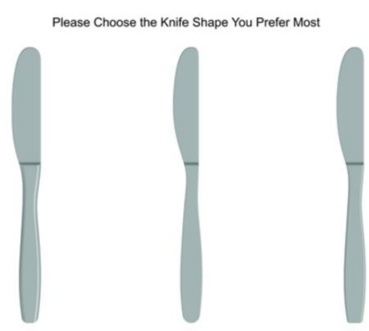


**Figure 2. Example visual choice-based conjoint question. The three attributes considered were the knife's slope, edge and end. (from** [53])

We also include the hierarchical choice model approach presented in [56,57] in this section because of the larger ramifications implied by its hierarchical structure. As shown in Figure 3, as taken from [57], a hierarchical structure was needed to implement an all-at-once model estimation linking the qualitative attributes (often a rating) used by respondents to choose a product, and the quantitative attributes associated with engineering design decisions. This approach was presented in an enterprise design context as the authors argued that detailed design decisions could be made for the entire system, or a single sub-system. While this work combined models of cost and product configuration, decisions were made around calculations of expected profit or net revenue.

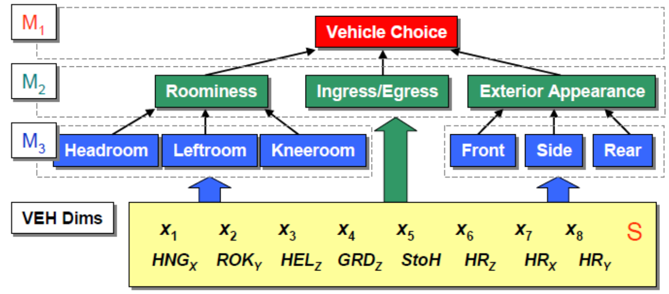


**Figure 3. All-at-Once Hierarchical Choice Model Estimation (from** [57]**). Engineering variables are the vehicle dimensions at the bottom of the figure.**

Other works of note that fall under this category are the exploration of convergent products in [58] that studied how to integrate design solutions from existing product categories to handle the functionality couplings that needed to be addressed. Additionally, work in [59] used three different machine learning methods on 5 years' worth of data associated with residential solar photovoltaic installations in a California market to identify the critical technical attributes that would drive the engineering design decisions. From a set of 34 technical attributes pulled from solar panel specification sheets, it was found that 3 of the attributes were critical in influencing demand.

Overall, most of the papers reviewed from the Design for Market Systems session assume that system attributes are well defined and that it is possible to define the corresponding combination of system design variables. While the statistical significance of system attributes can be challenged in model fitting (as discussed in the Form of Demand Model section), there is usually minimal discussion about how system attributes are selected and whether they are the parameters actually driving respondent choice (it is assumed that, at a minimum, a subset of the modeled system attributes influence choice in a meaningful way) without discussing the manner in which the system is purchased. We revisit, and challenge this assumption, when discussing ***Design for Place*** and ***Design for Promotion*** later in the paper.

**Cost of manufacture and other life cycle costs (C)**

System design and system attribute definition relates to the engineering aspect of the problem rather than the marketing domain. Aligned with the definition of the engineering space is the consideration of manufacturing and lifecycle costs. All papers that consider the optimization of net present value for a product must define some cost structure in a Design for Price problem. However, it is the work that extends the problem formulation to a product line or product family problem that is the focus of this subsection.

 

A product family deployment problem was introduced in [60] to explore compromises that must be made between decisions related to required engineering resources, product lineup configuration, sequence of product rollout and profit. Commonality decisions were incorporated in a combinatorial optimization problem to define the modules selected for the product line. Commonality is treated as a surrogate for cost savings in [61] and is used to establish a competing objective against market share for a product line design problem. The motivation behind this problem formulation was to explore the relationship between cost, market share and the number of product variants offered by the firm. A change in logit of preference share was used to determine the number of products that should be offered and both bottom-up and top-down platforming approaches were investigated. To support top-down product family design an activity-based costing method was presented in [62].

