ABSTRACT

Title of Dissertation: STRATEGIC PRODUCT DESIGN DECISIONS FOR UNCERTAIN, CONVERGING AND SERVICE ORIENTED MARKETS

Zhichao Wang, Doctor of Philosophy, 2012

Dissertation directed by: Shapour Azarm
Professor, Department of Mechanical Engineering

P. K. Kannan
Professor, Department of Marketing

Market driven product design decisions are receiving increasing attention in the engineering design research literature. Econometric models and marketing research techniques are being integrated into engineering design in order to assist with profit maximizing product design decisions. This stream of research is referred to as "Design for Market Systems" (DMS). The existing DMS approaches fall short when the market environment is complex. The complexity can be incurred by the uncertain action-reactions of market players which impose unexpected market responses to a new design. The complexity can originate from the emergence of a niche product which creates a new product market by integrating the features of two or more existing products categories. The complexity can also arise when the designer is challenged to handle the couplings of outsourced subsystems from suppliers and explore the integration of the product with service providers. The objective of the thesis is to overcome such limitations and facilitate design decisions by modeling and interpreting the complex market environment.

The research objective is achieved by three research thrusts. Thrust 1 examines the impact of action-reactions of market players on the long and short term design decisions for single category products using an agent based simulation approach. Thrust 2 concerns the design decisions for

"convergence products". A convergence product physically integrates two or more existing product categories into a common product form. Convergence products make the consumer choice behavior and profit implications of design alternatives differ significantly from the situation where only a single product market is involved. Thrust 3 explores product design decisions while considering the connection to the upstream suppliers and downstream service providers. The connection is achieved by a quantitative understanding of interoperability of physical product modules as well as between a physical product and a service provider.

STRATEGIC PRODUCT DESIGN DECISIONS FOR

UNCERTAIN, CONVERGING AND SERVICE ORIENTED MARKETS

By

Zhichao Wang

Dissertation submitted to the Faculty of Graduate School of the

University of Maryland, College Park in partial fulfillment

of the requirements for the degree of

Doctor of Philosophy

2012

Advisory Committee:

Professor	Shapour Azarm, Advisor/Chair
Professor	P. K. Kannan, Co-Advisor
Associate Professor	Jeffrey Herrmann
Professor	Subramanian Raghavan (Dean's representative)
Associate Professor	Linda Schmidt

To My Beloved Parents, Family and Friends

ACKNOWLEDGEMENTS

TABLE OF CONENTS

LIST OF FIGURES

LIST OF TABLES

NOMENCLATURE

NOMENCLATURE OF CHAPTER 2:

A_i	Action space of agent i
$A_i^{[R]+}$	Subset of action space for agent i containing actions with positive regret value
B	Indicator function for the sign of a regret function
$C_m^k(x_m^k)$	Cost function for manufacturer m at iteration k
$EAP_i^k(x)$	Empirical action profile function for agent i at iteration k
ECI_i^k	Empirical convergence index for agent i at iteration k
g	Inequality constraint function in the engineering design problem
M^k	Market share matrix at iteration k
m_{ij}^k	Market share of product i sold by retailer j at iteration k
N_m	Number of manufacturer agents
N_r	Number of retailer agents
$prob_i$	Probability that product i is purchased
q_h^k	Vector of quantiles representing the h'th dimension of $EAP_i^k(x)$
$r_{r,}^k$	Retail margin of retailer i at iteration k
$R_i^k(x)$	Regret function for agent i at iteration k
$[R_i^k(x)]^+$	Regret function with positive value
s_l	Size of market segment s
$S_i^k(x)$	Strategy function of agent i at iteration k
T_c	Convergence condition step parameter
u_i	Utility of product alternative i
w^k	Joint wholesale pricing action of all manufacturing firms at iteration k
w_i^k	Wholesale pricing action of firm i at time k
x	Action of agents
x_i^k	Action taken by agent i at iteration k
x_{-i}^k	Joint action of all agents except agent i at iteration k
y	Long term engineering design decision
z^k	Joint engineering design action of all manufacturing firms at iteration k
z_c	Continuous engineering design variables
z_d	Discrete engineering design variables
z_i^k	Engineering design actions of agent i at iteration k
Z_i	Feasible region of engineering design actions for agent i
β	Coefficient vector of utility function
ε	Error term in utility function
ε_c	Convergence condition tolerance
ξ_i	Customer observed attributes of choicealternative i
$\prod_m^k(x^k)$	Payoff for agent m at iteration k

NOMENCLATURE OF CHAPTER 3:

A	Parameter representing prior of $\boldsymbol{\tau}$
b, b_1, b_2	Discounting coefficients in production cost formulation
CI_i	Convergence Index with respect to existing product category i
D_i	Difference between convergence product and existing product i
$D_{i,j}$	Difference between convergence product and existing product i regarding functionality j
$d_{i,j,m}$	Difference between convergence product and existing product i regarding m'th module that enables functionality j
EM	Functionality enabling matrix
F	Binary vector indicating inclusion of functionalities in a design alternative
$F_{i,j}$	Binary indicating if product i has functionality j
IUE	Impact of usage evolution
$K(Q,X)$	Production cost as a function of quantity Q and product attribute X
K_1	Unit production cost when produced at quantity of 1
M	Binary vector indicating inclusion of modules in a design alternative
$M(F_j)$	Set of modules that enable functionality F_j
$N_{M(Fj)}$	Number of modules in set $M(F_j)$
N_c	Predicted market size for convergence product
N_i	Market size for existing product i
N_{ij}	Size of overlap for product markets i and j
$O_{i,j}$	Overlap(in percentage) of product markets i and j
$Q(\boldsymbol{x}^*)$	Predicted sales quantity for design alternative $\boldsymbol{x}^*$
p	Price
$Prob_0$	Choice probability for a design alternative at present
$Prob_1$	Choice probability for a design alternative in future
$\mathbf{S}_{i,p}$	Set of sub-modules for module i in existing product p
$\mathbf{S}_i(\mathbf{x})$	Set of sub-modules for module i in design alternative $\boldsymbol{x}$
SM	Binary vector indicating inclusion of sub-modules in a design alternative
$U_{i,j}$	Utility of choice alternative j for consumer i
U_{NC}	Utility for choosing "none" option
$\mathbf{V}_0$	Parameter representing prior of V_β
$\mathbf{V}_\beta$	Parameter representing prior of $\boldsymbol{\beta}_i$
x	Engineering design variables
X	Customer observed product attributes
$\mathbf{X}_j$	Customer observed product attributes of alternative j
$\mathbf{X}_i^n$	Customer observed product attributes of product n owned by consumer i
y	An observed choice made by a consumer
y	A sequence of observed choices made by a consumer
Z	Feasible region for attributes of sub-modules
$\mathbf{z}_{ij}$	Attributes of sub-module j of module i
$\mathbf{z}_{sm}$	Attributes of sub-module sm
$\bar{\boldsymbol{\tau}}$	Parameter for prior of $\boldsymbol{\tau}$
$\Pi(\mathbf{x};p)$	Profit Function
$\boldsymbol{\beta}_i$	Consumer i's preference coefficients

$\boldsymbol{\beta}_i{}^*$	Consumer i's preference coefficients for future
$\boldsymbol{\gamma}_{i,f}{}^i$	Coefficients relating attributes of a product to satisfaction that consumer i obtains by using functionality f at level l
ε	Error
$\xi^i{}_f{}^*$	Consumer i's usage conditions of functionality f for future
$\xi^i{}_{f,\,l}$	Binary indicating consumer i's usage of functionality f at frequency level l
$\xi_f{}^i$	Consumer i's usage conditions for functionality f
$\xi_{f,\,situation}^i$	Consumer i's need for specific usage situations regarding functionality f
$\xi_{f,\,access}^i$	Consumer i's need for instant access to functionality f
$\xi_{f,\,frequency}^i$	Consumer i's usage frequency of functionality f
ξ_i	Consumer i's usage conditions
$\xi_i{}^*$	Consumer i's usage conditions for future
$\xi_i{}^0$	Inherent component in consumer i's usage conditions
$\xi_i{}^1$	Variable component in consumer i's usage conditions
$\rho_{f,\,l}{}^i$	Consumer i's satisfaction by using functionality f at level l
$\rho_{f,\,l}{}^{i,n}$	Consumer i's satisfaction by using product n's functionality f at level l
τ	Coefficients relating consumers' usage conditions to their preferences
υ_0	Parameter for prior of V_β

NOMENCLATURE OF CHAPTER 4:

AF	Activity function dependency matrix
A_{ROI}	Area of region of interoperability
A_{ROO}	Area of region of operation
$\boldsymbol{g}$	Feasibility constraint functions
IM	Interoperability metric
KPA	Key performance attributes
m_s	Size of market segment s
$\boldsymbol{o}$	System outputs
$\boldsymbol{p}$	System parameters
$\mathbf{P}$	Set of all the possible values of an uncertain parameter
$Pr_{i,j}$	Probability that consumer i purchases product alternative j
ROI	Region of interoperability
ROO	Region of operation
$U_{i,j}$	Consumer i's utility for product alternative j
$U_{i,NC}$	Utility of "no-choice"
$\boldsymbol{x}$	Design variables
$\boldsymbol{X}_p$	Product attributes
$\boldsymbol{X}_s$	Service attributes
$\boldsymbol{y}$	Coupling variables
ε_i	Random utility error term

CHAPTER 1: INTRODUCTION

1.1 MOTIVATIONS, RESEARCH THRUSTS AND OBJECTIVES

Design for Market Systems (DMS) is receiving increasing attention in engineering design research. Along this line, econometric and marketing research models are integrated into decision based design frameworks to represent consumer and firm behaviors and estimate demand for design alternatives [e.g., Williams et al, 2008; Shiau and Michalek, 2009; Kumar et al, 2009; Frischknecht et al, 2010]. The market systems are characterized by the action-reactions of a variety of stakeholders, including consumers, competing manufacturers and retailers, who collectively influence the demand and profitability of a new product. Market structures can evolve particularly when design initiatives are made to blur the boundaries of previous loosely related product markets with a new niche product. The evolution of market structure eventually reshapes consumer preference and competition, pushing the designers to rethink their design decision strategies. Meanwhile, sourcing product subsystems from suppliers and integrating consumer products with services are increasingly common in many product categories. Such trends are challenging the designer to resolve the couplings of sourced subsystems (parts, modules, assemblies) along the upstream market, as well as the couplings between the product and service(s) along the downstream market. Yet the know-how knowledge for design decisions in engineering design falls short in the presence of such complexity. The proposed research aims at overcoming the challenges imposed by the complexity of market structures particularly as they affect engineering design decision making.

This dissertation investigates three research thrusts as shown in Figure 1.1. The first thrust, shown with the top panel in Figure 1.1, addresses engineering design decisions arising from action-reactions of market players, such as competing manufacturing firms and powerful retail channels, for a single product category. The second thrust, the middle panel in Figure 1.1, concerns the market driven engineering design decisions for "convergence products" which merges the functionalities of existing products and as such can open up new market opportunities. The third thrust, the bottom panel in Figure 1.1, focuses on the design decisions considering both upstream and downstream market system with interoperability considerations, which is particularly important given the trends that: (i) increasingly manufacturers are outsourcing subsystems from suppliers (i.e., upstream market system), and (ii) in many product markets (e.g., high-tech products such as smartphone and tablet computer), the consumers have the option to subscribe to a variety of services to use the functionalities of the products (i.e., downstream market system).
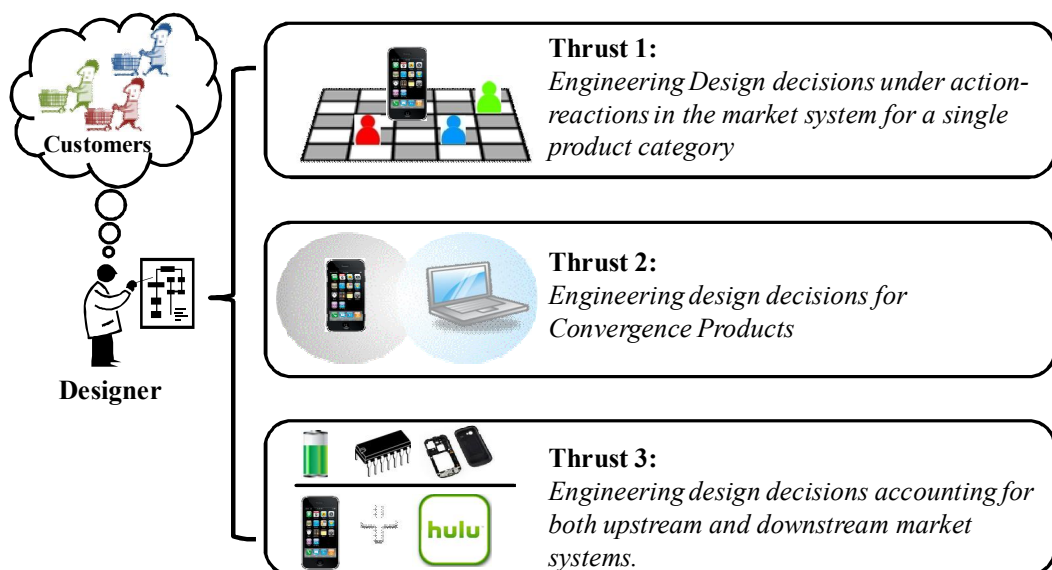
Figure 1.1 Research Framework and Thrust

Research Thrust 1: *Strategic engineering design decisions for uncertain market systems using an agent based approach.*

Objective of Thrust 1: *Investigate the long and short term design decisions in the presence of action-reactions of market players.*

The demand and profit of a new product can be significantly influenced by the market players, such as competing manufacturing firms and retail channels. The competing manufacturer firms can adjust prices and/or improve product features in order to battle the competitions. Retail channels controlling the access to customers can set the retail prices in pursuit of their own profits, which drives the demand for each manufacturer's product. Existing methods in DMS which considers such moves of market players use game theoretic models that can maximize a firm's profit with respect to product design and price variables given the Nash equilibrium of the market system. However, the existing game theoretic approaches can be limited in a number of ways, e.g., incapable of handling action-reactions which involve design of engineering system that are in a black-box form with discrete, non-differentiable and non-convex functions. In this thrust, an agent based approach is proposed for DMS that accounts for learning behaviors of the market players under uncertainty. A market system that is modeled with agents representing competing manufacturers and retailers who possess learning capabilities and based on some pre-specified rules are able to react and make decisions on the product design and pricing. The design decision integrates long term design decisions with short term design and pricing decisions to help a manufacturing firm maintain profitability and competitiveness.

An article based on this thrust has been published in the *Journal of Mechanical Design* [Wang et al., 2011(a)].

Research Thrust 2: *Customer driven design decisions for convergence products.*

Objective of Thrust 2: *Construct a profit maximizing design decision framework for convergence products.*

Convergence products are multifunctional designs which combine a number of distinct functionalities that existing individual products already provide. Examples can be found in a broad range of product categories such as office machines (e.g., "all-in-one" printers), consumer electronics (e.g., tablet computers) and information products (e.g., "Google TV"). Convergence products are becoming popular to both manufacturers and consumers for a number of reasons. First, a convergence product is generally built upon the technologies of existing products, which can significantly reduce the R&D effort and costs. Secondly, a convergence product can be appealing to the consumers who do not use the existing products but are interested in a combination of functionalities that a convergence product offers. Appealing as it may, a convergence product can be complicated to design. A convergence product combines the modules from the existing product categories but performs the functionalities in a different way compared to the existing products. On the other hand, predicting the demand for convergence products can be challenging due to the significant extent of heterogeneity with respect to the consumers' usage and preference of product features. The objective of this thrust is to develop a design decision framework that is specifically tailored for convergence products and maximizes a company's profit while considering sustainable future market

penetration, by accounting for the consumers' usages of the functionalities and their evolving heterogeneous preferences.

An article based on this thrust has been published in the *Journal of Mechanical Design* [Wang et al, 2011(b)].

Research Thrust 3: *Engineering design decisions accounting for both upstream and downstream market systems with interoperability considerations*.

Objective of Thrust 3: *Develop a mathematical model of system interoperability that can be used for product design selection considering*: *(i) supplier selection along the upstream market system, (ii) integration of the physical products with service providers, and (iii) both upstream and downstream market systems*.

Outsourcing components, modules, assemblies and so on from suppliers (upstream market systems) is replacing "in-house" design and production of many products. Here, a product is considered as a system consisting of many coupled components, modules, assemblies, or the subsystems. Since the designer does not have the control over the design of all the subsystems for a product being outsourced, understanding the compatibility (or interoperability) among the subsystems becomes particularly important. Variation of the design for one subsystem propagates through to all other subsystems, which can be exacerbated when the uncertainties are considered as well. This raises the need for a modeling framework in product design selection that accounts for subsystems capable of working well with each other under uncertainty.

Along the downstream market system, consumer product markets are characterized by increasingly close connections to the service sectors. Examples include mobile electronic devices such as smartphones and tablet computers which enable the consumers

to utilize a wide spectrum of services: digital content purchasing, web browsing, social network communication, GPS navigation, etc. Selecting service providers to partner with in order to achieve the product's functionalities to the fullest extent possible has become a critical task for product designers. On the other hand, consumers enjoy the majority of the functionalities of the devices when they are enabled in conjunction with service providers' offerings. The engineering products and the services are thus cast into an integral package to deliver value to the customer. Consumer satisfaction is eventually driven by the design of the product and the quality of the service in a synergetic manner.

This thrust aims at a design selection framework which accounts for both upstream market system (i.e., suppliers) and downstream market system (i.e., service providers and customers) to explore: (i) a mathematical model for interoperability, (ii) modeling of the couplings between the product and the offerings of service providers, and (iii) the integration of upstream and downstream market systems.

1.2 ORGANIZATION OF DISSERTATION

This dissertation is organized as in the following (Figure 1.2). Chapter 2 presents an agent based approach for design for market systems that accounts for learning behaviors of the market players under uncertainty. This chapter addresses the objective of research thrust 1. Chapter 3 presents a customer driven optimal design approach for convergence products. A modular design decision framework will be presented. Additionally, a hierarchical Bayes model is explored to understand the customers' usage and preferences for convergence products. This chapter addresses the objectives of research thrust 2. Chapter 4 addresses the third research thrust by investigating a demand/profit maximizing design selection method which integrates the considerations for both

upstream supplier selection and downstream service provider integration in the market

system. The integration is based on a mathematical model of system interoperability.

Finally, Chapter 5 presents concluding remarks, contributions and possible extensions of

the research presented in this dissertation.

```
┌─────────────────────────────────┐
│  CHAPTER 1: INTRODUCTION         │
│    Motivation, research          │
│    thrusts and objectives        │
└─────────────────────────────────┘
```

```
┌──────────────────┐  ┌──────────────────┐  ┌──────────────────┐
│  CHAPTER 2:      │  │  CHAPTER 3:       │  │  CHAPTER 4:       │
│ (RESEARCH        │  │ (RESEARCH         │  │ (RESEARCH         │
│  THRUST 1)       │  │  THRUST 2)        │  │  THRUST 3)        │
│                  │  │                   │  │  Design selection │
│ An agent based   │  │ Customer driven   │  │ considering       │
│ approach for     │  │ optimal design    │  │ upstream and      │
│ strategic design │  │ for convergence   │  │ downstream market │
│ decisions in     │  │ products          │  │ systems by        │
│ uncertain market │  │                   │  │ modeling          │
│ systems          │  │                   │  │ interoperability  │
└──────────────────┘  └──────────────────┘  └──────────────────┘
```

```
┌──────────────────────────────┐
│  CHAPTER5: CONCLUSION         │
│   Summary of dissertation,    │
│   contributions and future    │
│   research                    │
└──────────────────────────────┘
```

Figure 1.2 Dissertation Overview

CHAPTER 2: STRATEGIC DESIGN DECISIONS FOR UNCERTAIN MARKET SYSTEMS USING AN AGENT BASED APPROACH[1]

Market players, such as competing manufacturing firms and retail channels, can significantly influence the demand and profit of a new product. Existing methods in design for market systems use game theoretic models that can maximize a firm's profit with respect to product design and price variables given the Nash equilibrium of the market system. However, in the design for uncertain market systems, there is seldom equilibrium with players having fixed strategies in a given time period. In this chapter, an agent based approach for design for market systems is presented that accounts for learning behaviors of the market players under uncertainty. By learning behaviors it is meant that the market players gradually, over time, learn to play with better strategies based on action-reaction behaviors of other players. The objective is to model a market system with agents representing competing manufacturers and retailers who possess learning capabilities and based on some pre-specified rules are able to react and make decisions on the product design and pricing. The proposed agent based approach provides strategic design and pricing decisions for a manufacturing firm in response to possible reactions from market players in the short and long term horizons. The example results show that the proposed approach can produce competitive strategies for the firm by simulating market players' learning behaviors when they react only by setting prices, as compared to a game theoretic approach. Furthermore, it can yield profitable product design decisions and competitive strategies when competing firms react by changing

---

[1] This chapter addresses Research Thrust 1, as overviewed in Chapter 1. The material for this chapter is borrowed from (and is the same as) the paper: Wang, Z., Azarm, S., and Kannan, P. K., 2011, "Strategic Design Decisions for Uncertain Market Systems Using an Agent Based Approach", *Journal of Mechanical Design*, 133(4), pp. 041003.1 to 041003.11.

design variables in the short term — a case for which no previous method in design for market systems has been reported.

2.1 INTRODUCTION

The revenue that can be generated by a new product design is not only closely related to its design features but also dependent on the heterogeneous customer preferences and competition from competing manufacturing firms. A survey of a number of "Millennium Product" prize winning manufacturing companies, most of which small and middle sized, has revealed that integrating competitive considerations into product design is a primary reason for a firm's success [Whyte et al., 2003]. Additionally, major retail channels of a product category can significantly influence the revenue generation for a product [Williams et al., 2008]. It is therefore critical for a designer to consider the market environment (i.e., customers, competing firms, retailers) in making product design decisions that meet the goals of the firm such as maximizing profit and market penetration. While marketing survey techniques such as conjoint analysis [Green and Srinivasan, 1978] and others are available to capture customer preferences for a mature product category, predicting the behavior of competitors and retailers is more complex. An example is a manufacturer who redesigns some of its product features and/or adjusts the wholesale price to maintain its competitiveness [Hauser, 1988]. Major retailers make acceptance decisions of the new product and may have to rearrange their shelf spaces to accommodate a redesigned product [Williams et al., 2008]. These retailers may also have to implement pricing strategies such as adjusting retail margins and non-pricing strategies such as adding value to products by providing after-sale services [Iyer, 1998]. Major design features of a product may remain unchanged for a long time due to the research

and development intervals, but action-reactions of market players are observed in a much shorter time scale. A seemingly profitable design option at present could become a failure when market players make their moves in the future. In order to achieve an overall optimal profit, it is therefore vital for the designer to make design decisions on product attributes for long term considerations as well as to develop short term design and pricing strategies for anticipated reactions from market players.

Anticipating the reactions from the market players can be challenging in two ways. First, the decisions by the rival firms cannot be predicted deterministically. The study by Montgomery et al. [Montgomery et al., 2005] of a variety of firms and others [Gurnani and Lewis, 2008] reveal that although managers and designers are aware of the past and forthcoming actions of rival firms, they seldom can make optimal decisions by taking competition into account. It was suggested [Gurnani and Lewis, 2008] that the engineering design variables be represented by probability distributions to account for possible sub-optimal product design solutions and the probability that market players deviate from making optimal decisions. Secondly, market equilibrium arises through a process of actions and reactions among market players. Anticipating an action, e.g., a pricing decision, from a market player involves solving a decision problem. For instance, when a competing manufacturer makes a move, it solves a decision problem with respect to its design and price decisions. Considering the number of market players and their corresponding decision space together with the number of their interactions may result in a large number of decision options that will have to be resolved.

Engineering design methods that account for competition are reported in a number of existing papers, e.g., [Kumar et al., 2009; Besharati et al., 2006; Luo et al., 2005]. These

methods, while accounting for the fact that competing products can influence the demand of a new product, ignore potential reactions from competing firms. Several papers, e.g., [Hauser, 1988; Ofek and Savary, 2003; Choi et al., 1990; Dawid et al., 2001], consider competition for a new product development from a marketing perspective. However, these approaches either consider price competition only while ignoring changes in design [Choi et al., 1990] or they oversimplify design changes without taking into account engineering feasibility [Hauser, 1988; Ofek and Sarvary, 2003; Dawid et al., 2001].

Recent literature [Shiau and Michalek, 2009(a); Shiau and Michalek, 2009(b); Williams et al., 2011; Luo et al., 2007, Karimian, 2010] introduces product design methodologies which account for reactions of competing manufacturing firms and/or retail channels using a game theoretic approach. Specifically, a static, non-cooperative, one shot game with Nash Equilibrium under pure strategies [Gibbons, 1992] is widely used. In the game theoretic models, market players are assumed to pursue their own profits and have full information of the other competitors' strategies in their pursuit of the Nash Equilibrium. However, extant work in design for marketing systems using game theoretic approaches has three limitations. First, it can lead to a design solution that is only guaranteed to be optimal when market players take actions simultaneously. In a real world marketplace, such simultaneous moves rarely exist and thus the resulting Nash solution can become inapplicable in a real setting. In other words, previous works ignore how the equilibrium is arrived at. Secondly, it is assumed that managers and designers are able to predict the strategies of rival firms and make appropriate responses accordingly. Such assumption contradicts the empirical observations [Montgomery, et al., 2005] where managers seldom make decisions by anticipating competitive responses. Finally,

11

the game theoretic approaches [Shiau and Michalek, 2009(a); Shiau and Michalek, 2009(b); Williams et al., 2011; Luo et al., 2007] rely on formulating first order optimality conditions for each player, with respect to the firm's own decision variables, and solving a system of equations for all firms all-at-once. Unfortunately, the first order conditions are not applicable to engineering models that are in a black box form with discrete, non-differentiable and non-convex functions. In the proposed approach, an agent based model is used to overcome the shortcomings of the game theoretic approach. An agent based model (also referred to as a multi-agent system) refers to a system of agents that autonomously make decisions [Wooldridge, 2002] and interact by way of pre-specified rules such as learning protocols, to obtain a system level equilibrium [Miller, 2007]. Several types of multi-agent learning models are discussed in the literature. These include model-based learning, reinforcement learning and no-regret learning [Shoham et al., 2007]. The first two types have shortcomings that do not fit into our framework. For instance, model-based learning entails estimating other agents' strategies, which can be difficult and unrealistic to implement. Also, reinforcement learning is not proved to converge in a general setting [Young, 2004]. However, under a no-regret learning protocol (also referred to as regret matching), each agent has a probability distribution over its decision space representing the chance of making actions in each iteration. This distribution (or the potential strategy) can be adaptively updated using a history of past actions for all the agents. The no-regret learning follows the process that a firm devises its competitive strategy based on its experience over time. In addition, the no-regret learning models have been proved to converge to a "correlated equilibrium" which under

certain conditions is equivalent to the Nash Equilibrium under mixed strategies [Moon et al., 2008].

Finally, the literature reports on agent based approaches that have been used in solving engineering design problems for a single firm [Moon et al., 2008; Orsborn and Cagan, 2009; Campbell et al., 2004; Gorti et al., 1996; Grecu and Brown, 1996; Zhao and Jin, 2003]. The market system is either ignored or taken as exogenous in these studies. There is no reported product design decision model using an agent based method that accounts for the interactions among market players such as competing manufacturing firms and retail channels.

In this chapter, a product design decision making approach is proposed for both long term and short term design using an agent based model that is enabled by a multi-agent learning scheme. The proposed approach is distinguished from previous literature in that: (i) the approach handles competitions that involve designing complex engineering products with "black box" functions (i.e., functions that are implicit, discontinuous, non-differentiable and non-convex); (ii) the design decision accounts for an uncertain market system in which players update their strategies by learning; and (iii) an innovative concept of integrating long term design decisions with short term design and pricing decisions is used to help a manufacturing firm maintain profitability and competitiveness.

2.2 PROBLEM ASSUMPTIONS AND DEFINITION

This chapter aims at a single product design decision methodology for a mature product category. A mature product category is characterized by a stable market size and a fixed number of competing manufacturing firms and retail channels. Customer preferences are assumed to be common knowledge to the firms. The products

manufactured by different firms share the same set of attributes and are differentiated by the level of attributes. A manufacturer's wholesale prices for all the retail channels are assumed to be identical for simplicity. Also, the retailers are assumed to have common, stationary assortment compositions of products. That is, it is assumed that all products will be carried by all retailers, and that does not change overtime.

