Multidomain Demand Modeling in Design for Market Systems

by

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My greatest fortune during my Ph.D. was meeting Panos and Fred as my advisors. They have been my true mentors and fathers, and I felt their sincerity. If I could go back and get a chance to choose my advisors again, I would choose them as my advisors without hesitation. I really appreciate Panos and Fred, and I will never forget their warm hearts towards me. My second fortune is having my friends from the Optimal DEsign lab and the Design Science program. I can honestly say my life in the lab has been happy and not lonely because of my friends. Moreover, I would like to give appreciation to my committee members, Anocha and Matt, for their guidance and support. Also, I appreciate my Design Science professors, Diann and Colleen, for their encouragement.

Lastly, I thank God for being always with me. I would like to dedicate my thesis to my mother who has sacrificed everything for her son.

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ABSTRACT

Multidomain Demand Modeling in Design for Market Systems

by

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Design for Market Systems (DMS) research has aimed to develop enterprise-level design optimization approaches linking consumer demand and engineering design. Applying demand models to engineering optimization has allowed a design objective to consider enterprise profit beyond engineering performance. However, most demand models in DMS are based on conventional discrete choice analysis (DCA) that is limited to functional product attributes decided by engineering design decisions.

Consumers make choices based not only on functional product attributes (e.g., fuel economy) but also on non-functional attributes (e.g., vehicle form). Consequently, ignoring non-functional product attributes in demand modeling can lead to product designs less attractive to consumers. This dissertation focuses on two major non-functional product attributes: (i) aesthetic product form as a *perceptual product attribute* and (ii) services as *external product attributes*.

The issue with non-functional attributes is that they are not typically controlled by engineering designers. Instead, these attributes may be decided by designers in different domains such as industrial, service, or operations design.

A separate or sequential decision making in each design domain is not effective

if the design domains share design variables that lead to trade-offs between the domains' decisions. This dissertation offers a quantitative methodology to interface and reconcile decisions within different domains and guide the design process to balanced decisions.

A limitation in conventional DCA is that it handles functional and non-functional attributes within a single demand model. An aesthetic product form is generated by a potentially huge number of geometric variables; thus, it cannot be quantified simply and it is difficult to integrate with functional attributes. Similarly, when considering services, it is challenging to incorporate the relationship (or channel) between product and service attributes (or multiple providers) into a single demand model.

This dissertation proposes a multidomain demand modeling approach to integrate functional and non-functional attributes, whose values are decided by different design domains, into a single demand model. We employ consumer choice models from Marketing, systems design optimization from Engineering, machine learning algorithms and human-computer interaction from Computer Science, and location network models from Operations Research within a design optimization framework. This work addresses three demand models: (i) a demand model for engineering and industrial design, (ii) a demand model for engineering and service design, and (iii) a demand model for engineering and operations design. The benefits of this unified approach is demonstrated through three respective design applications including gasoline vehicle design, electric vehicle and charging station location design, and tablet and e-book service design.

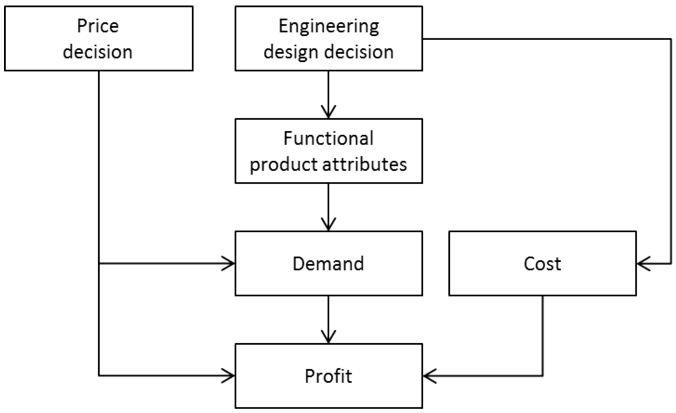
The contribution of this research is in helping resolve trade-offs between conflicted design domain decisions, by integrating disparate attributes into a multidomain demand model. This work consequently extends the scope of Design for Market Systems from product design to business model design by considering external product attributes.

CHAPTER I

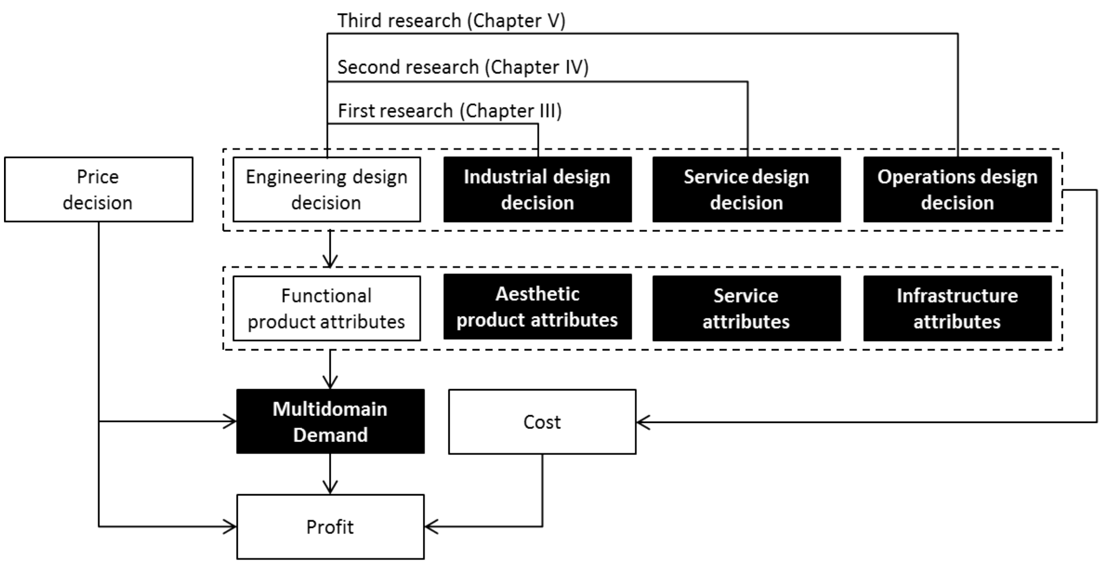
Introduction

Consumer preferences for a product are affected not only by functional product attributes (decided by the engineering design domain), but also by non-functional product attributes (decided by non-engineering design domains). Thus engineering designers alone may not find an optimal product design for the market system as a whole. This is because different domains often share design variables, and there are oftentimes trade-offs between product attributes (e.g., aesthetic attributes by industrial designers vs. functional attributes by engineering designers) that depend on these variables. Even if these different domains cooperate, making decisions sequentially and separately may not lead to an optimal product design for the enterprise. A decision maker therefore needs a method to quantify and control these disparate attributes together in order to achieve “balanced” design solutions. This dissertation details how consumer demand modeling can contribute to a reconciliation between these different design domains. Incorporating attributes of different domains into a single demand model can help a decision maker to resolve trade-offs between different design domains, and thus to find the optimal design for a market system.

Design for Market Systems (DMS) covers profit maximization product design research linking demand model and design decision model (*Michalek et al.*, 2005; *Lewis et al.*, 2006; *Frischknecht et al.*, 2010). The role of the demand model in



(a) DMS framework with *conventional* demand model



(b) DMS framework with *multidomain* demand model

Figure 1.1: Role of multidomain demand modeling in DMS

DMS is linking engineering design decisions with consumer preferences and, therefore, marketability. Most DMS research has adopted conventional discrete choice analysis (DCA) to predict product demand based on price and functional product attributes. The problem is that such a demand model is limited to examining engineering design decisions related to well defined or quantifiable functional attributes as shown in Fig. 1.1(a). This dissertation is motivated by two major non-functional attributes that can have significantly impact on product demand but cannot be controlled by engineering designers: First, aesthetic product form is a perceptual product attribute decided by industrial designers. Second, services are external product attributes decided by service or operations designers. We focus our attention on two types of service attributes: (a) Service content attributes (using a product as service platform), and (b) infrastructure attributes (supporting product usage). Previous DMS has not considered these types of non-functional attributes due to the absence of demand models that contain both functional and non-functional attributes.

1.1 Multidomain Demand Modeling

This dissertation proposes a 'multidomain demand model' to quantify trade-offs between design decisions from domains such as engineering, industrial, service, and operations designs as shown in Fig. 1.1(b). The dissertation details the theory and the benefits of this unified approach through these major studies: (i) Demand modeling for engineering and industrial design, (ii) demand modeling for engineering and service design, and (iii) demand modeling for engineering and operations design. This study also develops DMS frameworks using the proposed demand models, and demonstrates the proposed models in three respective design applications gasoline vehicle design, electric vehicle and charging station design, and tablet and e-book service design. These three studies and associated multidomain demand modeling approach are introduced briefly in Sections 1.1.1, 1.1.2, and 1.1.3.

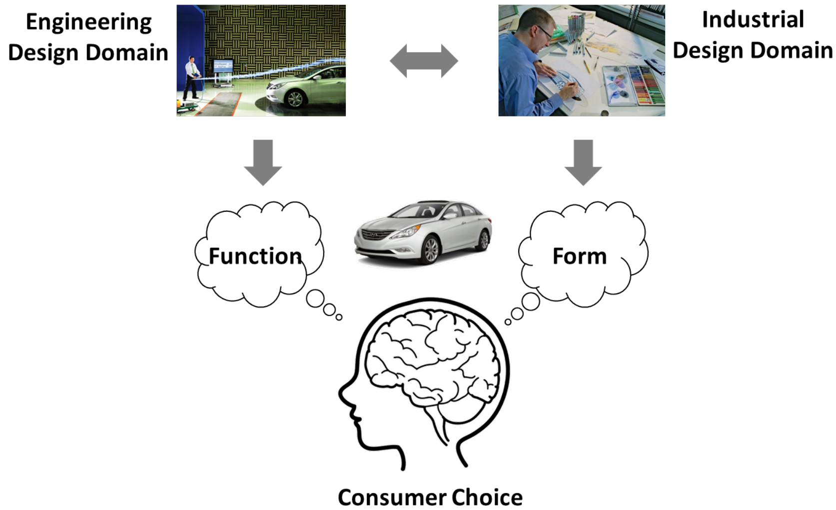


Figure 1.2: Multidomain demand modeling for engineering and industrial design (First research: Chapter III)

1.1.1 Modeling for Engineering and Industrial Design

Chapter III of this dissertation addresses the first research problem, which is how to model consumer demand and give design targets to engineering designers and industrial designers, where a consumer choice is a trade-off between product function and product form as shown in Fig. 1.2. Chapter III presents a mathematical approach using machine learning algorithms and optimizations, as well as a human interface interactions for online real-time preference elicitation.

The motivation for this study can be summarized as follows. First, in the automobile industry, marketers incorporate the vehicle form into overall consumer preference modeling to predict accurate market demand; product designers get target geometric design values from the marketers (*Dotson et al.*, 2012; *Sylcott et al.*, 2013a). However, vehicle form preference is not easy to quantify and to link with other functional attributes due to the large number of geometric features of the vehicle form, and the highly non-linear and heterogeneous nature of the form preference.

Second, the internet connectivity allows marketers to collect data from large number of people ("crowds") at low cost and to gather choice data from them very quickly.

However, one common problem is that online crowds are typically anonymous and they do not accept time delay in the generation of survey queries. Therefore, marketers have only a single chance to survey each subject, and cannot use the same subject in different surveys after a certain time. The demand modeler should then design a single survey without query time delay to build individual-level preference models. Previous research, e.g., on multidomain demand models, is not suitable for crowdsourcing because it employed two separate surveys, for form and overall preference models, and combined them (*Dotson et al.*, 2012; *Sylcott et al.*, 2013a).

Based on the above motivation of modeling individual-level form and overall preferences of an online crowd, we propose a multidomain demand modeling strategy that decomposes preferences into form preference and overall preference and adaptively combines them in real time. A bi-level adaptive conjoint analysis method is implemented to (i) modeling vehicle form preference based on 3D geometries and (ii) modeling overall preference by revealing tradeoffs between form and functional attributes, namely, price and fuel efficiency. We test this approach using Monte Carlo simulation and with an online crowd experiment. Results indicate that the proposed method can elicit more accurate individual-level preferences than conventional DCA.

1.1.2 Modeling for Engineering and Service Design

Chapter IV of this dissertation addresses the second research problem, which is how to model consumer demand and give design targets to engineering designers and service designers, where a consumer choice is a trade-off between product function and service content attributes, as shown in Fig. 1.3.

The scope of attribute types here is extended to include service attributes besides product attributes. The multidomain demand modeling effort now is towards handling product demand and service demand within a single demand model framework. By addressing service aspects in consumer choice, the proposed model can be used

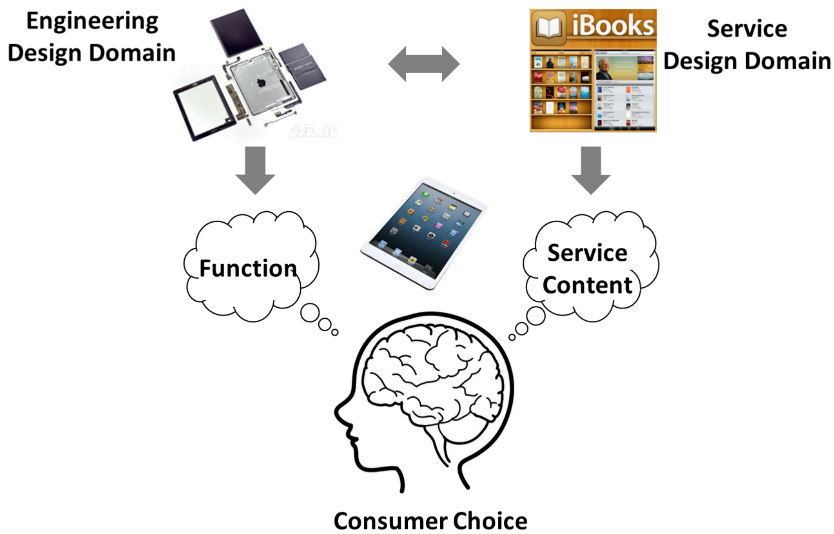


Figure 1.3: Multidomain demand modeling for engineering and service design (Second research: Chapter IV)

for optimal business model design besides optimal product design.

This research is motivated by the fact that integration of products and services is a common and profitable business model in many markets, for example, for electronic devices and digital service content. When customers choose a physical product and associated services sequentially (e.g., PCs and software; cell phones and apps; eReaders and eBooks), the product producer's channel structure should take this into account. That is, some products can use a range of services, while others cannot, and sharing a channel across market players requires strategic cooperation.

This study examines three types of channel: exclusive, where each product can use only its own proprietary services; non-exclusive asymmetric, where only some products can use multiple services; and non-exclusive symmetric, where all products can.

An enterprise-wide profit maximization framework is proposed to optimize products and services for all three channel types in a competitive marketplace. A tablet and e-book service example, using market-level information from four real firms and conjoint-based product-service choice data, is used to demonstrate the proposed

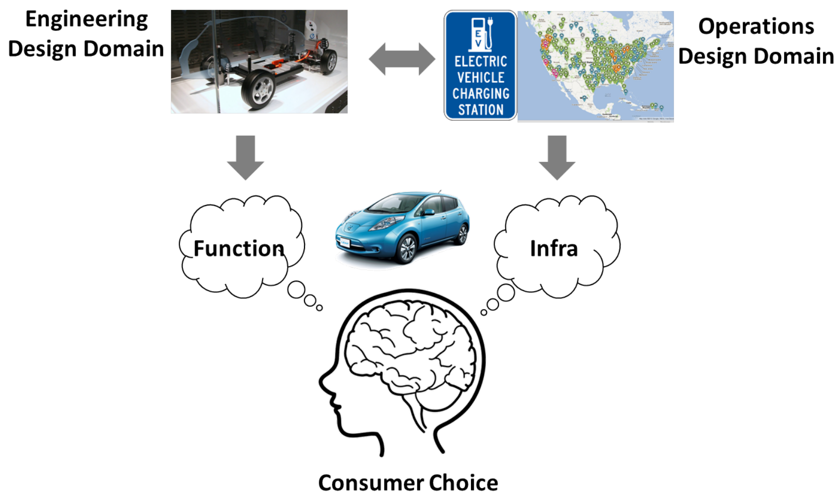


Figure 1.4: Multidomain demand modeling for engineering and operations design (Third research: Chapter V)

framework.

1.1.3 Modeling for Engineering and Operations Design

Chapter V of this dissertation addresses the third research problem, which is how to model consumer demand and give design targets to engineering designers and operations designers, where a consumer choice is a trade-off between product function and infrastructure attributes as shown in Fig. 1.4. Here the infrastructure is used as the extended concept of service supporting product usage and adoption rather than selling services. We focus on validating the advantage of the integrated decision-making approach using the multidomain demand model, as compared to a sequential decision-making approach.

The motivation regarding a real design problem is the fact that a major barrier in consumer adoption of electric vehicles (EVs) is 'range anxiety,' the concern that the vehicle will run out of power at an inopportune time. Range anxiety is caused by the current relatively low electric-only operational range and sparse public charging station infrastructure. Consequently, we must consider engineering and operations attributes together to design a marketable business model.

Range anxiety may be significantly mitigated if EV manufacturers and charging station operators work in partnership using a cooperative business model to balance EV performance and charging station coverage. This model is in contrast to a sequential decision-making model where manufacturers bring new EVs to the market first and then charging station operators decide on charging station deployment given EV specifications and market demand.

This study proposes a DMS framework to assess profitability of a cooperative business model using models from marketing, engineering, and operations. This model is demonstrated in a case study involving battery-electric vehicle design and direct-current fast charging station location network in Southeast Michigan. Results from such a study can inform both government and private enterprise decisions.

1.2 Contributions

The main contribution of this dissertation is to integrate into a single demand models consumer preferences about disparate attributes that depend on design decisions in different domains. The proposed model can be used as a quantitative decision making tool to resolve trade-offs between different design domains such as engineering, industrial, service, and operations, while conventional DCA in DMS has so far focused on only the engineering design domain.

Moreover, by considering external product attributes such as service content and infrastructure, the scope of DMS research is extended to optimal business model design beyond product design alone. As a practical contribution, the proposed model is demonstrated in vehicle and electric device design examples demonstrating the advantage of integrated decision-making for market systems.

1.3 Dissertation Overview

The dissertation proceeds as follows. Chapter II reviews related works for DMS, product demand modeling, and service demand modeling. Chapters III to V present the main three demand modeling studies of the dissertation: Chapter III proposes a multidomain demand model for engineering and industrial designs; Chapter IV develops a multidomain demand model for engineering and service designs; Chapter V presents a multidomain demand model for engineering and operations designs. Chapter VI concludes with a summary, contributions, and future work. The appendices provide detailed background information on the studies in Chapters III, IV, and V.

CHAPTER II

Literature Review

2.1 Design for Market Systems

2.1.1 Overview

Hazelrigg (1998) advocated for a Decision-Based Design (DBD) approach adopting the concept of rational decisions in selecting the design option with the highest expected value. He proposed a framework for DBD to maximize the value of a product (e.g., profit) as shown in Fig 2.1. DBD uses customer preferences for examining utility of a design decision, while conventional engineering optimization research has used product performance as design objectives. In adopting the DBD framework, several researches developed product demand models using discrete choice analysis (DCA) from marketing (e.g., *Wassenaar and Chen* (2003)).

Market systems are affected by not only consumer choice decisions but also dynamic market environments including competitions, economics, and regulations. Consequently, research in the emergent field of Design for Market Systems (DMS) addresses a multidisciplinary design optimization framework linking engineering, marketing, manufacturing, economics, and public policy considerations (e.g., *Michalek et al.* (2005); *Frischknecht et al.* (2010); *Kang et al.* (2014)). DBD and DMS research have been developed within the same engineering design community; consequently,

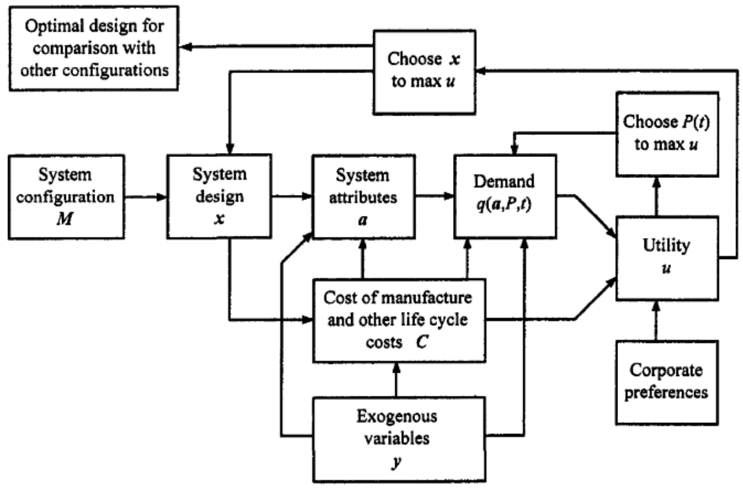


Figure 2.1: Framework of Decision-Based Design. Figure from *Hazelrigg* (1998).

these two research areas have became almost indistinguishable. This dissertation uses DMS as the broader concept including DBD. Table 2.1 summarizes previous main DMS studies.

Table 2.1: Previous DMS research

Literature	Design objective	Demand modeling	Design domains	Main considerations	Application
Hazelrigg (1998)	Product profit	vN-M utility[1]	Engineering	Solution strategy	Engineering education
Li and Azarm (2000)	Product profit, Market share	Conjoint	Engineering	Uncertainty	Cordless screwdriver
Gu et al. (2002)	Product profit	Demand curve	Engineering	Solution strategy	Aircraft concept sizing
Cooper and Papalambros (2003)	Product profit	Demand curve	Engineering	Demand, Technology	Hybrid medium truck

[1]Von Neumann-Morgenstern utility

Wassenaar and Chen (2003)	Product profit	MNL[2]	Engineering	Demand	Universal motor
Kim et al. (2004)	Product profit	MNL	Engineering	Solution strategy	Suspension system
Michalek et al. (2004)	Product profit	MNL	Engineering	Regulation, Competition	Vehicle
Wassenaar et al. (2004)	Market share	MNL, Latent variable model	Engineering	Demand	Vehicle
Georgiopoulos et al. (2005)	Firm's profit	Demand curve	Engineering	Investment, Regulation	Vehicles
Luo et al. (2005)	Market share, Design robustness	MNL	Engineering, Ergonomics	Robustness, Multi-objective	Handheld power tool
Michalek et al. (2005)	Product profit	MNL	Engineering	Solution strategy	Weight scale
Wassenaar et al. (2005)	Product profit	MNL, Kano	Engineering	Demand	Vehicle engine
Cooper et al. (2006)	Product profit	Demand curve	Engineering	Solution strategy	Hybrid electric truck
Kumar et al. (2006)	Product profit	MNL	Engineering	Solution strategy	Suspension system
Michalek et al. (2006)	Product profit	HB[3]	Engineering	Manufacturing, Product line	Weight scale
Olewnik and Lewis (2006)	Product profit	MNL	Engineering	Flexible system	Flexible room

[2]multinomial logit
[3]Hierarchical Bayes estimation

Kumar et al. (2007)	Market share	Nested logit, Ordered logit	Engineering	Demand	Vehicle package
Shiau and Michalek (2007)	Product profit	MNL	Engineering	Regulation, Competition	Vehicle
Shiau et al. (2007)	Product profit	MNL, Mixed logit	Engineering	Demand	Laptop computer
Frischknecht and Papalambros (2008)	Product profit, Fuel consumption	MNL	Engineering	Regulation, Competition	Vehicle
Williams et al. (2008)	Product profit	MNL	Engineering	Channel	Angle grinder
Hoyle et al. (2009)	Utility	Human appraisals, Ordered logit	Engineering	Demand	Vehicle package
Karimian and Herrmann (2009)	Product profit	Logit	Engineering	Solution strategy	Universal electric motor
Kumar et al. (2009)	Product profit	Nested logit	Engineering	Product family	Universal electric motor
Shiau and Michalek (2009a)	Product profit	MNL, Latent class model	Engineering	Competition	Pain reliever, Weight scale, Power grinder
Shiau and Michalek (2009b)	Product profit	MNL, Mixed logit	Engineering	Channel	Vehicle
Shiau et al. (2009)	Product profit	Mixed logit	Engineering	Regulation, Competition	Vehicle

Frischknecht et al. (2010)	Product profit	Econometric demand model	Engineering	Demand, Competition	Vehicle
Hoyle et al. (2010)	Utility	HB, Mixed logit, Ordered logit	Engineering	Demand	Vehicle package
He et al. (2011)	Market share	CSS[4], Mixed logit	Engineering	Demand	Vehicle
Hoyle et al. (2011)	Utility	HB, Cluster analysis, Ordered logit	Engineering	Demand	Vehicle package
Michalek et al. (2011)	Product profit	HB	Engineering	Product line, Demand	Weight scale
Wang et al. (2011a)	Product profit	MNL	Engineering	Channel, Competition	Angle grinder
Wang et al. (2011b)	Product profit	HB	Engineering	Convergence product	Laptop, Smartphone
Resende et al. (2012)	Product profit	MNL	Engineering	Demand uncertainty	Weight scale
Kang et al. (2013a)	Product-service profit	HB	Engineering, Service	Service	Tablet & E-book
Ma and Kim (2014)	Product profit	CPTM[5]	Engineering	Life cycle	Tablet
Morrow et al. (2014a)	Product profit	Consider-then-choose models	Engineering	Demand	Vehicle

[4]customer satisfaction survey
[5]continuous preference trend mining

Morrow et al. (2014b)	Product profit	Mixed logit	Engineering	Competition	Vehicle
Chapter III	Utility	SVM[6], HB	Engineering, Industrial	Aesthetic form, Demand	Vehicle exterior
Chapter IV	Product-service profit	HB	Engineering, Service	Service, Channel, Demand, Competition	Tablet & E-book
Chapter V, *Kang et al.* (2014)	Product-service profit	HB	Engineering, Operations	Infrastructure, Demand	Electric vehicle & charging station

Table 2.1 shows that most DMS research has focused on engineering design problems, and thus it has developed demand models for engineering design decisions. There is limited research in demand modeling for other design domains such as industrial, service, and operations. This dissertation addresses this limitation by extending the DMS research area from the engineering design domain to multiple design domains. The remainder of this chapter introduces the main considerations that previous DMS research has focused on, i.e., solution strategy, demand, competition, and regulation.

2.1.2 Solution strategy

A general DMS framework consists of demand, cost, design, regulation, and competition models as shown in Fig 2.2.

Most DMS frameworks solve the formulated design optimization problems using

[6] support vector machine

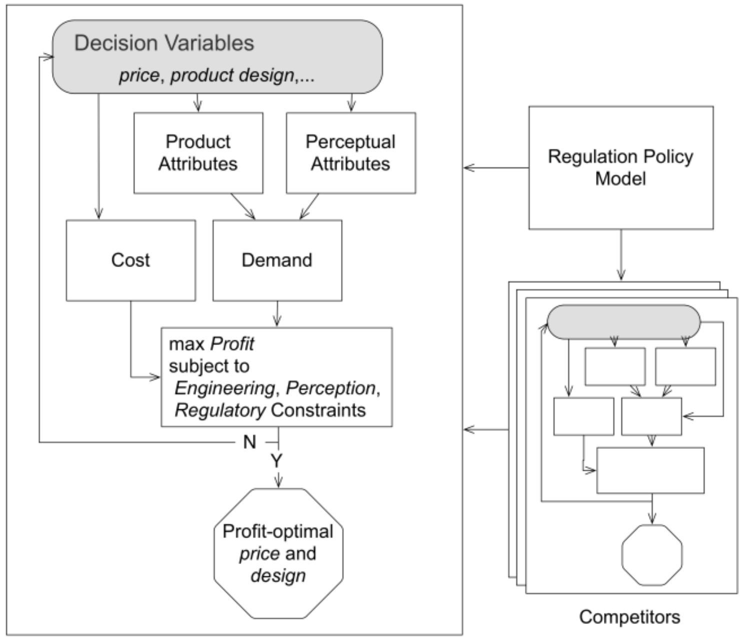


Figure 2.2: General framework of Design for Market Systems. Figure from *Frischknecht et al.* (2009).

the All-in-One (AIO) approach. A general optimization equation is stated as follows.

$$
\begin{aligned}
\max_{\mathbf{X},p} \quad & \Pi = q(p-c) \\
\text{subject to} \quad & lb \le \mathbf{X} \le ub \\
& lb \le p \le ub \\
\text{where} \quad & q = f_d(\mathbf{Z}, p) \\
& \mathbf{Z} = f_e(\mathbf{X}) \\
& c = f_c(\mathbf{X})
\end{aligned}
\tag{2.1}
$$

where Π is profit, q is demand, p is price, c is cost, $\mathbf{X}$ is engineering design variables, $\mathbf{Z}$ is product attributes, f_d is demand model, f_e is engineering model, and f_c is cost model.

On the other hand, some studies have used a decomposition-based approach. This is because, in industry, the AIO approach may not be practical due to the complexity of the engineering systems and the decentralized organization of marketing and engineering. *Gu et al.* (2002) has adopted collaborate optimization (CO) which is a bi-level optimization method for multidisciplinary design optimization (MDO). In the system-level optimization, enterprise decisions are made to maximize profit, then engineering performance targets are translated to subspace optimization. At the subspace-level optimization, multidisciplinary engineering design optimization and cost optimization are carried out to satisfy system-level targets.

The decomposition approach in DMS has been extended by adopting Analytical Target Cascading (ATC) which is a hierarchical optimization methodology for multi-level systems developed by *Kim* (2001). Theoretical convergence of the ATC coordination strategy was proven (*Michelena et al.*, 2003). The computational behavior was enhanced using Augmented Lagrangian relaxation (*Tosserams et al.*, 2006). ATC has been demonstrated in several industrial cases (e.g., *Kang et al.* (2012, 2013b)).

Cooper et al. (2006) applied ATC to multi-level engineering design optimization and proposed the concept of Analytical Target System (ATS) at the enterprise level to identify target engineering performances and then translate them into the engineering design problem as shown in Fig. 2.3. In that earlier version of ATS, engineering performance targets cascaded from the enterprise-level are fixed and there is no iteration between marketing and engineering decisions. *Michalek et al.* (2005) linked the marketing product planning subproblem and the engineering design subproblem using ATC to find iteratively a converged optimal design decision, as shown in Fig 2.4.

Karimian and Herrmann (2009) proposed a separation approach which decomposes a DMS problem into subproblems, and solves the subproblems sequentially without iteration. This approach has a limitation in that it cannot guarantee the globally optimal design, but it can reduce the computational cost significantly when product development time is a main concern in the design process.

Most hierarchical frameworks in DMS (e.g., *Gu et al.* (2002); *Michalek et al.* (2005); *Cooper et al.* (2006); *Kumar et al.* (2006)) are based on a top-down approach

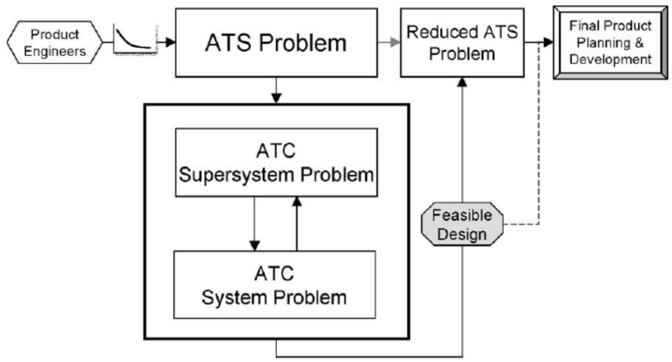


Figure 2.3: Framework for Analytical Target Setting. Figure from *Cooper et al.* (2006).

