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Integrating Consumer Preferences into Engineering Design

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ISBN 978-1-4471-4035-1 ISBN 978-1-4471-4036-8 (eBook)
DOI 10.1007/978-1-4471-4036-8
Springer London Heidelberg New York Dordrecht

Library of Congress Control Number: 2012936756

Printed on acid-free paper

Springer is part of Springer Science+Business Media (www.springer.com)

Preface

Since the late 1990s, there has been a growing recognition in the engineering design research community that decisions are a fundamental construct in engineering design [3]. This position and its premise naturally leads to the study of how engineering designers should make choices during the design process, representing the foundation of an emerging perspective on design theory called decision-based design (DBD). As defined in Chen et al. [1]:

> Decision-Based Design (DBD) is an approach to engineering design that recognizes the substantial role that decisions play in design and in other engineering activities, largely characterized by ambiguity, uncertainty, risk, and tradeoffs. Through the rigorous application of mathematical principles, DBD seeks to improve the degree to which these activities are performed and taught as rational, that is, self-consistent, processes.

DBD provides a framework [4] within which the design research community can conceive, articulate, verify, and promote theories of design beyond the traditional problem-solving view. To support the scholarly dialogs on the development of the DBD theory, the U.S. National Science Foundation (NSF) supported a series of workshops under the "Open Workshop on DBD." During the period of 1996–2005, the open workshop has engaged design theory researchers via electronic and Internet related technologies as well as 18 face-to-face meetings in scholarly and collegial dialog to establish a rigorous and common foundation for DBD [1]. The synergy built through the workshop led to many conference papers and journal publications, special editions of journals dedicated to DBD [2], successful research workshops, and a book entitled "Decision Making in Engineering Design" by the NSF workshop organizers (eds. Lewis K, Chen W and Schmidt L, [5]). As a result, the international design engineering technical conferences (IDETC) sponsored by the American Society of Mechanical Engineers (ASME) have established multiple technical sessions on DBD on various issues within DBD and research topics that grew out of the DBD paradigm. One example of such topic that attracts growing interest is on "Design for Market Systems." By integrating quantitative engineering and economic models, the focus of "design for market systems" is to develop the ability to understand, predict, and account for the market implications of design decisions, namely, to predict expected market responses based on customer choice behavior as a result of product design decisions [7]. As demonstrated in many works in this area, as well as in this book, modeling customer preferences and choice behavior is becoming an integral part of DBD.

This book is, to a large extent, a collection of research results on DBD developed by the Integrated Design Automation Laboratory (IDEAL) led by Professor Wei Chen at Northwestern University during the past decade. While the fundamental principles of decision analysis are generally applicable to decision making in engineering design, as we will illustrate in this book, making design decisions in a rigorous way is not trivial. This is due to the fact that engineering design is a complex decision-making process that involves multiple parties in an enterprise and requires tradeoffs of interests among different groups. The methods presented in this book represent our view of how DBD can be implemented in a rigorous way for engineering design. In particular, our book offers a more complete coverage of modeling and integrating customer preference into engineering design.

Building upon the fundamental principles of decision theory, this book presents a single-criterion approach to enterprise-driven DBD as a rigorous framework for integrating engineering design and business decision making. This book begins with introductions to the fundamentals of decision theory, economic analysis, and econometrics modeling, together with an examination of the limitations of some existing design selection methods. The core portion of the book describes the entire process and the associated analytical techniques for integrating customer preference modeling into the enterprise-driven DBD framework to bridge the gap between market analysis and engineering decision making. To facilitate the use of discrete choice analysis [6] as a fundamental technique for customer choice modeling in product design, methods for attribute identification, optimal design of human appraisal experiments, data collection, data analysis, and demand model estimation are presented and illustrated using engineering design case studies. The book also presents the state-of-the-art research methods that address current product design challenges, including hierarchical choice modeling to support complex systems design, latent variable modeling, choice modeling for usage-context based design, enterprise-driven approach to product family design, as well as multilevel optimization for DBD.

The content and format of this text has been designed to benefit a number of different audiences, including:

- Graduate students at all levels in engineering or product design disciplines;
- Instructors teaching design courses;
- Researchers in product design/development; and
- Design practitioners in the field facing the challenge of designing customer goods for a diverse population.

Each of the primary chapters contains example problem(s) which illustrate the techniques presented in the chapter as well as additional resources for computer implementation. Example problems can be practiced by the reader using the freely available open source software as recommended at the end of chapters in the "Additional Resources for Computational Implementation" section. Chapters 1–7 of this book cover the fundamental techniques, and would be the most appropriate for students or design practitioners. Chapters 8–12 cover advanced topics that would be of interest to graduate students and researchers working in the area of product design, customer choice modeling, or complex system design. Chapter 13 provides a summary of the DBD approach and also discusses potential future research directions.

This book is a collection of materials developed in the dissertations of several former and current doctoral students in the IDEAL at Northwestern University. While the majority of the chapters have been developed based on the dissertations of Christopher Hoyle (PhD 2009—now Oregon State University) and Henk Jan Wassenaar (PhD 2003—now Zilliant, Inc.), we would also like to thank the contributions from Lin He (PhD 2012), Deepak Kumar (PhD 2007—now Google), and Harrison Kim (Postdoc 2004—now University of Illinois at Urbana Champaign) to the materials presented in Chaps. 10–12, respectively. In understanding the role of decision theory in engineering design, we have benefited from the rich interactions with Dr. George Hazelrigg (NSF) and Professor Donald Saari (University of California at Irvine). The development of real engineering applications based on real market research data was made possible through close interactions with our industrial collaborators, including Drs. Nanxin Wang, Gina Gomez-Levi, and Agus Sudjianto from Ford Motor Company in developing the vehicle packaging design and engine design case studies; Drs. Jie Cheng and Jie Du from J.D. Power & Associates in collecting and analyzing vehicle market survey data; and Dr. Guenter Conzelman from Argonne National Laboratory (ANL) in developing the hybrid vehicle usage context-based choice modeling. Furthermore, at Northwestern University, our work has benefited greatly from the interdisciplinary research collaborations with Professor Frank Koppelman, who is an expert in transportation engineering and discrete choice analysis, and Professor Bruce Ankenman, an expert in design of experiments and statistical analysis. Our work on the DBD approach to address product design challenges (Chaps. 8–12) could not have reached its current depth without close collaborations with several faculty members in the engineering design community, in particular, Professor Bernard Yannou (Ecole Centrale Paris) on usage context-based design (Chap. 10), Professor Tim Simpson (Penn State) on product family design (Chap. 11), and Professor Panos Papalambros (University of Michigan) on multi-level DBD (Chap. 12).

Pursuit of many of the topics covered in this book received financial support from multiple sources. Theoretical developments of the Decision-Based Design approach and the associated demand modeling techniques received support from the U.S. NSF, including DMI-9896300 (2002–2005) (Program manager: George Hazelrigg), DMI-0503781 (2005–2006) (Program manager: Delcie Durham) and CMMI-0700585 (2007–2010) (Program managers: Judy Vance and Christina

Bloebaum). International collaboration with Ecole Centrale Paris, France was supported in the form of summer visits by Wei Chen and Christopher Hoyle as a supplement to CMMI-0700585. The collaborations with Ford Motor Company were supported by the Ford University Program (URP) (2003–2006; 2006–2009). The choice modeling of alternative fuel vehicles in collaboration with ANL was supported by initiative for sustainability and energy at northwestern (ISEN). Finally, we would like to point out that the views presented in this book are from the authors but not their sponsors.

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Contents

Part I
Theory

Chapter 1
Decision-Based Design: An Approach for Enterprise-Driven Engineering Design

The motivation for developing a decision-based design (DBD) approach for engineering design is introduced in this chapter. The DBD approach recognizes that engineering design is fundamentally an enterprise-driven decision-making process, and therefore uses principles of decision theory and economics principles in its formulation. Further, in this chapter an overview of DBD is provided as well as the organization of the book.

1.1 Motivation for Enterprise-Driven Decision-Based Design

Faster and more accessible technology has afforded businesses the ability to market products and services all around the globe to a diverse population of customers. Today's design engineers need an innovative mind, together with a strong understanding of consumer preferences. In the globally competitive market, a product's success depends upon both understanding the "big picture" to address enterprise needs, as well as attention to the "engineering details" to meet technical expectations. In response to these needs, enterprise-driven Decision-based design is a new engineering design paradigm that connects the decisions made in the engineering and marketing (i.e., enterprise) domains, by considering the economic benefit of an enterprise in producing a product, the real complexities in engineering systems design, and the heterogeneity of consumer preferences for such systems.

According to the US Accreditation Board for Engineering and Technology (ABET), engineering design is defined as: "The process of devising a system, component, or process to meet desired needs. It is a decision-making process (often iterative), in which the basic science and mathematics and engineering sciences are applied to convert resources optimally to meet a stated objective. Among the fundamental elements of the design process are the establishment of objectives and criteria, synthesis, analysis, construction, testing and evaluation."

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_1, © Springer-Verlag London 2013

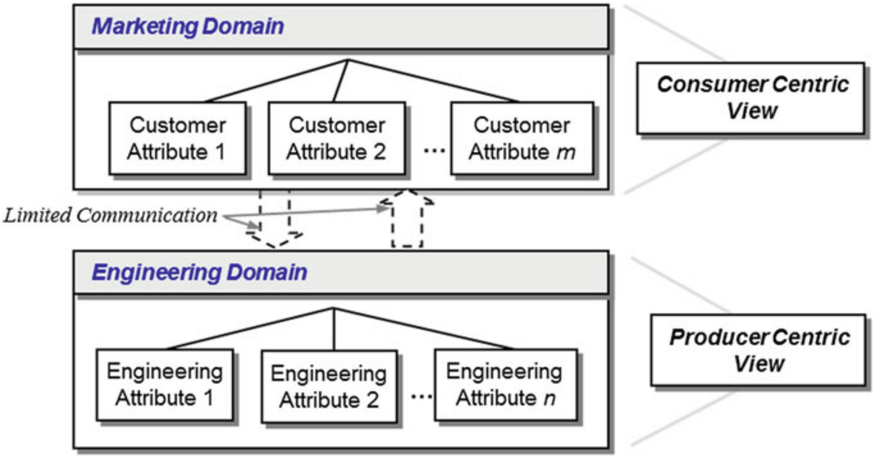

Fig. 1.1 Disconnected decision processes

It is interesting to note that the above definition recognizes design as a decision-making process, which is a notion shared by the DBD approach described in this book. Nevertheless, traditional engineering design is conducted primarily with an engineering-centric viewpoint, in which the objective is to achieve the best performance given in the budget available (i.e., monetary, human resources, etc.). In general, it has been noted in a variety of contexts [4, 11, 26] that each of the major functional domains within a firm, or enterprise, such as engineering, marketing, production, and management, generally seek to optimize a domain-specific objective, with limited input from the other functional domains. The disconnect between the marketing and engineering domains in a traditional product development decision-making process is shown in Fig. 1.1. Such a disconnected decision process cannot assure optimal decisions for an engineering system at the enterprise level, most importantly because the engineering-centric approach does not consider customer demand for the designs considered, whereas the marketing-centric approach does not consider the intricacies of engineering attribute coupling, and the resulting influence upon cost, for a product or system design.

The need to consider potential customer demand (consumer choice behavior) together with cost and performance when designing an engineering system, is necessary to estimate the potential profit for the designed system and to determine the benefit of a given design to an enterprise. The recognition that product decisions should be made with respect to maximizing the economic benefit to the enterprise has been made in fields, such as pricing and inventory control [18, 22], but has not been well established within the engineering design discipline. As will be shown thoroughly in this book, an estimation of demand as a function of product attributes must explicitly consider the heterogeneity of the customers and the market in which the product will compete, as illustrated in Fig. 1.2, as well as

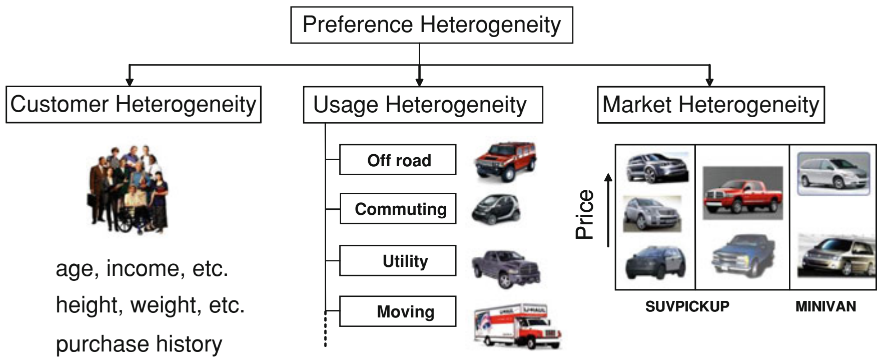

Fig. 1.2 Heterogeneity of the customers and the market

account for sources of uncertainty to make product decisions. Throughout multiple chapters of this book, state-of-the-art quantitative demand modeling approaches for modeling customer choice behaviors will be introduced.

The need for developing a rigorous engineering design framework also arises to overcome the limitations of many existing engineering design approaches. While more details will be provided in Chap. 2, it can be shown that many existing design methods consider only specific aspects of the design process in the decision maker's preference function, and therefore may lead to sub optimal results when considering the total economic benefit of a product. For example, methods such as Taguchi's robust design [17] and design for six-sigma [5] constitute preference systems in which it is assumed that meeting customer satisfaction is the primary goal of design decision making. Such methods seldom consider the cost associated with adding or improving a quality feature in a formal way. When multiple quality attributes are involved, designers end up assigning arbitrary targets, weights, and ranges for these quality attributes. In addition, many existing methods account for too few sources of uncertainty in the design process and cannot properly incorporate a designer's attitude towards risk in decision making; hence, there is a need to develop a rigorous design approach to assist designers in making unambiguous decisions.

1.2 Decision-Based Design: An Overview

There is a growing recognition that decisions are the fundamental construct in engineering design [8, 25, 27]. DBD is an emerging theoretic approach to engineering design that has been examined by many researchers. An Open Workshop on DBD was supported by the National science foundation during 1996–2005 [3]. Since then, many approaches to support decision making in engineering design and consumer demand modeling have been published in the literature (e.g. [1, 2, 6, 8, 9, 12–16, 19–23, 24, 25, 28, 29]).

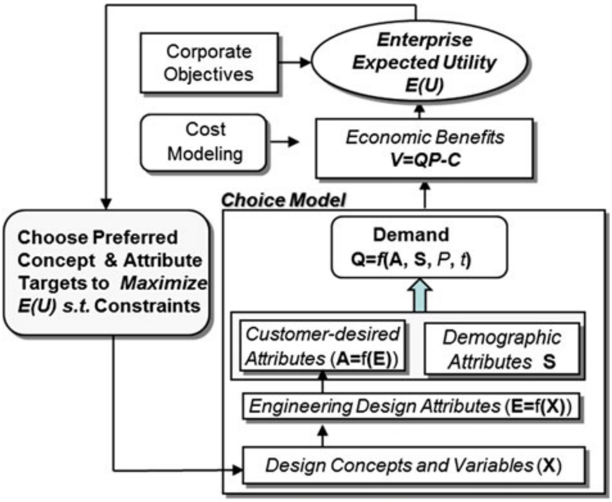

Fig. 1.3 Building blocks of the decision-based design framework

Within the context of this book, the DBD approach frames design as a decision-making process that seeks to maximize the value of a designed artifact under uncertainty and risk to the enterprise, while considering the interests of both the producer (decision maker) and the end-users. While the details of a complete DBD framework are provided in Chap. 4; Fig. 1.3 provides an overview of the building blocks of this framework, which merges the separate marketing and engineering domains into a single enterprise-level decision-making framework. The framework utilizes a decision-theoretic methodology to select the preferred product design alternative for the enterprise undertaking the design activity, and/or to set target levels of performance for the product. This is accomplished as shown in Fig. 1.3 through a hierarchical model linkage in which design concepts and design variables (**X**) are linked to demand, Q, through engineering analysis and attribute mapping between engineering attributes **E** (e.g., fuel economy, horsepower) and customer-desired product attributes **A** (e.g., comfort, performance). Also key is the inclusion of socio-demographic attributes **S** (e.g., age, income, height), in addition to customer-desired product attributes **A**, in the estimation of demand while capturing the heterogeneity of customer preferences.

Although the potential use of classical decision theory [10] for decision making in engineering design has been acknowledged in the literature, there is still a lack of consensus on how the DBD approach should be implemented for engineering design. One of the distinctive debated issues is how the value (utility[1]) of a design

[1] The word "utility" is used as it stands for the selection criterion in the presence of uncertainty, while the word "value" is often interpreted as a selection criterion without uncertainty.

should be formulated under a DBD framework. The common challenge lies in how to properly construct the utility under uncertainty to reflect the preference of the producer (decision maker) while considering the desires of the potential end-users. In the proposed enterprise-driven DBD approach in this book, a single criterion, V, which represents the economic benefit to the enterprise (i.e. value), typically profit, is employed as the selection criterion. This single-objective approach avoids the difficulties associated with weighting factors and multi-objective optimization, which can be shown to violate Arrow's impossibility theorem [7]—a topic to be further explored in Chap. 2. A utility function, U, which expresses the value of a designed artifact to the enterprise while considering the decision-maker's risk attitude, is created as a function of the selection criterion, V. A preferred concept, design variable values, and/or attribute targets are selected through the maximization of the expected utility $E(U)$ in the view of the enterprise's decision-makers. The choice model for estimating customer demand directly assesses the impact of product design on customer choices and plays a critical role in assessing both the revenue generated by a product as well as the manufacturing and other life cycle costs.

The DBD approach presented in this book is intended to facilitate the integration of engineering design decision making and business decision making. It is expected that this integration will facilitate the communication and collaboration of a company's employees in engineering, marketing, and management toward achieving the company's goal of making a profit. Application of the methodologies introduced in this book is expected to lead to more competitive products because products will be improved in a systematic way, considering not only the engineering requirements, but also the business interests, customers' preferences, competitors' products, and market behavior. The framework provides information that can facilitate the collaboration of engineers from various disciplines in focusing their quality engineering efforts on the most critical areas of the artifact being designed, thereby improving their productivity. Additionally, implementing Decision-Based Design can make the impact of decisions regarding design (and price) on demand, cost, and economic benefit tangible, providing support in negotiations with suppliers of parts/components, as well as facilitating assessment of the impact of design upgrades.

1.3 Organization of the Book

The DBD approach presented in this book is applicable in making engineering design decisions with the objective of maximizing the expected utility of the economic benefit of a product, e.g., profit (net revenue). As shown in Sect. 1.2, demand modeling is critical for implementing the DBD approach. Throughout this book, a wide range of demand modeling techniques, such as multinomial logit, nested logit, and mixed logit are progressively introduced in multiple chapters through multiple case studies. As illustrated, these demand modeling methods

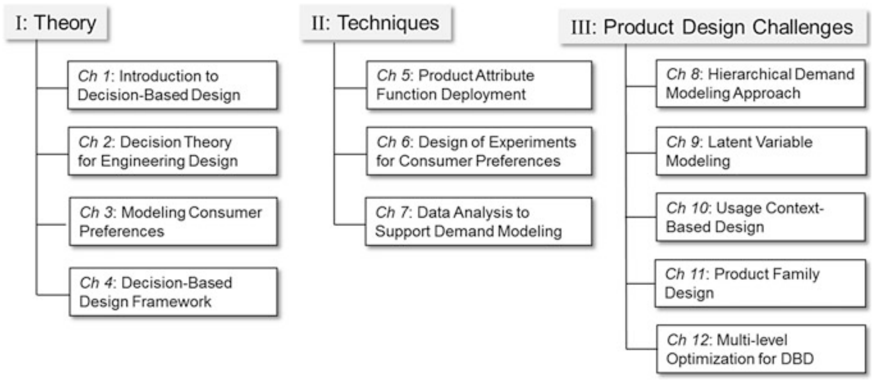

Fig. 1.4 Organization of the book by topic

enable the DBD method to be implemented for a wide range of design problems encountered, both in design research and in engineering practice. To help the reader best understand the DBD approach, this book is composed of three major parts as illustrated in Fig. 1.4. In Part I (Chaps. 1–4), the theoretic foundations of the DBD approach are provided, covering the fundamentals of decision theory in Chap. 2, the analytical techniques for modeling consumer preferences in Chap. 3, and a detailed description of the DBD framework in Chap. 4. The focus in Part II (Chaps. 5–7) is on introducing techniques that enable the integration of demand modeling techniques into the DBD framework. The techniques include both existing and newly developed methods, covering topics such as product attribute function deployment (PAFD) (Chap. 5), optimal design of human appraisal experiments for eliciting customer preferences (Chap. 6), and data analysis for modeling customers' choice behavior (Chap. 7). In Part III (Chaps. 8–12), advanced choice modeling issues and implementation for product design challenges, such as complex hierarchical systems (Chap. 8), latent variable modeling (Chap. 9), usage context-based design (Chap. 10), product family design (Chap. 11), and multilevel design optimization (Chap. 12) are addressed.

Key details of each chapter are provided as follows. In Part I, a brief introduction to decision theory is provided in Chap. 2 with an emphasis on modeling the decision-maker (designer)'s preference function. The limitations of design alternative selection methods that involve normalization, weighting, multi-attribute ranking, multi-attribute utility functions, or selection of multiple criteria are examined, which illustrate the need for a single-objective decision-based design technique. In Chap. 3, the fundamental analytical techniques for modeling customer preference and choice are presented. These methods are discrete choice analysis (DCA) for modeling customer choice and ordered logit (OL) for modeling customer preference expressed in the form of a rating. The design of a power saw is used as a step-by-step example to demonstrate the modeling techniques presented in this chapter. In Chap. 4, the detailed framework for DBD is presented, using DCA to estimate customer demand for a given design and a target market of customers. A systematic procedure for implementing the DBD framework is provided. The approaches are demonstrated through two design case studies—one using the design of a universal electric motor as an example and the other using the design of a passenger vehicle engine to demonstrate the approach for complex systems design.

In Part II, the product attribute function deployment (PAFD) method for attribute identification, concept selection, and target setting is presented in Chap. 5. The method utilizes the principles of decision-based design to provide a design process tool to implement DBD in engineering design practice and overcomes the limitations of the quality function deployment (QFD) method. The conceptual design of a pressure sensor for an automotive application is used to illustrate the use of the PAFD method. In Chap. 6, techniques for the design of experiments for eliciting customer preference are presented. Both standard experiments and optimal design of human appraisals are introduced as means to collect human preference data and build the necessary preference models to understand customer heterogeneity. The optimal design of a human appraisal experiment to elicit preferences for automotive occupant packaging is presented. To process and analyze the collected preference data, in Chap. 7, techniques are presented to statistically analyze preference data to understand customer heterogeneity as well as to preprocess the data to create efficient preference models. The data collected from the automobile packaging human appraisal in Chap. 6 are used in this chapter to illustrate the methods.

In Part III, a hierarchical demand modeling approach for complex systems design is first introduced in Chap. 8. The integrated bayesian hierarchical choice modeling (IBHCM) approach is presented as a comprehensive choice modeling approach for complex systems in which a large number of product attributes need to be considered at multiple levels of hierarchy and both qualitative and quantitative choice attributes exist. The IBHCM approach utilizes choice data as well as other preference data, such as that collected using the human appraisals presented in Chaps. 6 and 7, to create a choice model for vehicle occupant package design. In Chap. 9, we explore an approach that considers the customer's perception and attitude toward the product in demand modeling to enhance predictive accuracy. The integrated latent variable model for choice modeling is presented as an optional extension of the choice models used in previous chapters. The design of an automobile vehicle engine is used to illustrate the methods. To address the design challenges in usage context-based design (UCBD), in Chap. 10, we present a choice modeling framework for UCBD to quantify the impact of product usage context on customer choices. The taxonomy for UCBD is provided first. A step-by-step choice modeling procedure is introduced to support UCBD by explicitly modeling usage context's influence on both product performance and customer preference. Two case studies, a jigsaw example with stated preference data and a hybrid electric vehicle example with revealed preference data, are provided in this chapter. To address the design challenges in designing multiple products in a family, in Chap. 11, we present an extension of the DBD method to facilitate complex decision makings in product family design. First, we introduce the market segmentation grid to help understand the different product variants needed, and then introduce the nested logit model to estimate demand while considering the market segmentation. We then create a DBD product family formulation for making complex decisions in optimal product line positioning, optimal "commonality" design, and optimal levels of engineering design attributes. A case study of designing a family of electric motors is used to demonstrate the method. The multi-level optimization techniques for the DBD framework are introduced in Chap. 12. A multi-level optimization approach is needed when discipline-specific knowledge is required to formulate each aspect of the design problem and solving the DBD problem in an all-in-one formulation becomes impractical. The chapter begins with an introduction to multi-level optimization and the formulation of DBD using multi-level optimization. A search algorithm that coordinates the multilevel optimization solution process is then presented. A case study of an automobile suspension design is presented to demonstrate the multi-level DBD framework.

Conclusions and a summary of the book are provided in Chap. 13 as the closure. Areas and opportunities for future research in both DBD and consumer choice modeling are presented here as well. To assist readers in implementing the techniques presented in this book, additional resources for computer implementations are provided at the end of select chapters.

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Chapter 2
Decision Theory in Engineering Design

Nomenclature

A	Customer-desired Product Attributes
C	Total Product Cost
E	Engineering Design (ED) attributes
E(U)	Expected value of enterprise utility
IIA	Independence of Irrelevant Alternatives
P	Product Price
Q	Product Demand
S	Customer socio-demographic attributes
T	Time interval for which demand/market share is to be predicted
U	Enterprise utility
V	Selection criterion used by the enterprise (e.g., profit, market share, revenues, etc.)
X	Design options
Y	Exogenous variables (represent sources of uncertainty in the market)
Z	Design performance attributes
ε_{in}	Random unobservable part of the utility of alternative i by customer n

A fundamental aspect of decision-based design (DBD) is the application of decision theory to engineering design. In this chapter, we cover the fundamentals of decision theory, the desirable properties of a design selection method, and then explain why many multicriteria design selection methods used for engineering design can violate fundamental decision theory and economic principles. A detailed examination of the fundamental issues with some commonly used design approaches for design selection, for example, the quality function deployment (QFD) method, is provided. Finally we introduce the single-criterion enterprise-driven design approach to representing the decision maker's preference to overcome the limitations of other methodologies described in this chapter.

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_2,

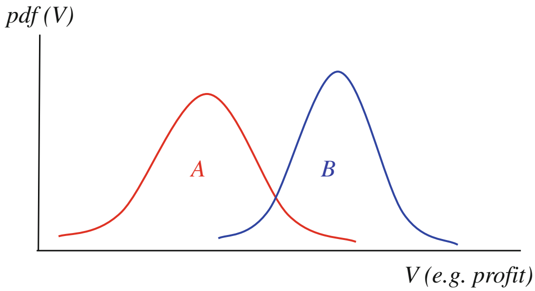


Fig. 2.1 Non-dominated distributions of design outcomes

2.1 Fundamentals of Decision Theory

Decision making is integral to the engineering design process and is an important element in nearly all phases of design. Viewing engineering design as a decision-making process recognizes the substantial role that decision theory can play in design and other engineering activities. Decision theory articulates the three key elements of a decision-making processes as:

- identification of *options* (alternatives) or choices X,
- development of *expectations* for the outcomes of each choice, and
- formulation of a system of *values* (V) for ranking the outcomes and thereby obtaining the preferred choice.

Engineering decision making can therefore be viewed as a process of modeling a decision scenario, resulting in a mapping from the design option space to the performance attribute space. Subsequently, a utility function is constructed that reflects the designer's (decision maker's) preference while considering trade-offs among system attributes and the risk attitude toward uncertainty. This section introduces the fundamental concepts and principles that have long been employed in traditional decision theory. The fundamentals in decision theory provide the mathematical rigor for DBD methods. It should be noted that this chapter is dedicated to modeling the preference of a designer as the decision maker, while the next chapter, Chap. 3, is about modeling the heterogenous customer preferences in the form of choice behavior. Before proceeding further, definitions of key concepts are provided, some of which are adopted from Krishnamurty [25], (Table 2.1).

According to Hazelrigg [17], decision theory is a framework for thinking logically about choices in the presence of uncertain outcomes. The only difference between deterministic optimization and decision-theoretic utility optimization is that decision theory allows for uncertainty in outcomes. As shown in Fig. 2.1, under uncertainty, the distribution of the outcomes of two alternatives, A and B, in terms of their value function (V), e.g., profit may overlap, which means that neither of these two alternatives dominates the other. In other words, it is possible that the outcome of alternative A could be preferred to the outcome of alternative B or vice versa since it is possible for the value of A to be greater than B due to the uncertain

Table 2.1 Definitions of key concepts

Key concepts	Description
Decision analysis	"Decision Analysis" describes a combination of philosophy, methodology, practice, and application useful in a formal introduction of logic and preferences to the decisions of the world [21]; "Decision Analysis" is a structured way of thinking about how the action taken in the current decision would lead to a result.
Decision	An irrevocable allocation of resources; the only thing one can control is the decision and how one can go about that decision.
Objective	An "objective" indicates the goal which the designer strives to achieve.
Attribute	A characteristic of design performance; also a measure of objective achievement.
Expectation	A distribution of attribute performances resulting from uncertainty.
Alternative (option)	An "alternative" is a particular set of controllable design variables, which constitutes a design instance with particular attribute performances. The purpose of engineering design is to find the alternative with highest "Value" or "Utility."
Weight/Scaling constant	A measure of the relative influence of each attribute on the entire design performance. In value trade-offs, "weight" is used, while in MAU, "scaling constant" is used.
Value	"Value" is a numerical quantity to quantify the goodness of a design alternative under certainty.
Utility	"Utility" is a numerical quantity to quantify the goodness of a design alternative under uncertainty.
Lottery assessment	A method used to elicit design preferences in expected utility theory. Based on vN-M axioms, a certainty equivalent is found to represent a lottery, then a mathematical expression is developed for a preference (utility) function.
Utility function	"Utility Function" is a mathematical mapping of value to utility, accounting for the decision maker's attitude toward risk.

outcomes. To make the selection, we can rely on the utility analysis in decision theory, which basically transforms the probability distribution of the value (V) into a single point called expected utility (U).

In contrast to engineering analysis, which is *descriptive* based on physics-based modeling, utility analysis in decision theory is a *prescriptive* or *normative* modeling tool that prescribes decision maker's preference. Decision theory first postulates a set of "axioms of rational behavior" [44]. From these axioms, it builds mathematical models of a decision maker's *preference* in such a way as to identify the option that would be chosen by assuming that decision maker was consistent, rational, and unbiased. The term "utility" refers to a preference function built on the axiomatic basis originally developed by von Neumann and Morgenstern. Six axioms are explained in detail by Thurston [41], where the definitions of the axioms are intended as a general introduction to an engineering design audience (these definitions are not repeated here). The first three axioms (*Axiom 1. Completeness of complete order, Axiom 2. Transitivity, and Axiom 3. Monotonicity*) enable one to structure the problem in such a way that the resulting rank ordering of alternatives is robust.

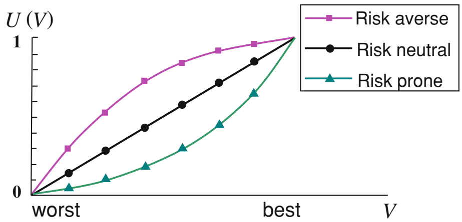


Fig. 2.2 Three types of risk attitudes

The next three axioms (*Axiom 4. Probabilities exist and can be quantified, Axiom 5. Monotonicity of Probability, and Axiom 6. Substitution independence*) help one structure a preference function considering the strength of preferences, willingness to make tradeoffs, and risk attitude under uncertainty.

Decision making, in general, can be made in deterministic and nondeterministic scenarios [32], even though nondeterministic scenarios are rare in real practice. Value theory-based methods deal with deterministic design cases while their complementary expected utility theory methods deal with decision making under uncertainty. Uncertainty is an inherent characteristic of decision making in engineering design, which can be due to inadequate understanding, incomplete information, and undifferentiated alternatives. Generally, the attitude to a risk situation can be divided into three categories, namely risk averse, risk prone, and risk neutral. As indicated by the different shapes of utility function *U(V)* in Fig. 2.2, decision makers who base their decision solely on the highest expected payoff or the lowest expected cost, i.e., on expected value, are *risk neutral*, and their utility function is linear. Decision makers who are willing to take on additional risk for higher payoffs are risk prone, and their utility function is convex indicating the expected consequence is less than the certainty equivalent. Decision makers who are not willing to take on additional risk for higher payoffs are risk averse, and their utility function is concave indicating that the expected consequence is greater than the certainty equivalent.

Maximizing expected utility captures the full range of uncertainty and the decision maker's attitude toward risk, unlike much simpler approaches, such as minimax, maximin, and minimax regret.

Expected utility theorem: Given a pair of alternatives, each with a range of possible outcomes and associated probabilities of occurrence (i.e., two lotteries), the preferred choice is the alternative (the lottery) that has the highest expected utility.

The expected utility for the example illustrated in Figs. 2.1 and 2.2 is expressed as:

$$\mathrm{E}(U) = \int U(V)\,pdf(V)\mathrm{d}V \tag{2.1}$$

Figure 2.3 illustrates how the certainty equivalent is established in constructing the utility function *U(V)* using a lottery assessment. Here, the *certainty* of a particular outcome of interest is a guaranteed result compared to the lottery between two extreme attribute values in which there is a probability p_o of

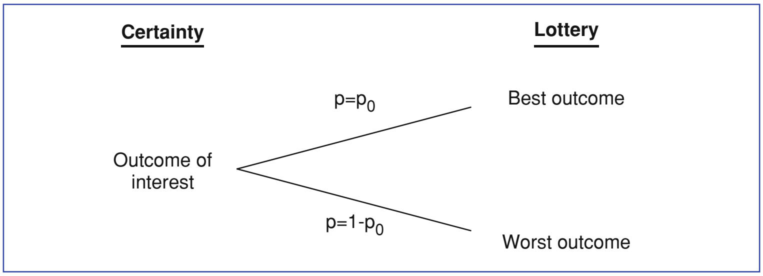


Fig. 2.3 Typical lottery question in utility function assessment

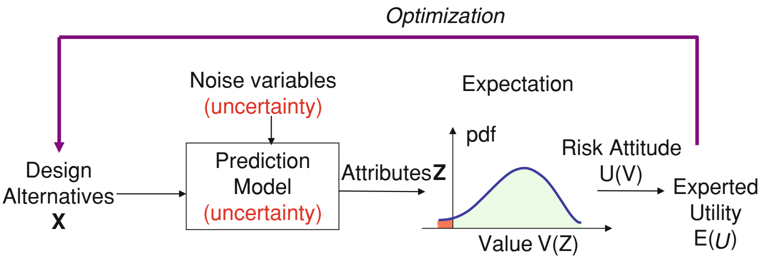


Fig. 2.4 Decision making under uncertainty using optimization

obtaining the best outcome and a probability of $1-p_o$ of obtaining the worst outcome. A probability of $p_o = 1$ causes the designer to choose the "lottery" where, similarly, a value of $p_o = 0$ will lead to the selection of the "certainty". "The value of p_o at which the designer is indifferent to the certainty equivalent of the lottery is characterized as the utility of the certainty equivalent for an outcome level. In effect, the utility of the certainty equivalent is equal to the mathematical expectation of the lottery, i.e., u (outcome of interest) $= p_0 u$ (best outcome) $+ (1-p_0)\, u$ (worst outcome). For instance, an indifference point at $p_o = 0.7$ with Best outcome = 1.0 and Worst outcome = 0.0 will result in the utility function value of *U (outcome of interest)* = 0.7.

In summary, engineering decision making can be viewed as an iterative optimization process (Fig. 2.4) where the best design alternative is identified to maximize the expected utility (or simply called utility). While the prediction model is used to map the design option space (**X**) to the performance attribute space (**Z**), due to the uncertainty of performance attributes associated with the uncertain noise variables and/or the uncertainty of the prediction model itself, a utility function *U(V)* that represents the decision maker's risk attitude needs to be constructed for the deterministic value function *V*; additionally, *V* is expressed as a function of multiple performance attributes **Z**. Constructing the functions of *U(V)* and *V*(**Z**) is arguably the most significant and most complex step in a decision-based engineering design process. An approximate alternative to constructing the utility function *U(V)* is to assume an exponential utility function to represent risk averse or risk prone attitudes, and a linear function (i.e., expected value) for risk neutral attitudes (e.g., for large enterprises). Beyond the lottery method, another approximation approach was presented by Cozzolino [12] in which previous decisions are used as the basis for the utility function. In this approach, the risk attitude used historically in decision making is applied to a new decision opportunity. An approach in which psychometric tests are utilized to assess risk attitude was presented by Pennings and Smidts [29]. In this approach, the results of psychometric tests are used to construct the risk attitude function. It was found that risk curves created from psychometric tests reflected a decision maker's self-reported attitude; however, the lottery method was found to better reflect actual decisions made by the decision maker. In the next few sections, we will explore the desired properties of a design selection method, identify the limitations of many existing approaches, and propose a rigorous approach to alternative selection in engineering design.

2.2 Desirable Properties of a Design Selection Method and Related Economic Principles

Fundamental to the development of a rigorous theory for design is the use of a valid approach to design alternative selection. A decision-maker should be confident that the alternative selection approach selects the best alternative from a given set of alternatives based on the decision maker's preference. Various multi-criteria-based alternative selection methods exist; however, their outcomes depend upon the alternative selection procedure used and they often fail to reflect the true quality of the alternatives. These are highly undesirable properties that should be avoided. To develop a rigorous approach to design selection it is necessary to examine the existing alternative selection procedures against a set of desired properties.

Many desirable properties can be formulated for a design alternative selection procedure, e.g., the alternative selection method should not impose preferences on a decision-maker. Hazelrigg [18] identified eleven favorable properties of an alternative selection method, which are consistent with Howard's favorable properties of an alternative selection method [20], the six axioms of Von Neumann and Morgenstern [44], and the general possibility theorem [1].

In this section, we examine existing alternative selection methods using Arrow's general possibility theorem and the related economic principles. First we introduce the notion of transitivity, which demonstrates the paradox of using multiple criteria for decision making in design.

The core of Arrow's general possibility theorem is formed by three properties: (1) *unrestricted domain*, (2) *Pareto optimality*, and (3) *independence of irrelevant alternatives*, which are presented next.

(1) *Unrestricted Domain* states that a criterion or attribute, i.e., the measure of value that facilitates rank ordering of alternatives, should be unrestricted. That is, the values that can be taken by the criterion and the decision function should be unrestricted. This desired property implies that it is not allowed to exclude alternatives based upon irrelevant constraints.
(2) *Pareto Optimality* states that if every criterion ranks alternative A before alternative B, then the set of criteria as a whole should rank alternative A before alternative B.
(3) *Independence of Irrelevant Alternatives* (IIA) a property few alternative selection approaches satisfy, states that the rank order of a given alternative should not depend on the alternative set, i.e., if alternative A is ranked before alternative B then A should still be ranked before B when alternative C is added (or removed from consideration). Any engineering design alternative selection method should satisfy the IIA property, because the number of engineering design alternatives is not only arbitrary, alternatives are added or removed during the design process as well. If the alternative selection depends on the alternative set then this implies that different outcomes are possible by only altering the alternative set, which is highly undesirable.

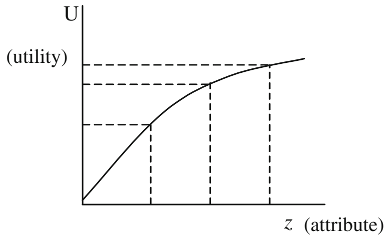
According to Arrow, *the only alternative selection procedure that satisfies these three properties is a dictatorship*. The proof of dictatorship can be found in Arrow and Raynaud [2]. A criterion is dictatorial if the ranking of the value function always corresponds to the alternative ordering of this criterion, no matter how the other criteria rank order the alternatives. Black [5] showed that if the criteria order is single-peaked then a rational alternative selection is possible, provided that the number of criteria is odd. Scott and Antonsson discussed the implication of Arrow's theorem for engineering design [36]. They conclude that under some restrictive conditions such as Black's Theorem (i.e., single-peakedness) it seems that Arrow's theorem need not be an obstacle for multi-criteria decision making in engineering design.

In addition to the desirable properties discussed, design can be seen in a broader sense as an economic activity, as it allocates resources like manpower, materials, money, and (calendar) time. Therefore, it should be consistent with economic theory. The following economic principles are of importance to engineering design.

Positive view of economists

It is assumed for the DBD approach presented in this book that the (common) objective of engineering design is to maximize profit. This is supported by the *positive* view of economists that the behavior of companies can be explained and predicted by assuming that companies act *as if* they maximize profit [27].

Fig. 2.5 Diminishing marginal utility



Opportunity cost

The opportunity cost is the cost of a good or service as measured by the alternative uses that are foregone by producing the good or service [27]. Alternatively, this can be interpreted as: the opportunity cost is equal to the alternatives which are given up when one purchases a certain good, i.e., the next best alternatives which are excluded by selecting the preferred alternative.

Diminishing marginal utility

Marginal utility of a particular good can be defined as the extra utility obtained by consuming one more unit of that particular good [27]. Diminishing Marginal Utility states that, the marginal utility decreases as more of a good is obtained. That is, the customer's utility increase of each additional unit obtained is less than the utility increase of the previously obtained unit (Fig. 2.5).

2.3 Paradox of Multi-Criteria Alternative Selection Methods for Engineering Design

The limitations of design alternative selection methods that involve normalization, weighting, multi-attribute ranking, or a multi-attribute utility (MAU) are examined in this section. A typical multi-attribute value function used for alternative selection is shown in Eq. (2.2), where the value of an alternative is thought to consist of a summation of criteria values z_i. The importance of each criterion is sometimes considered by specifying weights w_i.

$$u(z_1, \ldots, z_n) = \sum_{i=1}^{n} w_i z_i. \tag{2.2}$$

In the remaining of this section, we will examine the paradoxes that are associated with some commonly used multi-criteria alternative selection methods in engineering design. The implications of this examination are profound, as the paradox that occurs when using multiple criteria in design decision making also happens to any group decision making in design, which is often the case in practice where product designers, manufacturing engineers, and marketing personnel, etc. have to work together in product development, each possessing a different interest.

Table 2.2 Condorcet's voting paradox

preferences	A vs. B	B vs. C	C vs. A
Decision-maker I (A≻B≻C)	A	B	A
Decision-maker II (C≻A≻B)	A	C	C
Decision-maker III (B≻C≻A)	B	B	C
Group preference	A≻B	B≻C	C≻A

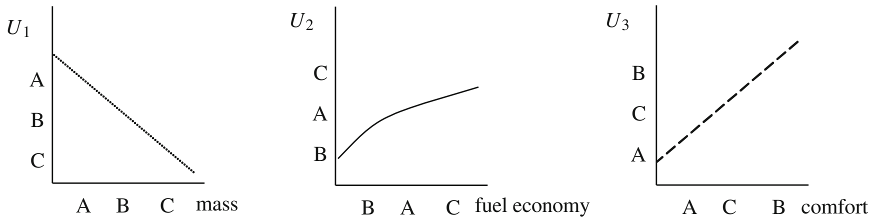


Fig. 2.6 Multi-criteria decision process for three criteria

2.3.1 Paradox of Multiple Decision Makers or Multicriteria Alternative Selection Processes

As a desirable property for rational decision making, *Transitivity* implies that when alternative A is preferred to alternative B, and alternative B is preferred to alternative C, then logically, alternative A should be preferred to alternative C [33, 34]. Condorcet [11] showed that group preference is not necessarily transitive, even if its individual members are transitive. Condorcet's voting paradox is presented in Table 2.2:

Table 2.2 shows the preferences of three decision-makers over a set of three alternatives A, B, and C, where "≻" symbolizes "is preferred to." Each decision-maker is transitive. However, pairwise comparisons of the alternatives (in each column) reveal that the transitive decision-makers together as a group prefer A to *B*, *B* to *C*, and *C* to *A* (i.e., *A* ≻*B* ≻C≻A), which is intransitive. This paradox is known as Condorcet's voting paradox. It is noted that while the paradox demonstrated in Table 2.1 employs multiple decision makers to reach an overall group preference, the paradox is equally applicable to use multiple design criteria to select an overall preferred design. This can be illustrated using a vehicle design problem, in which a decision maker wishes to select the preferred vehicle design (A, B, or C) based on three criteria, mass, fuel economy, and comfort, as shown in Fig. 2.6. His/her utility decreases with increasing mass, increases with increasing fuel economy, and increases with increasing comfort, resulting in preference functions (U_1, U_2, and U_3).

Using the three preference functions, the three alternatives A, B, and C can be ordered. The resulting preference ordering for preference function U_1 is A≻B≻C,

Table 2.3 American refrigerator design selection

Refrigerator	Attribute value		Normalized attribute value	
	A	B	A	B
Operating temperature (°F)	37.4	37.0	1.005	0.995
Energy consumption (kW/day)	5.0	5.1	0.990	1.010
Totals			1.995	2.005
Result: A preferred to B, choose A				

Table 2.4 European refrigerator design selection

Refrigerator	Attribute value		Normalized attribute value	
	A	B	A	B
Operating temperature (°C)	3.0	2.8	1.034	0.966
Energy consumption (kW/day)	5.0	5.1	0.990	1.010
Totals			2.025	1.975
Result: B preferred to A, choose B				

for U_2 the ordering is C≻A≻B, and for U_3 the ordering is B≻C≻A. The three preference orderings (A≻B≻C, C≻A≻B, and B≻C≻A) shown in Fig. 2.6 constitute Arrow's impossibility as previously shown in Sect. 2.2. Thus, the paradox can occur with multiple decision makers or multiple criteria. As introduced earlier in Sect. 2.2, Arrow formulated a set of desired properties that, when satisfied, avoids the paradox shown in Table 2.2 and thus facilitates rigorous alternative selection.