A "short term design" is defined as a manufacturing firm's strategy in making a minor design change that will serve its respective marketing objective (i.e., profit) in response to the actions of other firms in a short time period (e.g., weeks or months). An example of such strategies would be to redesign the product in a minor way and mimic the product features of competing firms while improving them in order to introduce a somewhat new and better product. In contrast, for a long term horizon (e.g., years), a "long term design" is defined as a firm's design decision in the long run which accounts for the anticipated reactions from a market system after introducing the new design. The combination of all long term design decision options (i.e., long term design subspace) and short term design options (i.e., short term design subspace) forms the entire design decision space. The combination of these two subspaces provides strategic opportunities for both long and short term changes in the product design features for a manufacturing firm. Such a hybrid pattern of changes is prevalent in the real-world design for market systems. For instance, Toyota introduced the 5th generation (long term design) of its mid-size sedan "Camry" into the North America market in 2001. The vehicle experienced minor improvements, for instance, availability of new customizable options annually until 2006 when its 6th generation was introduced with significant changes, e.g., modified exterior and interior design as well as the availability of a hybrid version. The

time horizon for the design changes can be industry specific. In the automobile industry, the "short term" is usually defined by a year while the "long term" can be in a scale of about 5 years.
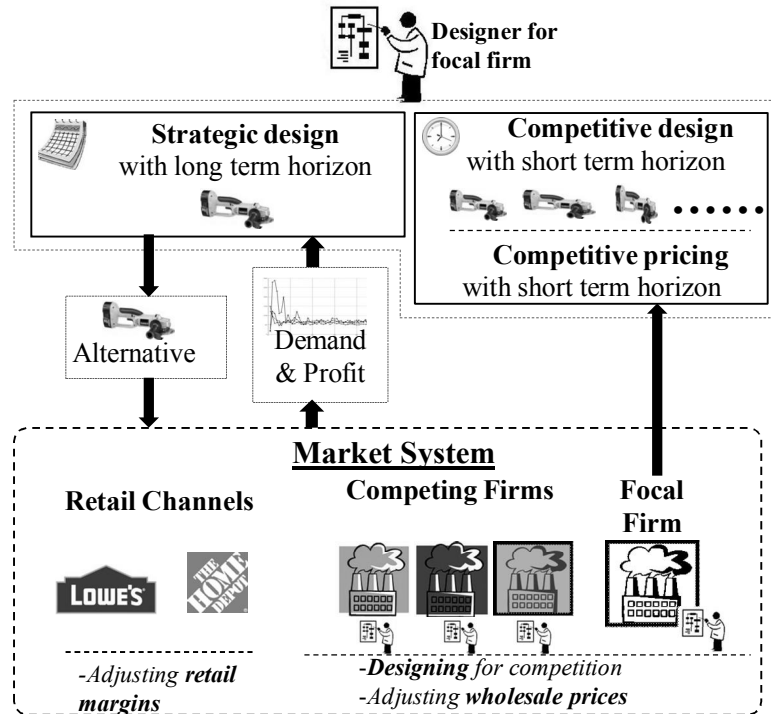
Figure 2.1 Problem Definition

The problem is defined as follows. A focal manufacturer refers to the one, as shown on the top of Figure 2.1, who develops a new product. The focal manufacturer selects the best long term design option by accounting for short term market responses. In the market system, major retail channels control the product's access to the customers and adjust retail margins in pursuit of their own profit. The competing manufacturers would immediately react to the changes in the market system (i.e., changes in designs and prices) by adjusting their own product features (i.e., their short term designs) and wholesale prices. The interactions in the market system foster changing features and demands of products and eventually lead the market to equilibrium. The designer needs

to answer two main questions, as will be explored in this chapter: (i) what is the most profitable long term design? (ii) Given the selected long term design, what is the short term design and pricing strategy given the action-reactions in the market system?

2.3 APPROACH

In the proposed approach, as shown in Figure 2.2, the outer loop (outside the dashed block) searches for the most profitable long term design option. While there are a number of approaches for generating design alternatives (e.g., [Bryand et al., 2005]), here it is assumed that a finite number of candidate long term design alternatives can be identified a priori. Each long term (trial) design alternative is then evaluated by the agent based model, inside the dashed. The agent based model (i) simulates the market equilibrium for the trial design alternative and (ii) iterates to search for the short term design and pricing option for the focal manufacturer. All the long term design options will be evaluated with respect to a pre-specified objective, i.e., maximum profit or market share. The optimal long term design option can therefore be evaluated for its optimality (in the diamond block of the outer loop, Figure 2.2). The overall design decision for the focal firm is the combination of (i) the optimal long term design option and (ii) the short term design and pricing decision obtained from the market equilibrium.

In the agent based model, "action" x_i^k for agent i is defined as the decision it makes in iteration k. For instance, the actions for a manufacturer agent can represent a short term engineering design decision. Additionally, "strategy" $S_i^k(x)$ of agent i is defined as a joint probability density function indicating the chance of playing a particular action x in iteration k. For instance, a 4-dimensional multivariate normal distribution can be used to represent a retailer's strategy and indicate the chances that the retailer sets retail margin

16

for the 4 products on its shelves. When an agent makes an action, it draws a sample from the strategy. Additionally, an "empirical action profile" $EAP_i^k(x)$ is defined as a probability density function representing the actions that agent i has played up to the k'th iteration in the simulation. $EAP_i^k(x)$ is useful in identifying system convergence and interpreting equilibrium. It is different from an agent's strategy $S_i^k(x)$ which implies the agent's belief on how the actions should be played.

As shown in Figure 2.2, the agent based simulation starts with a long term trial design option for the focal manufacturer. Market agents, i.e., manufacturing firms and retail channels, are initialized with their strategies being uniform distributions. After initialization, the agents go through an iterative learning process. An example of a learning process is to iteratively observe the payoffs as a result of actions by other agents. In this way, in each iteration, the agents update their strategies using a no-regret learning algorithm, given the past actions of all agents. The agents then make actions (each agent makes one action), i.e., draw samples from their updated strategies and report the actions to the agent based system (which simulates the market). In the initial iteration, the agents do not need to update strategies and they directly draw actions from the initial uniform distributions. Payoffs and regrets (i.e., important values for the learning
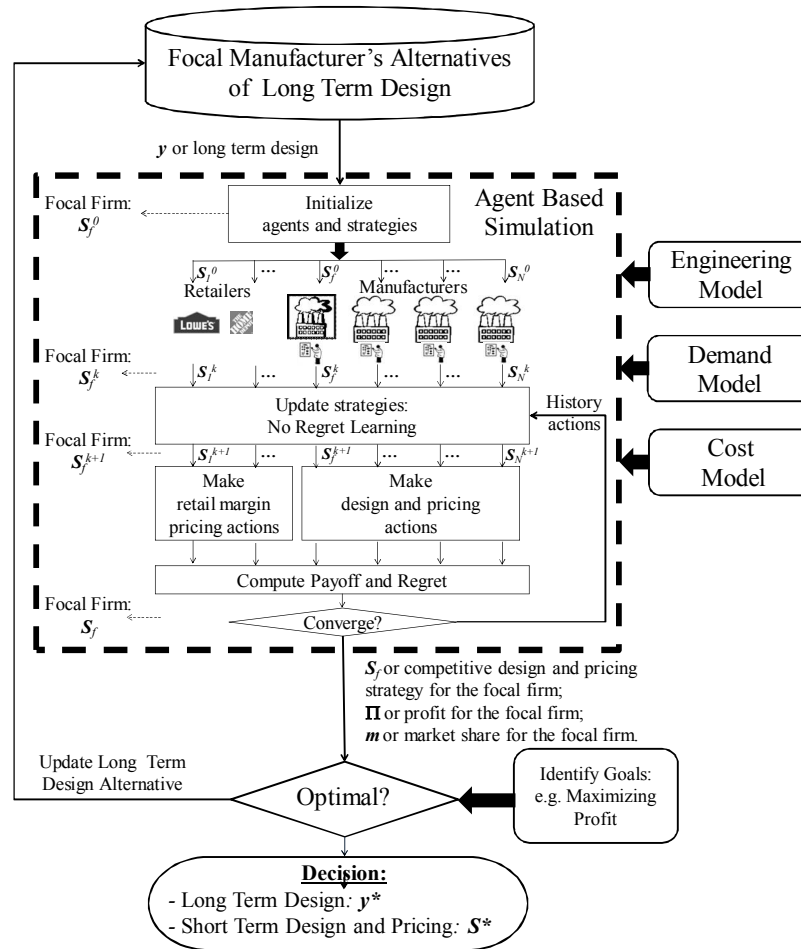
Figure 2.2 Approach

algorithm) of the agents are computed after all agents have played their actions. If the agent based system is not convergent, the actions of the agents are stored and the control is returned to the next iteration. The focal firm is modeled as one of the agents. Therefore, the process that the agent based system uses coincides with the process that the focal manufacturing firm uses in updating its strategy and searching for the short term design and pricing option. When the convergence of the system is reached, the market equilibrium solution (i.e., short term design and pricing strategies) will be forwarded to the outer loop for evaluating another long term design alternative. After completing the

evaluation of all long term and corresponding short term design alternatives, the long and short term design alternative with maximum profit can be selected.

The proposed agent based model is detailed in the following sections. The actions and payoffs for the agents are discussed in Sections 2.3.1 and 2.3.2. In Section 2.3.3, the no-regret learning protocol is introduced to model the way that the agents interact. Section 2.3.4 discusses the convergence of the agent based simulation and the interpretation of market equilibrium. Section 3.5 discusses the realism and validation regarding the proposed agent based model.

2.3.1 Agents' Actions

Three types of agents are considered in this study. These are agents representing manufacturers, retailers and customers. Each agent has its action space which consists of all feasible actions.

Customer agents. In the proposed approach, customers are modeled as "dummy agents". Customer agents simply make choices to maximize their utilities in any iteration and thus neither have actions nor update strategies from a profit maximizing perspective.

A Multinomial Logit (MNL) model [Anderson, 1992] is used to represent customer preferences. MNL builds upon the assumption of a random utility comprising an observable part which is a characteristic of the choice and an unobservable part which is stochastic, i.e., $u_i = \beta \cdot \xi_i + \varepsilon$. The entries in ξ_i represent product attributes which can be obtained by a mapping from the engineering design space. When the error term ε has a double exponential distribution, the probability that a customer chooses a product i among the N_m choices can be given by:

$$prob_i = \frac{exp(\beta x_i)}{\sum_{\theta=1}^{N_m} exp(\beta \xi_\theta)}. \tag{2.1}$$

Coefficient vector β can be estimated based on choice-based conjoint surveys using a latent class estimation to account for heterogeneity among customers [Williams et al., 2008]. The market share of a product alternative can be obtained by summing up the market share in each of the L customer segments weighted by segment sizes:

$$M_i = \sum_{l=1}^{L} s_l \cdot prob_i = \sum_{l=1}^{L} s_l \cdot \frac{exp(\beta_l \xi_i)}{\sum_{\theta=1}^{N_m} exp(\beta_l \xi_\theta)} \tag{2.2}$$

Manufacturer agents. Manufacturer agents are producers of product alternatives in the market system. The action of a manufacturer agent at iteration k is represented by a vector x_i^k combining the engineering design variables z_i^k and wholesale price w_i^k of its product: $x_i^k = (z_i^k, w_i^k)$. The action space A_i for a manufacturer agent is the union of engineering design space represented by a set of inequality constraints and the domain of non-negative real numbers representing the space of feasible pricing actions:

$$z_i^k \in Z = \{ z \mid g_i(z) \leq 0, i = 1...k \}; w_i^k \in R^+, \quad A_i = Z \cup R^+ \tag{2.3}$$

Retailer agents. Typical retailer behavior includes: (i) acceptance [Williams et al., 2008]—what product to carry in a category given the limited shelf space; (ii) pricing [Shiau and Michalek, 2009(b)]—what retail margin for the product should be considered? Both acceptance and pricing decisions by the retailers have significant impact on manufacturers' profits. Assuming there are a total number of n products, the action of a retailer i at iteration k is a vector in the n dimensional positive real number space: $r_i^k \in R^n_+$.

2.3.2 Agents' Payoffs

Since manufacturing firms and retailers are all assumed to be profit seeking, their payoffs are aligned with profits—in the following sections, the payoffs of all agents will be equivalent to their profits.

In an agent based model, each agent's payoff is influenced by the joint actions of all agents. Therefore, the payoff for an agent is a mapping from the union of all agents' action spaces to the real number space: $\Pi: A_1 \cup A_2 \cup \ldots \cup A_N \to R$. Assuming there are N_m manufacturer agents and N_r retailer agents, the joint actions of all agents at iteration k is denoted by: $x^k = (x_1^k, x_2^k, \ldots, x_{Nm+Nr}^k)$. Also, denote the actions of all agents but agent i at iteration k as: $x_{-i}^k = (x_1^k, x_2^k, \ldots, x_{i-1}^k, x_{i+1}^k, x_{Nm+Nr}^k)$.

A preliminary step for the assignment of payoffs for manufacturer and retailer agents is to obtain market shares. Consistent with the market structure, market share at iteration k can be denoted by an m by n matrix $M_k = (m_{ij}^k)_{mxn}$, with each entry m_{ij}^k denoting the market share of product i sold by retailer j at iteration k. The market consists of L segments with the size of each segment denoted by s_l. Therefore, out of a total number of ($N_m \times N_r$) alternatives, the market share of alternative ij is:

$$m_{ij}^k = \sum_{l=1}^{L} s_l \cdot \frac{exp(\beta_l \xi_{ij}^k)}{\sum_{\theta=1}^{N_m \cdot N_r} exp(\beta_l \xi_\theta^k)} \tag{2.4}$$

Manufacturer agents. The payoff of a manufacturer agent can be obtained by summing up the multiplication of net profit and market share at every retail channel that carries the firm's product:

$$\Pi_m^k(x^k) = \sum_{r=1}^{N_r} M_{ij}^k \cdot (w_m^k - C_m^k(x_m^k)), \ m = 1,2,\ldots N_m \tag{2.5}$$

Regarding production cost, a zero fixed cost is assumed and marginal production cost is denoted by $C_m^k(x_m^k)$. The marginal cost can be formulated as a linear function of design features, as practiced in [Williams et al., 2008]. The cost model can be estimated by a linear regression procedure using past production data which are easily accessible for a mature product category.

Retailer agents. The payoff of a retailer agent is the summation of profits generated by each product on its shelf space. Specifically, a retailer agent's payoff is given by:

$$\Pi_r^k(\mathbf{x}^k) = \sum_{m=1}^{N_m} M_{ij}^k \cdot r_{r,m}^k, \; m = 1,2,...N_m \qquad (2.6)$$

2.3.3 Protocol and Agent Strategies

The following assumptions are made regarding the short term actions of the market players: (i) they make decisions independently; (ii) they have no knowledge about the payoff functions and strategies of other players, though they know the payoff functions of their own and can observe the actions played by other players; (iii) they learn to improve their strategies overtime.

The No-Regret Matching (NRM) algorithm [Hart and Mas-Colell, 2000] is implemented to represent the market players' learning behaviors. The learning is carried out by examining "regrets". Observing the past actions of all the other agents in each iteration, the regret value for a specific action is measured by the difference between (i) the average payoff that the agent could have received if this action had been played all the time and (ii) the average payoff it has actually received. An action having a negative regret will not be played in the next iteration since the agent believes that such an action may not bring an attractive payoff according to the its experience, i.e., the payoff difference. An action with a positive regret, on the other hand, will be assigned a

probability proportional to the regret value which implies the likelihood that this action will be played in the next iteration. Following the regret update algorithm introduced by Marden et al. [Marden et al., 2007], the regret R as a function of action x is given by:

$$R_i^1(x) = R_0$$
$$R_i^{k+1}(x) = \frac{k-1}{k} R_i^k(x) + \frac{1}{k} \left(\Pi_i(x, x_{-i}^k) - \Pi_i(x^k) \right)$$

$$(2.7)$$

Here the subscript "-i" denotes all the agents but agent i.

The initial regret value R_0 is set to 0 because agents do not have regrets when no actions have been taken at the first iteration. Once the joint actions are obtained, an agent would have access to the updated regret since it has full knowledge of its own payoff function. However, the agents cannot guess the regret of other agents.

Given the regret function, the agents can specify their strategies. Marden et al. [Marden et al., 2007] developed the formulation for a finite and discrete action space:

$$S_i^k(x) = \frac{\left[R_i^k(x) \right]^+}{\sum_{x \in A_i} \left[R_i^k(x) \right]^+}$$

$$(2.8)$$

in which:

$$\left[R_i^k(x) \right]^+ = \begin{cases} 0, & \text{if } R_i^k(x) \leq 0 \\ R_i^k(x), & \text{if } R_i^k(x) > 0 \end{cases}$$

denotes the positive regrets. Eqn. (2.8) can be interpreted as follows. The probability of playing an action is proportional to its regret value. In order to guarantee that the probability over the action space sums to one, the strategy function is weighted by the sum of all positive regret values.

In an engineering product design decision problem, the above formulation is insufficient for representing the agents' actions since pricing decisions belong to the

continuous real number domain. An improved formulation is proposed here to address the continuous actions as in the following:

$$S_i^k(x) = \frac{B(x) \cdot R_i^k(x)}{\int\limits_{x \in A_i^{[R]+}} R_i^k(x) \cdot dx}$$

in which $B(x)$ is denoted as:

(2.9)

$$B(x) = \begin{cases} 0, \text{if } R_i^k(x) \leq 0 \\ 1, \text{if } R_i^k(x) > 0 \end{cases}$$

And

$$A_i^{[R]+} = \left\{ x \mid R_i^k(x) > 0 \right\}$$

It can be easily verified that $S_i^k(x)$ specified by Eqn. (2.9) sums up to one over the action space.

Meanwhile, the product design decisions are characterized by mixed discrete and continuous variables. The actions of a manufacturer agent are denoted by separating the discrete actions z_d which may represent discrete engineering design variables and continuous actions z_c which represents the continuous engineering design variables and wholesale price: $z=(z_c, z_d)$. Thus, the following equation sets strategy of a manufacturer agent over the mixed discrete and continuous action space:

$$S_i^k(x) = \frac{B(x) \cdot R_i^k(x)}{\sum\limits_{z_d} \left[\int\limits_{(z_c, \hat{z}_d) \in Zi} R_i^k(x) \cdot dz_c \right]}$$

(2.10)

Eqn. (2.10) is different from Eqn. (2.9) in that the denominator accounts for both continuous and discrete design variables. The denominator is obtained by first integrating over the space of continuous variables while taking discrete variables as fixed, then summing over all the feasible values of the discrete variables. The denominator of the

strategy function in Eqn. (2.10) involves integrations and summations which cannot be obtained analytically. Meanwhile, evaluating the probability distribution function of the strategy for a manufacturer agent involves assessing its action's feasibility by evaluating engineering constraints. Overall, the strategy functions are in a blackbox form and cannot be sampled analytically.

As discussed earlier, the agents play actions in each iteration by drawing samples from their strategies. The strategy as given by Eqn. (2.10) is not in the form of any standard distribution, which makes it difficult to sample. For implementation purpose, a numerical sampling technique is used, i.e., slice sampler, to draw samples from a black box probability density function. A slice sampler [Nean, 2003] is one of the Markov Chain Monte Carlo (MCMC) sampling techniques. The sampler creates a chain of sample points out of a given density function. When the chain of samples converges, the sequence of samples can be taken as an approximation to the original probability density function. The slice sampler can bring significant computational convenience to our approach because the sampler only requires knowing the density function to a proportional constant, that is, only the numerators in Eqn. (2.9) and Eqn. (2.10) need to be known. This property of slice sampler offers a way to circumvent the evaluation of complicated integrations and summations in the strategy functions. Practically, the generation of agents' actions can be accomplished by plugging the regret value (i.e., the numerators in the strategy functions), if positive, into a slice sampler and by obtaining a chain of samples representing the agents' strategy. In this study, the slice sampler is applied as a black box function: using the "slicesample' function from the Statistics Toolbox in Matlab 2010a [MathWorks, 2010]. In each iteration of the agent based

simulation, an agent creates a chain of samples based on the updated strategy using the slice sampler. It takes the convergent portion of the chain and draws one sample from it. This sample is taken as the action that the agent will report to the agent based system at the current iteration.

2.3.4 Market Equilibrium and Convergence

The proposed agent based simulation process needs to be run long enough in order to reach an interpretable equilibrium. No-regret matching algorithms, as indicated by the terminology, are proved to asymptotically converge to "no-regret" equilibrium where the regret for each agent approaches zero [Marden et al., 2007]. The equilibrium is interpreted as a "correlated equilibrium" which was first discussed by Aumann [Aumann, 1974]. Simply put, agents at equilibrium would have "no-regret" of playing random draws according to their strategies, given the history of interaction. Hart and Mas-Colell [Hart and Mas-Colell, 2000] provided analytical proofs that the empirical distributions of agents' actions (i.e., defined as $EAP_i^k(x)$ in this study) will converge to correlated equilibrium under the no-regret matching algorithm. Marden et al. proved that NRM converged to Nash Equilibrium in a "weakly acyclic game" [Marden et al., 2007]. In our case studies, convergence is observed even without those assumptions. However, due to the complexity of the decision problems for each agent in this study (e.g., decision spaces bounded by nonlinear and even "black-box" constraints), the existence and uniqueness of equilibrium can be difficult to prove.

It is worth noting that the "asymptotical convergence" [Marden et al., 2007] to zero regret may not be a desirable convergence criterion since it may require infinite number of iterations. As an alternative, an Empirical Convergence Index (*ECI*) is defined to

identify the convergence. *ECI* is defined as the change of the empirical action profile, i.e., $EAP_i^k(x)$, in two consecutive iterations. As given by Hart and Mas-Colell [Hart and Mas-Colell, 2000], the equilibrium strategy of an agent is represented by its $EAP_i^k(x)$. When the changes of $EAP_i^k(x)$ remain small enough for a certain number of iterations, it implies the convergence of the system. The *ECI* can be obtained by the following procedure.

First, empirical action profile is constructed: $EAP_i^k(x)$. The actions that have been played by an agent *i* up to iteration *k* compose a set of observations: { x_i^1 , x_i^2,..., x_i^{k-1} , x_i^k}. Each observation x_i^k is a vector, e.g., containing wholesale prices as well as engineering designs for a manufacturer agent. Therefore, $EAP_i^k(x)$ will be a multivariate density function. For the ease of interpretation, $EAP_i^k(x)$ is substituted by univariate functions $EAP_{ih}^k(x)$ corresponding to the marginal distributions for each dimension of the agent's actions. The observations for the *h'th* dimension can be obtained by ignoring the other dimensions of the observations in { x_i^1 , x_i^2,..., x_i^{k-1} , x_i^k}. A density function is then extrapolated from the observations using the kernel smoothing estimation technique—a non-parametric summarization of the underlying distribution structure of the observations. A number of numerical estimation toolboxes are available to use, for instance, Statistic Toolbox in Matlab offers a normal kernel estimation function. The results of the kernel smoothing estimation are vectors of samples representing the smoothed estimate of $EAP_{ih}^k(x)$.

Secondly, a vector of quantiles representing the shape of $EAP_{ih}^k(x)$ is obtained. For instance, quantiles of 2.5%, 25%, 50%, 75% and 97.5% can be used for computing *ECI* in the case studies. Denote the set of quantiles for $EAP_{ih}^k(x)$ by $q_h^k=\{q_{hj}^k\}$, *j=1,2,...J,*

where J is the total number of quantiles to be computed. *ECI* for agent i in iteration k is then defined as:

$$ECI_i^k = \sum_{h=1}^{H} ECI_{ih}^k = \sum_{h=1}^{H} \frac{1}{J} \cdot \frac{\left[\sum_{j=1}^{J} \left(q_{hj}^k - q_{hj}^{k-1} \right)^2 \right]^{\frac{1}{2}}}{max(q_{hj}^k) - min(q_{hj}^k)}, \quad (2.11)$$

Eqn. (2.11) represents changes in the $EAP_i^k(x)$ compared to the previous iteration. It is the summation of the changes of empirical profiles in each dimension of an agent's actions. The variations in the shape of profiles are represented by the averaged distance between the corresponding quantiles in two consecutive iterations scaled by the term " $max(q_{hj}^k) - min(q_{hj}^k)$ ".

The convergence criterion is defined as the following. For a given tolerance value ε_c and step parameter T_c, the agent based simulation is said to be converged up to iteration k if the following condition is met for any agent i:

$$\forall t \in \{ k - T_c, k - T_c + 1, \ldots, k - 1, k \}: \quad ECI_i^t \leq \varepsilon_c \quad (2.12)$$

2.3.5 Realism and Validation

The usage of "no regret" learning behavior is indeed motivated by the fact that managers, when making a decision, take the past into account. They tend to give favor to the strategies that "could have worked better" in the past—a tendency to reduce "regret". Such type of behavior was reflected in the work by Montgomery et al. [Montgomery et al., 2005]. The majority of managers were observed to take the past behaviors of competitors into account when making decisions on new product design and/or pricing; hardly any managers, on the other hand, were reported to account for future competitor's reactions. However, it is necessary to point out that the learning algorithm in the agent

based simulation does not mimic the real world behaviors of individual firms. It is not appropriate to take the agent based simulation process as a "step by step" prediction of the future moves of market players.

Fully validating the agent based simulation can be difficult but it is indeed verifiable. The research in behavioral game theory [Camerer, 2003] indicates that learning behaviors of social agents are only experimentally observed under limited circumstances. Using the real market data (i.e., price adjustments and feature changes) to examine the validity of the model can be potentially risky. Additionally, there can be a variety of other forces (i.e., entry of new competitors, advertisement and promotions) which are attributable to the firms' behaviors so an isolated market system is rarely available. Although validating the dynamic behavior is challenging, verifying the equilibrium is not. For instance, it is possible to verify if the result is indeed equilibrium. Upon convergence to equilibrium, the strategies (i.e., $EAP_i^k(x)$) of the agents are supposed to remain stable. This can be verified by looking at the convergence criterion proposed in the Section 2.3.4. This procedure is followed in the case studies. A more rigorous verification can be by matching the strategies obtained in the simulation to the definition of correlated equilibrium [Aumann, 1974] at which the no regret learning is supposed to converge. Part of the model, e.g., the representation of the choice behaviors of Customer agents using a Multinomial Logit model, has roots in consumer utility theories and can be verified by fitting the data collected from conjoint surveys [Green and Srinivasan, 1978].

2.4 CASE STUDY

The case study is formulated by extending the design problem of a cordless angle grinder, which was proposed in the previous literature [Williams et al., 2008]. The angle

grinder is a typical engineering product with subsystems such as motor, transmission and housing. The market for angle grinders is characterized by a number of major manufacturers such as DeWalt, Bosch and Milwaukee and a few powerful retailers such as Home Depot and Lowe's.

Table 2.1 Design variables of a cordless angle grinder

Description	Design Var.	Unit	Lower Bound	Upper Bound
Long term design variables				
Armature turns	N_c	turns	20	300
Stator turns	N_s	turns	10	200
Stator outer radius	R_o	mm	10	100
Stator thickness	T	mm	0.1	100
Gap thickness	L_{gap}	mm	0.05	70
Pinion Pitch	D_p	mm	9	30
Stack length	L	mm	10	200
Switch Type	S	N/A	1	4
Short term design variables				
Current	I	amps	6	12
Gear ratio	R	N/A	0.2	4

2.4.1 Engineering Design Model

The design variables for a cordless angle grinder are detailed in Table 2.1. Some of the variables are discrete, i.e., "Armature turns", "Stator turns" and "Switch Type". The variables "Current" and "Gear Ratio" are assigned to represent short term design changes, with the rest representing long term design. Such assignment is in favor of the convenience of demonstration since varying the "Current" and "Gear Ratio" is observed to change the market share of a product noticeably. Three long term design alternatives are considered in the study. Specifically, random values are generated for long term design variables except "Switch Type" and make the values identical across all the three alternatives. Therefore, the alternatives are differentiated, with respect to long term features, exclusively by the variable "Switch Type". The engineering constraints and the

cost model are consistent with those presented in the reference [Williams et al., 2008]. A mapping from the engineering design space to the customer observed attributes is also available in the literature [Williams et al., 2008].

2.4.2 Case Study Scenarios

Three case study scenarios are considered. The agent based model in each subsequent scenario builds upon that of the previous scenario and fosters increasingly complex market systems, as summarized in Table 2.2.

Table 2.2 Case study scenarios

	Changing Wholesale Prices	Changing Retail Margins	Changing Product Designs
Scenario 1	X		
Scenario 2	X	X	
Scenario 3	X	X	X

In scenario 1, the manufacturer agents only change wholesale prices and the retailers' margins are fixed. An arbitrarily chosen design alternative will be evaluated by using the agent based approach and game theoretic approach, and the results will be compared. Specifically, the "correlated equilibrium" market response anticipated by the agent based model will be compared to the Nash Equilibrium obtained using a game theoretic approach. Scenario 1 mirrors the commonly known price competition problem which can be solved using a game theoretic approach. Under the assumption of a multinomial logit (MNL) demand model, the price competition problem can be proved to have a unique Nash Equilibrium [Anderson et al., 1992]. The Nash Equilibrium can be obtained by setting the first order derivatives of the manufacturer agents' payoff functions with respect to their wholesale prices equal to zeros and solving a system of non-linear

equations. As such, a numerical minimization approach is adopted and is shown in Eqn. (2.13):

In scenario 2, retailer duopolies are added in and examine their impacts using the agent based approach. Since a choice model which incorporates heterogeneity and consider retailer duopoly is adopted, to the best of our knowledge there is no analytical proof that a unique Nash equilibrium exists under such setting. In contrast, the proposed agent based model will be shown to converge to equilibrium solutions of mixed strategies. The reason is that the analytical proof [Hart and Mas-Colell, 2000] regarding the NRM algorithm does not depend on the properties such as concavity of payoff functions, and therefore is not affected by the complications in this setting. This scenario serves as an intermediate step between scenarios 1 and 3.