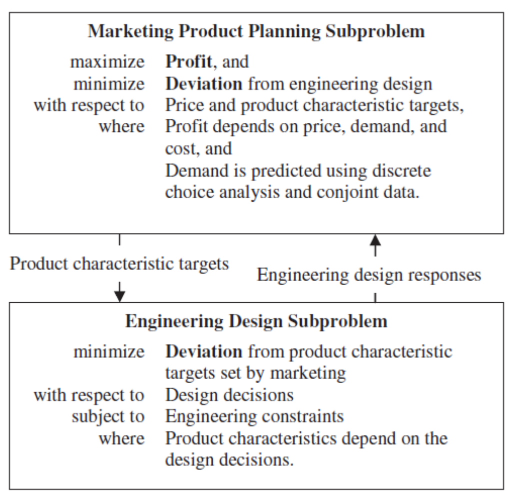


Figure 2.4: Analytical Target Cascading formulation for DMS. Figure from *Michalek et al.* (2005).

(i.e., the marketing decision model gives the system level targets to the engineering decision model). This top-down approach is easy to understand and many enterprises have such hierarchical structures between their marketing and engineering organizations. *Williams et al.* (2008) and *Michalek et al.* (2011) argued that the top-down approach will not work when marketing decisions are not feasible in terms of engineering design and, possibly, cost constraints. *Williams et al.* (2008) proposed a bottom-up framework beginning at the engineering-level with feasible engineering decision options. They argued that the bottom-up approach can be more logical to find marketable engineering design options than the top-down approach, where an enterprise has accurate cost and engineering models. In *Michalek et al.* (2011), ATC is used to balance the top-down and bottom-up approaches.

Most DMS research has addressed single objective optimization problems with the assumption that an enterprise's decision is based on maximizing profit. Some DMS research has addressed multi-objective design problems. *Luo et al.* (2005) showed the trade-off between market share and design robustness; *Frischknecht and Papalambros* (2008) used Pareto curves for profit and fuel consumption to explore how to align public and private interests.

2.1.3 Demand

Much DMS research has focused on enhancing demand models as shown in Table 2.1. Fig. 2.5 shows how a demand model is generally used for an enterprise-level design objective such as profit (*Kumar et al.*, 2009). Demand is estimated based on price and product attributes (customer-desired attributes) which are the responses of engineering design decisions. Customer demographic attributes and exogenous variables also can help to predict demand. The profit is calculated using estimated demand, price, and cost. The cost is calculated based on engineering design decisions and the estimated demand. In profit-optimization, price and engineering design vari-

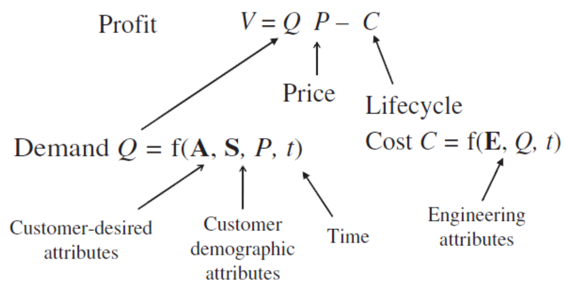


Figure 2.5: Role of demand model in DMS. Figure from *Kumar et al.* (2009).

ables are used as decision variables. Thus, demand modeling plays a critical role in linking engineering decisions with enterprise-wide decisions.

For demand modeling, *Wassenaar and Chen* (2003) adopted discrete choice analysis (DCA) assuming that a customer chooses a product whose utility is the highest among given product options. DCA has been widely used as the standard demand modeling technique in marketing and in DMS. To measure utility of each product option, the random utility concept is used,

$$u_{ij} = v_{ij} + \varepsilon_{ij}, \tag{2.2}$$

where u_{ij} is utility that product j provides to individual i, v is a deterministic component that can be observed, and ε_{ij} is an error component that cannot be observed.

In marketing, the deterministic component v_{ij} is generally assumed as a linear function of discrete levels of attributes and is defined as

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{ikl} z_{jkl}, \tag{2.3}$$

where z_{jkl} are binary dummy variables indicating product j possesses attribute k at level l, and β_{ikl} are the part-worth coefficients of attribute k at level l for individual i (*Green and Krieger*, 1996b).

The probability that individual i chooses product j from a set of options J can be defined as the probability that product j has a higher utility than all alternatives:

$$P_{ij} = \Pr[u_{ij} > u_{ij'}; \forall j' \in J] = \Pr[v_{ij} + \varepsilon_{ij} > v_{ij'} + \varepsilon_{ij'}; \forall j' \in J]. \tag{2.4}$$

If the error component ε_{ij} is assumed to be independently and identically distributed (iid) across choice alternatives and if it follows the extreme value distribution[7] (Gumbel, Weibull or double exponential), then the probability P_{ij} can be estimated by the multinomial logit (MNL) model as

$$P_{ij} = \frac{e^{v_{ij}}}{\sum_{j' \in J} e^{v_{ij'}}}. \tag{2.5}$$

MNL estimates part-worth coefficients using the maximum likelihood method with consumer preference data. The main limitation of MNL is the Independence of Irrelevant Alternatives (IIA) modeling assumption that the utility of each product alternatives has the same error component, so that the choice probability between two alternatives is not affected by other alternatives.

While MNL is the most widely-used demand modeling technique in DMS research as shown in Table 2.1, some DMS studies have used advanced DCA models such as mixed logit (*Shiau et al.*, 2007; *Shiau and Michalek*, 2009b; *Shiau et al.*, 2009; *Morrow et al.*, 2014b), nested logit (*Kumar et al.*, 2007, 2009), ordered logit (*Kumar et al.*, 2007; *Hoyle et al.*, 2011), and Hierarchical Bayesian (HB) models (*Michalek et al.*, 2006; *Hoyle et al.*, 2010; *He et al.*, 2011; *Michalek et al.*, 2011; *Wang et al.*, 2011b; *Kang et al.*, 2013a, 2014). *Kumar et al.* (2007) and *Hoyle et al.* (2010) have integrated different DCA models into a hierarchical structure.

MNL is an aggregate logit model assuming that consumer preference is homogeneous so that the part-worth coefficients in Eq. (2.3) are deterministic and the same across individuals. Mixed logit accounts for heterogeneity of consumer preferences

[7] $\Pr[\varepsilon < x] = \exp[-\exp(-x)]$

treating part-worth coefficients as a distribution across individuals. The mixed logit probability of choice is estimated as

$$P_{ij} = \int \frac{e^{v_{ij}}}{\sum\limits_{j' \in J} e^{v_{ij'}}} f(\boldsymbol{\beta}_i) d\boldsymbol{\beta}_i \approx \frac{1}{R} \sum_{r=1}^{R} \frac{e^{v_{ij}}}{\sum e^{v_{ij'}}}, \tag{2.6}$$

where $f(\boldsymbol{\beta}_i)$ is the joint probability density function of $\boldsymbol{\beta}_i$ distribution, and R is a infinite number of draws from the distribution (*Shiau et al.*, 2007). For practical purposes, the simulated probability can be approximated using the average of results from random draws. The advantages of mixed logit compared to MNL are that mixed logit captures heterogeneity and it is free of the IIA property.

However, mixed logit ignores correlations between part-worth coefficients, and multivariable sampling for maximum likelihood estimation is not practical due to high computational cost (*Shiau et al.*, 2007; *He et al.*, 2011). In marketing, the HB model (*Lenk et al.*, 1996; *Rossi and Allenby*, 2003) is regarded as a solution to this problem using Markov Chain Monte Carlo (MCMC) with a Gibbs sampler which draws part-worth coefficients from a joint normal distribution. Recent DMS research including this dissertation has begun to use HB models, and this technique will be introduced in detail in Chapter III.

While MNL assumes all pairs of choice alternatives have equal competition (i.e., IIA), the nested logit model accounts for unequal competition considering correlations among the choice alternatives. Nested logit allows to partition the set of choice alternatives into subsets (nests) of choice alternatives, so that the model can be used for demand modeling in multiple market segments (*Kumar et al.*, 2007, 2009). Where a consumer survey is based on ordinary rating rather than choice, the ordered logit model can be more useful than MNL (*Kumar et al.*, 2007; *Hoyle et al.*, 2011).

For preference data as an input of DCA, two different types of data such as stated preference (SP) data and revealed preference (RP) data can be used. SP data are gathered though surveys such as a conjoint survey to model new product demand (product not yet in the market). RP data are gathered from real purchase data of existing products in the market. While most DMS research has used SP data for demand modeling of new products, some studies have used RP data, e.g., *Wassenaar et al.* (2005).

Various consumer data considerations beyond choice data were proposed to enhance DCA. *Wassenaar et al.* (2004) used a latent variable such as perceived performance; *Wassenaar et al.* (2005) used the Kano method to decide the shape of preference function; *Hoyle et al.* (2009) used human appraisals; *He et al.* (2011) used the CSI (customer satisfaction index) to incorporate rating survey results into the choice model. Econometric modeling approaches were also employed fitting demand curves using historical data and stochastic forecast (*Georgiopoulos et al.*, 2005; *Cooper et al.*, 2006)

2.1.4 Regulation

DMS research considering government regulations has focused on vehicle designs in the US, such as safety requirements, emission standards, and fuel economy regulations in the US (*Shiau*, 2010). CAFE (Corporate Average Fuel Economy) regulation has been most widely considered in DMS, where the government places a financial penalty to automakers whose sales-weighted average of fuel efficiency of vehicles sold cannot meet the standard. (e.g., *Georgiopoulos* (2003); *Michalek et al.* (2004); *Shiau et al.* (2009))

Michalek et al. (2004) used CAFE, CO2 emission tax, and alternative fuel vehicle sales quotas as regulation constraints. *Frischknecht and Papalambros* (2008) has considered price ceiling as a regulation constraint. According to simulation results of *Shiau et al.* (2009), low CAFE standard is ignorable in the vehicle design optimization, moderate CAFE standard can be useful as an active constraint, and high

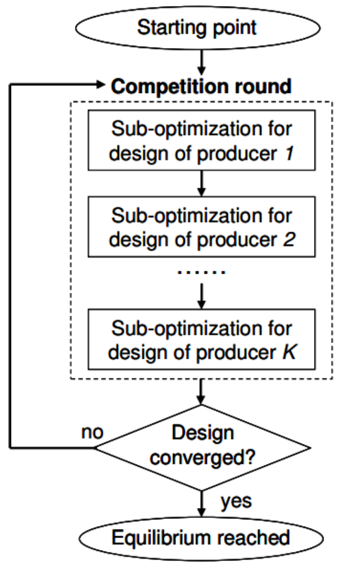


Figure 2.6: Sequential optimization algorithm in DMS for Nash equilibrium. Figure from *Shiau and Michalek* (2007).

CAFE standard can be violated to get the optimal vehicle design. This regulation consideration in DMS can give practical insights for policy makers to make reasonable standards for the regulation in automobile market.

2.1.5 Competition

Most DMS research addressing competition between producers (*Michalek et al.*, 2004; *Shiau and Michalek*, 2007, 2009b; *Shiau et al.*, 2009; *Frischknecht et al.*, 2010) has adopted Nash equilibrium in game theory, which refers to an equilibrium point where no producer can increase its profit anymore by changing its decision (*Tirole*, 1988). For practical application to the DMS framework, each producer optimizes its design decisions sequentially, while fixing the other competitors' previous optimal design decisions at each optimization round. This sequential optimization is iterated until all producers' design decisions cannot increase profit, which means their design decisions reach equilibrium. Fig. 2.6 shows the process of sequential optimization for Nash equilibrium.

Michalek et al. (2004) employed Nash equilibrium in DMS, and showed that decision making without competition considerations can overestimate the profit of optimal decisions. However, the sequential optimization process above can cause high computational cost, and cannot guarantee convergence to a globally optimal equilibrium point. *Shiau and Michalek* (2007) proposed an alternative method to search the equilibrium point directly using the first-order necessary condition (FOC) and second-order sufficient condition (SOC). While most DMS research has used a design-*and*-pricing approach optimizing design and pricing decisions simultaneously, *Morrow et al.* (2014b) proposed a design-*then*-pricing model optimizing design decisions first, then optimizing pricing decisions through competition (Bertrand-Nash equilibrium pricing).

Despite successful applications of Nash equilibrium to DMS, *Wang et al.* (2011a) presented the limitations of this approach. Nash equilibrium assumes that all producers' decisions occur simultaneously; all producers can predict each others' decisions; and the equilibrium point requires first-oder optimality conditions for each producer. These assumptions may not be applicable to real market competition situations and to non-differentiable engineering models.

2.2 Demand Modeling for Product Design

Two types of demand models for product design are reviewed here. Section 2.2.1 discusses eliciting form preference only. Section 2.2.2 discusses eliciting both form preference and overall preference. In addition, Section 2.2.3 reviews optimization and machine learning algorithms for advanced conjoint analysis.

2.2.1 Form Preference Modeling

Table 2.2 summarizes previous research focusing on eliciting form preference. Most of this research comes from the engineering design field rather than the marketing field.

Quadratic and linear functions have been used widely for parametric preference modeling. Interaction terms between design variables also have been addressed (*Kelly et al.*, 2011; *Sylcott et al.*, 2013b) because form geometries are not independent. Some research has not modeled parametric preference functions, because their purpose is not to quantify the preference surface but to find the most preferable form (*Ren and Papalambros*, 2011) or to understand the relationship between form preferences and some performance metric (*Reid et al.*, 2010, 2013; *Tseng et al.*, 2013). For estimation of function parameters, multinomial logit (MNL) models are used with choice surveys, and regression is used with rating surveys. Case studies are usually for vehicle design, because form preference is important in the automobile industry, and presents trade-offs with engineering performance metrics.

There are several limitations in this engineering design research. First, most research ignores consumer preference heterogeneity and models an aggregated preference function. *Orsborn et al.* (2009) has modeled an individual-level preference function using the Bradley-Terry-Luce (BTL) method without using population data, but this method is not useful for making accurate individual-level functions with a limited number of choice survey data. On the other hand, marketing research has modeled

Table 2.2: Previous research on eliciting form preference

Research	Parametric preference function	Parameter estimation	Heterogeneity	Survey	Query design	Product	Representation
Lai et al. (2005)	S/N ratio	Taguchi	Aggregate	Rating	Non-adaptive	Vehicle	2D
Swamy et al. (2007)	Cubic spline	MNL	Aggregate	Choice	Non-adaptive	Vehicle head-lights	2D
MacDonald et al. (2009)	Linear	MNL	Aggregate	Choice	Non-adaptive	Wine bottle	2D
Orsborn et al. (2009)	Quadratic	BTL	Individual	Choice	Non-adaptive	Vehicle	2D
Reid et al. (2010)	N/A	T-test & ANOVA	Aggregate	Rating, etc.	Non-adaptive	Vehicle	2D
Kelly et al. (2011)	Quadratic with interaction term	PREFMAP	Aggregate	Rating	Non-adaptive	Water bottle	2D
Petiot and Dagher (2011)	Quadratic	PREFMAP	Aggregate	Simulation	N/A	Vehicle head-lights	2D
Ren and Papalambros (2011)	Non parametric model	EGO	Individual	Choice	Adaptive	Vehicle	3D
Lugo et al. (2012)	Linear	Regression	Aggregate	Rating	Non-adaptive	Wheel rim	2D
Reid et al. (2012)	Linear	Regression	Aggregate	Rating	Non-adaptive	Vehicle	2D
Tseng et al. (2012)	Neural network	ANN	Aggregate	Rating	Non-adaptive	Vehicle	2D
Reid et al. (2013)	N/A	BTL	Aggregate	Choice	Non-adaptive	Vehicle & carafe	3D
Sylcott et al. (2013b)	Linear with interaction term	MNL	Aggregate	Choice	Non-adaptive	Vase & vehicle	2D
Tseng et al. (2013)	N/A	Correlation	Aggregate	Rating	Non-adaptive	Vehicle	2D

individual-level preferences with the Hierarchical Bayesian (HB) method shrinking individual-level partworth to the mean of population partworths (*Lenk et al.*, 1996; *Rossi and Allenby*, 2003). This will be explained again in Section 2.2.3. This dissertation addresses the heterogeneity issue using advanced machine learning algorithms.

Second, most research has used non-adaptive query designs. Since a complex product form such as a vehicle form consists of a large number of design variables or features, adaptive query design could offer better fit than conventional design of experiments (DOE). Marketing research has demonstrated that adaptive query design outperforms the case of limited choice data (*Toubia et al.*, 2003, 2004; *Toubia and Florès*, 2007; *Abernethy et al.*, 2008). This will be discussed again in Section 2.2.3. Beyond estimation performance, DOE may not be suitable at the early design stage where product form options are not decided yet. While visual conjoint uses pre-designed form options, adaptive query design can generate new form options in real time for each question, so that the overall design space can be tested without pre-designed form options. Our proposed method used an adaptive query design approach.

Third limitation is that most research uses 2D representation. Even though *Reid et al.* (2013) has applied a 3D representation for consumer surveys, this representation is not a parametric model, so that only pre-designed form options can be used. To control 3D rendering parametrically is a challenge, because all geometric features are dependent on each other. However, 3D realistic representation is essential to the perception of respondents. Our proposed method adopted the parametric vehicle design model of *Ren and Papalambros* (2011) which can generate 3D renderings with 19 continuous high-level design variables and 276 low-level design variables. This model will be explained in detail in Chapter III.

The last limitation is that most research has not performed validation tests such as hit rate checking that is the standard validation method of choice models in marketing. Most engineering design work has focused on proposing a modeling process without demonstrating the accuracy of the model.

2.2.2 Form and Overall Preferences Modeling

Engineers, industrial designers, and marketers oftentimes have conflicting design choices due to trade-offs between form and function attributes. For example, vehicle form is related to engineering requirements such as aerodynamics and system layout as well as cost considerations due to manufacturing complexity. That is why decision makers should find an optimal balance between product form and function based on consumer preference. Unfortunately, there is little research on revealing trade-off between form and overall preferences compared to research on form preference discussed in Section 2.2.1. The author found two papers addressing this research problem: *Dotson et al.* (2012) from marketing (collaboration with computer science) and *Sylcott et al.* (2013b) from engineering design. Table 2.3 summarizes the differences these between two previous studies and our proposed model.

Dotson et al. (2012) conducted two separate surveys: a rating survey for form preference, and then a choice survey for overall preference with visual form options selected based on rating survey results. When they incorporate form preference into the overall preference model, they used a covariance structure as an error term of the overall preference model, which is based on the Euclidean distance between form alternatives in the design space of physical dimensions. This covariance matrix can be easily updated by calculating the Euclidean distance between a new form alternative and the currently existing form alternatives in a database. This makes it possible to test new forms even after finishing a survey, in contrast to traditional pictorial conjoint analysis. But, there are some limitations of this research. This model has assumed that the Euclidean distance between form alternatives can approximate the form preference dissimilarity, but it is hard to be demonstrated. They have not modeled a parametric form preference. The covariance matrix cannot give designers

Table 2.3: Previous research on eliciting form and overall preferences

	Dotson et al. (2012)	*Sylcott et al.* (2013b)	This study
Survey	**Two separate surveys** (1) form: rating (2) overall: choice	**Three separate surveys** (1) form: choice (2) function: choice (3) overall: pairwise comparison	**Bi-level questions in single survey** (1) form: metric paired-comparison (2) overall: choice
Time delay between surveys	Yes	Yes	No (real time)
Query design	Non-adaptive	Non-adaptive	Adaptive
Preference function	Form: covariance structure Overall: linear	Form: quadratic Function: linear Overall: linear	Form: radial basis Overall: linear
Estimation	Form: Euclidian distance Overall: Bayesian	Bradley-Terry-Luce (BTL)	Form: Rank SVM mix Overall: Hierarchical Bayesian
Heterogeneity	Individual	Individual	Individual
Product	Vehicle	Vehicle	Vehicle
Representation	2D	2D	3D

the target design values, and it cannot be used to find the optimal design.

Sylcott et al. (2013b) conducted three separate conjoint surveys. First conjoint survey is for form preference; second conjoint survey is for function preference (without price); and the last conjoint survey is for overall preference using two meta-attributes such as form and function, where meta-attributes consist of three levels such as low, medium, and high. Based on the first and second surveys, three form levels and three function levels are selected, and then nine profiles are used for the third survey of conjoint analysis. There are some limitations of this research. Their work has not proposed a way to incorporate a form preference model into an overall preference model. They used the first and second surveys only for designing choice profiles of the last meta-conjoint survey. The meta-conjoint analysis cannot be linked with form preference and the function preference functions, and so this model cannot show how a form design variable can affect overall preference. They modeled individual-level preference functions without using population data, but this is not possible to model accurate individual-level preference functions with a limited number of choice data.

The common and main limitation of these work is that they survey and estimate form and overall preferences separately. Doing separate surveys with different crowd groups may not be a proper way to build an individual-level preference model because it cannot link form and overall preferences for the same individual. Even using separate surveys with a single group is not suitable for online-based surveys and crowd sourcing. This is because the previous research approaches require time for analyzing the data of the first survey to design the second survey. Online crowdsourcing does not allow such time delay. From this reason, our study proposes a bi-level conjoint survey conducted in real time that can model individual-level preference without time delay. The proposed method will be explained in detail in Chapter III.

Table 2.4: Advanced estimation methods (modified from *Toubia et al.* (2007a)

Research	Method	Shrinkage
Lenk et al. (1996) *Rossi and Allenby* (2003)	Hierarchical Bayesian	Yes
Toubia et al. (2003)	Metric paired-comparison analytic-center estimation	No
Cui and Curry (2005)	Support Vector Machine (SVM)	No
Evgeniou et al. (2005)	Support Vector Machine (SVM) mix	Yes
Toubia et al. (2004) *Toubia and Florès* (2007)	Adaptive choice-based analytic-center estimation	No
Evgeniou et al. (2007)	Heterogeneous partworth estimation with complexity control	Yes
This study	Form preference: Rank SVM mix Overall preference: Hierarchical Bayesian	Yes

2.2.3 Optimization and Machine Learning Algorithms

High computing power, web-based surveys and advanced methods in optimization and machine learning allow us to build a choice model more efficiently than traditional conjoint estimation such as the aggregate-level logit model (*Chapelle et al.*, 2004; *Netzer et al.*, 2008; *Toubia et al.*, 2007a). It is expected that these advanced methods can help to estimate a complex attribute such as form, and web-based adaptive and interactive query designs can be useful to generate form alternatives in real time instead of pre-designed form alternatives. Previous research is summarized according to two categories: Estimation methods as shown in Table 2.4, and adaptive query design methods as shown in Table 2.5.

Hierarchical Bayesian (HB) method for conjoint analysis is a popular method for estimation of individual-level partworths by shrinking individual-level partworth towards the population mean of partworths (*Lenk et al.*, 1996; *Rossi and Allenby*, 2003). Since the performance of HB has been demonstrated well in much previous marketing research, our study adopted HB for estimating the individual-level partworths of overall preference model.

Toubia et al. (2003) proposed a polyhedral method for metric paired-comparison which can be used for both estimation and adaptive metric paired-comparison query design. The basic idea in this method is that a polyhedron consisting of hyperplanes representing the constraints based on observation, this polyhedron can represent the set of feasible estimates. Then we can find the analytic center of this polyhedron defined as the point maximizing the distances to the hyperplanes of the polyhedron. *Toubia et al.* (2004) extended this polyhedral model for adaptive choice queries, and *Toubia and Florès* (2007) added a Bayesian interpretation.

Evgeniou et al. (2007) proposed a method for shrinking individual-level estimates towards population-level estimates like the HB concept. But they used a different shrinking method from HB by minimizing a convex loss function depending on only endogenous parameters while HB draws samples from posterior distributions depending on exogenous parameters.

Cui and Curry (2005) and *Evgeniou et al.* (2005) applied Support Vector Machine (SVM) into conjoint analysis. SVM is a popular machine learning algorithm generally used in classification problems. Especially, *Evgeniou et al.* (2005) proposed a SVM mix which can handle heterogeneity. The basic idea is that individual-level partworths can be shrinking towards population-level partworths using a linear sum of individual partworths and populations mean of partworths: $w_i^* = \gamma_i w_i + (1-\gamma_i)(\frac{1}{N}\sum_{i=1}^{N} w_i)$ for individual i where N is the number of individuals. This method can reduce computational cost dramatically compared to HB, and *Evgeniou et al.* (2005) demonstrated that this method performs at a similar level of accuracy as that of HB. Our research here adopts this method not only for estimation of form preference, but also for adaptive design for form and overall queries. Furthermore, we use a rank SVM mix with Gaussian kernel for handling non-linear form preference. This will be explained in detail in Chapter III.

Adaptive question design methods for conjoint analysis is typically based on "utility balance" which means that the profiles in each choice set have similar utilities

Table 2.5: Advanced question design methods (modified from *Toubia et al.* (2007a)

Research	Method	Sampling	Data using
Toubia et al. (2003)	Adaptive metric paired-comparison polyhedral question design	Minimize the volume of the polyhedron and minimize the length of its longest axis	Individual prior responses
Toubia et al. (2004) *Toubia and Florès* (2007)	Adaptive choice-based polyhedral question design	Minimize the volume of the polyhedron and minimize the length of its longest axis	Individual prior responses
Abernethy et al. (2008)	Hessian-based adaptive choice-based conjoint analysis	Maximize the smallest positive eigenvalue of the Hessian of the loss function	Individual prior responses
This study	Adaptive metric paired-comparison Support Vector Machine (SVM) mix question design	Minimize difference between utilities of new pairs and maximize Euclidean distance among all profiles	Other previous respondents responses and individual prior responses

based on prior beliefs of partworths, and this utility balance for the next query can be achieved based on estimated partworths of the previous answers (*Toubia et al.*, 2007a). This approach is also called "uncertainty sampling" for the query strategy in machine learning field (*Settles*, 2010). Previous research noted in Table 2.5 has demonstrated that adaptive query design outperforms non-adaptive query design, especially when response errors are low, heterogeneity is high, and the number of queries is very limited (*Toubia et al.*, 2007a).

Toubia et al. (2003), *Toubia et al.* (2004), and *Toubia and Florès* (2007) select the next query by minimizing the volume of polyhedron and the length of its longest axis. The basic concept of this method is to find the most efficient constraints (i.e., next queries) to reduce uncertainty of feasible estimates (i.e., polyhedron). *Abernethy et al.* (2008) defined uncertainty as the inverse of the Hessian of the loss function and selected the next query by maximizing the smallest positive eigenvalue of the Hessian of the loss function.

Our research uses the utility balance concept, but for more effectiveness, we use not only individual prior responses, but also other previous respondents responses. The previous research presented in Table 2.5 use only individual prior responses and they did not use the shrinkage approach of HB, because it has high computational cost. The adaptive query design using single respondent's response may not be efficient in the early steps of sampling questions when there is still not enough choice data. We use a SVM mix for adaptive query design that does not need high computational cost to shrink. It is expected to sample more efficient queries despite insufficient individual responses. This will be explained in detail in Chapter III.

2.3 Demand Modeling for Product-Service Design

2.3.1 Product-Service Systems

The term Product-Service System (PSS) was first introduced by *Goedkoop* (1999), defining "a marketable set of products and services capable of jointly fulfilling a user's need". PSS has since been regarded as a new emerging research area for an integrated product-service ecosystem (*Mont*, 2002; *Baines et al.*, 2007; *Roy and Baxter*, 2009). Besides the tablet and digital service market example discussed in the introduction, a frequently used example in PSS research is the case of Rolls-Royce PLC, which supplies total-care package services to airlines, as opposed to merely selling a gas turbine engine alone. This business model is called "power by the hour," and works by supplying the services to maintain and repair the engines and collecting data on product performance and using them to upgrade engine efficiency and reduce the cost and environmental impact (*Brady et al.*, 2006; *Baines et al.*, 2007; *Hudson et al.*, 2011). *Baines et al.* (2007) explained PSS as a special case of 'servicitization' with business model transformation of 'sale of product' to 'sale of use'. The core idea underlying product and service integration is addressed not only in PSS research, but has been discussed in other fields in various ways. To differentiate from other research fields, much PSS research has tried to address and develop new types of business models combining products and services that did not exist in conventional industry, and has also focused on reducing the environmental impact of production and consumption beyond achieving economic values (*Mont*, 2002). Although the range of extant PSS research is vast, relatively little is aimed at market-driven and profit maximization design approaches for producers to implement this paradigm in a practical manner (*Vasantha et al.*, 2012).

2.3.2 Profit Maximization in Product-Service Design

In marketing, profit maximization product design research has a rich and long history (*Green and Krieger*, 1991; *Moore et al.*, 1999). Marketing research has utilized conjoint-based methods to quantify customer preference and predict market shares. Early conjoint approaches used ranking of product profiles, which respondents found cumbersome, followed later by rating, which introduced issues with scale usage (e.g., two respondents could reply with the middle scale point, but mean different things by it). Econometric developments eventually led to the prevalence of choice-based conjoint, and further refinements using Bayesian estimation have allowed for better accommodation of preference heterogeneity - allowing superior inference regarding individual-level customer preference - as well as decreased reliance on presumptions about functional forms (*Rossi and Allenby*, 2003; *Orme*, 2009). Because demand can be written as a function of product attributes and price, conjoint thereby allows profit optimization (given a product cost model, which manufacturers can supply internally).

A similar profit maximization approach (based on the conjoint / choice model) has also been applied to service design (*Pullman and Moore*, 1999; *Easton and Pullman*, 2001; *Goodale et al.*, 2003). Most service design research addresses the operations aspect as well as the marketing aspect. This occurs because, although product design methods are applicable to service design, service possess unique characteristics - such as simultaneity of production and consumption, perishability, inability to stockpile, etc. - so that operations management techniques are needed to handle service capacity and demand management (*Pullman and Moore*, 1999). Service design research considers not only tangible services (i.e., technical features), but also how the service is delivered, such as waiting lines, service delays, scheduling, and congestion in the service facility (*Pullman and Moore*, 1999; *Easton and Pullman*, 2001; *Goodale et al.*, 2003). Several research papers have addressed product and service characteristics together. For example, *Cohen and Whang* (1997) designed the joint product/service bundle, addressing trade-offs between product profit and after-sales service profit, and *Verma et al.* (2001) addressed product and process attributes as key inputs into the "operating difficulty" of meeting customer demand patterns.

Real product design decisions, of course, cannot be made based only on marketing considerations. The marketer and engineer must consider the trade-offs between marketable design and feasible design (*Michalek et al.*, 2005; *Kang et al.*, 2007). While marketing research does not typically consider design feasibility, engineering design research has begun to adopt profit optimization as an enterprise-driven design objective subject to engineering constraints. This 'Design for Market Systems' approach integrates marketing, engineering, manufacturing, operations, and policy considerations into a profit-optimization framework (*Michalek et al.*, 2005; *Lewis et al.*, 2006; *Frischknecht et al.*, 2010; *Kang et al.*, 2014); most such research has focused on product design, not service design. *Kang et al.* (2013a) addressed trade-offs between product profit and service profit, and demonstrated that integrated design of products and services can achieve higher overall profit than product optimization alone. Specifically, enterprises can expect higher overall profit when they sacrifice product profit to attract more service customers; this work considered only an exclusive PS channel, so that customer service choices are fully determined after choosing a product. *Kang et al.* (2014) studied electric vehicle design and charging station location simultaneously to maximize product-service profit in the case where a product supplier and a service supplier cooperate and share profits and costs. This research showed that a cooperative business model between producers and service operators can overcome the adoption barrier more effectively than in a non-cooperative business model. This research, however, did not address other competitors' cooperation and asymmetric cooperation.