2.3.2 *Problems with Normalization, Scaling, and Translation*

Normalization is frequently used to address the dimension problem in multi-criteria approaches. However, when two or more attributes are considered, normalization itself may cause problems.

Consider the normalization of attribute z for k alternatives. One suggested way for normalization is to normalize with respect to the attribute mean value, see Eq. (2.3). Evidently, *the normalized values depend on the alternative set, i.e., the number of alternatives k and on the coincidental attribute values* z_i *of the alternatives. Therefore, the rank order of the alternatives can depend on the alternatives included in the alternative set, which constitutes a violation of Arrow's IIA property*. Another typical method for normalization is to normalize with respect to the attribute value range. The normalized value of alternative j, Nz_j then depends on the (coincidental) range. The lack of a rigorous method to determine the normalizing range can lead to the violation of the IIA property. As an example, some engineers prefer to work with the metric system while others prefer the imperial system. For most units the two systems only differ in scale, for example kilogram versus pound. Equation (2.3) shows that scaling the attribute values (z_1, z_2, …, z_k) with, for example, a constant a, i.e., (az_1, az_2, …, az_k), does not affect the normalized attribute value. However, if translation is involved, i.e., ($az_1 + b$, $az_2 + b$, …, $az_k + b$), then the normalized value is affected and the alternative selection depends on the transformation, see Eq. (2.4).

$$Nz_j = \frac{az_j}{\sum_{i=1}^{k} z_i} \tag{2.3}$$

$$Nz_j = \frac{az_j + b}{b + \frac{a}{k}\sum_{i=1}^{k} z_i}. \tag{2.4}$$

To demonstrate preference reversal caused by translation, assume two engineers design a small refrigerator and they generated exactly the same alternatives A and B described by operating temperature and energy consumption. The engineers select the preferred alternative using the sum of the normalized attribute values, where less is preferred. However, one design engineer is located in Europe and the other in America and both design engineers adhere to their numerical conventions. Therefore, the European engineer denotes temperature in degrees Celsius and the American in degrees Fahrenheit, and their relation, shown in Eq. (2.5), includes translation.

$$^\circ F = \frac{9}{5}{}^\circ C + 32. \tag{2.5}$$

The comparison and alternative selection of the American and European engineer are shown in Tables 2.3 and 2.4. How can it be that, though both design engineers consider the same alternatives, employ the same alternative selection approach (i.e., normalization by the average value), have the same preference (minimization), and assume equal importance of the criteria "operating temperature" and "energy consumption", they surprisingly select different alternatives?

The preference reversal shown in Table 2.3 and Table 2.4 is caused by the translation that occurs when converting centigrade Fahrenheit into centigrade Celsius and vice versa. Barzilai [4] asserts that this limitation associated with translation applies to all unit scales that lack a universal or absolute zero, including the analytic hierarchy process (AHP) [35]. AHP is a decision analysis approach with which decision makers evaluate multiple design alternatives by comparing one to another in pairs, with respect to a design criterion at a higher level in the hierarchy. Additionally, as normalization does not consider the importance of attributes, weights can be assigned to attributes that differ in importance. This, however, leads to another set of problems which is explained in the next section.

2.3.3 Problems with Assigning Weights

The importance of an attribute is normally taken into account by associating a certain weight w_i with each attribute i., e.g. see Eq. (2.2) for a simple, commonly used linear additive weighing function. Any method that involves assigning weights to attributes may lead to a subjective decision, i.e., the attribute weights are based upon the decision-maker's intuition, knowledge, and personal experience. An attribute is generally granted a higher weight when it is correlated to a product's success [2]. The weights are subject to fluctuation and likely differ when assessed at a different time or under different circumstances. An additional issue with a linear additive weighting function is that an attribute's value is assumed linear, regardless of the value of the attribute. This assumption violates the economic principle of marginal utility, which states that as more of a product is obtained, the marginal utility decreases. Another limitation is that the weighted sum method requires that the values of the attributes should be mutually independent with regard to preference (i.e., the value of one attribute should not depend on the value of another attribute [23]). This condition, however, is rarely checked.

2.3.4 Problems with Multi-Attribute Ranking

The problem with multi-attribute ranking methods occurs when more than two attributes are considered. A popular multi-attribute ranking approach is to employ a voting procedure, based upon the rank order of the alternatives. The alternatives could be ranked for each attribute. Subsequently, votes can be distributed depending on the alternative's rank and the attribute's importance. For example, in the majority voting method, only the highest ranked alternative receives a vote. For four alternatives this can be denoted as: [1, 0, 0, 0]. Other methods are avoiding the worst of the worst, denoted as [0, 0, 0, −1], voting for the two highest ranked alternatives: [1, 1, 0, 0], or the Borda Count [3, 2, 1, 0], to name a few. As shown by Saari [33, 34], the selection result is more a reflection of the underlying voting method than the quality of the alternatives. We illustrate this through the following example.

In 2001, Chicago won out over Denver and Dallas as the new location for the Boeing headquarters. Suppose 15 executives vote for either, Chicago, Dallas, or Denver (i.e., Chi, Dal, Den). The preferences of the executives are as follows: six prefer Dallas to Chicago and prefer Chicago to Denver, i.e., Dal$\succ$Chi$\succ$Den; five prefer Den$\succ$Chi$\succ$Dal; and four prefer Chi$\succ$Den$\succ$Dal. Voting by majority, i.e., [1, 0, 0], Dallas receives 6 votes, Denver 5 and Chicago ranks last with 4 votes using the preferences of the executives. Because Boeing headquarters relocated to Chicago, perhaps the group preference of Dal$\succ$Den$\succ$Chi with totals (6:5:4), obtained through the majority method does not accurately reflect the preference of the group. For instance, do our executives really prefer Denver to Chicago? Comparing Denver to

Chicago in a pairwise comparison (as in Sect. 2.3.1), the result is that the group prefers Chicago to Denver, 10 votes to 5. This result conflicts with the result of the previous selection of the location for the new headquarters. The preference reversal could occur because the majority voting method does not satisfy Arrow's IIA property discussed in Sect. 2.2. Comparing the results of other voting methods to the majority method: pairwise voting results in Chi≻Den≻Dal, the runoff procedure results in Den≻Dal≻Chi, the Borda Count leads to Chi≻Den≻Dal, and avoiding the worst of the worst gives Chi≻Den≻Dal. It appears that the outcome is determined by the voting method instead of the quality of the alternatives. Thus, voting methods can be prone to error when it comes to selecting the preferred alternative and therefore may cause problems when used for engineering design.

Along the same lines, Arrow's general possibility theorem [1] shows that group voting, analogous to the weighted sum method, can lead to intransitive outcomes. It indicates that neither the preference of a group of designers, nor that of the customers, can be captured by multi-attribute rankings. Paradoxes in multi-attribute rankings occur more frequently than one would expect. According to Coombs's condition [2], the chance of paradox is *over* 97% when six alternatives are ranked using multiple attributes. When ten alternatives with multiple attributes are considered, the chance of paradox is virtually 100%. Although extensive work has been done on minimizing the voting paradox, such as the Borda Count voting method by Saari [33, 34], these methods can only minimize voting paradoxes while not completely eliminating them. Although the Borda Count does not satisfy Arrow's general possibility theorem, Dym et al. [13] showed that rank reversals caused by IIA using the Borda Count are rare. However, other limitations prevent the Borda Count from being useful for engineering design decision making. These limitations include the sensitivity to strategic voting (i.e., any decision-maker can doom an alternative by ranking it last), the lack of a rigorous procedure to determine the attribute weights, and the neglect of relative position of the attribute values.

2.3.5 Problems with Multi-Attribute Utility Function

The MAU function [23], shown in Eq. (2.6), has been adopted by some designers to overcome the limitations associated with the weighted sum approach and multi-attribute rankings.

$$U(X_A) = \frac{1}{K}\left[\left[\prod_{i=1}^{n}\left(Kk_iU_i(x_i)+1\right)\right]-1\right] \tag{2.6}$$

In this equation, the k_i are single attribute scaling constants and K is normalizing constant so that $U(X_A)$ scales 0–1. In this method, utilities for individual attributes are combined using a multiplicative function form. However, as thoroughly examined by Thurston [40], there are a few perceived limitations of this approach. One major limitation is that the utilities of each attribute, U_i, which make up the MAU function, must be mutually independent [23]. Note that, independence is required regarding *preference*, which is different from functional independence which is not required. However, this condition of preference independence hardly ever checked.

Another limitation of the MAU method lies in assessing the single attribute scaling constants k_i [see Eq. (2.6)] where the designer is expected to provide rational judgments without knowing how each attribute contributes to the interest at the top system level, for example the profit in product design. A related issue is that the alternatives used in the lottery assessment are hypothetical, and assessing the scaling constants k_i is also often physically impossible. Experimental research of Holt and Laury suggests that individuals are not able to imagine how they would behave in real situations [19], i.e., there is a mismatch between behavior in hypothetical situations and in real situations. Another issue is that sometimes the attributes employed in a MAU approach are not of interest to the decision maker but to the customer. In such a situation the method implicitly assumes that a group of individuals (customers) can be represented by an average individual, whereas an average individual does not exist. A more thorough examination of modeling heterogeneous customers' interests in product selection is provided in Chap. 3.

2.3.6 Limitations of the Multi-Attribute Approach in Dealing with Uncertainty

In engineering design, the attribute performance levels are often uncertain due to various sources of uncertainty as a result of incomplete information, engineering assumptions, and modeling errors even though uncertainty is reduced as design moves from concept to final product. *The existing multi-attribute approaches are very limited in dealing with uncertainty*. In the presence of uncertainty, the preference of an alternative also depends on the level of uncertainty and the decision-maker's risk attitude. Uncertainty with respect to multi-attribute ranking methods means that the rankings cannot be determined with certainty, *not even if expected values are used*. Other methods comparable with multi-attribute ranking such as weighted sum method, analytical hierarchy process (AHP) [35], etc. mentioned earlier, fail to take into account the risk attitude of a decision-maker.

2.4 Limitations of Existing Design Approaches for Alternative Selection

In addition to Multi-Attribute Utility (MAU) method, there are many alternative selection approaches being used for engineering design, such as, Quality Function Deployment (QFD) [10], Pugh's selection matrix [42], analytical hierarchical process [35], Suh's axiomatic design [37], and design for six sigma [15]. However,

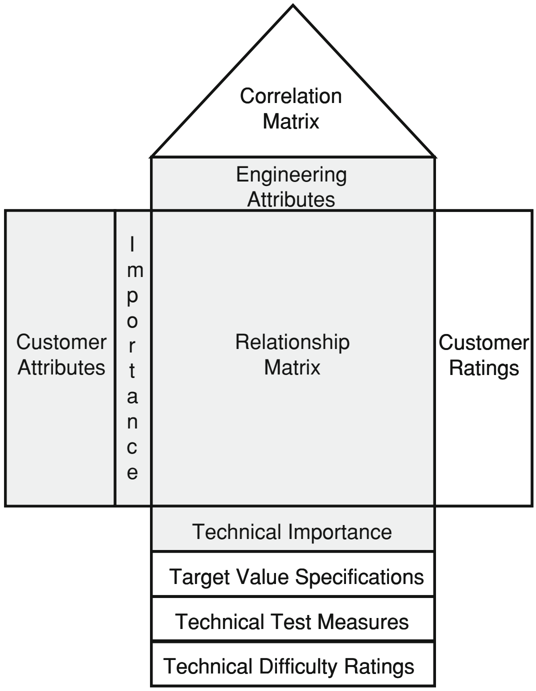


Fig. 2.7 House of quality, 1st house [28]

these methods are either subject to the paradox of multi-criteria selection methods as examined in Sect. 2.3, or assume that product design decisions made using a domain-specific selection criterion, such as minimizing product defects [38] or producing "uncoupled" designs [37] will result in a preferred design. To summarize, none of these processes attempt to set targets or select a design concept utilizing an enterprise-level decision criterion. Other relevant product planning tools include the requirements traceability matrix [30], which is used to organize and track product requirements to ensure all requirements are met by the design artifact; and the design structure matrix [7], which is utilized in systems engineering to decompose a system into components and determine the relationships among components. Neither of these tools is intended to be used as an enterprise-level decision-making tool, but rather each is used to help designers organize product or system requirements. QFD is designed as a tool to provide an enterprise-level view to engineering design; therefore in this section, a close examination of the limitations of the QFD method is provided.

QFD was developed to bridge the marketing and engineering domains using much simplified, consensus-driven qualitative analyses. This process was developed as a means to link product planning directly to the "Voice of the Customer." It remains the leading tool for setting engineering priorities, determining target levels of product performance through benchmarking and, when supplemented with Pugh's Method, selecting a design concept. As shown in Fig. 2.7, the primary feature of the QFD process is the house of quality (HoQ) [10], which provides an interfunctional product planning map to link engineering attributes to customer desires that are ranked in importance. The HoQ utilizes a weighted-sum multi-objective decision criterion, entailing technical test measures (benchmarking) analysis, technical importance rankings, and estimates of technical difficulty to enable a decision maker to set performance targets for a designed artifact. As mentioned, the QFD process has been supplemented by some practitioners with the Pugh Matrix for design concept selection [39]. The Pugh Matrix provides a method to compare alternative design concepts against customer requirements, with evaluations made relative to a base or favored concept, in a process independent from the HoQ analysis.

Much literature has demonstrated both the successes and issues with the QFD methodology [9]. We summarize here the issues using QFD as a design selection tool. First, according to Aungst et al. [3], using only customer and competitor information to set targets without consideration of the physics of engineering attribute interactions or other product objectives, such as market share and potential profit, can result in targets that can never be achieved in practice. Several proposed improvements to the QFD have been presented in the literature. Aungst et al. [3] have presented the Virtual Integrated Design Method. Their method uses a quantitative-rather than qualitative-link between the conventional four HoQ matrices, and adds a new 5th house to account for customer perceptual attributes which are determined using factor analysis. Brackin and Colton [6] have proposed a method in which analytical relationships between the engineering attributes and customer attributes are created, and real values of engineering attributes are used from an appropriate database to ensure targets are achievable. Locascio and Thurston [26] have combined the QFD ratings and rankings into a design utility function to determine performance targets using multi-objective optimization. Although these methods improve upon the target setting methodology of QFD, they utilize customer group importance rankings and engineering rankings which have been shown to be problematic [16].

In the QFD approach, the importance ranking assumes that all customer preferences are the same and can be represented by a group utility; however, based on Arrow's impossibility theorem (AIT), Hazelrigg [16] has shown that utility exists only at the individual, or disaggregate level. Each customer has a specific preference, and the demand for a product can only be determined by aggregating individual product choices. More recently, Van de Poel [43] has illustrated the methodological problems in the QFD process caused by the implications of AIT. Although the AHP was introduced [35] to aid in the determination of importance rankings. It is shown in Sect. 2.3 through the use of AIT that the importance weightings for ranking the importance of engineering attributes can be irrational when more than two attributes are ordered. Further, Olewnik and Lewis [28] have demonstrated through the use of designed experiments that the HoQ rating scale used in the relationship matrix yields results comparable to using random variables, or completely different scales in its place.

Additionally, due to its philosophy, the QFD method is overly biased toward meeting customer requirements. Prasad [31] presented an expanded QFD methodology called concurrent function deployment (CFD) that expands upon the customer attributes to consider other corporate objectives, such as cost and manufacturing. Similarly, Gershenson and Stauffer [14] developed taxonomy for design requirements for corporate stakeholders, in the form of a hierarchically organized requirements database. They consider not only end-user requirements as in conventional QFD analysis, but also corporate, regulatory and technical requirements. These methods still employ conventional weighting and ratings techniques.

Although the consideration of uncertainty is imperative in engineering design, particularly in the conceptual design phase, conventional QFD analysis offers only a deterministic approach to ranking importance and setting target performance. It lacks a mathematical framework to incorporate uncertainty into decision making. Recent work in the QFD methodology has focused on the use of fuzzy set theory to account for uncertainty in customer importance assessments [8, 22, 24]. While these approaches address the uncertainty in the human element of importance assessment, they do not address uncertainty in other elements of the decision process, such as in the technical requirements, or address the limitations of preference aggregation in the QFD method. Other significant limitations of QFD are the oversimplification of attribute-coupling in the "roof" of the HoQ, an inadequate reflection of the real design trade-offs due to the subjective nature of attribute ranking, and a lack of methodology for considering manufacturing/production constraints. Regarding the Pugh Matrix for concept selection, its major limitation is that it is not a comprehensive enterprise-level decision tool, but rather was formulated to make decisions in the engineering domain while considering product requirements, without consideration of uncertainty, customer demand, or enterprise profitability. In Chap. 5, the product attribute function deployment (PAFD) method that employs the principles of QFD to overcome the limitations of the QFD method is presented.

2.5 An Enterprise-Driven Design Approach to Modeling Designer Preference

Fundamental to any engineering design theory development is the use of an alternative selection method that is valid in the presence of uncertainty and risk. In Sects. 2.3 and 2.4, we examined the limitations of multi-criteria approaches and some other existing design approaches for alternative selection and showed that, in order to make rigorous design decisions, it is important to use a single-criterion approach to product design. This brings us to the desirable features of the single criterion that facilitates decision making in engineering design.

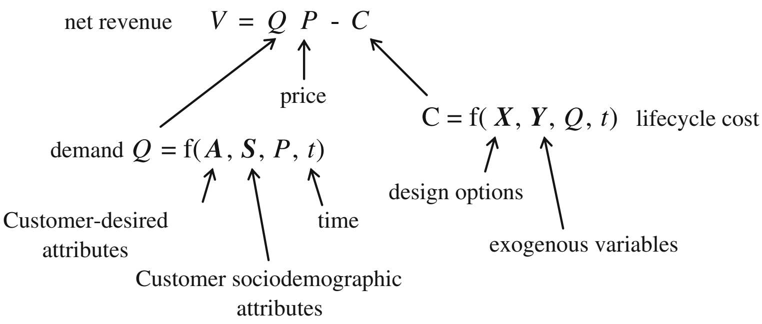


Fig. 2.8 Net revenue model for engineering design

When using a single-criterion approach to DBD, the selected single criterion should reflect the many different aspects involved in engineering design, such as product features, manufacturing considerations, and physical restrictions imposed by engineering disciplines as well as customer preferences. *Thus, the single criterion should facilitate consideration of the interests of both the customer and the producer*. Engineering design involves decision making under uncertainty. Therefore, *the single criterion should capture any uncertainty associated with the design alternatives,* given that engineering design should consider a product's entire lifecycle.

In a customer driven market it is not up to the designer to decide what the customer should like. Thus, the design engineer alone cannot determine the optimal levels of the product attributes like performance, quality, reliability, and safety. In Sect. 2.3.1, we discussed the paradox of aggregating the preferences of a group of decision makers based on the preferences of individuals. The same paradox associated with designers' decision making applies to aggregating the preferences of customers by treating them as a group. On the other hand, market share or customer demand is a more appropriate measure of the aggregated customers' preferences than modeling the utility of a group of customers. Hence, customer demand should be a part of the single criterion for decision making. The characteristics of the producer (i.e., manufacturing capabilities, management quality, etc.) are ultimately reflected in production cost, which is also a function of customer demand. An array of corporate interests like, profit, market share, profit margin, etc., can be linked with the engineering design alternatives and could serve as the single attribute (or criterion) for alternative selection, when the demand, price, and the cost of the design alternatives are known.

In the DBD framework presented in this work, we assume that the common objective of engineering design is to maximize profit. This assumption is supported by the *positive* view of economists that behavior of companies can be explained and predicted by assuming that companies act *as if* they maximize profit. Profit, or better, net revenue, can be modeled as the difference between revenue and expenditure, see Fig. 2.8. Using profit as the single criterion for engineering design alternative selection requires the formulation of an appropriate product cost model C, market demand model Q, and the engineering analysis models that capture the relationship between the design alternative descriptions **X** and the attributes **A** that customers consider when deciding what product to purchase.

In the DBD formulation, utilizing *profit*, Π, as the selection criterion (V) captures the needs of both the customer and the producer stakeholders, resulting in maximum benefit to the enterprise when utility is maximized. Profit is expressed as a function of product demand Q, price P, and total cost C, where demand Q, is expressed as a function of customer-desired attributes **A**, customers' demographic attributes **S**, price P, and time t:

$$V = \Pi = Q(A, S, P, t) \cdot P - C. \tag{2.7}$$

Similar to "customer attributes" in QFD, **A** are product characteristics that a customer typically considers when purchasing the product. To enable engineering decision making, qualitative customer-desired attributes **A** must be expressed as a function of quantitative engineering attributes **E** in the demand modeling phase. This functional relationship can consist of a *hierarchy* of models mapping **A** to **E** to establish the relationships necessary for decision making. Cost, C, is a function of the design attributes, **E** (which relate to Design Options X), exogenous variables, **Y** (the sources of uncertainty in the market), demand, Q, and time t. Price, P, is an attribute whose value is determined explicitly in the utility optimization process, or obtained from a separate price optimization process. Based upon these functional relationships, the selection criterion can be expressed as:

$$V = \Pi = Q(A(\mathbf{E}), S, P, t) \cdot P - C(E, Y, Q, t). \tag{2.8}$$

It should be noted that uncertainty is considered explicitly and the objective is expressed as the maximization of the expected enterprise utility $E(U)$, considering the enterprise risk attitude:

$$\mathbf{max}: \ E(U) = \int_V U(V) pdf(V) \, \mathrm{d}V \tag{2.9}$$

where V is the single selection criterion in Eq. (2.8).

A detailed explanation of the proposed DBD framework and the procedure of implementing it in engineering design will be provided in Chap. 4.

2.6 Summary

While the fundamental principles of decision analysis are generally applicable to decision making in engineering design, making design decisions in a rigorous way is not trivial. This is due to the fact that engineering design is a complex decision-making process that involves multiple parties in an enterprise and trade-offs of interests from different groups. Many believe that all aspects of alternative selection can only be captured by considering multiple criteria. However, the challenges of using multi-criteria-based alternative selection approaches lie in the selection of appropriate criteria, in determining the ‘importance’ of the criteria, and in combining the criteria into a single preference function, such that the trade-off of the various criteria is consistent with the decision-maker’s preferences. We conclude in this chapter that when three or more alternatives with multiple attributes are involved, normalizing procedures, weighting methods, multi-attribute ranking methods, and MAU functions cannot guarantee the selection of the best alternative in an unambiguous, rational, and consistent manner. This conclusion is astounding because all existing multi-criteria approaches and popular engineering design approaches possess these limitations in one way or another. In fact, the selection of attributes themselves may be biased and incomplete. Further, the votes or weights may be impaired due to personal and political interests. In other words, votes or weights do not necessarily coincide with the corporate interest of making profit. *These problems are absent if one, and only one, criterion is used for selecting the preferred design.* This single criterion should reflect many different issues involved in product design, such as product features, manufacturing issues, and physical restrictions imposed by engineering disciplines.

Through examining the limitations of existing design approaches such as QFD, we arrive at the conclusion that the design engineer should be very careful when choosing which alternative selection approach to use. It appears that only decisions that are based on a single criterion can avoid paradox associated using multiple criteria for decision making. The presence of uncertainty may have helped to obscure these limitations, as good decisions can have bad outcomes and bad decisions can have good outcomes. This occurs especially since only one design is produced at a time and cases cannot be repeated to test design methodologies. However, in the long run the accumulated outcome of good decisions will exceed the accumulated outcome of bad decisions. It is therefore important that a company aims at making good decisions. A DBD approach that bases its engineering design decision making on a single-criterion such as profit offers a methodology to do just that. In the next chapter (Chap. 3), we will present various techniques for modeling customer interests in the form of a demand model, which is a critical component of the DBD framework. The detailed steps for implementing the DBD framework in engineering design will be further discussed in Chap. 4.

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Chapter 3
Fundamentals of Analytical Techniques for Modeling Consumer Preferences and Choices

Nomenclature

A	Customer-desired product attributes
β	Utility model parameters
β_0	Utility model alternative specific constants
C	Total product cost
C_n	Alternative choice set
D	Aggregated market size
E	Engineering design (ED) attributes
J	Total number of alternatives in the choice set
k	Ordered Logit cutpoint
IIA	Independence of Irrelevant Alternatives
L	Likelihood function
P	Product price
Q	Product demand
ρ_0^2	Pseudo-R^2 (measure of model fit)
RP	Revealed preference
S	Customer socio-demographic attributes
SP	Stated preference
t	Time interval for which demand/market share is to be predicted
u_{in}	True utility of alternative i by customer n
V	Selection criterion used by the enterprise (e.g., profit, market share, revenues, etc.)
W_{in}	Deterministic part of the utility of alternative i by customer n
X	Design options
Y	Exogenous variables (represent sources of uncertainty in the market)
ε_{in}	Random unobservable part of the utility of alternative i by customer n
Z	Full set of attributes (**A**, **E**, and/or **S**)

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_3,

The fundamental principles of decision theory for modeling designer (decision maker) preference are introduced in Chap. 2. In this chapter, the analytical techniques for modeling customer preferences in product design are introduced in the form of demand modeling, or alternatively, choice modeling. As concluded in Sect. 2.5, a primary feature of the enterprise-driven design approach is estimation of a demand function, which is critical for assessing both a customer's willingness to purchase a product, as well as the benefit it brings to the producer. In this chapter, the demand modeling literature is first reviewed and the need for modeling the heterogeneity of customer preferences is shown. Next, a widely used choice modeling approach, discrete choice analysis (DCA) is introduced, which has the variants of Multinomial, Nested, and Mixed Logit Models. Ordered logit (OL) to model preferences for system attributes that are in the form of a rating is introduced next followed by a discussion of computational methods for estimating the DCA and OL models. Guidelines for addressing a wide range of issues, such as attribute and choice set selection, data collection, dynamic demand modeling, model validation, etc., in implementing demand modeling for product design are provided next. A walk-through example of model estimation and demand forecasting is presented in the final section.

3.1 Modeling Heterogeneous Customer Preference: State of the Art

Understanding customer preferences or their interests and needs is critically important in developing successful products. While many qualitative approaches, such as human-centered design [59], emotional design [60], and universal design or inclusive design [8], exist for identifying customer needs using methods like user observations and focus group studies, there is a lack of analytical techniques for predicting product demand (or customer choice) as a function of engineering design decisions and a targeted market population. Although such analytical modeling is important for integrating customer preferences into a rigorous engineering decision-making process, building a demand model is not a trivial task as it faces challenges inherent in modeling human behavior.

Early work in modeling customer preference can be traced back to market research, where various analytical methods such as Multiple Discriminant Analysis [34], Factor Analysis [18], Multidimensional Scaling [19], Conjoint Analysis [20, 22–25] and DCA [2, 73, 75] were developed. Methods for modeling customer preference can be broken down into two categories: *disaggregate approaches* to modeling demand, such as DCA, *which use data of individual customers* as opposed to *aggregate approaches* which use *group averages* and model market share of each alternative as a function of the characteristics of the alternatives and socio-demographic attributes of the group of customers being considered in the data set. Disaggregate approaches explain why an individual makes a particular choice given her/his circumstances, and therefore, better reflect changes in choice behavior due to changes in individual characteristics and the attributes of alternatives. Also, unlike aggregate models, disaggregate models are known to obtain unbiased coefficient estimates.

The most widely used disaggregate demand analysis technique is DCA [2]. While more details are provided in Sect. 3.2, DCA is fundamentally a probabilistic choice modeling approach. It is a flexible approach which can model choice using a utility function composed of observed *product* and *customer* level attributes, and can be estimated using survey or actual choice data, or a combination of both. Further, a "mixed" formulation of the model can be used to capture the distribution of unobserved, or random, preference heterogeneity. Using DCA to estimate demand entails estimating *choice probability* for a given design alternative over a sample population, and aggregating choice probability for a given design alternative to estimate its *choice share*, and ultimately its *demand*.

Cook [9] introduced a linear demand model derived from a Taylor series expansion using product value and price to estimate demand, assuming aggregate customer preferences. Li and Azarm [43] utilized paired comparison conjoint analysis [22] and estimated a deterministic linear part-worth utility model to estimate demand among the survey respondents for a given product. Wassenaar et al. [81, 83, 84] utilized DCA to model demand for an engineering system, demonstrating the method using a selection of quantitative product and customer attributes for a customer product and an automotive system. The approach was extended to include customer perceptual preferences through the introduction of latent variable modeling [57, 82]. Michalek et al. have considered random customer heterogeneity (i.e., the distribution of attribute preferences in a given data set) to enable the use of a DCA choice model. Recent research in demand modeling for engineering design has extended general demand modeling methodologies to understand preference inconsistencies for engineering design artifacts [51], optimal design under price competition [67], preferences for esthetic forms [62], the use of latent class analysis (LCA) [70], and the influence of product usage context [44].

One major benefit of DCA is its ability to capture the heterogeneity of customer preferences. Systematic heterogeneity is observed and described by an attribute of the customer, **S**, to explain his/her choice behavior. Random heterogeneity is not observed and is captured across respondents by assuming the model parameters are random, as opposed to fixed (see more details in Sect. 3.2.4). Random heterogeneity accounts for the fact that two people with the same attributes **S**, facing the same product attributes **A**, can make different choices.

In order to ensure comprehensive modeling of systematic heterogeneity and thus minimize unexplained heterogeneity, we present here a taxonomy of **S**. The proposed taxonomy of Fig. 3.1 is expressed as the following:

- $\mathbf{S}_1$: *Socio-Economic attributes* (e.g., age, income)
- $\mathbf{S}_2$: *Anthropometric variables* (e.g., stature, weight)
- $\mathbf{S}_3$: *Purchase History* (e.g., vehicle type last purchased)
- $\mathbf{S}_4$: *Usage Context attributes* (e.g., commute, off road)

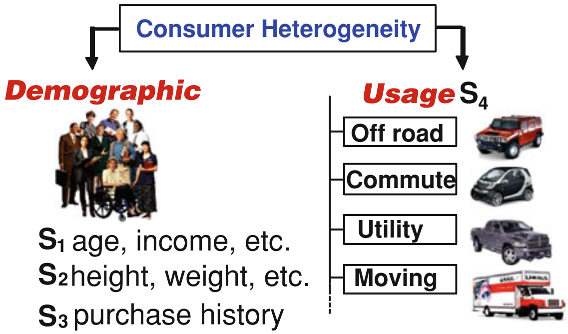


Fig. 3.1 Taxonomy of customer attributes S

Depending upon the degree of heterogeneity and the specific design problem, different types of DCA models, such as multinomial logit (MNL) models [29], nested logit models [39], and mixed logit models [75], have been utilized in design to capture heterogeneity in customer preferences. For instance, by allowing random taste variation across the population using a Hierarchical Bayes mixed logit model, Michalek (Michalek et al. [57] modeled heterogeneity in customer preference using random model parameters (i.e., random heterogeneity) without including the customer profile into choice modeling. Sullivan et al. [70] compared continuous representations of customer heterogeneity using Hierarchical Bayes mixed logit models with discrete representations using Latent Class mixed logit models the pros and cons of these two methods were identified. By introducing the customer profile attributes as explicit terms in the choice utility function, Hoyle et al. [33] introduced systematic customer heterogeneity, in addition to random heterogeneity, into a hierarchical choice modeling framework using a Hierarchical Bayes mixed logit model. Select major variants of the DCA techniques are introduced in more detail next.

3.2 Discrete Choice Analysis for Choice Modeling

3.2.1 Basic Concepts of Discrete Choice Analysis

Discrete Choice Analysis (DCA) [2, 37] is used to model product demand by capturing *individual* customers' choice behavior, in which performance of a given product is considered versus that of competitive products. DCA is based upon the assumption that individuals seek to maximize their personal *customer choice utility*, *u*, (not to be confused with enterprise utility, *U*) when selecting a product from a choice set. It should be noted that the customers could be either individual customers or industrial customers.

DCA *is a probabilistic choice modeling approach*, which originated in mathematical psychology [50, 52, 72, 77] and developed in parallel by economists and

Table 3.1 Example of a choice set for cell phone design

Choice Set # 31	Survey alternative (cellular phone)	Competing product A (cellular phone)	Competing product B (cordless phone)	None of these
A_1 Price	\$100	\$120	\$25	
A_2 Weight	3 oz	3.5 oz	6 oz	
A_3 Battery life	10 h	8 h	N/A	
A_4 Internet access	Yes	Yes	N/A	
A_5 …	…	…	…	
Indicate whether this is the product you want to buy and how many				

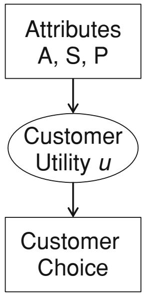
cognitive psychologists. DCA identifies patterns in choices customers make between competing products and generates *the probability* that an alternative is chosen. Disaggregate demand models built from DCA use data of individuals instead of group averages, which enables the variation of characteristics of individuals to be captured more accurately.

The origin of the application of DCA for demand estimation lies in transportation engineering, wherein the method was first employed to predict the choices travelers and shippers make between alternative modes of transportation [41, 68, 80]. A common assumption is that travelers maximize utility and that shippers minimize cost. The alternative modes of transportation are described by their features such as quality of service (travel time, frequency, route, reliability, infrastructure, price, etc.). The same principles can be applied to estimating the probability that a product design alternative is chosen from among a set of competing products by each customer. The choice probabilities for all customers of each individual competing product alternative can then be aggregated to estimate their demand and their choice shares.

A typical DCA is carried out in the following major phases: (1) Identify key customer-desired product attributes $\mathbf{A}$ and the range of price P; (2) Generate survey alternatives and collect quantitative choice data of proposed designs versus competing products. Survey alternatives can be generated with a factorial design, using the customer-desired attributes and price as factors. Each survey alternative *together with competing products* form a choice set. Table 3.1 shows an example of a choice set that could be used to collect choice data for cell phone design. Respondents are asked for each choice set *if* they want to purchase the proposed design or a competing product and to indicate how many; (3) Record customers' socioeconomic and demographic background $\boldsymbol{S}$; and (4) Create a model for demand estimation based on the probability of choice.

Multinomial analysis is a quantitative process for creating a demand model. As illustrated in Fig. 3.2, the method assumes the existence of an inexplicit, underlying utility function that *each* customer uses for making a decision in product

Fig. 3.2 Cause-effect relation in customer choice



selection. This utility follows a similar concept as the utility function introduced in Chap. 2. The difference is that the utility function introduced in Chap. 2 for the designer is *prescriptive* (prespecified) while the utility described here for a customer is *descriptive* (observed). The concept of random utility is adopted in DCA by assuming that the individual's true utility u consists of a deterministic part W and a random disturbance ε (see Eq. 3.1):

$$u_{in} = W_{in} + \varepsilon_{in}. \tag{3.1}$$

The deterministic part of the utility W_{in} can be parameterized as a function of observable independent variables $\mathbf{Z}$ (which includes customer-desired attributes $\mathbf{A}$, socio-demographic attributes $\mathbf{S}$, and price P) and unknown coefficients β, which can be estimated by observing the choices respondents make (Eq. (3.2)). The reason for including the socio-demographic attributes of customers is to capture the heterogeneous nature of customers, i.e., the observed utility varies across both design alternatives i and customers n:

$$W_{in} = f(\overbrace{\mathrm{A}_i, P_i, \mathbf{S}_n}^{\mathbf{Z}} : \beta_n). \tag{3.2}$$

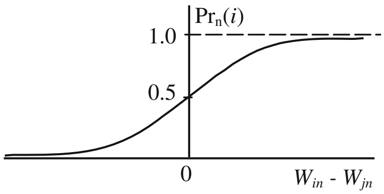
Depending on the assumptions made on the distribution of the random error term, different models with increasing degrees of sophistication can be used.

The choice probability of a given alternative is computed using the utility function, u. For example, the probability that alternative 1 is chosen from a choice set containing two alternatives (binary choice) depends upon the probability that the utility of alternative 1 exceeds the utility of alternative 2 or alternatively, depends upon the *probability that the difference between the disturbances does not exceed the difference of the deterministic parts of the utility*, as illustrated in Eq. (3.3):

$$\begin{aligned} \Pr_n(1)|[1,2] &= \Pr_n(W_{1n} + \varepsilon_{1n} \geq W_{2n} + \varepsilon_{2n}) \\ &= \Pr_n(\varepsilon_{2n} - \varepsilon_{1n} \leq W_{1n} - W_{2n}). \end{aligned} \tag{3.3}$$

Methods such as logit [2, 31] or probit [10, 31] can be used to form a choice model that predicts the choice probabilities. Probit assumes a multivariate normal distribution of the random disturbance ε, which allows complete flexibility of the variance–covariance matrix of the error terms. However, probit is computationally

Fig. 3.3 Binary logit choice model



burdensome as it requires integration of the multidimensional normal distribution. The binary probit choice model is presented in Eq. (3.4), where Φ() denotes the standard cumulative normal distribution function.

$$Pr_n(1)|[1,2] = \; Pr_n(u_{1n} \geq u_{2n}) = \Phi(W_{1n} - W_{2n}). \tag{3.4}$$

The normal distribution of the error term can be approximated with a logistical distribution (i.e., logit), which can be evaluated in a closed format. The logit model reduces computational burden by assuming that the error terms are independently and identically distributed across choice alternatives and observations (respondent choices). Equation (3.5) shows the choice probability of the binary logit model, where $\mathrm{Pr}_n(1)$ is the probability that respondent n chooses alternative 1 over alternative 2.

$$\begin{aligned} Pr_n(1)|[1,2] = \; Pr_n(u_{1n} \geq u_{2n}) &= \frac{1}{1 + e^{-(W_{1n} - W_{2n})}} \\ &= \frac{e^{W_{1n}}}{e^{W_{1n}} + e^{W_{2n}}} \end{aligned} \tag{3.5}$$

The binary logistical cumulative distribution function of the difference of the (deterministic) utilities $W_{1n} - W_{2n}$ is depicted in Fig. 3.3. Note that the predicted choice probability does not reach unity or zero. The binomial logit model is extended to the MNL model in Eq. (3.6) that predicts the probability that alternative i is chosen by the nth respondent from among J competing products.

$$Pr_n(i) = \frac{e^{W_{in}}}{\sum_{j=1}^{J} e^{W_{jn}}} \tag{3.6}$$

Estimation techniques such as the maximum log-likelihood method and the method of least squares can be used to determine the β-coefficients in Eq. (3.4) such that the model prediction of choices matches the observed choices (Fig. 3.4) as closely as possible. With a choice probability for each person and each design alternative, the demand for a given alternative can be computed. *The total demand for a particular design alternative i is the summation of the market segment's (expected) choice probability* Eq. (3.6) *multiplied by the segment's share of the total population* [2].

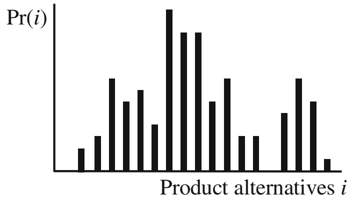


Fig. 3.4 Response rate probability distribution

The advantages of the DCA procedure can be summarized as:

(1) The method does not involve any ranking, weighting, or normalization, thus avoiding the paradox associated with many multicriteria approaches.
(2) Probabilistic choice addresses the uncertainties associated with unobserved taste variations, unobserved attributes, and model deficiencies.
(3) Competing products are considered, enabling analysis of market impact and competitive actions through "*what if*" scenarios.
(4) The choice alternatives do not necessarily share the same set of attributes or attribute levels (required for conjoint analysis), expanding market testing possibilities and leaving more freedom to the marketing engineer.
(5) The customer survey embedded in DCA resembles real purchasing behavior more closely, reducing respondent errors, and enabling the analysis of many attributes.

Specific choice models applicable for different applications and data sets are presented in the next section.

3.2.2 Multinomial Logit (MNL)

In the MNL model, the coefficients (β) in the observed customer choice utility function (W) for the product attributes are identical across all customers. However, heterogeneity is modeled by considering socio-demographic attributes $\mathbf{S}$ (e.g., customer's age, income, etc.) in the customer choice utility function. Assuming this utility function can be expressed as a linear combination of attributes, W follows the form:

$$W_{in} = \beta \cdot \mathbf{Z} = \beta_{0i} + \beta_{1i}\mathbf{S}_n + \beta_2\mathbf{A}_i + \beta_3(\mathbf{S}_n \cdot \mathbf{A}_i). \tag{3.7}$$

where β_{0i} is an *alternative specific constant* (ASC), $\boldsymbol{\beta}_{1i}$ is an *alternative specific variable* (ASV), and $\mathbf{Z}$ is the set containing $\mathbf{A}$ and $\mathbf{S}$. ASCs are utilized to represent preferences that are inherent and independent of specific attribute values. Conversely, ASVs are utilized to capture the heterogeneity of customer preference for each alternative due to the differing socio-demographic attributes $\mathbf{S}$ of each customer [2].The MNL model exhibits the independence of irrelevant alternatives (IIA) property, which leads to proportional substitution patterns among the alternatives considered. *Proportional substitution* implies that if a given design alternative is changed (i.e., the values of **A** for the design alternative are modified) such that its market share increases (or decreases), the increased (or decreased) change in market share of the given design alternative will result in an *equal* percent decrease (or increase) in market share for all other alternatives in the choice set. This may or may not be desirable depending upon the composition of the choice set. For example, if the design alternative which is modified is viewed by customers to be a valid substitute for any of the other design alternatives in the choice set, then proportional substitution may be a valid assumption. On the other hand, if the modified design alternative is not viewed as a valid substitute for some of the design alternatives in the choice set, the design modification should not influence the market share of those alternatives. For this case, proportional substitution is not a reasonable assumption. For such cases in which this property is undesirable, the *nested* or *mixed logit* formulations can be used to relax this assumption.

MNL is derived assuming that the error terms ε_{in} are independent and identically distributed (IID.) and follow a *Gumbel* distribution [55]. The Gumbel distribution $G = (\eta, 1/\mu)$ is characterized by two parameters η and $G = 1/\mu$. The parameter η is called the *mode* or the *location parameter* and $G = 1/\mu$ is called the *scale parameter,* which is proportional to the inverse of the variance. The expressions for the mean and variance of a Gumbel distributed random variable with the above-described parameters are as follows: Mean $= \eta + 0.577\mu$ and Variance $= \frac{\pi^2}{6}\mu^2$. Estimation of the customer choice utility function allows the demand, Q, for a choice alternative i to be determined by summing over the market population of size N, all probabilities, $\Pr_n(i)$, of a sampled individual, n, choosing alternative i from a set C_n of J competitive choice alternatives. The form of the choice probability function, $\Pr_n(i)$, for MNL models is given by the expression below:

$$\Pr_n(i : C_n) = \frac{e^{W^*_{in}/\mu}}{\sum_{j=1}^{J} e^{W^*_{jn}/\mu}} = \frac{e^{\beta^* \mathbf{Z}_{in}/\mu}}{\sum_{j=1}^{J} e^{\beta^* \mathbf{Z}_{jn}/\mu}}. \quad (3.8)$$

In this expression, $\Pr(i : C_n)$ refers to the probability of choosing alternative i from choice set C_n available to customer n. The μ refers to the scale parameter, and W^*_{in} and β^* are the un-scaled utility and model coefficients, respectively. When it is reasonable to assume that all alternatives are considered equivalently by customers, μ is set to 1 and the choice model is estimated as in Eq. (3.6) for unknown β's using Maximum Likelihood Estimation (MLE). This model is the MNL model. However, when the assumption that all alternatives are considered equivalently by customers is not realistic, multiple scale parameters, μ_k, are required and the Nested Logit model is utilized. The assumption of multiple scale parameters is appropriate when the data includes alternatives that correspond to multiple market segments (e.g., SUV, sports cars, trucks, sedans, in the automobile market), or when data are pooled from sources

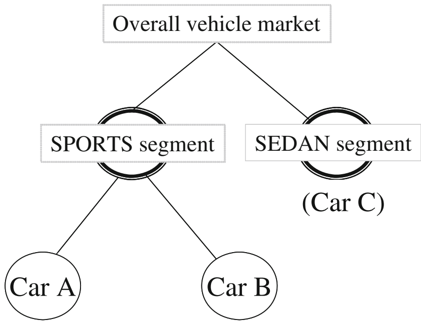


Fig. 3.5 Choice tree representation for a hypothetical automobile market

(e.g., purchase data that includes the actual alternatives in the market and survey data which includes hypothetical alternatives). The use of nested logit is introduced next.

3.2.3 Nested Logit (NL)

Nested Logit is a probabilistic modeling technique used to express the choice behavior of individual customers and can be used whenever some choice alternatives are similar to others [86]. The NL demand model has been applied in a variety of situations, including energy, travel demand forecasting, housing, telecommunications, and airline revenue management [4, 13, 15, 41, 76]. The mathematical structure of the NL demand model allows us to capture the dissimilar nature of competition in different product segments, and estimate more accurate and realistic demand models, i.e., it relaxes the proportional substitution pattern assumption of the MNL model.