In scenario 3, long term design alternatives are evaluated and selected using the proposed approach. In both scenario 2 and 3, the competition involves either non-concave profit functions for the market players or non-convex action spaces for engineering design actions. For demonstration purposes, the long term product design decision space is kept small with a finite number of design options, as shown in Table 2.3. Each alternative will be evaluated using the agent based model for its profitability. Given the profit that each alternative generates overtime, the most profitable long term design option can then be selected as the long term design. Correspondingly, the strategy of the focal firm in the agent based model is selected as the short term design. It is assumed that the market size for the product category is 1 million units throughout the case study scenarios.

2.4.2 Modeling Agents

Customer agents. In the angle grinder example, the customer's utility coefficients can be estimated through analyzing choice based conjoint surveys, which results in 4 segments with diverse preferences. The segment sizes (in percentage) are 36.40%, 26.62%, 13.17% and 23.81%. The values of coefficients for the demand model are available in [Williams et al., 2008].

Manufacturer agents. The agent based system consists of 4 different manufacturer agents performing short term designs and pricing of their angle grinders. Manufacturer 4 is the focal firm. The engineering design action space of each manufacturer is assumed to be the same, as defined by the lower and upper bounds in Table 2 and a number of engineering constraints [Williams et al., 2008]. In scenario 1 and 2, the designs of manufacturing agents are fixed, as given in Table 2.3. In scenario 3, the competitors change their short term designs while maintaining the values for long term design variables given in Table 2.4.

Table 2.3 Long term design options

Design Variables	N_c	N_s	R_o	T	L_{gap}
Alt. #1	262	97	46.9	34.0	0.28
Alt. #2	262	97	46.9	34.0	0.28
Alt. #3	262	97	46.9	34.0	0.28
Design Variables	I	L	R	D_p	S
Alt. #1	6	126.1	0.47	9.1	1
Alt. #2	6	126.1	0.47	9.1	3
Alt. #3	6	126.1	0.47	9.1	4

Table 2.4 Design variables of competing manufacturers

	N_c	N_s	R_o	T	L_{gap}
Mfr 1	297	75	68.1	48.7	0.07
Mfr 2	286	101	47.6	31.2	0.13
Mfr 3	300	69	52.1	28.1	0.06
Mfr 4	262	97	46.9	34.0	0.28
	D_p	L	S	I	R
Mfr 1	23.7	193.3	1	6	0.35
Mfr 2	21.0	161.3	4	9	1.14
Mfr 3	11.7	199	3	12	3.94
Mfr 4	9.1	126.1	3	6	0.47

Retailer agents. A retailer duopoly setting (i.e., two competing retailers) is used in the case study. Specifically, it is presumed that two retailer agents carry all the angle grinders produced by the 4 manufacturer agents. In the first scenario, the retailers are assumed to have constant retail margins as given in Table 2.5. In scenario 2 and 3, the retailers will react to the changes in the market system by setting retail margins over their assortments.

Table 2.5 Default retail margins

	Product 1	Product 2	Product 3	Product 4
Retailer 1	$48	$45	$55	$43
Retailer 2	$30	$31	$30	$43

2.5 RESULTS AND DISCUSSION

2.5.1 Scenario 1: Anticipating Wholesale Price Responses of Competitors to the New Product

Game theoretic approach yields the Nash Equilibrium prices of a non-cooperative game under pure strategies. The equilibrium prices and corresponding profits are presented in Table 2.6. The price set by Firm 3 is much higher than the other firms, which implies that this firm targets the higher-end market segments and sells expensive products.

Table 2.6 Nash equilibrium for price competition

	Firm 1	Firm 2	Firm 3	Firm 4 (Focal)
Price ($)	53.5	52.7	352.0	70.3
Profit ($M)	11.5	4.8	38.8	17.6

The proposed agent based approach simulates a process through which firms converge to equilibrium of mixed strategy by learning. The empirical action profiles (i.e., $EAP_i^k(x)$) of the firms are in Figure 2.3 (a) to Figure 2.3 (d).

There are two significant observations, as can be seen in Figure 2.3, regarding the empirical action profiles: shifting and shrinking. The shifting of the profile implies the changes in the potentially more profitable pricing option. The shrinking reveals the strengthening of an agent's belief on the pricing strategy, as more action-reaction history data becomes available. The "shift" can usually be observed at the beginning of simulation when agents learn to find more profitable actions; the "shrinking" often appear toward the convergence of the simulation when agents stop shifting the profiles. In Figure 2.3 (e) the agents' average profits are presented over iterations.
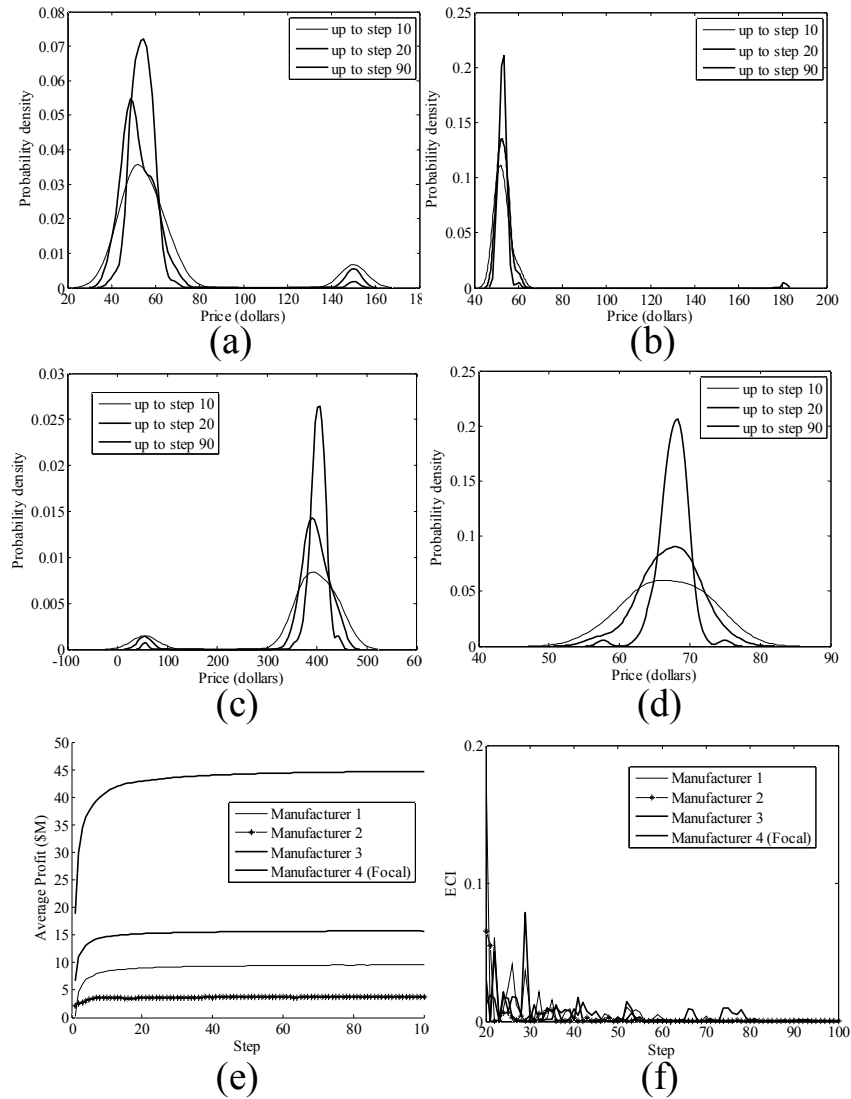
Figure 2.3 Result of scenario 1: (a) to (d) empirical action profile for manufacturer agent 1 to 4; (e) agent payoffs; (f) empirical convergence index

Figure 2.3(f) shows the process that *ECI* of each agent approaches zero—the criterion for the convergence of the simulation. The tolerance and step parameters are set as: ε_c=0.05 and T_c=20, respectively.

Comparing the results in Table 2.6 and Figure 2.3, the mean values of the pricing strategies obtained by the agent based approach appear to be close to the Nash Equilibrium prices obtained by the game theoretic approach. Therefore, both approaches

can be used to model the price competition and obtain similar results. However, it is necessary to clarify that this closeness does not imply equivalence. The game theoretic approach yields equilibrium in pure strategies—the players' actions are deterministic. The agent based approach, in comparison, leads to the equilibrium in mixed strategies—the players have probabilities of playing a certain action.

2.5.2 Scenario 2: Anticipating Wholesale Price Responses of Competitors and Retail Margin Changes of Duopoly Retailers

In this scenario, the first scenario is extended by allowing retailer duopolies to respond to the new product by adjusting margins. Adding more agents may make the environment more complex to "learn". It can be more difficult for an agent to see the difference in terms of profit between two feasible actions, since any changes in another agent's behavior can flip the comparison between the two. The more agents in the model, the more uncertainties are introduced. It is worth noting that the customer choice model incorporates the preferences for the two retailers and therefore makes them differentiated in the simulation. In the simulation results, retailer 1 tends to set high margins across the products it carries, which indicates that it learns overtime that the customers' purchase behaviors are less affected by the its price changes. Meanwhile, it achieves high profit over the iterations as compared to retailer 2, which indicates its dominating position in the retail market. In contrast, retailer 2 restricts its margins, on the average, to be lower than those of retailer 1 except for product 3—a higher-end product expensively priced as discussed in scenario 1. The profits of manufacturers 1, 2, and 4 (focal) remain at the same level as they did in the first scenario where retail margins are kept constant. The profit of manufacturer 3 experienced a significant drop due to the extra margin extracted

by retailers which results in an excessively high retail price that drives many customers away.

2.5.3 Scenario 3: Selecting Long Term Design Alternatives under both Price and Design Changes in a Market System

In this scenario, the proposed agent based design approach is applied to select long term design alternatives. Each long term design alternative goes through the agent based model for evaluation to obtain: (i) the profit for the focal firm towards the equilibrium, as shown on the left of Figure 2.4, and (ii) the short term design and pricing strategy for the focal firm, as shown on the right in Figure 2.4. The "Long Term Design Alternative 2" (which is the same design the focal firm has in scenario 1) is the most profitable one among the three options.

One important observation is that the profit for the focal firm gradually drops to around $5M when competitors learn to change prices and short term designs, compared to that around $15M when competitors only adjust prices in scenario 1. Based on the observation in this case study, the focal firm could be significantly overestimating its profit when developing a new product without anticipating the short term design changes of the competitors.

The right half of Figure 2.4 exhibits how the short term competing strategy, i.e., pricing and short term design, for the focal firm is obtained given the most profitable long term design alternative. The empirical action profile for pricing decision features a "shift" from an initially higher price to a less expensive price. Additionally, the "Gear Ratio" design strategy changes from an initial bimodal profile to a unimodal profile, which reveals the process through which the firm strengthens its belief on profitable short term

designs by learning. When competing firms gradually revise some design features and change prices to counter the new product, the new product may not generate as much profit for the focal firm as it does right after its entrance into the market. The competition actually forces the focal firm to consider price cuts and continue to revise the short term design features of the new product in order to maintain the profitability. Empirically, the short term design and pricing strategies need to be appropriately interpreted. There can be noticeable deviations in the distributions (e.g., the gear ratio strategy as shown in Figure 4) due to the randomizing nature of all the agents. Therefore, the designer should be provided not only the "peak" but also the "spread" regarding its strategies. For instance, the designer will be suggested to give the peak value priority but still consider other options within the 90% confidence interval for the gear ratio design strategy.

Meanwhile, the overall performance of the firms in terms of market shares and how they target the 4 different market segments in the short term horizon are analyzed. Manufacturer 1 is a small business with its shares in each segment below 10%. Manufacturer 2 dominates segment 2 by a share of 70%. Manufacturer 3 played as a monopoly in the third segment with the share of almost 100%. The focal firm (manufacturer 4) targets segment 1 with a share of about 30%.

Finally, it is necessary to point out that only a very limited number of options are compared for the focal manufacturer in the long term design space. There can be a much larger set of long term options to be considered. For instance, a sensitivity analysis is conducted for every long term design alternative by perturbing the outer radius R_0 of the motor by 5%. As shown in Figure 2.4, by increasing R_0 by 5% based on alternative 2, the focal firm would have achieved a profit for another \$2M. Conversely, the profit for

alternative 2 can fall below that of alternative 1 as well, which leads to the change of optimal long term design option. Additionally, a long term design alternative can exhibit varied sensitivity to different design variables. The sensitivity of alternative 2 is also tested regarding the "Stack length" denoted by L. This alternative is shown to be much less sensitive to L.
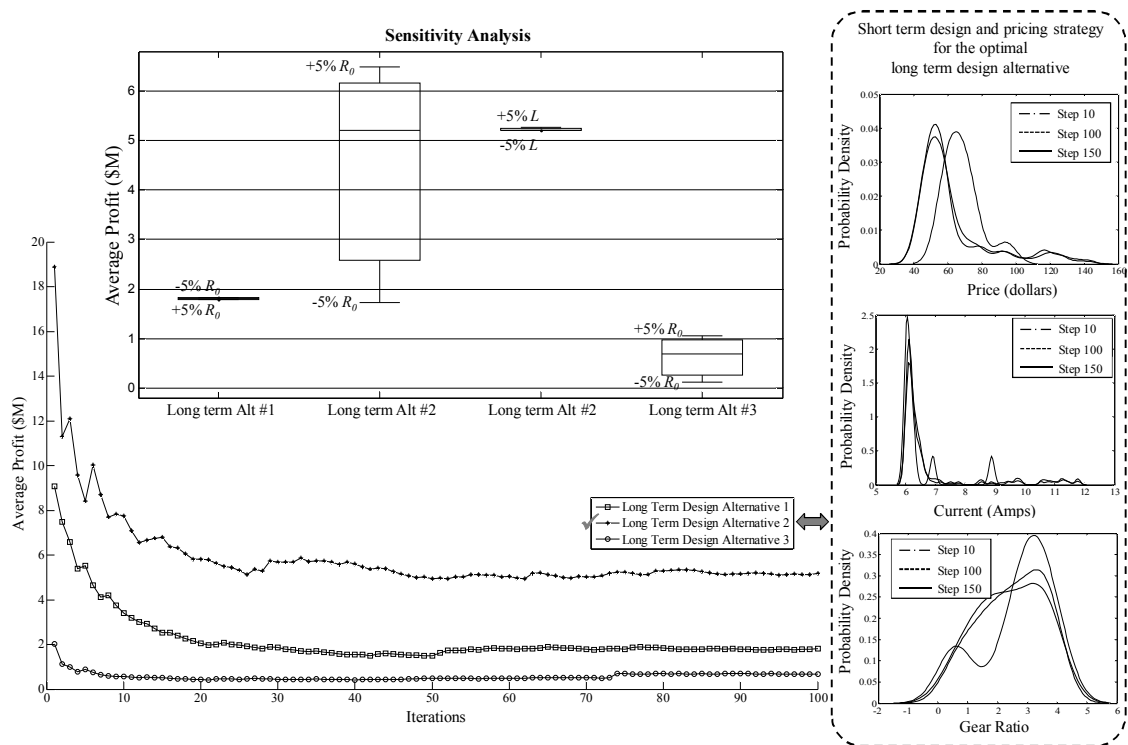

Figure 2.4 Results of Scenario 3

The simulations are programmed in Matlab and run on a desktop workstation with an 8 core CPU of 2.99GHz and 4GB memory. Parallel computing is used. For a given long term design alternative, the total computational time of the agent based simulation is approximately 9.67 hours for 150 iterations.

2.6 SUMMARY

In this chapter, an agent based approach is proposed for strategic design decisions in an uncertain market environment. The proposed approach overcomes the short comings

40

of previous approaches and is capable of handling competition involving complex design problems in which engineering systems is in black box form. Moreover, a more realistic perspective is taken in modeling the uncertain market system and accounting for the action-reactions among market players with learning behavior. Additionally, the approach provides the designer (i) a long term design decision which targets long term profitability and (ii) a short term design and pricing strategy which helps to maintain competitiveness in a short term horizon.

The proposed approach evaluates long term design alternatives and searches the short term design space using an agent based model. Market players such as competing manufacturing firms and retail channels are modeled as learning agents. A no-regret learning algorithm is used to model the market system and equilibrium of the system can be analytically guaranteed. In the case studies, the proposed approach is compared with the game theoretic approach reported in the previous literature. Our current results indicate that when competing manufacturing firms compete on pricing, the agent based approach results in a similar prediction of the market equilibrium compared to the game theoretic approach. The result also suggests that a firm can establish long term advantage in profit by strategically selecting design alternatives.

The next chapter will present a customer driven optimal design method for convergence products. Instead of focusing on the action-reactions of an existing (mature) product category, the next chapter aims at the design decisions in emerging product categories which integrates the features of existing product.

CHAPTER 3: CUSTOMER-DRIVEN OPTIMAL DESIGN FOR CONVERGENCE PRODUCTS[2]

Convergence products are multifunctional designs which are changing the way consumers use existing functionalities. Manufacturers' ventures in developing convergence products abound in the marketplace. Smartphones, tablet computers, internet TV, are just a few examples. The complexity of designing a convergence product can differ significantly from that of single function products which most research in Design for Market Systems aims at.

In this chapter, a new customer-driven approach for designing convergence products is proposed to address the following issues: (i) a design representation scheme that considers information from design solutions used in existing products: the representation facilitates the coupling of and combining multiple functionalities; (ii) a hierarchical Bayes model that evaluates consumers' heterogeneous choices while revealing how usage of multiple functionalities impacts consumers' preferences; and (iii) design metrics which help evaluate profitability of design alternatives and account for future market penetration given evolving consumer preferences. An example problem for designing a tablet computer is used to demonstrate the proposed approach. The data for the example is collected by conducting a choice-based conjoint survey which yielded 92 responses. The proposed approach is demonstrated with three scenarios differentiated by the consideration of consumer heterogeneity and future market penetration, while comparing how the resulting optimal design solutions for the convergence product differ.

---

[2] This chapter addresses Research Thrust 2, as overviewed in Chapter 1. The material for this chapter is borrowed from (and is the same as) the paper: Wang, Z., Kannan, P.K., and Azarm, S., 2011, "Customer-Driven Optimal Design for Convergence Products", *Journal of Mechanical Design*, 133(10), pp. 101010.1 to 101010.13.

3.1 INTRODUCTION

Consumers nowadays are facing a wide variety of new products which combine a number of distinct functionalities[3] that existing individual products already provide. Such products are found in a broad range of categories such as office machines (e.g., all-in-one printers), consumer electronics (e.g., tablet computers) and information products (e.g., Google TV). These products usually straddle two or more existing product categories by merging their previously developed and separate underlying technologies, which give rise to their name Convergence Products [Han et al., 2009]. Successfully developing a convergence product can greatly benefit a company in a number of ways. First, a convergence product is generally built upon the technologies of existing products, which can significantly reduce the R&D effort and costs. Secondly, a convergence product can attract new customers who do not use the existing products but are interested in a combination of functionalities that a convergence product offers. Moreover, convergence products can open up new product-market opportunity gaps (Figure 3.1) which can lead the firm to a position in the market where little or no direct competition exists. Appealing as it may be, a convergence product can be complicated to design. The success or failure of a convergence product can be closely related to the decisions in the early stages of design, yet little research has been conducted on a customer-driven design decision approach that is applicable to convergence products.

The objective of this chapter is to develop a design decision framework that maximizes a company's profit while considering sustainable future market penetration, by accounting for the consumers' usages of the functionalities and their evolving

---

[3] Functionality here is defined as the capacity of a product to fulfill a useful function and satisfy a customer need, e.g., a useful function that an iPad can fulfill is reading a book or magazine. Functionality can also refer to a "feature" of a product, e.g., iPad has an "e-book reading" feature.

heterogeneous preferences. While some convergence products flourish partly due to their improved user interface and software applications (e.g., tablet computers, smartphones), this study focuses primarily on the design decisions of the hardware and product features. However, studies using prototypes (e.g., Luo et al., 2008) can be employed to focus on perceived attributes such as screen quality, software ease of use, etc.. The proposed objective and framework differs from existing literature in three significant ways, which are elaborated below.
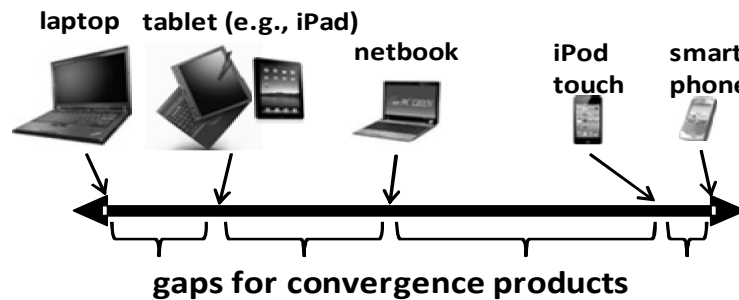

Figure 3.1 Opportunity Gaps for Convergence Products

First, a modular design representation scheme is proposed to integrate the design solutions from multiple existing product categories to generate design alternatives for a convergence product. The scheme accounts for the coupling of subsystems (functionalities) due to the very nature of a convergence product. Chen et al. [Chen et al., 2010] investigate the planning of fusion products (single product that operates multiple functionalities—a definition that is close to that of a convergence product) to maximize profit but overlook the engineering design aspect and consumer preferences for such products. Existing works in engineering design focus on the design of single category products [e.g., Li and Azarm, 2000], product line [e.g., Thevenot and Simpson, 2009] and

product platforms [e.g., Fellini et al., 2005]. Single product design methods do not handle the couplings of multiple products or functionalities. Product line/platform design approaches, on the other hand, consider the connections and variations among multiple products but are limited to the design of products falling under a single category. The practice of bringing different product categories together is called "bundling" [Stremersch and Tellis, 2002; Chung and Rao, 2003]. The recent work by Williams et al. [Williams et al., 2010] introduces a methodology to design a bundle of multi-category products but does not lead to design concepts that cast the functionalities into a single product. Meanwhile, modular design has been widely applied in the industry and existing literature have focused on the analysis of modularity [e.g., McAdams et al., 1999], and designing product line and/or platform [e.g., Gao et al., 2009; Dobrescu and Reich, 2003]. The proposed approach extends these works by enabling the integration of modular structures of different products/functionalities into one integrated framework. Additionally, the design decision for a convergence product requires bridging the parametric design stage and the concept selection stage, while accounting for how consumers will react to new designs. Existing engineering design methods in the design for market systems [e.g., Shiau and Michalek, 2009; Tucker and Kim, 2008; Kumar et al., 2009] are primarily useful to make parametric decisions with fixed modular structures of the functionality, with design concepts for the functionalities selected a priori.

Secondly, the approach in this chapter accounts for the consumers' heterogeneous choice behavior using a hierarchical Bayes model with its second level explaining how the consumers' usages of the existing functionalities influence their preferences for the attributes of the convergence product. Early approaches such as House of Quality

[Hauser and Clausing, 1988] collect customer needs and map them to the design specifications in a qualitative manner. Recent works in the area of design for market systems adapt econometric models to quantitatively measure the relationship between design alternatives and consumer choice [Frischknecht et al., 2010]. However, the existing works in product design only explain the heterogeneity of consumer needs in limited ways. The preferences of the consumers are assumed to be identical [e.g., Orsborn et al., 2009], grouped into a small number of classes [e.g., Williams et al., 2008, 2011], assumed to be random but having the same probability distribution [Shiau et al., 2007], or considered heterogeneous by incorporating demographic information as explanatory variables in the consumer utility function [Hoyle et al., 2011]. The study by Koukova et al. [Koukova et al., 2008; Koukova et al., 2012] shows that consumers do react to product offerings differently when they are made aware of usage situations. Some consumers may even carry existing products together with the convergence product because the products outperform each other in different usage occasions [Kane, 2010]. A similar hierarchical Bayes model structure has been used in Yang et al. [Yang et al., 2002] where the authors study the consumers' brand preferences for beverages under a variety of objective environment and subjective usage motivations, yet they do not address how the usage conditions influence the consumers' evaluations of the products' attributes.

Finally, the proposed approach introduces a design metric called Convergence Index (CI) to help position the convergence product with respect to existing product markets and use the index to predict the potential market size. The CI metric is used to map engineering design variables to a numerical value which reflects how close the convergence product is to existing products in terms of product architectures, which has

implications for the demand of convergence product relative to the existing products. The literature on Commonality Index [e.g., Thevenot and Simpson, 2004; Kota et al., 2000] reveals similarity among product line variants. The commonality metrics mostly rely on counting the number of shared components among the variants in a product family or product line. Counting the number of shared components ignores the variation in component attributes and the rearrangement of the modular structure which collectively leads to new ways of performing the existing functionalities—a key reason that a convergence product differentiates from existing ones. On the other hand, market segmentation techniques [e.g., Meyer and Lehnerd, 1997] differentiate products using customer level attributes. Ramdas and Sawhney [Ramdas and Sawhney, 2001] measure the potential market size for a product line expansion by modeling the probabilities that consumers purchase the product given a variety of line expansion options. The proposed CI compares products by propagating the variations at different levels of modules through a product modular hierarchy, in creating a distance metric that quantifies the degree of similarity between the products as a function of their product architectures.

Moreover, the proposed approach captures a product's impact on the consumers' usages using a logit model and considers a metric called Impact of Usage Evolution (IUE) to predict the effect on a product's future market performance. The work in marketing research by Heilman et al. [Heilman et al., 2000] attributes the consumers' evolving brand preferences to their cumulative purchase quantities of a specific brand. However, that work does not reveal the underlying product-consumer interaction process in which the consumers change preferences through using the products.

Section 3.2 gives the assumptions and problem definition. Section 3.3 presents the proposed framework and details of the methodology. Section 3.4 uses a case study for a tablet computer to demonstrate an application of the proposed methodology. Results for the case study are shown in Section 3.5 and highlights and concluding remarks are made in Section 3.6.

3.2 PROBLEM DEFINITION AND ASSUMPTIONS

The problem is defined as follows. As shown in Figure 3.2, a manufacturing company plans to design a convergence product which integrates the functionalities offered in a set of existing categories of products, e.g., Product A and Product B. Functionality refers to a feature of usage from the consumers' perspectives. For instance, a smartphone has the functionalities such as "sending emails", "receiving phone calls" and "browsing the web". The designer (or manager) is assumed to be able to identify the product categories a priori. A more detailed discussion of product categories or product markets can be found in the Lilien et al. [Lilien et al., 1995]. For instance, a product market can be defined by its title, such as "auto market" or "laptop market"; or can be defined from the customers' perspective and consists of products that potentially replace each other, e.g., printers of different brands for home usage constitute the home printer category.

The existing products, based on which the convergence product design is made, are assumed to be modular with their design solutions for the functionalities known. Here, a modular product refers to one that can be represented by a combination of physical and/or software units so that: (i) each unit has one or more functions and (ii) connections between the units are well defined [Ulrich, 2000]. The modules can be selected out of a "module library" which contains all candidate modules, with each module having a

variety of options to choose from. The design solution of a functionality is defined as the selection and specification of the modules which collectively enable that functionality. The designer can also consider a new functionality that none of the existing products provide. For a new functionality, it is assumed that a corresponding design solution is known a priori. On the demand side, it is presumed that the convergence product is targeted for heterogeneous consumers who will use at least one of the functionalities. The consumers use the functionalities in different usage situations and have diverse preferences for product attributes. The major cost of the product is incurred by purchasing its components or modules from the suppliers.
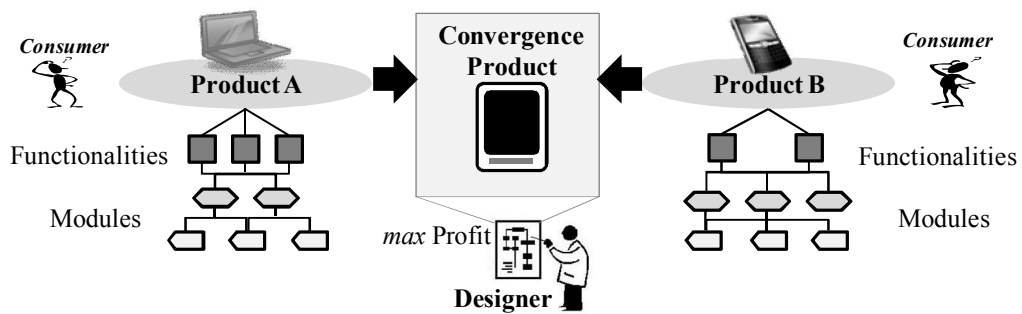

Figure 3.2 Problem Definition

3.3 METHODOLOGY

As shown in Figure 3.3, the proposed approach begins by first constructing a modular representation of functionalities after investigating the structures of existing product categories that are intended to be merged into a convergence product. This leads to a modular hierarchical representation framework and a set of constraints which define the engineering design space for the convergence product. The process of developing the modular framework is detailed in Section 3.3.1. The design alternatives will be generated and selected using a Genetic Algorithm [Deb, 2001]. The design alternatives are first

evaluated from the consumers' perspective by using a hierarchical Bayes choice model.