Finally, product architecture decisions were linked with decisions related to supply chain configuration in [63]. Outcomes from this approach combined commonality strategy with manufacturing site selection for module production, assembly and distribution. Such papers introduce an important element to the Marketing Mix discussion. The application of random utility models became more prevalent in market systems research as a means of representing the heterogeneity present in most product markets. Without an adequate consideration of cost, however, an optimization algorithm trying to maximize an objective of market share or revenue will increase the number of variants fielded without check. The incorporation of cost in a Design for Price problem provides a stepping stone for the consideration of retail channel structure, as discussed in ***Design for Place***.

**Form of demand model**

As described by Shocker and Srinivasan [20], the third step of their framework was to provide a behavioral model consistent with how people make their purchasing decisions. When considering Design for Price problem formulations, research into demand model form extends from data origin (where the data comes from and what survey instrument is used) to how advanced market research models provide different solutions to product design problems. The goal of this section is to highlight the scope of these efforts and demonstrate the quantity of engineering design research that has occurred in this space.

Before a model form can be selected, data must be collected so that model coefficients can be estimated. Research into data collection techniques include the development of an algorithm that allows for an optimal design of experiment to be created for human appraisal questions to avoid respondent fatigue [64] and development of an approach similar to Efficient Global Optimization [65] that uses feedback from prior responses to create the next set of questions [67]. A query algorithm that is capable of updating the user preference model during the data collection phase has also been introduced [68], which the added capability of reducing survey length by querying preferred designs from previous users with a similar preference structure.

Collection and fusion of survey data obtained directly from respondents is found in [66–68]. Modeling of customer interests and choice behavior at different stages of product design and development was studied in [66]. The results of this study indicated that a Decision Tree algorithm was more effective at predicting attribute relevance while Discrete Choice Analysis was more suited for estimating the share of an alternative. The unique nature of the data associated with Customer Satisfaction Surveys was explored in [67]. This study found that an integrated mixed logit approach was most effective because of the lack of choice set information, the use of subjective ratings for product attributes, and collinearity amongst attributes. Further, they found that Customer Satisfaction Surveys often violated the first rule of Shocker and Srinivasan's [20] framework in that the products captured in the survey (real products on the market) often did not represent a comprehensive enough range for each product attribute. The fusion of data from van Westendorp studies [69] and conjoint data was explored in [68], leading to an ability to use multinomial logit analysis and the development of a statistical test to measure the fusibility of disparate data sets.

After data is collected, the next step is choosing the form of the demand model to use. This has resulted in two major variations of effort. Those that explore the functional form and choice of demand model used, and research efforts that incorporate usage context into the form of the model.

Ramifications of model form for the vehicle automotive market were explored in [70]. Two different forms were considered: horizontal differentiation and conventional model forms aligned for vertical differentiation. Horizontal differentiation occurs when consumers disagree about the relative ordering of products (or product attribute levels), while vertical differentiation occurs when agreement aligns with the relative ordering of products (or attribute levels) but there is disagreement on willingness to pay. Model evaluation methods used in this work include fit, interpretability, predictive validity, and plausibility, allowing for only relative assessments of model quality. In stating their conclusions, the authors of [70] suggest the consideration of a two-stage decision process modeled on a consider-then-choose formulation that is further explored in [71]. Vehicle data was further used to explore the effectiveness of different discrete choice model forms in [72]. This study used three years of revealed preference data (2004-2006) and estimated multinomial logit models using an exhaustive combinatorial set of utility covariates. When simulating these models on the next year of data (2007), it was found that predictive capability was driven more by the presence of utility covariates and less to model form. Finally, the work in [73] was driven by the need to compare the relative performance (in terms of model fitness) and predictive ability of two heterogeneous market models (hierarchical Bayes mixed logit and latent class multinomial logit). The structure of estimated heterogeneous preferences from each model were explored to investigate why differences were observed both in model estimation and in the product solutions when a line of products was optimized in a share of preference problem. It was found that the continuous representation of heterogeneity offered by the hierarchical Bayes mixed logit model led to better model fitness, predictive ability, and reduced design error due to its larger degree of freedom.

Choice model form has also been manipulated by incorporating usage context [74,75]. The argument made in these works was that when dealing with an engineered system, an overreliance on marketing and demographic attributes would lead to incorrect predictions of the attributes that actually drive choice. Product performance is modeled as a function of the design and the context in which it is being used. Usage context is then incorporated into a respondent's utility function, allowing for market segmentation to be considered.