The Nested Logit (NL) model *incorporates elements of unequal competition* by modeling correlation among the choice alternatives. The NL technique assumes that the set of alternatives can be partitioned into subsets, called *nests*. The technique is best explained with an example. A hypothetical automobile market that only includes cars from the sports and sedan segments is considered. While the sports segment has two cars (i.e., A and B), the sedan segment has only one (i.e., C). The situation is represented in the choice tree shown in Fig. 3.5. While the grouping of the two sports segment alternatives in one nest and the sedan in the other nest represents the customer's decision-making process (i.e., he or she is assumed to consider sports cars A and B as more similar to each other than to sedan C), it also serves to illustrate the similarity in the error components. The following utility and error functions for the different alternatives further clarify this point:

$$\begin{array}{ll} \text{Utilites} & \text{Error terms} \\ U_C = W_C + \varepsilon_C; & \varepsilon_C \qquad\quad \sim G(0,1) \\ U_B = W_B + \varepsilon_B + \varepsilon_{\text{sports}}; & \varepsilon_B + \varepsilon_{\text{sports}} \sim G(0,1) \\ U_A = W_A + \varepsilon_A + \varepsilon_{\text{sports}}; & \varepsilon_A + \varepsilon_{\text{sports}} \sim G(0,1). \end{array} \tag{3.9}$$

It should be noted that the error terms for alternatives in the sports segment (i.e., A and B) are no longer independent; they share an error component (i.e., $\varepsilon_{\text{sports}}$). While both error components (i.e., ε_A & $\varepsilon_{\text{sports}}$ corresponding to alternative A, and ε_B & $\varepsilon_{\text{sports}}$ corresponding to alternative B) play a role in selecting between the entire sports segment and the family sedan segment, only the uncorrelated error components (i.e., ε_A for alternative A and ε_B for alternative B) are important when choosing among the nested alternatives A and B. The NL choice probability functions for the different car alternatives in the hypothetical vehicle market are listed next, and all expressions are with respect to customer n.

(a) For the alternative in the sedan segment:

$$Pr_n(C : C_n) = \frac{e^{W_{C,n}}}{e^{W_{C,n}} + e^{W_{C,n} + \mu_{\text{sports}} \cdot \Gamma_{\text{sports,n}}}} \tag{3.10}$$

(b) For the alternative in the sports segment:

$$Pr_n(A : C_n|\text{sports}) = \frac{e^{\frac{W_{A,n}}{\mu_{\text{sports}}}}}{e^{\frac{W_{A,n}}{\mu_{\text{sports}}}} + e^{\frac{W_{B,n}}{\mu_{\text{sports}}}}} \tag{3.11}$$

In these two probability expressions, $\Gamma_{n,\text{sports}}$ is equal to $ln\left(e^{\frac{W_{n,A}}{\mu_{\text{sports}}}} + e^{\frac{W_{n,B}}{\mu_{\text{sports}}}}\right)$ and is referred to as the logsum parameter and $C_n = \{\text{A,B,C}\}$ is the choice set available to customer n; $\text{Pr}_n(C : C_n)$ is the probability of choosing alternative C from the vehicle market, and $\text{Pr}_n(A : C_n|\text{sports})$ is the conditional probability of choosing alternative A assuming the sports segment has been already chosen. Finally, μ_{sports} is the scale parameter associated with the sports segment and plays an important role in modeling unequal competition. A value closer to 0 indicates that the alternatives in the sports segment (i.e., A and B) compete more closely with each other for market share than with alternatives that do not belong to the sports segment (i.e., C); a value closer to 1 indicates that the "within-segment" competition is not significant and all alternatives compete equally.

In Chap. 11, the NL demand model is applied to product family design to model the impact of product segmentation on the market share of each of the products in the family by exploiting NL's unique error structure. This is accomplished by grouping products in each market segment under a separate nest in an NL choice tree representation similar to the one shown in Fig. 3.5 which is then followed by

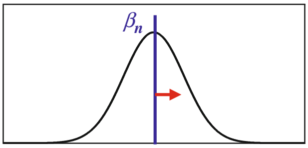


Fig. 3.6 Example of parameter distribution associated with random heterogeneity

the estimation of the NL model by determining the values of the unknown β's and scale parameter (μ) for each of the nests (i.e., segments).

3.2.4 Mixed Logit (MXL)

The mixed logit model (MXL) is distinguished from the MNL model in that it allows random taste variation, for example, the parameters β vary over respondents. This is achieved by allowing each individual person, n, to have his/her own set of model coefficients, β_n [66, 74, 75], see Fig. 3.6. In the MXL model, all model parameters, $\beta_{\mathrm{A},n}$, for customer-desired attributes are random, while the β_{S} are fixed to avoid the identification problems caused by allowing β to vary over alternatives i and people n [75]. The observed utility, W_{in}, in the MXL is given by:

$$W_{in}(\mathrm{MXL}) = \beta_{\mathrm{A},n}\mathbf{A}_i + \beta_{\mathrm{S}}\mathbf{S}_n + \beta_{\mathrm{A\cdot S}}(\mathbf{A}_i \cdot \mathbf{S}_n) \tag{3.12}$$

Therefore, the mixed logit probabilities are integrals of the MNL probabilities over a density of parameters, as expressed in the form:

$$Pr_n(i) = \int \left(\frac{\exp(W_{in}(\beta))}{\sum_j \exp(W_{jn}(\beta))} \right) pdf(\beta)\mathrm{d}\beta \tag{3.13}$$

where $pdf(\beta)$ is the probability density function of model parameters β. The mixed logit model has been demonstrated to be capable of approximating any random utility discrete choice model [75]. One of the most important advantages of the mixed logit model is that heterogeneity in customer preferences is decomposed into a systematic part, expressed by $\mathbf{S}$, and a random part expressed by random coefficients β; in MNL, only the systematic part is estimated, with the random heterogeneity lumped into the error term ε_{in}. No closed form solution exists for Eq. (3.13). Therefore in practical applications, the mixed logit choice probability is approximated (i.e., by $\hat{P}r_n(i)$) using numerical simulation by taking a finite number of draws $r = 1, 2, 3, \ldots, R$ from the distribution of β:

$$\hat{P}r_n(i) = \frac{1}{R}\sum_{r=1}^{R} Pr_{n,r}(i) = \frac{1}{R}\sum_{r=1}^{R} \frac{\exp(W_{in}(\beta_r))}{\sum_j \exp\left(W_{jn}(\beta_r)\right)} \tag{3.14}$$

where R is the number of random draws, $\Pr_{n,r}(i)$ is the probability of respondent n choosing product i in the rth draw, and β_r is the corresponding simulated random coefficients. In Sect. 3.4.2, the Hierarchical Bayes (HB) method to estimate mixed logit models is introduced. Also in Chap. 8, an example using this technique to capture preference uncertainty in the decision process is presented. It will be shown that explicitly capturing preference uncertainty results in a different demand estimation for a given design alternative than deterministic approaches.

3.2.5 Importance of Modeling Heterogeneous Customer Preferences

The importance of accounting for heterogeneity **S** in choice modeling results from the nonlinear relationship between observed customer choice utility, W_{in}, and choice probability, $\Pr_n(i)$, (or rating, $\Pr_n(R_p)$). The nonlinear, S-shaped (i.e., logistic) relationship between W_{in} and $\Pr_n(i)$ implies that a change to a given design alternative, i, (i.e., a change in value of $\mathbf{A_i}$) such that W_{in} changes for that design alternative, results in a *different* change in choice probability, $\Pr_n(i)$, for each individual. This behavior can be interpreted as individuals with strong preferences (positive or negative) for a particular alternative are not as likely to modify their choices when design changes are made, as individuals with weaker preferences.

The role of demographic descriptors (i.e., systematic heterogeneity), **S**, is to capture individual-level attributes which influence utility, W_{in}, to enable a better estimate of individual-level choice probability, $\Pr_n(i)$. The effect of preference heterogeneity is demonstrated graphically in Fig. 3.7, in which a MNL model (Sect. 3.2.2) for a given design alternative is estimated. The choice probability is given by the S-shaped curve in the figure. If a change is made to a given design alternative, such that a customer-desired attribute **A** of the alternative increases by 0.75 (causing an increase in utility for that alternative), the *effect* of this change in the utility upon choice behavior is different depending upon a customer's original choice probability (i.e., their choice probability before the change is made). If the customer had a low or high probability of choosing the alternative,for example, Customer 1 (*Cust 1*) or Customer 3 (*Cust 3*) in Fig. 3.7, the design change will not change their choice probability very much. This can be seen graphically in the figure that the choice probability for *Cust 1* and *Cust 3* only increases by 0.05. Alternatively, the change causes a much larger change in choice probability for Customer 2 (*Cust 2*) who has a more moderate original choice probability, increasing his/her choice probability from 0.4 to 0.6. This example demonstrates that a single choice probability for a given design alternative cannot be assumed for a given population, because the heterogeneity of customers results in different changes in choice probability for a given change in a design attribute **A**. Failing to account for heterogeneity leads to faulty demand estimations. For example, if it was assumed that all customers in the population had a choice probability for a given design alternative of 0.4, the increase in choice probability, and hence demand, would be significantly overestimated for a design change.

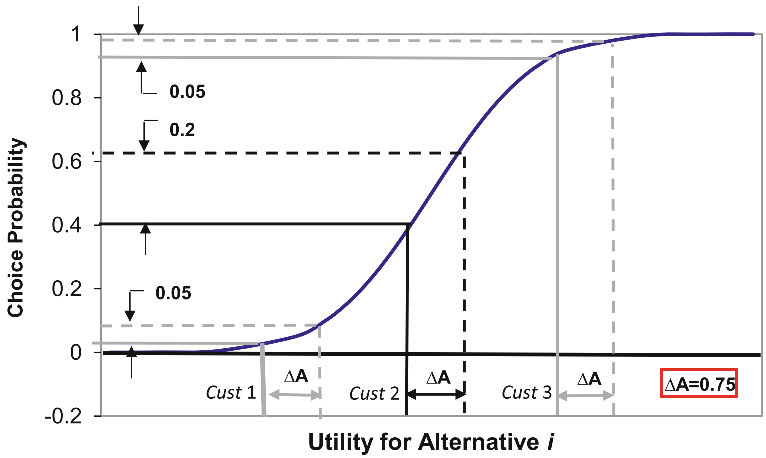


Fig. 3.7 Effect of S upon choice probability

The effect of including random heterogeneity (i.e., the MXL model of Sect. 3.2.4) is that it provides both a more rigorous representation of preference heterogeneity, as well as a relaxation of the IIA property of the discrete choice model [75]. Unlike a fixed parameter model, a random parameter model requires that the expected value of the choice probabilities be determined; therefore, each respondent utility function is an integration over β to find the expected value of $\Pr_n(i)$. This expected value of choice probability is different than the probability calculated using the mean value of β (i.e., the plug-in approach [66]) due to the nonlinear utility versus probability curve described previously. As was shown in [6], the MXL model results in different predictions of choice shares for a given design change compared to the MNL model due to the relaxation of IIA: IIA restricts the pair-wise choice probability ratios for each set of alternatives in the choice set to remain unchanged for a given design change. When using the MXL model to make choice estimates for a new market, the random heterogeneity of the new population is assumed to exhibit the same random heterogeneity as that in the model training data.

3.3 Ordered Logit for Modeling Rating Responses

In addition to choice modeling, methods are required to model customer preferences expressed as ratings as a function of quantitative engineering attributes and customer attributes. To fit a predictive model to survey ratings, or *ordinal data* (*e.g.*, 1 = poor, 2 = fair, 3 = good; rating from 1 to 10), as opposed to choices as developed in Sect. 3.2, alternative methods to standard linear regression are required. A key assumption of linear regression is violated when used to fit ordinal data because the

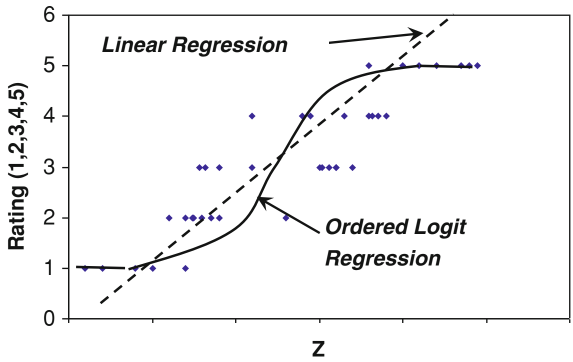


Fig. 3.8 Illustration of the variation of ratings versus explanatory variables Z [51]

expected model error cannot be assumed to be of zero mean with constant variance: the true value of the dependent variable is not a linear function of the explanatory variables **Z,** as shown Fig. 3.8 [56]. Further, an ordinal dependent variable is not unbounded as required by linear regression [49], but rather takes on a fixed number, p, of discrete values as defined by the survey design (e.g., rating scales of 1–10, 1–7).

For this reason, the *ordered logit model* is recommended to estimate models for ordinal customer ratings. Mckelvey and Zavonia [56] introduced ordered probit regression for ordinal data, in which the ordinal ratings were assumed to be discrete representations of a continuous underlying, normally distributed opinion or utility. McCullagh [53] introduced ordered logit in which the underlying distribution is logistically distributed, leading to the proportional odds model. In this model, the cumulative odds ratios are identical across ratings categories. Hedeker and Gibbons [30] developed a random effects ordered probit formulation, which considered the model parameters to be random and potentially functions of respondent level attributes (e.g., age, income), or *covariates*. Tamhane et al. [71] modeled the underlying utility response using the beta distribution to allow greater flexibility (i.e., not symmetric) and to enable a bounded response.

Ordered logit assumes that there are p ordered ratings, **R**, which are discrete representations of a continuous, underlying *utility*, u_{in}, associated with each alternative, i, that is rated by each survey respondent, n. In the ordered logit formulation, the underlying utility measure, u_{in}, is based upon the same concept as the discrete choice model utility in that it is assumed to be the sum of a parameterized observable component, $W_{in} = \beta \cdot \mathbf{Z}$, and an unobserved error component ε_{in}. Also in the OL approach, it is assumed that the error variance is the smallest at maximum or minimum values of **Z** and the largest for moderate values of **Z** (*i.e.,* responses at the ratings extremes are more certain than those in the middle regions). This appears to be a more realistic assumption compared to that used in linear regression. OL seeks to model the underlying utility, u_{in}, while the predicted discrete ratings, **R**, are estimated through the use of $(p-1)$ *cut points*, **k**, imposed on the distribution of the u_{in}, estimated to match the proportions of **R** present in the actual survey data. The ordered logit model is derived under the assumption that the probability, Pr, for any rating R_p is a function of observed utility and cut points, and that the unobserved errors ε_{in} are distributed logistically:

$$\begin{aligned}\Pr\left[R = R_p\right] &= \Pr\left[k_{p-1} < u < k_p\right] \quad (p = 1, 2, \ldots, P) \\ &= \frac{e^{k_p - \beta'\mathbf{Z}}}{1 + e^{k_p - \beta'\mathbf{Z}}} - \frac{e^{k_{p-1} - \beta'\mathbf{Z}}}{1 + e^{k_{p-1} - \beta'\mathbf{Z}}} \quad \left(k_0 = -\infty, k_p = +\infty\right)\end{aligned} \tag{3.15}$$

The model parameters, β, and cut points, $\mathbf{k}$, are determined using MLE or Bayesian estimation. A *random effects* (RE) version of the model (RE-OL) is used in this work in which a random intercept term is used to capture random heterogeneity [30]. In the RE-OL model, the random intercept term, β_n^0, captures random customer heterogeneity. The observed utility, W_{in}, in the RE-OL model is given by:

$$W_{in}(\text{RE-OL}) = \beta_n^0 + \beta_{\mathbf{A}}\mathbf{A}_i + \beta_{\mathbf{S}}\mathbf{S}_n + \beta_{\mathbf{A}\cdot\mathbf{S}}(\mathbf{A}_i \cdot \mathbf{S}_n) \tag{3.16}$$

The random intercept must be estimated on *multiple* observations for each person n (i.e., panel data is required) to prevent identification issues created by confounding of the random intercept and the error term. The directly analogous random-effects ordered logit model to the choice model of Eq. (3.16) is formulated as:

$$Pr_n\left(R_p\right) = \int \left(\frac{e^{k_p - W_{in}(\beta)}}{1 + e^{k_p - W_{jn}(\beta)}} - \frac{e^{k_{p-1} - W_{in}(\beta)}}{1 + e^{k_{p-1} - W_{jn}(\beta)}}\right) pdf\left(\beta^0\right) \mathrm{d}\beta^0 \tag{3.17}$$

where R_p is a rating and k_p is an ordered logit cut point [31]. Using Bayesian model estimation (as described in Sect. 3.4.2), the individual-level model coefficients ($\beta_{\mathbf{A},n}, \beta_n^0$) are estimated, with uncertainty in the estimate decreasing as more choices or ratings per respondent are observed.

When used for prediction purposes, the utility for an alternative, i, for a particular person, n, is first calculated, and then transformed to a rating using the ($p-1$) series of estimated utility cut points (k). Ratings represent relative, or *ordinal*, preferences for an attribute, as opposed to absolute, or *cardinal*, preferences and thus require special consideration in modeling. In Chap. 8, we will use ordered logit as part of the Integrated Hierarchical Bayesian Choice Modeling (IHBCM) approach for designing large scale systems while considering the preferences of the users towards subsystems and then system.

3.4 Computational Techniques for Estimation of DCA and OL Models

3.4.1 Maximum Likelihood Estimation

The choice model can be estimated using Maximum Likelihood Estimation (MLE) or Hierarchical Bayes Estimation (HBE). In the MLE method, model parameters (i.e., β) are estimated through maximization of the likelihood function L for the MNL or MXL model:

$$L(y_n|\beta) = \prod_{n=1}^{N} \prod_{i=1}^{J} (Pr_n(i))^{y_{ni}} \tag{3.18}$$

where y_n is the response, i.e., the individual choices in the MXL model. To aid the solution process, the log-likelihood function (*LL*) is typically maximized because the *LL* function is additive as opposed to multiplicative.

3.4.2 Hierarchical Bayes Estimation

In order to reduce the computational burden associated with multivariable sampling for MLE of the mixed logit model, Hierarchical Bayes Estimation methods were developed utilizing Markov Chain Monte Carlo methods with a Gibbs sampler to estimate the mixed logit model [66]. In the Hierarchical Bayes choice modeling paradigm [16], the choice probability is modeled using a method in which the posterior distribution of the β_n parameters, characterized by a mean b and covariance matrix Σ, is found as a function of the prior distribution of b^0 and Σ^0, and an information source of observations, Y. In the hierarchical prior distribution, the distribution of β_n is conditional upon the distribution of the population-level hyper-parameters b and Σ. The population-level hyper-parameters characterize the distribution of β_n in the population as a whole. Thus, model parameters β, b, and Σ are given by the parameter posterior distribution (the denominator is excluded for simplicity):

$$pdf(\beta, b, \Sigma|Y) \propto \prod_{n=1}^{N} L(y_n|\beta_n) pdf^0(\beta_n|b^0, \Sigma^0) pdf^0(b^0, \Sigma^0) \tag{3.19}$$

where pdf^0 is the prior distribution, L is the likelihood function of the MXL model (see Eq. 3.18), and b is the mean vector and Σ is the full variance–covariance matrix of β.

The expression in Eq. (3.19) demonstrates a fundamental difference between the HBE and MLE approaches: the Bayesian method estimates the *mean* of a distribution, whereas the MLE solution estimates the maximum, or *mode*, of a distribution. The HBE method has several advantages over MLE in terms of model estimation. If the prior distribution of β_n is assumed to be multivariate normally distributed, i.e., $\beta \sim MVN(b, \Sigma)$, estimation of random parameters is more computationally efficient than classical MLE methods. The Bayesian method allows for estimation of the true posterior distribution and recovery of the individual level β_n, unlike the MLE method which only provides point estimates of the mean b and variance Σ of the assumed distribution of β_n. Through the specification of hierarchical prior distributions, this solution technique estimates the posterior distribution of $\boldsymbol{\beta}$, and provides a mechanism for model updating through the definition of the prior distribution as information evolves. Readers may seek additional resources for computational implementation in Sect. 3.8.

3.5 Guidelines for Demand Estimation Process in Product Design

Practical guidelines for implementing the demand modeling process in product design are provided in this section.

3.5.1 Attributes and Choice Set Identification

Although fitting a mathematical model to a dataset using any set of explanatory variables (input of a demand model) is possible, the usefulness of such a model can be questionable. A useful demand model requires that the selection of customer-desired product attributes (i.e., the explanatory variables) be based on econometric reasoning, i.e., the selected customer attributes are indeed considered by the customers when choosing which alternative to purchase. There are several methods available to assess what product attributes are key to customers [63] and what competing alternatives should be considered in a discrete choice survey. Existing methods include focus groups [39], which can be used for both existing products and products that are completely new (e.g., innovative design). Focus groups can be combined with observation studies, where customers are observed in actual usage situations. The researcher observes how the customer uses the product, what features the customer uses, etc. When the product already exists in some form (e.g., competing products) then customer exit interviews (i.e., after purchase) can be used to identify customer desires. The advantage of exit interviews is that customers went through an actual purchase process, resulting in answers that are closer to reality. In recent studies [42, 79], text mining techniques are used to identify product attributes that are of interest to customers by examining the occurrence of product attribute names in online product evaluations by users. In Chap. 5, a method to identify customer-desired attributes and map these attributes to engineering attributes will be presented.

3.5.2 Data Collection, Stated Choice Versus Revealed Choice

Two main types of data are primarily usually used to model demand: stated preference (SP) data [48] and revealed preference (RP) data. RP data refer to actual choice, i.e., actual (purchase) behavior that is observed in real choice situations. SP data represent controlled choice experiments that ask the respondents to state their purchase *intent*. Surveys are used to learn how people are likely to respond to new products or new product features. In the marketing and transportation research literature, conjoint analysis (see details in Appendix) is a frequently applied SP research technique, which encompasses analysis of three types of customer preference data: ratings, rankings, and choice data (3, 5, 27, 45, 47). With stated choice, the survey respondent is asked to pick an alternative from a choice set in a process very similar to real purchase decisions. A choice set contains a number of competing alternatives: a "survey alternative" (i.e., a new product or the alternative with the improved design), one or more competing alternatives from competitors and sometimes a "no choice" alternative (i.e., do not purchase any of the alternatives). The alternatives are described by the customer-desired attributes (**A**), including important business aspects such as price and warranty. The choice sets can be generated using design of experiment techniques. The survey results (choice data) are recorded, along with the respondent's customer background (**S**) such as age, income, product usage, and so on. If RP is used, then no survey is needed, rather revealed data (e.g., sales data) needs to be collected.

Both stated choice and revealed choice have certain advantages and disadvantages [48]. Limitations of revealed choice are that it is not always clear in modeling what choice alternatives were available to the customer (or considered) at the time of purchase. On the other hand, stated choice is a controlled choice experiment. Unlike in revealed choice data, alternatives, the attributes **A**, and the attribute levels are controlled by the researcher and explicitly known to the respondent. However, a limitation of stated choice is that respondents do not need to commit to their choices (e.g., pay the purchase price), which can result in a mismatch between what respondents say what they will do and purchases they actually make. Additionally, the respondent may not have thought of some of the attributes or competing products used in the choice or may consider different attributes or competing products in a real purchase situation. As noted, not every competing product may be available to the respondent in a real purchase situation. Generally, revealed choice is preferred when similar products or services exist, for example, when redesigning a power tool, while stated choice is preferred for innovative new designs, product features, or services that do not yet exist. The relative merits and demerits of SP and RP data are summarized in Table 3.2.

Rather than treating SP and RP as competing valuation techniques, analysts have begun to view them in recent years as complementary, where the strengths of each type can be used to provide more precise and possibly more accurate models. This is known today as *data enrichment* or *model fusion* in the literature [46]. Combining the data allows for investigation of attribute levels not currently represented in the market using stated choice data, while capturing real choice behavior using RP data. Design of experiments techniques for collecting SP considering both customer-desired attributes (**A**) and customer background (**S**) are provided in Chap. 6. In Chap. 8 Sect. 8.4.2, a method for model fusion will be presented.

3.5.3 Data Collection, Survey Respondent Sampling

While it is often a challenge to collect sufficient information to estimate a choice model, in some cases, particularly in the case of RP data collected in large markets over a significant range of time, more data than what is manageable for model

Table 3.2 Comparison of RP and SP data (Adapted from [70])

Revealed preference data	Stated preference data
Based on actual market behavior	Based on hypothetical scenarios
Attribute measurement error	Attribute framing error
Limited attribute range	Extended attribute range
Attributes correlated	Attributes uncorrelated by design
Hard to measure intangibles	Intangibles can be incorporated
Cannot directly predict response to new alternative	Can elicit preferences for new alternatives
Preference indicator is choice	Preference indicators can be rank, rating or choice intention
Cognitively congruent with market demand behavior	May be cognitively noncongruent

estimation may be available. In this case, the data set must be sampled. Several techniques can be used to sample a population [2]; however, any sampling design starts with defining the target market population, i.e., which set of customers (customer socio-demographic distribution) buy what (competing) products, the target market population size, etc., and the definition of the sampling unit, for example, a customer or a product purchase. Two common sampling strategies are *random sampling* and *stratified random sampling*. Random sampling entails randomly drawing an observation (customer or product purchase) such that the probability of that observation to be drawn equals $1/N$, where N represents the market population. Random sampling ensures that the sample characteristics match with the target market (i.e., the market shares and customer background distribution match), provided that the sample is large enough. The choice behavior of a population subgroup cannot be adequately captured if this population subgroup is relatively small, such that random sampling results in too few observations of this subgroup, while obtaining large samples of large subgroups is unnecessarily expensive. Such situations can be addressed using stratified random sampling [2], which divides the market population into mutually exclusive and exhaustive segments. Random samples are then drawn from each market segment. However, the sample now no longer matches with the market population and demand models fitted on biased samples can be inaccurate. A demand model for each market segment can be constructed to predict the demand of each segment, which should then be properly weighted based on the relative size of the segment to the population to arrive at an unbiased estimate for the total market demand. Another approach to address population sample bias is to weight the individual observations, so that the weighted sample matches with the population. The market share sample bias can be compensated by scaling the alternative specific constants β_{0i} in the customer utility function W, which can be iteratively scaled such that the market shares predicted by the demand model match with the market shares found in the market [73].

3.5.4 Identification of Market Segments

Before a choice model is fit, a decision must be made regarding the set of customers, or the *Market Segments*, to target for the proposed choice model used for product design. Market segments are defined as a subset of the larger market made up of customers with one or more characteristics that cause them to demand similar products. Different measures of the customer may be used to determine the similarity, such as geographic location (e.g., urban vs. rural, east vs. west coast), socio-demographic attributes (e.g., gender, age, income), market behavior (e.g., knowledge of the market, product knowledge), or, as will be further discussed in Chap. 10, usage context for the product (e.g., outdoor vs. indoor use, heavy duty vs. light duty use). It is often a challenge to have knowledge of market segments a priori in a product design process; however, data analysis methods can be applied to market data collected (such as that described in Sects. 3.5.2 and 3.5.3) to determine the natural market segments.

The goal of any analytical technique to perform market segmentation on a data set is to minimize the *within* segment variation of the customers while maximizing the *between* segment variation of market segments. Meeting this goal leads to segments where customer preferences are relatively homogeneous within the segment, and each segment is fundamentally unique from other segments. One or more of the customer characteristics listed above can be used to define the segment; use of more characteristics generally leads to finer-grained segments as long as the characteristics have sufficient explanatory power in differentiating customers. A variety of statistical methods, such as cluster analysis, finite mixture models, factor analysis, or latent class analysis (LCA) have been utilized for market segmentation [85]. Of the methods, LCA has been utilized within the choice modeling domain due to the consistency of the approach with collected customer data, which is typically categorical or ordinal [75, 78].

LCA is a general method for data reduction for discrete categorical data, such as a customer's income bracket, gender, or product usage type category [54]. LCA assumes the multiple discrete variables are *indicators* of an overall discrete latent class (LC), or in the context of this section, a unique market segment. The latent class model can be considered a special case of the mixed logit model (Eq. 3.13) in which unique model coefficients, β_m, are estimated for each market segment, m, and the choice share of each market segment is given by s_m [75]:

$$Pr_n(i) = \sum_{m=1}^{M} s_m \left(\frac{\exp(W_{in}(\beta_m))}{\sum_j \exp(W_{jn}(\beta_m))} \right) \tag{3.20}$$

In this approach, each market segment (m) has its own set of model coefficients and thus its own utility function. A question is whether the **S** are still needed in the model since each class is selected to represent customers with relatively homogeneous preferences. Based on the discussion of Sect. 3.2.5, it is still recommended to include **S** in the latent class model. This is because there will remain heterogeneity within the classes since customers may be similar but not identical, and there may be important $\mathbf{A} \cdot \mathbf{S}$ interactions which are key in explaining customer choice behavior.

3.5.5 Fitting the Choice Model

Based on the collected discrete choice data, whether it be revealed or stated choice, modeling techniques such as logit [2, 31], or probit [9, 31] can be used to create a choice model that can predict the choices individual customers make and to forecast the market demand for a designed artifact. Details of the logit model have been introduced in Sect. 3.2. As discussed in Sects. 3.4.1 and 3.4.2, the maximum log-likelihood method or hierarchical Bayes methods can be used to fit the choice model (i.e., to estimate the β-coefficients). One could develop custom code to estimate a choice model (e.g., using MATLAB) or use commercial software that can handle discrete choice data and offer logit or probit modeling capabilities such as GENSTAT (www.vsn-intl.com), LIMDEP (www.limdep.com), SAS (www.sas.com), SPSS (www.spss.com), STATA (www.stata.com), SYSTAT (www.systa.com), and so on. In this book we use STATA for demand modeling for MNL and NL models, and WinBUGs [69] interfaced with *R* [33] for integrated choice and latent variable models.

Although Multinomial probit is far more general than MNL by allowing an unrestricted correlation structure and standard deviations for the disturbances (ε) in the model, the main obstacle to implementing Multinomial probit lies its difficulty in computing the multivariate normal probabilities for any dimensionality higher than two [26]. Therefore, MNL continues to be popular and is used throughout this book. Table 3.3 shows an example of a data input table for a MNL model, where for each customer the choice y is registered, along with the customer's socio-economic and demographic attributes $\mathbf{S}$ and the customer-desired product attributes $\mathbf{A}$.

One difficulty with choice models that predict choice as a function of the difference in customer utility (see Eq. 3.4) is the consideration of the customer socioeconomic and demographic attributes along with the customer-desired product attributes in the choice model's deterministic utility function W. The customer socio-demographic attributes, that do not vary across alternatives, drop out of the choice probability as shown for the MNL choice model in Eq. (3.21).

$$\Pr_n(i) = \frac{e^{W_{in}}}{\sum_{j=1}^{J} e^{W_{jn}}} = \frac{e^{S_n + A_{in}}}{\sum_{j=1}^{J} e^{S_n + A_{jn}}} = \frac{e^{S_n} e^{A_{in}}}{\sum_{j=1}^{J} e^{S_n} e^{A_{jn}}} \tag{3.21}$$

A method for avoiding this problem is to specify dummy variables for the customer background, which allows the coefficient to vary across alternatives [26], also known as alternative specific variables (ASVs) as introduced in Sect. 3.2.2. Table 3.4 shows how the data input table is adapted to include dummy variables.

Table 3.3 Multinomial logit input data table

Customer id	Alt. id.	Choice	Customer attributes **S**		Customer-desired product attributes **A**		
		Y	S_1	S_2	A_1	A_2	A_3
1	1	1	S_{11}	S_{21}	A_{11}	A_{21}	A_{31}
1	2	0	S_{11}	S_{21}	A_{12}	A_{22}	A_{32}
1	3	0	S_{11}	S_{21}	A_{13}	A_{23}	A_{33}
2	1	0	S_{12}	S_{22}	A_{11}	A_{21}	A_{31}
2	2	1	S_{12}	S_{22}	A_{12}	A_{22}	A_{32}
2	3	0	S_{12}	S_{22}	A_{13}	A_{23}	A_{33}
3	1	0	S_{13}	S_{23}	A_{11}	A_{21}	A_{31}
3	2	0	S_{13}	S_{23}	A_{12}	A_{22}	A_{32}
3	3	1	S_{13}	S_{23}	A_{13}	A_{23}	A_{33}

Table 3.4 Multinomial logit input table with ASVs

Grouped logit		Choice	Customer attributes **S**				Customer-desired attributes **A**		
Cust. id.	Alt. id.	Y	S_1	S_1	S_2	S_2	A_1	A_2	A_3
1	1	1	S_{11}	0	S_{21}	0	A_{11}	A_{21}	A_{31}
1	2	0	0	S_{11}	0	S_{21}	A_{12}	A_{22}	A_{32}
1	3	0	0	0	0	0	A_{13}	A_{23}	A_{33}
2	1	0	S_{12}	0	S_{22}	0	A_{11}	A_{21}	A_{31}
2	2	1	0	S_{12}	0	S_{22}	A_{12}	A_{22}	A_{32}
2	3	0	0	0	0	0	A_{13}	A_{23}	A_{33}
3	1	0	S_{13}	0	S_{23}	0	A_{11}	A_{21}	A_{31}
3	2	0	0	S_{13}	0	S_{23}	A_{12}	A_{22}	A_{32}
3	3	1	0	0	0	0	A_{13}	A_{23}	A_{33}

To create the dummy variables to represent the ASVs, first a set of dummy variables (with values equal 1) is added to the data set, with the size of the set equal to the number of choice alternatives, J, minus one (i.e., $J-1$). The reason that only $J-1$ dummy variables are required is that the dummy variable for the base alternative (i.e., alternative 3) is set to zero to set the scale of the ASVs (i.e., only differences in utility matter in the logit model). Finally, the alternative specific dummy variables are multiplied by the socio-demographic attributes (e.g., S_1 and S_2) to create alternative specific variables (e.g., S_{11}, S_{21}, S_{12}, S_{22}, etc.).

3.5.6 Demand Estimation Using the Choice Model

Different approaches are possible for determining the market demand once the choice model is obtained. A simplistic, but not advisable approach (see Sect. 3.6), is to assume average values for the socio-demographic attributes, in this case the choice model of Eq. (3.6) only needs to be evaluated once for each choice alternative i. This approach, though, may lead to significant errors since the characteristics of a group cannot be represented by an imaginary average individual. Results can be improved by using market segmentation as described in Sect. 3.5.4. However, the most rigorous and most accurate approach, sample enumeration, takes a random sample of the market population N, to predict for each sampled individual n the choice probabilities to estimate the demand for the entire market population [2]. The logit choice share estimation using a sample size N is presented in Eq. (3.22), where i denotes the choice alternative.

$$Q(i) = \sum_{n=1}^{N} Pr_n(i) = \sum_{n=1}^{N} \frac{e^{W_{in}}}{\sum_{j=1}^{J} e^{W_{jn}}} \tag{3.22}$$

The aforementioned approaches assume estimation of a choice model for the entire market population. The accuracy of demand prediction can be further improved by estimating a choice model per market segment to account for systematic variations of taste parameters (β coefficients) among population subgroups. A potentially more accurate approach is to use mixed logit model presented in Sect. 3.2.4, in which each customer is assumed to have his own set of "taste coefficients," i.e., a unique set of β_n. Including customer specific data in the customer background **S** that relates to the customer's (potential) use of the product is another method to improve the accuracy of the demand predictions. For example, in the case of a car one can think of annual mileage, type of usage (commuting/recreational), etc., as attributes of the customer that can be included in the model. This product usage data can be recorded for each respondent when conducting the survey. Further details of introducing usage context attributes into choice models are provided in Chap. 10.

A second approach for estimating the market demand is to use the choice model to predict the average choice probabilities (choice shares) of the market population, (e.g., by using sample enumeration) and then use separate, specialized, models to estimate the total market sales volume (D). An advantage of this approach is that the separate model that predicts the market sales may be more accurate in predicting the market sales volume by accounting for economic growth, seasonal effects, market trends, etc., potentially leading to more accurate demand predictions. Utilizing a separate market sales volume model can be further extended to develop a dynamic demand model, which is introduced next.

3.5.7 Dynamic Demand Modeling in Product Life Cycle

An issue of using demand models related to engineering design decision making is that the market introduction of the designed product is at some point in the future, while the demand model is assessed at current market conditions. Since Decision-Based Design (DBD) considers a product's entire lifecycle, the demand model needs to predict the demand for a period of time in the future, possibly spanning multiple years. Obviously, market conditions, competition, and market population are subject to change, affecting the accuracy of the demand predictions. To address this concern, the static demand can be first modeled as a function of product attributes and customer background, possibly including data relating to the customer's product usage. Separate models can then be constructed to predict changes in key customer-desired attributes of the alternatives, changes in demographics (e.g., birth rate, aging, ethnic shifts, etc.), socio-economics (e.g., income, education, etc.), and product usage (e.g., frequency, duration, type of use) over time, while a specialized model for market volume can predict changes in market volume [17], given expected macroeconomic developments, market trends, etc.

In the dynamic paradigm, demand for a given alternative, i, at time t, $Q(i)_t$, is the product of choice share, $C.S.(i)$ and the total *market size* (or aggregate market segment demand), $D(t)$, for a given market segment (e.g., automobile midsize sedan):

$$Q(i)_t = C.S.(i) \cdot D(t) \tag{3.23}$$

Approaches to dynamic choice modeling to predict the choice share $C.S.(i)$ can be broadly categorized into two primary approaches: (1) models in which the β parameters in the utility function are expressed as a function of time, i.e., $\beta = \beta(t)$; and (2) models in which the β parameters are updated as new information becomes available, i.e., $\Pr(\beta|e) = \frac{\Pr(e|\beta)\Pr(\beta)}{\Pr(e)}$, where e is the new information. The first approach has been addressed in the literature [35] by modeling $\beta(t)$ using an autoregressive process of order p, where p is the number of previous time periods over which autocorrelation is modeled. A simpler approach has also been applied [36] in which a separate demand model for a given market is estimated for each year of data available, and linear regression is used to express β as a function of t. Both share the common requirement that choice data over multiple time periods, ideally for the same demographic group, are needed. Changes in customer preferences over time are estimated based upon a historic rate of change. Both approaches, therefore, assume that the rate of change of future preference behavior will continue to follow the historic rate.

While utilizing historic trends in the estimation of a demand model is useful for forecasting purposes, particularly for stable markets, preferences may change in unpredictable ways, or the introduction of a new product (e.g., tablet computer) and the continued collection of information over time may reveal a greater understanding of preferences. The quantification of uncertainty and update of the choice model as information becomes available is well handled using the second approach which uses Bayesian updating. The Bayesian Choice Modeling approach has been applied primarily for estimating random taste variation [75], and has been developed for this purpose in a variety of product marketing contexts, such as modeling repeated purchase behavior [65, 66]. The use of the method for *updating* a marketing model as new information is available has been investigated in certain marketing contexts [58, 12].

In the area of forecasting future market size, *D(t)*, approaches have been largely empirical. One approach for market size estimation assumes that the market follows a

Geometric Brownian Motion path [11, 17], which has been used to model relatively stable markets in which demand is assumed to grow at a constant rate, but with local volatility. Alternatively, the Bass Technology Diffusion model [1, 61] has been assumed for generational new technology markets, which are characterized by exponential growth at the beginning of the product cycle, a peak market size, followed by exponential decrease as the next generation of technology becomes available.

The methods described for dynamic demand modeling are logical extensions to the models presented in the examples in this book, and are completely compatible with the DBD paradigm.

3.5.8 Choice Model Selection and Validation

The selection and validation of demand models can be approached in three complementary ways: (1) *statistical goodness of fit measures* and likelihood ratio tests (see [37, 2, 75] for details), (2) quality of the *behavioral interpretations* (i.e., the signs and magnitudes of the coefficients in the model), and (3) predictive capability of the models determined using *cross-validation* techniques. In addition, data from multiple sources (e.g., surveys, purchase data) are sometimes used to provide external validity. Details with respect to statistical goodness of fit and cross validation are provided as follows.

The statistical goodness of fit of demand models is usually evaluated by using likelihood estimates and pseudo R-square (ρ^2) values of the equally likely, or *zero* model (0), and the constants only model (C) as references:

$$\begin{aligned} \rho_0^2 &= 1 - \frac{LL(\beta)}{LL(0)} \\ \rho_c^2 &= 1 - \frac{LL(\beta)}{LL(\beta_c)} \end{aligned} \tag{3.24}$$

Here, in the above equation, ρ_0^2 and ρ_c^2 represent the pseudo R-square estimates, evaluated with respect to the *equally likely* model and the *constants only* model respectively. LL(0) and LL(β_c) represent the log-likelihood estimates for the two models respectively, while LL(β) represents the log-likelihood estimate for the model being evaluated. The *equally likely* model is a model that has no parameters, i.e., the individual is assumed to have equal probability of choosing any of the alternatives in the choice set available to him. The *constants only* model includes only a full set of constants, i.e., ASCs corresponding to each of the alternatives with one of the alternatives chosen as the reference alternative. From the above relationships, it is easy to see that only an *ideal model* would have $\rho_0^2 = 1$. In such a case, the log likelihood would be zero (note that $\ln(1) = 0$) and the actual and predicted choices would match perfectly.

Another test used to compare different choice models is the Chi-square test. In this test, models which have a *restricted–unrestricted* relationship with each other can be compared. Two statistical models are said to have a *restricted–unrestricted* relationship when the parameters of one of the models (called the *restricted* model and represented by β_r) form a proper subset[1] of the set of parameters of the other model (called the *unrestricted* model and represented by β_u). The *restricted* model can be rejected in favor of the *unrestricted* model if the following relationship is satisfied.

$$-2[LL(\beta_r) - LL(\beta_u)] > \chi^2_{NR} \tag{3.25}$$

In the above equation, LL(β_r) and LL(β_u) represent the log-likelihood estimates for the two models being considered, and χ^2_{NR} represents the Chi-square value corresponding to *NR* degrees of freedom. *NR* is the number of additional parameters that the *unrestricted* model has, compared with the *restricted* model. However, in most situations, a modified form of the above test is used, in which the *restricted* model is the zero model and the *unrestricted* model is the model in question.

Finally, a test that compares different models that do not necessarily have a *restricted–unrestricted* relationship is necessary (i.e., a nonnested test). While this test can be used to compare models that have such a relationship, it is more useful in cases where such a relationship does not exist. The nonnested test is used when considering any two models with different log-likelihood values. To evaluate the significance of rejecting the model with the lower likelihood value, the relationship presented below is used. Here, subscript *H* stands for the model with the higher likelihood value and the subscript *L* stands for the model with the lower likelihood value. ($K_H - K_L$) stands for the difference in the number of parameters between the two models and Φ(.) represents the standard cumulative normal distribution.

$$Significance\ of\ rejection = \Phi\left(\left[-\left[-2\left(\rho^2_H - \rho^2_L\right) \times LL(0)\right] + (K_H - K_L)\right]^{1/2}\right) \tag{3.26}$$

Achieving a good model fit indicated by error measures such as the log-likelihood ratio indicates that the model will predict well on the data used to fit the model. However, this does not guarantee accurate predictions of the demand model at new model inputs. *Cross-validation* [5] which does not require the collection of additional data is used for validating the demand model. Cross-validation entails dividing the data into *k* subsets of approximately equal size (*k*-fold cross validation). The choice model is then fitted *k* times using $k - 1$ subsets of data. Each time, the fitted choice model is used to predict the choice of the remaining data set to calculate the measure of error (e.g., log-likelihood score). The average of the obtained error measurements is the error of measure of the model. A lower *k* value is chosen for large data sets, in general a tenfold (k = 10) or fivefold cross-validation is recommended.

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[1] A *set* S_2 is a proper subset of another set S_1 if every element in S_2 is in S_1 and S_1 has some elements which are not in S_2.

When multiple models achieve similar maximum likelihood function fit, we face the choice of which model to use. A model with a high number of attributes may seem preferable as including a high number of customer-desired attributes in a choice model may better facilitate engineering decision making; more attributes provide a more accurate description of the desired features of a product. For example, to guide engineering decision making in engine design regarding the air intake design, engine configuration, firing order, exhaust design, engine mount design, noise insulation, which (among others) affect the sound quality as experienced by a car's occupants, the customer-desired attributes could include detailed attributes like: noise level, noise frequency, and harmonics. However, including too many attributes may lead to model over-fit, i.e., the model fits aspects of the data that are not due to underlying parametric features (e.g., sampling variability). Two criteria that can be used for comparing model fit and for determining whether including additional attributes is useful are *Akaike's Information Criterion* (AIC), Eq. (3.27), and the *Bayesian Information Criterion* (BIC) [26], Eq. (3.28). Both criteria penalize models for having too many explanatory variables.

$$AIC = -2L + 2p \tag{3.27}$$

$$BIC = -2L + p\ln(n) \tag{3.28}$$

where L is the Log Likelihood, p the number of explanatory variables and n the number of observations (sample size). According to both criteria, the best-fitting model is the model with the lowest score. A difference of 6 or more points on the BIC scale indicates that the model with the lower value is preferred [64]. In general, the BIC leads to models with fewer attributes than the AIC.

An issue that may arise when using large numbers of customer-desired attributes is collinearity, i.e., some customer-desired attributes may be explained by combinations of other attributes. If collinearity occurs then these customer-desired attributes cannot be used in the choice model simultaneously. Factor analysis [28] could be used to combine customer-desired attributes that can be correlated to each other into a fewer number of factors, thereby reducing the number of explanatory variables and the possibility of collinearity and overfitting the data.

In addition to the statistical measures for model selection and model validation, the model can also be examined for predictive validity and plausibility [14]. This includes ensuring the signs of coefficients are correct, and that the demand elasticities and substitution patterns are plausible.