2.3.3 Product-Service Channel Design

A PS channel here is defined as compatibility between product and service from the customer's perspective, and cooperation with a competitor's product and service from the producer's perspective. This is different from a conventional distribution channel between suppliers and retailers that most previous research has focused on (*Jeuland and Shugan*, 1983; *McGuire and Staelin*, 1983; *Lee and Staelin*, 1997; *Sudhir*, 2001; *Luo et al.*, 2007). First, the PS channel differs substantially from the distribution channel wherein products are delivered from supplier to customers via an intermediary retailer. In a PS channel, services are delivered through products. Second, in a PS channel, producers can be both product suppliers and service suppliers; in the case of service platforms (i.e., Appstore), there could be external service suppliers (i.e., App developers). Third, customers in a PS channel make multiple choices sequentially, while conventional channels consider a single choice made by customers. Specifically, a customer chooses a product first, and then chooses services *through* a product for the period of the product ownership. This is different from a complementary goods market, where a retailer sells a bundle of products and services to a customer just once. Fourth, the PS channel structure is a decision variable, while analyses have typically considered a predetermined fixed channel structure.

We can gain some insight from distribution channel research in the marketing science and management fields (*Jeuland and Shugan*, 1983; *McGuire and Staelin*, 1983; *Lee and Staelin*, 1997; *Sudhir*, 2001; *Luo et al.*, 2007; *Cai et al.*, 2012). This research has been based on profit maximization, focusing on pricing, given channel structures. The majority employ game theory, with the equilibrium condition that no players can gain more profit by altering their decisions. Since each channel player's decision can affect the other channel player's profit and subsequent actions, it is important to understand the relationship between channel decisions (e.g., *Jeuland and Shugan* (1983)). *Sudhir* (2001) has further categorized then-extant distribution channel research according to manufacturer-manufacturer interaction, manufacturer-retailer interaction, retailer pricing rule, demand functional form, and wholesale price information availability.

Some earlier channel research is more directly related to this study. *Cai et al.* (2012) addressed the combination of exclusive channel and revenue sharing strategies for complementary goods markets and modelled compensatory benefit by revenue sharing with commentary partners even if they sacrifice part of their potential market due to the exclusive channel decision. This concept could well be applicable to the PS channel situation; but modifications would be necessary, as in Cai's (2012) set-up suppliers provide products to the retailers, who sell complementary products/services simultaneously. *Luo et al.* (2007) integrated an individual-level preference model based on conjoint analysis and the game-theoretic model of suppliers and retailers in the market setting before the entry of a new product and after a new product entry. Retailers' acceptance decisions affect suppliers' products design decisions, so that this conceptualization can potentially be applied to the PS channel negotiation issue. In channels research, the use of internet-based sales mechanisms has emerged as a critical topic (*Hsiao and Chen*, 2013), and some engineering design research (*Williams et al.*, 2008; *Shiau and Michalek*, 2009b) has begun addressing the distribution channel to optimize a product design for suppliers' profit, subject to enhanced profitability of retailers. Both product price and product design are optimized, while most marketing channel research has focused solely on price as a decision variable. *Shiau and Michalek* (2009b) applied game theory, in a manner common to much marketing research, but focused on product design and the 'conventional' distribution channel. Separately, in terms of choice modelling, *Aribarg and Foutz* (2009) addressed category-based choice modelling for complementary products in a study of cell phones and service plans; this work considered the single choice case of a product-service bundle and not the sequential choices of product and multiple services.

Overall, both Marketing and Design, as disciplines, have started to address the complex task of optimizing subsets of product attribute, service attribute, and channel structure variables. To date, however, the channel structure has been either predetermined or closely linked to the nature of the products themselves, for example, through unique service providers. By contrast, here we consider the channel structure to interrelate with all other variables, and to allow standard game theoretic considerations to help choose among the high-dimensional space of possible joint product, service, and channel configurations when multiple services can be offered on each product.

2.4 Summary

This chapter reviewed three related works. Section 2.1 reviewed research in Design for Market Systems (DMS) focusing on solution strategy, demand, competition, and regulation modeling. Section 2.2 reviewed product demand modeling research focusing on (a) form preference modeling, (b) form and overall preferences modeling, and (c) optimization and machine learning algorithms. Section 2.3 reviewed product-service demand modeling research focusing on (a) product-service systems, (b) profit maximization product-service design, and (c) product-service channel design.

Based on this literature review, Chapters III to V present the main three demand modeling studies of the dissertation. Next chapter (Chapter III) proposes a multidomain demand model for engineering and industrial design.

CHAPTER III

Multidomain Demand Modeling for Engineering and Industrial Design

The main goal of this chapter is to integrate functional attributes, whose quantification is relatively straightforward, and aesthetic attributes - those whose quantification ordinarily requires extensive subjective intervention - into a single demand model. Specifically, we focus on disintermediated mathematical approaches within the context of a multidomain demand model. The proposed demand modeling structure is motivated by a partitioning and coordination scheme widely deployed in complex systems optimization. Machine learning algorithms are used for estimating and coordinating preferences on both aesthetic forms and functional attributes. A human-computer interaction process is developed for anonymous crowdsourcing of choice-based information in online environment.

We apply the proposed model to exterior shape design for a passenger vehicle, in part because automotive choice is widely believed to be strongly driven by both form and function. Demand modeling for the "look and feel" of an automobile is a rich research problem, because a vehicle's shape is determined by a huge number of geometric design values; moreover, consumer preferences for vehicle shapes may be nonmonotonic, highly non-linear, and heterogeneous. Moreover, vehicle exterior shape can affect engineering performance, such as aerodynamic efficiency and systems layout, which themselves result in functional attributes that consumers also value.

The expected contribution of this chapter is to help engineering and industrial designers to understand how vehicle shape design variables can affect both form preference and overall preference, as well as the trade-off between functional and aesthetic attributes. The proposed multidomain demand model can be further extended for specific perceptual product attributes, e.g., luxuriousness and eco-friendliness.

3.1 Introduction

Product form has long been acknowledged as an important attribute in consumer choice. Form preference modeling studies have been conducted in both marketing and product design fields with differing terminology, including "form" (*Bloch*, 1995; *Swamy et al.*, 2007; *Orsborn et al.*, 2009; *Orsborn and Cagan*, 2009; *Petiot and Dagher*, 2011; *Tseng et al.*, 2012; *Reid et al.*, 2013; *Sylcott et al.*, 2013a,b; *Tseng et al.*, 2013), "shape" (*MacDonald et al.*, 2009; *Kelly et al.*, 2011), "design" (*Landwehr et al.*, 2011; *Ren and Papalambros*, 2011), "silhouette" (*Reid et al.*, 2010, 2012), "profile" (*Lai et al.*, 2005), "appearance" (*Creusen and Schoormans*, 2005), and "styling" (*Dotson et al.*, 2012). Form often assumes a central role in real-world preference modeling problems. According to *Bloch* (1995), form helps products gain consumers' notice, helps communicate information of products to consumers, stimulates consumers' pleasure, and leaves a long-lasting impression on consumers' perception. In practice, marketers can predict sales significantly better by taking form into account (*Landwehr et al.*, 2011). In addition to its own importance, marketers and designers also find valuable trade-offs between form and functional attributes (*Dotson et al.*, 2012; *Sylcott et al.*, 2013a), as revealing these trade-offs could lead to better design decisions in terms of balancing product appeal and functionality (*Reid et al.*, 2012).

Product form can be composed of a large number of essentially geometric attributes, but mapping from the geometry of a product to how much people like it (i.e., form preference) is a complex and often discouraging exercise. A further challenge is quantifying how form preference affects a consumer's choice decision when functional attributes such as price and performance are also included. This research is motivated by the fact that marketers have long incorporated product form into overall preference modeling to predict consumer choice, so that product designers may obtain geometrical form design targets from marketers (*Dotson et al.*, 2012); for example, wanting a "sleek" car translates into certain physical shapes being closer to this design ideal than others. Another motivation is the internet allows marketers to avail of low-cost crowdsourcing to gather choice data relatively quickly. However, online "crowds" are typically anonymous – we cannot know who will take our survey among online crowd, even if we set a limit on qualifications of taking survey such as demographics, product ownership, etc. – and they have a low willingness to accept accept time delay or response latency. Therefore, marketers typically have only a single chance to survey each subject, and cannot be assured of gathering data from any particular subject in a follow-up survey later on. Ideally, one should rely on a single survey, without time delay and intervening, unobserved experiences, to build individual-level preference models.

To the authors' knowledge, there are few studies that combine the form preference model with one for overall preference. Both *Dotson et al.* (2012) and *Sylcott et al.* (2013a) conducted separate surveys, one each for modeling form and overall preferences. While the methodology is reasonable for an off-line, "controlled" group (i.e., under lab conditions), it is arguably less so when applied to an anonymous, large crowd, as data collected from the two surveys may correspond to different crowds that differ in crucial characteristics. Combining form and overall preference models from different crowds presents enormous challenges in accurately modeling individual-level preference (see, for example, *Feit et al.* (2010)). Moreover, no prior study has made use of realistic 3D rendering to assess preference, instead relying on 2D and sketchlevel representations, which can literally distort the appearances that the methodology is intended to account for.

To model individual-level form and overall preferences using online crowdsourcing, this paper proposes a new conjoint-based modeling methodology that disentangles form preference from overall preference and coordinates then adaptively, in real time. We apply the proposed "bi-level adaptive conjoint" analysis to (1) model vehicle form preference based on 3D geometries, and (2) model overall preference by revealing tradeoffs between form and functional attributes, namely, price and fuel efficiency. We demonstrate, via a Monte Carlo simulation and a crowd-based experiment, that the proposed method can elicit more accurate individual-level preferences than conventional conjoint analysis. We similarly discuss the potential for enhanced segmentation, e.g., whether price-sensitive consumers have marked preferences for certain styles, or assessing relative willingness-to-pay for small car buyers, etc.

The paper is structured as follows: Section 3.2 proposes the "bi-level adaptive conjoint" method. We show the advantage of the proposed method over traditional conjoint by simulations in Section 3.3 and using online crowd experiment in Section 3.4. Section 3.5 discusses findings and potential extensions, and concludes the paper.

3.2 Proposed Model

3.2.1 Overview

The proposed survey consists of iterative "bi-level" questions. A bi-level question consists of two sequential sub-questions, as shown in Fig. 3.1: one sub-question is a form question and the other sub-question is a purchase question, the latter including both form and function attributes. For the form question, we utilize a standard anchored scale task. That is, we present two 3D vehicle renderings and ask "Which of

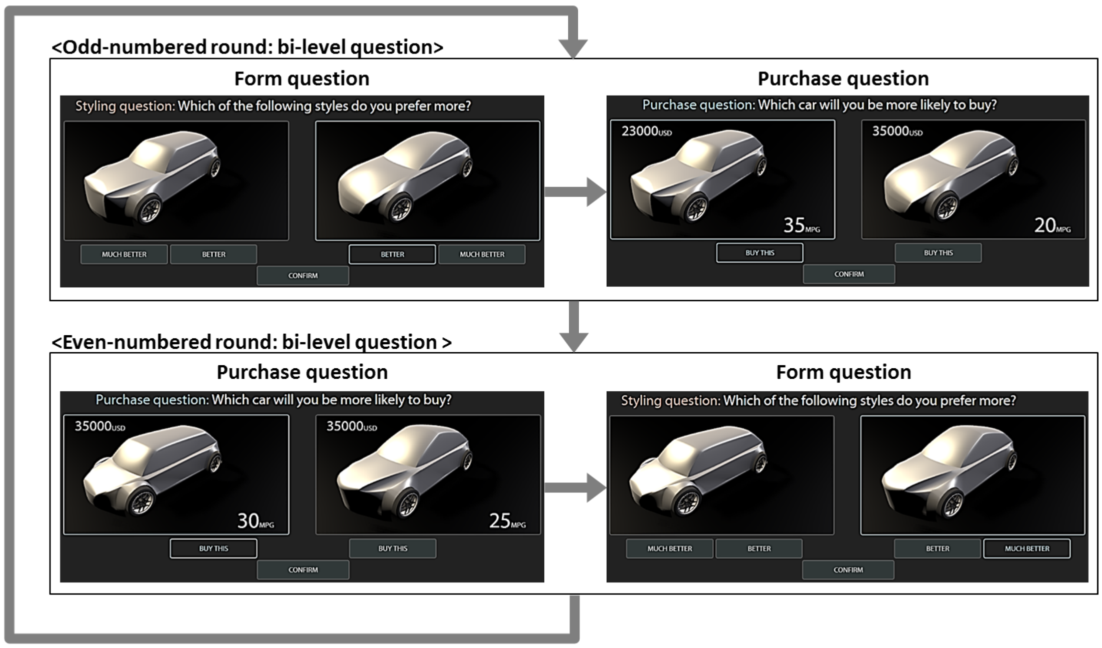


Figure 3.1: Iterative bi-level questions

the following styles do you prefer more?", to which the respondent makes a metric paired-comparison on an ordered 4-point scale; specifically, "left one is much better", "left one is better", "right one is better", or "right one is much better". Four points were used to allow a moderate degree of preference expression over a binary choice task, but without exact indifference, which provides little 'traction' for the forthcoming adaptive algorithm. Next, for the purchase question, we present the previous 3D vehicle renderings again with "functional attributes", such as price and MPG. The respondent is then asked "Which car will you be more likely to buy?", and engages in a binary choice task between the two presented vehicles. Such bi-level questions are repeated a specific number of times, set by the analyst. The potential tendency for respondents to maintain their choice on form question for the purchase question, irrespective of the newly supplied functional attribute information, is controlled for by counterbalancing, that is, by switching the order of the two sub-questions from round to round. The actual interactive interface used for this study can be accessed at vehiclechoicemodel.appspot.com.

We define that form preference of individual i is represented by her form score (i.e., form appeal) which is an output of her form preference model:

$$s_i = S_i(\mathbf{x}) + \epsilon_i \tag{3.1}$$

where $\mathbf{x}$ is a vector of design variables representing the form, s_i is the form score, S_i is the non-linear preference function, and ϵ_i is an error term. Based on the form score, the overall preference for individual i is then given by the following linear utility model:

$$U_i(s_i, \mathbf{a}) = \lambda_i s_i + \boldsymbol{\beta}_i^T \mathbf{a} + \varepsilon_i \tag{3.2}$$

where $\mathbf{a}$ is a vector of binary dummy variables of function attributes, $\boldsymbol{\beta}_i$ is the associated part-worths vector for functional attributes, s_i is the form score, λ_i is the weight of the form score, and ε_i is an error term. Two preference models (3.1) and (3.2) are coordinated in real time by iterative bi-level questioning, as in Fig. 3.1. The process for the odd-numbered rounds is as follows:

- Form question: an individual makes a metric paired-comparison between two forms created by design variables, $\mathbf{x}^{(1)}$ and $\mathbf{x}^{(2)}$. Preference model $S_i(\mathbf{x})$ in Eq. 3.1 is trained, then form scores, ${s_i}^{(1)}$ and ${s_i}^{(2)}$, are estimated. Two function attributes, $\mathbf{a}^{(1)}$ and $\mathbf{a}^{(2)}$, are sampled for the following purchase question.

- Purchase question: an individual makes a binary choice between two bundles of form and functions $[{s_i}^{(1)}, \mathbf{a}^{(1)}]$ and $[{s_i}^{(2)}, \mathbf{a}^{(2)}]$. The weight of the form score λ_i and the part-worths for functions $\boldsymbol{\beta}_i$ in Eq. 3.2 are estimated. Two forms, $\mathbf{x}^{(1)}$ and $\mathbf{x}^{(2)}$, for the following form question are sampled.

The overall process for querying, sampling, and learning is shown in Fig. 3.2, with each step is explained below it.

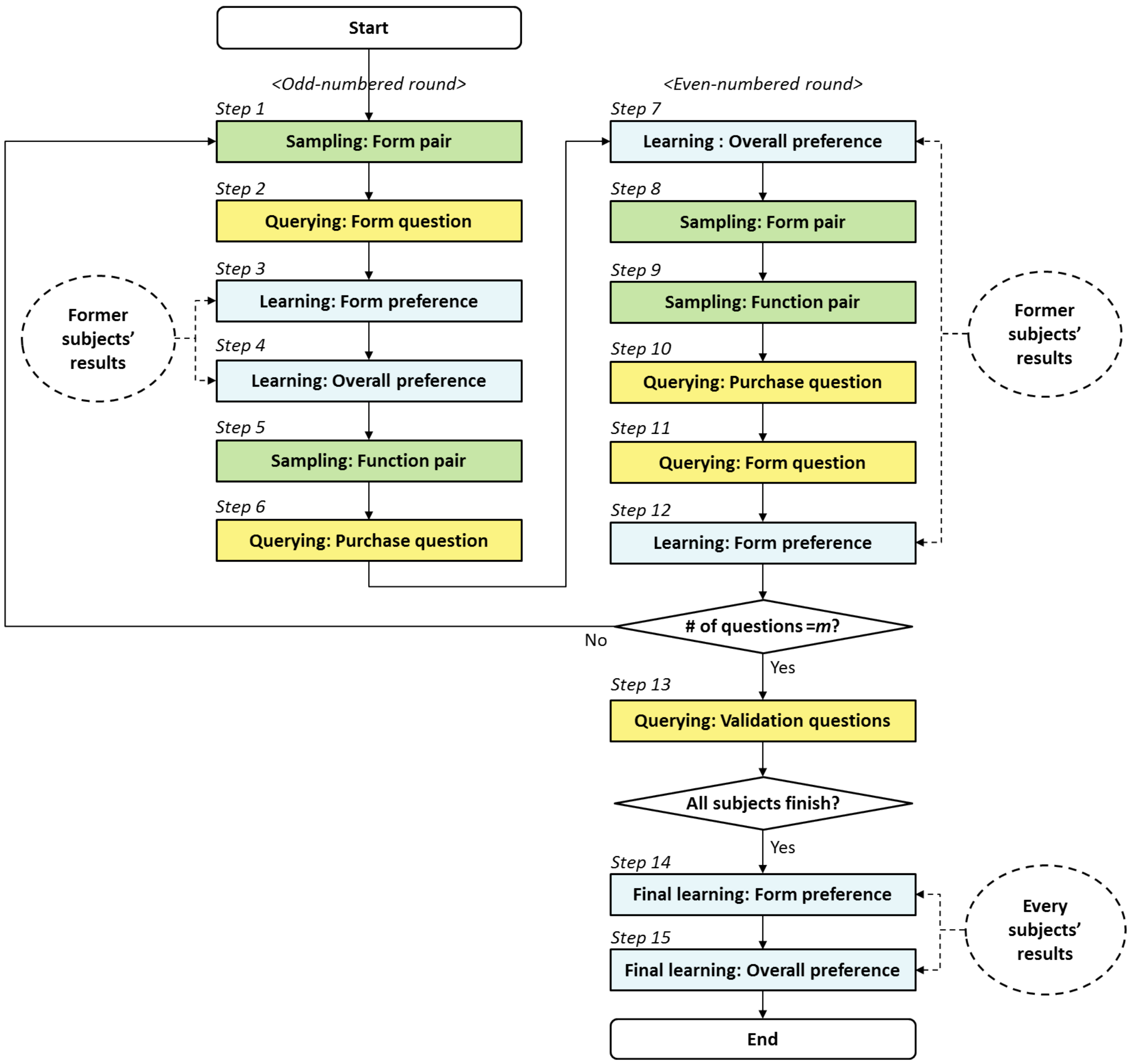


Figure 3.2: Overall process for querying, sampling, and learning

- Start. A new questionnaire is initialized when an individual accesses the website.

- Step 1: Sampling form pair. A pair of vehicle renderings are generated from the design space based on the current form preference model. The generated rendering pair is such that their expected form *preference* should be roughly equal, but their *shapes* should not only differ maximally from one another, but from all forms used before. If this is the first question for the current subject, a fixed form pair is used.

- Step 2: Querying form question. A metric paired-comparison response is received from the subject.

- Step 3: Learning form preference. A form preference model is trained based on previous form responses from this subject. Once the form model is learned (or updated if not the first round), the *form scores* of previously sampled vehicle renderings for the current subject are updated. Former subjects' form preference models are also used for shrinkage.

- Step 4: Learning overall preference. Except for the first round, the overall preference model is adjusted based on the updated form scores. Former subjects' overall preference models are also used for shrinkage.

- Step 5: Sampling function pair. Generate function attributes, i.e., price and MPG, for the current pair of vehicle forms based on the updated overall preference model.

- Step 6: Querying purchase question. A (binary) choice is received from the subject once the function attributes are shown along with the forms.

- Step 7: Learning overall preference. Same as Step 4. (Steps 1 through 7 complete an odd-numbered round in the questionnaire. The even-numbered round will then switch the order of the two questions, with steps as listed below.)

- Step 8: Sampling form pair. Same as Step 1.
- Step 9: Sampling function pair. Same as Step 5.
- Step 10: Querying purchase question. Same as Step 6.
- Step 11: Querying form question. Same as Step 2.
- Step 12: Learning form preference. Same as Step 3.
- If the iteration has reached the maximum round number, m, go to Step 13; otherwise, go to Step 1.
- Step 13: Querying validation question. Several validation sets will be presented to the subjects; these will be used to check hit rate.
- If all subjects have completed their surveys, go to Step 14; otherwise, wait until all have finished.
- Step 14: Final learning form preference. Finalize individual-level form preference models using all other subjects' results.
- Step 15: Final learning overall preference. Finalize individual-level overall preference models using all other subjects' results.
- End. Hit rate will be checked using responses to the validation questions.

Different machine learning algorithms are used for active learning (learning for sampling), and final learning ,as shown in Table 3.1. We used a rank SVM mix algorithm (see *Evgeniou et al.* (2005)) for active learning (step 3, 4, 7, and 12) and for final learning of form preference (step 14). We used Hierarchical Bayesian (HB) methods for final learning of overall preference (step 15). Active learning is for sampling

Table 3.1: Machine learning algorithms used in this proposed model

Type	Active learning (Learning for sampling)	Final learning
Form preference	Rank SVM mix (Gaussian kernel)	Rank SVM mix (Gaussian kernel)
Overall preference	Rank SVM mix (linear)	Hierarchical Bayesian (linear)

subsequent questions and is carried out in real time. Final learning is for finalizing preference models and validating them after finishing all surveys. Although HB methods are attractive for active learning, their high computational cost precludes their use in interactive online environments. We are agnostic, however, on specific machine learning algorithms, any of which can be replaced with alternatives better suited to the analyst's specific survey environment and research goals.

The rest of this section will elaborate on how these algorithms are applied in our proposed model: Section 3.2.2 will focus on the learning methods for both form and overall preference models, and Section 3.2.3 will focus on the sampling methods to generate 3D vehicle rendering and function attributes, such as price and MPG.

3.2.2 Learning Preferences

3.2.2.1 Form Preference Learning

As mentioned earlier, the form preference model in Eq. (3.1) is trained using a rank SVM mix algorithm with a Gaussian kernel. While the original SVM creates the linear decision function as maximum margin classifier between two separable categories (e.g., chosen profiles vs. unchosen profiles in conjoint survey) (*Vapnik and Vapnik*, 1998), kernel transformation allows the possibility of creating a nonlinear decision function in case a linear decision function cannot completely separate observations in the original space (*Boser et al.*, 1992). The basic idea of kernel transformation is mapping observations $\mathbf{x}$ in the original input space into $\phi(\mathbf{x})$ in the feature space (i.e., an unknown higher-dimensional space) and then finding a linear decision function in feature space.

Following *Joachims* (2002), Modeling preference from pairwise comparison data can be formulated as follows

$$\begin{array}{cc} \min_{\mathbf{w}} & \mathbf{w}^T\mathbf{w} \\ \text{subject to} & \mathbf{w}^T\phi(\mathbf{x}_j^{(1)}) - \mathbf{w}^T\phi(\mathbf{x}_j^{(2)}) \geq c_j,\ \forall j = 1, \ldots, m \\ \text{where} & c_j \in \{1, 2\} \end{array} \tag{3.3}$$

where $[\mathbf{x}_j^{(1)}, \mathbf{x}_j^{(2)}]$ is a pair of design variables that represent each form alternative in the j-th of m questions, $\mathbf{x}_j^{(1)}$ is of the chosen form, $\mathbf{x}_j^{(2)}$ is of the unchosen form, $\mathbf{w}$ is the normal vector of linear decision function $\mathbf{w}^T$, and c_j is the minimum margin, which means the difference between chosen and unchosen form preferences. Since we used two levels of metric in our case study (i.e., better or much better), there are two levels of minimum margin as an interval scale.When a form $\mathbf{x}_j^{(1)}$ is better than $\mathbf{x}_j^{(2)}$, c_j is 1, and when a form $\mathbf{x}_j^{(1)}$ is much better than $\mathbf{x}_j^{(2)}$, c_j is 2. Then we can have m constraints. By minimizing $\mathbf{w}^T\mathbf{w}$, we can maximize the margin between chosen form $\phi(\mathbf{x}_j^{(1)})$ and unchosen form $\phi(\mathbf{x}_j^{(2)})$ in feature space.

Kernel function K is defined as $K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i)^T\phi(\mathbf{x}_j)$ with respect to two observations $\mathbf{x}_i$ and $\mathbf{x}_j$. Specifically, the Gaussian kernel is defined as $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2)$, where the Gaussian parameter γ is typically set at $\gamma = 1/\text{number}$ of features (design variables) (*Chang and Lin*, 2011).

This SVM problem (3.3) can be transformed into dual form using Lagrangian multipliers.

$$\begin{array}{cc} \min_{\boldsymbol{\alpha}} & \frac{1}{2}\boldsymbol{\alpha}^T\mathbf{Q}\boldsymbol{\alpha} - \mathbf{c}^T\boldsymbol{\alpha} \\ \text{subject to} & \boldsymbol{\alpha} \geq 0 \end{array} \tag{3.4}$$

where, $\boldsymbol{\alpha}$ and $\mathbf{c}$ are Lagrangian multipliers and the vector of minimum margin of

Eq. (3.3), respectively. $\mathbf{Q}$ is defined as an m by m matrix with $Q_{ij} = K(x_i^{(1)}, x_j^{(1)}) - K(x_i^{(1)}, x_j^{(2)}) - K(x_i^{(2)}, x_j^{(1)}) + K(x_i^{(2)}, x_j^{(2)})$, where $i = 1, ..., m$, $j = 1, ..., m$, and m is the number of questions.

Based on Lagrangian multipliers, $\boldsymbol{\alpha}$, form preference model can be quantified as

$$S(\mathbf{x}) = \sum_{j=1}^{m} \alpha_j (K(\mathbf{x}, \mathbf{x}_j^{(1)}) - K(\mathbf{x}, \mathbf{x}_j^{(2)})) \tag{3.5}$$

where $\mathbf{x}$ is the vector of design variables, $\mathbf{x}_j^{(1)}$ contains the design variables of chosen form at j-th question, $\mathbf{x}_j^{(2)}$ contains the design variables of unchosen form at j-th question, α_j is the Lagrange multiplier for the j-th question, and m is the number of questions.

Note that design variables $\mathbf{x}$ in Eqs (3.3), (3.4), and (3.5) are used after normalization, that is, $\mathbf{x} = (\mathbf{x} - \mu)/\sigma$, where μ and σ are the mean and standard deviation of all $\mathbf{x}$ used across questionnaires, respectively. This pre-processing enables uniform handling of effectively differently-scaled design variables.

By intuition, since the Gaussian kernel function, $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2)$, is based on Euclidean distance, the form preference in Eq. (3.4) increases when new design variables $\mathbf{x}$ is close to chosen form $\mathbf{x}^{(1)}$, and decreases when $\mathbf{x}$ is close to unchosen form $\mathbf{x}^{(2)}$. The Gaussian kernel function can be suitable for form preference modeling which may be continuous and highly non-linear. However, trade-off between fit and complexity is important problem for estimating preference functions (*Toubia et al.*, 2007a). This is because complex models, such as those with nonlinear kernels, may not be able to predict well out-of-sample, while fitting well in-sample. SVM model can also avoid over-fitting by using the soft-margin method, which includes positive slack variables in the decision function (*Cortes and Vapnik*, 1995; *Cristianini and Shawe-Taylor*, 2000).

For eliciting individual-level preferences with limited data, we made use of the shrinkage concept, by adopting the linear sum method of *Evgeniou et al.* (2005), which calculates shrunk individual partworths based on the linear sum of individual partworths and the population partworth means, as in Eq. 3.6. *Evgeniou et al.* (2005) have demonstrated that this approach outperforms or performs similarly well as HB.

Since the form preference in this study is not modeled as a linear function, we model the shrunk individual form preference based on linear sum of individual form preference and the population form preference means. The final individual form preference model $S_i^*(\mathbf{x})$ is given by

$$S_i^*(\mathbf{x}) = \eta_i S_i(\mathbf{x}) + (1-\eta_i)\frac{1}{N}\sum_{i=1}^{N} S_i(\mathbf{x}) \tag{3.6}$$

where $\mathbf{x}$ is design variables, η_i is the weight between 0 and 1 for each individual i, and N is the number of individuals. Optimal η_i for the final estimation is can be determined by cross-validation. If η_i is small, the function of individual i shrinks more toward the population-level function. For active learning during survey, η_i should be selected manually by the analyst. When there aren't many former respondents, a large value of η_i can be used. When there are many former respondents, a smaller η_i value is appropriate.

3.2.2.2 Overall Preference Learning

For the overall preference model in Eq. (3.2), we estimate linear coefficients $\mathbf{W}_i = [\lambda_i, \boldsymbol{\beta}_i]$, where λ_i is form score weight and $\boldsymbol{\beta}_i$ is the partworth vector for function attributes. We used the rank SVM mix algorithm and Hierarchical Bayesian (HB) methods for active learning and final learning, respectively.

$$\begin{aligned} \min_{\mathbf{W}_i} \quad & \mathbf{W}_i^T\mathbf{W}_i \\ \text{subject to} \quad & \mathbf{W}_i^T\mathbf{X}_{ij}^{(1)} - \mathbf{W}_i^T\mathbf{X}_{ij}^{(2)} \geq 1,\ \forall j = 1,\dots,m \end{aligned} \tag{3.7}$$

where $\mathbf{W}_i = [\lambda_i, \boldsymbol{\beta}_i]$ is the vector of linear coefficients for the overall preference model, λ_i is the form score weight, $\boldsymbol{\beta}_i$ is the partworth vector for function attributes, $\mathbf{X}_{ij} = [s_{ij}, \mathbf{a}_{ij}]$ is the vector of input for overall preference function, s_{ij} is the form score, and $\mathbf{a}_{ij}$ is a vector of binary dummy variables of function attributes for the j-th question of individual i. Eq 3.7 can be transformed into dual form using Lagrangian multipliers $\boldsymbol{\alpha}$, as for Eq. (3.4). Then $\mathbf{W}_i$ is obtained as

$$\mathbf{W}_i = \sum_{j=1}^{m} (\mathbf{X}_{ij}^{(1)} - \mathbf{X}_{ij}^{(2)})^T \alpha_{ij}. \tag{3.8}$$

The linear sum method of *Evgeniou et al.* (2005) is also used to model individual-level overall preference. We get shrunken $\mathbf{W}_i^*$ as

$$\mathbf{W}_i^* = \eta_i \mathbf{W}_i + (1 - \eta_i) \frac{1}{N} \sum_{i=1}^{N} \mathbf{W}_i \tag{3.9}$$

where η_i is the weight (between 0 and 1) for individual i, and N is the number of individuals.