Network theory has also been used to understand the impact of a social network on new product adoption rates [76]. A three stage process was used to integrate the peer effect associated with a social network with the results from a discrete choice analysis. Further advancements of network analysis has led to the study of interactions between consideration behaviors by creating associations between product attributes and customer demographics [77], as shown in Figure 4.

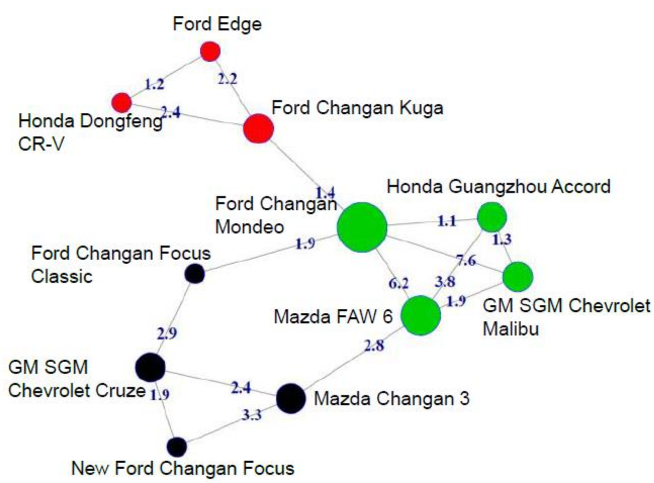


**Figure 4. An illustrative example of creating a network of vehicle associations to influence choice behavior (from** [77])

Finally, there has been a body of work that has explored the modeling of choice by transitioning away from traditional survey techniques. This began with the use of User Generated Content available on the web [78] – such as blogs, social networking interactions and online reviews – and extended to various machine learning approaches capable of mining transactional data for hidden purchasing patterns. This use of data mining has been used to:

- combine customer preference and technological obsolescence [79],
- create new choice modeling scenarios [80],
- explore the viability of Twitter as s source for product opinions that could inform models describing purchasing decisions [81],
- employ sparse coding and sparse restricted Boltzmann machines to yield high-accuracy predictions of preference [82],
- and, create market segments from online reviews focused on individual product attributes (such as zoom on a camera) and to identify attribute important rankings [83].

It is this transition toward an online environment where customers have access to data, reviews, and a selection of choices that we feel most significantly offer opportunities to extend the ***Design for Price*** framework to a ***Design for Place*** framework, as discussed later in the paper.

**Corporate preferences**

Moving toward the iterative nature of Hazelrigg's DBD framework, there is a direct relationship between corporate preference and the objective function used in a market simulation. While profit or revenue are often used in single objective optimization problem formulations, multiobjective formulations have been introduced that trade market share with profit/revenue, for example.

Two papers specifically stand out from the literature review. In [84] the relationship between changes in technology, competition, preference, and regulation is explored. This multiobjective formulation considers the tradeoff between a business objective (maximizing profit) and a social objective (minimizing environmental impact) when both price and product configuration are design variables.

Policy incentives are studied in [85] along with technology-adoption indifference curves, leading to a policy optimization problem that allows a firm to identify the most profitable product development efforts in response to a given policy environment. Further, it is discussed that government organizations could use the formulation to define policies that maximize technology adoption within a market given the design decisions of a firm.

**Optimization of product concept**

The establishment, either explicit or implied, or firm preferences in a Design for Price problem allows for the simultaneous optimization of both product configuration and product price. Such optimizations can occur in a static competitor market or in one where the competition is allowed to respond.

Optimization of a vehicle is performed in [86] by taking into account technology advancements, vehicle style, and customer preference changes due to fluctuations in the market. Here, the objective is maximizing the marketability of the vehicle subject to specified design constraints. The role of constraints are also explored in Foster and Ferguson [87] in the form of design prohibitions. Design prohibitions are defined to exist when two product attributes cannot mutually exist together on a defined configuration. The study conducted in the work explores whether it is more effective to incorporate the design prohibitions into the estimation of the design model or if the prohibitions should be enforced as constraints placed upon the optimization problem. The recommendation made by the authors is that constraints should be included in the optimization problem formulation and that prohibitions should not be enforced in model estimation.