3.6 Case Study: Walk-through of a Typical MNL Model Estimation

In this example, we illustrate how MNL analysis can be used to create a demand estimation model for an academic power saw design. First, product sales data are recast into data that can be used for demand modeling. This is followed by a discussion of the model estimation process, and illustration of the estimation of several demand models with different utility function structures; details on the statistical and behavioral measures used to evaluate the relative merits of demand models are provided as well.

3.6.1 Constructing the Choice Set

We assume there are three (3) competing power saw alternatives in the market, each characterized by different levels of customer-desired product attributes (speed and maintenance interval,[2] defined as **A**), and the price *P*. Power saw 1 is the high price, high speed alternative, but requires more frequent maintenance. Saw 2 is the medium price, medium speed, and low maintenance alternative, while saw 3 is the low speed, low price, and medium maintenance alternative. For illustrative purposes, we examine a small sample data set representing the RP of 15 customers, who buy these saws from different vendors. Only normalized data has been used for convenience of computation and interpretation, though normalization is not a requirement. Table 3.5 shows the sales data, along with the customer's income, which is the socio-demographic attribute **S** considered in this example. Having socio-economic and demographic (i.e., socio-demographic) information related to the customer's age, income, education, etc., is useful in explaining the heterogeneity in customer choices and also helps a company design its products to target different market segments. .

Table 3.6 shows the same three alternatives being sold at different prices by different vendors. Possible reasons of difference in prices could be due to different marketing strategies, different geographic locations, etc.

The data in Tables 3.5, 3.6 are combined and transformed into a format that can be readily used for MNL analysis as shown in Table 3.7, there are three rows of data for each customer, one for each choice alternative; each row in the data set contains the socioeconomic and demographic attributes **S** of the individual customers, the customer-desired product attributes **A** that describe the alternative, price *P*, and the customer's observed choice (recorded in Table 3.5). Note that customer choice is treated as a binary variable in MNL analysis (Table 3.7). For example, customer 1 chose power saw alternative 2, which is indicated by a non-zero entry in the *CHOICE* column in the row corresponding to customer 1 and alternative 2. A few assumptions are typically made for the MNL analysis. One assumption is the IIA assumption property (see Chap. 2 Sect. 2.2). Another important assumption is that customers are fully aware of the product's attributes and make rational choices based on this knowledge. It is also assumed that

[2] Defined as the time interval between successive maintenance visits.

Table 3.5 Customer sales data

Customer no.	Income	Vendor	Alternative chosen
1	0.44	A	2
2	0.62	B	3
3	0.81	C	1
4	0.32	D	3
5	0.78	E	2
6	1.00	F	1
7	0.84	G	1
8	0.39	H	2
9	0.55	I	3
10	0.62	J	3
11	0.66	K	1
12	0.50	L	3
13	0.43	M	1
14	0.76	N	1
15	0.32	O	3

customers did indeed consider all the three available alternatives before making their choices.

3.6.2 Walk-Through of a Typical MNL Model Estimation

The results presented here are obtained from STATA. Typically, developing a satisfactory demand model involves estimating models of increasing complicated specification. That is, one has to progressively increase the number of variables in the utility function of the demand model (Eq. 3.7) to obtain a model that not only has excellent statistical goodness of fit but also explains customer behavior in a manner consistent with our understanding of the market. The first step may involve building a zero-model, which is also known as the equally likely model. In our case, the zero-model would assign a choice probability of $^1/_3$ to each of the three power saws:

$$\text{For } 1 \leq n \leq 15 \quad \begin{array}{l} \Pr_n(1)[1,2,3] = {}^1/_3 \\ \Pr_n(2)[1,2,3] = {}^1/_3 \\ \Pr_n(3)[1,2,3] = {}^1/_3 \end{array}. \tag{3.29}$$

Here $\Pr_n(1)$ [1, 2, 3] represents the probability of customer n choosing alternative 1, when asked to choose from the alternative set $\{1, 2, 3\}$. The zero-model is generally used as a reference to compare the goodness of fit of other models as discussed in the previous subsection; however, the zero-model is not used for

Table 3.6 Vendor pricing information

Vendor	Alternative	Price
	1	0.97
A	2	0.73
	3	0.63
	1	1
B	2	0.72
	3	0.55
	1	0.95
C	2	0.75
	3	0.6
	1	0.93
D	2	0.75
	3	0.6
	1	0.98
E	2	0.71
	3	0.56
	1	0.95
F	2	0.71
	3	0.58
	1	0.95
G	2	0.81
	3	0.61
	1	0.93
H	2	0.77
	3	0.57
	1	0.96
I	2	0.8
	3	0.58
	1	1
J	2	0.79
	3	0.59
	1	0.96
K	2	0.77
	3	0.59
	1	0.93
L	2	0.77
	3	0.6
	1	0.9
M	2	0.74
	3	0.63
	1	0.94
N	2	0.73
	3	0.64
	1	0.96
O	2	0.75
	3	0.61

Table 3.7 Revealed preference data used for the analysis

Cust num	Alt id	Choice	Speed	Price	Maintenance interval	Income
1	1	0	1	0.97	0.64	0.44
1	2	1	0.71	0.73	1	0.44
1	3	0	0.67	0.63	0.89	0.44
2	1	0	1	1	0.64	0.62
2	2	0	0.71	0.72	1	0.62
2	3	1	0.67	0.55	0.89	0.62
3	1	1	1	0.95	0.64	0.81
3	2	0	0.71	0.75	1	0.81
3	3	0	0.67	0.6	0.89	0.81
4	1	0	1	0.93	0.64	0.32
4	2	0	0.71	0.75	1	0.32
4	3	1	0.67	0.6	0.89	0.32
5	1	0	1	0.98	0.64	0.78
5	2	1	0.71	0.71	1	0.78
5	3	0	0.67	0.56	0.89	0.78
6	1	1	1	0.95	0.64	1
6	2	0	0.71	0.71	1	1
6	3	0	0.67	0.58	0.89	1
7	1	1	1	0.95	0.64	0.84
7	2	0	0.71	0.81	1	0.84
7	3	0	0.67	0.61	0.89	0.84
8	1	0	1	0.93	0.64	0.39
8	2	1	0.71	0.77	1	0.39
8	3	0	0.67	0.57	0.89	0.39
9	1	0	1	0.96	0.64	0.55
9	2	0	0.71	0.8	1	0.55
9	3	1	0.67	0.58	0.89	0.55
10	1	0	1	1	0.64	0.62
10	2	0	0.71	0.79	1	0.62
10	3	1	0.67	0.59	0.89	0.62
11	1	1	1	0.96	0.64	0.66
11	2	0	0.71	0.77	1	0.66
11	3	0	0.67	0.59	0.89	0.66
12	1	0	1	0.93	0.64	0.5
12	2	0	0.71	0.77	1	0.5
12	3	1	0.67	0.6	0.89	0.5
13	1	1	1	0.9	0.64	0.43
13	2	0	0.71	0.74	1	0.43
13	3	0	0.67	0.63	0.89	0.43
14	1	1	1	0.94	0.64	0.76
14	2	0	0.71	0.73	1	0.76
14	3	0	0.67	0.64	0.89	0.76
15	1	0	1	0.96	0.64	0.32
15	2	0	0.71	0.75	1	0.32
15	3	1	0.67	0.61	0.89	0.32

prediction purposes since it does not consider the impact of product attributes and customers' demographic attributes. Note that the market share predictions (obtained by aggregating the choice probabilities for each alternative across all individuals) from this model are respectively $\left\{{}^1\!/_3, {}^1\!/_3, {}^1\!/_3\right\}$ for alternatives 1, 2 and 3, which do not match well with the observed market shares (i.e., $\{0.4, 0.2, 0.4\}$.

The estimation of the zero-model is usually followed by the estimation of a model that has only constants in the utility function. A *constants-only* model has only ASCs but no other explanatory variables like **A** and **S** in the utility function. ASCs are used to estimate the utility biases Eq. (3.7) due to excluded variables. The ASC corresponding to one of the alternatives is set to zero and the constants corresponding to the other alternatives are evaluated with respect to that reference (zero) alternative. For our data set, the *constants-only* model would carry two constants, for example, β_{01} and β_{02}, for alternative 1 and alternative 2, respectively. The ASC corresponding to alternative 3 (i.e., β_{03}) is then set to zero. As a result, the deterministic part of the utility function for each alternative would look as presented below:

$$\text{For } 1 \leq \mathrm{n} \leq 15,\quad \begin{array}{lccc} W_{1n} = & \beta_{01} & & \\ W_{2n} = & & \beta_{02} & \\ W_{3n} = & & & \beta_{03}(=0) \end{array} \tag{3.30}$$

The STATA output for this model is shown in Fig. 3.9. The output contains information on the iteration history of the log-likelihood values, number of observations in the data set (i.e., 45 with three observations for each customer in the sample data set). The output also includes statistical goodness of fit values like the pseudo R-square value, i.e., ρ_0^2, the log-likelihood ratio with respect to the zero-model as defined in Sect. 3.5.7 and values related to the Chi-square test. The model, as expected, has a higher log-likelihood value (-15.823) than the zero-model (-16.479). The ρ_0^2value is 0.0398, which is low and indicates that the model is not much better than the zero-model. The output "`Prob > chi2`" entry in Fig. 3.9 is the probability of significance with which the zero-model can be rejected in favor of the constants-only model, using the Chi-square test. "`LR chi2(0)`" is the left hand side of the Chi-square test. The Chi-square test shows that the zero-model can be rejected in favor of the *constants-only* model with a probability of $(1-0.5192) = 48.08\%$, which is low and reinforces the conclusion that the *constants-only* model does not explain much more variance in the data than the zero-model. The ASC corresponding to alternative 1 is estimated as zero, which implies that it is equal to the ASC corresponding to alternative 3. The confidence intervals and the statistical significance of the estimators, computed based on the standard errors for these estimators, show that the coefficients are not significantly different from zero since the 95% confidence intervals for both coefficients β_{01} and β_{02} (i.e., ASC_1 and ASC_2 in the STATA output) include

```
Iteration 0:   log likelihood =   -16.1443
Iteration 1:   log likelihood = -15.827368
Iteration 2:   log likelihood = -15.823803
Iteration 3:   log likelihood = -15.823803

Conditional (fixed-effects) logistic regression   Number of obs   =        45
                                                  LR chi2(2)      =      1.31
                                                  Prob > chi2     =    0.5192
Log likelihood = -15.823803                       Pseudo R2       =    0.0398

------------------------------------------------------------------------------
      chosen |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       ASC_1 |   6.81e-17   .5773503     0.00   1.000    -1.131586    1.131586
       ASC_2 |  -.6931472   .7071067    -0.98   0.327    -2.079051    .6927566
------------------------------------------------------------------------------
```

Fig. 3.9 STATA output for the *constants-only* model

zero. Statistical significance of the different estimators becomes more relevant in models with a more detailed specification, (i.e., models with more variables in the utility function). Explanatory variables are usually retained in the utility function, if the signs and magnitudes of the estimators are satisfactory even though they may not be statistically significant.

Based on the estimation of the utility function coefficients in the STATA output, the choice probabilities can be calculated as shown in Eq. (3.31):

$$\begin{aligned}
&\text{For } 1 \leq n \leq 15\\
&W_{1n} = \beta_{01} = 0\\
&W_{2n} = \beta_{02} = -0.6932\\
&W_{2n} = \beta_{03} = 0\\
&\Pr_n(1)[1,2,3] = \frac{e^{W_{1n}}}{(e^{W_{1n}}+e^{W_{2n}}+e^{W_{3n}})} = \frac{1}{(1+e^{-0.6932}+1)} = 0.4\\
&\Pr_n(2)[1,2,3] = \frac{e^{W_{2n}}}{(e^{W_{1n}}+e^{W_{2n}}+e^{W_{3n}})} = \frac{e^{-0.6932}}{(1+e^{-0.6932}+1)} = 0.2\\
&\Pr_n(3)[1,2,3] = \frac{e^{W_{2n}}}{(e^{W_{1n}}+e^{W_{2n}}+e^{W_{3n}})} = \frac{1}{(1+e^{-0.6932}+1)} = 0.4
\end{aligned} \tag{3.31}$$

The utility function values, as well as the choice probabilities are identical across all customers in the *constants-only* model. Therefore, the predicted market shares from the model are identical to the individual choice probabilities. Note that the predicted market share values match exactly with the observed market shares for this model. This result is expected since it is well known that any model, which has a *full set*[3] of ASCs (like the *constants-only* model presented here) will always produce an exact match between predicted market shares (aggregated choice probabilities) and observed market shares [2]; any difference between the two is only due to numerical (computational) error. While this model accurately predicts

[3] Any model considering choice data involving J alternatives is said to have a *full set* of alternative specific constants, if it has *(J − 1)* alternative specific constants.

market shares, it has no purposeful role in guiding engineering design, which requires the consideration of product attributes.

A model that includes the customer-desired product attributes **A** (speed and maintenance interval), price P, and the demographic characteristics **S** (customer income) is estimated assuming a linear form of the utility function. All demographic attributes are included as ASVs due to the nature of the MNL model. The coefficient of the income ASV for alternative 1 is set to zero and serves as the reference. The form of the deterministic part of the utility function is shown in Eq. (3.32),

$$\begin{aligned}
&\text{For } 1 \leq n \leq 15,\\
&W_{1n} = \beta_{speed}\left(A_{speed(1)}\right) + \beta_{\text{price}}\left(A_{\text{price}(1)}\right) + \beta_{\text{maintenance}}\left(A_{\text{maintenance}(1)}\right)\\
&W_{2n} = \beta_{speed}\left(A_{speed(2)}\right) + \beta_{\text{price}}\left(A_{\text{price}(2)}\right) + \beta_{\text{maintenance}}\left(A_{\text{maintenance}(2)}\right)\\
&\qquad\quad + \beta_{\text{income}(2)}\left(S_{\text{income}(n,2)}\right)\\
&W_{3n} = \beta_{speed}\left(A_{speed(3)}\right) + \beta_{\text{price}}\left(A_{\text{price}(3)}\right) + \beta_{\text{maintenance}}\left(A_{\text{maintenance}(3)}\right)\\
&\qquad\quad + \beta_{\text{income}(3)}\left(S_{\text{income}(n,3)}\right)
\end{aligned} \tag{3.32}$$

where $A_{\text{price}(j)}$, $A_{\text{speed}(j)}$, and $A_{\text{maintenance}(j)}$ represent the price, speed, and maintenance interval of alternative j, respectively. $S_{\text{income}(n,\ j)}$ represents the income of customer n, used as ASV for alternative j. Note that the β-coefficients of the product attributes (speed, price, and maintenance interval) are identical across all alternatives and all customers in the above utility functions. However, the coefficients for the alternative specific income variables do vary across alternatives. The results of the model estimation in STATA are shown in Figs. 3.10.

The signs of the coefficients in the utility function (as shown in the STATA output) indicate that customers prefer higher speeds, lower prices and higher maintenance intervals, which corresponds with our understanding of the market. Since the data in this example are normalized, the magnitudes of the coefficients also indicate the relative importance of the product attributes to the customers. The results indicate that customers view price as the most important factor and view speed as slightly less important, the maintenance interval of the product is considered least important. The coefficients of the demographic variables have to be interpreted in conjunction with background knowledge about the product. It is known that alternative 1 is the most expensive and alternative 3 is the least expensive. The income variables in the utility function have to be interpreted in that context. The negative signs of income_2 and income_3 indicate that customers with higher incomes view alternative 2 and alternative 3 less desirable than alternative 1. Also, the larger magnitude of the coefficient for income_3 indicates

```
Iteration 0:   log likelihood = -14.359848
Iteration 1:   log likelihood = -8.9144052
Iteration 2:   log likelihood = -7.9954175
Iteration 3:   log likelihood = -7.8154834
Iteration 4:   log likelihood = -7.8035352
Iteration 5:   log likelihood = -7.8034579

Conditional (fixed-effects) logistic regression   Number of obs   =         45
                                                  LR chi2(5)      =      17.35
                                                  Prob > chi2     =     0.0039
Log likelihood = -7.8034579                       Pseudo R2       =     0.5265

------------------------------------------------------------------------------
      choice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       speed |   47.08898   36.66279     1.28   0.199    -24.76876    118.9467
       price |  -55.95013   24.87006    -2.25   0.024    -104.6945   -7.205713
maintenanc~n |    28.0128   26.03458     1.08   0.282    -23.01405    79.03964
    income_2 |  -13.66506    7.74274    -1.76   0.078    -28.84055    1.510429
    income_3 |  -19.66365   9.744276    -2.02   0.044    -38.76208   -.5652178
------------------------------------------------------------------------------
```

Fig. 3.10 STATA output for the *linear* model

that customers with higher incomes would view alternative 3 (the low price, low speed alternative) less desirable than alternative 2. These results are reasonable and are consistent with our expectations, and therefore the model can be regarded favorably.

The log likelihood (−7.8035) and pseudo R-square ρ_0^2 (0.5265) values are much higher when compared to the zero-model and the *constants-only* model. Also, the Chi-square test indicates that the zero-model can be rejected in favor of the linear model, with a very high degree of statistical significance (1.0−0.0039) = 99.61%. It can be shown that the *linear* model is superior to the *constants-only* model in a similar fashion. However, some of the coefficients in the model are not statistically significant at the 95% level, primarily due to the small sample size used in this example (generally a minimum of 200 observations is desired). However, since these coefficients are consistent with our expectation, the variables are retained in the model.

Sample calculations of the utility functions and choice probabilities are provided for customer 3 in Eq. (3.33). The computations show that the predicted choice probability for alternative 1 is the highest. This agrees well with the actual choice of the customer recorded in Table 3.7. The comparison between the actual and predicted choice is provided for all customers in Table 3.8, showing that in most cases, the alternative with the highest choice probability (as predicted by the model) is the one chosen by the customer.

For $n = 3$,

$$W_{1n} = 47.09(1) - 55.95(0.95) + 28.01(0.64) = 11.86$$

$$W_{2n} = 47.09(0.71) - 55.95(0.75) + 28.01(1) - 13.67(0.44) = 8.42$$

$$W_{3n} = 47.09(0.67) - 55.95(0.60) + 28.01(0.89) - 19.66(0.44) = 6.98$$

For $n = 3$,

$$Pr_n(1)[1,2,3] = \frac{e^{W_{1n}}}{(e^{W_{1n}} + e^{W_{2n}} + e^{W_{3n}})} = \frac{e^{11.86}}{(e^{11.86} + e^{8.42} + e^{6.98})} = 0.96 \tag{3.33}$$

$$Pr_n(2)[1,2,3] = \frac{e^{W_{2n}}}{(e^{W_{1n}} + e^{W_{2n}} + e^{W_{3n}})} = \frac{e^{8.42}}{(e^{11.86} + e^{8.42} + e^{6.98})} = 0.03$$

$$Pr_n(3)[1,2,3] = \frac{e^{W_{2n}}}{(e^{W_{1n}} + e^{W_{2n}} + e^{W_{3n}})} = \frac{e^{6.98}}{(e^{11.86} + e^{8.42} + e^{6.98})} = 0.01$$

As noted before, aggregated predictions of choice probability, which translate to market share predictions, tend to agree with the actual market share values for unbiased models like the *constants-only* and the *linear* models presented here. However, the predictive capability of a demand model is better expressed when the model is tested on data that has not been used to estimate the model. The engine design example in Chap. 4 illustrates the use of cross validation for this purpose.

3.7 Summary

In this chapter, DCA is established as a systematic procedure to estimate customer choices, while the guidelines for implementing the discrete choice modeling approach in product design are provided. Several variants of logit choice modeling are introduced, the use of which will be further illustrated in upcoming chapters. It should be noted that, in contrast, to some existing design approaches that construct a single utility function for a group of customers, the demand modeling approach presented in this chapter predicts the choice for each individual customer, and finally sums the choice probabilities across individual decision makers (customers) to arrive at the market share of different products, thus avoiding the paradox associated with aggregating the utility or preference of a group of customers.

The demand modeling approach presented here is a critical part of the DBD framework which will be introduced in next chapter. Integrating demand modeling in product design is expected to facilitate the communication and collaboration of a company's employees in engineering, marketing, and management. Together with the DBD approach, the method will contribute to the development of more competitive products in a systematic way, considering not only the engineering requirements, but also the business interests, customer preferences, competing products, and market conditions.

Table 3.8 Comparison of actual and predicted individual choice

Casenum	Altid	Chosen	Predicted choice
1	1	0	0.018
1	2	1	0.866
1	3	0	0.115
2	1	0	0.008
2	2	0	0.304
2	3	1	0.687
3	1	1	0.962
3	2	0	0.031
3	3	0	0.007
4	1	0	0.021
4	2	0	0.178
4	3	1	0.800
5	1	0	0.243
5	2	1	0.591
5	3	0	0.166
6	1	1	0.977
6	2	0	0.022
6	3	0	0.001
7	1	1	0.997
7	2	0	0.001
7	3	0	0.002
8	1	0	0.019
8	2	1	0.020
8	3	0	0.961
9	1	0	0.128
9	2	0	0.015
9	3	1	0.857
10	1	0	0.092
10	2	0	0.069
10	3	1	0.838
11	1	1	0.631
11	2	0	0.090
11	3	0	0.279
12	1	0	0.429
12	2	0	0.101
12	3	1	0.470
13	1	1	0.567
13	2	0	0.347
13	3	0	0.086
14	1	1	0.899
14	2	0	0.100
14	3	0	0.001
15	1	0	0.006
15	2	0	0.279
15	3	1	0.715

3.8 Additional Resources for Computational Implementation

The following resources provide a good introduction to choice modeling, including the MNL, NL, MXL, and OL model, and the computational implementation considerations:

- Koppelman et al. [37] A self-instructing course in mode choice modeling. Multinomial and Nested Logit Models. US Department of Transportation.
- Train [75] Discrete choice methods with simulation. Cambridge University Press, Cambridge, MA.

To practice estimating the MNL, NL, MXL, and OL models, the following resources are available:

- The MNL, NL, MXL can be estimated in R (http://www.r-project.org/) using the `mlogit` package. The `mlogit` package also has example data sets for the MNL, NL, and MXL models.
- The OL model can be estimated in R (http://www.r-project.org/) using the `MASS` package and the `polr` function. Example data sets are available in the package.

Appendix A: Introduction to Conjoint Analysis

Conjoint analysis is a technique for measuring tradeoffs for analyzing survey responses concerning it is a method for simulating how customers might react to changes in current products or to new products introduced into an existing competitive array [23]. Conjoint analysts develop and present descriptions of alternative products or services that are prepared from fractional factorial experimental designs. They use various models to infer buyers' partworths for attribute levels, and enter the partworths into buyer choice simulators to predict how buyers will choose among products and services. Today it is used in many of the social sciences and applied sciences including marketing, product management, and operations research. The objective of conjoint analysis is to determine what combination of a limited number of attributes is most preferred by respondents. It is used frequently in testing customer acceptance of new product designs and assessing the appeal of advertisements. Respondents are shown a set of products, prototypes, mock-ups, or pictures. Each example is similar enough that customers will see them as close substitutes, but dissimilar enough that respondents can clearly determine a preference. Each example is composed of a unique combination of product features. The data may consist of individual ratings, rank-orders, or preferences among alternative combinations. The latter is referred to as Choice-Based Conjoint, and shares many features with DCA techniques, while the traditional conjoint analysis techniques typically use ratings data to estimate models based on Regression. Any number of algorithms may be used to estimate utility functions. The original methods were monotonic analysis of variance or linear programming techniques, but these are largely obsolete in contemporary marketing research practice. Far more popular are Hierarchical Bayesian (HB) procedures that operate on choice data. The utility functions indicate the perceived value of the feature and how sensitive customer perceptions and preferences are to changes in product features.

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Chapter 4
Decision-Based Design Framework

Nomenclature

A	Customer-desired product attributes
C	Total product cost
E	Engineering design (ED) attributes
E(U)	Expected value of enterprise utility
P	Product price
Q	Product demand
S	Customer socio-demographic attributes
t	Time interval for which demand/market share is to be predicted
U	Enterprise utility
u_{in}	True utility of alternative i by customer n
V	Selection criterion used by the enterprise (e.g., profit, market share, revenues, etc.)
W_{in}	Deterministic part of the utility of alternative i by customer n
X	Design options
Y	Exogenous variables (represent sources of uncertainty in the market)
ε_{in}	Random unobservable part of the utility of alternative i by customer n

With methods for modeling designer preference and customer preference presented in Chaps. 2 and 3, respectively, the decision-based design (DBD) framework and taxonomy is fully developed in this chapter. DBD is an integrated design approach that incorporates the interests from both producer and customers, where the discrete choice analysis (DCA) model for choice modeling, as well as cost models and enterprise objectives, are integrated. To demonstrate the DBD framework, a simple case study for an electric motor design is provided first. Next, an industrial example of vehicle engine design is presented, where techniques for implementing DBD for complex systems are introduced. In particular, determining attribute hierarchies in the DCA model and selecting the form of a DCA utility

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_4,

function using Kano's method are discussed. The use of the DBD approach to engineering design decision making is illustrated through these examples.

4.1 Decision-Based Design Framework and Taxonomy

The decision-based design (DBD) framework presented here [21] merges the separate marketing and engineering domains into a single enterprise-driven decision making framework. Building upon the DBD framework originally proposed by Hazelrigg [6], discrete choice analysis (DCA) is proposed in our framework as a systematic approach to establish the relationship between the customers-desired product attributes $\mathbf{A}$, price P, customer socio-demographic attributes $\mathbf{S}$ of the market population, time t, and the demand Q.

The DBD framework is shown in Fig. 4.1. The arrows in the DBD flowchart indicate the existence of relationships between the different entities (parameters) in DBD. We discern two different types of attributes, namely the engineering design attributes $\mathbf{E}$ and the *customer-desired product attributes* $\mathbf{A}$, which are product features and financial attributes (such as service and warranty) that a customer typically considers, when purchasing the product. *Engineering design attributes* $\mathbf{E}$ are any quantifiable product properties that are used in the engineering product development process (i.e., engineering specifications and requirements). The relationship between design options $\mathbf{X}$ and engineering design attributes $\mathbf{E}$ are determined through engineering analysis.

Alternative product designs, characterized by discrete or continuous *design options* $\mathbf{X}$, are determined during the "alternative generation" stage. It should be noted that design options $\mathbf{X}$ may include both engineering (product and process) design options and enterprise planning options, such as warranty options and annual percentage rate (APR) of auto loan, etc., both influence the customer-desired product attributes $\mathbf{A}$. Engineering design attributes $\mathbf{E}$, apart from including the quantification of the attributes $\mathbf{A}$, also include design attributes that are only of interest to design engineers. These attributes may act as physical constraints in DBD optimization, e.g., material stress for instance should not exceed the maximum allowable stress. Other engineering design attributes such as the product's weight will impact the total product cost C.

The *total product cost* C in the diagram accounts for all costs that occur during a product's life cycle, including the expenses for product development, manufacturing, overhead, storage, sales cost including distribution and marketing, warranty, liability, disposal, taxes, incentives, etc. Total product cost is impacted by the design options $\mathbf{X}$, exogenous variables $\mathbf{Y}$, engineering design attributes $\mathbf{E}$, and product demand (quantity) Q. Exogenous variables are uncertain parameters beyond the control of the design engineer (e.g., climate, legislation, demographics, financial markets, market trends). Since the product may be produced over several years, future costs of labor, capital, natural resources and supplies should be estimated, along with the availability of these production factors. Under the DBD

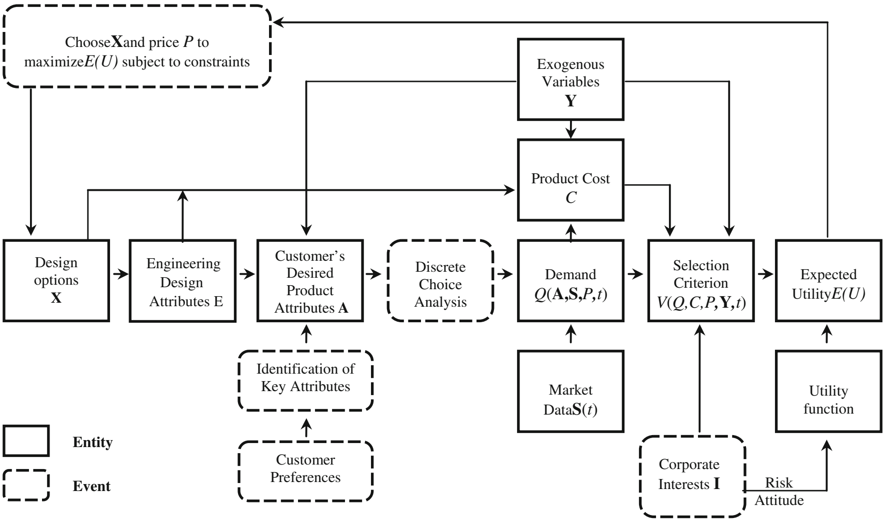


Fig. 4.1 Decision-based design framework

framework, a single *selection criterion V* is needed to facilitate a valid comparison between design alternatives and to determine which alternative should be preferred. Driven by maximizing the economic benefit a product can bring, the net present value of profit is used as the selection criterion to avoid subjective tradeoffs and problems of using multi-attribute utility as explained in Chap. 2. The time t is considered when discounting V to the net present value.

Owing to uncertainties in the calculations of **E**, **A**, C, Q, and **Y** the resulting selection criterion V is a distribution of values. Therefore, the (expected) net present value of the product designs cannot be compared directly. For example, it is likely that one prefers a lottery with equal chance of receiving \$400 or \$600 over a lottery with equal chance of receiving \$0 or \$1,000 even though the expected outcome for both lotteries is \$500. By assessing the risk attitude of the decision-maker the distribution of V is transformed into the expected utility E(U), which is an integration of the utility function $U(V)$ and the distribution of V, i.e., $f(V)$. $U(V)$ expresses the decision-maker's risk attitude and could be assessed with Von Neumann and Morgenstern lotteries as explained in Chap. 2.

The flowchart in Fig. 4.1 coincides with an optimization loop that identifies the best values for design options to maximize the expected utility. The optimal product design is determined by choosing both the design options **X** and the price P, such that the expected utility E(U) of the selection criterion is maximized while satisfying the constraints. It should be stressed that rigorous decision making only allows constraints that are logically or physically necessary to be active at the selection of the preferred alternative to avoid excluding otherwise, potentially valuable design alternatives.

4.2 Integration of Discrete Choice Analysis Into DBD for Demand Modeling

4.2.1 Economic Principles for Demand Analysis

As introduced in Chap. 2, a consequence of Arrow's general possibility theorem is that it is impossible to construct a social welfare function [1]. *Therefore we cannot maximize (group) utility directly.* However, the utility concept has been successful in identifying quantifiable factors that help predict the choices customers make by assuming that customers act as if they maximize some utility [13]. The economic theory supports the idea that demand can be derived from the utility maximization of the choices of each individual customer [5]. Gossen's second law states: a person maximizes his utility when he distributes his income among various goods so that he obtains the same amount of satisfaction from the last unit of each good purchased. *This implies that the demand and price for a product can be related to the utility of an individual customer, as well as to the demand and price of competing products; therefore, it is important to consider competing products when forming a demand model.*

Market equilibrium and market behavior can usually be explained by the interaction between supply and demand [13]. The marginalist principle states that a product has a decreasing marginal value (utility), i.e., people are only willing to buy more of a product at a lower price. Similarly, Ricardo's law of diminishing returns [14] states that the cost associated with producing one additional unit of a good increases as more of that good is produced. Marshall [10] showed that the forces of supply and demand *simultaneously* determine the price (Fig. 4.2). *The interaction between supply and demand stresses the importance of considering both the producer's interests (supply) and the customers' desires (demand) when developing a product.* Consequently, price should also be considered as a design variable, so that the relationship between demand, design options, and price needs to be established. For simplicity, *in later chapters of this book, price is considered as a part of the customer-desired product attributes* **A**.

4.2.2 Capability of Discrete Choice Analysis Approach in Avoiding Arrow's Impossibility

With the DCA approach, we do not attempt to draw conclusions based on aggregated data of a group of decision-makers but consider each decision-maker (customer) at the disaggregated, individual level. To illustrate this, consider the following statements: John owns a car. John owns a bike. We may correctly conclude that John owns a bike and a car. We cannot project such conclusions on a group of decision-makers. For example, consider 100 customers: 35 own a bike, 20

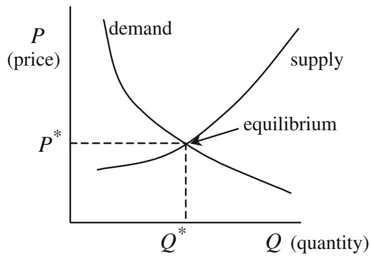


Fig. 4.2 Market equilibrium

own a bike and a car, and 45 own a car only. Then the following statements are true: the majority of the customers own a bike, the majority of the customers own a car. However, the conclusion that the majority of customers own a bike and a car is false. The examples above show that *a group of decision-makers cannot be represented by an imaginary average individual*. As such, Arrow showed that it is impossible to construct a single social welfare function [1] and it is therefore impossible to maximize some group utility, e.g., customer satisfaction as a group. With the proposed DBD framework, the designer's objective is to maximize the expected utility of profit, a single-criterion objective function. Therefore *DCA does not entail maximizing some customer utility function, but optimizing the summation of choice probabilities across individual decision-makers (customers), thereby avoiding Arrow's Impossibility.*

4.3 Procedure for Implementing the Proposed DBD Framework

Although demand modeling techniques exist in market research, little work addresses the specific needs of engineering design, in particular that which facilitates engineering decision making. In this chapter, we develop a systematic procedure for implementing the product design selection procedure under the DBD framework integrated with the demand modeling approach presented in Chap. 3. The implementation consists of six major steps: (1) Market research, (2) Alternative generation and engineering analysis, (3) Product cost modeling, (4) Construction of the demand model, (5) Determination of corporate objective and risk attitude, and finally, (6) Perform optimization to determine the preferred alternative. The steps are detailed below.

Step 1: Market Research

The goals of this first step are: (1) Gather market data like market size and attainable market share. (2) Identify the key customer-desired product attributes **A** and their desired levels. (3) Assess competitive products, i.e., determine the key attribute levels, price, warranty, and market share. The information gathered in Step 1 will be used to guide the successive steps in the DBD framework. For example, with the information such as the estimated sales volume, a designer can decide what options of production methods that should be considered, e.g., single product, series manufacturing, or mass fabrication methods.

The customer-desired attributes and the information about competitive products are important information for constructing the demand model. Customers' desired product attributes **A** can be identified by means of qualitative market research techniques, such as surveys, interviews, focus groups, etc. Typically, a respondent is asked to rate attributes in terms of: very important, important, less important, and unimportant or to rank order attributes according to importance or desirability. Another approach is to ask the respondent to distribute a fixed amount of money or tokens among the attributes to indicate how much he or she is willing to pay in order to receive or to improve that attribute [9]. This procedure forces the respondent to reveal his or her preference with respect to what are the most important (key) attributes **A**.

The attribute levels, warranty, price, and market share of competing products, combined with an estimate of the total market size could be used to derive a preliminary relation between the customer-desired attributes and the demand. Note that the relation is subject to disturbances such as the competitor's image, the customer's perception and expectation of the competing product, etc. Assessing competing products provides insight into what customer-desired attribute levels could be successful, providing focus to the engineering effort. Information about the competing products may be part of the market survey to enable a more accurate assessment of demand and market share. More details of methods for attributes and choice set identification can be found in Sect. 3.5.1.

Step 2: Alternative Generation and Engineering Analysis

Step 2 consists of generating alternative designs, characterized by discrete or continuous design options **X** and further, determining engineering attributes **E** and the customer-desired product attributes **A** as functions of the design options. Methods for generating concepts can be found in the engineering design literature [7, 8, 18, 20] and is not the focus of this book. Some engineering attributes act as physical constraints in DBD optimization: material stress for instance should not exceed the maximum allowable stress. Other engineering attributes such as the product weight will impact the product cost.

Step 3: Product Cost Modeling

The total product cost accounts for all costs that occur during a product's life cycle. The total product costs include the expenses for product development, manufacturing, overhead, storage, sales cost (such as distribution and marketing), warranty, liability, disposal, taxes, incentives, etc. The total product cost is influenced by the design options **X** including the production method, exogenous variables **Y**, engineering attributes **E**, and product demand (quantity) Q.

The manufacturing cost can be estimated by determining the cost as a function of the characteristics of existing similar products such as cost per part or per unit of weight [11, 12, 17]. Preferably, multiple data sources and estimation methods are used to forecast the cost. The outcomes of the different methods form a distribution of cost estimates, reflecting the uncertainty in the estimate. An alternative approach is to determine the total product cost of a particular alternative and to estimate the relation, including the uncertainty, between the total product cost and the cost sources such as the design options **X**, the manufacturing method, etc. Thurston and Liu [19] showed that an estimated distribution of cost is preferable to a best guess (i.e., point estimate), as a distribution enables inclusion of the decision-maker's risk attitude toward uncertainty in the evaluation of a product design.

Since the product may be produced during several years, future costs of labor, capital, natural resources, and supplies need to be estimated, along with the availability of these production factors. It might be necessary to consider the change of currency exchange rates when major components find their origins abroad.

Step 4: Construction of the Demand Model

A critical step for implementing the developed DBD framework is to establish the relation between the design alternatives and the market demand. As introduced in Chap. 3, DCA allows the examination of the market share impact of product features, price, service, and promotion on different classes of customers [3]. DCA predicts the probability that an alternative is selected over other choice alternatives. In the DBD framework, the probability of choice is extended to predict the probable market share of a design option.

Step 5: Determination of the Selection Criterion and the Risk Attitude

A selection criterion V is needed in order to make a choice between the product alternatives. The selection criterion should be able to capture all underlying effects as discussed in Sect. 4.1. Therefore, V is usually in the form of the economic benefit the product can bring to the decision-maker. To avoid subjective tradeoffs and problems associated with group decision making [1, 2], a single corporate interest, i.e., the net present value of profit, is used as the selection criterion. The remaining corporate interests, if any, could act as necessary conditions, i.e., constraints in DBD optimization. The risk attitude can be assessed using the utility function by following the methods introduced in Sect. 2.1.

Step 6: Perform Optimization to Obtain the Result

With Step 5, the set of equations (models) that enable the evaluation of the preferred product as function of the design options **X**, while reconciling with the corporate interests $\boldsymbol{I}$, engineering constraints, and risk attitude of the decision-maker is completed. The goal of this last step is to select the preferred design from the design space, defined by the design options **X**, that has the highest expected utility E(U) of the selection criterion V, subject to constraints that can be expressed as functions of the engineering attributes **E** and corporate interests $\boldsymbol{I}$. As the DBD optimization model is expected to be highly nonlinear and stochastic in nature, advanced optimization solution search techniques and data sampling techniques (for evaluating distributions) need to be employed. The forecasted demand for the selected product design could be verified by a small-scale market survey to ensure that the preferred product design is selected.

Next, the DBD framework will be illustrated using two case studies of increasing complexity.

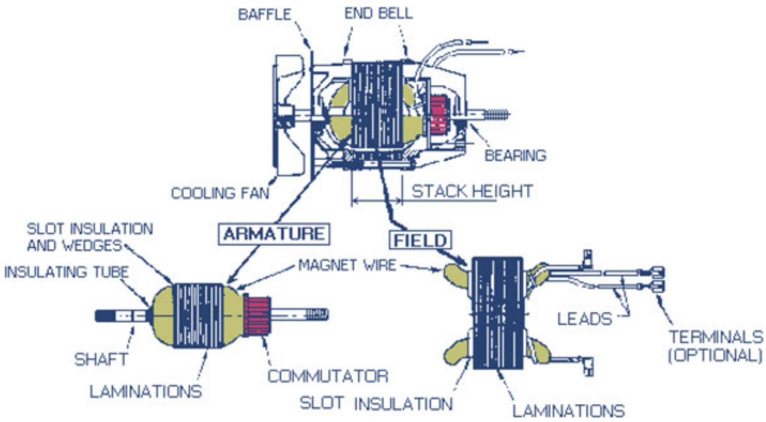


Fig. 4.3 Universal motor design [16]

4.4 Case Study 1: An Electric Motor Design Example

In this section, the proposed DBD procedure is demonstrated first through an academic problem: the electric universal motor design [16], shown in Fig. 4.3. We illustrate the implementation of our proposed DBD approach following the sequence of the six major steps presented in Sect. 4.3.

Step 1: Market Research

In this step an understanding of the market for universal motors market is gained, such as the market size, (potential) competing products, etc. A survey and focus group is used to identify the customer-desired product attributes **A** and their desired ranges.

Customers-Desired Attributes **A**: A universal motor often finds application in handheld power tools that are battery powered. It is therefore important to strive for low weight and maximum time the motor can operate on a single battery charge. The customer-desired attributes **A** in this example are therefore identified as operating time B and mass M. The operating time of a motor powered by a particular battery is prolonged if the motor is more energy efficient. Hence energy efficiency η is an engineering attribute. The power and the torque are also important to the customer and could be part of the customer key attributes. However, in this case study it is assumed that the company produces a family of universal motors [16]. This product family will be supplemented with a motor with a power P of 300 W and a torque T of 0.25 Nm. The power and the torque requirements are listed as *prescribed design requirements* as part of the customer-desired attributes.

Step 2: Alternative Generation and Engineering Analysis

Alternative Generation: The variables controlled by a design engineer are called the design options **X**, listed in Table 4.1. Note that the ranges are chosen as wide as technically feasible to ensure that preferred design alternatives are not

Table 4.1 Specification of the design options **X**

1. Current	$0.1 < I < 6.0$ (A)	Continuous
2. Motor radius	$10 < r_o < 150$ (mm)	Continuous
3. Stator thickness	$0.5 < t_s < 15.0$ (mm)	Continuous
4. Number of turns of rotor wire	$100 < N_r < 1{,}500$ (turns)	Continuous
5. Number of turns of stator wire	$1 < N_s < 500$ (turns)	Continuous
6. Cross-sectional area rotor wire	$0.01 < A_{\mathrm{rw}} < 2.0$ (mm^2)	Continuous
7. Cross-sectional area stator wire	$0.01 < A_{\mathrm{sw}} < 2.0$ (mm^2)	Continuous
8. Stack length	$10.0 < L < 200.0$ (mm)	Continuous

excluded from consideration. All variables are treated as continuous in this study, including the turns of wire to facilitate the optimization process. The motor has two stator poles p_{st}, the laminate thickness is set to 0.63 mm, and the air gap l_{gap} is set to 0.7 mm to simplify the problem. Varying the design options **X** generates a continuum of alternatives. The problem is now reduced to selecting the best possible alternative from this continuum.

Engineering Analysis: The engineering analysis establishes the analytical relationship between the customer-desired attributes **A** and the design options **X**, while considering the engineering attributes **E**. Performance parameters associated with design constraints are part of the engineering attributes. The magnetizing intensity in the motor is not allowed to exceed the physical flux carrying capacity of steel φ_{st} [16]. A feasible geometry constraint ensures that the thickness t_s of the stator does not exceed the radius r_o of the stator. The contributions to the motor mass, (i.e., the mass of the rotor, stator, and windings) and power losses (i.e., the losses occurring in the copper and brushes) are intermediary engineering attributes. The maximum allowable motor temperature depends on the insulation quality of the wire material. The wire insulation quality, which is assumed to vary slightly (uncertainty), affects the reliability of the motor. The motor temperature T_m is determined as a function of ambient temperature T_a, electrical losses (heat source), radiant surface A_{motor} and surface emissivity Em (dimensionless). All customer and engineering attributes, along with the important relationships, are listed in Table 4.2.

Step 3: Product Cost Modeling

The product cost analysis establishes the relationship between the design options **X** and the total product cost C of the universal motor's life cycle. The cost strongly depends on the motor's intended use whereas the automation level of the manufacturing process (manufacturer specific) heavily influences the capital-labor ratio. Further, cost can increase exponentially when dimensions outside the standard range are needed.