For final learning, a hierarchical binary logit model (*Rossi et al.*, 2005b), with weakly-informative and zero-centered priors, is used for estimation. At the upper level, $\mathbf{W}_i$ of individual i has a multivariate normal distribution, $\mathbf{W}_i \sim N(\boldsymbol{\theta}, \boldsymbol{\Lambda})$, where $\boldsymbol{\theta}$ is a vector of means of the distribution of individuals and $\boldsymbol{\Lambda}$ is the covariance matrix. At the lower level, choice probabilities take binary logit form,

$$\Pr(y_{ij} = 1) = \frac{\exp[\mathbf{W}_i^T \mathbf{X}_{ij}^{(1)}]}{\exp[\mathbf{W}_i^T \mathbf{X}_{ij}^{(1)}] + \exp[\mathbf{W}_i^T \mathbf{X}_{ij}^{(2)}]} = (1 + \exp[\mathbf{W}_i^T (\mathbf{X}_{ij}^{(2)} - \mathbf{X}_{ij}^{(1)})])^{-1} \tag{3.10}$$

where $\Pr(y_{ij} = 1)$ denotes the probability of selecting $\mathbf{X}_{ij}^{(1)}$; $\Pr(y_{ij} = 0)$ denotes the probability of selecting $\mathbf{X}_{ij}^{(2)}$ for j-th question of individual i; and $\mathbf{W}_i$ and $\mathbf{X}_{ij}$ are as in Eqs (3.8) and (3.9).

3.2.3 Sampling Questions

Adaptive question sampling is based on two criteria, as follows. (i) Utility balance: a profile pair comprising a question should have similar utility. (ii) Maximize minimum distance between data points: all data points, such as previous question profiles and new question profiles, should be spread in balanced manner. Using these two criteria, question sampling can be a single- or multi-objective problem. The first form alternative for the form pair is sampled by solving the single-objective problem as

$$\begin{aligned} \max_{\mathbf{x}_1^{new}} \quad & \textstyle\sum_{j=1}^{m_{\mathbf{x}^{old}}} \|\mathbf{x}_1^{new} - \mathbf{x}_j^{old}\|^2 \\ \text{subject to} \quad & lb \leq \mathbf{x}_1^{new} \leq ub \end{aligned} \tag{3.11}$$

where $\mathbf{x}_1^{new}$ is the first form alternative for the next question, $\mathbf{x}_j^{old}$ are the j-th form alternatives used in previous questions, and $m_{\mathbf{x}^{old}}$ is the number of form alternatives used before. The first form is sampled by maximizing Euclidean distance between data points.

The second form alternative for the form pair is sampled by solving the multi-objective problem as

$$\begin{aligned} \min_{\mathbf{x}_2^{new}} \quad & \upsilon_1 \exp(\|S(\mathbf{x}_2^{new}) - S(\mathbf{x}_1^{new})\|^2) - \upsilon_2(\|\mathbf{x}_2^{new} - \mathbf{x}_1^{new}\|^2 + \textstyle\sum_{j=1}^{m_{\mathbf{x}^{old}}} \|\mathbf{x}_2^{new} - \mathbf{x}_j^{old}\|^2) \\ \text{subject to} \quad & lb \leq \mathbf{x}_2^{new} \leq ub \end{aligned} \tag{3.12}$$

where $\mathbf{x}_2^{new}$ is the second form alternative for the next question; $S(\mathbf{x})$ is the form preference model; υ_1 is the associated weight for minimizing utility differences between form pairs (i.e., utility balance); and υ_2 is the associated weight for maximizing Euclidean distance between data points. $\mathbf{x}_2^{new}$ should be far away from not only used forms $\mathbf{x}_j^{old}$ but also the first form alternative $\mathbf{x}_1^{new}$ sampled in Eq. (3.11). υ_1 and υ_2

should be selected by the analyst based on specific characteristics of the parametric model for 3D rendering.

For form sampling, the problems (3.11) and (3.12) are solved here by genetic algorithms (GA). For sampling the next pair of function attributes, we can solve the same optimization problem as Eqs (3.11) and (3.12) by only replacing the form preference model $S(\mathbf{x})$ and design variables $\mathbf{x}$ into the overall preference model $U(s, \mathbf{a})$ and function attributes $\mathbf{a}$, respectively. In our study, function attributes are not continuous variables but binary dummies, so that testing all possible combinations of function attributes is feasible. Thus, we enumerated all possible combinations and compared them, instead of using GAs, to sample subsequent function pairs.

3.3 Simulation

3.3.1 Simulation Design

As explained at the outset, we presume that the choice modeler wants to model both individual-level form and overall preferences, but can pose but a limited number of questions to anonymous online crowd via a single-shot survey instrument. *Dotson et al.* (2012) and *Sylcott et al.* (2013a), as explained in Section 2.2.2, are not suitable to build an individual-level preference model for anonymous online environments, due to the need for time-intensive data analysis between the form question survey and design purchase questionnaire.

For just such environments, we simulated three possible modeling options, including the proposed model, as shown in Table 3.2. Model 1 is the "base" model, model 2 is the "half version" of the proposed model, and model 3 is the "full version" of the proposed model. The reason we tested the half version of the proposed model is to examine the effects of bi-level question structure and adaptive question design separately. These three models also are tested via an online experiment in Section 3.4.

Table 3.2: Simulation models and characteristics

Models	Querying	Learning	Sampling
Model 1 (Base: single-level)	Single level: 20 purchase questions	Form and overall: HB (linear)	Non-adaptive (DOE)
Model 2 (Half: bi-level)	Bi-level: 10 form questions & 10 purchase questions	Form: Rank SVM mix (nonlinear) Overall: HB (linear)	Non-adaptive (DOE)
Model 3 (Full: bi-level & adaptive)	Bi-level: 10 form questions & 10 purchase questions	Form: Rank SVM mix (nonlinear) Overall: HB (linear)	Adaptive

It is assumed that all models are informed by the survey responses of 100 subjects, with a total of 20 questions, including form and purchase questions. An online pilot study suggested that 20 questions are suitable for this particular application. For validation, we used 100 hold-out questions each for form and purchase questions (i.e., 200 total) to compute hit-rates. We used a form attribute consisting of 19 continuous design variables and two function attributes consisting of four discrete levels, as for the online experiment in Section 3.4.

Model 1 is the base model using only purchase questions and accommodating form and function with a single linear preference model, in line with conventional conjoint analysis techniques. Hierarchical Bayesian methods are used for specifying and estimating the linear preference model. For DOE (design of experiments), we used a Latin hypercube sampling method to generate questionnaire designs for both continuous and discrete variables.

Model 2 is the half version of the proposed model for testing bi-level structure and non-linear modeling effects. The bi-level structure makes it possible for form and overall preferences to be modeled using different techniques (i.e., a nonlinear model for form preference and a linear model for overall preference), after which the form model can be nested into the overall model. For the online experiment in Section 3.4, subjects may be more easily able to trade-off between form and functions because they are shown a pair of vehicle forms first, followed by price and MPG with the same forms. Form preference is modeled by a rank SVM mix (Gaussian nonlinear), and overall preference is modeled by HB (linear). Compared to model 1, model 2 sacrifices 10 purchase questions, while adding 10 separate form questions. A latin hypercube sampling method is used for DOE.

Model 3 is the full version of the proposed model for testing bi-level structure, non-linear modeling, and adaptive questionnaire design effects, all together. Querying and learning structure are the same as model 2, but model 3 uses adaptive sampling so that form and function profiles are generated in real time adaptively, so that each question has different form profiles (a potentially limitless number of forms).

Regarding software used in this study, for Latin hypercube sampling, we used the Matlab library (`lhsdesign`); for HB, we used the hierarchical binary logit model in a specific R package (`rhierBinLogit`) (*Rossi et al.*, 2005b); and for rank SVM, we modified the LIBSVM package (*Chang and Lin*, 2011).

Broadly speaking, for the simulation design, we adopted and modified the standard simulation design which has been widely used for conjoint analysis research throughout the marketing area (*Arora and Huber*, 2001; *Toubia et al.*, 2004; *Evgeniou et al.*, 2005; *Abernethy et al.*, 2008). A mainstay of previous research is that response accuracy is controlled by the magnitude of an individual's parameters (part-worths), while respondent heterogeneity is controlled by the variance of parameters (across respondents). We operationalize accuracy and respondent heterogeneity by setting them each to two levels, "low" and "high". For example, the magnitudes of parameters are set to β=0.5 and β=3 for low response accuracy and high accuracy, respectively. On a logit scale, these represent deviation in log-odds of 0.5 and 3.0 from a baseline of zero (i.e., β=0); or, in terms of probability, according to $(1+\exp[-\beta])^{-1}$, which translates into 0.62 and 0.95, respectively, on a probability baseline of $\frac{1}{2}$. The parameter variances are set relative to the level of β, to $\sigma^2 = 0.5\beta$ and $\sigma^2 = 3\beta$ for low respondent heterogeneity and high heterogeneity, respectively. Based on these parameters, four normal distributions are defined, β is drawn from each distribution, and then four levels partworths for each function attribute, $(-\beta, -\beta/3, \beta/3, \beta)$, are generated, keeping constant differences set to $2\beta/3$. Two function attributes such as price and MPG with four levels are used for the simulation.

For creating true preference functions of individual, 19 continuous design variables are defined for form attribute. This setting corresponds to the online experiment in Section 3.4. Here we generate a complex form preference model by using independent parameters $\boldsymbol{\gamma}$ and interaction parameters $\boldsymbol{\delta}$. For independent term of k-th design variable, γ_k is drawn from four pre-defined distributions similar to the method used for the function attributes, where k=1,2,...,19; four points $(-\gamma_k/3, \gamma_k, -\gamma_k, \gamma_k/3)$ are generated, and then cubic spline interpolation, Φ, is applied to create a continuous function with respect to k-th design variable x_k. For interaction term, we define and draw 171 interaction terms δ_{ij} representing relationship between i-th and j-th design variables where i and j are different. The number of possible pairs of 19 design variables is 171 (i.e. 19×18/2 = 171). Finally, form function, with respect to 19 design variables, is defined as follows, where the function is taken to be nonlinear and continuous.

$$S(\mathbf{x}) = \sum_{k=1}^{19} \Phi(\gamma_k, x_k) + \sum_{i \neq j}^{171} \delta_{ij} x_i x_j \tag{3.13}$$

The distributions of $\boldsymbol{\delta}$ were balanced in the sense that the independent terms and interaction terms were set to a 2:1 ratio. Following *Evgeniou et al.* (2005), we generate 1,000 random form profiles and 1,000 consumer form preference models, then compare the ratio of absolute values of independent term and interaction term (mean of 1000×1000 ratios), given the sigma of distribution of $\boldsymbol{\delta}$. Form score weight, λ, in Eq. 3.2 represents the importance of form preference. We selected λ that can make the ratio of absolute values of form score s and function attribute preference

Table 3.3: Consumer preference scenarios

Form importance	Response accuracy	Respondent hetero-geneity	Form score weight (λ)	Form attribute coefficients: Independent terms ($\boldsymbol{\gamma}$)	Form attribute coefficients: Interaction terms ($\boldsymbol{\delta}$)	Functional attributes partworths ($\boldsymbol{\beta}$)
Low	Low	Low	0.0043	$N(0.5, 0.25)$	$N(0, 4.8)$	$N(0.5, 0.25)$
Low	Low	High	0.0044	$N(0.5, 1.5)$	$N(0, 13.7)$	$N(0.5, 1.5)$
Low	High	Low	0.0028	$N(3, 1.5)$	$N(0, 56.25)$	$N(3, 1.5)$
Low	High	High	0.0057	$N(3, 9)$	$N(0, 88.36)$	$N(3, 9)$
High	Low	Low	0.0173	$N(0.5, 0.25)$	$N(0, 4.8)$	$N(0.5, 0.25)$
High	Low	High	0.0176	$N(0.5, 1.5)$	$N(0, 13.7)$	$N(0.5, 1.5)$
High	High	Low	0.0112	$N(3, 1.5)$	$N(0, 56.25)$	$N(3, 1.5)$
High	High	High	0.0230	$N(3, 9)$	$N(0, 88.36)$	$N(3, 9)$

Note: form attribute coefficients and functional attributes partworths are drawn from a normal distribution, $N(\mu, \sigma^2)$

$\boldsymbol{\beta}^T\mathbf{a}$ a to be 1:2 and 2:1 for low importance case and high importance case of forms, respectively. For this, we generate 10,000 random product profiles and 10,000 consumer preference models, then examine the ratio of absolute values of form score and function preference, then select the values that allow for the 1:2 and 2:1 ratios.

Consequently, we created eight consumer preference scenarios, and define their distributions as shown in Table 3.3. To check hit-rate, we generate five sets of all eight scenarios, so that total 40 scenarios are used for the simulation.

3.3.2 Simulation Results

Table 3.4 shows the results of the various simulation scenarios, where hit-rates are taken as the mean across the five sets. $(\cdot)^*$ indicates the best, or not significantly different from best at $p < 0.05$, across three models.

Except for one case (low form importance, low response accuracy, and high respondent heterogeneity), model 3 outperformed model 1 statistically for both form and overall hit-rates. For the form hit-rate, every case suggests that model 2 (bi-level structure and non-linear modeling) offers sizable improvements over model 1 (base).

Table 3.4: Hit rates of simulation

Simulation design			Form preference hit rate			Overall preference hit rate		
Form importance	Response accuracy	Respondent heterogeneity	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Low	Low	Low	50.8	65.2	**66.2***	90.5	91.9	**93.2***
Low	Low	High	51.0	**65.6***	**65.3***	91.6	91.7	90.1
Low	High	Low	52.0	63.3	**66.7***	92.7	**93.6***	**94.6***
Low	High	High	51.2	63.4	**65.2***	89.7	**92.3***	**92.8***
High	Low	Low	52.5	**65.1***	**66.1***	87.2	87.9	**90.1***
High	Low	High	52.3	**65.2***	**65.1***	87.2	**88.1***	**88.7***
High	High	Low	53.5	62.9	**66.3***	93.0	92.8	**94.4***
High	High	High	53.2	62.4	**64.7***	87.5	**88.5***	**89.8***

*Best or not significantly different than best at $p < 0.05$ across all models

Five out of eight cases has model 3 (adaptive questionnaire design) outperforming model 2 (non-adaptive questionnaire design). For overall hit-rate, half of cases favor model 2 over model 1, whereas 3 out of 8 favor model 3 over model 2. These simulation results suggest that the proposed bi-level and adaptive conjoint analysis can outperform the conventional one, even though it “sacrifices” 10 purchase questions. Notably from the perspective of the goals of the present study, form preference accuracy can be improved substantially (average 14%), enabling marketers to pass along more reasonable target design values to industrial designers and engineers.

We conducted a post-analysis, testing sensitivity to the total number of questions (form questions and purchase questions) on hit-rate, as shown in Fig. 3.3, using the results of model 1 and model 3 with what is arguably the most difficult scenario in Table 3.4 (i.e., high form importance, low response accuracy, and high heterogeneity). Except for the 10 questions case (i.e., 5 form questions and 5 purchase questions for model 3 vs. 10 purchase questions for model 1), model 3 consistently outperformed model 1. This owes to the fact that the form preference accuracy (for hit rate) of model 3 is always significantly better than for model 1, even though half of the purchase questions are sacrificed. More questions enable better form preference accuracy for

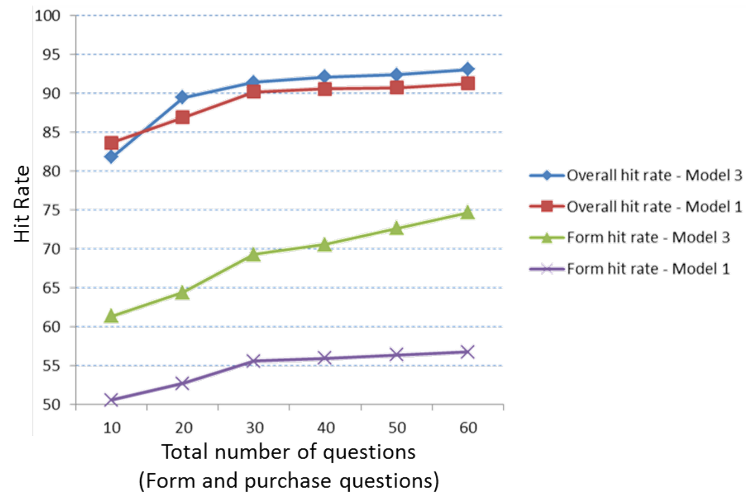


Figure 3.3: Sensitivity of the number of questions

model 3, while the performance of model 1 does not improve substantially after 30 questions. This test shows that form preference accuracy is more sensitive to the number of questions than overall preference accuracy in model 3.

3.4 Online experiment

We have launched three online surveys that correspond with the three models[1] simulated in Section 3.3 (see Table 3.2). Model 1 is the base model, using linear utility modeling with single-level questioning; Model 2 is the half version, using non-linear utility modeling with bi-level questioning; and Model 3 is the proposed model, using non-linear utility modeling with adaptive and bi-level questioning. Three online crowd groups were recruited through ClearVoice Research (*Clearvoice*, 2014), a prominent online panel provider, and each group includes 100 subjects for each survey. The demographic data for subjects are shown in the Appendix. A total of 20 questions are used for learning and 10 holdout questions (i.e., 5 form and 5 purchase holdout questions) are used to check hit-rates.

[1]Model 1: http://1.vehiclechoicemodel.appspot.com
Model 2: http://2.vehiclechoicemodel.appspot.com
Model 3: http://3.vehiclechoicemodel.appspot.com

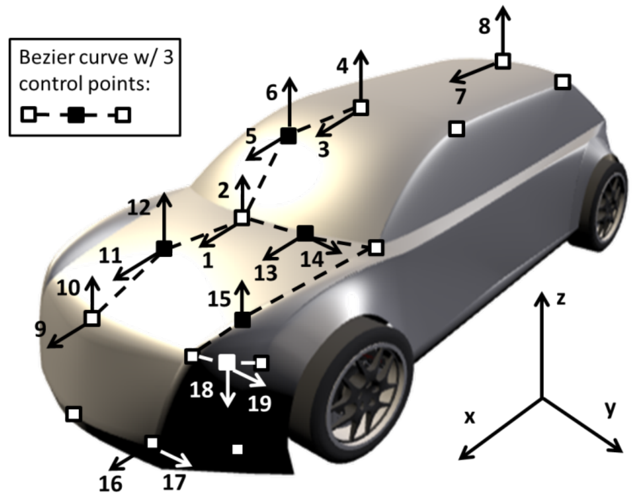


Figure 3.4: 19 design variables

For vehicle form representation, we adopted the 3D parametric vehicle shape model of *Ren and Papalambros* (2011). This parametric model generates 3D rendering using two-leveled structures. First, nineteen design variables **x** (ranging from 0 to 1) were decided upon. These variables control the coordinates of control points, which in turn defines the surfaces of the 3D model. Fig. 3.4 illustrates locations of all control points, some coordinates of which are controlled by the design variables while others are either fixed or adjusted automatically to maintain surface smoothness. During the training, the set of variable values are mapped to some 276 design features, each representing the distance between a pair of control points. These design features are controlled considering feasible (smooth and continuous) shapes, and these features generate a 3D vehicle rendering.

Here, form preferences of Model 2 and Model 3 are modeled with respect to 276 low-level design features using SVM, while form preference of Model 1 is modeled with respect to 19 high-level design variables using HB. This is because HB may not be able to estimate properly individual preferences for 276 design variables using only 20 choice data (*Dotson et al.*, 2012). For functional attributes, the five attribute levels for each vehicle price and MPG are selected based on sales data of CD car in US, as

Table 3.5: Function attributes levels

Level	Price (MSRP)	MPG (city/highway)	Percentile (market data)
1	\$23K	23/27	10th
2	\$25K	23/29	25th
3	\$26K	24/30	50th
4	\$29K	25/31	75th
5	\$31K	26/32	90th

Table 3.6: Hit rates of online experiment

	Form preference hit-rate	Overall preference hit-rate
Model 1 (Base: single-level)	54.4%	57.2%
Model 2 (Half: bi-level)	62.6%(8.2%)	65.0%(7.8%)
Model 3 (Full: bi-level & adaptive)	66.6%(12.2%)	69.8%(12.6%)

Note: Percentages in parentheses refer to differences of hit-rate from Model 1.

shown in Table 3.5.

Hit-rates of all three models for the online experiments are shown in Table 3.6. The results show that the proposed model has the highest performance among the three included here.

Model 2 (in Table 3.6) shows the effect of the bi-level structure. These results suggest that bi-level structure entails substantial improvements in prediction, 8.2% and 7.8% for form and overall preferences hit-rates, respectively, compared to Model 1. We believe this owes to the fact that bi-level structure allows for distinct and appropriate modeling techniques for each of form and overall preference modeling. Here, specifically, SVM was used for form preference modeling, and HB was used for overall preference modeling, but these choices can be crafted by the researcher for the application domain at hand.

Model 3 (again in Table 3.6) shows the effect of the bi-level structure with adaptive sampling. These results further suggest that Model 3 offers 12.2% and 12.6% improvements for form and overall preferences hit-rates, respectively, compared to Model 1. Moreover, Model 3 entails 4.0% and 4.8% improvements for form and overall preference hit-rates, respectively, compared to Model 2 (bi-level structure without adaptive sampling). This suggests that adaptive sampling is useful to elicit both non-linear form preferences and linear overall preferences.

The overall pattern of results provides evidence that the bi-level questionnaire structure and adaptive sampling are helpful in capturing empirical patterns in both form and overall preference. Specifically, the bi-level structure appears to have affected predictive accuracy for form preference more than for overall preference; and adaptive sampling affected overall preference predictions more than those for form.

The overarching purpose of this study is to model both form and function preferences together, within the confines of a one-shot survey, and to measure the tradeoffs among specific design variables and functional ones. However, we did test one more model that did not consider form attributes. Specifically, we removed form attributes from Model 1 to check overall preference prediction based on only functional attributes. In Model 1a, we trained the overall preference model using only function attribute, price and MPG, then checked hit-rate. The results were dramatic: the hit-rate increases to 64.6%, from the 57.2% of Model 1. This strongly suggests that predicting overall preference by incorporating form design variables and function attributes within single linear model is suboptimal as a general approach. Model 2 in fact shows still slightly better performance of overall preference hit-rate, even though Model 2 sacrifices 10 purchase questions and models form preference. The proposed method, Model 3, affords significantly better prediction (69.8%) for overall preference than Model 1a (64.6%) .

The proposed model can be useful for product design with market segmentation. For example, from our online experiment results, 100 subjects can be clustered into four groups by K-means according to form importance (λ), price importance, and MPG importance as shown in Fig. 3.5. Price importance and MPG importance are calculated by the difference between highest partworth and lowest partworth.

Four groups may be interpretable as:

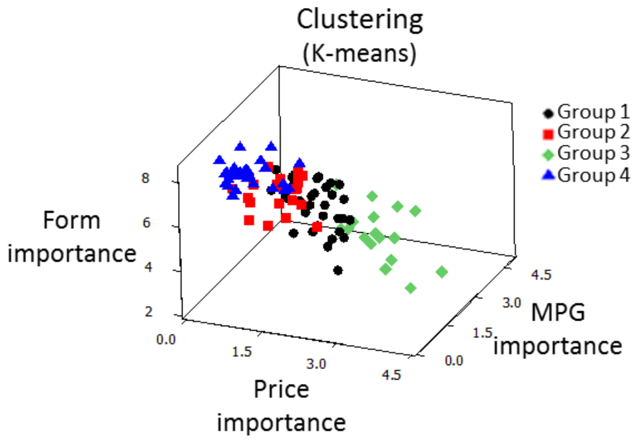


Figure 3.5: Clustering for market segmentation

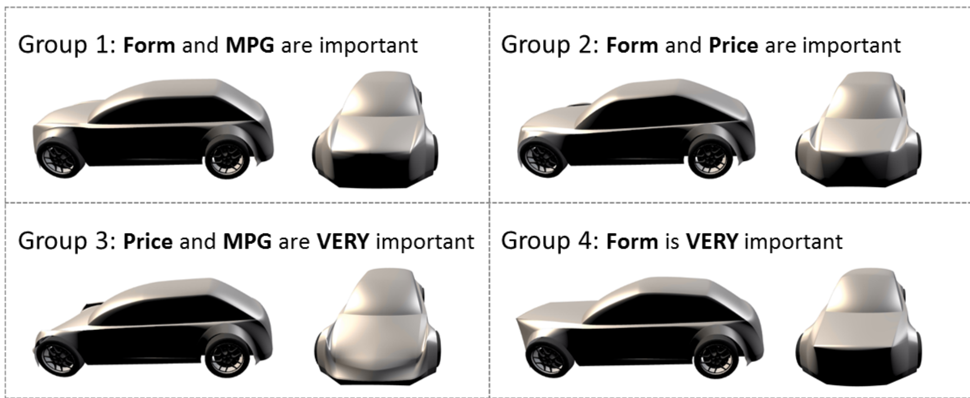


Figure 3.6: Optimal vehicle form of each group

- Group 1 – consumers who think form and MPG are important
- Group 2 – consumers who think form and price are important
- Group 3 – consumers who think price and MPG are very important
- Group 4 – consumers who think form is very important

To get the optimal vehicle form for each group, we maximized the sum of individual-level form preference models (i.e., aggregate objective function with the same weight) in each group. The obtained optimal vehicle forms are shown in Fig. 3.6.

This result does not represent the real market, because we used our own parametric vehicle design model and limited number of survey data. However, this approach can give a practical insight to marketers and designers on how to use form and function preference models for market segmentation. If a decision maker has his own parametric vehicle design models and manufacturing cost models, he can trade-off between form and function in each market segment, and estimate how much consumers are willing to pay.

3.5 Conclusion

It has been demonstrated by simulation and online experiment that the proposed bi-level adaptive conjoint analysis can effectively elicit both individual-level form and overall preferences using a single survey. The proposed model can sort out tradeoffs between specific design variables and function attributes in terms of eventual consumer choice. We summarize below the main challenges that remain in following up on this study, and associated contributions of our modeling approach.

The first such challenge was to design a single survey for individual-level preference modeling for both form and overall preferences. This paper presents a bi-level structure survey. Each round the user answers two pair-wise choice questions: (1) "Which of the following styles do you prefer more?" for vehicle 3D renderings, and (2) "Which car will you be more likely to buy?" for the same vehicle 3D renderings, coupled with functional attributes. Form scores (form appeal) are estimated based on user responses to question (1) and, as a consequence, the overall preference model can be trained using form scores as inputs and user responses to question (2). This approach makes it possible to build individual-level preference models without intervening time delays, and to use different modeling techniques in form (non-linear) and overall (linear) preferences. The experiment with real-time respondents showed that the bi-level structure survey offers substantial improvement in form preference modeling accuracy, compared to (single-level) conventional conjoint.

The second challenge was the requirement that one limit the number of questions overall, due to user fatigue in online settings, given that form preference modeling entails the burden of accommodating non-linear and continuous geometric attributes. To address this persistent problem, this paper presents a mechanism to adaptively generate form and function attributes based on responses of both the real-time respondent and previous respondents. While adaptive questionnaires have been investigated previously (*Toubia et al.*, 2003, 2004, 2007b; *Abernethy et al.*, 2008), this paper demonstrates its usage in a large and continuous design space and with a nonlinear underlying model. Moreover, this paper adopted not only Hierarchical Bayesian but also a more recent approach based on support vector machine mix (*Evgeniou et al.*, 2005) for shrinkage with relatively low computational cost. The online experiment of this study showed that adaptive sampling in bi-level structure offers a nontrivial degree of improvement in overall preference modeling accuracy, compared to non-adaptive sampling in a bi-level structure.

The third challenge was the lack of choice modeling research on complex 3D geometric forms. Most research has used 2D parametric models, but user choices made using 2D form representations can differ from those in reality (*Artacho-Ramirez et al.*, 2008; *Reid et al.*, 2013). This paper adopted an online parametric 3D rendering tool that generates vehicle forms with 19 continuous high-level design variables and 276 low-level design variables, and demonstrated that the proposed conjoint analysis can handle a large number of design variables and elicit preference effectively.

3.6 Summary

This chapter proposed a multidomain demand model for engineering and industrial design. The proposed model integrates functional attributes and aesthetic attributes into a single demand model. This helps decision makers to understand how vehicle shape design variables can affect both form preference and overall preference, as well as the trade-off between functional and aesthetic attributes.

Next chapter develops a multidomain demand model for engineering and service design.

CHAPTER IV

Multidomain Demand Modeling for Engineering and Service Design

This chapter expands the scope of demand modeling from product alone to *product and associated services*. While Chapter III focused on handling preferences on disparate attributes in a single product. this chapter dedicates to handling external product attributes and product attributes together. As the integrated product-service has emerged as an attractive business model, producers need to predict demands of both product and associated services and then co-design.

The demand model in this chapter considers multiple choices (i.e., a product and multiple services) rather than a single product choice in Chapter III. The business model used in this study assumes that a consumer chooses a product and then associated services sequentially during the horizon of product ownership, where products and services can be provided by the same producers. In this case, product demand can affect associated services demand, and the relationship between two demands can depend on product-service channels.

This chapter proposes a multidomain demand model as an interface system between engineering and service designs. The main challenge in this chapter is to figure out how to control product-service channels in demand model, and how to design optimal product-service channels. Based on the proposed demand modeling, profit-maximized product-service design framework will be applied to tablet and E-book service example.

4.1 Introduction

The formal integration of products and services has been regarded as an avenue to enhance both the profitability and sustainability of an enterprise (*Brady et al.*, 2006; *Hudson et al.*, 2011). Such "product-service systems" have been defined in the academic literature as "a marketable set of products and services capable of jointly fulfilling a user's need" to achieve more economic value and less environmental impact than conventional product-oriented businesses(*Mont*, 2002; *Baines et al.*, 2007; *Roy and Baxter*, 2009). An oft-cited example concerns the integration of tablets and digital services (e.g., iPad with App Store, Kindle with Amazon); as noted by an industry leader: "Some of the companies that have made tablets and put them on the market have not been successful – because they made *tablets*. They didn't make *services*." (*Hudson et al.*, 2011). That is, they were focused on the physical product being produced, not the integration of that product with the services from which many consumers derive primary value.