Computational cost is also considered in [88,89] and [90]. These works explore how estimates from the demand model can be used to reduce computational cost and improve solution quality when optimizing product line design problems. A targeted population strategy is introduced for both single and multiobjective problem formulations where respondent-level preference estimates from a hierarchical Bayes mixed logit model are used to seed the starting population of a genetic algorithm. This algorithm tailoring concept is extended in [90] by exploring modifications to the crossover operator in ways unique to a Design for Price design problem.

A responsive competitor is considered in [91] by allowing for pricing reactions. Three product design case studies are introduced and it is shown that a Stackelberg leader strategy outperforms a Nash strategy when the objective is profit. However, it is also shown that both strategies outperform one that ignores possible competitor reactions. The numerical stability of an optimization in such "design-then-pricing" problems is explored in [92] by comparing the outcomes when equilibrium prices are treated as an intermediate quantity and when prices are treated as variables that must satisfy a constraint describing equilibrium.

Finally, there were two papers that took completely different approaches to optimization problem formulation. A customization environment was considered in [93], changing the objective to one focused on minimizing customer sacrifice. Using probability of purchase and assigning a cost to the customization variables, the goal of the objective was to identify the components that should be made available for selection in a build-to-order environment. The work presented in [94] reflects more of a satisficing optimization formulation, as the goal of the paper is to understand if a computer can generate designs from survey results that satisfy style-based design goals.

**Exogenous variables**

While a majority of the research effort has been focused on understanding the impact of demand model form specification, or the ramifications of how consumer choice data is collected/modeled, there have been research efforts exploring the uncertainty sources present in a Design for Price problem. For example, a Bayesian approach from the econometrics literature is used in [95] to decompose the variance associated with the predictive distribution of profit into two parts – intrinsic uncertainty that cannot be avoided and the extrinsic uncertainty due to lack of precision in the model calibration parameters. Adopting a simulation based approach to decompose the variable can avoid the limitations analytical treatment encounter when non-normal distributions are encountered.

Resende et al. [96] also explore the uncertainty in a profit maximization problem by considering the role of firm-defined risk tolerance. An $\alpha$-profit metric is introduced as a way to ensure that the optimal solution has a $(1-\alpha)$ chance of exceeding the found value of profit given the distribution of possible outcomes in an uncertain market. Here, uncertainty is assumed to exist only in the model parameter estimates as it is assumed that the model is correctly specified in form.

Uncertainty in model parameter estimates is also explored in [97]. A confidence-based product line optimization problem is introduced by combining probabilistic part-worth values into a market simulation to quantify First Choice Share (FCS), confidence-level of the FCS, and choice inconsistency. A utility-theory based approach capable of handling conflicts in decision making [32] is used to demonstrate how a decision maker could choose a single design from the set of solutions. It should be noted that the decision making approach was motivated by the first direction of research that spawned from Hazelrigg's framework focused on the designer's decision-making process.

Finally, the work in [98] introduces a real options based approach to address the challenge of launching new product models over time in response to changing market requirements. Both price modifications and design modifications are considered, but a redesign decision must be made in advance since it requires greater engineering effort. A hybrid electric vehicle design problem is considered where gas price is uncertain over time.

**Lessons learned from the Design for Market Systems review**

The literature review conducted in this section shows that, over the last eight years, the engineering design community has spent significant effort exploring the impact of demand model choice/form by considering various sources of consumer inputs and different implementations of the random utility model. This application of economic theory to the demand model block of the DBD framework complemented the original motivation for the framework itself. In introducing the DBD framework Hazelrigg was more concerned with the decision-making challenges faced by the designer and how utility theory could be used to ensure rational choices were being made when selecting an alternative. The richer understanding of preference modeling (a representation of product demand) has been driven by the interest in achieving higher fidelity estimates of the relationship between product attributes and customer choice. Collectively, these research efforts have approached the Design for Price formulation by assuming that purchase choice is driven by a combination of technical product attributes, consumer-specific attributes and the social network of the customer.