In this hierarchical model, the first level represents how the design attributes influence
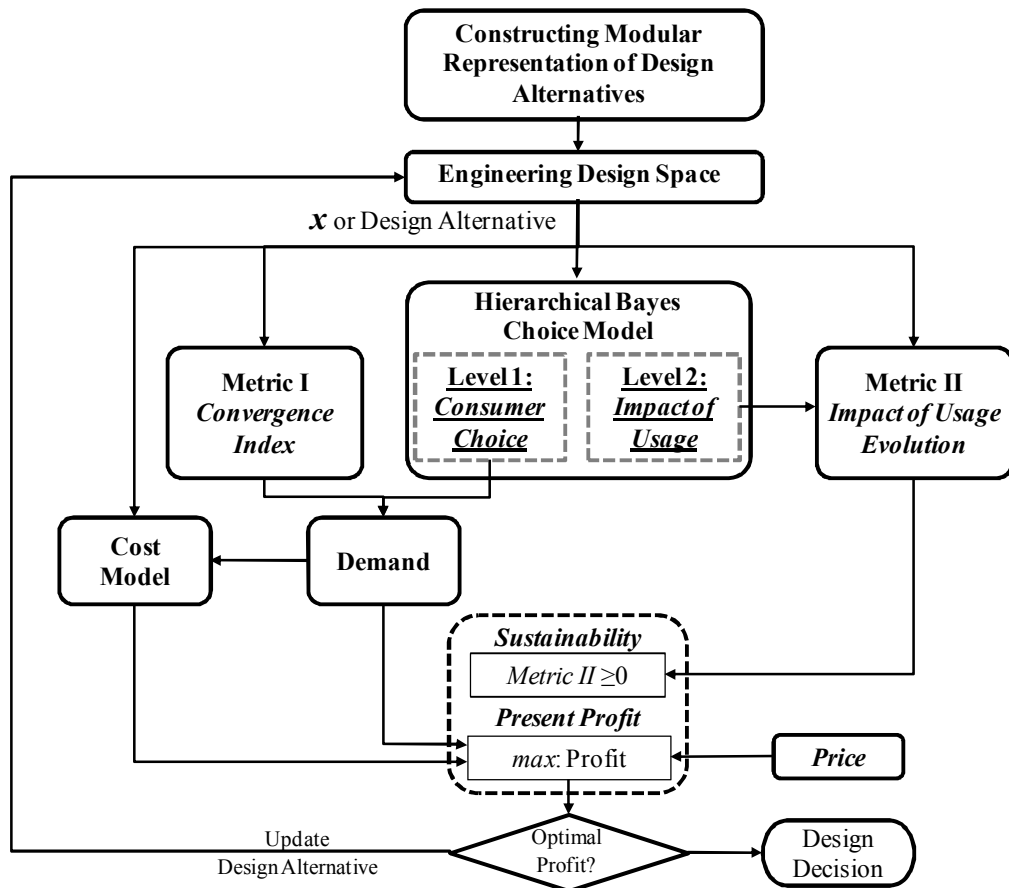

Figure 3.3 Design Decision Framework

each consumer's probability of choosing the product, and the second level reveals how

the consumers' usages of the functionalities influence their preferences. Section 3.3.2

elaborates on the development of the hierarchical Bayes model. Meanwhile, two metrics

are used to bridge the calculation of enterprise objectives such as profit. The first metric,

Convergence Index, reveals how similar the convergent product is to existing products,

which aids in the prediction of potential market size. The second metric, Impact of Usage

Evolution, evaluates the changes in a product's market share when the consumers' preferences change. The second metric takes into account the effect of product-customer interaction and indicates whether the market penetration of a design alternative is sustainable in the future. The two metrics are detailed in Section 3.3.4. The output of the first metric combined with the output of the first level of the choice model leads to the computation of the predicted demand. The cost model (Section 3.3.3) takes its inputs from both the design attributes and the predicted demand. The design alternatives will be selected by maximizing profit subject to the sustainability constraint in which *IUE* is confined to be non-negative. In this study, the price is kept fixed in order to separate the effect of changing design features on the profit.

3.3.1 Modular Design Representation

This section concerns the representation, generation and selection of engineering design alternatives.

A module is defined to be a functional unit that directly supports a functionality. Each module can be further decomposed into sub-modules—physical or software units which facilitate their parent module. The modular hierarchy is constructed by decomposing the functionalities of existing products into modules/sub-modules in three levels as shown in Figure 4. The top level, Functionality Level, contains all the functionalities that the products in the existing categories have. The Module Level includes all the modules that support at least one of the functionalities in the top level. The Sub-module Level consists of the functional units which build up the modules in the middle level.
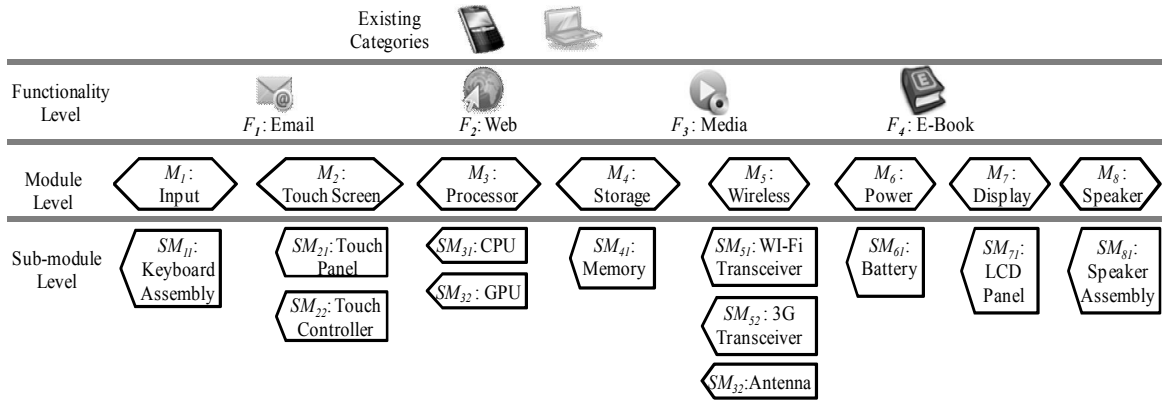
Figure 3.4 Modular Hierarchy Framework

Design Alternative Representation. A vector $\mathbf{F}=(F_i)_{1 \times f}$ is used to denote the inclusion of f functionalities, with each entry F_i set to 1 when the corresponding functionality i is present in a design alternative. A binary string $\mathbf{M}=(M_i)_{1 \times n}$ can be used to indicate the availability of n modules (e.g., $n=8$ in Figure 3.4), with each entry M_i set to 1 when the module i is present in a design alternative. The availability of sub-modules is denoted using $\mathbf{SM}$. Each entry of $\mathbf{SM}$, or SM_{ij}, is a binary variable denoting the inclusion of the j'th sub-module in module i. Additionally, a vector $\mathbf{z}_{ij}$ is defined to represent the attributes of sub-module j of module i. The entries of $\mathbf{z}_{ij}$ can take numerical values (e.g., the diagonal size of "SM_{71}: LCD Panel" in Figure 4) as well as nominal values (e.g., the material type of "SM_{61}: Battery" in Figure 4). In summary, a design alternative is represented by the collection $\mathbf{x} = \{\mathbf{F}, \mathbf{M}, \mathbf{SM}, \mathbf{z}\}$.

Functional Enabling Constraint. A functionality is enabled when all its required modules are present in a design alternative. An Enabling Matrix, denoted by $\mathbf{EM}=(EM_{ij})_{f \times n}$, is defined with $EM_{ij}=1$ if implementing function i requires module j and $EM_{ij}=0$ otherwise. The matrix $\mathbf{EM}$ can be determined by analyzing the modular decompositions of functionalities in the existing products. A necessary condition for a

design alternative to be feasible is that all the selected functionalities are enabled, which can be formulated as (the prime symbol is for transposition):

$$\mathbf{EM}_{f \times n} \cdot \mathbf{M'}_{1 \times n} = \mathbf{F} \tag{3.1}$$

Module Composition Constraint. When a module is selected in the convergence product, its sub-modules need to be selected such that the same composition can be found in at least one of the existing products. A necessary condition for a design alternative to be feasible can be stated as:

$$\exists k = 1, \dots, K : \forall i \in \{i \mid M_i = 1, i = 1, 2, \dots n\}, S_{i,k} \in S_i(x). \tag{3.2}$$

with $k=1,\dots,K$ indexing all the existing products.

Sub-module Feasibility Constraint. The attributes of sub-modules are constrained by lower/upper bounds (for numerical values) and set of options (for nominal values). $\mathbf{z} \in \mathbf{Z}$ is used to represent the feasible region for all the $\mathbf{z}_{i,j}$.

The engineering design space is therefore bounded by the above mentioned constraints: (i) Functional Enabling Constraint; (ii) Module Composition Constraints, and (iii) Sub-module Feasibility Constraint.

Design Alternative Generation and Selection. A Genetic Algorithm is used to generate and select design alternatives. The design alternatives are first translated into bit strings. The fitness function is aligned with profit and is maximized. The overall design optimization problem will be presented in Section 3.3.5.

3.3.2 Modeling Consumer Choice for Convergence Products: A Hierarchical Bayes Model

In this section, the demand for a design alternative **x** is evaluated.

53

Explaining Consumer Heterogeneity: Product Usage Conditions. Usage situations can drive a consumer's preference for the product attributes. Belk (1975) proposed a number of variables that could characterize usage situations. In this chapter, the categorizations in Belk's study are adapted and denote the usage conditions of functionality f for consumer i using a binary vector which includes three elements: $\xi_f^i = (\xi_{f,frequency}^i, \xi_{f,access}^i, \xi_{f,situation}^i)$. The element $\xi_{f,frequency}^i$ represents the usage frequency for functionality f. The element $\xi_{f,access}^i$ represents a consumer's need to get instant access to a certain functionality. The last element $\xi_{f,situation}^i$ denotes if a consumer considers himself/herself to use the product under a series of usage situations, for instance, searching, shopping or social networking for the functionality of "web browsing".

Hierarchical Bayes Choice Model. A two level model to represent consumers' choices is proposed. In the first level, a Multinomial Logit Model [McFadden, 1980] is used to formulate the probability that a consumer i chooses product j out of a set of J alternatives:

$$\Pr_i(y = j) = \frac{\exp(U_{i,j})}{\sum_{k=1}^{J}\exp(U_{i,k}) + \exp(U_{NC})} \tag{3.3}$$

in which:

$$U_{i,j} = \boldsymbol{\beta}_i' \mathbf{X}_j \tag{3.4}$$

The no-choice utility U_{NC} is set to 0 for the purpose of identification. The term $U_{i,k}$ denotes the utility for every competing convergence product. Eqn. (3.3) is simplified when only one convergence product is in the market. In this case, the consumers will choose between buying and not buying the product.

The second level model explains how the vector $\boldsymbol{\beta}_i$ is different for each consumer. A multivariate linear model is used to relate the usage conditions of consumer i to his/her preference:

$$(\boldsymbol{\beta}_1,...,\boldsymbol{\beta}_i,...,\boldsymbol{\beta}_I) = \boldsymbol{\tau}(\boldsymbol{\xi}_1,...,\boldsymbol{\xi}_i,...,\boldsymbol{\xi}_I) + \boldsymbol{\varepsilon} \qquad (3.5)$$

The coefficients to be estimated in Eqn. (3.4) and Eqn. (3.5) are: $\boldsymbol{\beta}_i$, $\boldsymbol{\tau}$. In the context of Bayesian statistics, the coefficients are taken as random variables. The designer postulates the prior distributions, updates the prior using consumer choice data, and obtains the posterior distributions for the coefficients. The data can be obtained using conjoint surveys [Green and Srinivasan, 1978].

Following the model structure proposed by Rossi et al. [Rossi et al., 2005], the hierarchical Bayes model is formulated as the following for Likelihood:

$$L(\mathbf{y},\mathbf{X} \mid \boldsymbol{\beta}) = \prod_{i=1}^{I} \prod_{t=1}^{T} \Pr_i(y = y_{i,t}) \qquad (3.6.1)$$

Priors:

$$(\boldsymbol{\beta}_1,...,\boldsymbol{\beta}_i,...,\boldsymbol{\beta}_I) = \boldsymbol{\tau}(\boldsymbol{\xi}_1,...,\boldsymbol{\xi}_i,...,\boldsymbol{\xi}_I) + \boldsymbol{\varepsilon} \qquad (3.6.2)$$

$$\boldsymbol{\varepsilon}_i \sim N(\mathbf{0},\mathbf{V}_\beta) \qquad (3.6.3)$$

$$vec(\boldsymbol{\tau} \mid \mathbf{V}_\beta) \sim N(vec(\bar{\boldsymbol{\tau}}), \mathbf{V}_\beta \otimes \mathbf{A}^{-1}) \qquad (3.6.4)$$

$$\mathbf{V}_\beta \sim IW(\mathbf{v}_0,\mathbf{V}_0) \qquad (3.6.5)$$

Posterior:

$$p(\boldsymbol{\beta},\boldsymbol{\tau},\boldsymbol{\varepsilon} \mid \mathbf{y},\mathbf{X},\boldsymbol{\xi}) = L(\mathbf{y},\mathbf{X} \mid \boldsymbol{\beta}) \cdot p(\boldsymbol{\beta} \mid \boldsymbol{\xi},\boldsymbol{\tau},\boldsymbol{\varepsilon}) \cdot p(\boldsymbol{\xi} \mid \boldsymbol{\varepsilon}) \cdot p(\boldsymbol{\varepsilon}) \qquad (3.6.6)$$

The diffuse prior distributions are specified to diminish the influence of bias in the prior distributions. For instance, the means of priors were set to **0** and a matrix 100**I** (**I** denotes identity matrix) is used as the variance matrix. In this way, the probability density profiles of the prior distributions are flat so that no significant favor is given to any particular value. In the formulation of priors, "*N*" denotes multivariate normal

distribution and "*IW*" denotes inverse wishart distribution. In Eqn. (3.6.4) the symbol "⊗"
refers to tensor product; the term "*vec*" denotes matrix vectorization.

Since the posterior distributions are usually not in closed forms, the Markov Chain
Monte Carlo (MCMC) simulation can be applied to draw samples from the posterior. The
output of MCMC is a chain of samples for all the coefficients: $\boldsymbol{\beta}_i^c$, $\boldsymbol{\tau}^c$, with $c=1,2,...,C$
indexing the samples in the chain. Considering the fact that a convergence product will
be the only option in the new category, the choice that a consumer makes is between to
purchase or not to purchase.

Given the estimate of parameters $\boldsymbol{\beta}_i^c$, the expected demand for a design alternative
with attributes **X*** can be formulated:

$$Q(\mathbf{X}*) = \frac{1}{C} \cdot N_c \cdot \sum_{i=1}^{I} \sum_{c=1}^{C} \frac{\exp(\boldsymbol{\beta}_i^c \mathbf{X}*)}{1+\exp(\boldsymbol{\beta}_i^c \mathbf{X}*)} \tag{3.7}$$

The formulation of market size N_c will be elaborated in Section 3.4.1.

3.3.3 Cost Model

Under a modular product structure, the production cost can be approximated by the
summation of the component costs and the assembly cost. Previous literature [Simpson
and Park, 2005] points out that the manufacturing cost is not only a function of product
designs but also relates to the quantity produced. This study accounted for the fact that (i)
the selection of components is dictated by the design specifications and (ii) the unit cost
of each component can be related to the order quantities. There are different ways to
explain the discounting effect when the quantity goes up. One way of interpreting it is
through the economy of scale argument in which increased quantity is considered to
lower the cost per unit produced. Another explanation is the learning curve effect which

models the fact that the manufacturing cost drops down gradually when the production process iterates. Additionally, the suppliers do offer discounts when the order quantity is large.

In general, it is assumed that some components exhibit the discounting effect whereas others are purchased at a constant unit cost. For the components whose cost relates to the quantities, the unit cost, denoted by K, is formulated following the specifications of learning curves:

$$K(Q) = K_1 \cdot Q^b \tag{3.8}$$

Taking the log of both sides, a log–linear cost function in b is obtained:

$$\log K(Q) = \log K_1 + b \log Q \tag{3.9}$$

Inserting relevant attribute of the component X_m, for instance, the diagonal size for the LCD display, the above formulation is extended to:

$$\log K(Q, X_m) = \log K_1 + b_1 \log Q + b_2 \log X_m \tag{3.10}$$

The above formulation can be estimated by collecting price quotes from component suppliers. A linear regression procedure will be used to obtain the coefficient b_1 and b_2. The above formulation can also be extended when a component is characterized by two or more attributes.

The total cost is formulated as the summation of the costs for all the components plus the assembly cost:

$$K(Q, \mathbf{X}) = K_0(\mathbf{X}) + \sum_{i=1}^{I_1} K_{1,i} \cdot Q^{b_{i,1}} X_i^{b_{i,2}} + \sum_{i=I_1}^{I_2} K_{1,i} \tag{3.11}$$

in which $i=1,\dots,I_1$ denotes the set of components whose unit costs are discountable; $i=I_1,\dots,I_2$ denotes the components whose unit costs are constant. $K_0(\mathbf{X})$ denotes the assembly cost.

3.3.4 Design Metrics

In this section, two design metrics are proposed, Convergence Index and Impact of Usage Evolution, to support the evaluation of fitness for a design alternative **x**.

A preliminary step to developing the metrics is to define the average product for each existing product category. It is assumed that all the competing products in each existing category can be identified *a priori*. The average product is a hypothetical product offering that averages the customer observed attributes of all the competing products in a given product category.

Convergence Index (*CI*) and Market Size. *CI* serves the purpose of comparing the similarity between the convergence product and the existing products. The computation of *CI* is carried out in four steps:

Step 1: Compute D_i which is the difference in design between the convergence product and the existing product i:

$$D_i = \frac{1}{J} \sum_{j=1}^{J} D_{i,j} \tag{3.12}$$

Step 2: Compute $D_{i,j}$ which reflects how the two products provide the same functionality j differently:

$$D_{i,j} = \begin{cases} 1, & \text{if } F_{1,j} \neq F_{2,j} \\ \dfrac{1}{N_{M(F_j)}} \sum_{m \in M(F_j)} d_{i,j,m}, & \text{if } F_{1,j} = F_{2,j} = 1 \\ 0, & \text{if } F_{1,j} = F_{2,j} = 0 \end{cases} \tag{3.13}$$

Eqn (3.13) primarily means the following: when functionality j is available in only one of the products being compared, the difference $D_{i,j}$ is set to 1 which is the largest possible value of the difference. When none of the products implement the functionality j, the difference decreases to the smallest value 0. Otherwise, $D_{i,j}$ sums over the difference

with respect to each module that enables functionality j as reflected by $d_{i,j,m}$ (to be computed in Step 3).

Step 3: Compute $d_{i,j,m}$:

$$d_{i,j,m} = \frac{1}{N_{S_m(\mathbf{x})}} \sum_{sm \in S_m(\mathbf{x})} \frac{\left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\| - \min \left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\|}{\max \left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\| - \min \left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\|} \tag{3.14}$$

The value of $d_{i,j,m}$ is normalized between 0 and 1. The term $\left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\|$ measures the difference with respect to the sub-module sm of module m. When a sub-module sm is built into only one of the products, the difference $\left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\|$ is 1. Otherwise:

$$\left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\| = \begin{cases} 0, & \text{if } \mathbf{z}_{sm} \text{ takes nominal values and } \mathbf{z}_{sm} = \mathbf{z}_{sm}^i \\ 1, & \text{if } \mathbf{z}_{sm} \text{ takes nominal values and } \mathbf{z}_{sm} \neq \mathbf{z}_{sm}^i \\ \left[\sum_{k=1}^{K} \left(\mathbf{z}_{sm,k} - \mathbf{z}_{sm,k}^i \right) \right]^{\frac{1}{2}}, & \text{if } \mathbf{z}_{sm} \text{ takes numerical values} \end{cases} \tag{3.15}$$

That is, when $\mathbf{z}_{sm}$ takes nominal values (i.e., as opposed to numerical values $\left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\|$ is set to 0 if the values $\mathbf{z}_{sm}$ and $\mathbf{z}_{sm}^i$ are the same; otherwise it is set to 1. When $\mathbf{z}_{sm}$ takes numerical values, $\left\| \mathbf{z}_{sm} - \mathbf{z}_{sm}^i \right\|$ can be taken as the distance between vectors z_{sm} and $z_{sm}i$.

Step 4: Compute CI based the formulations from Eqn. (3.12) to Eqn. (3.15):

$$CI_i = 1 - D_i \tag{3.16}$$

Consider a simple example of computing the convergence index for a tablet computer and a laptop. It is first demonstrated how the two products can be compared regarding the functionality of reading e-books. Assume that the functionality is enabled by (i) a storage module (M_1) with one sub-module flash memory (SM_{11}), and (ii) a display module (M_2)

with one sub-module LCD panel (SM_{21}). The size of the flash memory is denoted by a discrete variable z_{11} taking values such as 8GB, 16GB, etc. The diagonal dimension, in inches, of the LCD panel is denoted by a continuous variable z_{21} taking positive real values between 0 and 20. The tablet computer can be represented by $\{z_{11}=16GB, z_{21}=11\}$ and the laptop can be represented by $\{z_{11}=120GB, z_{21}=15\}$. Comparing the storage module using Eqn. (3.14) and (3.15), one obtains:

$$d_{Laptop,E-book,1} = \frac{\left\| \mathbf{z}_{sm11} - \mathbf{z}_{sm11}^{Laptop} \right\| - 0}{1 - 0} = 1 \qquad (3.17)$$

Similarly, for the display module, evaluating Eqn. (3.14) and (3.15) yields:

$$d_{Laptop,E-book,2} = \frac{\left\| \mathbf{z}_{sm21} - \mathbf{z}_{sm21}^{Laptop} \right\| - 0}{\sqrt{(20-0)^2} - 0} = \frac{\sqrt{(15-11)^2}}{\sqrt{(20-0)^2}} = 0.2 \qquad (3.18)$$

The above results will be put into Eqn. (3.13) to obtain:

$$D_{Laptop,E-book} = \frac{1}{2}\left(d_{Laptop,E-book,1} + d_{Laptop,E-book,2}\right) \qquad (3.19)$$
$$= 0.6$$

The above procedure can be carried out for other functionalities such as web browsing. Averaging the comparison for all the functionalities using Eqn. (3.12) yields D_{Laptop}. Eventually, the convergence index is computed using Eqn. (3.16).

The convergence index is then used to estimate the potential market size. The market size formulation only predicts the number of consumers who will potentially buy the convergence product. Whether the consumer will consider the convergence product as a complement or substitute to the existing product(s) will depend on his/her usage situations and unique preferences reflected by the hierarchical Bayes model in Eqn. (3.6). Consider a simple case of converging 2 existing product categories A and B, each with the market size of N_A and N_B. The overlap of the two markets (or number of consumers

who purchases both product A and product B) is denoted by N_{AB}. As a result, the estimated market size of a convergence product can be formulated as:

$$N_C = CI_A \cdot \left(N_A - N_A \cdot O_{AB}^A\right) + CI_B \cdot \left(N_B - N_B \cdot O_{AB}^B\right) + N_{AB} \qquad (3.20)$$

The above formulation can be generalized when three or more existing product categories are considered.

Impact of Usage Evolution (IUE). The product-consumer interaction is characterized by two stages. In the first stage, the purchase stage, a consumer makes a choice given his/her current preferences. In the second stage, the usage stage, the consumer starts using the new product and gradually adjusts his/her usage conditions. While the first stage happens at the time of purchasing, the second stage takes place over the longer time periods after the consumer buys and uses a product. The two stages are assumed to be independent. A separate model will be developed in the following to represent the effects in the second stage.

Specifically, the designer needs to consider how a product **x** may gradually change a consumer's usages ξ_i which eventually determines his/her preferences $\boldsymbol{\beta}_i$ for the forthcoming purchase occasions.

The usage condition for consumer i is considered to have an inherent component ξ_i^0 specific to this consumer and a variable component ξ_i^1 that results from using the products:

$$\xi_i = \left(\xi_i^0, \xi_i^1\right) \qquad (3.21)$$

In practice, the data on consumer's usage is usually observed as an ordinal measure. For instance, a consumer may claim his/her frequency of checking emails to be "every 1

hour", "every 2 hours" or "every 3 hours", rather than reporting continuous quantities. The term "latent satisfaction" is used to represent the underlying motive that consumer i chooses a specific level l for using functionality f. The latent satisfaction is modeled as the averaged effect of using all the products that a consumer currently owns, with the individual effects modeling linearly in terms of the products' attributes that he/she currently owns:

$$\rho_{f,l}^{i} = \frac{1}{P} \sum_{n=1}^{P} \rho_{f,l}^{i,n} \quad and \quad \rho_{f,l}^{i,n} = \gamma_{f,l}^{i} \mathbf{X}_{i}^{n} \tag{3.22}$$

in which P is the total number of products owned by consumer i.

The consumers are assumed to adapt their future usage levels such that their satisfactions are maximized. The Multinomial Logit Model formulation is used to capture this situation. Specifically, the probability that consumer i is observed to choose usage level l for functionality f is formulated as:

$$P\left(\xi_{f,l}^{i} = 1\right) = \frac{\exp\left(\rho_{f,l}^{i}\right)}{\sum_{l'=1}^{L} \exp\left(\rho_{f,l'}^{i}\right)} \tag{3.23.1}$$

in which:

$$\rho_{f,l}^{i} = \gamma_{f,l}^{i}\left(\sum_{n=1}^{P} \mathbf{X}_{i}^{n} / P\right) \tag{3.23.2}$$

The model can be estimated using a Bayesian multinomial logit regression procedure [Rossi et al., 2005]. The coefficients to be estimated are $\gamma_{f,l}^{i}$ vectors which are of the

same length as product attribute vectors $\mathbf{X}_i^n$. The log likelihood of the model is shown below:

$$LL(\xi \mid \gamma) = \sum_{i=1}^{I} \sum_{f=1}^{F} \left[I\left(\xi_{f,l}^i = 1\right) \cdot \left(\gamma_{f,l}^i \overline{\mathbf{X}_i} - \log\left(\sum_{l'=1}^{L} \exp\left(\gamma_{f,l'}^i \overline{\mathbf{X}_i}\right) \right) \right) \right]$$

where:

$$\overline{\mathbf{X}_i} = \left(\sum_{n=1}^{P} \mathbf{X}_i^n / P \right)$$

(3.24)

Now it is discussed how the above model helps a designer to infer the changes in consumers' preferences. For every design alternative with attribute $\mathbf{X}$, the designer will be able to predict the consumers' future usage frequencies (or levels) conditional on their purchase of the convergence product:

$$\xi_f^i * = \sum_{l=1}^{L} \xi_{f,l}^i \cdot P\left(\xi_f^i = l\right) = \sum_{l=1}^{L} \xi_{f,l}^i \cdot \frac{\exp\left(\rho_{f,l}^i\right)}{\sum_{l'=1}^{L} \exp\left(\rho_{f,l'}^i\right)}$$

(3.25.1)

in which :

$$\rho_{f,l}^i = \gamma_{f,l}^i \left(\sum_{n=1}^{P} \mathbf{X}_i^n / P \right)$$

(3.25.2)

The designer takes $\xi_f^i *$ as the prediction of the consumers' evolved usage conditions until the next purchase occasion. The future preferences of consumers are obtained using the second level of the hierarchical Bayes choice model shown in Eqn. (3.5). That is:

$$\boldsymbol{\beta}_i^* = \boldsymbol{\tau}\boldsymbol{\xi}_i^* \tag{3.26}$$

In addition to considering the profit, the designer needs to guarantee that the newly designed product will not lead the consumers to change their usages in a way such that their probability of buying the product in the future decreases. In other words, the expected market penetration in the future should not decrease. The *IUE* metric is therefore formulated as the difference between the current market penetration and the expected future market penetration. Specifically,

$$IUE = \left[Prob_0 \cdot Prob_1 + (1 - Prob_0) \cdot Prob_1 \right] - Prob_0 \tag{3.27.1}$$

$$Prob_0 = \frac{1}{C} \cdot \sum_{i=1}^{I} \sum_{c=1}^{C} \frac{\exp(\boldsymbol{\beta}_i^c \mathbf{X})}{1 + \exp(\boldsymbol{\beta}_i^c \mathbf{X})} \tag{3.27.2}$$

$$Prob_1 = \frac{1}{C} \cdot \sum_{i=1}^{I} \sum_{c=1}^{C} \frac{\exp(\boldsymbol{\tau}_i^c \boldsymbol{\xi}_i^* \mathbf{X})}{1 + \exp(\boldsymbol{\tau}_i^c \boldsymbol{\xi}_i^* \mathbf{X})} \tag{3.27.3}$$

in which $c=1,\ldots,C$ denotes a chain of samples obtained using the Bayesian estimation for the hierarchical Bayes choice model; $Prob_0$ denotes the current market share; $Prob_1$ denotes the expected future market share. The metric *IUE* will be constrained to be non-negative in the selection of design alternatives.