For a successful business operating in an integrated product-service market, producers must examine profitability jointly. Research in profit-maximizing *product* design methodology has long been a staple of academic marketing, especially via the conjoint approach (*Green and Krieger*, 1991; *Moore et al.*, 1999), with further applications to optimal service design (*Pullman and Moore*, 1999; *Easton and Pullman*, 2001; *Goodale et al.*, 2003). The engineering design research field has extended this approach to multi-disciplinary design in engineering, manufacturing, and policy (*Michalek et al.*, 2005; *Lewis et al.*, 2006; *Frischknecht et al.*, 2010). Most previous research in profit-maximizing design has focused, for reasons of tractability and data availability, on either the product or the service aspect in isolation. Some marketing research has addressed product and service design jointly, but only in such conventional settings such as after-sales service (*Cohen and Whang*, 1997) which takes the form of schedule maintenance or repair, and delivery service (*Verma et al.*, 2001), considering operating variables such as waiting time and service reliability. As such, it is not directly applicable to current market integration settings, such as e-devices and digital services, where the choice of services is an integral and preliminary aspect of product choice itself. While some research in the design literature has begun to address profit-maximizing product-service design (*Kang et al.*, 2013a, 2014), optimal product-service design with non-exclusive channels - those in which a producer's product can avail of services from other firms as well - has yet to be addressed. The product-service channel (PS channel) decision is the main topic in this study, where the PS channel represents (i) compatibility between product and service for customers' perspective and (ii) strategic cooperation with competitors' products and services.

The model put forth in the present study analyzes the following type of product-service market. (1) Producers supply both products and associated services; (2) according to available PS channels, customers can purchase other producers services as well; (3) customers first purchase a particular product, and subsequently purchase multiple services (through a service platform) for the period of product ownership; (4) decisions regarding PS channels among competitors requires contractual agreements. Within such a market set-up, we propose a joint optimization method with respect to three interrelated elements: PS channels; product prices and attributes; and service prices and attributes. Since the PS channel structure is a shared decision variable across competitors, we use standard game-theoretic techniques to establish and determine market equilibria. A tablet and e-book service example is used to demonstrate the proposed method.

The present paper follows *Kang et al.* (2013a), who showed that, since an integrated product-service business model has trade-offs between product profit and service profit, decision makers should design the product and service simultaneously and consider optimal balancing of product/service prices and attributes. Specifically, if a producer launches a product with a lower price than competitors, higher realized product demand can augment service demand and thereby enhance total profits. Even if product profit is sacrificed due to low product price, service profit can make up for the loss. However, in this previous study, PS channels were considered exclusive, so that product users of producer A can access only the services of producer A. When the PS channel is non-exclusive, product users of producer A can use services of other producers, B or C, so that product users of producer A are no longer guaranteed as to generate service demand for producer A. This additional source of consumer freedom in the PS channel renders product-service choice and demand far more complex to model, as well as dynamic. Since the particular PS channel availability is a shared decision variable, firms need to understand how PS channel decisions affect not only their own product and service demand levels, but also those of competitors' share channels.

The PS channel design problem is well exemplified by tablet and e-book service designs. Kindle/Amazon, Nook/Barnes&Noble (B&N), iPad/iBook, and Nexus/GooglePlay are supplying both tablets and their associated e-book services. Assuming all PS channels are exclusive, Kindle users can use only Amazon e-books; Amazon will supply e-books to only Kindle users; iPad users can use only iBook; and iBook will supply e-books to only iPad users. However, in reality, PS channels are non-exclusive and asymmetric. At the time of writing, a Kindle user can avail only of the Amazon e-book market because there is no iBook app in Amazon's App store; Amazon supplies e-book services to not only Kindle, but also the iPad through the Kindle app in Apple's App store. Therefore, iPad can use not only iBook but also Amazon e-books, while iBook supplies e-book services to only the iPad (*Carnoy*, 2011).

Third-party software may create additional channels, e.g., through PDF conversions, but these "informal", labor-intensive, non-quality-preserving (and in many cases of questionable legal status) channels are not addressed in the present framework.

That PS channel structure affects customer choices is clear from the fact that customers choose services from multiple providers, that is, other than the one explicitly provided by the manufacturer of their equipment. But this cuts both ways: choice of product is affected by which services will be available when using any particular one. In a non-exclusive channel structure, when choosing a product, customers can consider service quality and price, as well as how many services (i.e., service variety) are available through any particular product. After settling on a product, a customer can make ongoing choices from among possible service options, as meets their moment-to-moment needs. The PS channel thereby affects product choice and service demand. For example, an Amazon customer who has many Amazon e-books does not need to buy a Kindle specifically: s/he has other product choice options, such as the iPad kindle app. Analogously, an iPad user does not need to buy all, or indeed any, e-books through iBook, because other iPad-compatible options, like Amazon, are available.

More subtly, the PS channel structure affects producers' design decisions. When a producer supplies its services to other competitors' products, it allows users of those products to access its own content. For example, when that content is proprietary, those who chose the producer's product(s) merely to be able to access their content no longer have to. [Currently, many Apple programs are specific to their own operating system; those wishing to use these programs must purchase from Apple to do so. Porting the software to other operating systems might therefore lower product demand for Apple overall.] On the other hand, when a producer allows its product to use other competitors' services, its product becomes more attractive due to increased service variety; however, it may cede service demand to competitors. Thus, decisions to "open up" a device to services from others is a double-edged sword, involving trade-offs between demand/share for a product and that for its formerly exclusive services.

Because the PS channel decision is a shared, it is affected by competitors' decisions. First and most obviously, the PS channel decision requires acceptance from competitors. While deleting the channel - i.e., an equipment manufacturer deciding to no longer support content from a specific provider, or a provider electing to no longer serve a particular device - could be decided by only one partner, adding a channel requires an agreement between two producers, a decision that can hinge on predicted profit change for the two producers. If adding a channel brings more of a valued quantity (usually, profit, but potentially also sales or share) to both producers, it will, ceteris paribus, be accepted. Second, the PS channel can have different levels of ease of use. A producer may offer more advantages to its own PS channel than to a channel with other competitors. For example, in its early days, Apple allowed iPad users to shop for e-books (from Amazon) though Kindle app; however, Apple began to require a 30% portion of the revenue from each Amazon book purchase on iOS, perhaps in a bid to protect its own iBook service. Amazon decided not to include a store function in the Kindle app on iOS so that the Kindle app users could no longer shop Amazon e-books directly; instead, iPad users go the more laborious route of shopping Amazon e-books from a web-based store outside the app, sync them with the app on iPad, and then access them (*Carnoy*, 2011). In short, ease of use for services can vary according to competitors' PS decisions. In the current tablet market, the PS channel can also be controlled by the OS (operating system) itself.

In summary, producers need to strike an optimal balance between exclusive and non-exclusive PS channels to maximize overall product/service profit. They also need to anticipate potential profit changes of competitors to best negotiate a mutually beneficial channel decision. For example, a tablet producer (e.g., Apple) can only reasonably propose to support e-books from another firm if the arrangement is profitable to that firm, and we will use this insight, to our knowledge for the first time, to impose constraints on possible contractual solutions. It is important to note that optimal prices and attributes for both products and services depend on the PS channel structures themselves, and cannot be optimized for an in "exogenous" manner, then fed into the PS design problem as fixed quantities. That is, producers need to understand the relationship among all these variables, and then optimize them concurrently. Although much marketing science and management research (*Jeuland and Shugan*, 1983; *McGuire and Staelin*, 1983; *Lee and Staelin*, 1997; *Sudhir*, 2001; *Luo et al.*, 2007; *Cai et al.*, 2012) and some design research (*Williams et al.*, 2008; *Shiau and Michalek*, 2009b) has addressed distribution channels for maximizing profit, these are "conventional" channels between suppliers and retailers that have a given, fixed structure, and are not selected in terms of joint optimization.

The remainder of the paper is organized as follows. Section 4.2 introduces the product-service design profit maximization framework. In Section 4.3, we demonstrate the proposed method on the tablet and e-book services example and discuss results. Section 4.4 offers conclusions and direction for future research.

4.2 Proposed Model

4.2.1 Market setting

Here, we detail the market setting for the integrated product-service business model addressed in this paper. Fig. 4.1 depicts an example of some possible PS channel structures with two producers. Service choice examples are also shown, according to the PS channel structure.

It is important to underscore some of the key properties emerging from Fig. 4.1:

- A producer supplies a product and service together. Producer A supplies product p_A and associated service $\mathbf{s}_A$; producer B supplies product p_B and associated

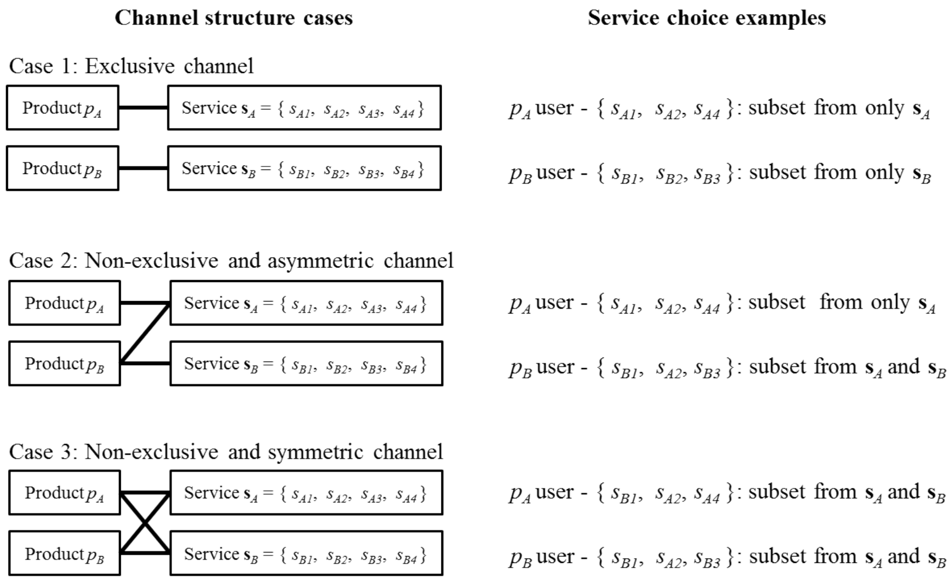


Figure 4.1: Examples of market settings

service $\mathbf{s}_B$.

- A service consists of multiple subservices: $\mathbf{s}_A$ includes $\{s_{Ai}\}$, that is, s_{A1}, s_{A2}, s_{A3}, and s_{A4} , while $\mathbf{s}_B$ includes s_{B1}, s_{B2}, s_{B3}, and s_{B4}.

- Subservices can be unique to a particular provider, or similar across providers. In the case of similar services, pairs such as (s_{A1}, s_{B1}), (s_{A2}, s_{B2}), (s_{A3}, s_{B3}), (s_{A4}, s_{B4}) may have different prices and qualities while providing functionally equivalent benefits to the user.

- Each customer chooses one product, either p_A or p_B; we do not model the situation where a user might elect to purchase both. S/he then chooses a service, either s_{Ai} or s_{Bi}. Service choice occurs multiple times during the horizon of product ownership (due to potential renewals, and which can vary across consumers), and elected services correspond to a subset of all available services. Duplication of equivalent services is technically allowable under this set-up, although is rarely economically advisable.

- In Case 1, which deals with *exclusive* channels, p_A users can use subservices from only $\mathbf{s}_A$; p_B users can use subservices from only $\mathbf{s}_B$.

- In Case 2 *non-exclusive* and *asymmetric* channels, p_A users can use subservices from only $\mathbf{s}_A$; but p_B users can use subservices from both $\mathbf{s}_A$ and $\mathbf{s}_B$ so that p_B users can choose some subservices from the pairs such as (s_{A1}, s_{B1}), (s_{A2}, s_{B2}), (s_{A3}, s_{B3}), (s_{A4}, s_{B4}). For example, a p_B user can choose $\{s_{B1}, s_{A2}, s_{B3}\}$ sequentially for using p_B.

- In Case 3, *non-exclusive* and *symmetric* channels, regardless of product choice, customers can choose any subservices.

- Adding a channel requires acceptance from competitors, while removing a channel can be decided by only one partner (unless specifically contractually disallowed). For example, when producer A wants to add a channel between p_A and $\mathbf{s}_B$ or a channel between $\mathbf{s}_A$ and p_B, acceptance by producer B is required.

We assume that a customer chooses a product based on product price, product attributes, and the PS channel; he/she chooses a service based on service price and attributes. Taking the example of the tablet and e-book service market, p_A and $\mathbf{s}_A$ can be the Kindle and Amazon market, respectively; p_B and $\mathbf{s}_B$ can be iPad and iBook markets, respectively. For example, $\{s_{A1}, s_{A2}, s_{A3}, ..., s_{AM}\}$ are e-books in the Amazon market and $\{s_{B1}, s_{B2}, s_{B3}, ..., s_{BM}\}$ are e-books in the iBook market. In practice, M, the number of total potential books, can number in the millions. Note that s_{At} and s_{Bt} are the same book, where t = 1, 2, 3,..., M, and can either can take on a value of 1, if the book is available, or 0 if it is not. In the product and service market, book price and shopping method can be different. Each customer can purchase a different number of e-books for a different period of product ownership.

4.2.2 Demand and profit modeling under product-service channel

We model products and services based on the market set-up described above, with a demand model that can be modified for different market settings. We adopt the latent (to the researcher) consumer utility concept underlying random-utility-based discrete choice models (*Green and Krieger*, 1996b), which have come to dominate both theoretical and applied work in the marketing field, as has Hierarchical Bayes (HB) choice-based conjoint (*Rossi and Allenby*, 2003; *Orme*, 2009), which is used to estimate heterogeneous customer preferences (often referred to as "part-worths" for discrete attributes).

Product demand modeling follows recent design research using the HB approach (*Michalek et al.*, 2011; *Kang et al.*, 2013a), which itself builds upon decades of research in marketing modeling (e.g., *Green et al.* (2001)). The basic process can be summarized as follows: (i) Choice data are gathered using a conjoint-based survey; (ii) HB choice model estimates parameters (i.e., part-worths) of individual-level preference function based on choice data are obtained; (iii) splines interpolate across discrete part-worths, enabling optimization over a continuous design space; (iv) market demand is predicted, based on choice probabilities and potential market size.

The individual-level discrete utility, v_{ipj}, of individual i and product p_j takes the usual linearized form with respect to discrete attributes levels, as

$$v_{ip_j} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{ikl} z_{jkl}, \tag{4.1}$$

where z_{jkl} are binary dummy variables indicating if alternative product j possesses attribute k at level l; z_{jkl} represent product price, product attributes, and service compatibility; β_{ikl} are the part-worth coefficient of attribute k at level l for individual i. Service compatibility is the response of the PS channel decision. For example, in Fig 4.1, there are four PS channel decision variables: Channels between $p_A - \mathbf{s}_A$,

$p_A - \mathbf{s}_B$, $p_B - \mathbf{s}_A$, and $p_B - \mathbf{s}_B$. Since channel decision variables here are binary dummy variables, if a variable is 1, a channel is connected (as depicted by lines in Fig 4.1); if it is 0, a channel is not connected. Note that $p_A - \mathbf{s}_A$ and $p_B - \mathbf{s}_B$ should always be connected. In this case, customers can have three levels of service compatibility: $\mathbf{s}_A$, $\mathbf{s}_B$, and $(\mathbf{s}_A, \mathbf{s}_B)$ according to product choice. If there are four producers, they will have $24 - 1 = 15$ levels of service compatibility, as shown later for our specific empirical example in Table 4.2.

The HB choice model estimates conjoint part-worths via a two-level process. At the "upper level", we assume individuals' part-worths, $\boldsymbol{\beta}_i$, follow a multivariate normal distribution, $\boldsymbol{\beta}_i \sim N(\boldsymbol{\theta}, \boldsymbol{\Lambda})$, where $\boldsymbol{\theta}$ indicates a vector of means of individuals' preferences and $\boldsymbol{\Lambda}$ is the covariance matrix; that is, the former ($\boldsymbol{\theta}$) suggests what a "typical" consumer would like, while the latter suggests how much variability there is in consumer preference (diagonal elements of $\boldsymbol{\Lambda}$), as well as how preferences for one attribute help predict those for a different attribute (off- diagonal elements of $\boldsymbol{\Lambda}$). At the "lower level", choice probabilities have logit form, which is particularly amenable to gradient and elasticity computation:

$$Pr_i(p_j) = \frac{\exp(v_{ip_j})}{\sum_{j' \in \mathbf{J}} \exp(v_{ip_j})}, \tag{4.2}$$

where $Pr_i(p_j)$ is the probability that individual i chooses product option p_j from a set of product alternatives $\mathbf{J}$. Markov chain Monte Carlo (MCMC) is used to generate posteriors of the part-worths of individuals i.

Product demand can be calculated, for various market scenarios, based on heterogeneous customer preference models. Either total or averaged demand can be used for optimization (as these contain identical information), so that projected (averaged across participants) demand is given by:

$$q_{p_j} = \frac{1}{I}\sum_{i=1}^{I} \mu Pr_i(p_j) \tag{4.3}$$

where q_{p_j} is the product demand of product option p_j, μ indicates the potential product market size (i.e., number of users), and I indicates total number of participants.

Next, *service* demand is calculated via conditional probability, given *product* choice and demand. A choice-based conjoint survey can conducted (as before) to gather service preference data; estimation of service attributes part-worths proceeds analogously to that for products. Note, however, that the setting is somewhat more complex, for the following reasons: (1) service alternative options depend on product choice; (2) services consist of subservices; and (3) service choice occurs on multiple occasions.

The individual level discrete utility, $v_{is_{h_t}}$, of individual i and service s_{h_t}, can be expressed in linear form with respect to discrete attributes levels as

$$v_{is_{h_t}} = \sum_{m=1}^{M}\sum_{n=1}^{N_m} \beta_{imn} z_{h_t mn}, \tag{4.4}$$

where h is a service platform, t indicates subservice, $z_{h_t mn}$ are binary dummy variables, $z_{h_t mn}$ represents service price and service attributes m at level n. Some service attributes can be decided by the PS channel; β_{imn} are the part-worth coefficients of service attribute m at level n for individual i. Using the HB choice model, β_{imn} are estimated, and then service choice probabilities can be calculated using the usual logit-based method as

$$Pr_i(s_{h_t} \mid p_j) = \frac{\exp(v_{is_{h_t}})}{\sum_{h' \in \mathbf{H}_{p_j}} \exp(v_{is_{h'_t}})}, \tag{4.5}$$

where $Pr_i(s_{h_t} \mid p_j)$ is the conditional probability that after individual i chooses product p_j, s/he chooses service option s_{h_t} from the set of service alternatives $\mathbf{H}_{p_j}$ of product p_j. Service alternatives are dictated by the PS channel decision.

Equations (4.4) and (4.5) represent, for simplicity of exposition, single choices for subservices (e.g., one e-book choice). Service demand can be calculated by summing all subservice choices over all products during the product's life cycle.

As before, the averaged (across consumers) demand value is used for profit optimization:

$$q_{s_h} = \frac{1}{I} \sum_{i=1}^{I} \sum_{t \in \mathbf{T}_i} \sum_{j' \in \mathbf{J}} \mu Pr_i(p_{j'}) Pr_i(s_{h_t} \mid p_{j'}), \tag{4.6}$$

where q_{s_h} is service demand of service option s_h, μ indicates (as before) the potential product market size, $Pr_i(p_{j'})$ is choice probability of product $p_{j'}$, $Pr_i(s_{h_t} \mid p_{j'})$ is conditional probability of service s_{h_t} given $p_{j'}$, $\mathbf{J}$ is a set of product alternatives, $\mathbf{T}_i$ is a set of service choices of individual i, and I indicates total number of individuals. The set $\mathbf{T}_i$ is can be determined by foreknowledge, an additional survey, or inferred from market statistics (e.g., e-book purchase history).

To illustrate, we apply Equations (4.1) to (4.6) to Case 2, that is, a non-exclusive and asymmetric channel (as in Fig. 4.1), for two products, A and B:

$$q_{p_A} = \frac{1}{I} \sum_{i=1}^{I} \mu \left[\frac{\exp(v_{ip_A})}{\exp(v_{ip_A}) + \exp(v_{ip_B}) + \exp(v_{ip_{none}})} \right] \tag{4.7}$$

$$q_{p_B} = \frac{1}{I} \sum_{i=1}^{I} \mu \left[\frac{\exp(v_{ip_B})}{\exp(v_{ip_A}) + \exp(v_{ip_B}) + \exp(v_{ip_{none}})} \right] \tag{4.8}$$

$$\begin{aligned} q_{\mathbf{s}_A} = \quad & \tfrac{1}{I} \textstyle\sum_{i=1}^{I} \sum_{t \in \mathbf{T}_i} \left[\mu \left[\frac{\exp(v_{ip_A})}{\exp(v_{ip_A}) + \exp(v_{ip_B}) + \exp(v_{ip_{none}})} \right] \left[\frac{\exp(v_{is_{A_t}})}{\exp(v_{is_{A_t}}) + \exp(v_{is_{none}})} \right] \right. \\ & \left. + \mu \left[\frac{\exp(v_{ip_B})}{\exp(v_{ip_A}) + \exp(v_{ip_B}) + \exp(v_{ip_{none}})} \right] \left[\frac{\exp(v_{is_{A_t}})}{\exp(v_{is_{A_t}}) + \exp(v_{is_{B_t}}) + \exp(v_{is_{none}})} \right] \right] \end{aligned} \tag{4.9}$$

$$q_{\mathbf{s}_B} = \frac{1}{I}\sum_{i=1}^{I}\sum_{t\in\mathbf{T}_i}\left[\mu\left[\frac{\exp(v_{ip_B})}{\exp(v_{ip_A})+\exp(v_{ip_B})+\exp(v_{ip_{none}})}\right]\left[\frac{\exp(v_{is_{B_t}})}{\exp(v_{is_{B_t}})+\exp(v_{is_{none}})}\right]\right] \tag{4.10}$$

Here, q_{p_A} and q_{p_B} are product demands of producer A and B, respectively, $q_{\mathbf{s}_A}$ and $q_{\mathbf{s}_B}$ are service demands of producer A and B, respectively, and "none" indicates the case where a customer "chooses the no-choice option", that is, refrains from choosing entirely. Note that that Eq. (4.9) has one more term than Eq. (4.10) because service $\mathbf{s}_A$ can be used by both p_A and p_B.

Based on the demand model given previously, product profit and service profit are calculated as

$$\Pi_{p_j} = q_{p_j}(P_{p_j} - C_{p_j}) \tag{4.11}$$

$$\Pi_{\mathbf{s}_h} = \frac{1}{I}\sum_{i=1}^{I}\sum_{t\in\mathbf{T}_i}\sum_{j'\in\mathbf{J}}\mu Pr_i(p_{j'})Pr_i(s_{h_t} \mid p_{j'})(P_{s_{h_t}} - C_{s_{h_t}}) \tag{4.12}$$

where Π_{p_j} is profit of product p_j, q_{p_j} is product demand, P_{p_j} is product price, C_{p_j} is product cost, Π_{s_h} is profit of service $\mathbf{s}_h$, $P_{s_{h_t}}$ is price of service s_{h_t}, $C_{s_{h_t}}$ is cost of service s_{h_t}, and other symbols retain their definitions from Eq. 4.6. For optimization, the sum of product profit and service profit is used as the objective, although modifications to include a known discount rate (because service profits are made after those for products) are straightforward.

4.2.3 Product-Service Design Framework

Based on the demand modeling above, we propose a profit optimization framework for product-service design as shown in Fig. 4.2. Before optimization, the current PS channel structure and competitors' product and service prices/attributes are set.

Decision variables are the PS channel structure, product price, product attributes, service prices, and service attributes. That is, these variables are set for the competitor, then optimized for the focal firm. Note that this framework is used for the design of a single product and multiple services for each producer. While it can be extended to product family design, this would require a (straightforward) modification of the present optimization framework.

The PS channel is a binary design variable, so that if a channel links a product and a service platform, its value is 1, otherwise, 0. When there are n producers in the market, the PS channel can be described as an $n \times n$ matrix, as shown in Table 4.1. Optimization amounts to a producer's choosing values within this matrix for its product and service options; note that diagonal values are 1 because products and services from the same manufacturer are always connected. Product demand is calculated based on product price, product attributes, and service compatibility as per Eq. (1) to (3). Using individuals' potential services sets, service demand is calculated based on service prices, service attributes, the PS channel, and product demand, through Eq. (4.4) to (4.6). Product profit and service profit are calculated using price, cost, and demand for products and services, through Eq. (4.11) and (4.12).

A notable feature of the proposed framework is that it uses a competitor's profit change as a constraint: When given producer wants to add channels with a competitor's product or service, if its design decision affects the competitor's profit positively, it is taken to be a feasible design decision; otherwise, it is not. That is, a producer can only reasonably propose channels to a competitor that will enhance that competitor's profit. For product and service constraints, three types - boundary, equality, or inequality - can be used. For feasibility constraints (e.g., whether a product's components can fit in its case), engineering or operation simulation models can be used as in previous research (*Kang et al.*, 2014). Optimization proceeds iteratively across

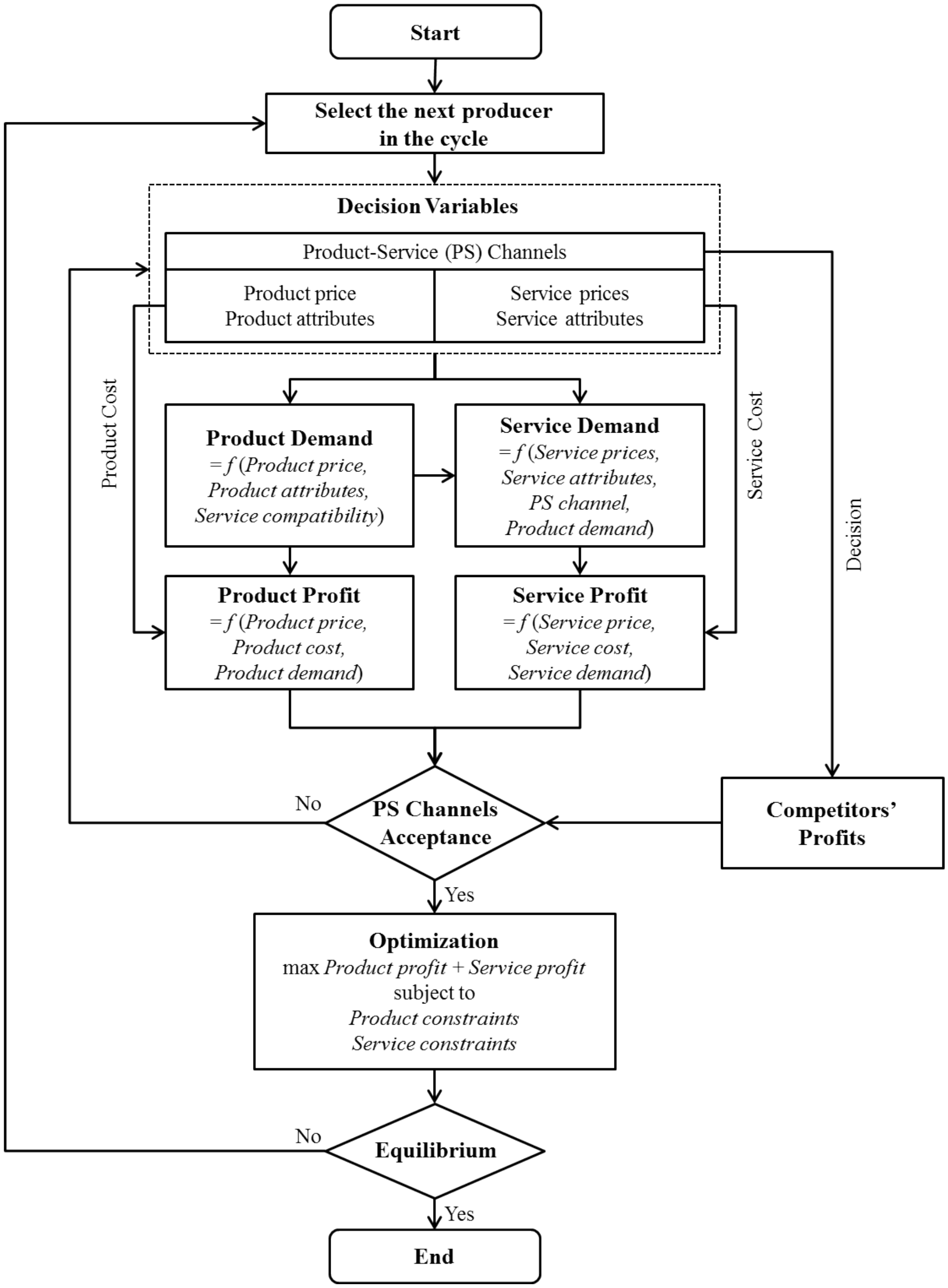


Figure 4.2: Profit maximization framework for product-service design

producers: After optimizing the overall profit of a focal producer, other competitors optimize their profit with the same process that the 'optimized' producer followed. These sequential optimizations proceed until all players (producers) cannot find a better design (i.e., one that increases profit). This results in a Nash equilibrium, a "solution concept" well studied in marketing and engineering design research (*Shiau and Michalek*, 2009b). Here we assume that, during the initial iteration, producers decide on *all* decision variables; for subsequent iterations, they decide only on product/service prices and channels. That is, because product design decisions are slow and costly to alter, we presume that producers first decide on product attributes, then engage in (iterative, sequential) optimization for prices and channels for both products and services.

4.3 Case Study: Tablet and E-book

4.3.1 Market setting

The proposed framework is demonstrated via tablet (product) and e-book (service) designs. Because the main purpose of this study is illustrative, market assumptions are deliberately generic, transparent, and simple, as follows. First, we selected four main producers, each of which has both tablet and e-book markets: (1) Kindle / Amazon Kindle books, (2) Nook / Barnes & Noble (B&N), (3) iPad / iBook, and (4) Nexus / GooglePlay books. The study focuses on single product designs rather (as opposed to product family designs), so assumes that each producer optimizes for a single 'flagship' tablet with full-color display; that is, we do not consider black and white e-readers and their interactions with the full-color market. For e-book services, price distribution across the four e-book markets are based on real observed prices of 20 best-seller e-books in each market (*Gilbert*, 2012). Specifically, we assume that these 20 best-seller e-books prices can serve as a reliable proxy for e-book price

Table 4.1: Market setting for case study

Product (Tablet)	Service (E-book market) Amazon $9.78 (2.14)[a]	B&N $9.98 (1.81)	iBook $10.41 (1.64)	GooglePlay $10.14 (2.32)
Kindle, $169, 7”, 16GB	1	0	0	0
Nook, $149, 7”, 16GB	0	1	0	0
iPad, $399, 9.7”, 16GB	1	1	1	1
Nexus, $229, 7”, 16GB	1	1	0	1

(a) Prices and figures in parentheses refer to average prices and standard deviations, respectively, across 20 best-seller books.

distributions (see Appendix A). The PS channel structure is based on the market situation at the time of writing. In addition, we assume that when a customer shops for an e-book from her tablet's producer, she does so via an in-tablet app, but uses a web-based interface for e-books from other competitors' (*Carnoy*, 2011).

Table 4.1 summarizes the market setting for the study, with four flagship tablets and four e-book markets. The e-book prices shown are averages of 20 best-sellers so, for example, Amazon's price of $9.78 compares favorably with those for B&N ($9.98), iBook ($10.41), and GooglePlay ($10.14). The binary indicators listed in Table 1 indicate whether a channel exists between tablet and e-book markets. Note, for example, that the PS channel is asymmetric: iPad users can access all four e-book services (row 3 of 4), while iBook does not supply e-book services to competitors (column 3 of 4).