A missing element across almost all work in Design for Price is validation of model form by the demonstration of true predictive capabilities and an understanding of the context (or heuristics [10]) under which a model form remains valid. Further, while Hazelrigg did notate demand as a function of time – opening the ability to model preference changes in a market over time in addition to diffusion rates of adoption – it is unclear whether the system attributes that drive choice in a ***Design for Price*** framework are the same for ***Design for Place*** and ***Design for Promotion*** frameworks.

The work of Shiau and Michalek [50] on the concept of market systems marked another pivotal transition in market-based design research. In addition to presenting a proof that clearly demonstrated the role of random coefficient and mixture models of customer choice in market based design problems (specifically that these models must be used in product line and product family design problems because optimal design frameworks employing multinomial logit models necessarily converge to a single optimum), they also introduced the concept of market structure to the engineering design community. This effectively initiated work within engineering design community in the domain of ***Design for Place***.

## DESIGN FOR PLACE

"In the marketing mix, the process of moving products from the producer to the intended user is called place. In other words, it is how your product is bought and where it is bought. This movement could be through a combination of intermediaries such as distributors, wholesalers and retailers. In addition, a newer method is the internet which itself is a marketplace now." (https://www.cleverism.com/place-four-ps-marketing-mix/)

In 2008, Shiau and Michalek [50] introduced a *market systems* problem formulation where demand is influenced both by the action of competitors and the structure of the manufacturer-retailer interaction. This work aligned with the concurrent efforts by Williams et al. [99] who considered retail channel acceptance as an influential parameter effecting engineering design decisions. These efforts highlight beginning efforts from the community to create a ***Design for Place*** framework. Specifically, Shiau and Michalek introduced three classes of competitor response and four different manufacturer-retailer formulations (as shown in Figure 5):

- Class I – competitor products remain fixed in terms of configuration and price
- Class II – competitor products remain fixed in configuration but can respond with price changes
- Class III – competitor products can respond with both configuration and price changes

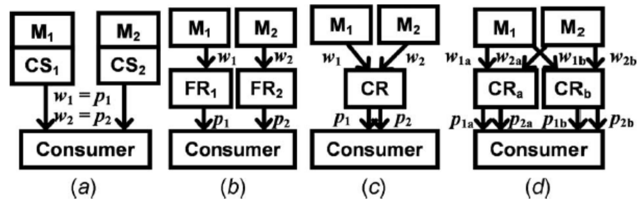


**Figure 5. Channel structure scenarios: (a) company store, (b) franchised retailer, (c) single common retailer, and (d) multiple common retailers (from** [50]**)**

The importance of Design for Place is the suggestion that a manufacturer may need to produce different product variants to sell in different retail channels. There has been little (if any) research explicitly focused on tailoring design to specific retail channels, although we posit that several topics explored outside the mainstream of Design for Price research are salient for Design for Place.

A nested multinomial logit approach was presented in [100] that considers correlations between product bundles and individual product categories. A nested optimization approach is used to define retail price by accounting for the relative clout of retailers in the market. This work is significant in that it demonstrated how engineering design decisions coupled with a neglect of the retailer's pricing decision could lead to unfavorable wholesale prices and poorly positioned products.

Accounting for uncertainty associated with other market players led to the development of an agent-based approach with learning behavior in [101]. Agents in this formulation represented both competing manufacturers (capable of changing product price and product configuration) and retailers (capable of changing pricing), as shown in Figure 6. A no-regret learning algorithm was used so that equilibrium was analytically guaranteed.

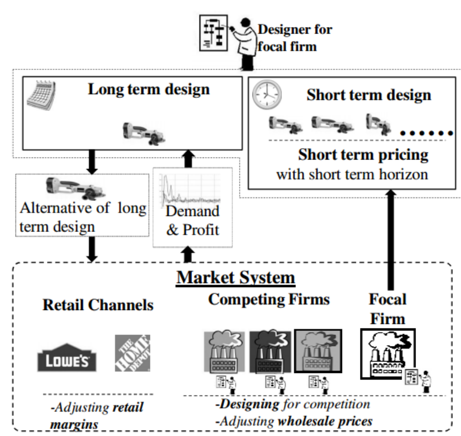


**Figure 6. Developing a Design for Place framework. Competition from competing manufacturers influences both short term design and long term design for a retail channel (from** [101]**)**

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Stochastic and robust models were used to model the supply chain and create a network structure between suppliers, manufacturers and retailers [102]. This work introduced disruption probabilities in the procurement process, and demand was modeled by a random variable with a normal distribution. Uncertainty analysis was also considered in [103] by exploring the challenge of interoperating sourced parts and services and relating those impacts to the overall marketing objectives.