3.3.5. The Design Optimization Problem

Assuming that the company is only marketing the convergence product, the profit function is formulated as:

$$\Pi(\mathbf{x}; p) = [p - K(Q, \mathbf{X})] \cdot Q(\mathbf{X}) \tag{3.28}$$

in which p denotes the price, $K(Q, \mathbf{X})$ denotes cost as defined in Eqn. (3.11) and $Q(\mathbf{X})$ denotes demand as defined in Eqn. (3.7).

The overall optimization problem is given as in the following:

$$\begin{aligned}
&\max_x \quad \Pi(\mathbf{x}; p) \\
&s.t. \quad g_i(\mathbf{x}) \leq 0, \quad i = 1,\dots,I \\
&\qquad\ h_j(\mathbf{x}) = 0, \quad j = 1,\dots,J
\end{aligned} \tag{3.29}$$

in which $g_i(\mathbf{x})$ denotes the inequality constraint functions such as engineering constraints as well as long term market penetration consideration $IUE \geq 0$; $h_j(\mathbf{x})$ denotes equality constraint functions such as Functional Enabling Constraint represented by Eqn. (3.1). The above design optimization problem is solved using a Genetic Algorithm [e.g., Williams et al., 2008; Khajavirad et al., 2009]. In this study, the Matlab's Global Optimization Toolbox [MathWorks, 2011] is used to implement the genetic algorithm.

3.4 CASE STUDY

A consumer electronics company is interested in developing a convergence product based on two of its existing categories: laptop and smartphone. Among the functionalities that the existing products have, the following are being considered: (i) reading/sending/receiving emails; (ii) web browsing; (iii) playing multimedia contents, and (iv) reading e-books. It is assumed that the existing products are mature categories whose product and market structures are well known. The annual market sizes of the existing categories Laptop (category A) and Smartphone (category B) are assumed to be:

N_A=17.9M (units) and N_B=28M (units) [Mintel Oxygen, 2008; Mintel Oxygen, 2010]. Using the data collected in the survey (to be elaborated in Section 4.3), the percentages of overlap in the two markets (percentages of consumers in each market who purchase both products) are: $O_{AB,A}$ =57.7% and $O_{AB,B}$=95.3%. The designer's objective is to find the optimal design which maximizes the company's profit by considering a sustainable future market penetration.

The engineering design model for this example is formulated in Section 3.4.1. Section 3.4.2 presents the computation of customer observed product attributes as functions of engineering design variables. Section 3.4.3 describes the procedure for collecting customer preference data. The production cost is modeled in Section 3.4.4. Finally, three different design scenarios for comparison are formulated in Section 3.4.5.

3.4.1. Engineering Design Model

The first step of designing the convergence product is to construct a modular hierarchy for it by investigating how existing categories implement the functionalities. It is assumed that an average product can be defined for each category. Figure 3.4 presents the modular hierarchy of the product architectures of the two existing product categories. Table 3.1 summarizes the design variables and number of bits for each variable when translated into a bit string.

Some design variables take binary values of 1 or 0, e.g., x_1 indicates if function "email" is available or not in a design alternative. Some design variables take nominal values, e.g., x_{25} represents the discrete options of memory size such as 8GB, 16GB, 32GB and 64GB. The rest of the variables take continuous values, e.g., x_{31} represents the

Table 3.1 Engineering Design Variables

Var.	Notation	Lower Bound. (Option)	Upper Bound. (Option)	Laptop	Smart phone
x_1	F_1	0	1	1	1
x_2	F_2	0	1	1	1
x_3	F_3	0	1	1	1
x_4	F_4	0	1	1	0
x_5	M_1	0	1	1	0
x_6	M_2	0	1	0	1
x_7	M_3	0	1	1	1
x_8	M_4	0	1	1	1
x_9	M_5	0	1	1	1
x_{10}	M_6	0	1	1	1
x_{11}	M_7	0	1	1	1
x_{12}	M_8	0	1	1	1
x_{13}	SM_{11}	0	1	1	0
x_{14}	SM_{21}	0	1	0	1
x_{15}	SM_{22}	0	1	0	1
x_{16}	SM_{31}	0	1	1	1
x_{17}	SM_{32}	0	1	1	0
x_{18}	SM_{41}	0	1	1	1
x_{19}	SM_{51}	0	1	1	1
x_{20}	SM_{52}	0	1	0	1
x_{21}	SM_{61}	0	1	1	1
x_{22}	SM_{71}	0	1	1	1
x_{23}	SM_{72}	0	1	1	1
x_{24}	z_{31} (CPU Type)	1 (CPU)	2 (GPU)	2	1
x_{25}	$z_{41,1}$ (Memory size)	0 (8GB)	4 (64GB)	250	8
x_{26}	$z_{41,2}$ (Memory type)	0 (Flash)	1 (Disk)	1	0
x_{27}	$z_{61,1}$ (Battery material)	0 (Ni-ion)	1 (Ni-poly)	0	1
x_{28}	$z_{61,2}$ (Battery diagonal)	1"	11"	14"	3.5"
x_{29}	$z_{61,3}$ (Battery depth)	0.1"	1"	0.5"	0.1"
x_{30}	$z_{71,1}$ (LCD Type)	SD	HD	HD	SD
x_{31}	$z_{71,2}$ (LCD Diagonal)	3"	12"	14"	3.1"
x_{32}	$z_{71,3}$ (LCD Ratio)	4:3	16:9	16:9	4:3

diagonal length of the LCD panel. The last two columns of Table 3.1 show the design alternatives corresponding to the average products in the two existing categories.

Meanwhile, the functional enabling matrix **EM** is shown in Figure 3.5. As shown in Figure 3.5, each entry of the matrix EM_{ij}, indicates if functionality i requires module j.

For instance, for functionality F_4 of "Reading E-books" and module M_7 of "Display", the corresponding entry $\mathbf{EM}_{ij}$ will be set to 1 since reading e-books requires a display module.

	M_1: Input	M_2: Touch Screen	M_3: Processor	M_4: Storage	M_5: Wireless	M_6: Power	M_7: Display	M_8: Speaker
F_1: Email	0	0	1	1	1	1	1	0
F_2: Web	0	0	1	0	1	1	1	0
F_3: Media	0	0	1	1	0	1	1	1
F_4: E-Book	0	0	1	1	0	1	1	0

Figure 3.5 Functional Enabling Matrix

3.4.2. Mapping of Engineering Design to Product Attributes Observed by Consumers

The engineering design variables need to be translated into attributes that consumers observe when making a purchase decision. Such attributes may include size, weight and other features of a product. In this study, 13 product attributes are selected to represent a convergence product. Table 3.2 enlists all of the attributes and elaborates on how they are obtained by a mapping from the engineering design space. Some of the models and parameters are obtained from the literature [Haskell, 2004]. Other parameters can be obtained from the electronic component distributors' websites [e.g., Mouser Electronics, 2011] or estimated.

Table 3.2 Customer Level Attributes and Formulations

1 Email: $X_1=x_1$,

2 Web Browsing: $X_2=x_2$,

3 Media Player: $X_3=x_3$,

4 E-book Reader: $X_4=x_4$,

5 Product size (*Product enclosure size measured by the product's diagonal in inches*): $X_5=x_5$ $size_{keyboard}$ +(1-x_5) $size_{touch}$,

$size_{keyboard}=1.4\,x_{31}$, $size_{touch}=max\{x_{31},x_{28}\}$

6 Product depth (*Summation of LCD display thickness, enclosure thickness and the battery thickness. The first two dimensions are assumed to be constant*): $X_6= t_{LCD} +t_{packaging} +t_{Battery}$,

$t_{LCD}=1$ (inch) , $t_{packaging}=0.5$ (inch), $t_{Battery}=x_{29}$ (inch) ,

7 Product weight (*Summation of the weights of all its components in lbs*): $X_7= w_{circuit}+ w_{hard\,drive}+ w_{keyboard}+ w_{packaging}+ w_{battery}$,

$w_{circuit}$=0.5 (lbs), $w_{hard\,drive}$=1 (lbs), $w_{keyboard}$=0.5 (lbs) ,

$w_{packaging}$=0.5 (lbs), $\rho_{battery,ni-ion}$=0.0863 (lbs/inch^3) ,

$\rho_{battery,ni-polymer}$=0.038 (lbs/inch^3), ρ_{LCD}=0.3 (lbs/inch) ,

$w_{battery} = I(x_{27}=1)\,\rho_{battery,ni-ion}\,x_{28}x_{29}+ I(x_{27}=2)\,\rho_{battery,ni-polymer}\,x_{28}x_{29}$,

8 Battery life

(*The battery life is obtained by dividing the battery capacity by the total power consumption. The battery capacity depends on the battery material and its power density. The power consumption sums over the power consumption of every module, e.g., CPU, Display, Memory and etc.*):

X_8=Capacity / Power ,

$Capacity=I(x_{27}=1)\,0.254^3\times0.48x_{28}^2\rho_{power,ni-ion}+ I(x_{27}=2)\,0.254^3\times0.48x_{28}^2\rho_{power,ni-polymer}$,

$Power= p_{cpu}+ p_{LCD}+ p_{Memory}+ p_{Wireless}$,

$\rho_{power,ni-ion}$=120 (w hr/L), $\rho_{power,ni-polymer}$=240 (w hr/L) ,

$\rho_{power,LCD}$=0.29 (w/inch^3), p_{cpu}=2.5 $I(x_{24}=1)$+30 $I(x_{24}=2)$,

p_{LCD}=0.48 x_{31}^2 $\rho_{power,LCD}$, $p_{Memory}= I(x_{26}=1)$+2 $I(x_{26}=1)$,

$p_{Wireless}$ =2 x_{19}+1.5 x_{20} ,

9 Input Module: $X_9=x_5+2x_6$,

10 Wireless Type: $X_{10}= x_{19}+2x_{20}$,

11 Display Type: $X_{11}=x_{30}$,

12 Memory Size: $X_{12}=x_{25}$,

13 Price: X_{13}=$500 .

3.4.3. Collecting Customer Preferences

The customer preference information is collected using a choice-based conjoint survey. The survey consists of three sections: (i) usage condition questions; (ii) 12 choice tasks each having three alternatives, and (iii) the existing products the respondent already own and their prices.

Survey Design. The challenge of designing the conjoint survey for a convergence product is the large number of attributes. For instance, given a total number of 13 attributes with each attributes having 3 levels, there are 3^{13} (or 1,594,323) possible

product profiles that need to be evaluated by respondents. In this study, the randomized design scheme suggested by Sawtooth Software CBC Module [Sawtooth, 2001] is adopted. Discussions regarding the efficiency of the design scheme is given by Sawtooth [Sawtooth, 2001]. The design scheme is also reviewed by Chrzan and Orme [Chrzan and Orme, 2000].

Survey Distribution and Data Collection. Qualtrics software [Qualtrics, 2010] was utilized for online survey interface development, survey distribution and data collection. The experimental design was exported into a spreadsheet which the Qualtrics software integrates into the web-based surveys. The online distribution was operated through the server in Netcentric Behavioral Laboratory in the R. H. Smith School of Business, University of Maryland, College Park. The survey was sent to 475 candidate respondents out of which a total of 125 responses were collected. After eliminating unusable responses, e.g., those with skipped questions, 92 out of the 125 responses were used to estimate the model parameters.

3.4.4. Cost Model Specifications

The product cost model parameters are obtained from online price quotations of electronic component distributors [e.g., Mouser, 2011]. The details of the cost model are presented in Table 3.3. For simplicity, the assembly cost is set to 0.

Table 3.3 Cost Modeling

Item	Cost
LCD Display	β_1=-0.1032, β_2=0.7965, $C_{0,LCD}$=50 (\$), C_{LCD}= $C_{0,LCD}$ Q^{β_1} $x_{31}^{\beta_2}$
Battery	$C_{battery,ni\text{-}ion}$=1 \$/(w hr), $C_{battery,ni\text{-}polymer}$=2 \$/(w hr) $C_{battery}$=x_{21} ($I(x_{27}$=1) $C_{battery,ni\text{-}ion}$+ $I(x_{27}$=2)$C_{battery,ni\text{-}ion}$)
Memory Cost	$C_{flash,0}$=4 (\$/GB), $C_{hard\ drive,0}$=0.07 (\$/GB) C_{memory}= x_{25} ($I(x_{26}$=1) $C_{battery,ni\text{-}ion}$+ $I(x_{26}$=2)$C_{battery,ni\text{-}ion}$)
Integrated Circuits	C_{cpu}=18.5 (\$), C_{gpu}=6.5 (\$), C_{wifi}=19 (\$), C_{3G}=19 (\$) C_{other}=37 (\$)
Miscellaneous	$C_{keyboard}$=2 (\$), $C_{speaker}$=2 (\$), $C_{enclosure}$=12 (\$)

3.4.5. Scenario Development

Three scenarios for the case study were considered, as shown in Table 3.4. In each scenario a different design optimization problem is solved.

Table 3.4 Case Study Scenarios

	Scenario 1	Scenario 2	Scenario 3
Optimal Profit	✓	✓	✓
Heterogeneity		✓	✓
Impact of Usage Evolution			✓

Scenario 1: In this scenario, it is assumed that consumer preferences are homogeneous. That is, a single vector β is used to represent the preference of every consumer. This is variation to the model presented in Eqns. (3.3) and (3.4) as a benchmark. A design selection is therefore made to satisfy an average consumer. Meanwhile, the model has only one hierarchy, that is, the impact of usage conditions on the consumers' preferences is ignored. This scenario serves as a benchmark to compare the difference in design solutions with and without consumer heterogeneity considerations.

Scenario 2: The second scenario considers heterogeneous consumer preferences. That is, the full model presented in Section 3.3.2 is used to represent the consumers' choice behaviors. The designer optimizes profit but ignores the fact that consumers preferences can change over time as they use the convergence product. In this way, the design decision is made in favor of current profit without considering the product's future market penetrations.

Scenario 3: The last scenario extends the decision in Scenario 2 by accounting for the impact of usage evolutions or IUE. The design optimization problem is to find the optimal design for the convergence product for maximum profit while ensuring that the

future market penetration of the product will not decrease due to the changes in the consumers' preferences.

3.5 RESULTS

3.5.1. Estimations of Consumer Choice Models for Three Scenarios

The hierarchical Bayes model was estimated using a Markov Chain Monte Carlo sampling procedure. The procedure introduced by Rossi et al. [Rossi et al., 2005] was adapted to obtain the samples for the posterior distributions. The diffuse prior distributions were specified to diminish the influence of bias in the prior distributions. For instance, the means of priors were set equal to 0 and used $100\mathbf{I}$ as the variance matrix.

In the case study, the sampling algorithm was run for 20,000 steps and the last 3,000 samples were used to represent the posterior distributions. Due to the stochastic nature of the sampling procedure, the algorithm had to be run multiple times to check the consistency of the sample mean of the posterior distributions. More details regarding the method to assess such results, e.g., convergence of the chain and robustness of the posterior, are discussed by Gill [Gill, 2008].

For Scenario 1, interestingly, a homogenous preference model is assumed (using one vector to represent the preferences of all the consumers) but a bi-model posterior distribution is observed. For instance, the part-worth corresponding to the feature "Email" appears to be a mixture of two normal distributions with different mean values. Such contradiction reveals that the preferences of the consumers are indeed heterogeneous.

In Scenarios 2 and 3, the consumer preferences are estimated using the full model in Eqn. (3.6). That is, each consumer has a unique vector representing his/her preferences and the preference is related to the consumer's usage of the functionalities.

The significance of the estimation results can be revealed by computing Deviance Information Criterion (*DIC*) suggested by Spiegelhalter et al. [Spiegelhalter et al., 2002]. *DIC* is a popular measurement in the Bayesian statistics as an alternative for Hypothesis testing. Generally, a model with better goodness of fit can be associated with a smaller *DIC* value. The estimation result yields *DIC*=2407.7. Meanwhile, the model corresponding to the null hypothesis (i.e., setting **β=0**) yields DIC_0=3060.9. The noticeable difference between *DIC* and DIC_0 supports the significance of the estimation. It also demonstrates that the sample size of the data collected in the survey is sufficient to lead to a meaningful result.

3.5.2. Estimation of Consumer Usage Evolutions

In the third scenario, the optimal design decision will be made subject to an additional constraint that future market penetration of the convergence product should be non-decreasing. To enforce this constraint, the model discussed in Section 3.3.4 will be estimated first. The data include how the consumers are using the relevant functionalities now and what products they have purchased. In the online survey, a variety of questions were asked regarding usage conditions and at the end asked about their ownership of products such as laptops and smartphones. The prices of the products were collected as well.

It is assumed that the variable component of a consumer's usage is the frequency of using the functionalities. For instance, a consumer can adjust how often he/she reads e-books. This assumption is for simplicity so as to make the size of the regression problem manageable. Additionally, the attributes of the products that a consumer already owns are inferred using their responses for the prices of the products. The information about the

attributes and prices of typical products in the marketplace are collected by visiting the websites of major manufacturers and retailers. The attributes of the typical products for the laptop and smartphone categories are presented in Table 3.5 (for the prices of smartphones showed the price for unlocked versions without service contracts). For a product that is not listed, the attributes were estimated using a linear interpolation based on price.

Table 3.5 Typical Products in Laptop and Smartphone Markets

	Laptops			Smartphones		
	1	2	3	1	2	3
Price	$450	$800	$1.2k	$359	$400	$599
Email	1	1	1	1	1	1
Web	1	1	1	1	1	1
Media	1	1	1	1	1	1
Ebook	1	1	1	0	0	0
Size	10.1"	15.6"	13.3"	4.8"	3.5"	4.8"
Depth	1.3"	1.3"	0.95"	0.55"	0.6"	0.56"
Weight	3"	6.51"	4.5"	0.22"	0.3"	0.25"
Battery	9.5 hrs	9 hrs	10 hrs	4.5 hrs	6 hrs	6 hrs
Input	Keyboard	Keyboard	Keyboard	Touch	Keyboard Touch	Touch
Wireless	Wi-Fi	Wi-Fi	Wi-Fi	Wi-Fi 3G	Wi-Fi 3G	Wi-Fi 3G
Display	HD	HD	HD	SD	SD	SD
Memory	250GB	500GB	250GB	0.25GB	16GB	1GB

Using the data collected in the survey one is able to estimate the coefficient in the model of usage evolution or the γ matrix in Eqn. (3.23). For any given design alternative **x** with attributes **X**, a consumer's future usage conditions (or $\xi_f^i *$) are obtained using the procedures proposed in Eqn. (3.25). The updated usage conditions eventually lead to a mismatch between the present and forthcoming purchase decisions of the same consumer and *IUE* can be computed using Eqn. (3.27).

3.5.3. Solutions and Discussion

The attributes of the optimal design solutions for the three scenarios are compared in Figure 6. The results are discussed in the following sub-sections.

Scenario 1: Effect of CI. In Scenario 1, the optimal design is a hand-held electronic device with relatively small size and light weight, and is capable of sending/receiving emails, browsing the web and reading e-books. It is worth noting that the convergence index with respect to laptops is above 0.6 whereas for smartphones it is about 0.2, which is counterintuitive since the hand-held device seems to be closer to a smartphone in terms of size and weight. This effect is explained by looking at how the convergence indices are computed. The *CI* metric considers not only a number of customer observed attributes but also the engineering designs for each functionality. The selection of the modules for each functionality turns out to be much closer to that in a laptop and therefore results in a larger value of convergence index to laptops. In this scenario, the consumer choice model is a single level model which assumes the usages of functionalities have not influence on the consumers' preferences. As a result, the metric *IUE* is not computed.

Scenario 2: Effect of Consumer Heterogeneity. In the second scenario, the consumers are considered as heterogeneous and the heterogeneity is due to their different ways of using the functionalities. The optimal design differs significantly from that in Scenario 1. A tablet size device was obtained which can only be used for media playing and e-book reading. The device therefore lacks wireless communication. The expected profit has improved from $8,092.8M in Scenario 1 to $8,624.9M, though the unit cost also increases from $114.4 to $135. The device operates with fewer functionalities (2 functionalities in Scenario 2 versus 3 in Scenario 1) but incurs higher cost, which reflects

75

the designers intention to concentrate on a small number of functionalities but deliver higher satisfaction to the consumers for each functionality (e.g., providing consumers a larger screen to watch videos and read e-books). The sustainability of market penetration is ignored in this scenario. That is, the designer only considers short term profitability while ignores how consumers will change their preferences. As a result, a negative *IUE* of -0.9% was obtained. In other words, the future market penetration of the optimal design will decrease.

Scenario 3: Effect of IUE. In Scenario 3 the designer extends the design optimization problem in Scenario 2 for a sustainable market penetration. The functionalities of the optimal design in this scenario include email, web and e-book. Another difference in comparing to the design in Scenario 2 is the inclusion of keyboard as another input module. The rearrangement of the functionalities results in an increase of unit production cost from $135 to $149.3 and the short term profit drops from $8,624.9M to $8,013.5M. The decrease in short term profit is justified by a positive *IUE* value of 0.32% which indicates an increase of the market penetration in the long run. From an optimization perspective, considering a sustainable market penetration imposes an additional constraint to the design decision problem and shrinks the feasible region. As a result, the maximum profit cannot be as high as that in a less constrained problem. In terms of convergence indices, the optimal design resides in a place between the optimal designs in the previous scenarios. The distinction is due to consumer heterogeneity as well as sustainability of future market penetration.

It is worth noting that the attribute values of "battery life" of the three designs are very small. Although these values do not violate engineering feasibility constraints, they

contradict the product attributes observed in the real world market. In the conjoint survey, the attribute levels of "battery life" are presented at "2 hours", "6 hours" and "10 hours". The partworths for "battery life" at other values are obtained using a linear interpolation method. In other words, the customer survey does not accurately capture the consumers' responses for battery life values smaller than 2 hours. One way of correcting this is to add more attribute levels into the conjoint survey in order to obtain a more accurate measurement of the consumers' responses. Another solution is to impose a constraint on the attribute "battery life", for instance, an inequality constraint which screens out the design alternatives with battery life values smaller than, say, 2 hours. The above three scenarios each represents a different design decision problem. Therefore, it may not be legitimate to make a choice among the three optimal design solutions. The designer needs to identify the appropriate scenario based on the market trend then derive the optimal solution as the design decision. For instance, if the technology forecasts indicate that the market might change very fast (that is, new developments are imminent which might lead to paradigm shifts) then the designer might as well take a short term approach to maximize profit and not consider *IUE* as in Scenario 3. There is no right or wrong scenario between 2 and 3, it is just the question of which scenario meshes well with management objectives for the convergence product.
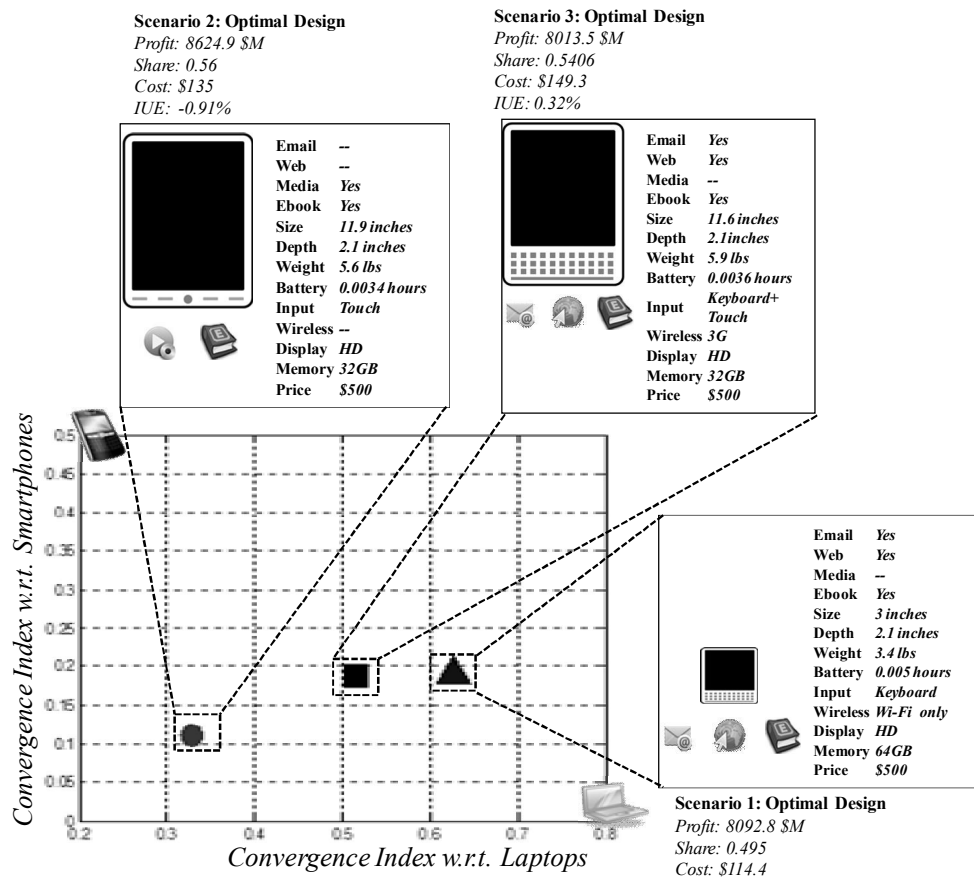
Figure 3.6 Comparison of Optimal Designs

3.6 SUMMARY

In this research thrust, a design decision framework is proposed for designing convergence products. A modular design framework is developed to integrate design solutions from multiple existing product categories and handle the couplings of functionalities for the convergence product, a problem that has not been addressed in extant literature but is an important one given the proliferation of convergence products. There are two important distinctions vis-à-vis prior work in that the proposed approach (1) accounts for the heterogeneous consumer choice behaviors by using a hierarchical Bayes model with its second level relating the consumers' preferences to their diverse ways of using the functionalities, and (2) considers two design metrics, Convergence Index (*CI*)

and Impact of Usage Evolution (*IUE*) to assist the designer's profit maximization decision. *CI* predicts the potential market size for the convergence product by measuring its similarity to existing product categories; *IUE* considers the changes in consumer usage conditions and their preferences in the forthcoming purchase occasions and predicts how such adaptation influences future market penetration. An optimal design is obtained to maximize the company's profit while considering a sustainable future market penetration.

In this chapter, the feasibility of combining modules from different product categories is implicitly assumed. For instance, the design method does not account for the fact that combining the "processor" of a smartphone and the "memory" of a laptop may not be necessarily feasible. In general, the capability of two (or more) systems to work together particularly under uncertainty can be challenging to analyze. The next chapter will mathematically model such capabilities of coupled systems. Additionally, both upstream market system (i.e., suppliers) and downstream market system (i.e., service providers) will be considered in the design selection decision.

CHAPTER 4: DESIGN FOR UPSTREAM AND DOWNSTREAM MARKET SYSTEMS WITH INTEROPERABILITY CONSIDERATIONS

The economic globalization and emerging high tech markets are pushing product design decision makers to account for both upstream and downstream market systems. Sourcing different components, modules, assemblies (or subsystems) of a product from a variety of domestic and overseas suppliers is becoming increasingly common. Consumer electronics companies such as Apple, Dell and others outsource the majority (if not all) of the components they need from their suppliers. Such practice has also been prevalent in other industries such as automobiles for decades. In this context, the specification of each module and the coupling or interoperability among different modules has become critically important particularly when the manufacturer does not have full control over its supply chain. Moreover, the product designer is often challenged to account for the interoperability by determining how well the sourced modules can work with each other under uncertainty. One example of such uncertainty can be the variations of usage conditions: using a cordless power tool to drill a piece of wood versus a piece of metal incurs different levels of loading on the motor, which in turn propagates through the couplings among the subsystems such as the transmission (gears) and battery.

Additionally, emerging high tech product markets are becoming increasingly connected to the service sector. Many consumer products, for instance, smartphones and tablet computers, rely on a variety of service providers to deliver their functions. Selecting service providers to partner in order to achieve the product's functionalities to the fullest extent possible has become a critical task for product designers.

With a focus on interoperability, this chapter aims at a design selection framework which accounts for both upstream market system (i.e., suppliers) and downstream market system (i.e., service providers and customers) to devise and explore: (i) a modeling approach that can be used for analysis of interoperability among subsystems of a product, (ii) a modeling approach that accounts for the couplings between the product design decisions and the offerings of service providers, and (iii) an integration of design decisions with respect to both upstream and downstream market systems.