4.3.2 Demand modeling

We conducted two choice-based conjoint surveys, for tablet choice and e-book choice, sequentially. 152 US respondents were surveyed using Amazons Mechanical Turk (*Amazon*, 2012a) and Sawtooth Software (*Orme*, 2009). Respondent demographics were broadly consistent with the US in general: 41% male, 59% female; 20% were 15-24 years of age, 49% 25-34, 16% 35-44, and 15% older than 45; 72% and

Table 4.2: Attribute levels and relative importance in tablet choice

Attributes	Levels	Estimated Importance
Compatible e-books	15 levels: {Amazon} / {B&N} / {iBook} / {GooglePlay} / {Amazon, B&N} / {Amazon, iBook} / {Amazon, GooglePlay}/ {B&N, iBook} / {B&N, GooglePlay} / {iBook, GooglePlay} / {Amazon, B&N, iBook} / {Amazon, B&N, GooglePlay} / {Amazon, iBook, GooglePlay} / {B&N, iBook, GooglePlay} / {Amazon, B&N, iBook, GooglePlay}	30.5%
Tablet brand	4 levels: Kindle HD / Nook HD / iPad / Nexus	19.3%
Tablet price	5 levels: \$129 / \$199 / \$299 / \$399 / \$499	28.2%
Display size	5 levels: 7" / 7.9" / 8.9" / 9.7" / 10"	9.8%
Storage	5 levels: 8GB / 16GB / 32GB / 64GB / 128GB	12.2%

58% of respondents reported tablet and e-book use experiences, respectively. Analogous figures for the US (*Census*, 2012; *Research*) are: tablet users are 47% male and 53% female; 18% are 15-24 years of age, 19% 25-34, 24% 35-44, and 40% are over 45. Because our focus is on methodology rather than empirical modeling, such small deviations between sample and population demographics seem satisfactory.

For the tablet choice-based conjoint survey, five attributes - compatible e-books, tablet brand, price, display size, and storage - were included, as shown in Table 4.2. Respondents were asked to suppose that they are considering purchasing a tablet, with the specific objective of being able to read e-books, and that their tablet choices would determine which of multiple compatible e-book services would be available to them. They understood the nature of co-branding; for example, when the tablet brand is Kindle HD, compatible e-book options always include Amazon (as evidenced by ones along the diagonal in Table 4.1). As is typical, each choice set included a small number (in this case, three) tablet profiles along with a "none", that is, the so-called "no choice option".

Previous respondents from the tablet survey were surveyed again, supposing they

Table 4.3: Attribute levels and relative importance in e-book choice

Attributes	Levels	Estimated Importance
E-book market	4 levels: Amazon / B&N / iBook / GooglePlay	42.6%
E-book price (best-seller)	4 levels: \$8.99 / \$9.99 / \$1.99 / \$11.99	39.5%
Easy of shopping[(a)]	2 levels: By app / By web-based store outside app	17.9%

(a) When tablet and e-book market are from the same producer, e-books can be purchased by an in-tablet app.

had bought a tablet and then wanted to purchase an e-book. For the e-book choice-based conjoint survey, three attributes of known importance were included - e-book market, e-book price, and ease of shopping - and are shown in Table 4.3. Subjects were told that prices for the same book can vary across markets. As mentioned earlier, customers can buy a book from the market of their tablet's producer via an in-tablet app, or from another seller using a web-based store. This reflects the reality that using your tablet brand's e-book market is simply more convenient than buying from a competitor. As in the tablet conjoint, each choice set included three e-book profiles and a "none" choice option.

Using HB estimation (as per Section 4.2.2), individual preference functions were quantified for each of the 152 respondents. Tables 4.2 and 4.3 list average relative importance for each attribute, while Appendix B lists estimated part-worths for each level separately. MCMC draws were 'thinned' to every tenth; burn-in was 50,000 (these were discarded); and inference proceeds from the final 50,000 draws, which were used to obtain preference part-worths. Lastly, cubic splines interpolation allows the estimation of continuous preference functions from the discrete part-worths used in the study (see *Michalek et al.* (2011)).

The conjoint survey was supplemented by follow-up questions aimed at assessing eventual service demand, e.g., "Suppose you buy a new tablet now. How long do you intend to use it?" and "Supposing you use the e-book service, how often are you likely to purchase E-books?" Mean and standard deviation of the period of product ownership were 4.4 years and 2.7 years, respectively; analogous values for frequency of e-book purchase were 19.2 and 15.8 books per year, respectively. These data were used in calculating individual level service demand. Recall that we used price data on 20 e-books (*Gilbert*, 2012), some of which were the same across the four markets, while others differed. For optimization purposes, we used average prices.

Since tablets are multi-purpose products, estimate the market "share" and size for tablets among e-book users is challenging. Summary statistics can provide benchmarks: 457 million e-books were sold in 2012 (*USATODAY*, 2013), 25% of e-books are read on tablets (*Books*, 2012), and the average number of e-books read (among those who read electronically) is 24 books per year (*Rainie*, 2012). Based on this data, a rough estimate of projected tablet demand used for e-reading is 4.76M (i.e., 457M × 25% / 24). Because this is an input figure that 'scales linearly' within the model, improved estimates of market size can be easily slotted into the methodology.

4.3.3 Cost and optimization modeling

For tablet cost modeling, we adapted conventions from previous tablet design research (*Wang et al.*, 2011b) focusing on display and memory storage costs:

$$C_{d_j} = C_{d_0} q_{d_j}^{b_1} z_{d_j}^{b_2} \tag{4.13}$$

$$C_{m_j} = C_{m_0} z_{m_j} \tag{4.14}$$

where C_{d_j} is cost of LCD display j, C_{d_0} is \$50 (of variable cost), q_{d_j} is demand for displays, z_{d_j} is display size in inches, b_1 and b_2 are parameters with values -0.1032 and

0.7965, respectively, C_{m_j} is cost of flash memory j, C_{m_0} is \$4 (of variable cost), and z_{m_j} is memory size in Gigabytes (GB). Display costs follow economies of scale, while other costs are considered constant with respect to demand / production, including costs for batteries, integrated circuits, and 'miscellaneous', which are assumed to be \$115 in total (*Wang et al.*, 2011b). E-book prices can be broken down into margin, royalty fees, taxes, and delivery costs. Since the royalty fees make up a majority of an e-book's price (*Amazon*, 2012b), we consider only the royalty fee as the cost of e-book service provision, and used iBook's royalty rate, 70% (*Mill city press*, 2012).

The decision variables are the PS channels ($z_1, ..., z_{16} = 0$ or 1), tablet price ($\$129 \leq z_{17} \leq \$499$), display size ($7 \leq z_{18} \leq 10$), memory storage size ($8 \leq z_{19} \leq 128$), and e-book price change ($-\$2 \leq z_{20} \leq +\$2$). The PS channel decisions are binary decision variables. Since we have four products and services, the PS channel matrix, as mentioned previously, is 4 by 4, so the space of possible channel combinations has size $2^{(4\times4)} = 65,536$. However, some of these are impermissible: the PS channels between the same producers (i.e., on the diagonal) must be set to 1, and a producer can control only its channels so that each producer has possible PS channel options of $2^6 = 64$. Each producer optimizes its decision sequentially so that tablet brand and e-book market brand are optimized in order. As discussed earlier, in terms of PS channel acceptance between competitors, *removing* a PS channel does not require the other party's agreement, while *adding* a PS channel is possible only when neither player's profits are harmed. Profit optimization is achieved subject to this PS channel constraint in addition to tablet and e-book design boundary constraints.

For the equilibrium calculation, optimization is carried out in order (determined at random) of Amazon, B&N, Apple, and Google; this is repeated until the optimal design decisions of all producers have converged, and profit cannot be enhanced by further changes. Previous producers' (optimal) decisions are used for the next producer's optimization, as parameters of the demand model. Because product features cannot

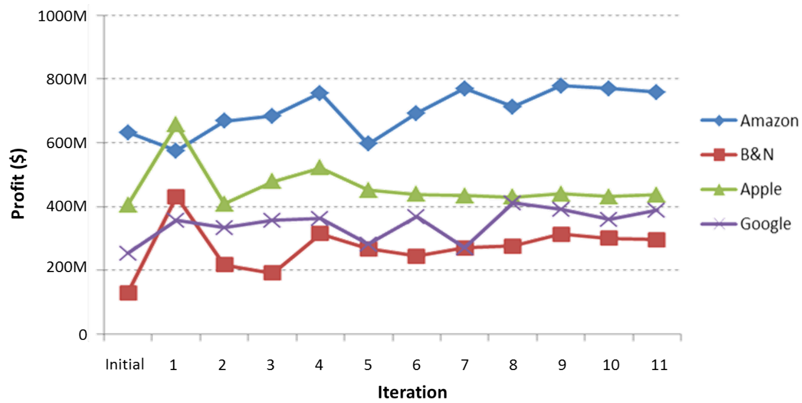


Figure 4.3: Sequential profit maximizations for four producers

be changed frequently, we assume that producers first decide on all decision variables, including product attributes, and secondarily decide only on product/service prices and channels. Since the design problem is a mixed integer optimization, we used genetic algorithms (GA) (*MathWorks*, 2014a) to solve the profit optimization problem. Owing to high computational costs for performing all optimization and validation at the individual level, the following procedure was used. For optimization, mean part-worths were calculated and used as inputs; for validation, demand was computed at the individual-level, then averages, as per Eq. (4.3).

4.3.4 Optimization results and discussion

Fig. 4.3 shows how the optimal profit of each producer changed and converged over the iteration history, where the x-axis indicates the iteration and y-axis profit ($). The profit of each producer is the response to its optimal design at each iteration. At the 11^{th} iteration, all profits are nearly converged; that is, no design change can entail more profit for any producer. Figs. 4.4 and 4.5 similarly suggest that all optimal decision values have converged. Note again that product attributes are optimized and fixed at the first iteration, while product/service prices and channel decisions are re-optimized at each subsequent iteration.

Fig. 4.6 lists optimal design decisions, including the PS channel and product/service

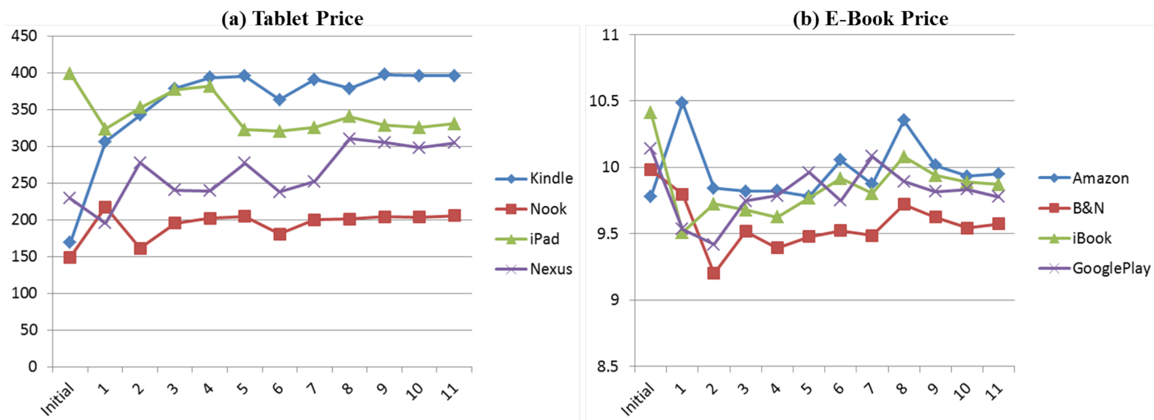


Figure 4.4: Convergence of price decisions of each producer

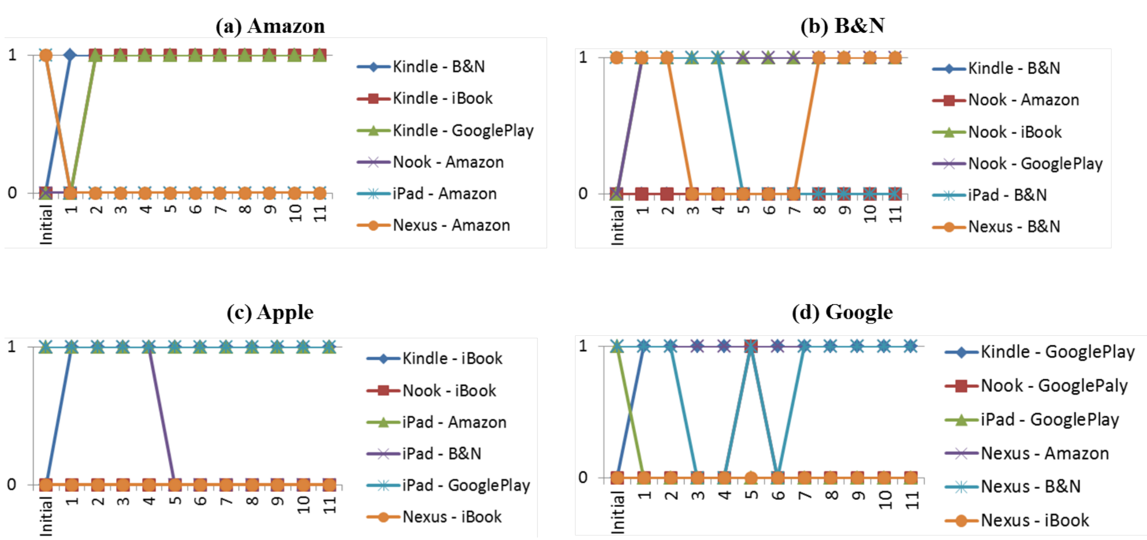


Figure 4.5: Convergence of channel decisions of each producer

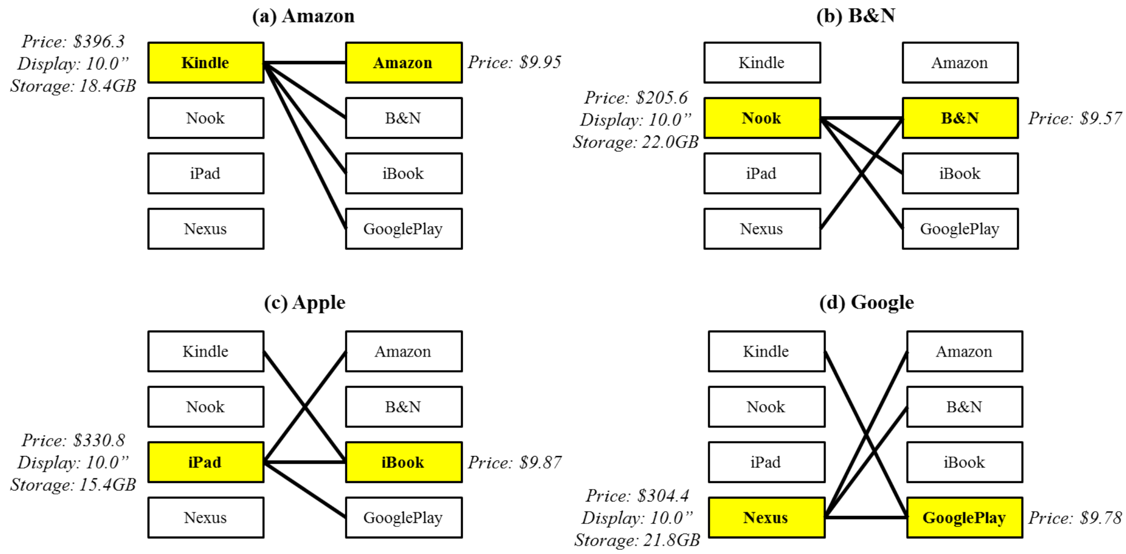


Figure 4.6: Optimal design decisions for each producer

attributes of each producer, where initial values are shown in Table 4.1. For Amazon, the Kindle's optimal price, display, and storage are \$396.3, 10", and 18.4GB, respectively; optimal e-book price (for Amazon) is \$9.95; and the optimal channel arrangement is for Kindle users to be able to use all competitors' e-book services, while Amazon supplies e-books to only Kindle users. Table 4.4 lists market responses of optimal decisions, where the values shown are means of the market response distribution based on 152 (heterogeneous) customer preference parameters. Optimal profits result when each producer optimizes its own situation; however, because the channel is not exclusive, service profit can arise not only from the same producer's product, but also competitors' products. For example, B&N supplies e-books to Nook and Nexus, so that 95% of service profit comes from Nook users and 5% of service profit comes from Nexus users.

The proposed demand model can also help determine where the service profit comes from. Market shares of products and services in each case are shown in the last two columns. We must underscore that the various assumptions made to restrict attention to the focal variables (e.g., the lack of black-and-white tablets) suggests the

Table 4.4: Market responses of optimal decisions

Producer	Overall Profit ($)	Product Profit ($)	Service Profit ($)	Service Profit from (%)	Product M/S (%)	Service M/S (%)
Amazon	759M	312M	447M	Kindle: 100% Nook: iPad: Nexus:	Kindle: 47% Nook: 14% iPad: 12% Nexus: 13%	Amazon: 38% B&N: 29% iBook: 17% GooglePlay: 16%
B&N	297M	-138M	435M	Kindle: Nook: 95% iPad: Nexus: 5%	Kindle: 27% Nook: 43% iPad: 11% Nexus: 7%	Amazon: 25% B&N: 38% iBook: 18% GooglePlay: 19%
Apple	437M	155M	282M	Kindle: 7% Nook: iPad: 93% Nexus:	Kindle: 19% Nook: 24% iPad: 39% Nexus: 8%	Amazon: 32% B&N: 24% iBook: 23% GooglePlay: 22%
Google	388M	577M	331M	Kindle: 11% Nook: iPad: Nexus: 89%	Kindle: 18% Nook: 9% iPad: 25% Nexus: 38%	Amazon: 35% B&N: 18% iBook: 19% GooglePlay: 27%

results should be applied with caution to the actual market for these four producers. However, the simulation results do suggest that the proposed model yields results with reasonable face validity, and can help decision makers understand market behavior.

4.4 Conclusion

Over the last decade, more and more products have been endowed with "intelligence", in the sense of incorporating information technology, connectivity, and enhancements via non-physical "updates". They are, quite literally, more than the sum of their parts. When a consumer chooses a cell phone, for example, she must envision which apps it can run, and therefore the degree of choice and competition in that related, service-based marketplace. Traditional demand models, primarily from marketing and engineering design, can decompose both the product and service decisions, and help optimize them separately. Difficulties arise, however, when these decisions are conjoined and are necessarily sequential, with product choice preceding service access. This paper proposed a framework designed to optimize over several disparate, but interacting, elements - PS channel, product price, product attributes, service prices, and service attributes - jointly, using the objective of overall product and service profits. Notably, it does so for three distinct multi-channel structures, exclusive, non-exclusive asymmetric, and exclusive asymmetric. Such a framework helps producers understand how PS channel decisions affect not only their own customer demand and profit patterns, but those of all market players. An extensive simulation and optimization, using summary market information (e.g., for prices) and conjoint choice data for both tablet and E-books, illustrated how the model can be used for a real product category, and how channel structures affect demands and profit levels for a producer's products and related services.

We view the proposed framework as evolutionary, building firmly on widely-used techniques in economics, marketing, and engineering design. In that light, there are a number of novel features of the framework that serve to unify aspects of the techniques developed in those cognate literatures. First, the demand model in this framework accommodates the actual, sequential nature of choice of product and multiple associated services; previous customer choice research had, by contrast, focused on a single choice of a product or a product-service bundle. Second, the PS channel structure was accommodated via decision variables, not as pre-determined parameters; previous distribution channel research in this area has largely examined price optimization under a given channel structure. Lastly - and we believe this to be a methodological innovation with the potential for broad application - the proposed framework considers competitors profit changes as (non-negativity) constraints, owing to the fact that PS channels are shared decisions requiring acceptance from both product producers and service providers.

4.5 Summary

This chapter proposed a multidomain demand model for engineering and service design. The proposed model integrates product demand and service demand into a single demand model framework. An enterprise-wide profit maximization framework was proposed to optimize products and services for three types of channel (i.e., exclusive, non-exclusive asymmetric, and exclusive asymmetric) in a competitive marketplace.

Next chapter presents a multidomain demand model for engineering and operations design.

CHAPTER V

Multidomain Demand Modeling for Engineering and Operations Design

This chapter expands the scope of services consumed along with a product as discussed in Chapter IV, to the infrastructure supporting the use of a product. The business model used in this study assumes that usability of a product is affected by infrastructure design so that a consumer chooses a product considering infrastructure attributes along with product attributes.

This chapter focuses on mapping consumer preference between the demand model and design simulation models of different domains. While Chapter III and IV focused on proposing a new demand modeling approach, this chapter dedicated to developing DMS (Design for Market Systems) framework for cooperative decision-making in partnership, and demonstrates the advantage of this approach compared to the sequential decision-making case.

As a design application, we addressed how Electric Vehicle (EV) and charging station attributes affect consumer adoption of EVs; how EV design decisions are coupled with charging station design decisions. The proposed multidomain demand model and integrated decision-making framework is developed for an interface system between engineering design (i.e., to find optimal EV function) and operations design (i.e, to find optimal charging station locations). Especially, the proposed EV demand model reflects geographical input of target consumers: the charging station coverage is estimated based on consumers locations, and EV demand for each target city is predicted considering charging station coverage for each city.

5.1 Introduction

In the Electric Vehicle (EV) market, one can identify five key players besides the consumers themselves (*Vardera*, 2010): Original Equipment Manufacturers (OEMs) assemble vehicles and sell them to consumers; battery manufacturers supply batteries to OEMs; utilities supply electricity to charging stations; charging station manufacturers supply Electric Vehicle Supply Equipment (EVSE) to utilities; and governments support all related activities through a variety of policies.

EVs face several consumer adoption barriers such as vehicle operating range, vehicle cost, perceived safety, unusual emergency situations, reliability, vehicle size and performance, infrastructure support, long charging time, high charging cost, and long payback period expectations (*Vardera*, 2010; *Egbue and Long*, 2012). The individual market players mentioned above are expending significant effort to overcome such barriers. In this paper, we adopt the argument that to overcome these barriers effectively, the market players must use a holistic approach to develop cooperatively integrated business models rather than just pursue their individual business models (*Kley et al.*, 2011). In this spirit, we present a mathematical formulation of a decision-making (optimization) framework that can support an integrated business model. Some of the market players are already cooperating in the market using business to business (B2B) models. For example, cooperation of OEMs and battery manufacturers or cooperation of utilities and charging station manufacturers are common. In the current study, we address a cooperative business model between two groups: EV manufacturers (i.e., OEMs and battery manufacturers) and charging station operators (i.e., utilities and charging station manufacturers).

A major barrier to consumer adoption is *range anxiety.* The consumer perception of its importance depends not only on the actual operating range determined by the design of the vehicle and its battery (vs. that of a conventional fuel vehicle) but also on the availability of charging stations and required charging times when the consumer plans a particular, possibly long, trip. Thus, consumers hesitate to buy EVs due to range anxiety, EV manufacturers hesitate to develop and produce EVs due to small market demand, and charging station operators hesitate to invest in charging infrastructure for the same reason (*Melaina and Bremson*, 2008).

Addressing range anxiety requires coordination of engineering business decisions by EV manufacturers and operation business decisions by charging station operators. For example, a short range vehicle in a market with ample charging stations may induce less range anxiety than a long range vehicle in a market with sparse charging stations. Interestingly, research shows that the average daily driving range in the US is less than 20 miles (*Pearre et al.*, 2011; *Smart and Schey*, 2012), and so range anxiety may be due more to a psychological need for security in an occasional long trip. Appealing to consumers through, say, joint advertising, for both EV performances and public charging stations coverage as a 'bundle' could be more effective in EV technology adoption. This approach could also address the issue of high initial vehicle cost due to a large battery pack that accounts for almost half of total consumer vehicle cost (*Wikipedia*, 2014).

EV manufacturers and charging station operators can partner to identify optimal 'system' balance between vehicle performance and charging station infrastructure to maximize market share or profit for both parties. A cooperative example in the US is the EV project supported by the U.S. Department of Energy engaging partners such as ECOtality, Nissan LEAF, and Chevrolet Volt in major states (*ECOtality*, 2014); the ChargePoint program supported by Coulomb Technologies is a cooperation among Chevrolet, Ford, and Smart USA (*ChargePoint*, 2014); Reliant Energy is working with

Nissan in Houston, and Southern California Edison is working with Ford in California. Such cooperations typically focus only on funding for installation of EVSEs in target EV markets rather than the broader cooperation suggested here.

In this study, we consider a charging infrastructure with direct current (DC) fast charging stations for commuting between major cities or trips longer than the range offered by a typical EV in the current market. EVs generally use three types of charging modes (or stations), Level 1, Level 2, and DC fast. It takes at least three hours to recharge a battery using Levels 1 or 2, while DC fast can recharge a battery to 80% capacity (for safety reasons) within 30 minutes. DC fast charging stations are considered promising for a future public charging infrastructure, but there were only 154 stations in the US as of 2012 (*Young*, 2014).

The proposed decision-making framework combines the EV design and charging station location network design problems. EV manufactures decide on vehicle price and attributes such as range, MPGe (miles per gallon gasoline equivalent), top speed, and acceleration (0 to 60 mph). Charging station operators decide on charging fee, how many stations to build, and where these stations should be located considering EV range offered by the manufacturer. The optimization objective is to maximize overall profit, and it is assumed that EV manufacturers and charging station operators invest together and share the profits. Optimization results show that a cooperative business model (i.e., integrated decision-making for overall profit) is more profitable than a sequential business model (i.e., engineering decision-making and then operating decision-making for maximizing each player's profit) for both partners.

The remainder of the paper is organized as follows. Section 5.2 introduces the decision-making framework and associated models. Section 5.3 presents an implementation case study for an EV market in Southeast Michigan. Section 5.4 and Section 5.5 discuss results, conclusions and limitations.

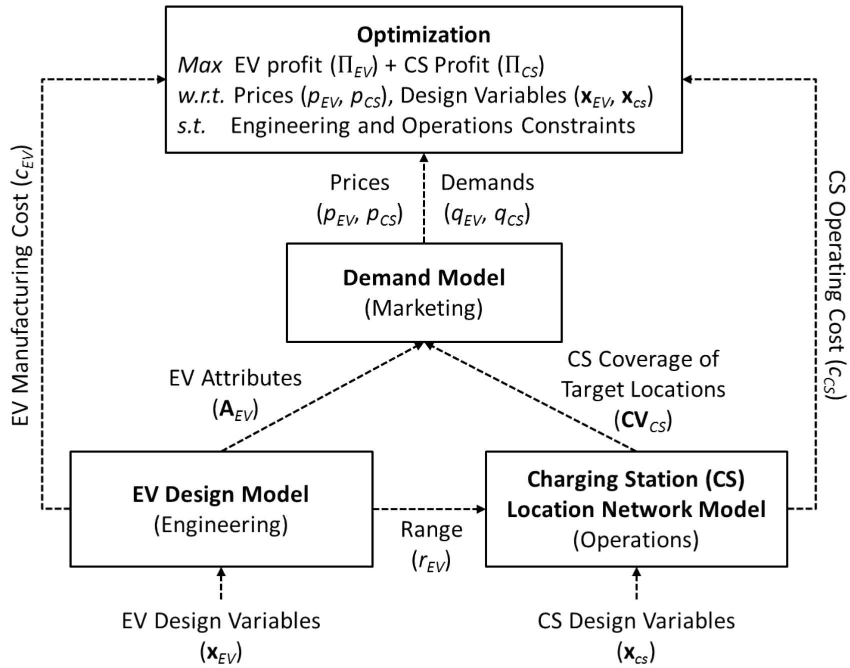


Figure 5.1: Framework of decision making

5.2 Integrated Decision Making Framework

5.2.1 Framework

The decision-making framework consists of three models for marketing, engineering and operations with shared decision variables. The framework is given in Fig. 5.1.

The EV design model represents the engineering problem with EV design variables ($\mathbf{x}_{EV}$) such as battery ($\mathbf{B}_{EV}$), motor ($\mathbf{M}_{EV}$), and gear (G_{EV}) designs as variable inputs; and EV attributes ($\mathbf{A}_{EV}$) such as range (r_{EV}), MPGe (mpg_{EV}), top speed (sp_{EV}), and acceleration (acc_{EV}) as outputs. These outputs are used as inputs to the marketing and operations models.

The DC fast Charging Station (CS) location network model represents the operations problem with CS design variables ($\mathbf{x}_{CS}$) such as number (N_{CS}) and locations ($\mathbf{L}_{CS}$) of stations as variable inputs, EV range (r_{EV}) as input from engineering, and charging station coverage ($\mathbf{CV}_{CS}$) as the output. This output is used as input to the marketing model. Coverage is defined as the percentage of possible paths a consumer can drive from his origin (e.g., home) without running out of power by using DC fast charging stations.

The marketing model predicts EV and charging station demands (q_{EV}, q_{CS}) using the EV attributes ($\mathbf{A}_{EV}$) from the engineering model and charging station coverage ($\mathbf{CV}_{CS}$) from the operations model as inputs, as well as EV price (p_{EV}) and charging fee (p_{CS}) as variable inputs.

The optimization objective is to maximize overall profit ($\Pi_{EV} + \Pi_{CS}$) from EVs and charging stations with respect to the variables: EV price (p_{EV}), charging fee (p_{CS}), EV design ($\mathbf{x}_{EV}$), and charging station design ($\mathbf{x}_{CS}$).

The overall optimization equation is stated as follows.

$$\begin{aligned} \max_{\bar{\mathbf{x}}} \quad & \Pi_{EV} + \Pi_{CS} \\ & = (p_{EV} - c_{EV})q_{EV} + (p_{CS} - c_{EC})q_{CS} - c_{CS} \end{aligned} \tag{5.1}$$

with respect to

$$\begin{aligned} \bar{\mathbf{x}} &= [p_{EV}, p_{CS}, \mathbf{x}_{EV}, \mathbf{x}_{CS}] \\ \mathbf{x}_{EV} &= [\mathbf{B}_{EV}, \mathbf{M}_{EV}, G_{EV}] \\ \mathbf{x}_{CS} &= [N_{CS}, \mathbf{L}_{CS}] \end{aligned} \tag{5.2}$$

subject to

$$lb \leq \bar{\mathbf{x}} \leq ub \tag{5.3}$$

$$\mathbf{g}(\mathbf{A}_{EV}) \leq 0 \tag{5.4}$$

where

$$\mathbf{A}_{EV} = [r_{EV}, mpg_{EV}, sp_{EV}, acc_{EV}] \tag{5.5}$$

$$[c_{EV}, c_{CS}] = f_c(\mathbf{x}_{EV}, \mathbf{x}_{CS}) \tag{5.6}$$

$$[q_{EV}, q_{CS}] = f_q(p_{EV}, p_{CS}, \mathbf{A}_{EV}, \mathbf{CV}_{CS}) \tag{5.7}$$

$$\mathbf{A}_{EV} = f_{EV}(\mathbf{x}_{EV}) \tag{5.8}$$

$$\mathbf{CV}_{CS} = f_{CS}(\mathbf{x}_{CS}, r_{EV}) \tag{5.9}$$

where $\bar{\mathbf{x}}$ in Eq. (5.2) are decision variables, Eq. (5.3) are boundary constraints, and Eq. (5.4) are inequality constraints for EV attributes as shown in Table 5.2. Furthermore, f_c, f_q, f_{EV}, and f_{CS} are linking cost, demand, engineering, and operations outputs to decision variables, respectively. Each model is explained in more detail in the next sections.