We propose a future vision for Design for Place that extends from the random utility model traditionally used in Design for Price research. In a random utility model a customer's stated choices of products are regressed on product attributes (typically brand, price, and features of the product). Revealed preference models can also be estimated by using real purchase data. This model implicitly relates product choice to product features, which is a reasonable assumption under the following conditions [104,105]:

- Customers recognize the product features used as independent variables in the choice model
- Product attribute information is available equally for all alternatives (this is commonly known as a Complete Information assumption)
- The respondent has unrestricted access to all alternatives (this is commonly known as a Complete Availability assumption)

The motivation for research in ***Design for Place*** is the prospect that the validity of these assumptions varies as a function of the marketing channel. These assumptions seem plausible for transactions in traditional retail outlets, in which products are available to the consumer for direct comparison, the purchase is an interactive process between the customer and the merchant, and the numbers of available product alternatives are limited by shelf space constraints.

However, market dynamics are shifting increased volumes of transactions from traditional retail outlets to online merchants and the assumptions underlying the conventional random utility model grow weaker. In the online environment, products are not available for direct comparison and shoppers rely on incomplete and/or imperfect information from published product specifications, photos, or videos [106,107]. Further, the purchase decision is typically much less interactive [108]; a customer's communication with merchants may be asynchronous and even indirect if sales support functions have been outsourced. In this environment, user-generated product reviews become a primary source of information. However, this data is highly unstructured and often contradictory [109]. The relationships of product attributes derived from user-generated product reviews could be expected (at best) to relate indirectly to those included in a highly structured discrete choice model. Finally, the numbers of product alternatives available from online merchants are typically exceedingly large relative to offerings in traditional retail outlets. Under these conditions, customers will likely apply heuristics to limit their choice sets and customer choice models used to inform product design and estimate product demand must accurately account for differences in choice behavior exhibited when purchasing through different retail channels.

As the community begins to develop approaches tailored toward Design for Place formulations, the following techniques and considerations might apply for online channels:

- Modeling customer heuristics for limiting choice using techniques like lexicographic choice models [110,111] or non-compensatory models [71,112].
- Using natural language processing combined with machine learning [113,114] to automatically annotate unstructured online reviews such that their structures afford estimation of traditional discrete choice models.
- Agent-based choice models accounting for the more complicated dynamics of online purchasing. Consumers often lack the data and/or are not inclined to apply traditional "rational" decision making methods in online spaces (often characterized by daunting numbers of alternatives and limited access to necessary information). Instead, customers may rely on the judgments of opinion leaders (professional reviewers or those with elevated status in social networks). Such opinion leaders would need to be incorporated in agent-based models as acting between the buyers, retailers, and designers/manufacturers/producers. This may lead to a change in corporate strategy where the designer delivers to the value of the opinion leaders who in turn influence the customers to purchase specific products.
- Understanding the core causes of a product getting a minimal (1 or 2) star review in an online environment. Specific negative feedback in such reviews may directly map to a failure to meet either basic needs or performance needs, as defined by the Kano model [115,116]. Fundamental to the Kano model is that customers will not have a negative reaction to a missing delighter, but will have a significant negative reaction to missing or poorly implemented basic and performance needs. One approach to ensuring delivery on basic and performance needs may be formulating the need as an inequality constraint in the optimization problem statement. Further, there is a need to understand the relationship between delighting a customer and a positive review. One hypothesis to be tested is that a fundamentally new solution can delight a customer group and lead to a 5 star review as long as all basic and performance needs are satisfied [117–119].