The chapter is organized as following. Section 4.1 reviews the related research and positions the proposed method against the previous works. Section 4.2 defines the terminologies and describes the problem definition. Section 4.3 discusses the proposed method. Section 4.4 presents two case studies, namely, design selection of a cordless angle grinder where only upstream interoperability is considered and the design selection for a tablet computer where both upstream and downstream interoperability are considered. Conclusions are provided in Section 4.5.

4.1 INTRODUCTION

This chapter extends the existing research along three directions as discussed in the following.

I. Proposing a mathematical model of interoperability.

A major challenge in design selection with a supply chain based market is to manage the couplings among the modules so that each module can operate well in concert with other modules. Examples of methods that handle couplings are reported in a different context, as in Multidisciplinary Design Optimization (MDO), e.g., Analytic Target Cascading method [Kim, 2001] and Collaborative Optimization method [Braun, 1996].

Particularly, the concept of "systems of systems" has been proposed [Sobieszczanski-Sobieski, 2008; Arroyo et al., 2009] to address the analysis of a set of closely coupled systems. MDO approaches usually assume the designer has control over all subsystems. Yet these methods can become difficult to implement in a market system where manufacturers source modules from different suppliers instead of having full control (designing and building all of the modules in-house).

This chapter proposes a new approach for handling coupling or interoperability among subsystems of a product sourced from supplies. Interoperability refers to the capabilities of different systems (or subsystem) to work together [IEEE, 2000]. A commonly agreed definition of interoperability is not available. Existing works have proposed standards and qualitative recommendations to improve interoperability, for instance, for software engineering applications [e.g., Morris et al., 2004] and for a network of systems to exchange information [e.g., Tolk and Muguira, 2003]. Here, interoperability is referred to as the capabilities of subsystems (or modules of a product) to maintain their engineering feasibility when coupled with other subsystems under uncertainty. A quantitative metric for evaluating interoperability, particularly as applicable to product design, has not yet been reported.

On the other hand, multidisciplinary robust optimization methods have been investigated to consider both interval [e.g., Li and Azarm, 2008] and probabilistic [e.g., Liu et al., 2006] uncertainties, particularly with interdisciplinary uncertainty propagations (i.e., transmission of uncertainties among subsystems through the coupling variables). Robust optimization methods [e.g., Li and Azarm, 2008] obtain a design solution in such a way that the coupling variables stay within an acceptable range. Such conditions can be

difficult to achieve if there are significant variations in the parameters such that the coupling variables are no longer consistent across the systems. Meanwhile, in a design selection problem where the subsystems are procured from different suppliers, the product designer can hardly confine the coupling variables because the subsystems are provided by different suppliers. In this study, each subsystem is considered to have a range of operations under which the system operation remains feasible (or acceptable) given the uncertainties in the inputs.

The objective for this part of the research thus becomes formulating a general mathematical model for selecting a combination of subsystems (or modules) such that the ranges of operation among the subsystems (couplings) overlap as much as possible (or are acceptable).

II. Accounting for the couplings between products and services to address downstream interoperability with service providers.

There is an increasing number of products whose functionalities are closely coupled with functionalities offered by service providers, for instance, smartphone (coupled with wireless services) and tablet computers (coupled with digital content services). For such products, the main issue in the design selection is the interoperability between the design of the product and the associated service(s). This area has received little attention in the existing literature. On the other hand, Product-Service Systems (PSS) have been investigated as the manufacturers' initiatives to introduce a variety of services as add-ons to the product offering in order to improve profitability [Baines et al., 2007]. Examples include automobiles with financing services [Williams, 2006], elevators with maintenance services, copiers with leasing and rental services, etc. However, the reported

PSS methods overlook products whose functions are closely coupled with the services, particularly from the designer's point of view. For instance, the quality of digital video streaming services depends on the capabilities of the mobile devices or computers through which the service is delivered. In contrast to the previous works, this study explicitly models such couplings by accounting for the interoperability between the product functions and service activities. In addition, service providers are considered as a different player in the downstream market system, as opposed to the existing PSS frameworks in which the manufacturer itself is considered as the service provider [Baines et al., 2007]. For example, wireless services are usually offered by telecommunication service providers rather than the mobile phone manufactures. The practice of marketing combinations of products and services has also been studied in the business domains. For instance, Shanker et al. [Shanker et al., 2009] review a number of strategies of combining products and services. Aribarg and Foutz [Aribarg and Foutz, 2009] study the consumer choice decision when purchasing a product (e.g., a cell phone) and the corresponding service (e.g., wireless service plan). But the reported works do not consider the implications of combining products and services from the perspective of product design.

The objective for this part of the research is thus to exploring a method that accounts for interoperability among the product modules and the services while making product design selection.

III. Integrating the considerations of upstream market players (suppliers) and downstream market players (service providers and customers) for design selection with interoperability

Existing works in engineering design have accounted for upstream and downstream market systems. For instance, the upstream market system has been considered by combining design decisions and supply chain configuration decisions [Chiu and Okudan, 2011]. Downstream market system is considered by integrating consumer choice behavior and the action-reactions of competitors like manufacturers and retailers [e.g., Hoyle et al., 2010; Shiau and Michalek, 2009; Williams et al., 2011] for design decisions. Meanwhile, despite the efforts to adapt engineering design methods to design product-service systems [Kim et al., 2010], no previous work has been found that considers the integration of service providers as downstream market players combined with upstream supply chain players with interoperability considerations.

The objective for this part of the research is to devise an integrated decision framework which considers: (i) interoperability of modules sourced from upstream suppliers, (ii) downstream customer demand, and (iii) interoperability of the product with downstream service providers' offerings.

4.2 TERMINOLOGY, PROBLEM DEFINITION AND FRAMEWORK

4.2.1 Terminology

The term "system" refers to a mathematical representation of an engineered system. Every system i can be modeled as a "black-box" with inputs x_i, outputs o_i, and parameters p_i defining the system as shown in Figure 4.1(a). The input x_i is usually interpreted as design variables whose values can be specified by the designer. For instance, x_i can represent the physical dimensions of a component. Parameters (i.e., p_i) are values which the designer cannot control, e.g., density of steel, conductivity of cooper, material's yield strength, usage conditions and so on. For the majority of engineered system, the values of

the parameters are uncertain. In this way, instead of a fixed value, a parameter can be considered to have either finite or infinite number of possible values. Denote the set of all possible values of p_i using $\mathbf{P}_i$. Vector $\boldsymbol{p} = \{ \boldsymbol{p}_1, \boldsymbol{p}_2, \ldots\ldots\}$ is used to denote the collection of $\boldsymbol{p}_i$ for all i. In this study, each system is assumed to have its own design variables (i.e., $\boldsymbol{x}_i$) and parameters (i.e., $\boldsymbol{p}_i$). The shared variables and parameters among different systems (or subsystems) are not considered.

Another type of input (or output) is a coupling variable, denoted by $\boldsymbol{y}_{ij}$. A coupling variable is usually the input of one system (or subsystem) and the output of another. The values of the output coupling variables for a system can be determined once the design variables, parameters and input coupling variables of the coupled systems are given. Figure 4.1(b) presents an example of two coupled systems, namely, System 1 and System 2. The coupling variable $\boldsymbol{y}_{12}$ is an output from System 1 and an input to System 2. Meanwhile, the coupling variable $\boldsymbol{y}_{21}$ is an output from System 2 and input to System 1. The mapping from system input to output can be denoted by $(\boldsymbol{o}_i, \boldsymbol{y}_{ij}) = \boldsymbol{f}_i(\boldsymbol{x}_i, \boldsymbol{p}_i, \boldsymbol{y}_{ji})$. The system output $\boldsymbol{o}_i$ can include a number of constraint functions, i.e., $\boldsymbol{g}_i(\boldsymbol{x}_i, \boldsymbol{p}_i, \boldsymbol{y}_{ji}) \leq 0$.

The term "module" refers to a physical or software unit of a product which performs one or more functions. In general, a product can be considered as an integrated system with several (or many modules) with each module being considered as one of the subsystems of the product. In this study, the term "subsystem" and "module" are used interchangeably.

The term "interoperability" is a range reflecting the extent to which two (or more) coupled systems (or subsystems) can operate together seamlessly. The formulation of interoperability will be presented in Section 4.3. In this study, "upstream interoperability"

refers to the interoperability among the product modules; "downstream interoperability" refers to the interoperability between the product and the service(s).

<div align="center">(a)   (b)</div>
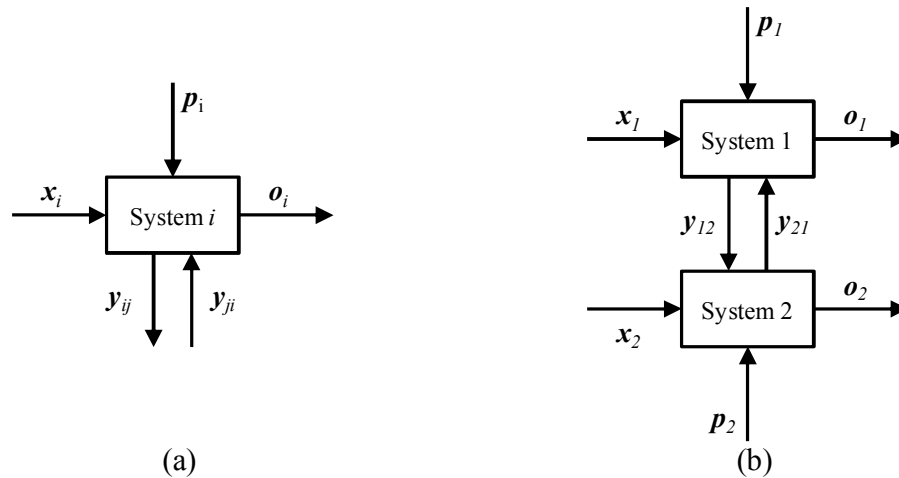
Figure 4.1 Definitions: (a) system, (b) two coupled systems

4.2.2 Problem Definition, Assumptions and Framework

The problem is defined as following. As shown in Figure 4.2, a manufacturing company is positioned in the market system with both upstream and downstream market players. Along the upstream, the manufacturer sources product modules designed by a variety of suppliers. Each module has a number of candidate suppliers to choose from. It is assumed that, for each subsystem (or module), the design specifications from the candidate suppliers are different. Along the downstream, the product is purchased by customers having heterogeneous choice behaviors. The customers purchase the product and subscribe to the associated services in order to perform the functionalities of the product.

The following are the key assumptions. (i) The product is modular with all the modules sourced from suppliers. Thus the product design problem is essentially a module selection problem. There is a "library" of modules with each module having a variety of

options (or suppliers) to choose from. (ii) the product has at least one function which requires the consumers to subscribe to services, for instance, a smartphone requires the consumers to subscribe to the wireless data service from the service providers. (iii) each service can be decomposed into a number of activities. For instance, an activity for the service of "digital video streaming" can be "transmitting digital content". The service activities are supported by the corresponding modules of the product. For instance, the activity "transmitting digital content" may require a "wireless connectivity" module of the product. Additionally, the product designer should decide which service provider to integrate with. (iv) For both upstream and downstream market systems, the competitors are considered to be static. That is, the action-reactions of market players are not considered.

The objective of the designer is to achieve the optimal demand (D) and/or market share, when accounting for the interoperability for both upstream and downstream markets, as shown in Figure 4.2.
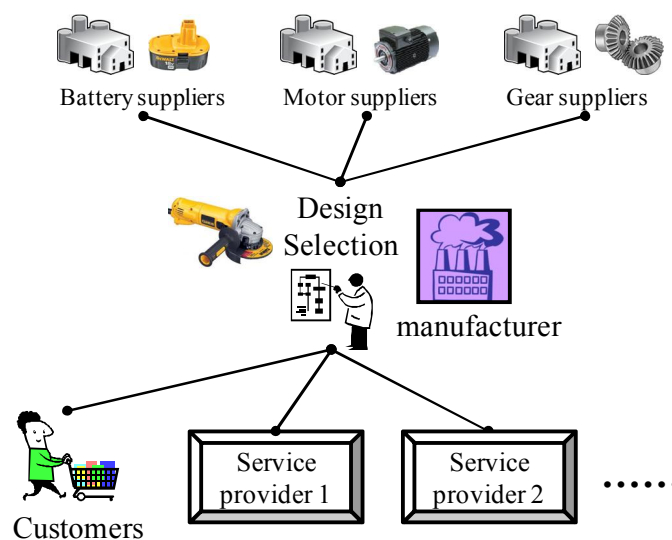
Figure 4.2 Problem Definition

The design selection framework is presented in Figure 4.3. A vector x_p denotes the design specification of all the product modules. A finite number of feasible values for x_p are available from a lookup table which contains the design specifications from all the suppliers' offerings. The function $g(x_p) \leq 0$ represents engineering constraints such as the upper limit on the maximum torque input to a gear set. Likewise, a vector x_s denotes the service attributes available from a lookup table containing the attributes of all the service providers' offerings. The designer selects the alternative with the maximum demand subject to the condition that interoperability is within an acceptable threshold specified by the designer. The threshold for upstream and downstream interoperability can be different. The market share can be estimated by the aggregation of probability of choice at the individual consumer level. The consumers' purchase decisions are determined by both the product attributes (i.e., X_p) and service attributes (i.e., X_s). The attributes are functions of design specifications of selected product modules and services. For instance, the attribute of "product weight" for an angle grinder is a function of the design specifications for material selection, geometrical dimensions, etc.
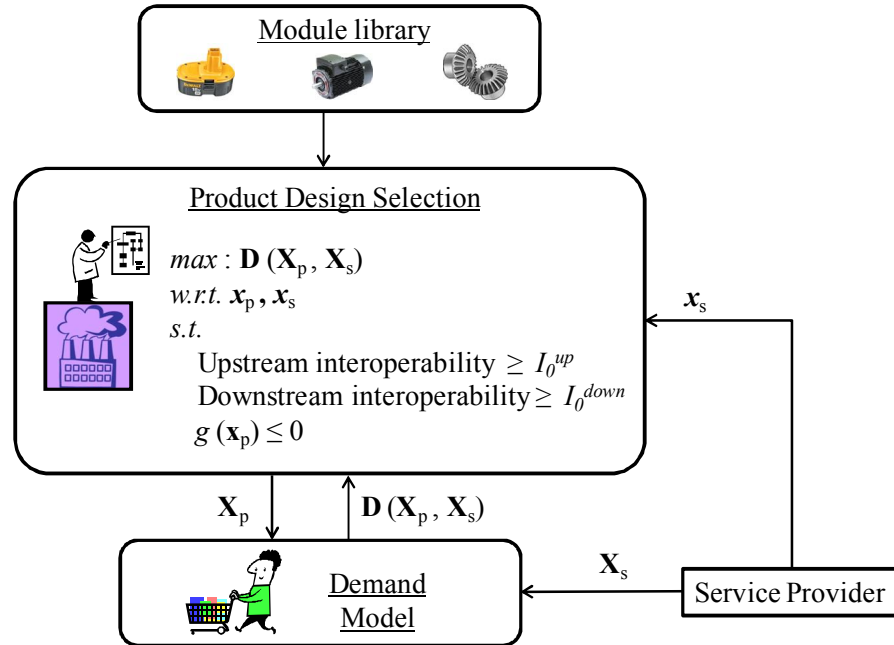
Figure 4.3 Design Selection Framework

4.3 METHODOLOGY

This section describes the design selection method. A mathematical formulation of interoperability, along with a numerical procedure to estimate interoperability will be presented in Section 4.3.1. The proposed model is then used for computing the interoperability along the upstream market system and then extended to analyze the interoperability along the downstream market system in Section 4.3.2. The consideration of customers along the downstream market system borrows the methods from the previous research [e.g., Williams et al., 2008] and will be discussed in Section 4.3.3.

4.3.1 Modeling Upstream Interoperability

The mathematical formulation of interoperability is discussed in four steps.

(i) *Definition of Interoperability*. Interoperability is defined as a capability of two (or more) systems to maintain their feasibility when coupled under uncertainty. Consider the example of two coupled systems as shown in Figure 4.1(b). Each system has a set of

functions f_i which maps the inputs (i.e. x_i, p_i and y_{ji}) to outputs (i.e., o_i, and y_{ij}). Each system has a set of engineering constraints $g_i(x_i, p_i, y_{ji}) \leq 0$ denoting the feasibility of the system. Consider the example presented in Figure 4.1(b). The two systems are coupled by the variables y_{12} and y_{21}. Therefore, the two systems are said to be interoperable for a given design (x_1, x_2) and parameter (p_1, p_2), if there exists values of coupling variables (y_{12}, y_{21}) such that:

$$y_{12} = f_1(y_{21}; x_1, p_1), g_1(y_{21}; x_1, p_1) \leq 0 \text{ , and}$$
$$y_{21} = f_2(y_{12}; x_2, p_2), g_2(y_{12}; x_2, p_2) \leq 0 \tag{4.1}$$

A point (y_{12}, y_{21}) which makes two systems interoperable is named as an *Interoperable Point*. In general, two coupled systems can have more than one interoperable point when their designs (x_1, x_2) are given. This is because the position of the interoperable point can change as the value of system parameters (p_1, p_2) varies. Meanwhile, the interoperable point(s) changes as the design (x_1, x_2) changes.

(ii) *Region of Operation* (**ROO**) *and Region of Interoperability* (**ROI**). In a design selection problem defined in Section 4.2.2, the designer of the product only has a finite number of options for the values of design variables due to the fact that the modules are sourced from suppliers. Additionally, there can be uncertainties in the parameters. It is thus desirable that a module *i* can be interoperable with another coupled module at a variety of interoperable points for the entire range of uncertainties in system parameters. To begin with, the *Region of Operation (***ROO***)* for a module (or subsystem) *i* is defined as:

$$\textbf{\textit{ROO}}_i = \left\{ y \mid \exists p_i \in \textbf{\textit{P}}_i : y_{ij} = f_i(y; x_i, p_i), g_i(y; x_i, p_i) \leq 0, \forall j \neq i \right\} \tag{4.2}$$

The above equation defines a region in which subsystem i is feasible for any given value of input coupling variables and uncertain parameters. The variations in the parameters can be characterized by probabilistic density functions. For instance, the parameter p_i can be assumed to be normally distributed: $p_i \sim N(\mu, \sigma_2)$. Or p_i can be considered to have an interval uncertainty and assumed to be uniformly distributed: $p_i \in [\underline{p_i}, \overline{p_i}]$ with $\underline{p_i}$ and $\overline{p_i}$ being the lower and upper bounds.

By comparing Eqns. (4.1) and (4.2), it can be understood that the interoperable points are essentially the intersections of regions of operations of the two systems for a range of uncertain parameters. The designer's interest is therefore in such intersections because these intersections are the regions where the subsystems can be interoperable. The intersection is called the *Region of Interoperability* (**ROI**), defined as following:

$$\textbf{ROI} = \bigcap_{i=1,\dots,I} \textbf{ROO}_i \qquad (4.3)$$

More specifically:

$$\textbf{ROI} = \left\{ y \mid \exists p \in P : y_{ij} = f_i(y; x_i, p_i), g_i(y; x_i, p_i) \le 0, \forall i, \forall j \right\} \qquad (4.4)$$

Consider the two system example shown in Figure 4.1(b). A graphical interpretation of region of operation and region of interoperability is shown in Figure 4.4. At a given x_1, **ROO**$_1$ consists of all the points (y_{12}, y_{21}) such that for any given value for y_{21} and a range of p_1: $y_{12} = f_1(y_{21}, x_1, p_1)$ and $g_1(y_{21}, x_1, p_1) \le 0$, is feasible. Likewise, **ROO**$_2$ consists of points such that for any given y_{12} and a range of p_2, the input-output mapping and feasibility of System 2 are maintained. The region of interoperability is therefore the intersection of the two **ROO**'s
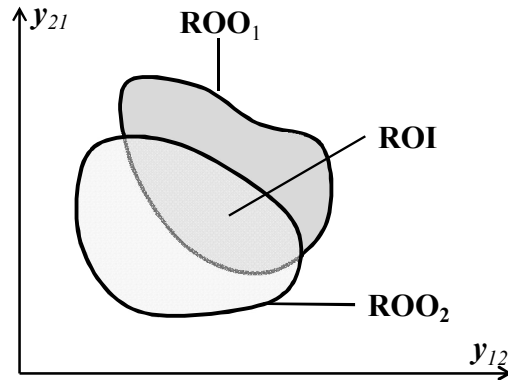
Figure 4.4 Regions of Operation (ROO) and Region of Interoperability (ROI)

ROO and **ROI** can be interpreted in many ways depending on the area of application. In the design of a cordless angle grinder (to be presented in Section 4.4 as a case study), System 1 is an electric motor and System 2 is a bevel gear transmission. The two systems are coupled by the coupling variables "Torque" and "Shaft mass" as presented in Figure 4.5.
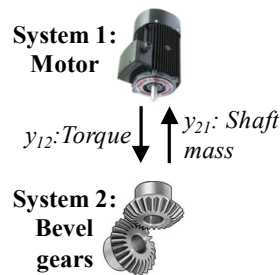
Figure 4.5 Interpretation of ROO and ROI: A Cordless Angle Grinder Example

(iii) *Interoperability Metric*. The interoperability of system i can be reflected by the area ratio of the region of interoperability (i.e., **ROI**) over the summation of regions of operation (i.e., **ROO**$_i$ for all i). In general, the area ratio will become volume ratio (for three dimensions) or hyper volume ratio (for more than three dimensions) when the coupling variables have more than two dimensions.

The interoperability metric is thus a numerical value between 0 and 1. Denote the area of **ROI** as A_{ROI} and area of **ROO**$_i$ as $A_{ROO,i}$. The interoperability metric (*IM*) can then be formulated as:

$$IM = \frac{A_{ROI}}{\displaystyle\sum_i A_{ROO,i}} \qquad (4.5)$$

 (iv) *Calculating the Interoperability Metric: A Monte Carlo Method*. The input-output mappings of many engineering systems are nonlinear, discrete or in a black-box form. In general, the region of operation may not be of any particular shape, which makes the area of **ROO** and **ROI** difficult to obtain in a closed form. A numerical method based on a Monte Carlo sampling procedure is proposed to approximate the value of *IM*.

As shown in Figure 4.6, the procedure can be carried out in two steps.
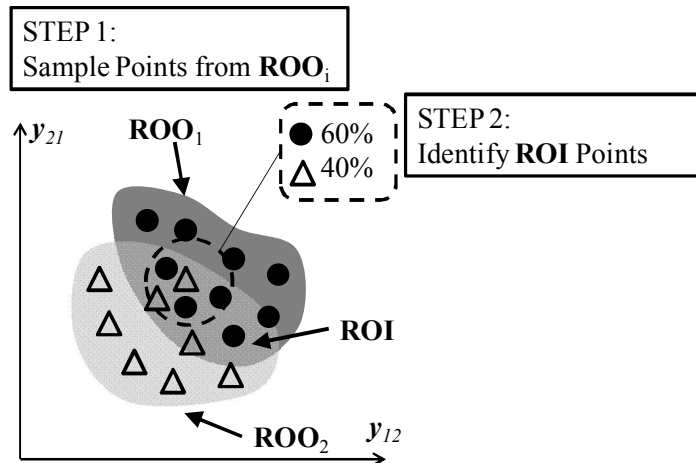
Figure 4.6 Calculate IM: A Monte Carlo Procedure

Step 1: Perform the following operation for each subsystem (x_i is fixed). First generate random samples of coupling variables y_{ji} and parameters p_i for system i. Next, obtain a corresponding system output y_{ij} using $y_{ij}=f_i (y_{ji} , x_i , p_i)$. The samples will be evaluated based on Eqn. (4.2) to decide if it belongs to **ROO**$_i$. The samples which do not

belong to any **ROO**$_i$ will be deleted. Denote the number of points in **ROO**$_i$ as N_i with $i=1,...,I$ where I denotes the total number of coupled systems.

Step 2: This step aims at finding out the points in each **ROO** which fall into the **ROI** using its definition in Eqn. (4.4). For each given point y from the **ROO** of a subsystem i, verifying Eqn. (4.4) means the following: if there exists a $p_i^* \in P_i$ (for all i) such that: $y_{ij} = f_i(y_{ji}, x_i, p_i^*)$ and $g_i(y_{ji}, x_i, p_i^*) \leq 0$ (for all i and all j), then y is indeed a point in **ROI**. This verification is equivalent to solving the following problem:

$$\min_{p_i \in P_i} \left| y_{ij} - f_i(y, x_i, p_i) \right| + max[0, g_i(y, x_i, p_i)] \tag{4.6}$$

This optimization problem should be solved for every point in **ROO**$_i$ (for all i). Denote the number of points in **ROO**$_i$ that falls into **ROI** with $N_{\text{ROI}, i}$. This can be computationally expensive. As such an alternative (heuristic) procedure is proposed next.

Step 2—an alternative heuristic procedure. For each point y in **ROO**$_i$, check the samples of p obtained in Step 1 and find out if there exists one (or multiple) $p = \{p_1, p_2,...\}$ such that: (i) $\left| y_{jk} - f_j(y; x_j, p_j) \right| \leq \varepsilon$ for all $j \neq i$ and k, and (ii) $g_j(y_{ij}; x_j, p_j) \leq 0$ for all j. The tolerance ε needs to be specified by the designer. If both conditions are satisfied, the point y can be considered to satisfy Eqn. (4.4). After repeating the above for every point in **ROO**$_i$, denote the total number of points of subsystem i falling into **ROI** (i.e., satisfying Eqn. (4.4)) with $N_{\text{ROI}, i}$. The above needs to be conducted for every subsystem i.

In this way, *IM* can be approximated by:

$$IM = \frac{A_{ROI}}{\sum_i A_{ROO,i}} = \frac{1}{\sum_i \dfrac{A_{ROO,i}}{A_{ROI}}} \approx \frac{1}{\sum_i \dfrac{N_i}{N_{ROI,i}}} \tag{4.7}$$

4.3.2 Modeling downstream interoperability

Service by a provider (e.g., wireless by Verizon, video streaming by Amazon) is a process consisting of interrelated activities. This definition follows the research in service modeling [e.g., Shostack, 1984]. For instance, a digital video streaming service can be considered to be composed of activities such as "transmitting/receiving video signal", "processing video data signal" and "playing video content". The implementation of activities depends on the functionalities of the product. For instance, an activity for the service of "digital video streaming" can be "transmitting digital content". Performing such an activity requires a product function of "send/receive wireless signal". The interoperability of a product and a service is ultimately determined by the interoperability between the product modules and service activities. The concept of the interoperability metric discussed in 4.3.1 can be extended to service domain to measure the interoperability, as discussed by the following three steps:

(1) Construct Activity Function Dependency Matrix. An activity needs to be supported by function(s) which the product modules implement. Note that for some activities two or more product functions may be needed. An "Activity Function Dependency Matrix" is defined to represent such dependency between service activities and product functions. Specifically: $\mathbf{AF}=(AF)_{ij}$, $i=1,\dots I, j=1,\dots J$, where $AF_{ij}=1$ if activity i depends on function j, $AF_{ij}=0$ if it does not. The entries in the matrix AF indicates all the activity-function pairs for which interoperability needs to be calculated.

(2) Identify Key Performance Attributes. For each activity-module pair as denoted by $AF_{ij}=1$, Key Performance Attributes (KPA) is defined as a vector characterizing the

interface between the activity and the module. Index the activity-module pairs using $t=1,\ldots,T$. Similarly to the region of operation for a module, the region of operation for an activity is defined as a region in the space of KPA parameters in which the activity can operate. The KPA is comparable to the coupling variables for analyzing physical systems.

(3) Calculate Interoperability. The interoperability metric is obtained by calculating the percentage of intersecting areas between the **ROO** of service activities and product modules, and aggregating the ratio over all the dependent activity-module pairs:

$$IM = \frac{A_{ROI}}{\sum_t A_{ROO,t}}$$

(4.8)

where a index of $t=1,\ldots,T$ denotes the activity-function pairs.

4.3.3 Modeling individual level customer choice behavior

Another group of critical players along the downstream market are the customers. The designer's objectives, either the profit or market share, depend heavily on the customer's purchase decision. A popular model representing the purchase decisions is Multinomial Logit model [McFadden, 1980]. In this study, the customers' choice behavior is modeled using the latent class Multinomial Logit model proposed in the previous literature [Williams et al., 2008].

Denote the customers using i ($i=1,\ldots,I$) and the choice alternatives using j ($j=1,\ldots,J$). Following the model in [McFadden, 1980], a customer's preference can be represented by a random utility function:

$$U_{i,j} = \beta_{i,p}\mathbf{X}_{j,p} + \beta_{i,s}\mathbf{X}_{j,s} + \varepsilon_i$$

(4.9)

in which $U_{i,j}$ denotes the utility for customer i for choosing alternative j, $\mathbf{X}_p$ represents the attributes of the product and $\mathbf{X}_s$ represents the attributes of the service(s). $\mathbf{X}_p$ can be

97

obtained using a mapping from the product design specifications. The term ε_i is the error term with a double exponential distribution. Assume that the customer makes the purchase decision by choosing the alternative with the maximum utility. The probability that the customer i chooses alternative j can be formulated as:

$$Pr_{i,j} = \frac{exp(U_{i,j})}{\sum_k exp(U_{i,k}) + exp(U_{i,NC})} \tag{4.10}$$

where $U_{i,NC}$ denotes the utility of "no-choice" option (i.e., to purchase none of the alternatives).