5.2.2 Electric Vehicle Design Model (Engineering)

The engineering performance model of a Battery Electric Vehicle (BEV), f_{EV}, in Eq. (5.8) is built using the AMESim software. The subsystem models include analytical expressions from the AMESim libraries (*AMESim*, 2014). Previous research showed that analytical models of EV systems are appropriate for efficient system-level simulations in the early design stage, and their adequate fidelity has been assured through comparison with finite element models or laboratory measurements (*Chan*, 2000; *Lee and Tolbert*, 2009; *Tenner et al.*, 2011).

The engineering model here consists of driver, control unit, motor torque control, battery, inverter, permanent magnet synchronous motor, and vehicle models as shown in Fig. 5.2. The overall architecture and vehicle parameters for the modeled vehicle are similar to the Nissan Leaf. The subsystems designed in the study are lithium-ion battery, permanent magnet synchronous motor, and gearing. Six design variables and their lower and upper bounds are summarized in Table 5.1. Four responses (attributes) and associated inequality constraints are are summarized in Table 5.2. These practical inequality constraints are placed to ensure highway driving feasibility.

5.2.2.1 Battery Design

We use the simple battery model shown in Fig. 5.3 where OCV is open circuit voltage, r is internal resistance, I is current, CF is filtering capacitance, and U is

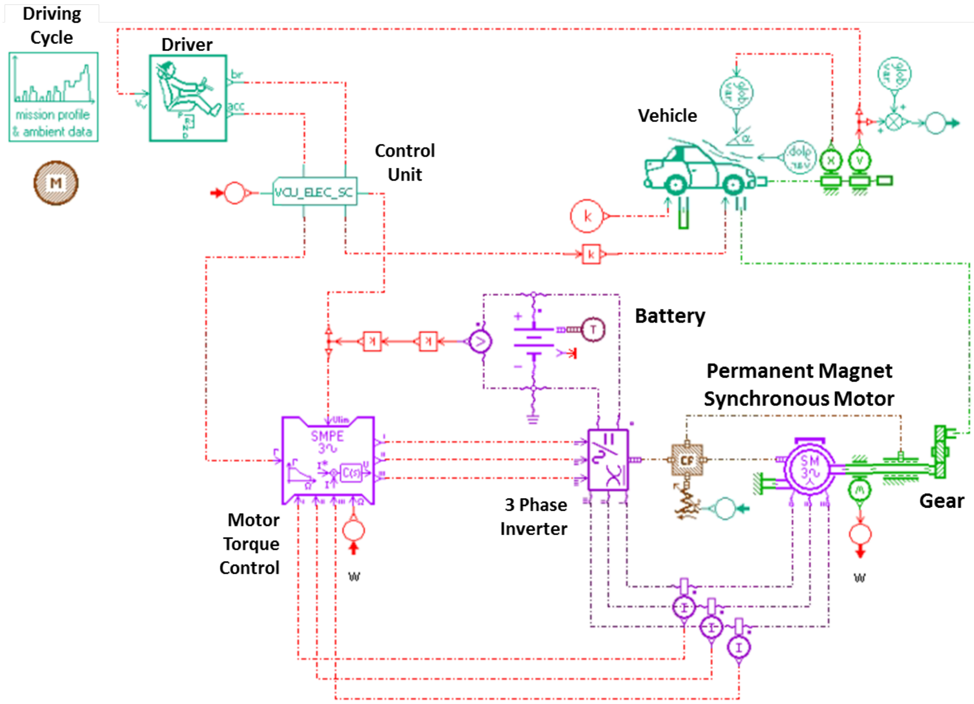


Figure 5.2: Engineering simulation model

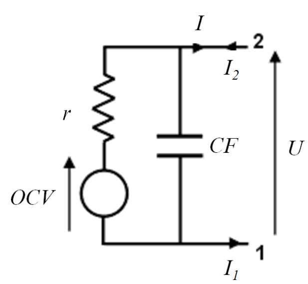


Figure 5.3: Battery model (*AMESim*, 2014)

the output voltage. Based on this model, state of charge (SOC), output voltage, and heat flow rate (i.e., thermal losses) are computed as outputs of the simulation.

Battery design variables are the number of cells in series in one branch and the number of branches in parallel, and they are used to calculate the following battery characteristics:

$$C_{bt} = C_{cell} \cdot n_p \tag{5.10}$$

$$CF_{bt} = CF_{cell} \cdot \frac{n_p}{n_s} \tag{5.11}$$

Table 5.1: Design variables of engineering model

System	Symbol	Design variables	Lower bound	Upper bound
Battery	n_s	Number of cells in series in one branch	80	200
	n_p	Number of branches in parallel	1	4
Motor	L_d	Stator inductance of the d-axis	1.62mH	3.42mH
	L_q	Stator inductance of the q-axis	1.98mH	4.18mH
	R_s	Stator resistance	0.001Ω	0.1Ω
	p	Number of pole pairs	1	4
Gear	G	Gear ratio	2	12

Table 5.2: Responses and inequality constraints of engineering model

Response	Constraint
Top speed (sp_{EV})	≥70 mph
Acceleration (0 to 60 mph) (acc_{EV})	≤30 sec
Range (r_{EV})	N/A
MPGe (mpg_{EV})	N/A

$$OCV_{bt} = OCV_{cell} \cdot n_s \tag{5.12}$$

$$r_{bt} = r_{cell} \cdot \frac{n_s}{n_p} \tag{5.13}$$

Here n_s and n_p are the number of cells in series in one branch and the number of branches in parallel, respectively; C_{bt} is battery capacity, C_{cell} is cell capacity, CF_{bt} is battery filtering capacitance, CF_{cell} is cell filtering capacitance, OCV_{bt} is battery open circuit voltage, OCV_{cell} is cell open circuit voltage, r_{bt} is battery internal resistance, and r_{cell} is cell internal resistance. Since OCV_{cell} and r_{cell} are affected by SOC, OCV_{cell} and r_{cell} are computed by linear interpolation of available experimental data. All parameter values in the above equations are based on Nissan Leaf battery cell tests (*EERE*, 2011a).

From the battery characteristics above, SOC, output voltage, and heat flow rate are computed:

$$\frac{dSOC}{dt} = 100 \cdot \frac{I_2}{C_{bt}} \tag{5.14}$$

$$\frac{dU}{dt} = \frac{I_2 - \frac{U - OCV_{bt}}{r_{bt}}}{CF_{bt}} \tag{5.15}$$

$$dh = \frac{(U - OCV_{bt})^2}{r_{bt}} \tag{5.16}$$

where U is the output voltage and dh is heat flow rate based on Joule's losses.

5.2.2.2 Motor Design

The motor model outputs such as torque and heat flow rate are computed using permanent magnet flux linkages, stator inductance, and the number of pole pairs as design variables.

The stator flux linkages are computed from the equations

$$\varphi_d = L_d I_d + \sqrt{\frac{3}{2}}\varphi_{PM} \tag{5.17}$$

$$\varphi_q = L_q I_q \tag{5.18}$$

where φ_{PM} is permanent magnet flux linkage, φ_d and φ_q are stator flux linkages of the d-axis and q-axis, respectively, L_d and L_q are stator inductances of the d-axis and q-axis, respectively, and I_d and I_q are stator currents of the d-axis and q-axis, respectively. The toque and heat flow rates are then computed from

$$T = p(\varphi_d I_q - \varphi_q I_d) \tag{5.19}$$

$$dh = R_s I_d^2 + R_s I_q^2 \tag{5.20}$$

where T is torque, p is number of pole pairs, dh is heat flow rate, and R_s is stator resistance.

5.2.2.3 Gear Ratio Design and Other Parameters

For the rotary mechanical gear ratio, we use the equations

$$w_{motor} = G \cdot w_{axle} \tag{5.21}$$

$$T_{axle} = G \cdot T_{motor} \tag{5.22}$$

where w_{motor} is motor velocity, w_{axle} is axle velocity, T_{motor} is motor torque, and T_{axle} is axle torque. Range and MPGe are computed on the EPA Highway Fuel Economy Driving Cycle, the standard way to compare EV performance in the market. Top speed and acceleration are computed for straight line running. We set initial vehicle mass, dimensions, and drag coefficient based on Nissan Leaf specifications (*Wikipedia*, 2014; *EERE*, 2011b). Battery and motor masses change depending on variable design values: battery mass (kg) = total number of cells ($n_s \times n_p$) $\times$ mass of a cell, where approximate mass of a cell in Nissan Leaf is 1.53kg (*EERE*, 2011b); motor mass (kg) = 21.6 + 0.532 $\times$ motor power (kW) (*Simpson*, 2006). The relation of driving performance and the size of battery pack is nonlinear because larger battery mass diminishes driving performance while more battery capacity improves driving range (*Karabasoglu and Michalek*, 2013).

5.2.2.4 EV Manufacturing Cost

Since our design variables are for battery and motor designs, battery pack cost and motor cost are variable costs in the EV manufacturing cost model. The remaining costs are considered fixed. Battery cost currently ranges from \$300 to \$600 per kWh; it is decreasing with time and is expected to reach \$250 per kWh by 2020 *Traut et al.* (2012); *Henry and Lovellette* (2003). We used \$500/kWh as battery cost for the case study, and performed a parametric study with respect to this cost parameter. For motor cost calculation, we used the cost model in (*Simpson*, 2006): motor cost (\$) =

16 $\times$ motor power (kW) + 385. We assumed that fixed cost is \$6,000, resulting in a manufacturing cost for an EV with 24kWh battery estimated as \$12,000 and 80kW motor estimated as \$1,665.

5.2.3 Charging Station Location Network Model (Operations)

In the operations model, we focused on DC fast charging stations for round trips between cities using highways. Two different types of DC fast charging station coverage are used in the study: *local path coverage*, a charging station attribute in the consumer demand model; and *total flow coverage*, an objective of location modeling. Local path coverage is defined as the percentage of possible paths (i.e., shortest round trips from a city of residence to another city using the highway) a consumer can drive without running out of power using DC fast charging stations. For example, if a consumer lives in a city out of 19 cites in the target state and he can drive to all 18 cities using DC fast charging stations, local path coverage for his city is 100%. We assume that consumers fully charge the EV in their home, drive to a destination with the shortest highway, then drive back home. If a battery runs out and there are DC fast charging stations on the way, they use DC fast charging stations; otherwise, they use other options such as Level 1 or Level 2 charging stations. We assume that there are Level 1 or 2 charging stations in every city, but they are not suitable for trips between cities due to long charging time. For local path coverage, if the coverage is 100%, a consumer can drive from his city of residence to any other select city using only DC fast charging stations; if the coverage is 50%, a consumer can drive only 50% of the possible paths using DC fast charging stations, and he needs to use Level 1 or 2 charging stations for the other 50% of the possible paths. When the locations of charging stations are decided, the local path coverage of each city will be different, because possible paths are different according to each city (origin) as shown in Fig. 5.6.

Total flow coverage is defined as the percentage of total traffic flows that can be recharged. Possible paths for total flow coverage are defined as combinations of paths from one city to another. For example, if there are 19 cities in the target state, the number of possible paths is $19 \times 18 / 2 = 171$. Since each possible path has different amount of traffic flow, a path with more flow should have more relative weight on charging station location decisions. Maximizing flow coverage is the overall desirable goal to decide the optimal locations of charging stations.

However, a consumer cares about his vehicle recharge need rather than the total recharged flow volume, and only about local paths including his city of residence. This is why total flow coverage is used for optimal locations, while local path coverage is used in the consumer demand model. The demand model in next chapter below predicts demand for each city based on local path coverage, then adds up the demands for all cities to estimate total demand in the region of interest.

5.2.3.1 Location Model

The location model for fast DC charging stations, f_{CS} in Eq. (5.9), is established using practices in geographical analysis. Hodgson (1990) first proposed the Flow Capturing Location-allocation Model (FCLM) (*Hodgson*, 1990). In this study, we adopt a model variant called the Flow Refueling Location Model (FRLM) (*Kuby and Lim*, 2005; *Kuby et al.*, 2005; *Kuby and Lim*, 2007; *Upchurch et al.*, 2009; *Lim and Kuby*, 2010; *Kim and Kuby*, 2012) that has been widely used to find optimal locations of refueling facilities for alternative-fuel vehicles with limited range.

The standard FRLM (*Kuby and Lim*, 2005) is used in the study resulting in a mixed-integer linear programming problem to maximize the flow coverage with respect to location of charging stations given the number of stations and EV range.

$$\max_{\mathbf{x},\mathbf{y},\mathbf{v}} \quad \sum_{q \in Q} f_q y_q \tag{5.23}$$

Subject to

$$\sum_{h \in H} b_{qh} v_h \geq y_q \quad \forall q \in Q \tag{5.24}$$

$$a_{hk} x_k \geq v_h \quad \forall h \in H;\ k \in K \tag{5.25}$$

$$\sum_{k \in K} x_k = p \tag{5.26}$$

$$x_k \in \{0, 1\} \quad \forall k, h, q \tag{5.27}$$

$$0 \leq v_h \leq 1 \quad \forall h \tag{5.28}$$

$$0 \leq y_q \leq 1 \quad \forall q \tag{5.29}$$

where

- q is the index of O-D pairs (O is an origin, D is a destination, and O-D pairs indicate the shortest paths for each pair)
- Q is the set of all O-D pairs
- f_q is the flow volume on the shortest path between O-D pair q
- $y_q = 1$ if $f_q$is captured, 0 otherwise
- k is a potential station location
- K is the set of all potential station locations
- h is the index of combinations of stations
- H is the set of all potential station combinations
- $b_{qh} = 1$ if station combination h are open, 0 otherwise
- $v_h = 1$ if all stations in combination h are open, 0 otherwise
- $a_{hk} = 1$ if station k is in combination h, 0 otherwise

- $x_k = 1$ if a station is located at k, 0 otherwise
- p is the number of stations to be located.

The objective function Eq. (5.23) maximizes the total flow volume (flow coverage % can also be used) that can be recharged with p stations. The flow between two cities, f_q, is calculated by a gravity model based on the city population and path distance (i.e., flow = population of city A x population of city B / path distance^2). In the constraints Eq. (5.24), at least one eligible combination of stations h should be open for path q to be recharged. In Eq. (5.25), v_h should be held to zero unless all stations k in combination h are open. In Eq. (5.26), p stations are required to be built. In Eq. (5.27), the charging station location variables x_k are defined as binary variables. Although v_h and y_q are also defined as binary variables, they can be relaxed as continuous variables with lower and upper bounds in Eqs. (5.28) and (5.29), respectively. This trick can allow us to find an all-integer solution by reducing the number of required binary variables. More detail explanation can be found in *Kuby and Lim* (2005).

Before using the FRLM, we must pre-generate all combinations of stations, H, that can recharge a path following six steps (*Kuby and Lim*, 2007):

1. Generate the shortest path for all O-D pairs q, and establish an empty master list of all combinations h.
2. Generate a temporary list of all station combinations h of nodes on path q.
3. Remove station combinations that cannot recharge an EV of the given range on path q.
4. If any combination h is still on the list for path q:
   Add it to the master list of station combinations if it is not already there.

Record b_{qh}=1 if station combination h can recharge path q and 0 otherwise.

Record a_{hk}=1 if station k is in combination h, or 0 otherwise.

5. Repeat Steps 2-5 for all paths q.

For this location problem, Lim and Kuby (2010) have shown that use of a genetic algorithm (GA) can have better performance in finding the global optimum than a mixed-integer linear programming (MILP) algorithm. In the present study, we use GA to solve the location optimization problem with variables being the number of stations, station locations, and EV range; and output being the optimal flow coverage.

Fig. 5.5 shows the optimal number and locations of charging stations for the region of Southeast Michigan explained further in the case study below. Fig. 5.4 shows how the local path coverage for Ann Arbor, Michigan, residents changes according to the number of charging stations and EV range. More charging stations and larger EV range typically result in larger local path coverage for each city. Since the optimal locations are decided to maximize total flow coverage not local path coverage for each city, small populated cities oftentimes are not served by this optimal locations. That is why local path coverage for Ann Arbor, Michigan in Fig. 5.4 sometimes decreases despite more charging stations and larger EV range.

5.2.3.2 DC Fast Charging Station Operating Cost

The cost of DC fast charging station infrastructure can be decomposed into variable cost, such as electricity cost, and fixed cost such as installation, equipment and maintenance cost. We use 10.28 cents per kWh as electricity cost based on average retail price for transportation in the US for rolling 12-month periods ending in January 2014 (*EIA*, 2014). Fixed costs depend on the condition of stations. Here we used $75,000 for installation and equipment cost, and $5,500 for maintenance cost for one year (*Schroeder and Traber*, 2012). We evaluate profit and costs for charging

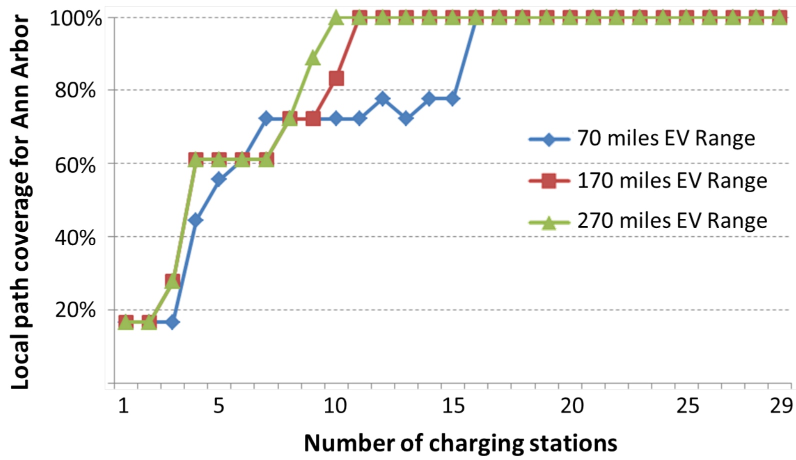


Figure 5.4: Local path coverage of charging stations for Ann Arbor, Michigan, residents

stations over a ten-year period with discount rate 10% where the life cycle of EVs is assumed to be ten years.

5.2.4 Demand Model (Marketing)

Demands for EV and DC fast charging stations are predicted sequentially considering a heterogeneous market.

5.2.4.1 EV Demand

Hierarchical Bayesian (HB) choice-based conjoint (*Rossi et al.*, 2005a; *Orme*, 2009) is used for building a heterogeneous EV demand model. Choice data are gathered using choice-based conjoint analysis. Individual-level discrete utility functions are estimated using the HB choice model. Spline curves are fitted to the individual-level posterior modes for each conjoint part-worth. Market demand is then calculated with choice probabilities based on individual-level utility functions and market potential.

The individual level discrete utility v_{ij} is a linear function of discrete levels of attributes and defined as,

$$v_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_k} \beta_{ikl} z_{jkl} \tag{5.30}$$

where z_{jkl} are binary dummy variables indicating alternative j possesses attribute k at level l, and β_{ikl} are the part-worth coefficients of attribute k at level l for individual i *Green and Krieger* (1996a).

The HB choice model has two levels. At the upper level, an individual's part-worths, β_i, have a multivariate normal distribution, $\beta_i \sim N(\theta, \Lambda)$, where θ is a vector of means of the distribution of individuals and Λ is the covariance matrix of that distribution. At the lower level, choice probabilities for a logit model are used:

$$P_{ij} = \frac{e^{v_{ij}}}{\sum\limits_{j' \in J} e^{v_{ij'}}} \tag{5.31}$$

where P_{ij} indicates probability individual i chooses option j from a set of alternatives J. Markov Chain Monte Carlo (MCMC) is used to estimate the individual's part-worth. The utility function in Eq. (5.30) based on the HB choice model cannot be used for continuous design decisions because the function is discrete. We calculate interpolated values of discrete part-worths using cubic splines so that choice probabilities for continuous design decisions can be estimated.

Average market demand is calculated based on individual level choice probabilities as

$$q_j = \frac{1}{I} \sum_{i=1}^{I} s P_{ij} \tag{5.32}$$

where q_j is market demand of option j, s is the potential market size, and I is total number of individuals. Note that this averaging of individual market demands is used only for optimization. When we compare demands of different design decisions, each individual level market demand should be compared to account for heterogeneity. In this case, the comparison tells us what percentage of the individual market cases for one design decision is better than the other design decision as shown in Fig. 5.7.

EV demand is computed with Eq. (5.32) using the attributes and levels of EV and charging station shown in Table 5.3, selected based on previous research and

Table 5.3: Attribute levels and importance

Attributes	Unit	Level 1	2	3	4	5	Importance
Local path coverage	%	0	25	50	75	100	27.2%
Charging fee	$	0	2	5	8	10	13.7%
Vehicle price	$	20K	30K	40K	50K	60K	32.0%
Range	miles	70	120	170	220	270	15.5%
Fuel efficiency	MPGe	70	100	130	160	190	3.8%
Top speed	mph	70	85	100	115	130	3.9%
Acceleration (0 to 60 mph)	sec	8	13	19	25	30	3.9%

the current EV market (*Hidrue et al.*, 2011). Demands for each city are computed first, then are summed up for total demand in a state, because local path coverage of charging stations depends on each city location. The potential market sizes of each city are assumed according to population size so that local path coverage in a more populated city will have more influence on optimal decisions. DC fast charging fee ($) is the battery 80% capacity charging fee. For easy comparison with a gasoline vehicle, the average gas price in Michigan ($3.776 per gallon on April 6, 2014 (*GasBuddy*, 2014)) was provided in the conjoint survey.

5.2.4.2 DC Fast Charging Station Demand

Public DC fast charging station demands for each city are estimated sequentially based on EV demand. This is because EV drivers are potential consumers of charging stations during the EV and charging station life cycles. Many scenarios of charging behavior can be considered (*Peterson and Michalek*, 2012). Here we estimate DC fast charging events based on observed data of EV users from a particular EV project (*Smart and Schey*, 2012; *ECOtality*, 2013), which showed that the mean number of charging events per vehicle-day driven is 1.05, and approximately 4.64% of charging events are from public DC fast charging stations. We predict charging station demand over ten years to evaluate profitability of the infrastructure investment. A parametric study on the impact of these assumed parameter values was included in the case study.

5.3 Case Study: Southeast Michigan Market

The proposed decision-making framework is applied on the potential EV market in Southeast Michigan. In the operations model, the relevant portion of Michigan's highway network used to to determine possible paths and flows is shown in Fig. 5.5. There are no public DC fast charging stations in Michigan at the time of this writing. A total of 29 locations (19 cities and 10 junctions) are selected as candidates for charging station locations. Nineteen cities are selected based on their population, with some neighboring cities grouped and treated as a single one. Circle nodes indicate cities where charging stations exist, size of circles represents the size of population, lines indicate shortest highway paths, numbers indicate path distances between nodes, and triangles indicate additional junctions needed for charging stations because of limited EV range.

For the marketing demand model, 124 subjects who live in Southeast Michigan were engaged through ClearVoice Research (*Clearvoice*, 2014) and surveyed on-line using Sawtooth Software (*Orme*, 2009). The subjects consisted of 40% males and 60% females; 3% were 18 to 24 years of age, 20% were 25 to 34 years of age, 22% were 35 to 44 years of age, 14% were 45 to 54 years of age, 26% were 55 to 64 years of age, and 15% were more than 65 years of age. Table 5.3 shows the average relative importance of the attribute in the model based on estimated part-worths of attributes levels. The charging station coverage and vehicle price are evidently important in consumer choices. For MCMC in Hierarchical Bayesian modeling, every tenth draw from the last 50,000 (of 100,000 total) draws were used to obtain the individual's parameter. The total 2014 US EV sales can be projected to 76,820 because it is predicted that EV sales will increase by 67% in 2014 compared to 2013 (*Loveday*,

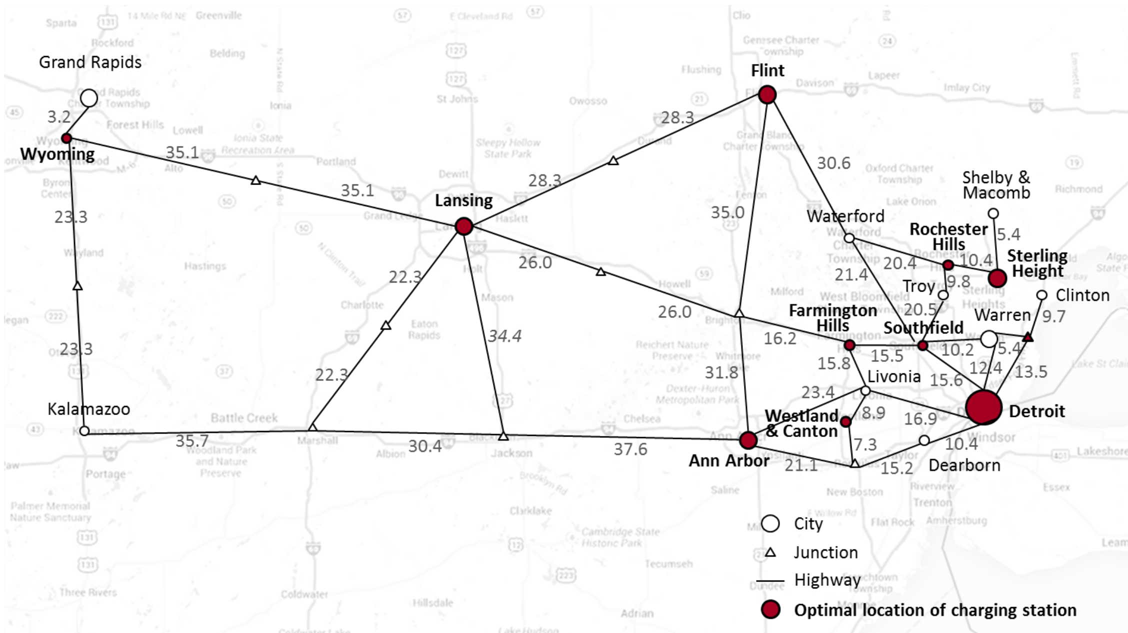


Figure 5.5: Southeast Michigan highway network and optimal locations of charging stations

2014; *IHS*, 2014). We assume the potential EV market size depends on population size. Since the population of the targeted 19 cities in SE Michigan makes up 0.85% of the US population (*Census*, 2014), the potential EV market size of Southeast Michigan was assumed to be 656 in this study. Then, potential market sizes for each city were assigned based on city population size. Two EV competitors operating in Michigan were assumed in computing market share so that the sum of demands of three manufactures and no choice makes 100%.

Matlab's implementation of the GA (*MathWorks*, 2014b) was used to solve the mixed integer optimization problem of Eq. (5.1). We ran three GAs in parallel with different initial guesses[1], and the best result is reported in this study. The results were very close giving some assurance of GA convergence. The computed optimal decision values are summarized in Table 5.4. Response values for these optimal decision values are shown in the left-hand column (cooperative business model) in Table 5.5.

[1]On an Intel i7 CPU 860@2.80GHz and 8.00GB RAM, an optimization run took 36 hours on average.

Table 5.4: Optimal decision values

Model	Variable	Optimal value
Marketing	Vehicle price	$44,211
	Charging fee	$4.0
Engineering	Number of cells in series in one branch	164
	Number of branches in parallel	1
	Stator inductance of the d-axis	1.80mH
	Stator inductance of the q-axis	2.21mH
	Stator resistance	0.052Ω
	Number of pole pairs	3
	Gear ratio	3.87
Operations	Number of stations (out of 29 candidates)	11
	Stations locations	See Fig. 5.5

Note that market responses correspond to the average values of 124 market scenarios using individual-level demand models. Since we considered a heterogeneous market in demand modeling, market response are represented by the distribution of individual responses. The results indicate that the charging station operator must build eleven stations (out of 29 candidates) located in ten cities (i.e., Wyoming, Lansing, Ann Arbor, Flint, Farmington hills, Westland & Canton, Detroit, Southfield, Rochester hills, and Sterling height) and in one junction between Warren and Clinton, see Fig. 5.5. DC fast charging station local path coverages for 19 cities are shown in Fig. 5.6.

5.4 Discussion

Two different business models are compared in order to determine the value of the cooperative business model, described so far. The cooperative business model considers EV manufacturer and fast charging station operator as a single decision entity and finds optimal decisions for EV and stations simultaneously by maximizing overall profit (i.e., EV profit + charging station profit). For this business model, EV manufacturers are encouraged to expand their business to charging station operations

Table 5.5: Responses of two business models

		Cooperative business model	Sequential business model
Market response	Total profit	\$8.39M	\$2.80M
	EV profit	\$9.52M	\$2.78M
	Station profit	-\$1.13M	\$0.02M
	Market share	55.8%	20.0%
EV attributes and specs	Vehicle price	\$44,211	\$40,208
	Range	105.2miles	108.9miles
	Top speed	117.8mph	119.2mph
	Acceleration	13.2sec	12.3sec
	MPGe	172.0	166.8
	Battery capacity	20.6kWh	22.0kWh
	Motor power	93.3kW	99.6kW
EV cost	Battery cost	\$10,314	\$11,006
	Motor cost	\$1,879	\$1,978
Charging station attributes	Charging fee	\$4.0	\$10.0
	Number of stations	11	1 (Detroit)
	Local path coverage (average of 19 cities)	97.1%	16.4%
Charging station cost	Installation and equipment	\$825,000	\$75,000
	Maintenance (10 years)	\$371,746	\$33,795

Note: Market response shown in this table is the mean of market response distribution.

or partner with existing utilities or charging station manufacturers, sharing investment and profit. The second business model is a 'sequential' model similar to current practice, where the EV OEM designs EVs to maximize OEM profit, and the charging station provider makes location decisions for given EV designs to maximize operation profit.

Results for these two business models are compared in Table 5.5. It is shown that the cooperative model brings higher overall profit and market share than the sequential model, where market responses are average values of 124 responses based on the individual demand models. For comparison of heterogeneous market scenarios, we compared 124 responses as shown in Fig. 5.7, so that 84% of responses shows that the cooperative business model offers more profit than the sequential one (i.e., positive

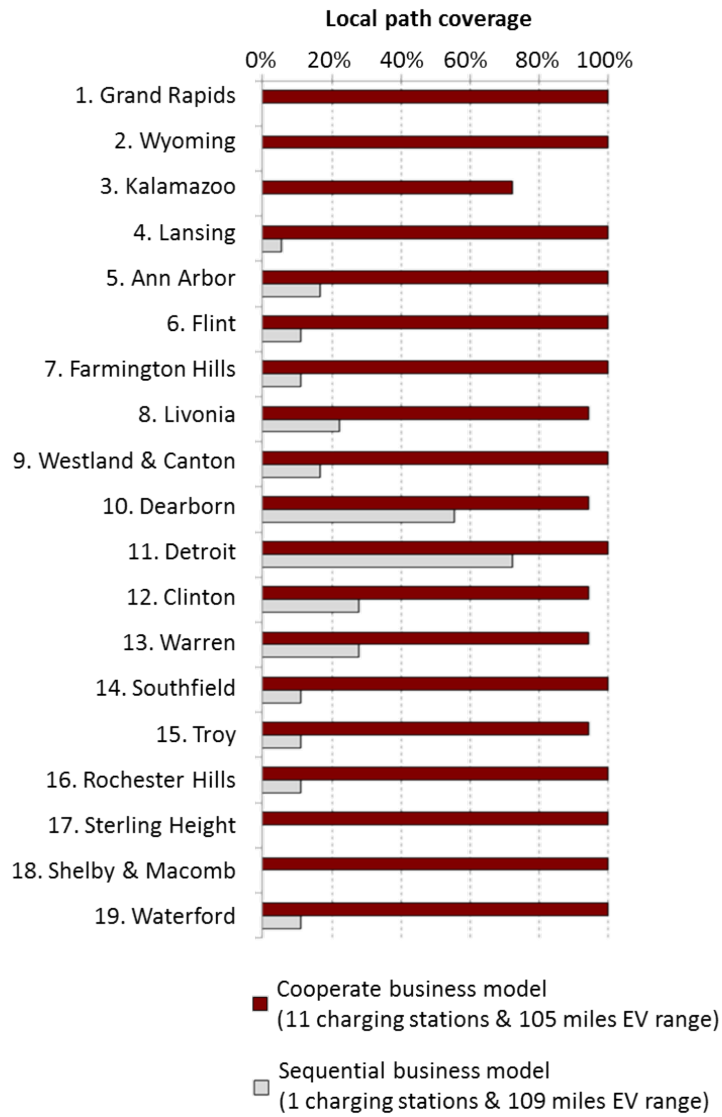


Figure 5.6: Charging stations coverage for each city under two business models

difference).