The total product cost C is based on design, material, labor, capital, and repair/warranty costs. The material cost C_M is determined as a function of the demand Q and the cost for the steel of the rotor and stator, and the copper wires. The cost of the wire depends on the wire diameter. Standard ranges are 0.52–0.65 mm for the

Table 4.2 Attributes and physical relations

Customer-desired product attributes **A**	
Mass M (kg)	$M = M_w + M_s + M_r$
Operating time B (h)	$B = 1\ \eta$
Power P (W)	$P = P_{\text{in}} - P_{\text{loss}} = 300$
Torque T (Nm)	$T = \text{K}\ \varphi\ \text{I} = 0.25$
Engineering attributes **E**	
Efficiency η (dimensionless)	$\eta = (P_{\text{in}} - P_{\text{loss}})/P_{\text{in}}$
Rotor wire length l_{rw} (m)	$l_{\text{rw}} = 2\text{L} + 4(r_o - t_s - l_{\text{gap}})\ N_r$
Stator wire length l_{sw} (m)	$l_{\text{sw}} = p_{\text{st}}\ (2\text{L} + 4(r_o - t_s)\ N_s$
Rotor wire resistance R_r (Ohm)	$R_r = \rho\ l_{\text{rw}}/A_{\text{rw}}$
Stator wire resistance R_s (Ohm)	$R_s = \rho\ l_{\text{sw}}/A_{\text{sw}}$
Power loss P_{loss} (W)	$P_{\text{loss}} = \text{I}^2\ (R_r + R_s) + 2\ \text{I}$
Mass windings M_w (kg)	$M_w = (l_{\text{rw}}\ A_{\text{rw}} + l_{\text{sw}}\ A_{\text{sw}})\ \rho_{\text{copper}}$
Mass stator M_s (kg)	$M_s = \pi\ \text{L}\ (r_o^2 - (r_o - t_s)^2)\ \rho_{\text{steel}}$
Mass rotor M_r (kg)	$M_r = \pi\ \text{L}\ (r_o - t_s - l_{\text{gap}})^2\ \rho_{\text{steel}}$
Flux carrying cap. of steel φ_{st} (A turns/m)	$\varphi_{\text{st}} \leq 5{,}000$
Motor constant K (dimensionless)	$\text{K} = N_c\ \pi$
Magnetizing intensity H (A turns/m)	$H = N_c\ \text{I}/(l_c + l_r + 2l_{\text{gap})}$
Magneto magnetic force $\mathfrak{J}$ (A turns)	$\mathfrak{J} = N_s\ \text{I}$
Magnetic flux (Wb)	$\varphi = \mathfrak{J}/\mathfrak{R}$
Motor surface area A_{motor} (m^3)	$A_{\text{motor}} = 2\ \pi\ r_o\ \text{L} + \pi\ r_o{}^2$
Motor temperature T_m (°C)	$T_m = T_a + \text{I}^2\ \text{R}/A_{\text{motor}}\ \text{Em}$

rotor wire and 0.9–1.1 mm for the stator wire. Labor cost C_L is determined from the cost split labor/material, which is based on a 30/70 ratio rule of thumb. This cost split depends on the automation level of finishing processes (manufacturer specific). It is assumed that the cost increases quadratically when the production quantity deviates from the optimal production capacity due to inefficiencies. For this example, the repair/warranty cost depends upon the reliability of the motor. It is assumed that the reliability depends solely on the motor temperature T_m. G(T_m) is the computed fraction of motors that need repair during the warranty period. The warranty period and the impact of marketing, and the associated marketing cost, are not considered in this example. Using the identified design options **X**, estimation of the total cost, C^k, for each design concept, k, is calculated using:

$$C^k(\mathbf{X}^k, \mathbf{Y}, Q, t) = \sum_P C_D^k\left(\mathbf{X}^k, \mathbf{Y}, Q, t\right) + C_C^k(t) + C_F^k(t) + C_R \tag{4.1}$$

where $C_D^k\left(\mathbf{X}^k, \mathbf{Y}, Q, t\right)$ is the material (C_M), processing (including labor) (C_L), and capacity cost (C_{cap}) for each design option, P is the number of design options, $C_C^k(t)$ is the cost of capital, $C_F^k(t)$ is corporate overhead cost for each design concept (design cost), and C_R is the warranty cost. It is assumed that all costs remain constant except the labor cost, which is expected to rise 3% annually. Additionally, the total cost depends on the demand, which is expected to grow 5% annually. The total cost is summarized in Table 4.3.

Table 4.3 Total product cost

Total cost (USD)	
Material cost C_M	$C_M = Q\ (M_w\ P_{\text{copper}} + (M_s + M_r)\ P_{\text{steel}})$
Labor cost C_L	$C_L = 30\ L_g\ C_M/70$
Capacity cost C_{cap}	$C_{\text{cap}} = 50\ [(Q - 5 \times 10^5)/1{,}000]^2$
Capital cost C_c	$C_c = A_c\ Q/(4.5 \times 10^6 + Q)$
Design (fixed) cost C_F	$C_F = 500{,}000$
Repair, warranty C_R	$C_R = 1.5\ P\ Q\ \mathrm{G}(T_m)$

Table 4.4 Exogenous variables (normal distribution)

Exogenous variable **Y**	Mean	Standard deviation
Stack length L (mm)	Variable	0.0005 + 0.02 Mean
Labor cost growth factor L_g	1.03	0.02
Demand Q (motors/year)	Variable	0.01 Mean
Demand growth factor	1.05	0.04
Wire insulation quality (^{o}C)	90	2

Exogenous Variables Y and Uncertainty Handling: The exogenous variables considered in this case study are: stack length variation, labor cost growth factor L_g, demand uncertainty (as a result of the demand analysis), the demand growth, and the wire insulation quality. The variation of the stack length L affects the mass M, efficiency η, operating time B, total product cost C, and demand Q. The labor cost growth factor L_g affects the uncertainty of the predicted demand. The demand growth factor, and varying wire insulation quality affect the total product cost C. All exogenous variables ultimately impact the selection criterion V. The effect of uncertainty on the selection criterion is assessed by Monte Carlo simulation. An overview of the exogenous variables is presented in Table 4.4.

Step 4: Construction of the Demand Model

The demand Q is determined as a function of the customer-desired attributes **A**, price P, and the socio-demographic attributes of the market population **S**. The demand is estimated using the Multinomial Logit DCA model introduced in the previous chapter. The choice set of this example contains three alternatives. The alternatives are: the "survey alternative" (i.e., the new motor design), "any other motor", by which is meant any other motor brand the respondent knows, and the third choice alternative is "none of these," i.e., the survey respondent chooses not to buy any of the motors listed in the choice set. The customer key attributes and price are considered at three levels each. The choice alternative "any other motor" is considered at one level of mass, operating time, and price, listed in Table 4.5.

A total of 27 alternative combinations are generated (full factorial design). Hence, 27 different choice sets are possible with the attributes listed in Table 4.5. An example of a choice set is shown in Table 4.6.

Multinomial Logit Choice Model: Choice behaviors of the respondents are modeled by an additive utility function. It should be noted that the utility function

Table 4.5 Attributes and levels used in the survey

Attribute name	Survey alternative	Any other motor
Mass M (kg)	0.2	1.0
	0.6	
	1.0	
Operating time B (h)	0.40	0.80
	0.65	
	0.90	
Price P (USD)	5.00	5.75
	6.50	
	8.00	

Table 4.6 Example of a choice set

Choice set # 17	Survey alternative	Any other motor	None of these
Power (W)	300	300	
Torque (Nm)	0.25	0.25	
Mass (kg)	0.6	1.0	
Operating time (h)	0.90	0.80	
Price (USD)	\$6.50	\$5.75	
Indicate whether this is the product you want to buy and how many			

can assume any form that best fits the data set. The attributes $\boldsymbol{Z_i}$ describe each choice alternative **A**, price P, and socio-demographic background of the market population **S**.

Two classes of customers are discerned; a class of customers older than 35 years, and a class with an age less than 35 years. Table 4.7 shows the multinomial choice model and coefficient estimates of the universal motor demand. The utility of "None of these" is used as base reference, and β_1 and β_2 provide the Alternative Specific Constants for the survey alternative and any other motor, respectively. The β-coefficients 3, 4, and 5 correspond to the customer-desired attributes **A**. The socioeconomic attribute "income" and price P is considered in the combined price/income attribute, corresponding to β_6 and β_7. β_8 through β_{11} are coefficients for the two age categories.

The probable choice can be predicted with the multinomial choice model and Eq. (4.2), given the customer class, income level, the product attributes, and price.

$$\Pr_n(1)|[1,2,3] = \frac{e^{u_{1n}}}{e^{u_{1n}} + e^{u_{2n}} + e^{u_{3n}}} \tag{4.2}$$

In this equation, u_{1n} denotes the nth customer's utility of the "survey alternative," u_{2n} the utility of the "any other motor" alternative, and u_{3n} the utility of the "none of these" alternative. $\Pr_n(1)$ is the predicted probability that alternative 1 is chosen from the three choice alternatives. The aggregated predicted choice probabilities and the market size data are used to estimate the demand.

Table 4.7 Multinomial choice model

	Choice set alternative attributes [$\mathbf{Z}_i$ ($\mathbf{A}$, P, $\mathbf{S}$)]			
β coefficient	Survey alternative	Any other motor	None of these	β-coefficient estimate
β_1	1	0	0	−2.22
β_2	0	1	0	−1.63
β_3	Mass	Mass	0	−103.40
β_4	Operating time	Operating time	0	−206.94
β_5	0	0	Operating time	52.36
β_6	Price/income	Price/income	0	−13.83
β_7	0	0	Price/income	5.03
β_8	Age $\leq$ 35 years	Age $\leq$ 35 years	0	0.21
β_9	0	0	Age $\leq$ 35 years	0.11
β_{10}	Age > 35 years	Age > 35 years	0	−0.09
β_{11}	0	0	Age > 35 years	−0.12

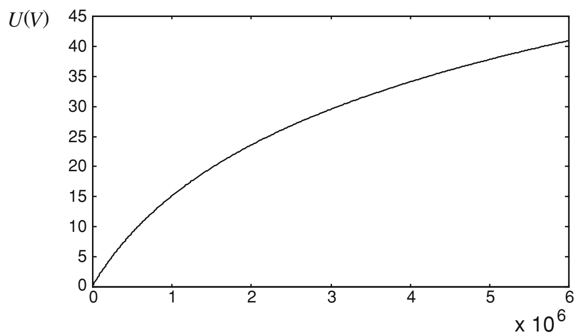


Fig. 4.4 Utility function $U(V)$ of the net present value of profit

Step 5: Determination of the Selection Criterion and Risk Attitude

The selection criterion V is the net present value of the net cash flow. The utility function that accounts for the risk attitude is listed in Fig. 4.4. The discount rate D_r is chosen as 15%. The optimization problem is summarized in Fig. 4.5.

Step 6: Optimization for Determining the Preferred Alternative

The preferred design alternative with the highest expected utility of the net present value of profit, while considering the engineering constraints, is determined using nonlinear optimization techniques (Sequential Quadratic Programming). The results of the preferred alternative are presented in Table 4.8. Figures 4.6 and 4.7 show the probability distributions of the demand (resulting from **Y**), and the net present value of the profit of the preferred design alternative, respectively.

It is observed that although the distributions of input uncertainty are normal as shown in Table 4.4, the output distribution of the accumulated net present value of the profit shown in Fig. 4.7 is non-symmetric. This is mainly because of the assumption that the manufacturing cost rises significantly when the demand

GIVEN	
Terminal voltage V_t	115 [Volt]
Stator poles p_{st}	2
Production quantity	500,000 [motors/year] (estimate)
Product life cycle	5 [year]
Discount rate D_r	15 %
Customer key attributes *A* (Table 4.2)	
Engineering attributes *E* (Table 4.2)	
Determines the analytical relationship between ***X*** and ***A***	
Demand model *Q*	
The demand model is obtained using the multinomial logit technique to fit the discrete choice survey data	
Cost model *C* (Table 4.3)	
Determines the analytical relationship between ***X*** and *C*	
Corporate interests *I*	
None other than the single selection criterion *V*	
Single criterion *V*	
Net revenue	$V = Q\,P - C$
Utility function U(*V*)	
$U(V) = -274 + 20 \log(V + 5.9\ 10^6)$	
Market Data *S* (Socioeconomic and demographic attributes)	
55% younger than 30 years. (Table 4.7)	
FIND	
Design options ***X*** (Table 4.1) and price *P*	
SUBJECT TO	
Power requirement	P = 300 [Watt]
Torque requirement	T = 0.25 [Nm]
Maximum motor radius	$r_{o,max} = 150$ [mm]
Feasible geometry	$t < r_o$
Magnetizing intensity	$H_{max} \leq 5000$ [Wb]

Fig. 4.5 Problem description

deviates from the optimum production capacity. It is also noted that there is a probability of financial loss, which again brings out the importance of considering the designer's risk attitude. Table 4.8 shows the preferred values of the design options **X,** as well as **E** and economic benefits, resulting from utility maximization. These values are used by the engineering team for designing the universal motor.

4.5 Case Study 2: Vehicle Engine Design Example

For engineering design it is necessary to develop an approach to demand modeling that can deal with a large number of product attributes that are of interest to customers. In this section, we present an implementation of the DCA demand

Table 4.8 Results of the DBD problem

Power	299.7 (W)	
Torque	0.249 (Nm)	
Preferred design options	Current	3.63 (A)
	Motor radius	31.9 (mm)
	Stator thickness	5.8 (mm)
	Number of turns of rotor wire	989 (turns)
	Number of turns of stator wire	55 (turns)
	Cross-sectional area rotor wire	0.26 (mm^2)
	Cross-sectional area stator wire	0.46 (mm^2)
	Stack length	22.5 (mm)
Engineering attributes	Efficiency	0.66
	Magnetizing intensity	2,193 (A Turns/m)
Customer-desired product attributes	Mass	0.97 (kg)
	Operating time	0.66 (h)
	Price	6.58 (USD)
Results	Expected demand (year 5)	510,000 (motors)
	Expected profit (accumulated)	4,100,000 (USD)

Fig. 4.6 Demand (year 5) distribution

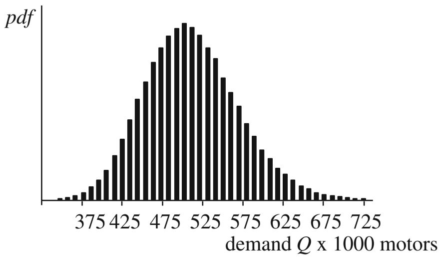
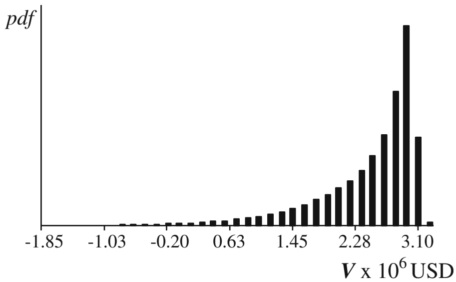


Fig. 4.7 Net present value distribution



modeling approach to constructing a vehicle demand model with emphasis on evaluating engine design changes in a DBD model [22]. This example is used to show the complications in both *system hierarchy* and *attributes hierarchy* in a large-scale system design. Our approach is to develop a hierarchical structure of attributes in demand modeling with a limited number of “generalized customer-desired attributes" at the system level (e.g., durability, comfort, ease of use, safety, and price of a vehicle) and more specific "subsystem attributes" (e.g., engine noise, and type of car seats) lower in the hierarchy. The demand model developed in this case study can be used to assess the impact of engine design changes on vehicle demand, facilitating the evaluation of engine design and making proper tradeoffs between performance and cost. Twelve vehicles (7 models, 12 trims) are considered in the demand model representing the midsize vehicle segment, which includes vehicles such as Ford Taurus, Toyota Camry, and Honda Accord. All data illustrated are normalized to protect proprietary rights of the data providers. Our implementation is subject to the assumption that customers only consider these 12 vehicle trims when purchasing a vehicle. The demand model developed in this case study is a static model, i.e., demand changes over time are not considered. In "what if" studies and in DBD optimization, we assume that only the design of one vehicle changes at a time, while the other vehicle designs are kept the same.

Understanding Systems and Attributes Hierarchy

For complex systems like a vehicle, a hierarchical representation is used to cascade the customer desires into attributes that can be represented using engineering language. Figure 4.8 provides an example of how the top-level customer desires can be mapped to specific customer desires (in customer language), to customers-desired attributes **A**, and then to engineering design attributes **E** in vehicle design. Establishing such a mapping relationship is especially important in the design of complex engineering systems. The number of levels involved can be more (or less) than illustrated.

From a market analysis point of view, the input **A** of a demand model could be attributes with physical units (e.g., fuel economy) or without (e.g., level of comfort). However, to assist engineering decision making, attributes **A** related to engineering performance need to be converted into quantifiable attributes **E**. The set of engineering design attributes **E**, apart from including the quantifications of some of the attributes **A**, also include attributes that are only of interest to design engineers, e.g., stress level of a structure. These attributes might be introduced as intermediate variables or variables that impose physical restrictions on the design or impact the total product cost C. On the other hand, some of the non-performance-related attributes **A** are not influenced by the engineering design attributes **E**, but by financial attributes. Therefore, **A** *and* **E** *can be viewed as two sets that share a number of common elements.*

To integrate the demand model into the DBD framework introduced in Sect. 4.1, the engineering analysis (modeling) needs to be carried further to establish the relationship between design options **X** and attributes **A**. As an example of mapping customer desires to a specific design, we show at the right side of Fig. 4.8 that "noise while idling" can be considered as an attribute (**A**) that belongs to the group of "performance" under "product benefit," while radiated sound and engine mount vibration can be considered as attributes **E** for measuring the engine sound while idling. Attributes **A** are often used directly in a survey when using stated preference for demand modeling (see Sect. 3.5.2). On the other hand, when using revealed preference for demand modeling, quantitative

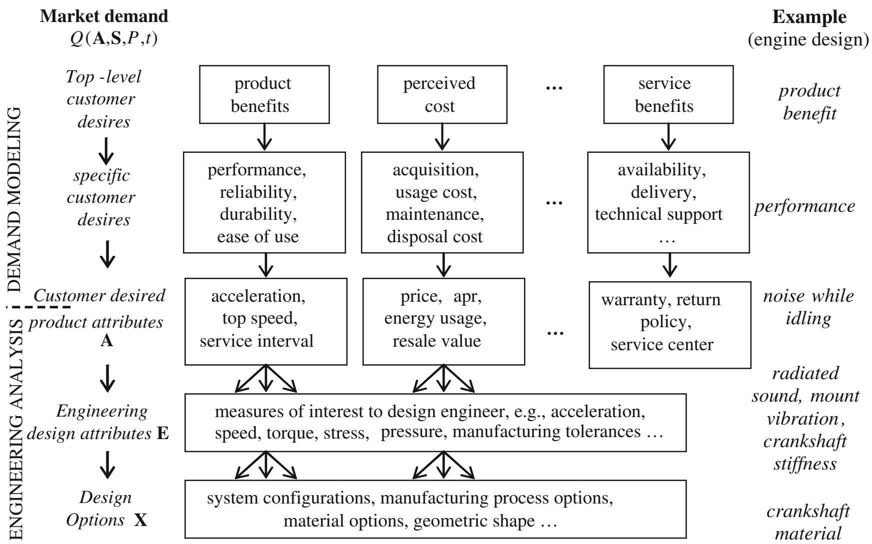


Fig. 4.8 Mapping top-level customer desires to design options

engineering design attributes **E** could be used as explanatory (i.e., independent) variables of the demand model to facilitate engineering decision making. In the latter case, the demand model is expressed as $Q(\mathbf{E}, \mathbf{S}, P, t)$.

Engineering models can relate radiated sound to other engineering design attributes such as main bearing clearance and crankshaft stiffness. Finally, crankshaft stiffness can be modeled as a function of the design options such as crankshaft material, pin diameter, and cheek thickness.

Vehicle Demand Modeling—Attributes and Choice Set Identification

For the demand modeling illustrated next, we identify five groups of top-level customer desires related to vehicle choice at the vehicle system level based on J.D. Power's vehicle quality survey (VQS). These are: engine/transmission performance, comfort and convenience, ride and handling performance, product image, and price/cost (see Table 4.9). For reasons of simplicity, customer desires related to sound system, seats, and style are not considered. The attributes considered in the demand model are presented in Table 4.9, which shows a representative mapping of top-level customer desires to engineering design attributes. Engine and transmission performance can be taken as an example of this mapping process. The specific customer desires include performance during rapid acceleration, passing power at highway speeds, a pleasant sound while idling and at full throttle acceleration, and low vibration levels. Interaction between engineering experts at the Ford Motor Company and market research specialists from J.D. Power helped identify these engineering design attributes corresponding to their specific customer desires. The design options in this vehicle engine design case study are represented by the different settings of attribute levels in Table 4.9.

Table 4.9 Customer-desired attributes structure for vehicle engine design example

Top-level customer desires	Specific customer desires	Attributes
Engine and transmission performance	Performance	Horsepower
		Torque
		Low-end torque
		Displacement
	Noise	Noise @ 2,000 rpm (highway)
		Noise @ 4,000 rpm (accelerating)
	Vibration	Overall vibration level
		Vibration @ 2,000 rpm (highway)
		Vibration @ 4,000 rpm (accelerating)
Comfort and Convenience	Comfort	Front-legroom
		Front-headroom
		Rear-legroom
		Rear-headroom
	Convenience	Trunk space
		Range between fuel stops
Ride and Handling	Handling	Roll gradient (deg/g)
	Steering	SWA@0.5 g (deg) window
		Rolling parking efforts
		Static parking efforts
	Ride	Choppiness (M/sec^2/min)
Product image	Brand	Vehicle make
	Origin	USA/import
	Reliability	Initial quality index (IQS)
	Durability	Vehicle dependability index (VDI)
	Vehicle size	Vehicle mass
		Vehicle width
		Vehicle length
Product cost	Acquisition cost	MSRP (price)
		Rebate
	Usage cost	APR
		Fuel economy
		Resale index

Vehicle Demand Modeling—Data Collection

The demand model is created using revealed choice data at the respondent level provided by J.D. Power and Associates (JDPA). The data consist of 2,552 observed individual vehicle purchases (of the seven vehicles—12 trims considered in this case study) of the year 2,000 vehicle market in the USA, including respondents' background. Therefore, in total the database contains 30,624 observations (2,552 respondents * 12 vehicles). The values of the customer-desired product attributes related to the general vehicle descriptions of the 12 discrete choices, such as weight, fuel economy, and legroom are obtained from Ward's Automotive. The values of other attributes such as, ride, handling, noise, and

Table 4.10 Partial demand model input data table (normalized)

Customer id	Vehicle id	Observed choice	Customer background			Attributes			
			Gender	Age	Income	MSRP price	Horsepower	Torque	Fuel economy
1	1	0	0	27	5	1.07	1.13	1.09	0.96
1	2	1	0	27	5	0.87	0.89	0.85	1.15
1	3	0	0	27	5	1.15	1.09	1.02	0.98
1	4	0	0	27	5	1.02	1.06	1.02	0.90
1	5	0	0	27	5	1.05	1.08	1.12	0.98
1	6	0	0	27	5	0.89	0.77	0.82	1.12
1	7	0	0	27	5	0.96	1.04	0.94	1.00
1	8	0	0	27	5	0.89	0.93	0.97	1.00
1	9	0	0	27	5	1.07	1.02	1.10	1.00
1	10	0	0	27	5	1.03	0.92	0.98	1.02
1	11	0	0	27	5	1.11	1.23	1.16	0.98
1	12	0	0	27	5	0.89	0.83	0.94	0.94

vibration are provided by Ford. A representative section of the choice set input data table for one customer is presented in Table 4.10.

For each respondent there are 12 rows of data in the database, one for each choice alternative, each row containing the customer background, the vehicle attributes, and the respondent's observed choice (real purchase). The customer choice is treated as a binary variable, and in this particular case the customer selected vehicle 2.

To understand the data used for modeling, the correlation of a number of vehicle attributes with socio-demographic attributes is presented in Table 4.11. The following conclusions can be deducted from Table 4.11. (Note, the variables gender and USA/import of Table 4.11 are binary variables that is, female = 1, and import = 1, otherwise 0.) For example, the negative sign of the correlations related to gender for wheelbase, vehicle width, and vehicle length

indicates that women apparently buy smaller vehicles. The negative coefficient (−0.220) for USA/import indicates that older customers tend to prefer domestic vehicles. The negative coefficient for rebate and USA/Import (−0.869) shows that imports are generally sold with smaller rebates. The correlation between customer background (gender, age, and income) and customer-desired attributes appears to be very weak, which is desirable. That is, highly correlated variables are prone to being collinear, giving problems when estimating the demand model coefficients. Further, high correlation between the dependent variable (in this case the vehicle choice) and independent explanatory variables (i.e., design attributes and customer demographic attributes) implies that few variables are sufficient to predict vehicle choice, limiting the use of many explanatory variables (engineering design attributes) in the demand model, which are required for engineering design decision making.

Table 4.11 Partial correlation matrix of vehicle attributes and customer background

	Gender	Age	Income	USA/import
Gender	1			
Age	−0.192	1		
Income	−0.074	−0.176	1	
USA/import	0.150	−0.220	0.087	1
MSRP_price	0.006	−0.041	0.141	0.183
Rebate	−0.101	0.256	−0.141	−0.869
APR	−0.072	0.173	−0.017	−0.425
Resale index	0.178	−0.215	0.031	0.869
VDI (dependability)	−0.117	0.036	0.024	−0.746
IQS (initial quality)	−0.162	0.187	−0.059	−0.928
Horsepower/mass	−0.011	−0.104	0.180	0.212
Torque/mass	−0.051	−0.005	0.148	0.013
Low-end torque/mass	−0.087	0.036	0.120	−0.255
Fuel economy	0.127	−0.047	−0.102	0.444
Fuel range	0.138	−0.063	−0.045	0.680
Wheel base	−0.106	0.076	0.050	−0.667
Vehicle width	−0.119	0.157	−0.066	−0.918
Vehicle length	−0.149	0.154	−0.038	−0.907
Front-headroom	−0.013	−0.103	0.145	0.290
Front-legroom	0.072	−0.094	0.116	0.762
Rear-headroom	−0.162	0.132	0.053	−0.695
Rear-legroom	−0.140	0.157	0.013	−0.731
Trunk space	−0.132	0.139	0.004	−0.844

Vehicle Demand Modeling—Multinomial Logit

In this case study we use STATA to estimate the choice model. A linear customer utility function shape is initially considered by the modeler for the utility function used in the multinomial logit choice model and dividing up the market population in different segments is not considered. Over 200 customer utility functions with different combinations of linear and interaction items were examined by the modeler, illustrating the effort typically involved in developing a demand model. Eventually, a model using 38 explanatory variable items (including attribute interactions) was selected based on the Bayesian Information Criterion score (BIC) (see description in Chap. 3, Sect. 3.5.8).

The observed and the estimated market shares for the 12 vehicle models of the final demand model are shown in Table 4.12. It shows that the observed choice rate/market shares and the market shares as predicted by the model match quite well as would be expected for a model with a full set of alternative specific constants and in-sample prediction. The MS_R2, i.e., the R-square error measure of the observed market shares *versus* predicted market shares for this model is 0.995851.

Table 4.12 Observed and estimated market shares for vehicle demand model

Vehicle id	Choice Rate (#)	Market shares	
		Observed	Estimated
1	251	0.098354	0.098814
2	190	0.074451	0.074544
3	335	0.131270	0.130938
4	220	0.086207	0.086117
5	231	0.090517	0.090972
6	192	0.075235	0.075440
7	199	0.077978	0.077447
8	167	0.065439	0.064866
9	67	0.026254	0.027256
10	435	0.170455	0.170324
11	213	0.083464	0.083507
12	52	0.020376	0.019776

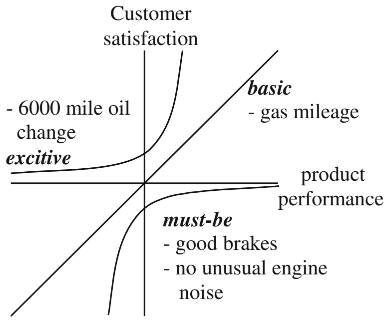


Fig. 4.9 Kano diagram of customer satisfaction

Determining the Shape of Customer Utility Function

The Kano method [15] is used to further improve the predictive accuracy by identifying appropriate shapes for the customer utility function of the choice model. The Kano method, introduced in the late 1970s by Dr. Noriaki Kano of Tokyo Rika University, provides an approach to determine the generalized shape of the relation between product performance and customer satisfaction by classifying the customer attributes into three distinctive categories: *must-be*, *basic*, and *excitive*, shown in Fig. 4.9 (note: these terms may be named differently in various references). The three categories are described briefly; details regarding the classification process can be found in the literature. *Must-be* attributes are expected by the customer and only cause dissatisfaction if not met, e.g., unusual engine noise. Customer satisfaction never rises above neutral no matter how good the engine sounds; however, the customer will be dissatisfied if unusual engine noise occurs. Improving the performance of *basic* attributes increases satisfaction proportionally (i.e., linear), e.g., gas mileage (unless gas mileage is really bad). The *excitive* attributes increase satisfaction significantly for the reason that the customer does not expect them. For instance, a (unexpected) long interval for the oil-change interval may be expected to

Table 4.13 Comparison between linear and quadratic customer utility function fits

	Kano (quadratic)	Regular (linear)
MS_R2	0.998293	0.995984
Maximum likelihood	−5,820.69	−5,831.48
BIC	11,930.61	11,941.85

significantly increase satisfaction. Attributes are thought to move over time from *excitive* to basic to must-be. For example, cup holders were once *excitive* when first introduced but are now expected and their absence can lead to great dissatisfaction.

According to Kano study results at Ford Motor Company, all attributes should be considered as *basic* (i.e., linear) except for *fuel economy beyond* 27.5 *mpg* which can be classified as *excitive*. The econometric reasoning for this is the following: fuel economy is considered *basic* if the fuel mileage is near what is expected for the vehicle's class, in this case the midsize market segment.

However, when the fuel mileage is significantly higher than its competitors, it becomes a distinguishing feature, e.g., "I bought this vehicle because of its remarkable fuel economy." We tested a quadratic function shape for the key customer attributes "fuel economy" and "range between fuel stops" in the customer utility function of the demand model. The BIC score shown in Table 4.13 indicates that the demand model using the utility function shape as assessed by the Kano method provides a better fit for the collected data given that the BIC score improved by more than six points.

Cross Validation of Demand Model

The predictive capability of a demand model cannot be assessed using in-sample data, i.e., the data that are used to estimate the demand model, but rather have to be carried out through model validation. Due to the limited scope of our case study, we will not use the current market demand data to validate the demand model. The approach we take for validating the final vehicle demand model is through the technique of cross validation [4] which does not require the collection of additional data. The data set consisting of 2,552 individuals is divided into five subsets of approximately equal size using random sampling. The model is fitted to the combined data of four out of the five data sets. The fitted model is then used to predict the choice for the remaining (out of sample) choice set and the R-square value for the market shares, which is used as error measure, is calculated. This procedure is repeated 5-fold, every time using a different data set from the five data sets for prediction and error measure calculation. The R-square value of the (in-sample) demand model fitted on the full data set is 0.99. The R-square value decreased to an average 0.92 for the five cross validation tests, which is still an acceptable value. The cross validation shows that the accuracy of the obtained demand model is satisfactory.

Market Share Prediction and "*What if*" Scenarios

The impact of attribute level changes (which reflect engineering design changes) on the vehicle market shares can be predicted by updating the vehicle

Table 4.14 Results of "*What if*" scenarios

Vehicle Id	Market shares (%)			
	Base	Scenario 1	Scenario 2	Scenario 3
1	9.84	9.81	9.41	9.38
2	7.45	7.47	7.18	7.15
3	13.13	12.91	12.42	12.37
4	8.62	8.53	8.21	8.18
5	9.05	8.81	12.15	12.08
6	7.52	7.37	7.12	7.08
7	7.80	7.63	7.38	7.34
8	6.54	6.45	6.20	6.17
9	2.63	2.71	2.62	2.60
10	17.05	17.09	16.49	16.41
11	8.35	9.25	8.92	8.87
12	2.04	1.95	1.89	2.36

descriptions and recalculating the predicted choice probabilities for each individual. To illustrate how the demand model can be used to study the impact of design changes and possible actions of competitors, we consider the following "*what if*" scenarios. Vehicle 11 and vehicle 12 are two trims of one vehicle model from the same manufacturer; one of them is a basic version, while the other is a more powerful luxury version. We assume that the manufacturer decides to improve the fuel efficiency of the base model (vehicle 11) by 10%; the impact on the market shares is shown in Table 4.14 under the heading "scenario 1." The model results show that increasing the fuel efficiency of vehicle 11 increases its market share from 8.35 to 9.25%, but it also shows that vehicle 12's market share is negatively affected. This negative impact of feature upgrades of a product on other members of the same manufacturer is known in the marketing literature as "cannibalism." It implies that *the product being designed should not be considered in isolation*. Scenario 2 shows the impact on the market shares if the producer of vehicle 5 decides to introduce a rebate of $500 to boost its market share. Finally, Scenario 3 shows the impact of increasing vehicle 12's engine power by 5%.

In addition to the market share, the feasibility or the desirability of design changes depends on the impact on profit, which necessitates the consideration of the cost of such changes. This is considered in the DBD design alternative selection example in the following section.

Decision-Based Design for Vehicle Engine Alternative Selection

The DBD model is used to select the best engine design from five different engine design configurations, considered for vehicle 11. To simplify matters, the design options are represented by the setting of the attribute values rather than the design options themselves. The cost model considers the impact of the performance improvements related to power, torque, and low-end torque on the total cost. Low-

Table 4.15 Design alternatives for decision-based design case study

	Design alternative (Vehicle 11) (% change attribute level)				
Design #	1	2	3	4	5
Price	5	0	5	0	−5
Hp	3	3	3	3	0
Torque	3	3	0	0	−10
Low-end torque	3	3	0	0	−10

end torque is the maximum torque an engine produces at approximately 2,000 rpm and is important for accelerating to pass a vehicle when driving at highway speed.

The five alternative engine designs for vehicle 11 are presented in Table 4.15. Engine design 1 offers increased power, torque, and low-end torque by 3% and a price increase of 5% relative to the performance of the existing engine used in vehicle 11. Engine design 2 is similar in performance to Engine design 1 but is sold at the base price. Engine design 3 offers a 3% power and 5% price increase relative to the base model, while the performance of Engine design 4 is the same as Engine design 3 but sold at the base price. A fifth engine design alternative (Engine design 5) is added by considering reusing an existing engine design for vehicle 11 from a different vehicle model, which is less powerful but enables a reduction in price of 5% when compared with the base model. The market size M of the 12 midsize vehicles is estimated at 1,000,000 vehicles annually. Uncertainty is introduced by assuming a normal distribution of the market size with a standard deviation of 50,000 vehicles. To facilitate the consideration of the impact of engine changes of vehicle 11 on vehicle 12 and on the same manufacturer's profit, we assume that vehicle 12 contributes $1,100 per vehicle to the profit.

The manufacturer's expected utility is obtained by assuming a risk-averse attitude, which is obtained by taking the log of the profit. The DBD optimization problem, shown in Fig. 4.10, is formulated as follows: *given* the vehicle demand model and decision-maker's risk attitude, *maximize* the expected utility of profit *with respect to* price, horsepower, torque, and low-end torque.

The market share impact (% change) for the 12 vehicles and the impact on the profit (in millions of dollars) of the manufacturer of vehicle 11 and vehicle 12 together with the expected utility for the five design alternatives (vehicle 11) are presented in Table 4.16. Examining the table, it is noted that under design alternative 1, increasing the horsepower, torque, and low-end torque with 3% and price with 5% leads to a 9.7% market share gain for vehicle 11 and a drop of vehicle 12's market share by 3.8%. When considering the (maximum of) expected utility of the five design alternatives, it appears that design alternative 4, consisting of a 3% torque increase while leaving the price unchanged, should be preferred. It should be noted that even though the DBD model is used to select the best design among a set of discrete alternatives in this study, the DBD model can also be used to select the best alternative among a range of

Table 4.16 Market share impact (% change), profit ($ million), and expected utility for case study

Vehicle Id	Design alternative				
	1	2	3	4	5
1	−0.4	−0.6	0.1	−0.1	0.2
2	−0.8	−0.9	−0.3	−0.5	−0.1
3	−1.1	−1.3	−0.6	−0.9	−0.5
4	−1.0	−1.1	−0.5	−0.7	−0.3
5	−0.3	−0.5	0.1	−0.1	0.4
6	−0.6	−0.7	−0.1	−0.4	0.1
7	−1.5	−1.7	−1.1	−1.3	−0.8
8	−1.8	−1.9	−1.3	−1.5	−1.0
9	2.9	2.7	3.4	3.1	3.7
10	−1.0	−1.1	−0.5	−0.7	−0.3
11	9.7	11.4	4.4	7.0	2.0
12	−3.8	−3.9	−3.4	−3.6	−3.0
Expected impact on profit	77.77	77.00	87.60	89.10	31.01
Expected utility	90.84	90.78	91.43	91.52	86.24

GIVEN
Market size M 1000,000 vehicles annually
Standard deviation σ_M 50,000
Customer-driven design attributes *A*
Demand model *Q*
The demand model is obtained using the multinomial logit technique to fit the discrete choice survey data
Cost model *C*
Determines the relationship between ***A*** and C
Corporate interests *I*
None other than the single selection criterion, V
Single criterion *V*
Net revenue $V = Q\,P - C$
Utility function $U(V)$
$U(V) = \log(V)$
Market Data *S* (Socioeconomic and demographic attributes)
Data related to gender, age, and income

FIND
Key customer attributes ***A*** and price P

MAXIMIZE
Expected utility of the net present value of profit V

Fig. 4.10 Vehicle engine DBD description

continuous decision variables via optimization as demonstrated in the universal motor case study (Fig. 4.5).

4.6 Summary

In this chapter the DBD framework that utilizes a single criterion for design alternative selection is presented. A systematic procedure for implementing the DBD approach is described. In contrast to some existing design approaches that construct a single utility function for a group of customers, the presented DBD approach optimizes a single-criterion utility function representing the economic benefit of a product to the enterprise. As part of the profit estimation, the demand modeling based on DCA predicts the choice for each individual customer and finally sums the choice probabilities across individual decision-makers (customers) to arrive at the market share of different products, thus avoiding the paradox associated with aggregating the utility or preference of a group of customers.

DCA is further established as a systematic procedure to estimate demand, which is critical for assessing the benefits a product brings to both the producer and the customers. The transformation of top-level customer desire groups to specific customer desires, and further into quantifiable engineering design attributes is introduced to bridge the gap between market analysis and engineering. As such, the customers' desired product attributes form the link between the design options and demand (and consequently profit), thus facilitating engineering design decision making. The Kano Method is used to provide econometric justification for selecting the shape of the customer utility function, which better captures the underlying purchase behavior, and enhances the predictive capability of demand models.

Employing the Kano Method to select and econometrically justify the customer utility function shape is a first step in improving the predictive capabilities of the proposed demand modeling approach. In Chap. 8, the handling of attributes will be improved by using the hierarchical choice modeling approach for the design of large-scale or complex systems, in which the set of customer-desired or socio-economic attributes is large and the attributes exist as a hierarchy within the design. Another approach that can be adapted to enhance capturing of the customer's perception of the product attributes is through consideration of the unobservable top-level customer desires in the customer utility function using latent variables. The latent variable modeling approach will be presented in Chap. 9.

While the DBD framework has been presented in this chapter, an necessary task is the creation of a tool to implement the method in a real engineering design setting. In the following chapter, a design process tool will be introduced to aid engineers and other design stakeholders implement the methods presented in this chapter.

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Part II
Techniques

Chapter 5
Product Attribute Function Deployment for Attribute Identification, Concept Selection, and Target Setting

Nomenclature

$\mathbf{A}$	Customer-desired product attributes
β	MNL coefficient of customer's utility function
C	Total product cost
C_D	Material and manufacturing cost for a design option
C_C	Capital cost for a design option
C_F	Fixed overhead corporate costs
ε_{in}	Random disturbance of customer choice utility of alternative i by customer n
$\mathbf{E}$	Engineering design attributes
$\mathbf{E^T}$	Target levels of engineering design attributes
$\mathbf{E_A}$	Engineering design attributes resulting from customer's desired attributes
$\mathbf{E_C}$	Engineering design attributes resulting from corporate requirements
$\mathbf{E_R}$	Engineering design attributes resulting from regulatory requirements
$\mathbf{E_P}$	Engineering design attributes resulting from physical requirements
$\mathrm{E}(U)$	Expected value of enterprise utility
$\mathbf{Fe}$	Design features
J	Set of competitive alternatives
MAP	Manifold absolute pressure
MNL	Multinomial logit
Mf	Manufacturing process attributes
P	Product price
Q	Product demand
$\mathbf{S}$	Customer demographic attributes
t	Time interval for which demand/market share is to be predicted
U	Enterprise utility, in units of *utils*
u_{in}	True customer choice utility of alternative i by customer n
V	Selection criterion used by the enterprise (e.g., profit, market share, revenues, etc.)

DOI: 10.1007/978-1-4471-4036-8_5,

W_{in}	Observed part of the customer choice utility of alternative i by customer n
X	Design options/High-level options in conceptual design
Y	Exogenous variables (represent sources of uncertainty in the market)

In this chapter, we provide a systematic method for determining the attributes to appear in the customer utility functions such as those used in discrete choice analysis (DCA) and ordered logit (OL) modeling as introduced in Chap. 3 for implementing the decision-based design (DBD) approach. The product attribute function deployment (PAFD) method overcomes the limitations of the qualitative matrix principles of popular design tools, such as quality function deployment (QFD), to map qualitative customer needs into quantitative engineering attributes by following the DBD principles. The PAFD is a process tool for implementation of DBD, for design concept selection and setting targets in conceptual design. A case study of the design of an automotive pressure sensor is provided to illustrate the method as well as demonstrate its advantages over the existing method.

5.1 The Product Attribute Function Deployment Method

Product planning requires a design process tool to establish engineering priorities, select the preferred design concept, and set target levels of engineering performance while considering the needs of both the customer and producer. QFD [4] (see introduction in Chap. 2), is an existing design process tool to translate customer needs into engineering characteristics; however, as noted in Chap. 2, significant limitations have been identified with such process tools. While QFD provides a useful visual format and encourages an interdisciplinary design process, it relies upon subjective performance assessments and potentially faulty rating and ranking methods.

The PAFD method [9] introduced in this chapter extends the qualitative matrix principles of QFD while utilizing the quantitative decision-making process of DBD. Combining the strengths of the QFD and DBD methods, the PAFD method is a multi–stage process that utilizes two “houses” to establish the qualitative attribute mapping to help set engineering priorities, select the preferred design concept, and determine target values, $\mathbf{E}^{\mathrm{T}}$, for the engineering attributes. Because PAFD is intended as a replacement for QFD, a comparison of analogous QFD and PAFD process steps, categorized into three primary stages, is shown in Fig. 5.1. In the first stage of both methods, customer preferences are quantified. PAFD uses a DCA model to express customer *demand* for an entire product relative to the existing competing products, whereas QFD uses a ranking of customer *preferences* for specific product attributes to assess customer acceptance of a product as a whole. In the second stage, the engineering design is characterized. PAFD utilizes preliminary analysis models to capture the costs and technical trade-offs among **E** (details provided later), whereas QFD uses the technical difficulty rating and

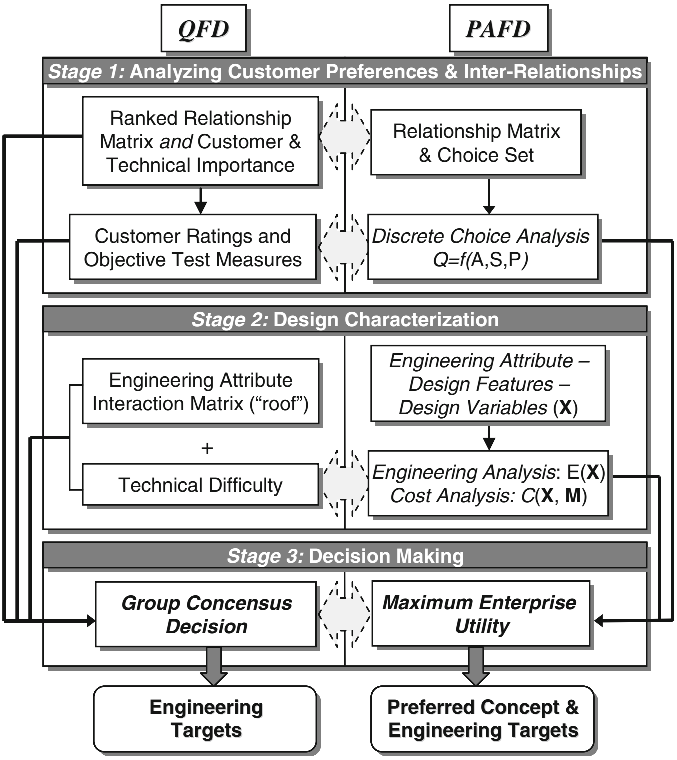


Fig. 5.1 Comparison of QFD to PAFD processes

correlation matrix mapping. PAFD explicitly considers engineering attributes resulting from customer, corporate, and regulatory sources, whereas QFD is primarily focused upon those engineering attributes resulting from customer-desired attributes, **A**.

In the third stage, PAFD provides design decisions in a single-step maximization of enterprise utility formulation, whereas QFD sets priorities using several ratings and rankings which must be synthesized by a human decision maker(s). The following subsections describe the three stages of PAFD in detail, with comparison to equivalent QFD processes.

5.1.1 Mapping of Attributes

Stages 1–3 provide a mapping methodology as follows.