The above formulation can be extended. For instance, a latent class model can be used to account for the heterogeneity of the customers. Specifically, the customers are grouped into unique "segments". The preferences are identical within a segment but different across segments. A latent class model is formulated as:

$$\text{Pr}_{i,j} = \sum_{s=1}^{S} m_s \cdot \frac{exp(U_{i,j})}{\sum_k exp(U_{i,k}) + exp(U_{i,NC})} \tag{4.11}$$

in which m_s represents the size of segment s in percentage. It can also be interpreted as the probability that a customer belongs to segment s. By summing the probability in Eqn. (4.11) over all the customers, the market share can be obtained as the aggregated probability of choice.

4.4 EXAMPLES

The proposed design selection method is demonstrated by two case studies. In the first case study, a design selection problem for a cordless angle grinder is considered. This example is used to demonstrate the application of the interoperability metric for modeling upstream (supplier) interoperability while considering the demand in the

downstream market system. In the second case study, a tablet computer design selection problem is presented which considers both upstream (supplier) and downstream (service provider) interoperabilities.

4.4.1 Design Selection for Cordless Angle Grinder

A cordless angle grinder is a handheld electric power tool which can be used to remove surface material from a work piece. The example considered consists of three subsystems: a battery (or subsystem 1), an electric motor (or subsystem 2), and a bevel gear set (or subsystem 3). The engineering design model is adapted from the previous work by Li et al. [Li et al., 2010] with the following changes. Specifically, the shared input for the three subsystems as presented in [Li et al. 2010] are converted into inputs for individual subsystems; additionally, the one way coupling between the "battery pack" and "electric motor" subsystems are changed from "Current" to "Voltage". The design variables for each subsystem are shown in Table 4.1. The battery and the motor subsystems are coupled by the coupling variable "Voltage" (or y_{12}) which is an output from the battery. The motor and the bevel gear subsystems are coupled by the coupling variables "Torque Load" (or y_{23}) and "Shaft Mass" (or y_{32}). Each subsystem has its own set of constraints including lower and upper bounds of the design variables, as well as inequality constraints (equality constraints are converted into two equivalent inequality constraints.). For instance, the bevel gear system is constrained by the condition that the maximum stress on the gear teeth does not exceed the limit. The parameters are considered to have interval uncertainty. The range of uncertainty for all parameters is assumed to be -50% to +50% around the nominal values.

Table 4.1 Angle Grinder Subsystems and Design Variables

Battery (Subsystem 1)		Motor (Subsystem 2)		Bevel Gear (Subsystem 3)	
$x_{p,1}$	Battery cell height (mm)	$x_{p,8}$	Armature turns	$x_{p,16}$	Gear ratio
$x_{p,2}$	Ni reactant sheet thickness (um)	$x_{p,9}$	Stator turns	$x_{p,17}$	Pinion pitch (m)
$x_{p,3}$	Cd reactant sheet thickness (um)	$x_{p,10}$	Stator outer radius (m)	$x_{p,18}$	Motor-gear shaft length (m)
$x_{p,4}$	Separator sheet thickness (um)	$x_{p,11}$	Stator thickness (m)	y_{23}	Torque load
$x_{p,5}$	Battery cell coil turns	$x_{p,12}$	Gap length (m)		
$x_{p,6}$	No. of cells	$x_{p,13}$	Stack length (m)		
$x_{p,7}$	Current (amps)	$x_{p,14}$	Motor-gear shaft diameter (m)		
		$x_{p,15}$	Load RPM		
		y_{12}	Voltage (v)		
		y_{32}	Shaft mass		

The design selection problem is shown in Figure 4.7. The three key subsystems (or modules) are assumed to be sourced from suppliers. Each module has 10 candidate suppliers and there is only one option available from each supplier. Thus the total number of design alternatives equals 10^3 or 1000. Table 4.2 presents the design specifications of the suppliers' offerings. The design specifications are randomly generated under the condition that the feasibility constraints of each subsystem are satisfied.
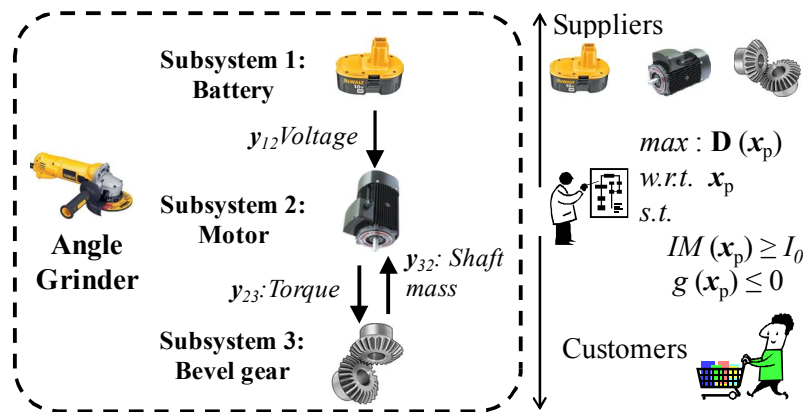
Figure 4.7 Case Study 1: Cordless Angle Grinder

Along the downstream, the product is targeted at a heterogeneous customer population with diverse preferences. The latent class multinomial logit model proposed

by Williams et al. [Williams et al., 2008] is applied. The model categorizes the market into 4 segments. Customer observed product attributes include price, brand, amp, battery life, girth, weight and retail channel. The customers' choice decisions are made out of four competing cordless angel grinders including the new product. In this study, the price is fixed at $50. The proposed method can be easily extended to handle pricing decisions by adding one additional decision variable.

The design selection proceeds as follows. The designer evaluates all combinations of battery, motor and gear from different suppliers. Each alternative is evaluated against the interoperability metric as well as downstream market share. The alternative which yields the maximum market share is selected if it is feasible and leads to a value of the

Table 4.2 Angle Grinder Suppliers' Design Specifications

Battery Suppliers									
1	2	3	4	5	6	7	8	9	10
$x_{p,1}$	50.993	18.905	64.819	27.657	19.512	58.965	19.795	78.364	79.995	74.464
$x_{p,2}$	4.711	3.917	23.891	40.693	42.524	33.087	15.326	28.551	39.325	5.029
$x_{p,3}$	47.822	64.835	33.854	53.659	53.113	75.258	34.933	94.657	64.585	59.595
$x_{p,4}$	15.601	76.095	38.877	66.209	28.930	21.725	40.959	75.463	26.079	68.609
$x_{p,5}$	1.073	1.694	1.518	1.565	1.891	1.102	1.532	1.735	1.482	1.739
$x_{p,6}$	1.881	1.603	1.443	1.593	1.510	1.124	1.150	1.006	1.827	1.760
$x_{p,7}$	2.032	1.543	1.985	1.048	1.858	1.708	2.215	2.031	1.042	1.115

Motor Suppliers									
1	2	3	4	5	6	7	8	9	10
$x_{p,8}$	165.051	128.302	55.602	216.380	126.107	24.216	194.793	69.877	185.981	175.139
$x_{p,9}$	173.732	174.796	190.834	69.362	121.356	188.606	99.047	90.141	73.929	129.414
$x_{p,10}$	0.009	0.006	0.007	0.009	0.006	0.008	0.003	0.010	0.008	0.008
$x_{p,11}$	0.031	0.057	0.041	0.031	0.035	0.037	0.034	0.057	0.023	0.052
$x_{p,12}$	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
$x_{p,13}$	0.014	0.016	0.013	0.012	0.019	0.018	0.012	0.013	0.016	0.018
$x_{p,14}$	36109	32471	50429	54408	49670	67044	14830	70898	77829	19055
$x_{p,15}$	0.001	0.003	0.002	0.004	0.001	0.004	0.003	0.004	0.003	0.005

Bevel Gear Suppliers									
1	2	3	4	5	6	7	8	9	10
$x_{p,16}$	0.321	0.233	0.262	0.343	0.215	0.390	0.317	0.231	0.235	0.369
$x_{p,17}$	0.013	0.014	0.014	0.018	0.012	0.019	0.009	0.010	0.010	0.013
$x_{p,18}$	0.010	0.006	0.007	0.006	0.005	0.005	0.006	0.009	0.005	0.005

interoperability metric higher than a given threshold. In this case study, the thresholds for the interoperability metric are obtained by finding out the Pareto frontier with two objectives: (i) maximize upstream interoperability, and (ii) maximize downstream demand. The interoperability metric values of the Pareto points are used as the thresholds. The design selection decisions obtained at all the thresholds will be shown.

The design selection results are presented in Table 4.3. First, a benchmark design decision is obtained by assuming that the subsystems are manufactured in-house rather than being sourced from the suppliers. That is, the designer can choose the design variable values (since they are assumed to be continuous) without being limited by the suppliers' options. Therefore, the design space is larger than that in the design selection problem as defined in Figure 4.7. The objective in the benchmark problem is to minimize cost. The cost model is borrowed from the attribute based model proposed by [Williams et al., 2008]. Neither the upstream interoperability nor the downstream demand is considered in the benchmark.

Figure 4.8 presents the scatter plot of all the 1000 candidate designs. Note that there are only a finite number of combinations of product attribute values. Therefore, the demand (or market share) for the design selection alternatives as shown in Figure 4.8 form a number of parallel lines. The Pareto frontier is highlighted using black diamonds. The "Pareto point 1" in Table 4.3 represents the design having the maximum demand along the Pareto frontier. The "Pareto point 2" in Table 4.3 represents the design having the maximum upstream interoperability along the Pareto frontier.

By looking at the benchmark design, the interoperability is low comparing to either one of the two Pareto design points. Even though the modules are all produced in-house

102

by a single manufacturer, the interoperability is not necessarily better since the design

decision is only driven by the cost. This is observed in other real world situations as well:

when the designer tries to reduce the production cost, the product performance may be

sacrificed. Note that the benchmark design actually achieves a higher level of demand

than both Pareto designs. This is primarily due to the fact that the design space is larger in

the benchmark problem. Comparing the two Pareto designs, the interoperability metric

values are very close. Following this observation, the designer is given the freedom to

pursue better market penetration without decreasing the interoperability significantly.

Table 4.3 Angle Grinder Design Results

System	Design Variables	Benchmark 1: Min Cost (in-house)	Pareto point 1: Maximum demand	Pareto point 2: Maximum interoperability
Battery	Supplier No.	N/A	9	4
	$x_{p,1}$	13.188	79.995	27.657
	$x_{p,2}$	2.127	39.325	40.693
	$x_{p,3}$	4.343	64.585	53.659
	$x_{p,4}$	5.274	26.079	66.209
	$x_{p,5}$	849.788	1.482	1.565
	$x_{p,6}$	1.044	1.827	1.593
	$x_{p,7}$	1.000	1.042	1.048
Motor	Supplier No.	N/A	6	6
	$x_{p,8}$	158.784	24.216	24.216
	$x_{p,9}$	10.000	188.606	188.606
	$x_{p,10}$	0.010	0.008	0.008
	$x_{p,11}$	0.076	0.037	0.037
	$x_{p,12}$	0.001	0.001	0.001
	$x_{p,13}$	0.020	0.018	0.018
	$x_{p,14}$	1002.256	67044	67044
	$x_{p,15}$	0.005	0.004	0.004
Bevel gear	Supplier No.	N/A	2	7
	$x_{p,16}$	3.804	0.233	0.317
	$x_{p,17}$	0.030	0.014	0.009
	$x_{p,18}$	0.010	0.006	0.006
Interoperability metric		0.103	0.265	0.266
Demand (market share)		0.515	0.434	0.433
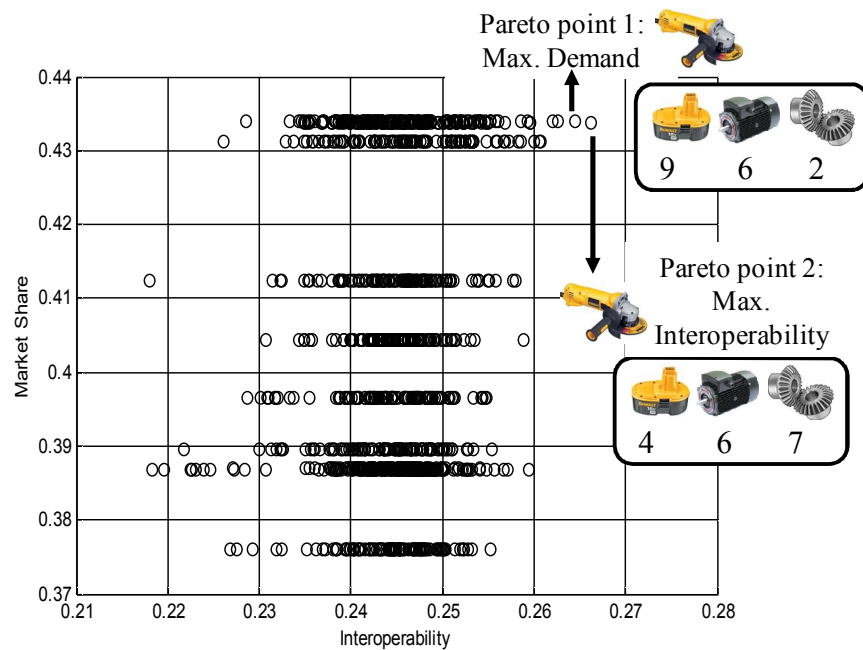
Figure 4.8 Pareto Frontier of Angle Grinder Example

One important decision which a designer (manufacturer) usually has to deal with is: how to choose a supplier and establish a long term contract? Using the proposed interoperability metric, the designer can evaluate the suppliers from an engineering design perspective. The "average interoperability" of each supplier's module can be obtained by combining the module with available options from all the other subsystems, and calculate the mean value of the interoperability metric of all such combinations. For instance, for a motor supplier's offering, the motor can be potentially combined with 10 battery options and 10 bevel gear options (100 combinations in total). Average interoperability reflects the ability of a supplier's offering to be compatible with all the other suppliers. Knowing the average interoperability is particularly important if for those subsystems which cannot be easily modified for an extended period of time—either due to the manufacturer-supplier contract or due to the long research and development

104

interval. In this way, for instance, the designer may want to choose a motor with the highest average interoperability so that the design can be easily adapted if changes are made with respect to the supply of the battery or the bevel gear subsystem. As shown in Figure 4.9, the best suppliers are, respectively: supplier 10 for battery (average *IM*=0.246), supplier 6 for the motor (average *IM*=0.251), and supplier 4 (average *IM*=0.245), for the gear.
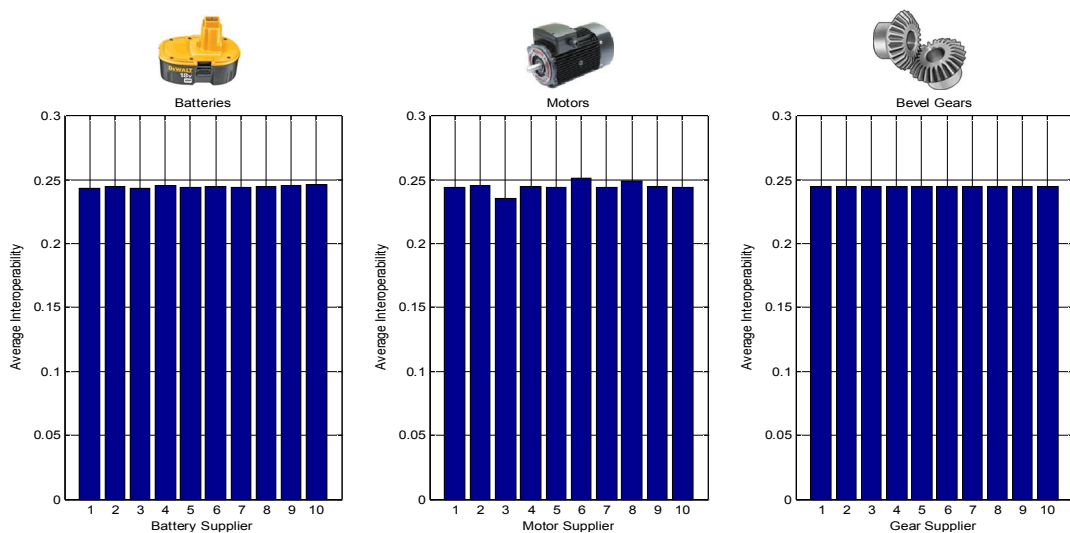
Figure 4.9 Average Interoperability of Angle Grinder Suppliers

4.4.2 Product Design Selection and Service Integration for a Tablet Computer

In the second case study, the product design selection for a tablet computer considering both the upstream (suppliers) and downstream (service providers) is considered. The designer sources the electronic components such as: microprocessor, LCD display panel, wireless connectivity module and battery. Table 4.4 lists the suppliers and the attributes of each supplier's offerings. The upstream interoperability involves the coupling between the processor and LCD display. Specifically, the processing capability of the processor in terms of resolution will be compared with the LCD display resolution.

Table 4.5 presents a simple model for computing engineering characteristics such as battery life, product weight and bit rate.

Table 4.4 Tablet Computer Suppliers

Module 1: LCD Supplier No.	$x_{p,1}$ Size (inches)	$x_{p,2}$ Resolution (horizontal px)	$x_{p,3}$ Power consumption (watts)	$x_{p,4}$ Weight (g)
1	5.7	480	5.6	250
2	7	480	5.75	175
3	9.7	768	9	165
4	10.1	800	10	185

Module 2: Microprocessor Supplier No.	$x_{p,5}$ Color processing capacity (Bits per pixel)	$x_{p,6}$ Resolution processing capacity (horizontal px)
1	24	1080
2	16	1050
3	60	1080

Module 3: Battery Supplier No.	$x_{p,7}$ Weight (g)	$x_{p,8}$ Capacity (Watt Hour)	$x_{p,9}$ size (inches)
1	150	37	6
2	200	50	7
3	250	60	10

Module 4: Wireless Supplier No.	$x_{p,10}$ Connection options
1	4G
2	Wi-Fi
3	Wi-Fi + 4G

Along the downstream, the designer also needs to make the decision of selecting the service providers. Two categories of digital services are to be supported by the product, namely, video streaming and electronic newspaper subscription. Each category of service has two candidate service providers to select from. The video streaming is a service which instantly transmits video contents (e.g., TV episodes and/or movies) to electronic devices through internet connections. Examples of existing service providers include Netflix and Hulu. The newspaper subscription service delivers the digital copies of newspapers to the electronic devices. Major players in the market include Amazon Kindle and Barnes and Noble. The interoperability along the downstream involves the couplings between the product functions and service activities. For instance, the

microprocessor provides functionalities such as processing video signal, the wireless connectivity module transmits and receives signal from service providers, the LCD display present sthe video contents to the user and the battery provides power for the other modules. Table 4.5 presents a list of KPAs for each service and their corresponding product modules. The corresponding product modules for each service activity are shown in the parenthesis. The KPAs have both numerical and categorical values. For the numerical values, the numbers in Table 4.6 indicates the upper bounds of the corresponding KPA.

Table 4.5 Tablet Computer Engineering Attribute Calculations

Bit rate (Mbs)	Br=R*C*F, where: R: resolution (total pixels) C: Color (bits per pixel) F: Frame rate (frames per second)
Power Consumption	P=P0+Pprocessor+Plcd
Battery Life	BL=Bc/P, where: Bc: battery capacity (Watt Hour)
Product Weight	W=W_{LCD}+W_{battey}+W_0

The demand model is a basic Multinomial Logit model as formulated in Eqn. (4.11). The customer level attributes include: LCD screen size and resolution, price, product weight, battery life, wireless connection, video streaming service picture quality and selection range, newspaper subscription content quality and selection range. The values of the coefficients in the demand model are simulated.

Table 4.6 Downstream Service Providers

Video Streaming	$x_{s,1}$ Transmit Content (Wireless)	$x_{s,2}$ Display Content (Microprocessor)
Service Provider 1	Bit rate: 2.5 Mbs	720 px
Service Provider 2	Bit rate: 5 Mbs	1080 px
Newspaper Subscription	$x_{s,3}$ Display Content (Microprocessor)	$x_{s,4}$ Newspaper Delivery (Wireless)
Service Provider 1	Color	Instant/Download
Service Provider 2	Black and White	Download

Table 4.7 presents the design selection results. The design selection involves the evaluation of 432 design alternatives (i.e., combinations of 4 suppliers for LCD module,

Table 4.7 Tablet Computer Design Selection Results

Modules	Attributes/Parameters	Design #1 max Demand	Design #2 max downstream interoperability	Design #3 max upstream interoperability
LCD Display	supplier No.	2	4	4
	Size (inches)	7	10.1	10.1
	Resolution (horizontal pixels)	480	800	800
Processor	Module supplier No.	3	1	2
	Color (bits per pixel)	60	24	16
	Resolution (horizontal pixels)	1080	1080	1050
Battery	supplier No.	1	3	3
	Battery weight (g)	150	250	250
	Battery capacity (wh)	37	60	60
	Battery size (inches)	6	10	10
Wireless Connection	supplier No.	2	3	3
	Wireless connection	Wi-Fi only	Wi-Fi and 4G	Wi-Fi and 4G
Digital Video Streaming Service	Video streaming service provider No.	1	2	2
	Transmission bit rate (Mbs)	2.5	5	5
	Content resolution (pixels)	720	1080	1080
Newspaper Subscription Service	Newspaper subscription provider No.	1	2	2
	Content color (B&W/Color)	Color	B&W	B&W
	Delivery (Wi-fi, 4G or both)	Wi-Fi and 4G	Wi-Fi	Wi-Fi
Upstream interoperability		0.422	0.231	0.222
Downstream interoperability		0.170	0.426	0.432
Demand (market share)		0.999	0.714	0.354

3 suppliers for the Processor module, 3 suppliers for the Battery module, 3 suppliers for the Wireless module, 2 service providers for Digital Video Streaming, and 2 service providers for Newspaper Subscription). Each alternative is evaluated against three objectives: (i) to maximize downstream demand, (ii) to maximize downstream (service) interoperability and (iii) to maximize upstream (product) interoperability. The Pareto

frontier consists of 12 design alternatives. Three Pareto points having the highest value for each objective are presented in Table 4.7. The demand maximizing design (or design #1) integrates the smallest LCD display with the lowest level of resolution. It also involves a wireless module having Wi-Fi only even if its downstream service providers offer both downloading (requiring either Wi-Fi or 4G) and instant access (requiring 4G) to the digital contents. Therefore, the downstream interoperability metric value is less than 50% of those of the other two designs. The designs maximizing upstream and downstream interoperability differ only in terms of the selection of processors. The downstream interoperability maximizing design (i.e., design #2) selects a processor with slightly better color and resolution processing capabilities. As a result, it "over qualifies" regarding the newspaper subscription service which only provides black and white contents, which leads to a small decrease in the downstream interoperability.

4.5 SUMMARY

This chapter presents a solution to the challenges of design selection in the context of both upstream and downstream market systems while considering interoperability. A model for system interoperability is proposed that can help the designer measure the compatibility of product modules and selecting upstream suppliers. The formulation is general and can be applicable to other fields of study such as analyzing "system of systems" (system engineering) and mechanical tolerancing (mechanical design). Additionally, the framework contributes to the existing literature in engineering design by filling the gap of quantitatively understanding the couplings between physical (tangible) product modules and intangible service components. Considering both product design and downstream service providers is increasingly important as evidenced in many high-

tech product markets where the products' functions heavily rely on the customers' subscription to associated services. Finally, this study links the upstream and downstream market systems by considering the key market players such as: suppliers, manufacturer (designer), service provider and customers in the product design selection decisions.

In the next chapter, the dissertation will be concluded. Contributions will be summarized and future research directions will be discussed.

CHAPTER 5: CONCLUSION

This dissertation investigates the product design decisions for market systems by integrating engineering design and marketing considerations. The design decisions attempt to maximize manufacturer profit and/or demand by accounting for: (i) the action-reactions of market players, such as competing manufacturers, retail channels; (ii) convergence of existing product categories into a new niche market and (iii) interoperability along both upstream and downstream market systems.

This chapter is organized as following. Section 5.1 provides concluding remarks for each research thrust. Section 5.2 highlights the contributions of the dissertation research. Section 5.3 discusses the limitations of the methods and present future research directions.

5.1 SUMMARY OF DISSERTATION

In Chapter 2, an agent based approach is presented to support design decisions in the market system with interactive market players. Specifically:

- The design decision method supports the designers for both long term and short term decisions. Long term decisions involve selecting the product features that cannot be changed in a long term horizon; whereas short term decisions concerns the strategies to react to the moves of market players for the short term, for instance, price competition, product feature improvements, retail channels' pricing changes, etc.

- An agent based simulation is proposed in order to (i) obtain market equilibrium in terms of demand and profit for the short term horizon, and (ii) devise short term design and pricing strategies for the focal manufacturer. Market players such as competing manufacturing firms and retail channels are modeled as learning agents. By learning it means the market players gradually learn to react to the moves of each

other. A no-regret learning algorithm is used to model the market system and equilibrium of the system can be analytically guaranteed.

- In the case studies, the proposed approach is compared with game theoretic approach reported in the previous literature. The results indicate that when competing manufacturing firms compete on pricing, the agent based approach results in a similar prediction of the market equilibrium compared to the game theoretic approach. Additionally, the proposed method is shown to be applicable when competing manufactures also react by improving designs—a situation where the game theoretic approach cannot be applied. The result also suggests that a firm can establish long term advantage in profit by strategically selecting design alternatives.

In Chapter 3, a profit maximizing design decision framework is investigated for convergence products. Specifically:

- A modular design method is introduced for designing convergence products by selecting the modules from related existing product categories. The convergence product is designed by merging the modular structures of the existing product categories. The engineering design framework ensures that a selected product functionality will be supported by the product modules and sub-modules.

- A hierarchical Bayes choice model is investigated to account for the heterogeneity of consumer preferences. Specifically, the model (i) represents the consumers' purchase decisions at the individual customer level and (ii) explains the heterogeneity of the preferences of different consumers. The coefficients representing the consumers' preferences for product attributes are formulated as functions of the individual specific usage situations of product functionalities. The model assumes that the

consumers devote significant cognitive effort to the evaluation of candidate products. This assumption is enforced in the choice-based conjoint survey where the respondents are asked to report their usage conditions of product features, consider the product attributes and then select the favorite product alternatives. However, in the real world market, there are consumers who make purchase decisions without devoting much cognitive effort, for instance, those who make impulsive purchase decisions. Such exceptions are not accounted for in the proposed model. Other models need to be explored to study the choice behavior of such customer segments.

- Two metrics are proposed to assist the designer's profit maximizing decision. The "Convergence Index" quantitatively reflects the similarity of the product architecture of a convergence product with respect to existing product categories. The index helps the designer to anticipate the size of the market for a convergence product—a new niche market which does not exist within any existing product categories. "Index of Usage Evolution" (*IUE*) considers the changes in consumer usage conditions and their preferences in the forthcoming purchase occasions and predicts how such adaptation influences future market penetration. *IUE* can be used align the design decision with not only the profit in the short run, but also a sustainable market penetration in the future.

- The design optimization approach in Chapter 3 is demonstrated by solving a case study of designing a tablet computer and comparing the optimal designs under three different scenarios. It is worth noting that convergence products are potentially applicable to many product categories beyond consumer electronics—home appliances, power tools, medical devices—just to name a few.

In Chapter 4, the proposed design selection method adopts a more holistic perspective by considering both upstream and downstream market systems while considering interoperability. Specifically:

- A mathematical model of interoperability is presented which defines (i) the Region of Operation (**ROO**), and (ii) the Region of Interoperation (**ROI**) which reflects the intersection of the **ROO** for the coupled systems—the region where the systems can work with each other. The formulation of interoperability is general and can be applicable beyond the design for market systems.

- Using the mathematical formulation of system interoperability, the proposed method can help the designers make selection decisions when the product modules are to be outsourced. In other words, the method accounts for the suppliers along the upstream market system by analyzing the interoperability among outsourced subsystems (or modules). This idea is also extended to the downstream market system to evaluate the interoperability between a physical product and a service. The extension is of particular importance given the emerging trend in many high-tech product markets where customers utilize the features of the product by subscribing to a variety of services.

5.2 SUMMARY OF CONTRIBUTIONS

The proposed agent based approach in Research Thrust 1 addresses the strategic design decisions in an uncertain market environment. Specifically:

- This dissertation provides a new approach for strategic product design decisions for uncertain market systems when the existing game theoretic methods cannot provide solutions. In other words, the proposed design decision method can

handle competitions involving complex design problems in which engineering systems is in black-box form.