Referring back to the DBD framework, addressing Design for Place problems will challenge existing formulation assumptions about the blocks associated with system attributes, demand, and exogenous variables. It may not be true that the attributes influencing demand are the demographic and technical attributes often used in Design for Price problems. Rather, the technical attributes of a system may lead to online reviews that have a greater influence on purchase behavior. Further, Design for Place problems will lead to more complex optimization problem formulations requiring improved computational efficiency and MDO frameworks that were originally created for Design for Product problem formulations. Problem formulations might need to be extended for retail environments that consider a system of systems model [120–122] where a retail channel allows for customers to shop multiple sellers for a variety of different products.

Design for Place and Design for Price problems have at least one important similarity. An assumption behind both scenarios is that customer motivation is given and that we as engineers are designing products with the goal of best meeting their mental model of what the product should be. In transitioning to the final Design for P – Promotion – it is possible to actively design the product-price strategy in a way that reshapes the customer's motivational pattern.

**DESIGN FOR PROMOTION**

As discussed in [123], advertising, sales promotions, direct marketing, personal selling and public relations are the five major promotional tools used in marketing. The use of such promotional tools to strategically influence customer behavior was also highlighted by Shocker and Srinivasan [20]. In addition to discussing that product bundles should be targeted to individual market segments they stated that promotion could:

> *"potentially affect perceptions concerning the location of the promoted product or competitive products as well as the saliences of attributes and locations of ideal points . . . Indeed the framework could some day provide the basis for comparing product, promotion, and other elements of the marketing mix in terms of their effectiveness (over time) in achieving desired marketing objectives."*

There have been some early efforts to consider Design for Promotion in the *Design for Market Systems* session. Much of this work is formulated around the concept of product-service coordination. For example, the work in [124] explored how similarity between customer requirements or functions could be used to support the acquisition of new services. More recently, the work by Sinha et al. explored the relationship between member acquisition and value in a two-sided market [125]. Starting with a mathematical foundation using canonical affinity curves, a simulation of a two-sided market is created by considering a system of users and developers.

We propose a future vision for Design for Promotion where engineers reshape customer motivational patterns through a combination of engineering design decisions and marketing techniques. Possible research opportunities include:

- Understanding how tradespace visualization tools [6] could be used to guide discussions with marketing staffs to develop an appropriate messaging campaign. This could involve determining the dimensions in system attribute space where the company's product offerings are non-dominated because of the inclusion of existing product features or new product features that could be offered. Rather than responding to perceived customer tradeoffs between product attributes, a strategy could be formed that (i) actively shifts a customer's attention to attributes reflective of the product line's strength, and/or (ii) influences public opinion to assign higher value to an attribute that the manufacturer specifically wants to highlight.
- Exploring optimization problem formulations that provide excess performance capabilities or over-achieve in feature inclusion so that marketing staff have room to maneuver in creating promotional strategies, especially in response to uncertain competitor behavior or other exogenous factors. The nature of this problem formulation could be similar to the inclusion of slack variables used in classical optimization techniques [4].
- Exploring the relationship between system and lifecycle costs, system attributes, and the strategic positioning of products in the market segmentation grid especially with respect to price point. In Design for Price problems the magnitude of the price variable is driven by the demand model. In Design for Promotion, price is strategically balanced by customer demand and promotional considerations, allowing specific price points to be defined and cost efficiencies [126] to be explored.
- Building on the problem formulation introduced in [38] where analytical target cascading was used to integrate business objectives and engineering considerations by including how resources could be most effectively allocated toward promotional tools.
- Understanding how principles of systems-of-systems [127] engineering can be extended to promotional strategies that bundle products and product-service combinations.
- Exploring how control strategies – such a proportional and derivative control – can be used to influence the dynamic variations in product sales by controlling price discounts and promotions [128].
- Building on existing mathematical models of product adoption [76,129] by linking engineering design decisions to social media presence for a product [114] in a way that identifies possible lead users and the promotional strategies needed to acceleration adoption rates.
- Understanding the relationship between promotion and product customization [130]. This would involve identifying the product attributes that provide delight [131,132] and the subsequent promotional strategies needed to engage a heterogeneous market in a way that encourages adoption.