Stage 1: Analyzing Customer Preferences and Attribute Interrelationships

A "house" structure is used to accomplish the Stage 1 processes of the PAFD method. Similar to conventional QFD analysis is the deployment of mapping

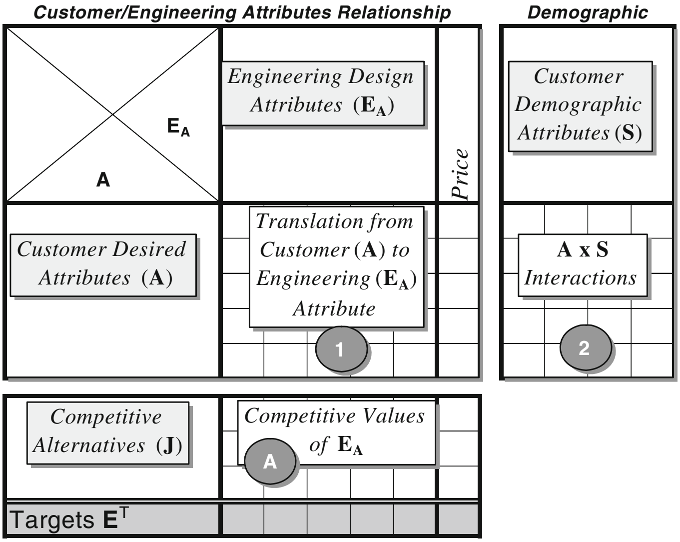


Fig. 5.2 House 1 of the PAFD method

between **E** and **A**, as well as the collection of engineering attribute levels from competitors' products (competitive analysis). The engineering attributes determined in this matrix are the **E** related to customer-desired attributes **A**, identified as $\mathbf{E_A}$. Also unique to PAFD, customer demographic attributes **S** and the **A**·**S** interactions (later transformed to $\mathbf{E_A}$ ·**S** for demand modeling) are identified to account for the heterogeneity of individual customers. This part of the expansion facilitates the construction of the DCA demand model to capture the impact of engineering design (engineering attributes) on customers' purchase behavior through estimation of product demand. As shown in Fig. 5.2, House 1 contains two relationship matrices:

- *Matrix 1*: Mapping customer-desired attributes, **A**, to engineering design attributes, $\mathbf{E}_{\mathrm{A}}$.
- *Matrix 2*: Identifying interactions between demographic attributes, **S**, and **A**.

Additionally, a table is provided for tabulating competitive alternatives in the choice set:

- *Table A*: Table of competitive alternatives J with corresponding levels of $\mathbf{E}_{\mathrm{A}}$ and price, P as well as Engineering Targets E^T.

The house can also be extended for use with the Latent Variable modeling approach presented in Chap. 9 by introducing an additional mapping between perceptual customer-desired attributes, **A**, to indicators, **I**, which is not shown in Fig. 5.2 for simplicity.

The relationship matrices in PAFD show only the qualitative linking between attributes. Unlike QFD, a rating scale (i.e., 1, 3, 9) is not utilized to characterize the strength of the relationship; however, an "$\times$" is used to indicate the presence of a relationship. The purpose of completing these relationship matrices is to ensure that each of the **A** has a corresponding $\mathbf{E}_\mathrm{A}$ (vector) and that interrelationships among **A**, $\mathbf{E_A}$, **S,** are clearly identified to enable choice modeling. The "roof", which identifies the coupling of engineering attributes in QFD, has been eliminated in PAFD because engineering attribute interactions will be modeled explicitly using preliminary engineering analyses in Stage 2, to better associate the coupling with a specific design concept. As illustrated in the case study in Sect. 5.2, the coupling of multiple engineering attributes, $\mathbf{E_A}$, can largely depend on the chosen design concept, with $\mathbf{E_A}$ coupling in different ways for different design concepts.

Stage 2: Design Characterization

This stage of PAFD results in *preliminary* engineering and cost analysis models which are intended to capture the high-level relationship between design concepts and both engineering performance and cost, as opposed to use in creating detailed product designs. The PAFD analyses explicitly consider specific design concepts, whereas the QFD analyses require the design characterization to be carried out at the engineering attribute level, with rankings of technical difficulty and attribute interactions used in place of established engineering and cost analysis methods.

To begin Stage 2, the $\mathbf{E}_\mathrm{A}$ established in House 1 become one set of engineering attributes tabulated in House 2 (price, P, is not included in Stage 2 because its value will be determined directly in Stage 3) as shown in Fig. 5.3. Unlike QFD analysis which is primarily focused upon the Voice of the Customer, the $\mathbf{E}_\mathrm{A}$ form just one subset of the entire set of engineering attributes **E** in PAFD. In addition, those attributes which a customer does not consider explicitly in product selection but are essential to producer's interests [5], specifically those resulting from corporate $\mathbf{E}_\mathrm{C}$, regulatory $\mathbf{E}_\mathrm{R}$, and physical requirements $\mathbf{E}_\mathrm{P}$, are also identified. This expanded set ensures that all requirements of the design are considered in the decision-making phase to make certain achievable targets are set.

With a comprehensive set of **E** determined and tabulated, designs can now be generated to fulfill those requirements. A *design concept* is defined as a high-level system configuration, composed of multiple subsystems and corresponding key *design features*, **Fe**. To facilitate preliminary cost and engineering analysis, each design feature, Fe_i, is represented by integer, discrete, or continuous *design variables*, **X**, such as material types, dimensions, etc. For each design concept, the attribute mapping in House 2 provides the qualitative relationship between the **E** and **X** through a mapping of **E** to **Fe** as shown in Fig. 5.3. From the qualitative relationship, the quantitative functional relationship, $E_i = f(\mathbf{X})_i$, is established using preliminary engineering analysis. In cases where design options are highly conceptual, and an analytical relationship cannot be established, the range of achievable levels of **E** can be estimated. The design variables (**X**) selected *are the minimum, high-level* set necessary to estimate the cost, C_i, of each feature and to represent the coupling of the design features in the decision-making process (Stage 3). The specific form and complete set of the X_i will be established in the detailed design process.

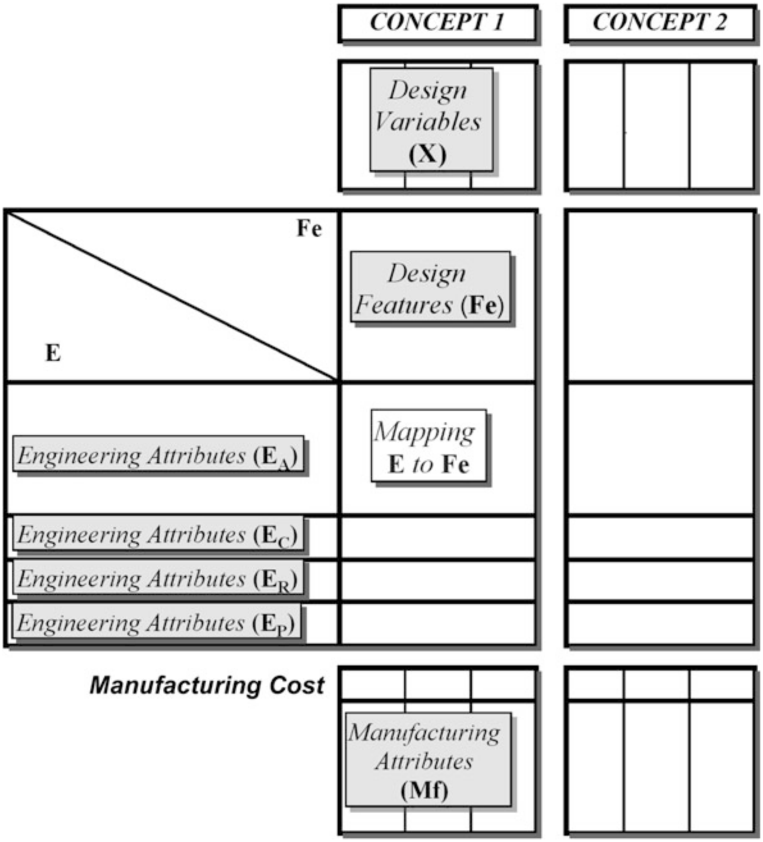


Fig. 5.3 House 2 of the PAFD method

After establishing the set of design concepts and specific high-level design features, preliminary *manufacturing process attributes*, **Mf**, are identified for each concept, and mapped to **Fe** (Fig. 5.3). The **Mf** are used to estimate processing costs and to identify constraints on **X** resulting from manufacturing process limitations to be considered in the decision-making stage of PAFD, as well as to ensure appropriate manufacturing processes are identified for each design feature. Using the identified **X** and **Mf**, estimation of the total cost, C^{k}, for each design concept, k, is calculated using:

$$C^{k}(\mathbf{X}^{k}, \mathbf{Y}, Q, t) = \sum_{R} C_{D}^{k}\left(\mathbf{X}^{k}, \mathbf{Y}, Q, t\right) + C_{C}^{k}(t) + C_{F}^{k}(t) \tag{5.1}$$

where $C_D^k(\mathbf{X}^k, \mathbf{Y}, Q, t)$ is the material and processing cost for each design feature, R is the number of design features, $C_C^k(t)$ is the cost of capital, and $C_F^k(t)$ is fixed corporate overhead cost for each design concept. The reason for establishing both preliminary engineering and cost analysis in PAFD is to capture the real trade-off behavior of engineering attributes, in order to ensure design selections resulting from the tool are optimal, and target performances are actually achievable.

The number of design concepts considered in PAFD is not fixed, with the house structure repeated for each additional concept to be evaluated. The design concepts and key design features can be generated using several methods available in the literature. Brainstorming and functional decomposition techniques [11, 12] can be utilized to generate the design concepts and corresponding design features, while TRIZ (Theory of Inventive Problem Solving) principles [1] can be employed to aid in the creative process. Optionally, Suh's axiomatic design method [13] can also be employed with PAFD, enforcing an uncoupled or decoupled relationship between the $\mathbf{E}$ and $\mathbf{X}$ and the $\mathbf{Mf}$ and $\mathbf{X}$. While the features of the design concepts can vary significantly, it is assumed that the concepts share a common set of engineering performance (attributes) $\mathbf{E_A}$ that matter to customers.

Stage 3: DBD: Design Concept Selection & Target Setting (Decision making)

As shown schematically in Fig. 5.1, PAFD evaluates designs through the maximization of expected enterprise utility $E(U)$, using the single selection criterion, V, constructed from the DCA demand (stage 1), engineering, and cost models (stage 2). In addition to selecting a preferred design concept and setting performance targets, PAFD, like QFD, can also aid in setting engineering priority through evaluation of parameter (β) importance in the DCA model and sensitivity analysis of the $E(U)$ function to determine which product attributes should receive the greatest resource allocation during the detailed design phase. In contrast, the evaluation process used by QFD is a (human) group consensus decision, in which the multi-attribute decision criterion requires synthesis of technical importance, technical test measures, technical difficulty, and attribute correlations by the decision maker(s). Engineering targets are set individually for each engineering attribute, based upon the best measured performances from the competing products. This methodology has been shown to be potentially faulty in Chap. 2.

Because the preliminary engineering and cost models are used for the purpose of capturing attribute trade-off behavior and are typically analytical expressions, the computational expense of evaluating such models, and hence the expense of the PAFD design selection method, is minimal. Additionally, $\mathbf{X}$ can often be represented by discrete values in the conceptual design phase, for example representing catalog component options [2]. The maximization of utility can be evaluated using a genetic algorithm which is commonly used in conceptual design selection when a combination of discrete and continuous design variables are present [6]. Constraints are of the form $g(\mathbf{X}, \mathbf{E}) \leq 0$, and are estimated for each design concept based upon corporate, regulatory, physical, and manufacturing constraints upon the $\mathbf{X}$ and $\mathbf{E}(\mathbf{X})$ identified in House 2.

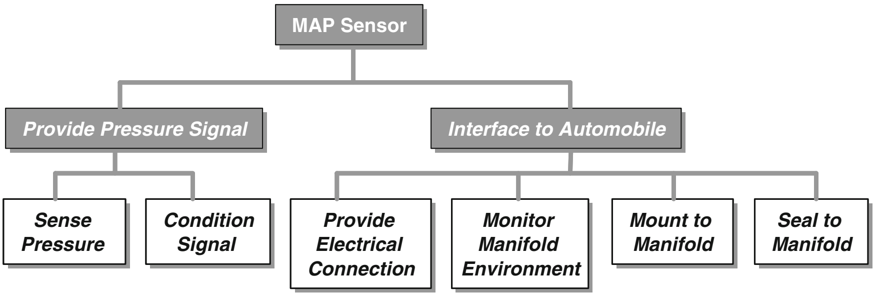


Fig. 5.4 MAP sensor functions

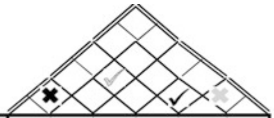
5.1.2 Estimation of a Choice Model Using PAFD

The DCA choice model is estimated using the $\mathbf{E}_{\mathrm{A}}$, P, and $\mathbf{S}$ identified in House 1 as explanatory variables, with J comprising the set of choice alternatives based on competitors' products. Unlike the competitive analysis in QFD (customer ratings), the competitive alternative set used in PAFD is for the purpose of estimating the DCA model as described previously. The values of $\mathbf{E_A}$ and P for each alternative together with the customer product *choice* form the basis for model estimation. The choice set is composed of either actual customer purchase choices or simulated product choices, such as those resulting from a market survey, as described previously. For a market survey, the list of $\mathbf{A}$ and $\mathbf{E_A}$ can help guide survey construction by providing an indication of the attributes that should be varied among the products presented in the survey [10].

The form of the parameters in the choice model requires insight into customer choice behavior, with potentially several model iterations needed to maximize the model goodness of fit. Linear (e.g., E_i) and transformed (e.g., E_i^2) forms of the variables are explored during the modeling process based upon expected choice behavior. The relationship matrices are used to guide the modeling of $A_i{\cdot}S_i$ interactions in terms of the $\mathbf{E}_{\mathrm{A}}$ and $\mathbf{S}$ necessary to make decisions at the engineering design level.

5.2 Case Study: Automotive Pressure Sensor Design

The conceptual design of an automotive pressure sensor is used as a case study to demonstrate the PAFD methodology. The specific example considered is to design a standard next generation Manifold Absolute Pressure (MAP) sensor for the automotive industry. The MAP sensor measures the air pressure in the intake manifold for fuel and timing calculations performed by the engine computer. The customers are *industrial customers*, composed of both automobile manufacturers and engine system sub–suppliers. The targeted market is the mid-size sedan segment. A high level function diagram of a MAP sensor is shown in Fig. 5.4.



Engineering Attribute (E) / Customer Attribute (A)	Importance	− Sense Element Accuracy	+ Pressure Span	+ Temperature Range	− Housing Footprint	+ Natural frequency housing	− Connector Mating Force	Customer Ratings 1 ⟵⟶ 5 (L) (H)			
High Accuracy	8	9	3					A	C	Our	B
Wide Pressure Range	6		9					A	B	Our	C
Withstand Temperature Extremes	6			9				C	Our	A	B
Small dimensional footprint	4		1		9		1	C	A	B	Our
Withstand High Vibration	4			1	3	9	1	A	Our	C	B
Low Connector Mating Force	2						9	Our	C	A	B
Technical Test Measures: Sensor A		2.0	80	145	18	1.4	35				
Technical Test Measures: Sensor B		1.0	185	180	16	2.1	25				
Technical Test Measures: Sensor C		1.5	250	140	26.0	1.7	35				
Technical Test Measures: *Our*		1.2	240	150	15	1.6	40				
Technical Difficulty		8	4	3	5	7	2				
Technical Importance		*72*	*82*	*58*	*48*	*36*	*26*				
Targets		**1.0**	**250**	**180**	**15**	**1600**	**35**				

Fig. 5.5 HoQ in original QFD analysis of MAP sensor

Multiple sensing technologies exist for pressure measurement, and each technology drives specific corresponding high-level design features, resulting in differing levels of performance and cost structure for each design concept. Therefore, before detailed design of the sensor begins, the preferred design concept must be selected and target levels of product performance must be established. A *risk-averse* attitude is assumed for the enterprise, and the market size is assumed to grow by 10%/yr. over the time interval, *t*, of 4 years considered in the forecast. Both a QFD and PAFD analysis are conducted to better illustrate the parallels between the two methodologies, with the differences in the resulting design decisions demonstrated.

5.2.1 QFD Analysis of MAP Sensor

To begin the QFD analysis, the **A** (e.g., *High Accuracy* and *Withstand Temperature Extremes*) and the key $\mathbf{E_A}$, such as *Housing Footprint* (mm^2) and *Temperature Range* (°C), are placed in the appropriate rows and columns of the HoQ as shown in Fig. 5.5.

The engineering team must rank-order the importance of each **A**, fundamentally establishing a "group utility" for each attribute as described previously, and determine a "direction for improvement" for each of the $\mathbf{E_A}$ based on engineering judgment, as shown by the "+" and "–" signs preceding each $\mathbf{E_A}$. The relationship matrix is then completed, with the engineering team determining the strength of relationship between the $\mathbf{E_A}$ and **A**, using a largely subjective evaluation based on the experience level of the team members. With the relationship matrix complete, the *Technical Importance* is calculated for each E_A to determine engineering priority for each attribute, with a higher importance rating indicating higher engineering priority. The "roof" *Correlation Matrix* is completed, with ✔ indicating positive correlation and × negative correlation between attributes (e.g., negative correlation indicates a performance improvement to one attribute degrades the performance of another attribute), and the *Technical Difficulty* rating is estimated (higher number indicates greater difficulty). These analyses can be viewed as highly simplified, empirical forms of the engineering, and cost analyses explicitly formulated in the PAFD method.

To complete the *Customer Ratings*, a market study (Stated Preference) is conducted in which several customers are surveyed to determine customer perceptions of current competitive MAP sensors on the market. The respondents are asked to rank-order the performance of three competitive sensors (labeled A, B, C), plus the current generation sensor (*Our*), with respect to each **A** they have identified, with the ranking results shown in Fig. 5.5. For example, the customer group evaluation for *High Accuracy* indicates that Sensor B is perceived as having the highest accuracy and Sensor A the lowest accuracy. Note that with QFD, the customer ranking must be aggregated in order to achieve a single rank-order for each **A**, a process shown to be potentially problematic [8]. To complete the QFD analysis, the actual measured performance level of each engineering attribute is determined for each of the four sensors and documented in the *Technical Test Measures* portion of the HoQ.

With the HoQ completed, performance targets for the sensor are determined through a multi-attribute consideration of the *Technical Test Measures*, *Customer Ratings*, *Technical Difficulty*, and *Correlation Matrix*. The performance target decision is made relative to the current levels of performance of *Our* sensor, with the values identified in the *Technical Test Measures* representing the best known levels of performance for each **E** which should be targeted by the new sensor. The *Technical Difficulty* and *Correlation Matrix* provide subjective constraints upon performance. Using the QFD methodology, the targets are shown at the bottom of the HoQ in Fig. 5.5. It was decided that the new sensor should have improved target performances for *Accuracy*, *Pressure Span*, and *Temperature Range*, since these have high technical importance, and *Our* current sensor is not perceived as the market leader in these areas. Also, it was decided to improve the target for *Connector Mating Force* since it has a very low technical difficulty. It was decided not to improve the target for *Housing Footprint*, since *Our* sensor is the market leader, or *Natural Frequency* due to high technical difficulty and low technical importance. With targets set, product design concepts may be further brainstormed by an engineering team, and the preferred concept selected with a tool external to the HoQ, such as Pugh's Method.

Customer/Engineering Attributes Relationship								Demographic			
DCA Variables / Engineering Attributes (E_A) / Customer Desired Attributes (A)	AC	PS	TR	FT	NF	MF		AR	ER	MS	
	Element Accuracy (% Error)	Pressure Span (kPa)	Temperature Range (°C)	Housing Footprint (cm^2)	Natural frequency housing (Hz)	Connector Mating Force (N)	**Sensor Price ($)**	Vehicle Origin: Asia	Vehicle Origin: Europe	Vehicle Market Segment	*Interaction Parameters* (β_3)
High Accuracy	×	×						×	×	×	✳
Wide Pressure Range		×								×	**0.3**
Withstand Temperature Extremes			×		×						
Small dimensional footprint				×							
Withstand High Vibration				×	×						
Low Connector Mating Force						×					
Sensor A	2.0	80	145	17.7	1400	35	10.0	Base	Base	Base	Base
Sensor B	1.0	185	180	16.4	2100	25	10.2	**7.4**	**7.0**	**7.3**	**-6.4**
Sensor C	1.5	250	140	26.0	1700	35	12.4	**8.0**	**9.5**	**12.8**	**-6.7**
Our	*1.2*	*240*	*150*	*14.6*	*1600*	*40*	*11.5*	**7.1**	**7.9**	**-2.4**	**-5.6**
DCA Parameters (β_1)	**-2.8**	✳	**0.02**	**-0.4**	**-0.001**	✳	**-6.9**	*ASV* (β_2)	*ASV* (β_2)	*ASV* (β_2)	*ASC*
Normalized DCA Parameters (β_1)	-5.6	✳	2.9	-9.6	-3.1	✳	-85.6				
Targets E^T											

Fig. 5.6 PAFD house 1 for MAP sensor

5.2.2 PAFD Analysis of MAP Sensor

Stage 1: Understanding MAP Sensor Requirements and Interrelationships

As the first step in PAFD, customer-desired attributes **A** and engineering attributes $\mathbf{E}_A$ are placed in the appropriate rows and columns in the same manner as the QFD analysis (Fig. 5.6). In contrast to QFD analysis, demographic attributes **S** (e.g., *Vehicle Market Segment*) are also identified and tabulated. Note that the **S** for the industrial customers are company-specific attributes, such as the corporate location or the specific market niche in which the company competes. As described previously, the **S** account for the heterogeneity of customer choice, *i.e.* they explain why different customers choose different MAP sensors for similar applications. With **A**, $\mathbf{E}_A$, and **S** identified, hypothesized relationships are marked by an "×" in matrix 1 identifying the linking of the $\mathbf{E}_A$ to **A**, and in matrix 2 identifying the potential interactions among the **S** and **A** which influence choice behavior, such as the interaction of *High Accuracy* and *Vehicle Market Segment*.

To acquire the choice data necessary to estimate the DCA model, simulated sensor purchase data (Revealed Preference) was utilized, unlike the QFD analysis in which respondents were asked to rank-order the performance of each sensor for each **A**. The purchase data for *Our* sensor represents the current generation sensor on the market; alternatively, a *Stated Preference* survey [10] could be conducted using prototypes of the new sensor design, if desired. The demographic data **S** for each customer in the data set is recorded in the PAFD method. A sample of the purchase and recorded demographic data **S** is shown in Appendix A. A MNL DCA model is formulated as a function of the values of $\mathbf{E}_{\mathrm{A}}$, P, and **S** using the choice data collected for the four sensors. The model parameters (β) estimated to create a choice model with good fit statistics are composed of linear (e.g., *Accuracy*, *Temperature Range*), interaction (e.g., *Accuracy* · *Vehicle Market Segment*) and alternative-specific variables (e.g., $Alternative_j$ · *Vehicle Market Segment*), with alternative-specific constants included to capture inherent preferences for each alternative. The results are shown in House 1 (Fig. 5.6), which has been extended from the template shown in Fig. 5.2 to include a summary of the β parameters in the gray region (note that not all E_A enter W as indicated by a ✳, as some parameters are not statistically significant or are highly correlated with other E_A). Referring to the equation for W_{in} in Chap. 3, the β parameters establish the customer choice utility function, W, of each alternative. In particular, each alternative shares a common set of product selection attribute parameters, which form the *common* customer choice utility function:

$$\begin{aligned} W_{Common} = {} & -2.8(AC_i) + 0.02(TR_i) - 0.4(FT_i) - 0.001(NF_i) - 6.9(PRICE_i) \\ & + 0.3(PS_i \times MS). \end{aligned} \tag{5.2}$$

The specific customer choice utility functions for each of the competitive alternatives is then determined for use in Stage 3, using the common utility formulation of Chap. 3:

$$\begin{aligned} W_{\mathbf{A}n} &= (W_{common})|_{i=1} \\ W_{\mathbf{B}n} &= -6.4 + (W_{common})|_{i=2} + 7.4(AR) + 7.0(ER) + 7.3(MS) \\ W_{\mathbf{C}n} &= -6.7 + (W_{common})|_{i=3} + 8.0(AR) + 9.5(ER) + 12.8(MS). \end{aligned} \tag{5.3}$$

A customer choice utility function is also developed for *Our* sensor design:

$$W_{\mathbf{OUR}n} = -5.6 + (W_{common})|_{i=4} + 7.1(AR) + 7.9(ER) - 2.4(MS). \tag{5.4}$$

Examination of the utility function provides insight into customer choice behavior. The sign of the parameter indicates the effect of an attribute upon W, for example increasing the *Price* ($\beta = -6.9$) of a sensor decreases W, and hence the probability of choice of that sensor, *ceteris paribus*. Additionally, the effect of **S** upon utility can also be examined. For example, W and hence the probability of choice of Sensors B, C, and *Our* increases relative to the reference (Sensor A) if the customer is located in Asia (AR) or Europe (ER); the greatest increase in W is for Sensor C as indicated by the magnitude of the β parameters for AR ($\beta = 8.0$) and ER ($\beta = 9.5$) in the $W_{\mathbf{C}n}$ expression. To understand the engineering priority of each $\mathbf{E_A}$ and $\mathbf{E_A} \times \mathbf{S}$ in terms of their impact on demand, the β coefficients can be normalized as shown in the last row of Fig. 5.6 to allow the importance of each attribute to be estimated based upon its magnitude. For example, *Price* is the most important attribute ($\beta_{\mathrm{NORM}} = -85.6$) while *Temperature Range* is the least important ($\beta_{\mathrm{NORM}} = 2.9$).

With a customer choice utility function available for each alternative, Eq. (5.4) can be utilized to determine the demand for the new design concepts based upon the values of $\mathbf{E_A}$ and P substituted into Eq. (5.4) during the decision-making phase in Stage 3.

Stage 2: MAP Sensor Design Concepts Identification and Characterization

Stage 2 begins by transferring the $\mathbf{E}_{\mathrm{A}}$ identified in House 1 to the **E** Column in House 2, Fig. 5.7, and establishing the additional engineering design attributes derived from corporate, regulatory, and physical requirements, such as *Common Platform* as $\mathbf{E}_{\mathrm{C}}$, *UL Flammability Resistance* as $\mathbf{E}_{\mathrm{R}}$, and *Housing Stress* as $\mathbf{E}_{\mathrm{P}}$, to form the complete set of **E**. With **E** identified, design concepts and their corresponding design features **Fe** can be formulated. For this problem, two design concepts were identified: *Concept 1* utilizes a piezoresistive (PRT) sensing element with a micromachined sensing diaphragm, which senses pressure due to bending of the diaphragm, and *Concept 2* utilizes a two–plate capacitive sense element, which senses pressure due to a change in the capacitor plate separation distance.

Both design concepts are shown in Fig. 5.8. Due to differences in the designs of the sensing elements, the piezoresistive concept is inherently less-expensive and results in a smaller package, whereas the capacitive concept is more robust to temperature and pressure extremes.

The key design features for each concept are established and the corresponding high-level design variables, **X**, to model the technical trade-offs and cost for the decision-making problem are determined and tabulated (Fig. 5.7). For example, piezoresistive sense element *thickness* is a continuous variable to be determined based upon the trade-off among element length, manufacturing limitations, and cost; integrated circuit A/D discretization *resolution* is a discrete variable to be determined based upon the trade-off between sensor accuracy and cost. Key conceptual manufacturing processes, **Mf**, (e.g., micro-machining, injection molding, etc.) are identified for each design concept, and placed in the columns corresponding to the associated design feature, **Fe**, shown in Fig. 5.7. Manufacturing process costs are also estimated for each design feature for use in the cost model (Eq. 5.1).

As demonstrated by this case study, the technology selection drives specific design features and the corresponding set of design variables for a given design concept. For example, the packaging of each sensor is fundamentally different as shown in Fig. 5.8: Concept 1 uses an injection–molded housing with integral pressure port and connector, whereas Concept 2 requires a separate port and connector component because of the large size and electrical interconnect of the capacitive element.

Also noted, each set of high-level design variables **X** for a given concept has a different functional relationship with **E** ($\mathbf{E} = f(\mathbf{X})$). Concept 1 utilizes the piezoresistive sensing element with a resistance output given by the relation [7]:

		DESIGN CONCEPT 1					DESIGN CONCEPT 2					
	Design Variables (X)	Length, Thickness	Resolution, Error (T)	Width, Length, Polymer Mating Force	Thickness, Material	Thickness, Material	Area, Separation	Resolution, Error (T)	Width, Length, Polymer	Thickness, Material	Mating Force	Thickness, Material
	***Component Design Features* (Fe)** / ***System Engineering Attributes* (E)**	Piezoresistive Sense Element	Digital Signal conditioning IC	Integral housing/USCAR connector	Steel Housing Reinforcement	Rubber Pressure Seals	Capacitive Sense Element	Digital Signal conditioning IC	Polymer Housing	Steel Housing Reinforcement	USCAR Connector	Rubber Pressure Seals
E_A	Sense Element Accuracy (%)	×	×				×	×				
E_A	Pressure Span (kPa)	×	×			×	×	×				×
E_A	Temperature Range (°C)	×		×			×		×			
E_A	Housing Footprint (cm^2)			×					×			
E_A	Natural frequency housing (kHz)				×					×		
E_A	Connector Mating Force (N)			×							×	
E_C	Common Platform	×	×				×	×			×	
E_R	UL Flammability Resistance			×					×		×	
E_T	Housing Stress (kPa)				×					×		
	Estimated Manufacturing Cost	$0.25	*	$1.00	$0.10	$0.20	$0.40	*	$0.40	$0.10	$0.55	$0.20
	Manufacturing Attributes (Mf)	*Micromachining*	** Catalog*	*Insert Molding*	*Stamping*	*Transfer Molding*	*Micromachining*	** Catalog*	*Injection Molding*	*Stamping*	*Insert Molding*	*Transfer Molding*

Fig. 5.7 PAFD engineering design house 2 for the MAP sensor

$$Pressure\,Span = k(\Delta L_E/L_E) \tag{5.5}$$

where the engineering attribute is *Pressure Span*, the design variable is diaphragm length L_E, and the piezoresistive k-factor, k, is a constant. Concept 2 utilizes a capacitive output given by:

$$Pressure\,Span = \varepsilon_0\varepsilon_r(A_E/\Delta D_E) \tag{5.6}$$

where the engineering attribute is *Pressure Span*, the design variables are the plate area, A_E, and the plate separation distance, D_E, with absolute and relative dielectric

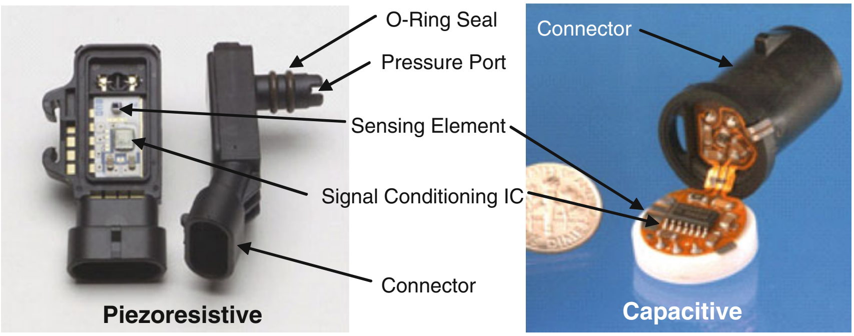


Fig. 5.8 Comparisons of concepts 1 and 2

constants, ε_0, and ε_r. A list of all engineering relations used in this analysis is provided in Appendix A. These analyses are intended to be preliminary analyses to capture the fundamental trade-offs among the critical design variables, and will be refined during the detailed design phase to enable final design of the sensor.

Each concept requires a specific manufacturing process, and the different sets of **Mf** result in a differing cost structure and place different constraints upon the **X**. For example, the micromachining process used to manufacture the diaphragm of the piezoresistive sense element results in a minimum diaphragm thickness limitation, and hence, places a constraint on the minimum size of the sense element, independent of engineering analysis. Also confirmed by this study is that engineering design attributes, **E**, resulting purely from customer-desired attributes, **A**, are not sufficient to create an engineering specification (target setting). For example, consideration of the stresses induced by the manufacturing process on the sensor housing leads to a key constraint upon the sensor housing design which would not have resulted from customer-desired attributes.

Stage 3: Design Concept Selection and Target Setting

Stage 3 of PAFD is conducted by formulating the decision-making problem as shown in Table 5.1.

Three types of uncertainty are considered in the selection process:

- *Demand Model Uncertainty*: Uncertainty in all DCA model parameters (i.e., βs), as quantified by the standard error (S.E.) estimates, is considered.
- *Cost Estimation Uncertainty*: Because the costs are estimated, uncertainty in the estimates must be considered. It is assumed that the cost estimates for Concept 1 have $\pm$ 10% error, while estimates for Concept 2 have $\pm$ 30% error, since it is assumed that the designers are more familiar with the design and costs of Concept 1.
- *Design Variable Uncertainty*: The piezoresistive sense element thickness, T_E, and Capacitive sense element plate separation distance, D_E, are normally distributed random variables due to known variation in the element manufacturing processes.

Table 5.1 Pressure sensor decision-making formulation

Given	
Mid-size sedan market size: 1,000,000 [sensors/year] for 4 years	
Demographic data of targeted industrial customers **S**	
Engineering attributes E_A (*PAFD*: *House 1*)	
$\mathbf{E_A}$ determined as a function of the high-level design options **X** (**E**(**X**))	
Design concept (*PAFD: House 2*)	
Two (2) design concepts considered (piezoresistive & capacitive sensing)	
Sources of uncertainty Y	
DCA model parameters	S.E. of β
Cost estimates	$C^1 = \pm 10\%$, $C^2 = \pm 30\%$
Normal distribution of T_E and D_E	$\sigma = (0.1)\ \mu$
Cost model (*PAFD: House 2*)	
Cost of each alternative given by Eq.(5.1).	
Demand model Q (*PAFD: House 1*)	
Obtained from the MNL model of the competitive alternative attribute data.	
Single criterion $V = QP$-C	
FIND:	
Design variables **X**, target engineering levels $\mathbf{E^T}$ (PAFD: House 1) and Price *P*	
MAXIMIZE:	
E(*U*), assuming an enterprise risk-averse attitude	
SUBJECT TO (PAFD: House 2):	
$g(\mathbf{X}, \mathbf{E}) \leq 0$	$T_E - 14.0 \leq 0$; $D_E - 12.0 \leq 0$: *Constraints from Mf*
$g(\mathbf{X}, \mathbf{E}) \leq 0$	$PS - 80.0 \leq 0$; $NF - 1400.0 \leq 0$: *Constraints from* E_C *and* E_P

These uncertainties create risk in the decision process. The preferred concept, considering uncertainty, depends upon the decision-maker's (i.e., the enterprise) risk attitude. The risk attitude assumed by the enterprise in this case study is moderately risk-averse. However, the decision-making process will be demonstrated for risk-averse, risk-neutral, and risk-seeking attitudes.

5.2.3 Comparison of PAFD and QFD Results

The results of the PAFD decision process are shown graphically in Fig. 5.9 (a) in which the full distributions of profit for both concepts are shown. Figure 5.9 (b) illustrates the expected utility of each concept considering a variety of enterprise risk attitudes. The risk attitude is modeled using an exponential utility function in which higher relative risk tolerance indicates increasing risk-seeking.

As demonstrated, Concept 1 is preferred for risk-averse, risk-neutral, and moderate risk-seeking attitudes. However, Concept 2 is preferred for a high risk-seeking attitude, since the greater uncertainty in Concept 2 results in a higher upside potential than Concept 1.

The results of both the PAFD and QFD analyses corresponding to a moderate risk-averse attitude are shown in Table 5.2. The PAFD decision results in performance targets $\mathbf{E}^{\mathrm{T}}$, and values of demand, price, and cost for both Concepts 1

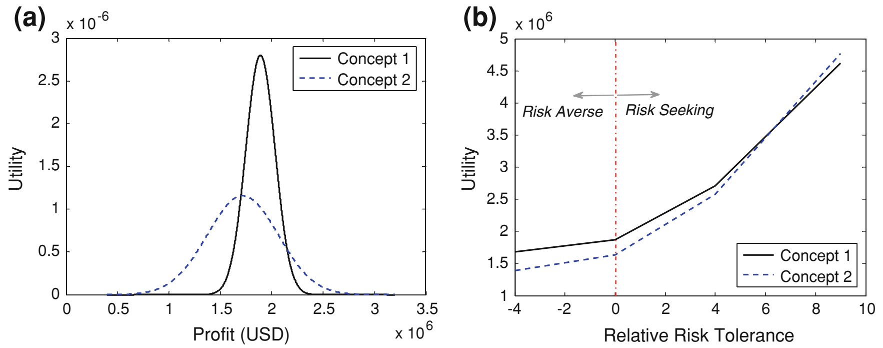


Fig. 5.9 **a** and **b**: Comparison of profit and utility for concepts 1 and 2

Table 5.2 Comparison of Decision Results–Preferred Concept (shaded)

Engineering attribute E	PAFD (E^T) Concept 1	PAFD (E^T) Concept 2	QFD (E^T)
Sense element accuracy (%)	1.23	1.19	1.0
Full-scale span (kPa)	176.0	185.0	250.0
Temperature range (°C)	150.0	150.0	180.0
Housing footprint (cm^2)	16.9	17.2	14.6
Natural frequency (Hz)	1400.0	1425.0	1600.0
Connector mating force (N)	40.0	40.0	35.0
Q: Demand/year (*# sensors*)	416,000	433,000	541,000
P: Unit price (*USD*)	$10.40	$10.58	$10.40
C: *Unit cost* (*USD*)	$9.25	$9.66	$10.32
Expected profit (USD)	$1,905,000	$1,706,000	$173,000
Expected (*U*) (*utils*)	1,683,000	1,393,000	170,000

and 2. The preferred design concept for this problem is *Concept 1*, which results in the highest utility for the enterprise considering uncertainty ($E(U)$ = 1,683,000 *utils*). The QFD analysis results in performance targets only, which are not associated with a design concept, and additionally QFD has no mechanism for determining price *P*. For the purpose of comparison, the unit price of the QFD design is set at the same price ($10.40) as Concept 1 (the preferred design from the PAFD method) and profit and utility estimated using this price.

Compared to the PAFD results, the QFD identifies targets based upon the best values of $\mathbf{E}_A$ identified in the competitive analysis, which subsequently leads to a lower value of $E(U)$ of 170,000 *utils*. The reason the QFD resulted in such low enterprise utility is that although the estimated demand, *Q*, for a sensor meeting the targets set by QFD is higher than those identified by PAFD, the cost to make such a sensor is significantly higher ($10.32). As described in Section Chap. 2, QFD is biased toward meeting customer product desires and does not explicitly consider cost, leading to a sensor design with good customer acceptance potential but low expected enterprise utility. Additionally, because parameter relationships identified through engineering analysis and constraints determined in the PAFD Stage 2 process are not utilized, it is not known with confidence if these QFD targets can actually be achieved in the subsequent sensor design. For the PAFD analysis, the target levels identified for the preferred concept reflects the actual achievable levels of $\mathbf{E}_A$ which maximize enterprise utility for this design concept, based upon the constraints imposed in the decision-making problem. This is further illustrated by noting that Concept 2 has different values of $\mathbf{E}^T$ corresponding to the maximum enterprise utility for that particular concept.

To set engineering priority using the PAFD analysis, a global sensitivity analysis [3] is conducted as recommended previously to study the total effect of individual engineering attributes on the *E(U)*. The results of this analysis indicate that the greatest resource allocation should be made to achieving the targets for *Housing Footprint* and *Pressure Span*, due to the sensitivity of enterprise utility to these parameters. For QFD, the *Technical Importance* measure is used to establish engineering priority, resulting in selection of *High Accuracy* and *Pressure Span* as the highest priority. The difference in priority results from the different focuses of the two tools, with PAFD focused upon maximizing enterprise utility and QFD focused primarily upon customer product acceptance. In summary, the PAFD method has provided a clear conceptual direction and engineering targets necessary to begin the detailed design of the MAP sensor; detailed engineering analysis can be utilized to create the specific feature designs which meet these targets.

5.2.4 Validation and Discussion of the PAFD Method

A primary feature of the PAFD is the use of a DCA model to predict customer demand for a design option. The choice model was validated using a cross-validation method, in which the data is partitioned into training and test sets [14]. The results show approximately a 5–10% error in predicting the choice share on the test sets; however, such errors equally affect predictions for both Concepts 1 and 2 and do not change design selection result. To explore the effect of demand model specification on the selection process, a model was used in the process which did not include country (i.e., Asia, Europe) attributes. For such a model, cross-validation indicated greater errors on the test sets (10–18% errors) and did result in higher predicted choice share and approximately 8% higher profit for Concept 1 and 10% higher profit for Concept 2; however, the selection process was not affected as Concept 1 is still preferred for risk-averse, risk-neutral, and moderate risk-seeking attitudes using this model.

The case study presented demonstrates the advantages of the proposed PAFD method. It has been shown to preserve the primary strengths of QFD by offering a visual tool, maintaining ease of use, and promoting team work. The method can be expanded beyond the three stages shown in Fig. 5.1, for example to include a specific stage for the design of choice experiments described in Chap. 6.

The method can also find application in the service industry, to design the service to best meet the needs of both the customers and the enterprise providing the service.

The PAFD method can identify a preferred solution in situations in which cost and performance models can be formulated, and the risk attitude of the enterprise can be formalized. A potential limitation of the PAFD method is that it is based on the assumption that a DCA choice model can be estimated to represent customer preferences. This assumption would not be valid in cases where the customer is a single or small group of customers (such as for a component sub-supplier of a major system), for highly specified designs, or in industries which do not have the infrastructure for customer preference data collection.

5.3 Summary

In this chapter, The PAFD method is presented to offer a mathematically rigorous, decision-theoretic process tool for use during the product planning phase of a product development program. The need for developing such a method results from a close examination of the needs during the conceptual design phase, and the limitations of current methods, such as QFD, currently used for this purpose. The PAFD method extends the QFD mapping matrix concept to qualitatively identify relationships and interactions among product design attributes while employing the DBD principles to provide rigorous quantitative assessments for design decisions. In conceptual design, the PAFD method is used to identify attributes for modeling customer utility functions, select the preferred design concept, set target levels of engineering performance, and set engineering priorities. The PAFD method can be implemented, with minor modification, to work with alternative enterprise-driven design approaches to provide the necessary quantitative assessments.

In addition to presenting the PAFD method, a comprehensive comparison of QFD and PAFD is provided, demonstrating the parallels between the two methods and the improvements achieved by utilizing DBD principles in the new tool. The use of single-objective utility maximization provides a rigorous mathematical framework for decision making under uncertainty, alleviating the difficulties associated with weighting factors and multi-objective decision making in QFD. The use of profit as a single criterion better captures the real design trade-offs, incorporating the needs from both the producer and customer to set engineering targets consistent with enterprise objectives. The heterogeneity of customers is captured through the inclusion of demographic attributes, **S**, in the DCA model, addressing the aggregation issues present in QFD. The subjective ratings and rankings present in QFD are replaced with established methodologies in engineering, cost, and decision analysis to set targets for performance which can be achieved in practice. Uncertainty is explicitly addressed through the use of expected enterprise utility as the decision criterion.

A case study involving the conceptual design of a Manifold Absolute Pressure (MAP) sensor is used to illustrate the benefits of the PAFD method. Complex trade-offs among engineering, manufacturing, and customer considerations which would result in a difficult synthesis and subsequent decision-making process using QFD are resolved effectively using the PAFD approach. While the PAFD method has been demonstrated as a method for design concept selection, it provides a general design process tool that can be utilized throughout the design process, such as the vehicle target setting case study of Chap. 8 or Chap. 9. The simple choice model presented here, in which it was assumed that the mapping from qualitative customer-desired attributes to engineering attributes is straightforward, can be replaced with the Bayesian Hierarchical Choice Model of Chap. 8 or the Latent Variable approach of Chap. 9 for a complex system.

Appendix A: Sample Data of Map Sensor Problem

Table A.1 Sample of choice set used for estimation of DCA model

Customer	Demographic S		Purchase
	Region	Market segment	
Customer 1	North America	\$30,000.00	Our
Customer 2	North America	\$29,000.00	Our
Customer 3	Asia	\$22,000.00	Sensor A
Customer 4	North America	\$24,000.00	Sensor B
Customer 5	North America	\$24,500.00	Sensor B
Customer 6	Asia	\$34,000.00	Sensor C

Table A.2 Analytical relationships between E and X

Engineering attribute **E**	Concept 1 **E** as a function of $\mathbf{X}^1$	Concept 2 **E** as a function of $\mathbf{X}^2$
Sense element accuracy	ε(calibration) + ε(A/D)	ε(calibration) + ε(A/D)
Full-scale span	$k \times \Delta l/l$	$\varepsilon_0 \varepsilon_r A/\Delta d$
Temperature range	Min[$T_{\max}$(IC), T_g(Housing)]	Min[$T_{\max}$(IC), T_g(Housing)]
Housing footprint	Housing width × length	Housing width × length
Natural frequency	$Cn_j\sqrt{EI/\rho AL^4}$	$Cn_j\sqrt{EI/\rho AL^4}$
Connector mating force	25, 35, 40	25, 35, 40

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Chapter 6
Design of Experiments for Eliciting Customer Preferences

Nomenclature

A	Customer-desired product attributes
α	Pairwise correlation coefficient for multinomial covariance matrix
$\boldsymbol{\beta}$	Choice model coefficient in customer's utility function
B	Number of configurations given to a single respondent
$\mathbf{D}_n$	Derivative of $\boldsymbol{\pi}_i$
det	Matrix determinant
E	Engineering Attributes
ε_{in}	Random unobservable part of the utility of configuration i for respondent n
$\mathbf{f}(\mathbf{x})$	Extended experiment design point, including intercept/cutpoints, interaction, and higher ordered terms than $\mathbf{x}$
f	PDF of the logistic distribution
F	CDF of the logistic distribution
$\mathbf{F}$	Extended design matrix
G	Candidate set of design points
GLS	Generalized least squares (Regression)
i	A configuration
inv	Matrix inverse
$\mathbf{k}$, k_p	Ordered logit cutpoints
M	Number of configurations in a complete experimental design
$\mathbf{M}$	Fisher information matrix of an experimental design
n	A block or respondent
OLS	Ordinary least squares (Regression)
P	Number of ordered ratings categories
$\mathbf{P}$	Working correlation matrix
π_{inp}	Probability of rating p for respondent n and configuration i
$\mathbf{R}$	Ratings
ρ	Pairwise ratings correlation coefficient
ρ^2	Model fit statistic for ordered logit/probit model

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_6,

σ_u	Variance at the respondent level
σ_ε	Variance at the observation level
$\mathbf{S}$	Human attributes
T	Number of tries conducted in the algorithm
u_{in}	Utility of configuration i for respondent n in the ordered logit/probit equation
$\mathbf{V}$	Asymptotic variance-covariance matrix
$\mathbf{x}$	Design point for product and human factors. A sub-set of $\mathbf{f}(\mathbf{x})$
$\mathbf{X}$	Extended design matrix, composed of $\mathbf{f}(\mathbf{x})$

In this chapter, the survey methods needed to elicit the customer preference data to estimate a discrete choice analysis (DCA) or ordered logit (OL) model, are introduced. The survey methods are based upon established Design of Experiments methodologies, but adapted for the specific needs of stated preference experiments. We first present an overview of the design of experiments methodology. We next focus upon surveys designed for eliciting choice responses to estimate a DCA model, covering both standard experiments as well as optimal conjoint experiment methods. Furthermore, we present both standard and optimal experiments for rating responses to estimate an OL model. We finish the chapter with an experimental design case study to elicit preferences for automobile occupant packaging design.