- The agent based method provides a more realistic perspective in modeling the uncertain market system as compared to existing game theoretic models, by accounting for the action-reactions among market players with learning behavior.

- The approach provides the product designers, for the first time in literature, a method to pursue profitability by simultaneously determining: (i) the product features that cannot be changed for a long term horizon and (ii) the strategies to compete in the short term horizon by changing prices and product features that can be rapidly changed.

The customer driven design decision framework proposed in Research Thrust 2 addresses the challenges arising from the converging product markets. Specifically:

- A modular design framework is developed to integrate design solutions from multiple existing product categories and handle the couplings of functionalities for the convergence product, a problem that has not been addressed in extant literature but is an important one given the proliferation of convergence products.

- A new way of accounting for the heterogeneous consumer choice behaviors in product design decisions is investigated. The proposed hierarchical Bayes model considers the preference of each individual consumer and relates the preference to their unique ways of using the product functionalities.

- The proposed Convergence Index (*CI*) predicts the potential market size for the convergence product by measuring its similarity to existing product categories; the proposed Index of Usage Evolution (*IUE*) considers the changes of consumer

usage conditions and their preferences in the forthcoming purchase occasions, which helps the product designers to focus beyond the objective of maximizing profit and pursue a sustainable market penetration in the future.

Finally, the approach proposed in research thrust 3 provides a general formulation for analyzing system interoperability, which facilitates the design selection decision for both upstream and downstream market systems. Specifically:

- A general model of system interoperability is proposed to analyze the ability of coupled systems to work together under uncertainty. The method fills the gap of a quantitative model to analyze system interoperability whereas the existing methods are primarily qualitative.

- For the first time in Design for Market Systems, the downstream service providers are considered by accounting for the couplings between a physical product and intangible services using the proposed interoperability model.

- The dissertation proposes the first method to connect the decisions regarding both the upstream supplier selection and downstream integration with service providers. The method addresses the challenges arising from the increasingly common practices of outsourcing product modules from suppliers (along the upstream market system) and bundling products with services (along the downstream market system).

5.3 LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Research Thrust 1: For demonstration purpose, the case study in this thrust only presented a finite number of design alternatives. The addition of an optimizer to the outer loop (i.e., the selection of long term design options) will enable the proposed approach to

search the long term design space systematically particularly when there are numerous (perhaps even infinite) number of long term alternatives. There are also many other directions for extending the current approach. For instance, the current approach can be computationally expensive when a large number of agents with multiple action dimensions enter into the model. The agents' strategies are represented by probability density functions in black box form and therefore require Monte Carlo Markov Chain (MCMC) sampling steps to draw samples in every iteration in the simulation. This disadvantage can be alleviated to some extent by utilizing computers with multiple processors and perform agents sampling in parallel. Additionally, using approximation assisted optimization techniques [e.g., Hu et al., 2012] can overcome the issue by replacing the computationally expensive simulations with meta-models.

Research Thrust 2: The results of this research thrust suggest that when consumer heterogeneity is considered, the design decision is in favor of concentrating on fewer functionalities while providing better performances for each functionality. That is, instead of designing a product that has many functionalities to satisfy every consumer, the design is more focused on the needs of a subset of consumers and creates better value for this sub-population. (This, of course, is an empirical result dependent on the population surveyed). Such an observation motivates a need for designing a line of convergence products to further exploit the heterogeneous consumer needs. Additionally, the proposed method does not account for competitors' actions. The attributes of the competing products are assumed to be static and the subsequent entrants into the convergence product market are ignored. The action-reactions of competitors as well as the new entrants into the new niche market can be considered in the future research.

Moreover, the optimal design can be sensitive to the definition of "existing product categories" and corresponding average products. Finally, the proposed modular structure primarily reflects the configuration of physical modules. For many product categories such as consumer electronics, software modules are also critical features of product differentiation. One future direction is to explore how the designer can sustain the market penetration by selecting the appropriate hardware platform and a series of future improvements for the software modules.

Research Thrust 3: There are a few ways to address the limitations of this research thrust in the future. First, the numerical procedure discussed in Section 4.3.1, in general, cannot be analytically proved to provide an accurate approximation to the value of interoperability metric. The future research can be conducted to determine the validity as well as the accuracy of the numerical procedure. Meanwhile, the computational efficiency of the numerical method which computes the interoperability metric should be improved so as to integrate the model with an optimizer and explore a much larger design decision space. Additionally, a more comprehensive understanding of consumer choice behavior is needed, particularly with respect to how consumers account for their subscriptions of services when they make purchase decisions for physical products. Finally, the assumption of "static competitions" can be relaxed to extend the framework by accounting for strategic action-reactions of the upstream market players (e.g., the suppliers) and downstream market players (e.g., service providers and retail channels).

APPENDIX: CHOICE BASED CONJOINT SURVEY FOR CASE STUDY IN RESEARCH THRUST 2

This appendix presents the design of the customer survey as discussed in Chapter 3 (research thrust 2). The response data can be obtained from the online electronic companion for [Wang et al., 2011(a)] at http://dx.doi.org/10.1115/1.4004977.
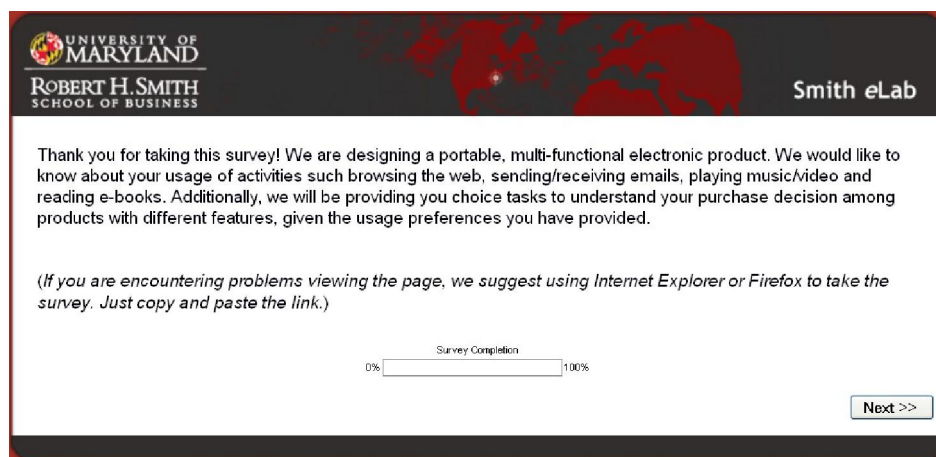
Section 1. Welcome Page and Brief Introductions

Section 2.1. Product Usage Questions: Email

Section 2.2. Product Usage Questions: Web Browsing

Section 2.3. Product Usage Questions: Media Player

Section 2.4. Product Usage Questions: E-Book

Section 3.1. Introduction to Choice Tasks

Section 3.2. Example Choice Task

UNIVERSITY OF
MARYLAND
ROBERT H. SMITH
SCHOOL OF BUSINESS

Smith *eLab*

For each product below, please indicate whether or not you own the product. If Yes, please indicate on the sliding scale below the approximate price (in $) you paid for the product. If No, please check the appropriate box against each product.

DO
NOT
OWN

100   200   300   400   500   600   700   800   900   1000

Laptop

Netbook

Smart phone

E-book reader

PDA

Survey Completion
0%   100%

<< Back   Next >>

Section 4. Question Regarding the Products Which the Respondent Already Owns

REFERENCE

1. Allenby, G. M., Rossi, P. E., and McCulloch, R. E., 2005, "Hierarchical Bayes Models: A Practitioners Guide", available at: http://ssrn.com/abstract=655541. Last Checked on June 24, 2012.

2. Anderson, S. P., Palma, A.d., and Thisse, J., 1992, "Discrete Choice Theory of Product Differentiation", Cambridge, MA, MIT Press, 1992.

3. Aribarg, A. and Foutz, N. Z., 2009, "Category-Based Screening in Choice of Complementary Products", *Journal of Marketing Research*, 46(4), pp. 518 to 530.

4. Arroyo, S. F., Cramer, E. J., Dennis, J. E., and Frank, P. D., 2009, "Comparing Problem Formulations for Coupled Set of Components", *Optimization and Engineering*, 10(4), pp. 557 to 573.

5. Aumann, R., 1974, "Subjectivity and Correlation in Randomized Strategies", Journal of Mathematical Economics, 1(1), pp. 67 to 96.

6. Baines, T. S., Lightfoot, H. W., Evans, S., et al., 2007, "State-of-the-art in Product-Service Systems", *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 221(10), pp. 1543 to 1552.

7. Belk, R. W., 1975, "Situational Variables and Consumer-Behavior", *Journal of Consumer Research*, 2(3), pp. 157 to164.

8. Besharati, B., Luo, L., Azarm, S., and Kannan, P. K., 2006, "Multi-Objective Single Product Robust Optimization: An Integrated Design and Marketing Approach," *Journal of Mechanical Design*, 128(4), pp. 884 to 892.

9. Braun, R. D., 1996, "Collaborative Optimization: An Architecture for Large Scale Distributed Design," Ph.D. thesis, Stanford University, Stanford, CA.

10. Bryant, C. R., McAdams, D. A., Stone, R. B., Kurtoglu, T., and Campbell, M. I., 2005, "A Computational Technique for Concept Generation", *Proceedings of the ASME 2005 Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, September 24-28, Long Beach, California, USA.

11. Camerer, C. F., 2003, "Behavioral Game Theory: Experiments in Strategic Interaction", Princeton University Press, Princeton, NJ.

12. Campbell, M. I., Cagan, J., and Kotovsky, K., 2004, "Agent-Based Synthesis of Electromechanical Design Configurations", *Journal of Mechanical Design,* 122(1), pp. 61 to 69.

13. Chen, Y., Carrillo, J. E., Vakharia, A. J., and Sin, P., 2010, "Fusion Product Planning: A Market Offering Perspective", *Decision Sciences*, 41(2), pp. 325 to 353.

14. Chiu, M., and Okudan, G., 2011, "An Integrative Methodology for Product and Supply Chain Design Decisions at the Product Design Stage", *Journal of Mechanical Design*, 133(2), pp. 021008-1 to 021008-15.

15. Choi, S. C., Desarbo, W. S., and Harker, P. T., 1990, "Product Positioning under Price Competition", *Management Science*, 36(2), pp. 175 to 199.

16. Chrzan, K., and Orme, B., 2000, "An Overview and Comparison of Design Strategies for Choice-Based Conjoint Analysis", *Sawtooth Software*, available at: http://www.sawtoothsoftware.com/download/techpap/desgncbc.pdf. Last checked on June 24, 2012.

17. Chung, J., and Rao, V. R., 2003, "A General Choice Model for Bundles with Multiple-Category Products: Application to Market Segmentation and Optimal Pricing for Bundles", *Journal of Marketing Research*, 40(2), pp. 115 to 130.

18. Dawid, H., Reimann, M., and Bullnheimer, B., 2001, "To Innovate or Not to Innovate?", *IEEE Transactions On Evolutionary Computation*, 5(5), pp. 471 to 481.

19. Deb, K., 2001, "Multi-Objective Optimization using Evolutionary Algorithms", John Wiley & Sons, Chichester, NY, USA.

20. Dobrescu, G., and Reich, Y., 2003, "Progressive Sharing of Modules among Product Variants", *Computer-Aided Design*, 35(9), pp. 791 to 806.

21. Fellini R., Kokkolaras, M., Papalambros, P., and Perez-Duarte, A., 2005, "Platform Selection under Performance Bounds in Optimal Design of Product Families", *Journal of Mechanical Design*, 127(4), pp. 524 to 535.

22. Frischknecht, B. D., Whitefoot, K., and Papalambros, P. Y., 2010, "On the Suitability of Econometric Demand Models in Design for Market Systems", *Journal of Mechanical Design*, 132(12), pp. 121007.1 to 121007.11.

23. Gao, F., Xiao, G., and Simpson, T. W., 2009, "Module-scale-based Product Platform Planning", *Research in Engineering Design*, 20(2), pp. 129 to 141.

24. Gibbons, R.,1992, "Game Theory for Applied Economists", Princeton, New Jersey, Princeton University Press.

25. Gill, J., 2008, "Bayesian Methods: A Social and Behavioral Sciences Approach, Second Edition", Chapman and Hall/CRC, Boca Raton, FL.

26. Gorti, S. R., Humair, S., Sriram, R. D., Talukdar, S., and Murthy, S., 1996, "Solving Constraint Satisfaction Problems Using ATeams", *AI EDAM-Artificial Intelligence For Engineering Design Analysis And Manufacturing*, 10(1), pp. 1 to 19.

27. Grecu, D. L., and Brown, D. C., 1996, "Learning By Single Function Agents During Spring Design", *Artificial Intelligence in Design*, John Gero and Fay Sudweeks (eds.) Kluwer Academic Publishers, pp. 409 to 428.

28. Green, P. E., and Srinivasan, V., 1978, "Conjoint Analysis in Consumer Research: Issues and Outlook", *The Journal of Consumer Research*, 5(2), pp. 103 to 123.

29. Gurnani, A., and Lewis, K., 2008, "Collaborative, Decentralized Engineering Design at the Edge of Rationality", *Journal of Mechanical Design*, 130(12), pp. 121101.1 to 121101.9.

30. Han J. K., Chung, S. W., and Sohn, Y. S., 2009, "Technology Convergence: When Do Consumers Prefer Converged Products to Dedicated Products?" *Journal of Marketing*, 73(4), pp. 97-108.

31. Hart, S., and Mas-Colell, A., 2000, "A Simple Adaptive Procedure Leading to Correlated Equilibrium", *Econometrica*, 68(5), pp. 1127 to 1150.

32. Hauser, J. R., 1988, "Competitive Price and Positioning Strategies", *Marketing Science*, 7(1), pp. 76 to 91.

33. Hauser, J. R., and Clausing, D., 1988, "The House of Quality", *Harvard Business Review*, 66(3), pp. 63 to 73.

34. Heilman, C. M., Bowman, D., and Wright, G. P., 2000, "The Evolution of Brand Preferences and Choice Behaviors of Consumers New to a Market", *Journal of Marketing Research*, 37(2), pp. 139 to 155.

35. Hoyle, C., Chen, W., Wang, N., and Gomez-levi, G., 2011 "Understanding and Modeling Heterogeneity of Human Preferences for Engineering Design", *Journal of Engineering Design*, 22(8), pp. 583 to 601.

36. Hoyle, C., Chen, W., Wang, N., and Koppelman, F. S., 2010, "Integrated Bayesian Hierarchical Choice Modeling to Capture Heterogeneous Consumer Preferences in Engineering Design", *Journal of Mechanical Design*, 132(12), pp. 121010.1 to 121010.11.

37. Hu, W., Almansoori, A., Kannan, P. K., Azarm, S., and Wang, Z., 2012, "Corporate Dashboards for Integrated Business and Engineering Decisions in Oil Refineries: An Agent-Based Approach", *Decision Support Systems*, 52(3), pp. 729 to741.

38. Huskell, B., 2004, "Portable Electronics Product Design and Development", McGraw-Hill, New York, USA.

39. IEEE Standards Information Network, 2000, "The Authoritative Dictionary of IEEE Standards Terms (IEEE 100)", Seventh Edition, IEEE, New York, NY.

40. Iyer, G., 1998, "Coordinating Channels under Price and Nonprice Competition", *Marketing Science*, 17(4), pp. 338 to 355.

41. Kane, Y. I., 2010, "Apple Puts iPad Sales at Two Million", *Wall Street Journal*, available at: http://online.wsj.com/article/SB10001424052748703406604575278740134863582.html?KEYWORDS=ipad+sale+5+million, Last checked on January 12, 2011.

42. Kane, Y. I., 2010, "The Only Tech These Geeks Lack Is a Cart to Haul Their Gadgets", *Wall Street Journal*, available at:

http://online.wsj.com/article/SB10001424052748703514904575602703106692326.html, Last checked on January 12, 2011.

43. Karimian, P., 2010, "Separating Product Family Design Optimization Problems", Ph.D. Dissertation, University of Maryland, College Park, pp. 43 to 89.

44. Khajavirad, A., Michalek, J. J., and Simpson, T. W., 2009, "An efficient decomposed multiobjective Genetic Algorithm for Solving the Joint Product Platform Selection and Product Family Design Problem with Generalized Commonality", *Structural and Multidisciplinary Optimization*, 39(2), pp. 187 to 201.

45. Kim, H. M., 2001, "Target Cascading in Optimal System Design," Ph.D. thesis, University of Michigan, Ann Arbor, MI.

46. Kim, Y. S., Lee, S. W., Maeng, J. W., and Cho, C. K., 2010, "Product-Service Systems Design Process Based on Activities and Functions", *Proceedings of the ASME 2010 International Design Engineering Technical Conference & Computer Information in Engineering Conference*, August, 15-18, 2010, Montreal, Quebec, Canada.

47. Kota, S., Sethuraman, K., and Miller, R., 2000, "A Metric for Evaluating Design Commonality in Product Families", *Journal of Mechanical Design*, 122(4), pp. 403 to 410.

48. Koukova N. T., Kannan, P. K., and Kirmani, A., 2012, "Multi-Format Digital Products: How Design Attributes Interact with Usage Situations to Determine Choice", *Journal of Marketing Research*, 29(1), pp. 100 to 114.

49. Koukova N. T., Kannan, P. K., and Ratchford, B. T., 2008, "Product Form Bundling: Implications for Marketing Digital Products", *Journal of Retailing*, 84(2), pp. 181 to 194.

50. Kumar, D., Chen, W., and Simpson, T. W., 2009, "A Market Driven Approach to Product Family Design", *International Journal of Production Research*, 47(1), pp.71 to 104.

51. Kumar, D., Chen, W., and Simpson, T. W., 2009, "A Market-Driven Approach to Product Family Design", *International Journal of Production Research*, 47(1), pp. 71 to 104.

52. Li, H., and Azarm, S., 2000, "Product Design Selection under Uncertainty and with Competitive Advantage", *Journal of Mechanical Design*, 122(4), pp. 411 to 418.

53. Li, M., and Azarm, S., 2008, "Multiobjective collaborative Robust Optimization (McRO) with Interval Uncertainty and Interdisciplinary Uncertainty Propagation," Journal of Mechanical Design, 130(8), pp. 081402-1 to 081402 to 12.

54. Li, M., Hamel, J., and Azarm, S., 2010, "Optimal Uncertainty Reduction for Multi-Disciplinary Multi-Output Systems Using Sensitivity Analysis," *Structural and Multidisciplinary Optimization*, 40(1-6), pp. 77 to 96.

55. Lilien, G.L., Kotler, P., and Moorthy, K.S., 1995, "Marketing Models", Prentice Hall, Upper Saddle River, NJ.

56. Liu, H., Chen, W., Kokkolaras, M., Papalambros, P., and Kim, H., 2006, "Probabilistic Analytical Target Cascading—A Moment Matching Formulation for Multilevel Optimization under Uncertainty", *Journal of Mechanical Design*, 128(4), pp. 991 to 1000.

57. Luo, L, Kannan, P. K., and Ratchford, B. T., 2008, "Incorporating Subjective Characteristics in Product Design and Evaluations".*Journal of Marketing Research*. 45(2), pp.182 to 194.

58. Luo, L., Kannan, P. K., Besharati, B., and Azarm, S., 2005, "Design of Robust New Products under Variability: Marketing Meets Design", *Journal of Product Innovation Management*, Special Issue: "Marketing Meets Design", 22(2), pp. 177 to 192.

59. Luo, L., Kannan, P.K., and Ratchford, B. T., 2007, "New Product Development Under Channel Acceptance", *Marketing Science*, 26(2), pp. 149 to 163,

60. Marden, J. R., Arslan, G., and Shamma, J. S., 2007, "Regret based dynamics: convergence in weakly acyclic games", *Proceedings of the 6th International Joint Conference on Autonomous Agents and Multiagent Systems*, May 14 to 18, 2007, Honolulu, Hawaii, USA.

61. MathWorks, 2010, "slicesample", *Statistics Toolbox, R2010b Documentation*, http://www.mathworks.com/help/toolbox/stats/slicesample.html. Last checked on June 24, 2012.

62. MathWorks, 2011, "Using the Genetic Algorithm (Global Optimization Toolbox)", Available at: http://www.mathworks.com/help/toolbox/gads/f6010dfi3.html, Last checked: June 24, 2012.

63. McAdams, D. A., Stone, R. B., and Wood, K. L., 1999, "Functional Interdependence and Product Similarity Based on Customer Need", *Research in Engineering Design*, 11(1), pp. 1 to 19.

64. McFadden, D., 1980, "Econometric Models for Probabilistic Choice among Products", *Journal of Business*, 53(3), pp. 13 to 29.

65. Meyer, M. H., and Lehnerd, A. P., 1997, "The Power of Product Platforms: Building Value and Cost Leadership", Free Press: New York.

66. Miller, J. H., 2007, "Complex Adaptive Systems: An Introduction to Computational Models of Social Life", Princeton, New Jersey, Princeton University Press.

67. Mintel Oxygen, 2008, "Home Personal Computers - US - December 2008, Segment Performance—Laptops".

68. Mintel Oxygen, 2010, "Mobile Phones - US - June 2010, Segment Performance—Smartphones".

69. Montgomery, D. B., Moore, M. C., and Urbany, J. E., 2005, "Reasoning about Competitive Reactions: Evidence from Executives", *Marketing Science*, 24(1), pp. 138 to 149.

70. Moon, S. K., Simpson, T. W., and Kumara, S. R. T., 2008, "A Strategic Module-Based Platform Design Method for Developing Customized Products in Dynamic and Uncertain Market Environments", *Proceedings of the ASME 2008 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, August 3 to 6, 2008, Brooklyn, New York, USA.

71. Morris, E., Levine, L., Meyers, C., Place, P., and Plakosh, D., 2004, "System of Systems Interoperability (SOSI): Final Report", Carnegie Mellon University, Pittsburgh, PA. available at: http://www.dtic.mil/cgi-bin/GetTRDoc?AD=ADA455619, Last checked: June 22, 2012.

72. Mouser Electronics, "Mouser Electronics-Electronic Component Distributor", Available at: http://www.mouser.com/. Last Check on 12 January, 2011.

73. Nean, R. M., 2003, "Slice Sampling", *The Annals of Statistics*, 30(3), pp. 705 to 767.

74. Ofek, E., and Sarvary, M., 2003, "R&D, Marketing, and the Success of Next-Generation Products", *Marketing Science*, 22(3), pp. 355 to 370.

75. Orsborn, S., and Cagan, J., 2009, "Multiagent Shape Grammar Implementation: Automatically Generating Form Concepts According to a Preference Function", *Journal of Mechanical Design*, 131(12), pp. 121007.1 to 121007.10.

76. Orsborn, S., Cagan, J., and Boatwright, P., 2009, "Quantifying Aesthetic Form Preference in a Utility Function", *Journal of Mechanical Design*, 131(6), pp. 061001.1 to 061001.10.

77. Qualtrics, 2010, "Survey Design", available at: http://www.qualtrics.com/survey-design/, Last check on 12 January, 2011.

78. Ramdas, K., and Sawhney, M. S., 2001, "A Cross-Functional Approach to Evaluating Multiple Line Extensions for Assembled Products", *Management Science*, 47(1), pp. 22 to 36.

79. Rossi, P. E., Allenby, G. M., and McCulloch, R., 2005, "Bayesian Statistics and Marketing", Wiley, Hoboken, New Jersey.

80. Sawtooth Software Inc., 2001, "Sawtooth Choice-Based Conjoint User Manual", Sequim, WA.

81. Shankar, V., Berry, L. L., and Dotzel, T., 2009, "A Practical Guide to Combining Products and Services", *Harvard Business Review*, 87(11), pp. 94 to 99.

82. Shiau, C. N., and Michalek, J. J., 2009(a), "Should Designers Worry About Market Systems?", *Journal of Mechanical Design*, 131(1), pp. 011011.1-011011.9.

83. Shiau, C. N., and Michalek, J. J., 2009(b), "Optimal Product Design under Price Competition", *Journal of Mechanical Design*, 131(7), pp. 071003.1 to 071003.10.

84. Shiau, C., Tseng, L. H., Heutchy, A. W., and Michalek, J., 2007, "Design Optimization of a Laptop Computer Using Aggregate and Mixed Logit Demand Models with Consumer Survey Data", *Proceedings of the ASME 2007 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, September 4 to 7, 2007, Las Vegas, Nevada, USA.

85. Shoham, Y., Powers, R., and Grenager, T., 2007, "If Multi-Agent Learning Is The Answer, What Is the Question?", *Artificial Intelligence*, 171(7), pp. 365 to 377.

86. Shostack, G. L., 1984, "Designing Services that Deliver", *Harvard Business Review*, 62(1), pp. 133 to 139.

87. Simpson, T. W., and Park, J., 2005, "Development of a Production Cost Estimation Framework to Support Product Family Design", *International Journal of Production Research*, 43(4), pp. 731 to 772.

88. Sobieszczanski-Sobieski, J., 2008, "Integrated System-of-Systems Synthesis", *AIAA Journal*, 46(5), pp. 1072 to 1080.

89. Spiegelhalter, D. J., Best, N. G., Carlin, B. P., and van der Linde, A., 2002, "Bayesian Measures of Model Complexity and Fit", *Journal of Royal Statistical Society, Series B (Statistical Methodology)*, 64(4), pp. 583 to 640.

90. Strmersch, S., and Tellis, G. J., 2002, "Stragetic Bundling of Products and Prices: A New Synthesis for Marketing", *Journal of Marketing*, 66(1), pp. 55 to 72.

91. Thevenot, H. J., and Simpson, T. W., 2004, "A Comparison of Commonality Indices for Product Family Design" *Proceedings of the ASME 2004 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, September 28 to October 2, 2004, Salt Lake City, Utah, USA.

92. Thevenot, H. J., and Simpson, T. W., 2009, "A product dissection-based methodology to Benchmark Product Family Design Alternatives", *Journal of Mechanical Design*, 131(4), pp. 041002-1 to 041002-9.

93. Tolk, A., and Muguira, J. A., 2003, "The Levels of Conceptual Interoperability Model", *2003 Fall Simulation Interoperability Workshop*, Orlando, Florida, September , 2003.

94. Tucker, C. S., and Kim, H. M., 2008, "Optimal Product Portfolio Formulation by Merging Predictive Data Mining with Multilevel Optimization", *Journal of Mechanical Design*, 130(4), pp. 041103.1 to 041103.15.

95. Ulrich, K. T., and Eppinger, S. D., 2000, "Product Design and Development", Irwin MeGraw-Hill, Boston, MA.

96. Wang, Z., Azarm, S., and Kannan, P. K., 2011(a), "Strategic Product Design Decisions for Uncertain Market Systems Using an Agent Based Approach", *Journal of Mechanical Design*, 133(4), pp. 041003.1 to 041003.11.

97. Wang, Z., Kannan, P. K., and Azarm, S., 2011(b), "Customer-Driven Optimal Design for Convergence Products", *Journal of Mechanical Design*, 133(10), pp. 101010.1 to 101010.13.

98. Wang, Z., Azarm, S., and P. K. Kannan, 2010, "Strategic Design Decisions for Uncertain Market Systems Using an Agent Based Approach," *Proceedings of the ASME International Design Engineering Technical Conference*, August 15 to 18, Montreal, Canada.

99. Whyte, J. K., Davies, A., Salter, A. J., and Gann, D. M., 2003, "Designing to Compete: Lessons from Millennium Product Winners", *Design Studies*, 24(5), pp. 395-409.

100. Williams, A., 2006, "Product-Service Systems in the Automotive Industry: the Case of Micro-Factory Retailing", *Journal of Cleaner Production*, 14(2), pp. 172 to 184.

101. Williams, N., Azarm, S., and Kannan, P. K., 2008, "Engineering Product Design Optimization for Retail Channel Acceptance", *Journal of Mechanical Design*, 130(6), pp. 061402-1 to 061402-10.

102. Williams, N., Azarm, S., and Kannan, P. K., 2010, "Multicategory Design of Bundled Products for Retail Channels Under Uncertainty and Competition", *Journal of Mechanical Design*, 132(3), pp. 031003.1 to 031003.10.

103. Williams, N., Kannan, P. K., and Azarm, S., 2011, "Retail Channel Structure Impact on Strategic Engineering Product Design," *Management Science*, 57(5), pp. 897 to 914.

104. Wooldridge, M., 2002, "An Introduction to MultiAgent Systems", Chichester, England, John Wiley & Sons Ltd.

105. Yang, S., Allenby, G. M., and Fenell, G., 2002, "Modeling Variation in Brand Preference-the roles of objective environment and motivating conditions", *Marketing Science*, 21(1), pp. 14-31.

106. Young, H. P., 2004, "Strategic Learning and Its Limits", Oxford, England; New York, Oxford University Press.

107.   Zhao, L., and Jin, Y., 2003, "Work Structure Based Collaborative Engineering Design", *Proceedings of the ASME 2003 Design Engineering Technical Conferences & Computers and Information in Engineering Conference*, September 2-6, 2003, Chicago, Illinois, USA.