Formulating ***Design for Promotion*** problems requires elements from all other Design for P frameworks: multiobjective and multidisciplinary optimization approaches used to solve ***Design for Product*** problems, understanding how demand is influenced by system attributes, price and time as done in ***Design for Price*** formulations, and understanding the distribution channels and purchasing environments modeled in ***Design for Place*** formulations. However, rather than simply responding to the needs of the customer by creating products, Design for Promotion problem formulations must model how engineering design decisions and marketing tools can be used simultaneously to actively modify customer purchasing behavior in line with defined corporate preferences.

## CONCLUSIONS

The goal of this paper was to review the current state-of-the-art in market-driven product design research and understand how far we have come as a community in progressing through the Four Ps of Marketing (Product, Price, Place and Promotion). We argue that work in ***Design for Product*** is mainly a requirement-driven process that is supported by advancements in nonlinear optimization, multiobjective problem formulation and multidisciplinary design problem architectures. A transition to ***Design for Price*** involved the engineering design community linking preference and demand to the generation of new product concepts. The Decision-based Design framework introduced by George Hazelrigg provided a comprehensive scope for market-driven design problems and facilitated two different research developments. The first direction focused on the engineer's decision-making process by applying normative decision analysis and methods for eliciting engineer preference toward alternatives. Simultaneously, this framework sparked significant exploration of the impact of demand model choice/form and how customer preferences for product attributes could be captured. The communities richer understand of preference modeling allows for Design for Price problem formulations that relate purchase choice to a combination of technical product attributes, consumer-specific attributes and the social network of the customer. This has been done in the interest of achieving higher fidelity estimates of how engineering design decisions actually influence market behavior, though additional work is needed to demonstrate the true predictive capabilities of random utility models for engineering design problems and to gain a richer understanding of the context under which a model form remains valid.

There has been significantly less work in the areas of ***Design for Place*** and ***Design for Promotion***, though these problems are extremely rich, represent the changing dynamics of today's market, and challenge some of the assumptions made by our community when solving Design for Price problems. The importance of ***Design for Place*** is the suggestion that a manufacturer may need to produce different product variants to sell in different retail channels. As market dynamics shift transactions from retail outlets to online merchants the assumptions behind the conventional random utility model grow weaker. Online environments change the way that people compare products, information is not always available or can be conflicting, and the number of alternatives that consumers must sort through can be substantially large. Research opportunities in Design for Place include modeling customer heuristics for limiting choice across various retail channels, understanding how natural language processing and machine learning can be used to automatically structure reviews in a way that can inform the estimation of consumer choice models, the development of richer agent-based models, a better understanding of what product attributes actually drive purchasing decisions, and the integration of existing design tools (such as the Kano model) toward understanding how product attributes map to the score associated with an online review.

Finally, ***Design for Promotion*** challenges a common assumption associated with the other Design for P problems in that product-price strategies can be designed in a way to actively reshape a customer's motivational pattern driving purchasing decisions. We argue that clearer communication between engineers and marketing staffs is needed to develop effective messaging campaigns that (i) actively shifts a customer's attention to attributes reflective of the product line's strength, and/or (ii) influences public opinion to assign higher value to an attribute that the manufacturer specifically wants to highlight. Research opportunities in this space include exploring optimization problem formulations that integrate slack variables as a means of providing maneuverability in response to uncertain competitor behavior or other uncontrollable market factors, relating costs and strategic product placement especially in the context of price points, adding to current optimization problem formulations by considering how resources for promotional tools can be most effectively allocated, and integrating product adoption models, social media and engineering design decisions as a way of driving market success especially for new technologies or customized products.

Most importantly, formulating ***Design for Promotion*** problems requires elements from all other Design for P frameworks: multiobjective and multidisciplinary optimization approaches used to solve ***Design for Product*** problems, understanding how demand is influenced by system attributes, price and time (***Design for Price)***, and understanding the distribution channels and purchasing environments modeled in ***Design for Place*** formulations.

Over the last 9 years, the engineering design community has made significant advancements progressing through ***Design for Product*** and ***Design for Price***. There remains significant opportunity for the community to come together – and collaborate with our other colleagues both in engineering design and in other disciplines – to tackle the complicated problems of ***Design for Place*** and ***Design for Promotion*** that have not received the necessary level of attention. It is our hope that this paper serves as a framework that drives *Design for Market Systems* research over the next decade.

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