6.1 Introduction to Design of Experiments Methodology

In the previous chapters, we discussed the need to collect data using market surveys or other means to estimate a DCA (or OL) model. A key issue not addressed in those chapters is what methodologies should be used to acquire the necessary data to build the model. Additionally for Chaps 8 and 9, preference data are required not only to fit a DCA model to predict choice, but also to fit an OL model to predict ratings. This highlights a general need for the development of a standardized approach for designing experiments to assess customer preferences, using *Choice* (for choice data) or *Human Appraisal* (for ratings data) experiments. Choice and human appraisal experiments are used to assess customers' opinions of a given product design, and are unique in that the experiment response is a function of both the product engineering attributes $\mathbf{E}$ and the socio-demographic attributes $\mathbf{S}$.

The choice and human appraisal experiments can be designed using Design of Experiments (DOE) methodology. The general area of DOE has a long and rich history in statistics; an early text on the topic which laid the foundations upon which modern DOE methodology is built was published by Fisher in 1935 [5]. Since then, the basic methodology has been refined and expanded by statisticians [3, 26], and specialized methodologies based on the fundamental principles have been extended for use in gathering preferences, generally classified as stated preference (or stated choice) methods in the field of preference modeling [21, 33]. In addition to the

Table 6.1 Example of factors, levels, and responses for choice experiment

Alternative	Choice	Speed	Price	Maintenance interval
1	0	1	0.97	0.64
2	1	0.71	0.73	1
3	0	0.67	0.63	0.89

standard experiment designs available in the DOE literature, methods for optimal design of experiments are also available for building custom experimental designs for situations in which standard designs are not efficient, or specific constraints on the testing conditions are present [1]. As noted by Hensher et al. [10] in their choice modeling primer, the field of DOE is too extensive to be covered comprehensively in a single chapter. Therefore, the focus of this chapter is to provide an overview of the basic concepts in DOE and to point the reader to the many resources available for designing experiments. An example of an optimal experimental design for collecting rating data in a human appraisal is presented as an example of how optimal DOE methods can be used to create an efficient experiment, given the model to be estimated from the data and the constraints on conducting the experiment [13].

6.2 Overview of Design of Experiments for Preference Modeling

The goal of DOE is to utilize a systematic method to observe the effect that differing *levels*, or values, of a *factor*, or attribute, have on a *response* variable. Different combinations of levels for each factor define a specific treatment combination, or *design alternative*. In the context of choice modeling, an example of factors (i.e., speed, price, maintenance interval), levels (e.g., 1, 0.71, 0.67), design alternatives (e.g., 1, 2, 3), and responses (i.e., Choice) is given in Table 6.1.

In this example, the levels (i.e., values) of the three factors (i.e., customer-desired attributes), which define the design are varied to create unique design alternatives. These design alternatives are then presented to a respondent, who selects one as the preferred alternative, representing his (her) response. In the context of a human appraisal experiment where the respondents rate different design alternatives as opposed to making a choice, the methodology is the same except that the response is different, as illustrated in Table 6.2. As seen in the table, the only difference is that a rating on a scale of one to five is given for each design alternative, as opposed to the binary choose/do not choose response.

The goal of DOE methodology is then to determine the levels of the factors and the combinations of the factor levels which define a design alternative that will lead parameters to the best model possible for the data collected, i.e., the experiment which will minimize errors in the fitted model and minimize correlation among the model parameters (i.e., maximize orthogonality). Therefore, a major consideration in experimental design is the *statistical efficiency* of the design,

Table 6.2 Example of factors, levels, and responses for ratings experiment

Alternative	Rating (1–5)	Speed	Price	Maintenance interval
1	3	1	0.97	0.64
2	5	0.71	0.73	1
3	1	0.67	0.63	0.89

which is a measure of how efficient a given experimental design is with respect to a given reference design for minimizing error in the fitted model.

In standard DOE methodology, the experiment designer must select the number of factors, or attributes, to study in the experiment, given by m, and the number of levels each factor can attain, l. For example, we may select three factors to study, and specify that each factor can achieve two levels (known as a two-level experiment). The number of factors determines the set of attributes (**A** or **E**) that can appear in the estimated DCA or OL model, the number of levels determines the order that the attributes can enter the model. A two-level ($l = 2$) experiment only allows the attributes to enter the model linearly, while a three-level ($l = 3$) experiment will allow estimation of quadratic effects of the attributes. An *effect* is the specific mathematical form of an attribute in a model (e.g., linear effect, quadratic effect, interaction effect). The levels in the experiment design are typically defined by a *coding*, such as -1 for the minimum value of an attribute and +1 for the maximum value of an attribute. The abstract coding must be associated with a particular attribute value to physically conduct the experiment. This requires that the *range* that each attribute can achieve must also be determined. For example, in the power saw example of Table 6.1, the range of speeds achievable by a power saw must be determined. An important assumption in DOE methodology is that we have knowledge of the factors that define a design alternative in the minds of survey respondents. In the power saw example, different combinations of speed, price, and maintenance interval must produce unique design alternatives in the minds of survey respondents. Attributes which may be of interest to engineers, such as tensile strength of steel or hardness of polymer, but are not noticed by potential customers, are not appropriate for use in designing a choice or human appraisal experiment. Therefore, it is recommended that prework be conducted in the form of focus groups, expert opinion, or analysis of previous experiments to determine factors, i.e., the customer-desired attributes, to consider in the experiment. Another assumption is that the factors can be set to levels (e.g., min or max of range) as specified by the experimental design. If it is desired to use existing products as the choice alternatives in the experiment, such as power saws available at a hardware store, it will be difficult if not impossible to find a set of power saws, which can achieve the combination of factor levels defined by the DOE. Another key concept in DOE is that the design alternatives must be randomized when presented to the evaluator, to ensure the error has a random distribution.

Table 6.3 Example of 2^3 full factorial experiment

Alt #	*A*	*B*	*C*	*AB*	*AC*	*BC*	*ABC*
1	−1	−1	−1	+1	+1	+1	−1
2	+1	−1	−1	−1	−1	+1	+1
3	−1	+1	−1	−1	+1	−1	+1
4	+1	+1	−1	+1	−1	−1	−1
5	−1	−1	+1	+1	−1	−1	+1
6	+1	−1	+1	−1	+1	−1	−1
7	−1	+1	+1	−1	−1	+1	−1
8	+1	+1	+1	+1	+1	+1	+1

6.2.1 Standard Methods for Design of Experiments

Once the number of factors, the number of levels, and the range of each factor is defined, the experiment designer has the following choice of experiment types:

1. *Full Factorial Experiment*: In this experiment type, all combinations of factor levels are tested in the form of design alternatives. The number of design alternatives that must be evaluated is given by l^m. For example if there are three factors, given as *A*, *B*, and *C*, and we define two levels for each factor, the number of alternatives that must be evaluated is $2^3 = 8$. An example of a full factorial experiment is given in Table 6.3.
   In this table, the coding (−1, +1) refers to the minimum and maximum level achievable by each factor. Also note that only the levels for main effects, i.e., *A*, *B*, and *C*, must be determined, the interaction effects are computed through multiplication of the factor codings, e.g., $AB|_{\text{Alt 1}} = (-1) \cdot (-1) = 1$. The 2^3 full factorial experiment can also be viewed graphically as shown in Fig. 6.1. In this presentation, the cube represents the available design space (i.e., the range available for each attribute), and the nodes represent the design alternatives (1–8). The location of the node defines the factor combination of the design alternative, with design alternative 1 represented by the (−1, −1, −1) point and alternative 8 by the (+1, +1, +1) point in space.
   The advantage of the full factorial design of experiments is that the results can be used to estimate a model which not only contains all three factors, but also the interaction effects between the factors, i.e., $A{\cdot}B$, $A{\cdot}C$, $B{\cdot}C$, and $A{\cdot}B{\cdot}C$. Also, all effects are orthogonal, resulting in uncorrelated model parameters which aids in interpretation of the parameter estimates in a DCA or OL model. If we are interested in determining the higher order effects of the factors, such as the quadratic effects of A^2, B^2, and C^2, we can use a higher level experiment, such as a three-level experiment. In this case, the number of design alternatives to be evaluated would be $3^3 = 27$. Because the full factorial experiment allows recovery of all main and interaction effects with the highest statistical efficiency, it serves as the reference for computing efficiency when designing reduced-size experiments. The disadvantage of the full factorial experiment is the potentially

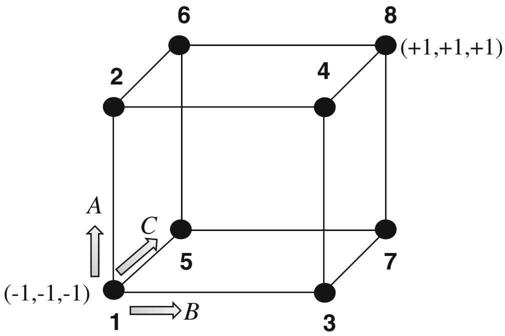

Fig. 6.1 Graphical representation of a 2^3 full factorial experiment

large number of design alternatives that must be evaluated; for example, for a product defined by eight customer-desired attributes, the number of alternatives that must be evaluated to estimate a linear model is $2^8 = 256$. If it is believed that there are nonlinear effects, $3^8 = 6561$ design alternatives would need to be evaluated, clearly an expensive and time consuming task!

Standard factorial experiments can be found in texts (e.g., [3, 26]), or generated using statistical software such as Minitab, SPSS, the Matlab statistical tool box, or the BHH2 package for *R*.

2. *Fractional Factorial Experiment*: In this class of experiments, the number of design alternatives (or treatment combinations) to be evaluated can be significantly reduced, but at a cost in the reliability of effects that can be recovered from the experiment. To reduce the number, the ability to reliably discern between certain effects is sacrificed, as defined by the specified *design resolution* of the fractional factorial experiment. Our ability to discern effects is a result of *confounding* (or *aliasing*) of effects, such as a confounding of a main effect (e.g., attribute *A*) and an interaction effect (e.g., interaction *BC*). Common design resolutions used in fractional factorial experiments are as follows (note that the descriptions only list the lowest order interactions in the confounding pattern, higher order interactions may also be present):

- Resolution **III**: Main effects may be confounded with two-factor interactions.
- Resolution **IV**: Main effects may be confounded with three-factor interactions, and two-factor interactions may be confounded with other two-factor interactions.
- Resolution **V**: Main effects may be confounded with four-factor interactions and two-factor interactions may be confounded with three-factor interactions.

The resolution of the experiment selected depends upon the belief in the significance of the confounding effects. For example, if it is believed that all three-factor interactions (and higher) are negligible, all main effects in a resolution IV design and all main and two-factor interactions in a resolution V design can be estimated. The resolution can be computed by deriving the *generating relation* for a given design, or it can be looked up from a table of designs (e.g., [3]), or

Table 6.4 Example of $2_{III}^{(5-2)}$ fractional factorial experiment

Alt #	A	B	C	$D = AB$	$E = AC$	BC	ABC
1	−1	−1	−1	+1	+1	+1	−1
2	+1	−1	−1	−1	−1	+1	+1
3	−1	+1	−1	−1	+1	−1	+1
4	+1	+1	−1	+1	−1	−1	−1
5	−1	−1	+1	+1	−1	−1	+1
6	+1	−1	+1	−1	+1	−1	−1
7	−1	+1	+1	−1	−1	+1	−1
8	+1	+1	+1	+1	+1	+1	+1

determined from a statistical software package, such as Minitab. The fractional amount of a fractional factorial is defined by the constant ψ, which determines the fraction of a full factorial that will be administered, using the relation $fraction = \left(\frac{1}{2}\right)^{\psi}$. For example, if $\psi = 2$, ¼ of the full factorial will be administered.

An example of a fractional factorial experiment is given in Table 6.4. The experiment is a "two to the five minus two, resolution three" design. This means that the experiment is a two-level design (i.e., linear main effects), with five factors ($A{-}E$), but using only a ¼ replication (i.e., $(½)^2$) of the full factorial (which would require $2^5 = 32$ trials). The design is generated using the generating relations $D = AB$ (i.e., the interaction AB in the 2^3 full factorial experiment is now also factor D) and $E = AC$.

This experiment requires the same number of design alternatives to be evaluated (i.e., 8) as a full factorial of Table 6.3, but allows estimation of five factors (i.e., main effects) instead of three in the resulting model. The confounding pattern for this resolution III design indicates that main effects (i.e., $A{-}E$) will be confounded with two-factor interactions (and higher), and the two-factor interactions will be confounded with other two-factor interactions (and higher). An example of a confounding pattern is given for interaction AB, which is confounded with D (due to the generating relation) as well as BCE ($AB{\cdot}BCE = ACE = I$) and $ACDE$ ($AB{\cdot}ACDE = BCDE = BCDAC = ABD = I$).

Standard fraction factorial experiments can be found in texts (e.g., [3, 26]), or generated using statistical software, such as Minitab, SPSS, the Matlab statistical tool box, or the BHH2 package for *R*.

3. *Orthogonal Array Experiment*: Orthogonal array experiments are most closely associated with Taguchi methods [28]. This class of experiments evolved from the quality engineering domain pioneered by Taguchi [34], as opposed to the statistical domain pioneered by Fisher [5]. Orthogonal arrays can be viewed as an alternative to fractional factorial experiments to reduce the number of design alternatives, which must be evaluated in a choice or human appraisal experiment. Due to the different philosophy, literature on orthogonal arrays tends to have its own terminology and the experiments have a different structure. For example, the coding of levels is different in that it uses positive integers for the

Table 6.5 Example of L_8 orthogonal array

Alt #	*A*	*B*	*C*	*D*	*E*	*F*	*G*
1	1	1	1	1	1	1	1
2	1	1	1	2	1	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

levels, so a three-level experiment would be coded as (1, 2, 3) for the three levels, as opposed to the (−1, 0, +1) coding used in factorial experiments. Also, the experiments are labeled using the convention of "L" followed by the number of experimental runs (or design alternatives) that must be evaluated, for example L_4, L_8, L_{18}, etc. One significant difference from fractional factorial experiments is that orthogonal arrays are primarily concerned with determination of the main effects, as opposed to interaction effects. This results in the need to evaluate relatively few design alternatives compared to fractional factorials, but at the expense of recovering interaction effects. For example, only eight alternatives need to be evaluated to determine the linear effect of seven factors ($A-G$) using an L_8 experiment shown in Table 6.5.

A criticism of orthogonal arrays is that their design tends to be more complicated than necessary and the designs generally do not perform well with respect to statistical efficiency when compared to fraction factorial experiments [2]. Standard designs for orthogonal arrays can be found in texts (e.g., [28]) or in statistical software, such as Minitab, SPSS, or the DoE.base package for *R*.

4. *Optimal Fraction Factorial Experiment (Optimal DOE)*: As noted, the previous experiment designs have a defined structure for a given number of factors m, levels l, and in the case of fractional factorials, the fractional constant ψ. The designs are therefore standard, and can be looked up in a text or generated by software as noted in the preceding paragraphs. Issues with using standard experiments are that the confounding pattern, the number of alternatives to be evaluated, and the factor combinations are strictly defined by m, l, and ψ. Also, the fractional factorial experiments are most efficient for a linear regression model, not necessarily for other types of models, such as a DCA or OL model. Experiments with humans also may lead to violation of the underlying principles of standard experiments, due to the fact choices made or ratings evaluations may depend upon the style or attitudes of the respondent. In standard experiments, any errors are attributed to random disturbances, and therefore it is assumed that errors in the resulting model are only random ($\varepsilon_{\text{rand}}$). For this reason, Optimal DOE methodology [1] was developed to allow more freedom in experiment design, while ensuring that the resulting designs still maintained high statistical efficiency. As will be described in Sect. 6.4, optimal DOE selects the experimental design by maximizing the determinant of the Fisher

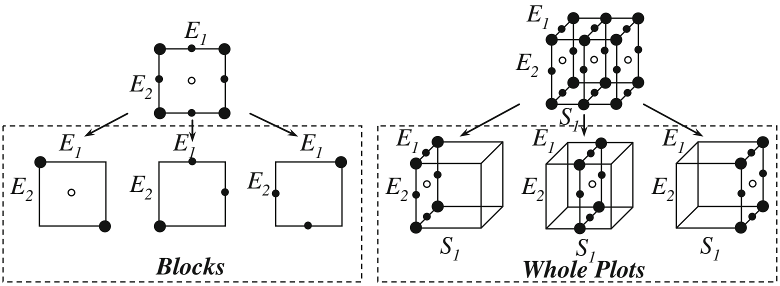

Fig. 6.2 The structure of a blocked and split-plot experiments [6]

Information matrix, which is a function of both the type of model to be estimated (e.g., DCA, OL) with the collected data, and the specific factor, or attribute, effects which one wishes to include in the model (e.g., main effects, interaction effects, non-linear effects).

While these general types of experiments are available to the researcher, the experiments can be enhanced to account for other types of error structures beyond just the random disturbance $\varepsilon_{\text{rand}}$. In the next subsection, we will introduce methods for accounting for other sources of error in the experiment design process.

6.2.2 Blocked and Split-Plot Design of Experiments

Blocked and Split-Plot designs have been used extensively in physical experimentation. These experiments are used in situations in which the design alternatives cannot be presented in a completely randomized fashion, as required to assume that the only error present is random error, $\varepsilon_{\text{rand}}$. In this case, the larger experiment, for example a full or fractional factorial experiment, is subdivided into individual *experimental units* which are each administered at a single time in a randomized fashion. Therefore, a blocked or split-plot experiment can be thought of as an experiment composed of individual, randomized experimental units. The difference between block and split-plot designs is illustrated in Fig. 6.2. The larger experimental unit (composed of many individual experimental design alternatives) in a blocked experiment is called a *block*, whereas the larger experimental unit in a split-plot experiment is called a *whole plot*. Each block or whole plot consists of a number of experimental design factors, for example engineering attributes $\mathbf{x} = (E_1, E_2, \ldots E_j)$, the values of which are determined by a design criterion, such as D-optimality to be discussed in the Sect. 6.4. The primary difference between a blocked versus split-plot design is that in a split-plot design, *whole-plot factors*, such as a socio-demographic factor S_1, remain unchanged for a given experimental unit (i.e., they are not completely randomized). In blocked experiments, there are no corresponding larger experimental unit (or block level) factors such as the whole-plot factors, i.e., the larger experiment is not divided up based upon an attribute such as S_1. Therefore, the goal of a split-plot design is the selection of the design alternatives *under* each whole-plot factor, whereas in a blocked design the goal is the allocation of design alternatives to each block.

A demonstration experiment with two **E** and one **S**, which is presumably used to estimate a linear regression model, with quadratic effects in **E** and linear effects in **S**, is used to demonstrate the terminology that will be used in Sect. 6.4 to develop the optimal DOE method to design split-plot and blocked experimental designs. In the proposed experimental design approach, both **E** and **S** comprise the experimental factor set, **x**:

$$\mathbf{x} = [\,E_1 \quad E_2 \quad S_1\,]. \tag{6.1}$$

The complete set of effects, **E** and **S**, which appear in the resulting prediction model (e.g., the OL model), such as an intercept and linear, quadratic, and interaction effects, form the extended design point, denoted by **f(x)**:

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} 1 & E_1 & E_2 & S_1 & E_1^2 & E_2^2 & E_1E_2 & S_1E_1 & S_1E_2 \end{bmatrix}. \tag{6.2}$$

The matrix of all extended design points (i.e., all effects in the model) in the complete experiment form the extended design matrix, denoted as **F**, e.g.,

$$\mathbf{F} = \begin{bmatrix} 1 & -1 & -1 & -1 & +1 & +1 & +1 & +1 & +1 \\ 1 & +1 & 0 & -1 & +1 & 0 & 0 & -1 & 0 \\ 1 & 0 & +1 & -1 & 0 & +1 & 0 & 0 & -1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}. \tag{6.3}$$

The motivation for split-plot design methodology is the inclusion of "hard-to-change" factors, e.g., a respondent's socio-demographic attributes, in the experimental design. These hard-to-change factors are the whole-plot factors, which are not completely randomized as with the other design factors, and remain at a fixed level during the completion of a given whole-plot experiment. Alternatively, blocked experiments are motivated by the need to minimize the effects of known or theorized uncontrollable factors, such as the rating style of each respondent in a human appraisal experiment, not included as a design factor (i.e., **E** or **S**), but believed to have an influence on the experiment response. Therefore, the goal in blocked experiments is to distribute the experimental design points among homogeneous blocks, or respondents, to minimize the effects of uncontrollable factors.

Section 6.2 has provided a brief introduction to the terminology and concepts in experiment design. In Sect. 6.8, the reader is referred to a selection of the many excellent text and software resources available for understanding and designing experiments. The remainder of this chapter will be concerned with designing experiments for stated preference experiments.

6.3 Stated Preference Experiments

Stated preference (SP) experiments for product evaluations are unique in that the socio-demographic attributes of the respondent have an *observable, systematic* influence upon the response. For example, a person's height, weight, and age will influence how they experience a product such as an automobile in which they must exit, enter, and operate. Another unique feature specific to choice experiments is that the design alternatives must be grouped into *choice sets* (C_n) to be presented to the respondent [15, 21, 33], as opposed to presenting the design alternatives in a random order to the respondent as is assumed in standard experimental design.

6.3.1 Design Approaches for Stated Preference Experiments

Standard experimental designs are generally difficult to adapt for SP experiments conducted with the goal of creating DCA and OL models to understand respondent preferences as a function of product and socio-demographic attributes. Standard split-plot designs based upon standard full factorial or fractional factorial designs to support preference modeling, considering significant respondent blocking, do not exist [3, 27]. Orthogonal array designs [28], such as the L_{18} design (i.e., 8 factors evaluated with 18 design alternatives), are small enough such that each person can complete the entire experiment and thus blocking is not required and the split-plot design is relatively straightforward; however, while such designs allow estimation of linear and quadratic terms, interactions cannot generally be estimated. Also, these approaches provide no guidance for grouping alternatives into specific choice sets for choice experiments.

Experiments using standard DOE methodology specifically for SP experiments, with the goal of minimizing the number of configurations for each respondent to evaluate, have been developed for certain applications. Adaptive Conjoint Analysis [8] uses a prescreening of preferences for factor levels to optimize the alternatives presented; however, this approach requires gaining access to resources for the prescreening tests and ignores the importance of factor interactions. Specific to grouping the design alternatives for choice experiments, Street et al. [33] have presented a number of approaches to create choice sets using standard experiment designs. One such approach is the L^{MA} approach [21], in which paired choice experiments (i.e., the size of the choice set is two) are created using a standard experiment with twice the number of factors as needed to describe the alternatives. The first half of the factor set defines alternative 1 and the second half defines alternative 2. For example, if a design alternative is defined by five factors (attributes), an experiment design containing ten factors is selected and factors from one to five define alternative 1 while factors from six to ten define alternative 2. While this approach is suitable for small choice sets and a small number of attributes, it can be challenging to scale to larger problems. Based on the

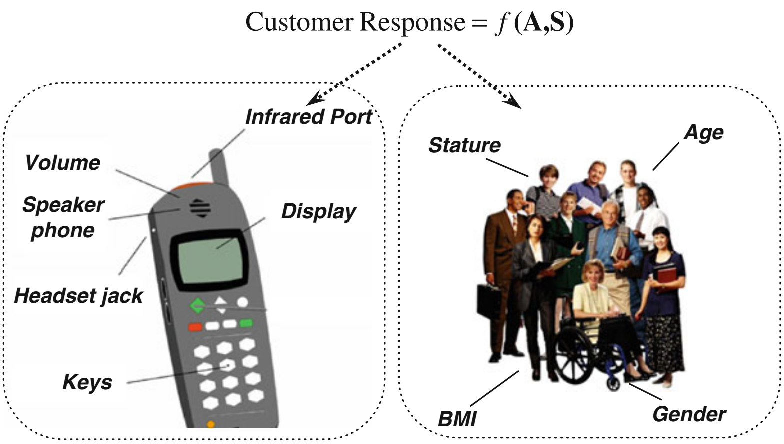

Fig. 6.3 Response as a function of product and human attributes

limitations of existing approaches, an approach using the *D*-optimality criterion is implemented as the method for selecting a stated preference experiment.

To select experimental designs for SP experiments, given a constraint on the number of configurations rated by a single respondent (due to fatigue), multiple product and socio-demographic attributes, and the need to create choice sets, optimal design of experiment methods are adapted to the specific needs of this class of experiments [1]. Optimal design of experiments (DOE) have been studied for general conjoint experiments, e.g., Kessels et al. [16] and Street et al. [33], and have also been applied to multinomial logit (MNL) DCA models [15, 18, 29]. In this chapter, we will demonstrate using optimal DOE methodology to design a human appraisal experiment for estimating a random effects OL model, considering the combined split-plot and block structure of the stated preference experiments.

6.3.2 *Characteristics of Stated Preference Experiments*

As noted previously, a stated preference experiment is characterized by an interaction between the human respondent and the product design; therefore, the set of factors which influence the response from a given respondent for a given product *alternative* are both *product* attributes, denoted by **A**, and respondent *socio-demographic* attributes, denoted by **S**, as illustrated in Fig. 6.3.

Socio-demographic attributes are defined as characteristics, primarily anthropomorphic characteristics, such as stature or body mass index (BMI) of a respondent which influence how the respondent experiences the system. In stated preference experiments, the response for a given experiment could be the identification of a preferred configuration, or *choice*, from the configuration set, a *rank-ordering* of the configurations evaluated, or a *rating* for each configuration [21]. In the example of Sect. 6.6, the response considered is in the form of a discrete *rating*, on a scale selected by the survey administrator. The number of rating categories should be limited to between 4 and 11 categories [4, 9] (scales of 0–10, 1–5, and 1–7 are popular in application) to balance the competing desires of maximizing information recovery (i.e., maximize number of categories) versus minimizing scale usage heterogeneity (i.e., minimize number of categories). Rating responses represent an *ordinal* scale, in which higher ratings represent stronger positive preference for a given product configuration. The most popular models for estimating ratings as a function of independent variables are the ordered *probit* [25] and *OL* [24] models. These models assume that a respondent rating is a discrete realization of a continuous underlying opinion, or *utility*, for a given product configuration. In the example presented in this chapter, the OL model described in Chap. 3 is used; however, the approach presented can easily be adapted to the ordered probit model (or other related models).

6.3.3 Issues in Stated Preference Experiments

The primary issues with stated preference experiments are as follows:

- Unique rating style of each respondent.
- Potentially a large number of product and demographic factors to investigate.
- Need to create a response surface (i.e., quadratic terms) due to nonlinearity of the response and the effect of interactions.
- Fatigue of human respondents.
- Need specifically include or exclude specific factor combinations.
- For choice experiments, the design alternatives must be organized into choice sets.

These issues are described as follows in this subsection.

In stated preference experiments, a single respondent often evaluates several product configurations in sequence due to time and cost constraints. This implies that stated preference experiments will naturally have a *random block effect*, as each person's ratings will have some level of correlation depending on the rating style of the respondent. A block is a set of experiments conducted under homogeneous but uncontrolled external conditions. Blocking is necessary since the overall experiment can be quite large. This is because the number of engineering attributes which potentially characterize a customer-desired attribute, as identified using a process, such as the PAFD method, can be extensive. Also, SP Experiments are naturally *split-plot* designs [3], because it is unrealistic to completely randomize human attributes since a single respondent represents a set of fixed human attributes, and it is most efficient to have a single respondent evaluate an entire block of experiments, or configurations, at a single time. Split-plot experiments are characterized by one or more factors remaining unchanged for a given set of experiments.

In general, the goal of a stated preference experiment is to create a response surface model, thus requiring a minimum of three levels of each product attribute (three levels cannot always be achieved for human attributes which are categorical, such as gender). The desire to create a response surface is based upon findings in psychometrics, in which it has been found that the human sensation magnitude to a given stimuli intensity follows a power law relationship [32]. A three-level experiment enables approximation of the power law relationship using linear and quadratic terms in the prediction model (e.g., the OL model).

A key issue to consider in stated preference experiments is user fatigue [18]. Unlike computer or industrial experiments, fatigue will create additional error in the response in a stated preference experiment. The number of trials or configurations, B, given to each respondent must be managed to ensure the effects of fatigue are limited. Another important issue in stated preference experiments is the inclusion or exclusion of certain (experimental) design points of interest. The reason for specific inclusion or exclusion of design points is due to the interaction effects of certain factors, which may be theorized to be highly significant and important. If the interaction effect is achievable in the product, it would be of particular interest to study the impact of the interaction, whereas if the interaction is unachievable in the real product, it may be of interest to exclude such a combination. The design of experiments with excluded combinations has been studied by previous researchers, e.g., Steckel et al. [31]. As discussed at the beginning of this section, another unique characteristic specific to choice experiments is the need to create choice sets to present to the respondent, as well as a method to create these choice sets of a specific size.

An example of a human appraisal used throughout this chapter is the design of an automotive occupant package. A respondent's rating of a particular package configuration is dependent not only upon the product attributes ($\mathbf{A}$), such as the amount of headroom, knee room, etc. in the package, but also the socio-demographic attributes of the respondent ($\mathbf{S}$), such as his/her stature, weight, gender, etc. Also, these experiments are characterized by a block effect because, after controlling for the respondents' socio-demographic attributes, each respondent will retain a certain correlation among their ratings which must be accounted for in the resulting model.

This section has provided an overview of the defining characteristics and issues involved in designing stated preference experiments. In the next sections, we will present the derivation and an example using optimal DOE methodology to design a human appraisal when the response is in the form of a rating. The data collected from this experiment would be suitable for estimating a random effects OL model as introduced in Chap. 3 and is designed to address the unique features of a SP experiment as listed in Sect. 6.3.3. While the methodology is presented for designing experiments with rating responses, approaches for designing choice experiments will also be discussed.

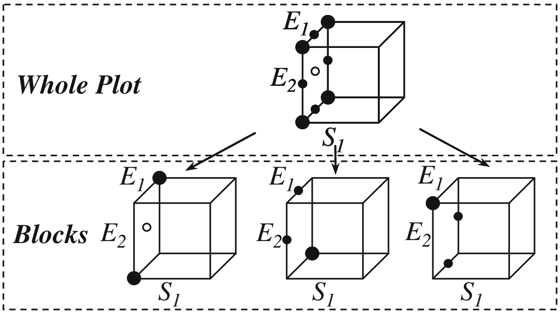

Fig. 6.4 The structure of the human appraisal blocked split-plot experiment [6]

6.4 Optimal Experimental Design Method for Human Appraisals Using Rating Responses

In our proposed experimental design method, the human appraisal experiment is considered as both a split-plot and a blocked experiment. The socio-demographic attributes **S** form the whole-plot factors because they represent hard-to-change factors. As discussed in the introduction, a single respondent, characterized by a fixed socio-demographic profile **S**, rates several configurations in succession due to the expense and inconvenience of requiring people to evaluate configurations randomly over time. Also, each whole-plot experiment may be too large for a single respondent to complete due to the fatigue issues discussed in Sect. 6.1. Each whole plot may therefore be distributed among multiple survey respondents, each with the same **S**, in the form of blocks. The blocked split-plot design is illustrated in Fig. 6.4. In this diagram, the respondent socio-demographic factors, **S**, are the whole-plot factors, and the product factors, **E**, are the split-plot factors.

In this chapter, Optimal Design of Experiments (DOE) methodology will be used to select the preferred human appraisal experiment. In optimal DOE, a *candidate set* of design points G, typically the design points of a full factorial experiment in the desired number of factors, is provided to an algorithm, which uses a defined *criterion* to select the optimal design points from the set to achieve a design of any arbitrary size, M. A key concept in Optimal DOE is that the form of the model to be estimated, i.e., the form of the extended design point $\mathbf{f(x)}$, must be specified a priori to determine the optimal design which supports the specified model.

6.4.1 Optimal Experimental Design Selection Criterion

Various criteria for selecting the optimal experimental design are available, the most widely used being *D-Optimality*. In general, several criteria exist for selecting a preferred experimental design. Popular criteria in the literature are D, A, G, and V (also known as I, Q, or IV) optimality, which are all functions of the Fisher Information matrix, **M,** of the extended design matrix, **F**. The D and

A criteria are related to making precise estimates of the model parameters (**β**), whereas the *G* and *V* criteria are concerned with minimizing the overall prediction variance of the resulting model. While any optimality criterion can be used with the approach presented in this work, the approach is presented using the *D*-optimality criterion for several reasons. Firstly, *D*-optimality is widely used as an optimality criterion and is computationally inexpensive for experiment selection compared to some of the other criteria, such as *V*-optimality. Additionally, *D*-optimal designs have been shown to be highly efficient (i.e., provide efficient model building) with respect to the other optimality criteria (i.e., *G*, *A*, and *V*), whereas *G*, *A*, and *V*-optimal designs generally are not efficient with respect to *D*-optimality [6]. Also, because the models estimated must be validated in some manner, *D*-optimal designs provide precise estimates of the resulting model parameters (**β**) which can be interpreted for expected sign and magnitude as part of the model validation process. *D*-optimality is achieved algorithmically through maximization of the determinant of the Fisher Information matrix, **M,** or the *D*-criterion, of a given experiment design:

$$\max\ \det(\mathbf{M}). \tag{6.4}$$

The Fisher Information matrix for the Ordinary Least Squares (OLS) fixed-effect model parameters, **β**, can be expressed as [1]:

$$\mathbf{M} = \sigma_{\varepsilon}^{-2}\mathbf{F}'\mathbf{F}. \tag{6.5}$$

As seen in Eq. (6.5), **M** for an OLS model is a function of the extended design matrix, **F**, and the random error variance, σ_{ε}, (which, without loss of generality, can be assumed to be 1 for experiment optimization purposes) both of which are independent of the model parameters **β**. In the case of Generalized Least Squares (GLS), Goos [6] has derived the information matrix for the random block effects model, in which each experiment respondent forms a block. The variance–covariance matrix of the rating observations, **R**, for a single respondent n, $\mathbf{cov}(\mathbf{R}_n)$, is of the form:

$$\mathbf{V}_n = \begin{bmatrix} \left(\sigma_{\varepsilon}^2 + \sigma_u^2\right) & \sigma_u^2 & \cdots & \sigma_u^2 \\ \sigma_u^2 & \left(\sigma_{\varepsilon}^2 + \sigma_u^2\right) & \cdots & \sigma_u^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_u^2 & \sigma_u^2 & \cdots & \left(\sigma_{\varepsilon}^2 + \sigma_u^2\right) \end{bmatrix} \tag{6.6}$$

where σ_u is the variance at the *respondent* level, and σ_{ε} is the variance at the *observation* level. The information matrix for all observations can then be written as:

$$\mathbf{M} = \mathbf{F}'\mathbf{V}^{-1}\mathbf{F} = \sigma_{\varepsilon}^{-2}\left\{\mathbf{F}'\mathbf{F} - \sum_{n=1}^{N}\frac{\rho}{1+\rho(B_n-1)}\left(\mathbf{F}'_n\mathbf{1}_{B_n}\right)\left(\mathbf{F}'_n\mathbf{1}_{B_n}\right)'\right\},\ \text{where}\ \rho = \frac{\sigma_u^2}{\left(\sigma_{\varepsilon}^2+\sigma_u^2\right)}, \tag{6.7}$$

B_n is the number of configurations in block n (of N blocks), and $\mathbf{1}_{B_n}$is a square matrix of ones of size B_n. In this case, an estimate of ρ, which is a measure of the ratio of *across*-respondent to *within*-respondent variance, is needed to select the optimal design. For this reason, such experimental designs are referred to as *semi-Bayesian* designs, since they require a prior estimation of ρ. The expression for **M** given in Eq. (6.7) is only valid if the model to be estimated is a (least squares) linear regression model. It is therefore not valid for the human appraisal experiments in this work which are to be modeled using OL.

6.4.2 Derivation of Human Appraisal Experiment Selection Criterion

A complementary derivation is proposed to support estimation of the OL model. The OL model can be written as:

$$\Pr\left(R_{in} = R_{inp}\right) = \pi_{inp}(\boldsymbol{\beta}) = F\left(k_p - \mathbf{x}'_{in}\boldsymbol{\beta}\right) - F\left(k_{p-1} - \mathbf{x}'_{in}\boldsymbol{\beta}\right), \tag{6.8}$$

where R_{in} is the discrete rating for respondent, or block, n (of N blocks) and configuration i (of B configurations), k is an OL cutpoint, p is a rating category (of P categories, such as 1–10), and F is the Cumulative Distribution Function (CDF) of the logistic distribution (this CDF can be replaced with the standard normal CDF, Φ, if the ordered probit model is to be used).

To enable selection of a D-optimal design to support the OL model, an expression for the information matrix (needed to calculate the D-criterion) that can be estimated without prior knowledge of the resulting model parameters, i.e., $\boldsymbol{\beta}$, is needed. In general, the information matrix for the OL model can be expressed as [19]:

$$\mathbf{M} = \sum_{n=1}^{N} \mathbf{D}'_n \mathbf{V}_n^{-1} \mathbf{D}_n, \tag{6.9}$$

where $\mathbf{V}_n$ is the asymptotic variance–covariance matrix for block n. $\mathbf{D}_n$ is the derivative of $\boldsymbol{\pi}_n$ with respect to $\boldsymbol{\beta}$:

$$\mathbf{D}_n = \mathbf{D}_n(\boldsymbol{\beta}) = d\boldsymbol{\pi}_n(\boldsymbol{\beta})/\mathrm{d}\boldsymbol{\beta}, \tag{6.10}$$

where the $(P-1)$ vector of ratings probabilities for a single individual n for configuration i is given as $\boldsymbol{\pi}_{in} = \left(\pi_{in1}, \pi_{in2}, \ldots \pi_{in,P-1}\right)$ and $\boldsymbol{\pi}_n = \left(\boldsymbol{\pi}_{1n}, \boldsymbol{\pi}_{2n}, \ldots \boldsymbol{\pi}_{Bn}\right)'$. The asymptotic variance–covariance matrix, $\mathbf{V}_n$, for the ordinal model, such as OL, can be written in block-matrix form as [38]:

$$\mathbf{V}_n = \begin{bmatrix} \mathbf{V}_{11} & \mathbf{V}_{12} & \cdots & \mathbf{V}_{1T} \\ \mathbf{V}_{21} & \mathbf{V}_{22} & \cdots & \mathbf{V}_{2T} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{V}_{T1} & \mathbf{V}_{T2} & \cdots & \mathbf{V}_{TT} \end{bmatrix}, \tag{6.11}$$

where the on-diagonal matrices are *multinomial* covariance matrices, $\mathbf{V}_{tt} = \mathrm{diag}(\boldsymbol{\pi}_{ni}) - \boldsymbol{\pi}_{ni}\pi'_{ni}$, and the off-diagonal matrices, $\mathbf{V}_{ts}$ $(t \neq s)$, are the *within-block* covariance matrices between any two responses in a block. These matrices are generally calculated as part of the model estimation process using collected data; therefore, a method for estimating them for experimental design purposes must be devised.

The on-diagonal multinomial covariance matrices ($\mathbf{V}_{tt}$) can be calculated from knowledge of the ratings probabilities; however, the within-block covariance matrix ($\mathbf{V}_{ts}$) requires additional derivation. In general, the $\mathbf{V}_{ts}$ matrix follows the form [19]:

$$\mathbf{V}_{ts} = \left(\mathbf{B}^{1/2}\right)'\mathbf{P}_{tn}\left(\mathbf{B}^{1/2}\right), \tag{6.12}$$

where $\mathbf{P}$ is the "working" correlation matrix, and $\mathbf{B}$ is a matrix determined by the correlation structure. The selection of $\mathbf{B}$ and $\mathbf{P}$ depends upon the form of the model to be estimated with the experimental response data [11, 12, 40]. The proper specification for $\mathbf{P}_{tn}$ for the random effects OL model has been found to be the "exchangeable" structure. In the "exchangeable" structure, $\mathbf{P}_{tn}$ is a diagonal matrix with all diagonal elements of $\mathbf{P}_{tn} = \alpha$, implying equal correlation among all observations in a given block. In this formulation, α is the pair-wise correlation coefficient between elements in the $\mathbf{V}_{tt}$ matrices, similar to the correlation coefficient ρ applicable for the scalar variance–covariance matrix of Eq. (6.6). The recommended specification for $\mathbf{B}$ for the random effects model is $\mathbf{V}_{tt}$ [11, 12]. Therefore $\mathbf{V}_{ts}$ can be written as:

$$\mathbf{V}_{ts} = \left(\mathbf{V}_{tt}^{1/2}\right)'\mathbf{diag}(\alpha)\left(\mathbf{V}_{tt}^{1/2}\right)\ t \neq s. \tag{6.13}$$

In viewing Eqs. (6.10), (6.11), and (6.13), it can be seen that in order to calculate $\mathbf{M}$, estimates for $\boldsymbol{\pi}_n$ and α are required. The pairwise correlation coefficient α is not reported in the random effects OL modeling process, which provides a challenge to determining a reasonable estimate for α from previous experiments or the literature. However, the coefficient ρ is reported in the modeling process, and it has been found that α can be estimated using ρ by the relation $\alpha \approx \rho/P$ to enable calculation of $\mathbf{V}_{ts}$. This estimate is based upon the assumption that ρ should be "distributed" over the P ratings categories in the working correlation matrix, such that the influence of α and ρ are equivalent in the respective information matrix calculations of Eqs. (6.7) and (6.9). Because a ratings prediction model is not available before the experiment is conducted, the rating category (e.g., 1–10) probabilities, $\boldsymbol{\pi}_n$, must be estimated directly. They can be estimated from prior knowledge from a previous experiment, or if no prior knowledge is available, an equal probability of each rating category can be assumed. Because estimates of the entire response probability vectors, $\boldsymbol{\pi}_{in}$, are needed to calculate $\mathbf{V}_n$ and $\mathbf{D}_n$ to compute $\mathbf{M}$, such experimental designs are referred to as *Bayesian* designs [1].

6.4.3 Optimal Human Appraisal Algorithmic Implementation

The algorithmic implementation for selecting the optimal blocked split-plot design follows the approach provided in [7], with the least squares information matrix of Eq. (6.7) used in their approach replaced with that of Eq. (6.9) for the new approach. In general, the experimental design is built sequentially, with points from the candidate set (G) having the highest prediction variance $\mathrm{var}\{\hat{R}(\mathbf{x})\}$ added to the experiment to maximize the D-criterion. The prediction variance for any value of **f(x)** must be calculated to determine the point from G to add to the experiment. For the GLS model, **f(x)** is a vector and the prediction variance can be calculated as $\mathrm{var}\{\hat{R}(\mathbf{x})\} = \sigma_\varepsilon^2 \mathbf{f}'(\mathbf{x})\mathbf{M}^{-1}\mathbf{f}(\mathbf{x})$; however in case of the ordinal model, each **f(x)** results in a matrix of terms for each of the ($P-1$) rating categories. The prediction variance for any point to be added to the design can be estimated using the delta method for asymptotic variance [35]:

$$\mathrm{var}\{\hat{R}(\mathbf{x})\}_p = \mathrm{var}\{\pi_{in}(\boldsymbol{\beta})\}_p \approx \left(\frac{d\pi_p(\boldsymbol{\beta})}{d\boldsymbol{\beta}}\right)' \mathbf{M}^{-1} \left(\frac{d\pi_p(\boldsymbol{\beta})}{d\boldsymbol{\beta}}\right) \tag{6.14}$$

As seen in Eq. (6.14), the prediction variance is calculated for each of P ratings categories, leading to a vector of prediction variances for each design point **f(x)**. Therefore, the design point with the highest summed *total* prediction variance is added to the experiment:

$$var\{\hat{R}(\mathbf{x})\} = \sum_{p=1}^{P} \mathrm{var}\{\pi_{in}(\boldsymbol{\beta})\}_p \tag{6.15}$$

To implement the algorithm, a simplified method of expressing $\mathbf{M}$ is given in Appendix A. An overview of the algorithm is shown in Fig. 6.5 and described as follows:

1. *Generate a set of candidate points*, G, for the product attributes, **A**, from which to select the optimal set. G is typically the points of a full factorial experiment in the number of factors desired. Specific factor combinations to be specifically excluded from the candidate set, or specifically included in the final experiment design are also specified.
2. *Create an experimental design for the desired human whole-plot factors*, **S**. This design can be a full or fractional factorial in human attributes, depending upon the size of **S** and the number of respondents. Randomly assign the whole plot factors to each block, n.