The cooperative model requires relatively lower EV performance in range, top speed, acceleration, battery capacity, and motor power than the sequential one, even if the vehicle price is higher. Regarding charging station attributes, the sequential model could not build enough charging stations (i.e., one station for Detroit and 16.4% coverage) and offered higher charging fee than the cooperative model.

One may conclude that, under the modeling assumptions made, a non-cooperative

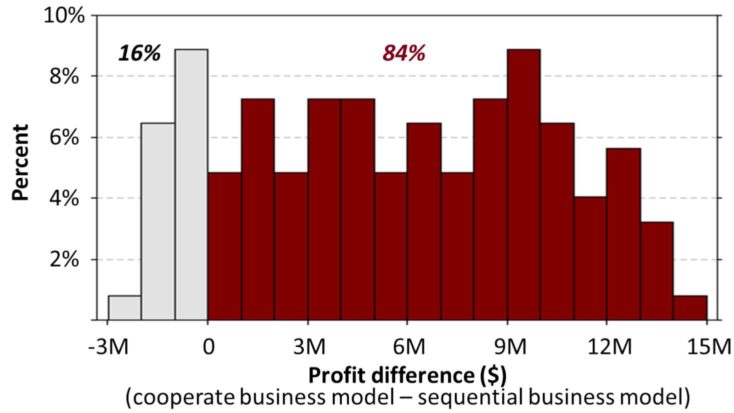


Figure 5.7: Histogram of profit differences between results from the two business models

business model does not improve the attractiveness of EVs to consumers. While the sparse charging station infrastructure of the sequential model can be the main reason of range anxiety, a balance between EV performance and charging station infrastructure can effectively reduce consumer range anxiety. The cooperative model allows for more market share by supplying low charging fee and larger charging station coverage to consumers despite lower performance and higher vehicle price than the sequential model. Since the cooperative model allows negative profit of charging stations, attractive charging station attributes can boost EV adoption share, resulting in higher overall profit than the sum of the two positive individual profits from EV and charging stations in the sequential model. This is an example of examining a product-service system in an integrated business model (*Kang et al.*, 2013a).

A parametric study for different battery cost parameters and sensitivity analysis for different charging behaviors (i.e., % of DC fast charging station events out of all charging events) were examined in a post-optimal analysis. The parametric study in Fig. 5.8 shows that when battery cost decreases from $500 to $200, optimal profit can increase by 31% with optimal 114 EV range. Sensitivity analysis shows that when DC charging event (%) increases by 1%, the profit increases by 0.25%. Since the goal of this study is not to advocate specific decision values but to propose a modeling

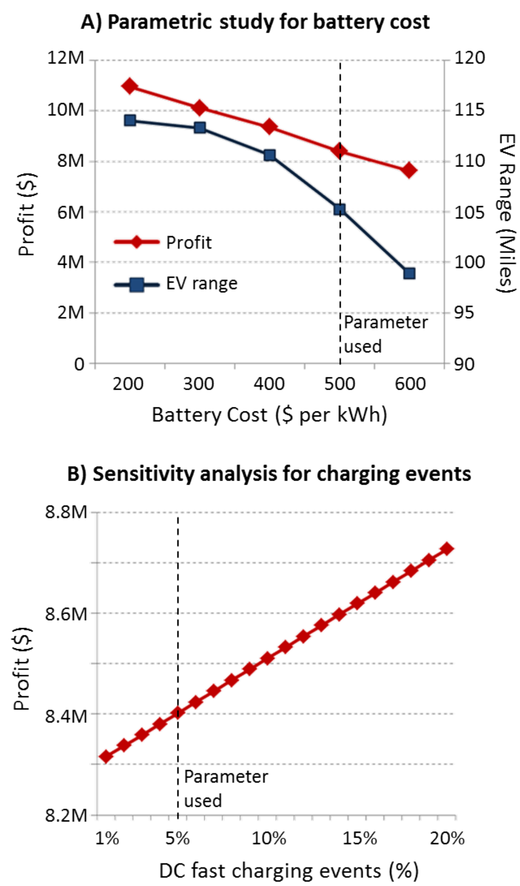


Figure 5.8: Post-optimal analysis

framework, decision makers can adopt different market assumptions (parameters) for their decisions.

5.5 Conclusion

The proposed integrated decision-making framework allows quantification of the tradeoffs among various business models for the EV market. A cooperative business model presents more advantages than the existing non-cooperative business model. The results clearly depend on the modeling assumptions made; however, these are generally sufficiently plausible to support the case for a cooperative approach to improve consumer adoption of EVs.

5.6 Summary

This chapter proposed a multidomain demand model for engineering and operations design; developed a DMS framework to assess profitability of a cooperative business model using models from marketing, engineering, and operations. This study validated the advantage of the integrated decision-making approach using the multidomain demand model, as compared to a sequential decision-making approach.

Next chapter concludes with a summary, contributions, and future work.

CHAPTER VI

Conclusions

6.1 Summary

Previous Design for Market Systems (DMS) research has focused on modeling engineering design attributes used in demand models, largely, limited to product functional attributes. Engineering design-oriented demand models that ignore the effects of non-functional product attributes (e.g., perceptual product attributes and external product attributes) on consumer choice are likely to lead to missed market opportunities. This dissertation proposed a multidomain demand modeling approach to handle disparate (functional and non-functional attributes) to account for decisions coming from various design domains such as engineering, industrial, service, and operations. We integrated consumer preferences on these disparate attributes into a single demand modeling framework. This proposed demand model was applied to design problems linking it with multidisciplinary functional performance sinulation models for joint decision making across multiple design domains. The three main studies of this dissertation are summarized in Table 6.1.

In Chapter III, the multidomain demand model was applied to find a balanced design decision between the engineering and industrial design domains. The scope of attributes addressed in that study refers to the disparate attributes of engineering functionality and aesthetic form in a single product. Our approach used machine

Table 6.1: Summary of three multidomain demand models

Chapter	Attributes scope	Choice scenario	Design domains	Design scope
III	Internal product: function & form	Single choice	Engineering & industrial design	Product
IV	External product: function & service contents	Sequential choice	Engineering & service design	Business model
III	External product: function & infrastructure	Single choice	Engineering & operations design	Business model

learning algorithms and a human computer interaction process to create and incorporate an aesthetic vehicle form preference model into an overall preference model. This demand model has a bi-level and nested structure. At the first-level, form preference is modeled based on 3D geometric variables representing a vehicle's shape. At the second-level, the overall consumer preference is modeled revealing tradeoffs between form preferences and function preferences. This model was demonstrated both by Monte Carlo simulation and crowdsourced online user surveys. A Hierarchical Bayesian (HB) conjoint model was used as the base model, and prediction performance was tested. In both simulation and online surveys, the model showed substantial better prediction performance than the base model. The model can be extended to handle other perceptual attributes besides product form attributes.

In Chapter IV, a multidomain demand model was proposed to reach balanced design decisions between the engineering and service design domains. Compared to Chapter III, the scope of attributes was extended from internal product attributes to external product attributes such as those associated with services; and the choice scenario was extended from the single choice case to the sequential and multiple choices case (i.e., product choice first, then multiple associated service choices). The study accounted for the impact of product-service channels on consumer demand, and focused on linking product demand and service demand models under different channel structures. A channel in this study was assumed to be a shared decision across market players and, therefore, decision-making required strategic cooperation. The study showed channels can significantly affect customer demand and profit for all players. The proposed demand model estimated service demand based on the conditional choice probability given a product choice under non-exclusive product-service channels. We demonstrated the model in a tablet and e-book service examples. The simulation results showed that including channel decisions is necessary in product-service design. This is because, when a producer supplies its service to competitors' products, this service can attract competitors' product users so that service profit can be obtained from competitors' product users besides its own product users; on the other hand, in this exclusive channel situation, a producer can lose product demand to competitors using its service. Competition between producers was also addressed applying game theory with shared channel design variables.

In Chapter V, a multidomain demand model was proposed to rearch a balanced design decision between the engineering and operations design domains. Compared to Chapters III and IV, the scope of attributes was extended from product-service attributes to product-infrastructure attributes; the design target was extended from product-service of a single producer to the cooperative business model of multiple market players. This study addressed the Electric Vehicle (EV) market that is suffering from low consumer adoption, and proposed a DMS framework for a cooperative business model that allows EV manufacturers and charging station operators to work in partnership. The proposed model was compared to a non-cooperative (sequential decision-making) model where manufacturers bring new EVs to the market first and operators decide on charging station deployment. In simulation, the cooperative business model presented higher profit than the non-cooperative business model. The cooperative model requires relatively lower EV performance than the sequential one, even if the vehicle price is higher. For charging station attributes, the sequential model shows that operators cannot build enough charging stations and will offer higher charging fees than the cooperative model. This results showed that a balance between EV performance and charging station infrastructure can effectively increase the marketability of EVs. Moreover, while product-service design in Chapter IV showed that the optimal decision sacrifices product profit to get more service profit, the product-infrastructure design in Chapter V showed that the optimal decision sacrifices infrastructure profit to get more product profit. In both cases, the overall combined profit is higher.

6.2 Contributions

The primary contribution of this dissertation is that we have integrated consumer preferences on disparate (functional and non-functional) attributes into a single demand model to resolve trade-offs between different design domain decisions. These disparate attributes can be internal or external to the designing organization. First, the dissertation has integrated disparate internal attributes preferences for a product into a single demand model. Chapter III proposed a multidomain demand model to incorporate aesthetic form preference into overall preference. This modeling allows engineering designers and industrial designers to cooperate in consumer data-driven new product design. The proposed demand model has a bi-level structure, but it requires only a single survey and operates in real time so that the model can be used with online crowdsourcing. Moreover, the proposed human computer interaction process reflects the natural behavior of consumer choice where one sees product price first and form next, or in reverse order.

Second, the dissertation has integrated disparate external attributes preferences for a product into a single demand model. Chapter IV linked product demand and service demand for cooperating between engineering designers and service designers. The proposed demand model addressed the channel impact on product-service demand, and found optimal channel decisions alongside product-service design. Chapter V integrated product preferences for coordinating decisions between engineering designers and operations designers. The proposed demand model addressed how the heterogeneous target consumers' locations and the infrastructure deployment affect new product adoption.

An additional contribution is that we extended the usage of DMS from the engineering design problem to "business model" design problem. The dissertation proposed an optimal business model decision making approach with product, service, and infrastructure design considerations. This approach can be used not only for a single producer but also for multiple producers in partnership in a cooperative business model. Advantages of the cooperative business model compared to the non-cooperative business model were demonstrated in Chapter V.

A practical contribution of the dissertation is the demonstration of the theory in case studies such as automobile design, tablet & e-book designs, and EV and charging station location designs. The simulation-based results can give a practical insight to a decision maker in each design domain, and different market scenarios can be tested.

6.3 Limitation and Future Work

There are several limitations and avenues for future work for this dissertation. In Chapter III, it is difficult to cover the entirety of the design space with parametric design variables, although product representations used in the proposed conjoint survey should be controlled parametrically. Parametric shape models can present modest changes in shape from the base shape, but this may not be applicable to big design changes. Next, active learning with respect to a large number of design variables entails ever greater computational costs, even if advanced machine learning techniques can reduce computational costs compared to HB. Since we use responses of former subjects for active learning, the computational burden becomes greater when we have survey responses from many subjects. Moreover, ideally we need to test a wider variety of machine learning algorithms. Here we used SVM , but this may not be the best methodology for this sort of preference modeling. The proposed bi-level adaptive structure can be fruitfully deployed in conjunction with a variety of machine learning algorithms.

In Chapter IV, the framework should be tested in different product classes and contractual contexts, to determine its general applicability and robustness throughout product-service systems. Moreover, the proposed framework can be extended to product or service family design, although this will require detailed knowledge of consumer preference heterogeneity, which can in theory be assessed using pre-market forecasting methods.

In Chapter V, a government policy model can be integrated in the proposed framework to explore quantitatively how government incentives and regulations can affect market decisions.

Immediate future work is about integrating all models presented in this dissertation into a holistic design framework with engineering, marketing, operations, public policy and industrial design considerations. For example, we may extend the DMS framework for EV market in Chapter V as shown in Fig 6.1. Table 6.2 presents the nomenclature for this framework. Each discipline has a local optimization problem, and the system level optimization problem is stated as follows.

$$\max_{\bar{\mathbf{X}}} \quad \Pi_{EV} + \Pi_{CS} = (P_{EV} - C_{EV})D_{EV} + (P_{CS} - C_{EC})D_{CS} - C_{CS} \tag{6.1}$$

with respect to

$$\bar{\mathbf{X}} = [\mathbf{X}_{EV}, \mathbf{X}_{form}, \mathbf{X}_{CS}, P_{EV}, P_{CS}, S_{EV}, S_{CS}, S_{tax}] \tag{6.2}$$

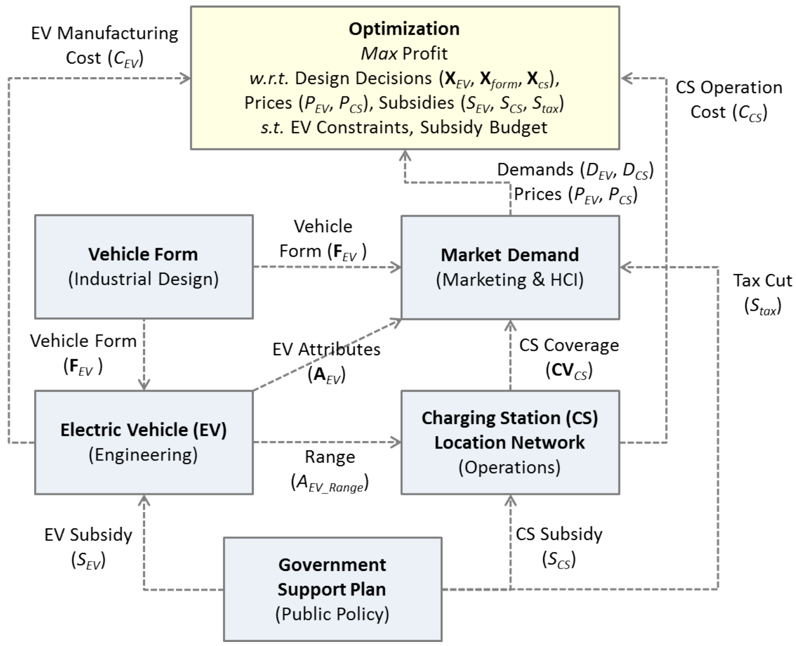


Figure 6.1: Future DMS framework

subject to

$$
\begin{aligned}
lb \leq \mathbf{X} \leq ub \\
\mathbf{g}_{EV}(\mathbf{A}_{EV}) \leq \mathbf{0} \\
S_{EV} + S_{CS} + S_{tax} \leq ub
\end{aligned} \tag{6.3}
$$

where

$$
\begin{aligned}
\mathbf{X}_{EV} = [\mathbf{B}_{EV}, \mathbf{M}_{EV}, G_{EV}] \\
\mathbf{X}_{CS} = [\mathbf{L}_{CS}, N_{CS}] \\
\mathbf{A}_{EV} = [A_{EV_{range}}, A_{EV_{mpge}}, A_{EV_{speed}}, A_{EV_{accel}}]
\end{aligned} \tag{6.4}
$$

$$
\begin{aligned}
[D_{EV}, D_{CS}] = f_{demand}(P_{EV}, P_{CS}, S_{tax}, \mathbf{A}_{EV}, \mathbf{F}_{EV}, \mathbf{CS}_{CS}) \\
\mathbf{F}_{EV} = f_{form}(\mathbf{X}_{form}) \\
\mathbf{A}_{EV} = f_{EV}(\mathbf{X}_{EV}, \mathbf{F}_{EV}) \\
\mathbf{CV}_{CS} = f_{CS}(\mathbf{X}_{CS}, A_{EV_{range}})
\end{aligned} \tag{6.5}
$$

- Objective Eq. (6.1): Maximize overall profit from EVs and charging stations.

- Design decisions Eq. (6.2): EV design $\mathbf{X}_{EV}$, vehicle form $\mathbf{X}_{form}$, charging station (CS) design $\mathbf{X}_{CS}$, EV price P_{EV}, charging fee P_{CS}, government subsidies $\mathbf{S}$ for

EV, CS, and consumer's tax cut.

- Constraints Eq. (6.3): Design variables $\mathbf{X}$ have lower and upper bounds; EV attributes $\mathbf{A}_{EV}$ have inequality constraints $\mathbf{g}_{EV}$ to satisfy current market standards; and government subsidies, S_{EV}, S_{CS}, and S_{tax}, cannot exceed budget.

- Variables and responses Eq. (6.4): EV design variables $\mathbf{X}_{EV}$ include battery design variables $\mathbf{B}_{EV}$, motor design variables $\mathbf{M}_{EV}$, and gear ratio G_{EV}. CS design variables $\mathbf{X}_{CS}$ include CS locations $\mathbf{L}_{CS}$ and the number of CS N_{CS}. EV attributes $\mathbf{A}_{EV}$ include range, MPGe, top speed, and acceleration.

- Multidisciplinary functions Eq. (6.5): In demand model f_{demand}, demand $\mathbf{D}$ of EV and CS are predicted based on EV price P_{EV}, charging fee P_{CS}, tax cut S_{tax}, EV attributes $\mathbf{A}_{EV}$, EV form $\mathbf{X}_{form}$, and CS coverage $\mathbf{CV}_{CS}$; in vehicle form model f_{form}, EV form $\mathbf{F}_{EV}$ is generated by form design variables $\mathbf{X}_{form}$; in EV design model f_{EV}, EV attributes $\mathbf{A}_{EV}$ are simulated based on EV design variables $\mathbf{X}_{EV}$ and EV form $\mathbf{F}_{EV}$; and in CS location network model f_{CS}, CS coverage $\mathbf{CV}_{CS}$ for target locations is obtained based on CS design variables $\mathbf{X}_{CS}$ and EV range $A_{EV_{range}}$.

In summary, this future work will offer an integrated decision making framework for EV market systems considering engineering (EV design), operation (CS location network), industrial design (vehicle form design), marketing and HCI (market demand), and public policy (government support plan). This framework can help manufacturers, operators, consumers, and policy makers to understand the relationship among each other in EV market systems. Then, the proposed framework makes it possible to identify optimal balance among the design decisions from different disciplines when they are coupled and have trade-offs. In addition, we will analyze sensitivities of the solution by varying input parameters and assumptions.

Table 6.2: Nomenclature for future DMS framework

Type	Decision Variables	Responses of Models	Others
Vehicle Form (Industrial Deisgn)	$\mathbf{X}_{form}$: Form design variables	$\mathbf{F}_{EV}$: Vehicle form	
Electric Vehicle (EV) (Engineering Design)	$\mathbf{X}_{EV}$: EV design variables	$\mathbf{A}_{EV}$: EV attributes	C_{EV}: EV manufacturing cost
	$\mathbf{B}_{EV}$: Battery design variables	$A_{EV_{range}}$: Range	
	$\mathbf{M}_{EV}$: Motor design variables	$A_{EV_{mpge}}$: Miles per gallon gasoline equivalent	
	G_{EV}: Gear ratio	$A_{EV_{speed}}$: Top speed	
		$A_{EV_{accel}}$: Acceleration	
Charging Station (CS) (Operations Design)	$\mathbf{X}_{CS}$: CS design variables	$\mathbf{CS}_{CS}$: CS coverage of each location	C_{CS}: CS operation cost
	$\mathbf{L}_{CS}$: CS locations		C_{EC}: Electric cost
	N_{CS}: Number of CS		
Demand (Marketing)	P_{EV}: EV price	D_{EV}: EV demand	
	P_{CS}: Charging fee	D_{CS}: CS demand	
Govenment Support (Public Policy)	S_{EV}: EV subsidy		
	S_{CS}: CS subsidy		
	S_{tax}: Tax cut		

APPENDICES

APPENDIX A

Survey Data

Table A.1: Demographic data for subjects in Chapter III (1/3)

Question	Choice	Model 1	Model 2	Model 3
What is your gender?	Male	51	45	46
	Female	49	55	54
	Total	100	100	100
What is your age?	15 - 24 yrs	3	2	6
	25 - 34 yrs	9	10	18
	35 - 44 yrs	16	23	22
	45 - 54 yrs	25	22	20
	55 - 64 yrs	27	32	16
	65 - 74 yrs	16	8	16
	75 - 84 yrs	4	3	1
	More than 84 yrs	0	0	1
	Total	100	100	100
How would you classify yourself?	African-American	5	6	8
	Caucasian	89	79	77
	Native American	3	1	2
	Hispanic/Latino	1	5	6
	Asian-American	2	4	4
	Other	0	5	3
	Total	100	100	100
Where is your home located?	Metropolitan city	13	10	13
	Suburban community of a larger city	44	35	41
	Small town or rural city	37	45	42
	Farming area	6	10	4
	Total	100	100	100
Please indicate the highest level of education you have completed.	Grade school	0	0	1
	Some high school	4	5	5
	High school graduate	12	23	13
	Some trade school	2	5	2
	Trade school graduate	7	9	5
	Some community college	11	15	10
	Graduate with two-year degree	13	7	11
	Some university	5	12	14
	Graduate with bachelor's degree	25	15	18
	Some postgraduate study	6	1	4
	Postgraduate degree	15	8	16
	Other	0	0	1
	Total	100	100	100

Table A.2: Demographic data for subjects in Chapter III (2/3)

Question	Choice	Model 1	Model 2	Model 3
Which one of the following best describes your current occupation?	Armed services	0	1	1
	Senior executive	2	0	3
	Mid-level manager	8	2	8
	Entry-level professional	4	2	2
	Owner, Self-employed	10	11	10
	Clerical	8	3	4
	Technician	0	4	1
	Police, Postal, Fire	2	3	4
	Sales	3	2	5
	Teacher, Educator	2	2	5
	Professional, Specialty	11	3	8
	Farming, Forestry, Fishing	0	1	1
	Service worker (food, cleaning)	3	0	2
	Precision production, Craftsworker	0	3	1
	Driver, Machine operator	2	1	1
	Fabricator, Laborer	0	2	1
	Student	2	6	4
	Homemaker	12	19	15
	Retired	25	28	15
	Other	6	7	9
	Total	100	100	100
Please check your approximate total annual household income from all sources (before taxes).	$15,000 or less	5	9	7
	$15,001 - $20,000	5	7	5
	$20,001 - $25,000	5	7	3
	$25,001 - $30,000	8	9	7
	$30,001 - $35,000	7	6	8
	$35,001 - $40,000	7	5	9
	$40,001 - $45,000	5	4	5
	$45,001 - $50,000	10	13	7
	$50,001 - $55,000	5	2	3
	$55,001 - $65,000	4	6	4
	$65,001 - $75,000	3	9	8
	$75,001 - $85,000	7	9	8
	$85,001 - $100,000	6	4	6
	$100,001 - $125,000	7	3	2
	$125,001 - $150,000	9	2	7
	$150,001 - $200,000	3	0	2
	$200,001 - $300,000	2	1	1
	$300,001 - $400,000	0	0	1
	Over $400,000	0	0	0
	Prefer not to answer	2	4	7
	Total	100	100	100

Table A.3: Demographic data for subjects in Chapter III (3/3)

Question	Choice	Model 1	Model 2	Model 3
Please indicate your marital status.	Married	57	51	57
	Single, never married	24	22	27
	Divorced, widowed, separated	19	27	16
	Total	100	100	100
How many family members do you have? (Including yourself)	1	21	18	21
	2	31	34	34
	3	15	17	13
	4	16	15	18
	5	8	6	10
	6	2	2	2
	7	1	5	1
	8	1	0	0
	9	1	0	0
	More than 9	4	3	1
	Total	100	100	100
How many children do you have?	0	46	35	35
	1	10	15	19
	2	24	20	27
	3	12	16	14
	4	4	6	4
	5	2	4	0
	6	2	3	0
	7	0	0	0
	8	0	0	1
	More than 8	0	1	0
	Total	100	100	100
Is your spouse employed?	Yes	35	41	42
	No	29	13	22
	I don't have a spouse	36	46	36
	Total	100	100	100

Table A.4: 20 best-seller prices in Chapter IV (*Gilbert*, 2012)

No	E-book title (author)	E-book price ($)			
		Amazon	B&N	iBook	Google
1	The Help (Kathrynn Stockett)	9.99	9.99	9.99	12.99
2	The Hunger Games (Suzanne Collins)	5.00	8.99	None	5.00
3	Water for Elephants (Sara Gruen)	6.73	6.73	9.99	5.99
4	The Girl Who Played With Fire (Stieg Larsson)	9.99	9.99	9.99	9.99
5	Inheritance (Christopher Paolini)	13.99	13.99	13.99	13.99
6	The Son Of Neptune (Rick Riordan)	9.99	10.00	11.99	11.99
7	The Litigators (John Grisham)	9.99	9.99	9.99	9.99
8	A Game of Thrones (George R.R. Martin)	8.99	8.99	8.99	8.99
9	The Confession (John Grisham)	9.99	9.99	9.99	9.99
10	The Best of Me (Nicholas Sparks)	9.99	9.99	9.99	9.99
11	Smokin' Seventeen (Janet Evanovich)	8.99	8.99	8.99	8.99
12	Bossypants (Tina Fey)	12.99	12.99	12.99	12.99
13	11/22/63 (Stephen King)	9.99	9.99	9.99	9.99
14	Cutting for Stone (Abraham Verghese)	9.99	9.99	9.99	9.99
15	The Throne of Fire (Rick Riordan)	7.99	7.99	9.99	10.99
16	Room (Emma Donoghue)	9.99	9.99	9.99	9.99
17	The 17 Day Diet (Dr. Mike Moreno)	12.99	12.99	12.99	12.99
18	Something Borrowed (Emily Giffin)	7.99	7.99	7.99	7.99
19	The Lincoln Lawyer (Michael Connelly)	7.99	7.99	7.99	7.99
20	Sarah's Key (Tatiana de Rosnay)	11.99	11.99	11.99	11.99

APPENDIX B

Part-worths of Conjoint Analysis

Table B.1: Part-worths of product attributes in Chapter III

Attributes		Mean	STD
Form importance		5.92	1.52
Price	$23K	0.00	0.00
	$25K	-0.10	0.61
	$26K	-0.20	1.08
	$29K	-0.80	1.34
	$31K	-1.38	1.77
MPG (city/highway)	23/27	0.00	0.00
	23/29	0.22	0.52
	24/30	0.31	0.91
	25/31	0.65	0.93
	26/32	0.77	1.31

Table B.2: Part-worths of product attributes in Chapter IV

Attributes	Levels	Mean	STD	Importance
Compatible e-books	Amazon	-0.86	1.16	30.5%
	B&N	-3.12	0.92	
	iBook	-3.10	1.41	
	GooglePlay	-2.60	1.01	
	Amazon, B&N	1.03	0.90	
	Amazon, iBook	0.97	0.88	
	Amazon, GooglePlay	1.11	0.97	
	B&N, iBook	-1.28	1.11	
	B&N, GooglePlay	-1.06	0.83	
	iBook, GooglePlay	-1.22	1.23	
	Amazon, B&N, iBook	2.33	0.87	
	Amazon, B&N, GooglePlay	2.30	0.97	
	Amazon, iBook, GooglePlay	2.05	0.89	
	B&N, iBook, GooglePlay	0.33	1.14	
	Amazon, B&N, iBook, GooglePlay	3.12	0.89	
Tablet brand	Kindle	0.62	1.76	19.3%
	Nook	-0.91	1.39	
	iPad	0.91	2.39	
	Nexus	-0.62	1.60	
Tablet price	$129	3.41	3.25	28.2%
	$199	2.31	1.82	
	$299	0.32	0.89	
	$399	-1.98	1.98	
	$499	-4.06	2.85	
Display size	7”	-0.48	0.83	9.8%
	7.9”	-0.13	0.74	
	8.9”	0.04	0.63	
	9.7”	0.10	0.84	
	10”	0.48	0.77	
Storage	8GB	-1.77	1.40	12.2%
	16GB	-0.54	0.88	
	32GB	0.37	0.48	
	64GB	0.78	0.76	
	128GB	1.16	1.15	
None		-1.72	3.78	

Table B.3: Part-worths of service attributes in Chapter IV

Attributes	Levels	Mean	STD	Importance
E-book market	Amazon	1.33	2.26	42.6%
	B&N	-0.65	1.31	
	iBook	-0.41	1.41	
	GooglePlay	-0.27	1.56	
E-book price (best-seller)	$8.99	3.63	3.86	39.5%
	$9.99	1.20	1.07	
	$10.99	-1.92	2.10	
	$11.99	-2.91	2.77	
Easy to shop	By app	1.61	2.43	17.9%
	By web-based store outside app	-1.61	2.43	
None		-3.33	3.07	

Table B.4: Part-worths of EV and charging station attributes in Chapter V

Attributes	Levels	Mean	STD	Importance
Local path coverage	0%	-2.80	2.16	27.2%
	25%	-0.78	0.92	
	50%	0.26	0.57	
	75%	1.27	1.06	
	100%	2.05	1.76	
Charging fee	$0	0.73	0.76	13.7%
	$2	0.45	0.45	
	$5	0.40	0.42	
	$8	-0.48	0.71	
	$10	-1.11	0.89	
Vehicle price	$20K	2.56	2.13	32.0%
	$30K	1.70	1.38	
	$40K	0.51	0.86	
	$50K	-1.49	1.51	
	$60K	-3.28	2.26	
Range	70 miles	-1.44	1.00	15.5%
	120 miles	-0.17	0.51	
	170 miles	0.10	0.46	
	220 miles	0.61	0.51	
	270 miles	0.91	0.83	
Fuel efficiency	70 MPGe	-0.29	0.29	3.8%
	100 MPGe	-0.05	0.19	
	130 MPGe	0.02	0.12	
	160 MPGe	0.11	0.20	
	190 MPGe	0.21	0.31	
Top speed	70 mph	-0.26	0.30	3.9%
	85 mph	-0.23	0.29	
	100 mph	0.04	0.16	
	115 mph	0.20	0.27	
	130 mph	0.26	0.32	
Acceleration (0 to 60 mph)	8 sec	0.30	0.37	3.9%
	13 sec	0.11	0.17	
	19 sec	-0.09	0.14	
	25 sec	-0.15	0.18	
	30 sec	-0.18	0.21	
None		0.61	3.31	

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