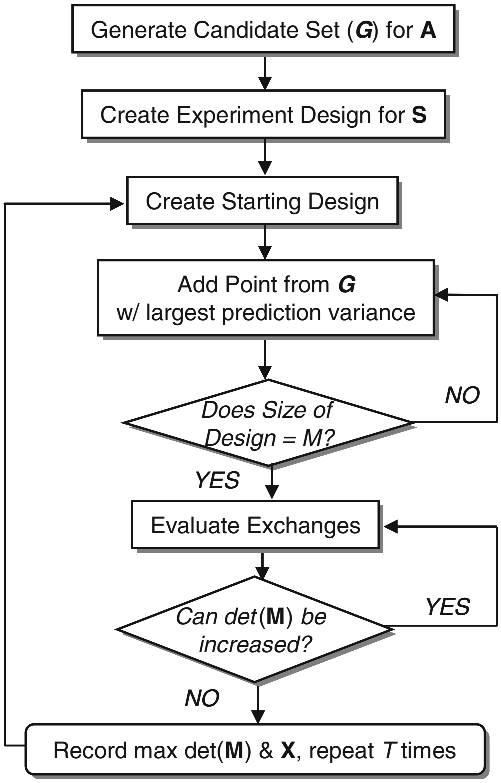

Fig. 6.5 Algorithmic implementation of the optimal experimental design method

3. *Create a starting design*. To begin building the experimental design, a starting design is composed of a randomly selected small number of points from the candidate set and randomly assigned to the blocks. Compute the initial information matrix, **M**, and the determinant, det(**M**).
4. *Determine the point in the candidate set G with the largest prediction variance*, $\mathrm{var}\left\{\hat{R}(\mathbf{x})\right\}$. Randomly assign this point to a block, and update **M** and det(**M**). Repeat this process until each block receives *B* configurations, forming an experiment design of size *M*.
5. *Evaluate exchanges*. Since the design was started with a random selection of points, there may be points in the candidate set *G* which will increase the *D*-criterion. Each point in the current design is evaluated to determine if its replacement by a point in the candidate set will increase the *D*-criterion. This is continued until no further increases can be established.
6. *Record the D-Criterion and repeat steps 3–5*. Steps 3–5 constitute a single *try*, each with a local maximum for *D*-Optimality based on the starting design of Step 3. *T* tries (e.g., 100 tries) can be conducted to search for the global maximum.

6.5 Optimal Experimental Design for Choice Experiments

As discussed in Sect. 6.3, optimal DOE is desired for creating choice experiments; however, unique challenges exist in extending the method presented in this section for choice experiments. One challenge is that the DCA model, whether it is a MNL, NL or MXL model, is a grouped model, i.e., the estimation of a choice probability of a single design alternative depends upon the utility of not only the design alternative of interest but also the utility of all alternatives in the choice set. The other challenge is that unlike the random effects OL model, the corresponding random parameter DCA model (i.e., the mixed logit model) has randomness in multiple model parameters, and a single respondent level variance σ_{u} as assumed in Eq. (6.7) is not available.

Based on these challenges, two general approaches to using optimal DOE for choice experiments have been proposed in the literature. In the first approach, the information matrix for the DCA model is approximated using the information matrix for the linear regression model to overcome the difficulties in generating an information matrix for a DCA model, e.g., [18, 33]. The simplification is justified based upon research showing that the experiments, which are efficient with respect to the linear regression model are generally efficient with respect to the MNL model. Choice sets are subsequently created using blocking: each block represents a single choice set, which is the size of the block. Each choice set can be given to a different respondent, or respondents can be given multiple choice sets. A refinement of this approach can be made by using nested block experiments [23]. In this approach, two levels of blocking are used: the first level is a blocking done with respect to the respondents, and the second level determines the choice sets given to each respondent. For example, if we intend to use ten respondents, and give each respondent five choices sets each to evaluate, with four choice alternatives per set, this would result in a total experiment design of size $10 \cdot 5 \cdot 4 = 200$. This experiment would result in ten level-one blocks corresponding to the ten respondents; each level-one block would contain five level-two blocks (of size four each), corresponding to the five choice sets per respondent.

A second approach uses the actual information matrix for the DCA model in the optimal DOE algorithm directly, e.g., [17, 39]. Since the choice probability of a single design alternative is a function of all alternatives in the choice set, this approach creates experiments in which the alternatives are naturally grouped into choice sets of a size specified by the algorithm. This approach has been applied to the MNL model [17] and further extended to the MXL model [39]. The choice sets are not assigned to particular respondents in the approach, but rather a number of choice sets are determined which must be subsequently assigned to respondents by the test administrator, due to the mathematical difficulties required to include split-plot and blocking in the algorithm.

While optimal experiments for SP experiments are statistically efficient, Louviere et al. have noted [22, 20] that experiments which are "optimal" with respect to statistical efficiency, but not necessary with respect to the objectives of the choice experiment, may not be ideal. For example, optimal experiments may increase the cognitive burden on test respondents, leading to decreased consistency

Fig. 6.6 Programmable vehicle model (PVM) [37]

in respondent responses as statistical efficiency increases. Another issue to consider is experiment design robustness, i.e., ensuring that the collected experiment data is robust to different choice models, such as an MNL, NL, or MXL, fit to the data, since multiple models may be fit and tested as outlined in Chap. 3. These are considerations to be made before applying the optimal DOE for a given study.

6.6 Case Study: Automotive Occupant Packaging

A case study using an automotive occupant packaging human appraisal is used to demonstrate the optimal DOE methodology developed in the previous section, as well as the advantages of using the blocked split-plot experimental design methodology for human appraisal. The occupant packaging appraisal is performed on a Programmable Vehicle Model (PVM) as shown in Fig. 6.6, which is capable of creating a wide range of parametric representations of an occupant package through a computer controlled interface.

6.6.1 Design of PVM Experiments

A human appraisal experiment has been previously conducted by Ford Motor Co. using the PVM to evaluate occupant package design specifically for headroom. In the experiment conducted, headroom design is characterized by three dimensions as defined by the Society of Automotive Engineers (SAE) J1100 (Society of Automotive Engineers [30]: **L38** (frontal), **W35** (lateral), and **H61** (vertical). These three product factors [$\mathbf{x}^* = (E_1, E_2, E_3)$] were used to create a full $\mathbf{3^2 4^1}$ factorial experiment (i.e., 36 trials) which was given to each of 100 human appraisal respondents, for a total of 3600 ratings responses. The responses were given on a (discrete) scale of 2–10, with 10 representing highest satisfaction with the headroom, and 2 representing the least satisfaction, leading to $P = 9$. Socio-demographic profile (**S**) factors were not used in the design of the experiment; however, the **S** were treated as *covariates* in that the human profile of each person was recorded, but no attempts were made to control the profiles of the respondents in the experimental design process. The data set with ratings responses were used to create a full quadratic response surface model, used to predict a customer headroom rating for a given occupant package design and a given target market human. This data set is referred to as data set ***Full*** in the case study. Conducting an experiment of this size was very time consuming and costly for Ford, and methods to conduct more efficient experiments are needed. Using this example in which data has already been collected, we will demonstrate that the experimental design methodology presented in this chapter allows selection of an experimental design, which can be used to estimate a comparable model with significantly fewer experimental design points than used in the ***Full*** data set. In the new methodology, the $3^2 4^1$ full factorial experiment forms the candidate set for the optimization algorithm. Additionally, a set of potentially significant socio-demographic attributes, **S**, is included in the design of the experiment as whole-plot factors. The socio-demographic profile attributes included are respondent *gender* (Gen) and *stature* (Stat). An issue to address in the experimental design of **S** is that exact levels cannot be practically achieved for all **S** (e.g., stature) in a real human appraisal design. In this case, human attribute *ranges* are assigned to a level in the design of an experiment, for example statures between 54″ and 57″ are coded as the −1 level and those between 73″ and 76″ are coded as the +1 level. These human attribute "bins" are needed to ensure that the proper respondents are selected for the experiment; however, the actual recorded human measurements (e.g., stature, weight, age) are used in the model estimation process. A criterion for selecting the bins is to ensure that 5 and 95 percentile human-measurement respondents of the target population are included in the bins. If more levels (i.e., bins) can be afforded, respondents closer to the human mean (e.g., 50 percentile) should be included; however, it is most important from a *D*-optimality perspective to include 5 and 95 percentile respondents. At the time of the experiment, additional human and socio-demographic attributes of a respondent can be recorded and treated as covariates in the modeling process.

To demonstrate the ability of the new method to manage the size of an experiment, the number of configurations given to each respondent is reduced from 36 to a block size of **18**. The whole-plot experiment design is composed of two levels of gender (i.e., male, female) and four levels of stature (using stature ranges), leading to a $2^1 4^1$ whole plot experiment design. Two respondents (i.e., blocks) are assigned to each whole plot for a total of 16 respondents (or blocks, n), leading to a total of $M = 288$

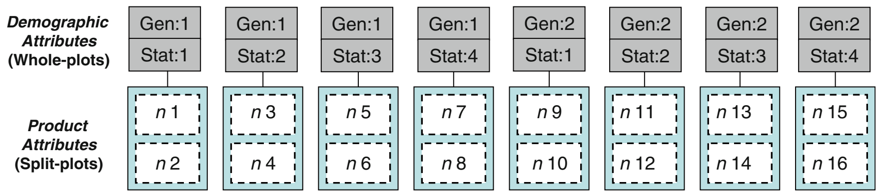

Fig. 6.7 Occupant package blocked split-plot human appraisal experiment

total trials, versus 3600 in the ***Full*** experiment described above. A summary of the experimental design is shown in Fig. 6.7.

The exact form of the model to be estimated is known for this case study from previous work, enabling specification of model form **f(x)** as defined in Eq. (6.2). The model form contains full quadratic terms for **E** (linear, squared, interaction) and linear terms for **S** (no **S**·**E** interactions). With **f**(**x**) specified, the algorithm can be used to select the best 18 configurations to give to each of the 16 respondents. As discussed in Sect. 6.4 a *prior* ratings probability estimate is needed to calculate **M**. For this study, it is assumed that the probability, π_{nip}, of each rating R_p for each respondent n and each configuration i is equally probable, i.e., $\pi_{nip} = 1/9 = 0.11$. Also, it is known from a previous experiment that the correlation among ratings of a single respondent is $\rho = 0.3$. The use of equal ratings probabilities assumes there is *no* prior information about the ratings responses. If prior information is available, (e.g., middle ratings are more likely than extreme ratings) such information can be incorporated to improve the experiment design. In this experiment, the best experiment as selected by the algorithm presents each respondent with a *different* set of configurations, demonstrating that the use of the same 18 point fractional factorial experiment (of the original $3^2 4^1$ = 36 experiments) for each respondent is not optimal for a human appraisal experiment. The data set with observations based upon this design is labeled ***D-Opt***, with an example of the configurations assigned to the first three respondents shown in Appendix B. For comparison, an additional set of experimental designs is created. In these designs, 16 respondents are randomly selected from the original 100 respondents and 18 observations are randomly selected from the 36 total observations for each respondent. A total of 100 such random experiments are created, such that experimental design comparisons are made to the *mean* random experimental design, to ensure that any comparisons are made based upon a typical random experiment and not an outlying design. This set of experimental designs is labeled ***Rand***.

6.6.2 Results of Random Effects Ordered Logit Model Estimation

With the three experimental designs established, a random-effects OL model is estimated using each of the three data sets. A summary of the experimental efficiency as measured by *D*-efficiency, model fit as measured by ρ_0^2 [36], and average rating

Table 6.6 Summary of experiment and model statistics

	Number experiments	*D*-Efficiency (%)	Model fit ρ_0^2	Prediction error (%)
Full	3600	–	0.373	2.80
D-Opt	288	79.7	0.485	6.90
Rand	288	35.8 ± 1.6[a]	0.375	14.60

[a] The mean and ± 1 standard deviation are shown

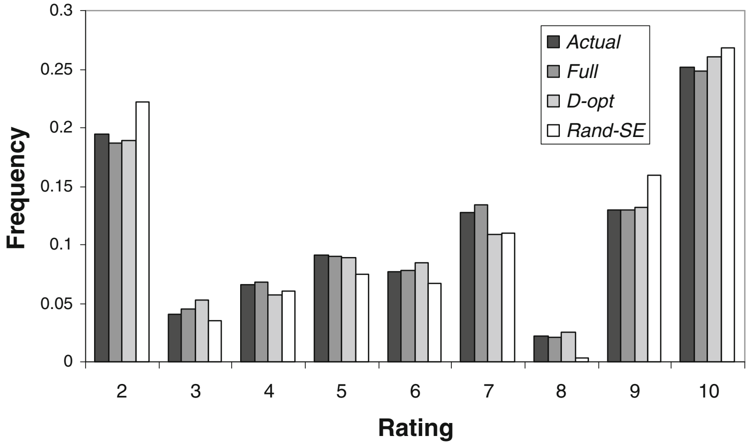

Fig. 6.8 Comparison of ratings predictions to actual ratings

prediction error [14] are shown in Table 6.6. In the case of the ***Rand*** experiment designs, the model fit is evaluated using experimental data with a mean *D*-efficiency.

D-efficiency is a measure of the relative efficiency of an experiment versus a base experiment, for example the ***Full*** experiment in this work. As seen in the table, the *D*-efficiency of the ***D-Opt*** experiment is high, ensuring low variance estimates of the model parameters, whereas the mean *D*-efficiency of the ***Rand*** experiment is quite low and will result in poor model parameter estimates. The ρ_0^2 statistic varies between zero and one and is a function of the log-likelihood of the estimated model, with higher ρ_0^2 indicating a better “model fit”. The ρ_0^2 for the ***D-Opt*** model is significantly higher than that of the ***Full*** model. The explanation for this can be provided by reviewing the assumptions of OL modeling and the nature of ratings. Ratings tend to have higher variance in the middle ratings versus those at the extremes [25]. *D*-optimality tends to bias toward including those configurations with the most extreme settings. Thus by selecting the *D*-Optimal configurations from the full PVM data set, a more efficient estimation of the model $\boldsymbol{\beta}$ parameters, and hence utility, is accomplished for the assumed model. The fit of this mean ***Rand*** model is similar to the ***Full*** model, which is consistent with the fact that the points were randomly selected, so similar model fits are expected. The prediction error is the ratings misclassification error when using the three models to estimate ratings in the full 3600 observation data set. The effects of the prediction error on the resulting ratings predictions can be seen graphically in

Table 6.7 Summary of headroom rating model parameters

	Full model		D-Opt model		Rand model	
	Coefficient	Standard errors	Coefficient	Standard errors	Coefficient	Standard errors
L38	2.61	0.368	4.50	0.731*	2.49	1.449
W35	2.03	0.359	2.11	0.970	2.83	1.376*
H61	12.09	0.491	13.01	2.165**	10.61	1.838*
$L38^2$	−0.74	0.292	−0.76	0.852	−0.23	1.111**
$W35^2$	−1.23	0.291	−1.08	1.562	−2.14	1.104*
$H61^2$	−2.55	0.354	−2.40	1.693	−0.89	1.325*
L38*W35	0.19	0.211	−0.16	0.820	0.13	0.826
L38*H61	−0.32	0.270	−0.16	0.949	−1.15	1.093*
W35*H61	0.49	0.261	0.20	0.857	0.85	1.010
Gender	−0.78	0.494	−0.56	0.726	0.14	1.115**
Stature	−2.24	1.008	−1.81	1.425	−0.94	2.763
resp. σ_u^2	2.95	0.452	1.73	0.780	2.57	1.071

Fig. 6.8. As shown, the prediction error of the mean ***Rand*** model is significantly higher than the other two models.

The estimated model parameters, $\boldsymbol{\beta}$, for the utility function are shown in Table 6.7, along with the standard errors of the parameters (the cut points, **k**, are not shown since these estimates are similar for all three models). We can compare model attributes, such as the relative magnitudes and signs of parameters and the general interpretation of the models, in addition to the model statistics. Considering the model estimated on the ***Full*** data set to be the baseline, it is seen that the model estimated using the ***D-Opt*** data set is close in interpretation. The signs of the parameters agree (except for the insignificant L38*W35 interaction). The ranking of parameter importance as measured by the parameter magnitudes is the same in both models. Vertical headroom clearance (H61) is found to be the most important dimension influencing a respondent's perception of headroom. The next most important dimension is frontal headroom clearance (L38), followed by lateral headroom clearance (W35). The human attributes indicate that taller respondents and female respondents (gender is a dummy variable: 0 = male, 1 = female) systematically respond with lower headroom ratings (on average) than shorter and male respondents, respectively. The ratio of parameters (e.g., W35/H61) is similar in both models, with the exception of L38 which is more important in the ***D-Opt*** model. The reason for this could be explained by the improved model fit statistic, ρ_0^2, of the ***D-Opt*** model as described previously.

The model parameters in the ***D-Opt*** and ***Rand*** models are compared to those in the ***Full*** model using a *t*-test, in which the null hypothesis is that the model parameters are not different. The model parameters in which the null hypothesis can be rejected with 95% confidence are marked with *, whereas those rejected with 90% confidence are marked with ** in Table 6.7. As seen in the table, the

Table 6.8 Comparison of three-factor to eight-factor human appraisal experiment

Product factors	3 Factors, 3 Levels		8 Factors, 3 Levels	
Human factors	$2^1 4^1$		2^3	
	Mean	Standard deviation	Mean	Standard deviation
D-optimal exp	2.24E + 59		8.10E + 140	
Random exp	6.17E + 52	5.3E + 52	9.77E + 105	1.1E + 107
D-efficiency random	45.0%	2.1%	29.4%	4.2%

Rand model contains significantly more parameters which differ from the ***Full*** model than the ***D-Opt*** model. Such results are expected due to the lower *D*-efficiency of the ***Rand*** experiment, which results in less precise estimates of the model parameters than the higher efficiency ***D-Opt*** model.

While the *D*-optimization algorithm has been shown to be effective for this example, its true utility is in experiments with large numbers of product attribute factors (e.g., 6–9) and several human attributes. In such a case, the candidate set will be several hundred to several thousands of potential points, and the task of choosing the appropriate set of points for each respondent is not as straightforward as in the previous example. To demonstrate, an experiment designed for the PVM to elicit preferences for the roominess and ingress/egress of the vehicle occupant package is used. In this simplified experiment, eight product factors are examined by eight respondents, and it is desired to estimate all linear, quadratic, and all two-factor $\mathbf{E}\cdot\mathbf{E}$ and $\mathbf{E}\cdot\mathbf{S}$ interactions. Respondents are selected based upon three human factors at two levels (a 2^3 full factorial human experiment). The experiment design for the product attributes is conducted by selecting 18 points from a 3^8 full factorial (i.e., C_{6561}^{18}) for each respondent. In this example, the *D*-optimal experimental design is found with the algorithm, and 100 randomly selected experimental designs are also generated for comparison as in the previous example. In this comparison, the *D*-optimal experiment is the baseline for the efficiency comparison, since comparison to an experiment in which each respondent receives the 3^8 full factorial, product factor experiment (i.e., 6561 configurations) is not a realistic baseline. In Table 6.8, the mean *D*-efficiency of the eight-factor random experiments in this example is compared to the mean *D*-efficiency of the random three-factor experiments of the previous example. As shown, the efficiency of the random three-factor experiment has a mean *D*-efficiency of 45.0%, whereas the random eight-factor experiment has a mean *D*-efficiency of 29.4%. The variance of the random eight-factor experiment is higher than the three-factor experiment as would be expected in selecting 18 points from 6561 (C_{6561}^{18}) versus 36 (C_{36}^{18}) points for each respondent. As shown previously in Table 6.7, reduced *D*-efficiency results in reduced precision when estimating model parameters.

6.7 Summary

In addition to an overview of design of experiment techniques for eliciting customer preferences in the forms of both choice experiments and rating experiments, an algorithmic approach for selection of the optimal design of experiments for human appraisal (rating) experiments has been developed, demonstrated, and validated in this chapter. An algorithmic approach is necessary for human appraisals due to the large number of potential design and human attributes, coupled with issues of respondent fatigue in such experiments. Human appraisal experiments have been shown to be unique in that the experiment response is a function of both the product attributes and the human attributes of the respondent. They are characterized as split-plot designs, in which the respondent human attributes form the hard-to-change whole-plot factors while the product attributes form the split-plot factors. The experiments are also characterized by random block effects, in which the configurations evaluated by a single respondent form a block. The experimental design algorithm presented seeks to identify the experimental design, which maximizes the determinant of the Fisher Information Matrix, or D-criterion, of a given design, assuming that the model to be estimated is an OL model.

The case study and subsequent discussion demonstrate many of the key features of the optimization algorithm. Most importantly, it was shown that the algorithm allows efficient model estimation with a minimal number of experiment points. For the vehicle headroom appraisal, previous methods had used 3600 experiment points, while a comparable model was estimated using 288 experiment points selected using the proposed algorithm. Also, it was shown that randomly selecting 288 points from the full 3600 point experiment produces an inferior model, and the utility of the algorithm increases as the number of experiment factors increases. The optimization algorithm distributes a different set of experiment points to each respondent, demonstrating that using a standard fractional factorial to reduce the number of trials per person is not the best alternative for human appraisals. This methodology is used to design a human appraisal experiment to understand preferences for automobile occupant package design. The data collected from this human appraisal is used to build random effects OL models, which are utilized in the Bayesian Hierarchical Choice Model of Chap. 8.

6.8 Additional Resources for Computational Implementation

The following texts provide a comprehensive introduction to Design of Experiments:

- Box GEP, Hunter JS, Hunter WG (2005) Statistics for experimenters: Design, innovation, and discovery. John Wiley & Son, New York
- Montgomery DC (2005) Design and analysis of experiments. John Wiley and Sons, Inc., New York

The following text provides a comprehensive treatment of Optimal Design of Experiments:

- Atkinson AC, Donev AN (1992) Optimum experimental designs. Oxford University Press, Oxford

The following packages in R (http://www.r-project.org/) are available for designing experiments:

- The package `DoE.base` provides the function `fac.design` to create factorial designs and the function `oa.design` for creating orthogonal arrays.
- The package `AlgDesign` provides the function `optFederov` to create optimal designs using the Federov exchange algorithm and the function `optBlock` to create optimal blocked experiments.

Appendix A: Simplified Method of Expressing M

This appendix provides a method for expressing the information matrix, **M**, and estimating the prediction variance of a given extended design point, **f(x)**, for use in the optimization algorithm. The ordinal data GLM information matrix of Eq. (6.9) can be written in analogous fashion to the GLS formulation of Eq. (6.7) [14]. An $\mathbf{H}_n$ matrix is defined as a matrix of derivatives of the logistic CDF as $\mathbf{H}_n = \mathrm{diag}\left(f_{n1}, f_{n2}, \ldots f_{n(P-1)}\right)$. The extended design point $\mathbf{f}(\mathbf{x}_{in})$ for a given respondent and given configuration is defined as:

$$\mathbf{f}(\mathbf{x}_{in}) = \begin{bmatrix} 1 & 0 & \cdots & 0 & -\mathbf{x}_{in} \\ 0 & 1 & \cdots & 0 & -\mathbf{x}_{in} \\ \vdots & \vdots & \ddots & \vdots & -\mathbf{x}_{in} \\ 0 & 0 & 0 & 1 & -\mathbf{x}_{in} \end{bmatrix}. \tag{A.1}$$

A $\mathbf{C}_n$ matrix defined as:

$$\mathbf{C}_n = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ -1 & 1 & \cdots & 0 \\ 0 & -1 & \cdots & 0 \\ \vdots & \vdots & \ddots & 1 \\ 0 & 0 & \cdots & -1 \end{bmatrix}. \tag{A.2}$$

With $\mathbf{C}_n$, $\mathbf{H}_n$ and **f(x)** defined, the information matrix can be written as [14]:

$$\mathbf{M} = \sum_{n=1}^{N} \mathbf{F}'_n \mathbf{W}_n^{-1} \mathbf{F}_n \tag{A.3}$$

where $\mathbf{W}_n^{-1} = \mathbf{H}_n \mathbf{C}'_n \mathbf{V}_n^{-1} \mathbf{C}_n \mathbf{H}_n$, and **F** is the extended design matrix composed of the **f(x)**.

Appendix B: Example of Experimental Configuration Blocks

Table B.1 Example of three experimental configuration blocks

Config	L38	W35	H61	Gender	Stature	Resp.
1	−1	−1	−1	−1	−0.33	1
2	−1	−1	1	−1	−0.33	1
3	−1	0	−0.33	−1	−0.33	1
4	−1	0	1	−1	−0.33	1
5	−1	1	−1	−1	−0.33	1
6	−1	1	0.33	−1	−0.33	1
7	−1	1	1	−1	−0.33	1
8	0	−1	−1	−1	−0.33	1
9	0	−1	1	−1	−0.33	1
10	0	0	1	−1	−0.33	1
11	0	1	−1	−1	−0.33	1
12	1	−1	−1	−1	−0.33	1
13	1	−1	−1	−1	−0.33	1
14	1	−1	0.33	−1	−0.33	1
15	1	0	1	−1	−0.33	1
16	1	1	−1	−1	−0.33	1
17	1	1	0.33	−1	−0.33	1
18	1	1	1	−1	−0.33	1
1	−1	−1	−1	1	0.33	2
2	−1	−1	−1	1	0.33	2
3	−1	−1	1	1	0.33	2
4	−1	0	1	1	0.33	2
5	−1	1	−0.33	1	0.33	2
6	−1	1	−0.33	1	0.33	2
7	−1	1	1	1	0.33	2
8	0	−1	−1	1	0.33	2
9	0	0	−1	1	0.33	2
10	0	0	−0.33	1	0.33	2
11	0	1	1	1	0.33	2
12	1	−1	−0.33	1	0.33	2
13	1	−1	1	1	0.33	2
14	1	−1	1	1	0.33	2
15	1	0	1	1	0.33	2
16	1	1	−1	1	0.33	2
17	1	1	−1	1	0.33	2
18	1	1	1	1	0.33	2
1	−1	−1	−1	1	1	3
2	−1	−1	−1	1	1	3
3	−1	−1	1	1	1	3
4	−1	−1	1	1	1	3
5	−1	1	−1	1	1	3
6	−1	1	−1	1	1	3

(continued)

Table B.1 (continued)

Config	L38	W35	H61	Gender	Stature	Resp.
7	−1	1	1	1	1	3
8	−1	1	1	1	1	3
9	0	1	−0.33	1	1	3
10	0	1	1	1	1	3
11	1	−1	−1	1	1	3
12	1	−1	−1	1	1	3
13	1	−1	1	1	1	3
14	1	−1	1	1	1	3
15	1	0	−1	1	1	3
16	1	1	−1	1	1	3
17	1	1	0.33	1	1	3
18	1	1	1	1	1	3

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Chapter 7
Data Analysis Techniques to Support Demand Model Estimation

Nomenclature

A	Customer-desired product attributes
AIC	Akaike information criterion
β	Discrete choice or ordered logit model coefficient for customer-desired attributes in a customer's utility function
bs	Bias
$C.S.$	Choice share (aggregate product choice probability)
df	Degree of freedom
Ds	Degree of dissimilarity
E	Engineering attributes
ε_{in}	Random disturbance of customer choice utility of alternative i by customer n
i	A configuration or alternative
$\mathbf{k}$, k_p	Ordered logit cut-points
L^2	Likelihood ratio test
LL	Log-likelihood
n	A respondent
PVM	Programmable vehicle model
ρ_0^2	Model fit statistic for discrete choice and ordered logit models
S	Demographic attributes
SS	Sum of squares
su	Scale usage
$styl$	Rating style
σ_u	Variance at the respondent level
σ_ε	Variance at the observation level
u_{in}	True customer choice utility of alternative i by customer n
W_{in}	Observed part of the customer choice utility of alternative i by customer n

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_7,

In this chapter, we present methods to analyze the data collected in the stated (customer) preference experiments. These methods are employed to ensure the data is processed to maximize the predictive capability of the resulting discrete choice analysis (DCA) and ordered logit (OL) models. First, multivariate statistical methodology for data analysis is introduced. Four methods for data exploration, or preprocessing, are introduced, followed by three methods for creating predictive models from the collected and preprocessed data. The first of the preprocessing methods is Latent Class Analysis (LCA), which is presented as a method to reduce a set of survey responses to a few key measures of customer preference. Next, we introduce Analysis of Variance (ANOVA) methods to understand the importance of product and human attributes on responses; this is followed by Hierarchical Clustering to understand the influence of rating style on the measured responses. Smoothing Spline Regression (SSR) is used to understand the shape of the factors to be used in the resulting predictive models. In terms of predictive modeling, three methods are compared. The baseline method is OL modeling; this method is compared to more recent methods in the area of machine learning, or data mining, such as Decision Tree or Bayesian Network analysis. The automobile occupant packaging problem as presented in Chap. 6 is again used as the case study throughout this chapter.

7.1 Introduction to Multivariate Statistical Methods

In this chapter, statistical methods are introduced to analyze data collected in stated preference experiments to support creation of preference models used in the DBD framework. Analyzing and creating models from data collected from a human appraisal experiment presents unique issues not encountered with data collected from the typical industrial and scientific experiments usually considered in design of experiments methodology [1, 10]. The key issues in human appraisals are:

- responses are more difficult to elicit,
- respondents may utilize different rating styles,
- the shape of the response factor curve may not be approximately linear, and
- interactions may be highly significant.

To address these issues, several analysis and modeling methodologies are presented in this chapter to combine multiple customer responses into a set of combined measures, to understand the influence of respondent heterogeneity on rating responses, and to gain further insight into the experiment using alternate data analysis methods. These methods are generally classified as *Multivariate Statistical Analysis* (or Multivariate Analysis) methods [7]. Multivariate analysis is a set of methods for the analysis of more than one statistical variable. This set of statistical variables can be either classified as multiple model inputs, such as a set of **A**, **E** or **S** variables, or multiple model outputs, such as a set of rating responses made by an individual. The goal of these analysis methods is to understand the relationships between the variables and their relevance to the particular problem being solved, such as estimating a demand model for the DBD method. In this chapter, we will differentiate between methods used for exploring the data, or *preprocessing* the data, versus those used for *predictive modeling* from the data collected. While there are a wide range of methods available for data exploration, we will utilize four specific methods applied to an example human appraisal experiment on vehicle packaging design [6].

(1) In the human appraisals, multiple responses are often collected from the respondent for a single desirable aspect of design, e.g., roominess. The reason multiple responses are collected is because it can be challenging to devise a single survey question to capture the respondents' true opinion of the particular aspect as a whole, especially if the aspect is qualitative. To determine a measure to use in the modeling process, LCA [9] is used to create a combined measure for each respondent to fully describe his/her overall opinion of certain aspect of design.
(2) To understand the overall influence of design factors, socio-economic factors, rating style, and errors, the ANOVA method [4] is used.
(3) Heterogeneity of the survey respondents has much influence on the rating responses given. The effect of *systematic* heterogeneity, which is heterogeneity that can be captured with a human variable in the model, is investigated using SSR [17].
(4) *Random* heterogeneity, which is heterogeneity not directly observed but rather captured in a distribution of respondent-specific intercepts, is investigated using *Cluster Analysis* (CA) [7].

With respect to creating models from the collected data, three *predictive modeling* techniques will be examined in this chapter:

(1) *Random-effects ordered logit* (RE-OL) models for the prediction of ratings for a given population and a given design are estimated; these models are used in the Bayesian Hierarchical Choice Modeling approach of Chap. 8, or optionally in the Latent Variable approach of Chap. 9. In addition to utilizing the results of the previous analyses, interaction effects are also investigated in the RE-OL modeling process.
(2) A *Decision Tree* [2] will be utilized to create a model of a rating response as a function of the **E** (or **A**) and **S** available in the data set. The decision tree does not create a parametric model but rather a graphical representation of the relationships in the data.
(3) *Bayesian Networks* [11] will be used to both create a non-parametric rating model comparable to the OL model, as well as to understand other relationships in the data.

The methods presented in this chapter are useful for understanding the heterogeneous preferences within a customer population, and will be applicable for understanding preferences for system, subsystem, or component design.

7.2 Programmable Vehicle Model (PVM) for Human Appraisal Experiments

Chapter 6 outlined the process for designing human appraisal experiments, and employed a three-factor headroom experiment conducted by using the Programmable Vehicle Model (PVM) at the Ford Motor Company [15] to demonstrate the methodology. In this chapter, the same practical example is used to demonstrate the use of multivariate statistical methods for data analysis. The PVM experiments are utilized to aid in determining preferences for automobile occupant package design, specifically regarding the *roominess*, *ingress* and *egress* quality of the package. Details of the factors, levels, responses, experiments, and survey questions used in the PVM experiments are introduced in this section. In the PVM experiment, each respondent is presented with several package configurations, for which they evaluate and express their opinion in the form of a rating (e.g. 1–5, 0–10); this is a standard method for quantifying preferences for subjective attributes [8]. The intent is to use the data collected in the experiments to build OL models to predict customer preferences (i.e. ratings) for a given set of customers and for a given occupant package design.

The full design of the PVM roominess/ingress/egress experiment is created using the optimal design of experiments (DOE) methodology of Chap. 6. The combined experiment consists of eight product factors, determined from a mapping of customer-desired attributes (**A**) to engineering attributes (**E**), to influence roominess, ingress, and egress. The eight factors used in the human appraisal experiment correspond to dimensions defined for control of the Ford Motor Co. PVM:

1. E_1: Hinge position in X (HNG_X)
2. E_2: Rocker position in Y (ROK_Y)
3. E_3: Heel position in Z (HEL_Z)
4. E_4: Ground position in Z (GRD_Z)
5. E_5: Sill position in Z (StoH)
6. E_6: Roof position in Z (HR_Z)
7. E_7: Front header position in X (HR_X)
8. E_8: Side rail position in Y (HR_Y)

The relationship among the product attributes and roominess and ingress/egress aspects is illustrated in Fig. 7.1. All product factors, E_1–E_8, assume three levels to create a response surface OL model (i.e. -1, 0, 1), in accordance with the power law response assumption discussed in Chap. 6, Sect. 6.3.3.

Three human attributes have been hypothesized to influence roominess/ingress/egress opinions:

1. S_1: Gender (Gend)
2. S_2: Body mass index (BMI)
3. S_3: Stature (Stat)

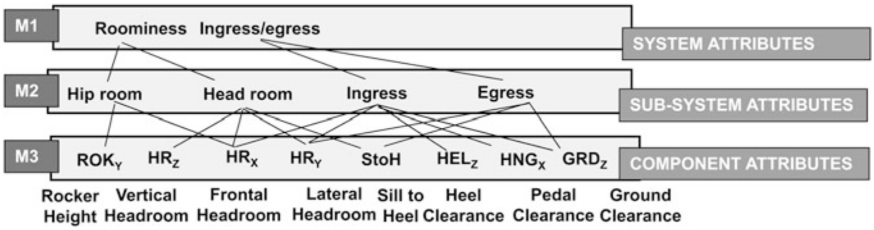


Fig. 7.1 Relationship among product attributes and roominess/ingress/egress

Table 7.1 Levels of human factors (**S**) used in PVM experiment

	Gender		BMI		Stat: M (in)	Stat: F (in)
−1	Male	−1	<24	−1	65–68	58–62
+1	Female	0	24–30	−0.33	68–71	62–65
		+1	>30	+0.33	71–73	65–68
				+1	73–78	68–74

In this experiment, gender assumes two levels (i.e. male, female), BMI three levels (i.e. low, medium, high), and stature (or height) four levels (i.e. small, medium–small, medium–large, large), and human attribute bins are used for both BMI and stature as described in Chap. 6, Sect. 6.5. The levels used for the human attributes are shown in Table 7.1.

It is desired to estimate the following terms in the resulting roominess/ingress/egress models:

- Linear terms for all design factors (**E**) and all demographic factors (**S**) (11 terms)
- Quadratic terms for all **E** (eight terms)
- All two-factor **E** · **E** and **E** · **S** interactions (28 **E** · **E** and 24 **E** · **S** terms)
- The OL cut-points (all cut-points count as one term in the **X** matrix)

The total number of terms, i.e., the size of the $f(x)$ vector, is 72, which is the number of unique configurations required in the experiment. Based upon previous studies conducted by Ford Motor Co., it has been found that a respondent can evaluate 18 configurations before fatiguing, leading to a block size, B, of 18 for each respondent. Based on the number of terms to be estimated and the block size, the minimum number of unique blocks needed in the experiment is four. Based on the size of the full factorial demographic design of 24 ($2^1 3^1 4^1 = 24$) and the desire to have two respondents per demographic class, the experiment requires a total number of respondents (or blocks), N, of 48, each evaluating 18 configurations for a total experiment size, M, of 864. In this experiment, there are also several factor combinations to specifically exclude:

- no pairing of $GRD_Z = -1$ and $HEL_Z = +1$
- no pairing of $GRD_Z = -1$ and StoH $= -1$

- no pairing of $GRD_Z = +1$ and $StoH = +1$
- no pairing of $GRD_Z = +1$, $HEL_Z = -1$, and $ROK_Y > -1$.

With the parameters necessary to run the algorithm of Chap. 6 determined, the experiment is designed.

A practical issue encountered with the full experiment is that the resources required for the full experiment could not be secured, and therefore only one half of the experiment is conducted. The *D*-optimal algorithm is used to identify a two-part experiment in which the first two blocks (i.e. blocks 1 and 2) of 18 enable the estimation of 36 selected model terms, while the second two blocks (i.e. blocks 3 and 4) are *augmented* to the original two blocks to allow estimation of the remaining 36 terms. The 36 model terms selected which can be estimated with completion of blocks 1 and 2 are as follows:

- Linear terms for design factors (**E**) and all demographic factors (**S**) (eight product terms)
- Quadratic terms for all **E** (eight terms)
- Two-factor $\mathbf{E} \cdot \mathbf{E}$ interactions from $E_1 \cdot E_2$ through $E_4 \cdot E_5$ (19 terms)
- All the OL cut-points (one term)

Conducting the experiment in two parts reduces the *D*-efficiency to 84.6% of the original experiment, but reduces the first part of the experiment *N* to 24 and *M* to 432. The experimental design for unique blocks 1 and 2 used in this study is shown in Table 7.2. Because two blocks are used, a fractional factorial experiment for the human attribute whole plots (**S**) is needed. The *D*-optimal algorithm is used to identify the most efficient fractional factorial design for the demographic attributes shown in Table 7.3. While the 12 types of respondents are identified in the table, we have specified that we want to evaluate two respondents from each demographic class, resulting in 24 respondents. A total of 30 terms can be estimated from the whole-plot demographic experiment:

- Individual block effects (24 terms).
- Linear terms for demographic factors (**S**) (three terms).
- Two-factor $\mathbf{S} \cdot \mathbf{S}$ interactions (three terms).

With a complete experimental design for **E** (i.e. split-plot factors) and **S** (i.e. whole-plot factors) the logistics of conducting the experiment are addressed. For each of the 18 configurations presented, the respondent is asked to evaluate the following subsystem designs and to provide ratings to ten responses as follows (rating scale to be used shown in parentheses):

1. *Ingress*. Acceptability (1–4), Effort (1–5), and Space (1–5)
2. *Interior*. Headroom (1–5), Leftroom (1–5), Kneeroom (1–5), and Roominess (1–5)
3. *Egress*. Acceptability (1–5), Effort (1–5), and Space (1–5)

An example of the questions given to each respondent is provided in Fig. 7.2.

Table 7.2 Block 1 and 2 experimental design for product factors (E)

E_1	E_2	E_3	E_4	E_5	E_6	E_7	E_8
SgRP to hinge (HNG_X)	SgRP to rocker **Y** (ROK_Y)	SgRP to heel **Z** (HEL_Z)	SgRP to ground **Z** (GRD_Z)	Sill to heel (StoH)	SgRP to roof **Z** (HR_Z)	SgRP to Frt Hdr X (HR_X)	SgRP to side rail **Y** (HR_Y)
1	−1	−1	−1	−1	−1	−1	−1
−1	−1	1	1	0	1	−1	−1
−1	−1	−1	0	1	1	−1	−1
1	1	1	−1	1	1	0	−1
1	−1	1	−1	−1	−1	1	−1
−1	1	1	−1	−1	−1	1	−1
−1	1	−1	−1	1	0	1	−1
1	−1	1	−1	1	0	1	−1
0	0	0	−1	1	1	1	−1
1	1	1	−1	−1	0	−1	0
−1	−1	−1	1	−1	−1	−1	1
1	−1	1	1	0	−1	−1	1
1	1	0	1	−1	1	−1	1
1	1	1	−1	1	−1	0	1
−1	0	−1	0	1	−1	1	1
1	−1	−1	0	0	1	1	1
−1	1	0	0	1	1	1	1
−1	−1	1	−1	1	1	1	1
−1	1	1	−1	1	−1	−1	−1
1	−1	0	0	0	1	−1	−1
−1	−1	1	−1	1	−1	0	−1
1	0	0	0	0	0	0	−1
1	−1	1	1	−1	1	0	−1
1	1	−1	−1	−1	−1	1	−1
−1	−1	−1	1	−1	−1	1	−1
1	−1	−1	1	0	1	1	−1
−1	1	−1	−1	−1	−1	−1	0
−1	1	1	1	0	−1	1	0
−1	1	1	1	−1	−1	−1	1
1	−1	−1	0	1	−1	−1	1
−1	−1	−1	−1	1	−1	−1	1
0	1	−1	−1	0	0	−1	1
1	1	−1	0	1	1	−1	1
−1	−1	0	−1	−1	0	1	1
−1	1	−1	−1	−1	1	1	1
1	0	1	−1	−1	1	1	1

An abbreviated example of the recorded ratings for a single respondent is given in Fig. 7.3.

In addition to the human attributes used in the experimental design, several additional human and socio-economic attributes (referred to as the set of respondent demographic attributes) are recorded at the time of the experiment,

Table 7.3 Experimental design for demographic attributes

S_1	S_2	S_3
Gender (Gend)	BMI (BMI)	Stature (Stat)
M	<24	65–68
M	>30	65–68
M	>30	68–71
M	<24	71–73
M	24–30	73–78
M	>30	73–78
F	<24	58–62
F	>30	58–62
F	<24	62–65
F	24–30	65–68
F	<24	68–74
F	>30	68–74

1. How acceptable is this vehicle configuration for ingress? This is rated on a 1 to 4 scale with the following definition for each rating as you can see posted in front of the vehicle: 1 is “very unacceptable”, 2 is “somewhat unacceptable”, 3 is “somewhat acceptable” and 4 is “very acceptable”.

Very unacceptable	Somewhat unacceptable	Somewhat acceptable	Very acceptable
1	2	3	4

2. What is the overall ease of ingress, for the vehicle? This includes evaluation of stepping up and passing through the door opening. This question is rated on a 1 to 5 scale, again as you can see posted in front of the vehicle, with the following definition for each rating: 1 is “very strong effort”, 2 is “strong effort”, 3 is “moderate effort”, 4 is “weak effort”, and 5 is “no effort at all”.

Very strong effort	Strong effort	Moderate effort	Weak effort	No effort at all
1	2	3	4	5

Fig. 7.2 Example PVM human appraisal questions

including seated height, age, and current vehicle ownership. Additionally, as noted in the experimental protocol, the respondent is allowed to adjust the position of the seat, and the respondents’ lateral seat positions and seat back angles are also recorded.

With completion of the experiments and a complete data set for the 24 respondents, the multivariate statistical data analysis methods are implemented in the remainder of the chapter to preprocess the data, build useful models, and understand the data collected. In this chapter, all factor values are normalized on the scale [0, 1] for modeling and analysis, except where noted.

Name: S34

Recorded Anthropomorphic and Demographic Information

Gender	Height	Seated Height	Weight	Shoe Size	Heel Height	Age*	Current Vehicle	BMI
	in.	in.	lb	in.	in.	Category		
F	66.5	35.8	121	10.25	2.0	3	Taurus X	19.21

Recorded Ratings

		Ingress			Interior				Egress		
#		Acceptable	Ease/effort	Space	Headroom	Left Room	Knee Room	Roominess	Acceptable	Ease/effort	Space
1	6000	1	1	1	1	4	4	2	1	1	1
2	1504	1	1	1	1	4	4	1	2	2	2
3	5317	1	2	1	1	5	5	2	1	2	1

Fig. 7.3 Example of PVM ratings from one respondent

7.3 Methods for Data Preprocessing (Understanding)

7.3.1 *Latent Class Analysis for Response Reduction*

Methodology. As noted in Sect. 7.1, multiple ratings are collected for each subsystem design, e.g., ingress, however, it is desired to create a single measure as an input to the choice model. LCA is used to identify similarity in rating responses, as opposed to similarity in customer populations as in the Discrete Choice Analysis literature [14]. LCA is a general method for data reduction for discrete categorical or ordinal data, analogous to factor analysis used for continuous variables [9]. LCA assumes that several discrete variables, such as the multiple ratings given by each person for a given subsystem design, are *indicators* of an overall discrete *latent class* (LC), such as an overall opinion of ingress or egress. LCA provides a single LC response for each subsystem response (e.g. ingress), based upon the value of the indicators. This predicted LC can be used as the ingress or egress response in a parametric model, such as the discrete choice model, analogous to the use of factor scores resulting from factor analysis for continuous variables.

LCA assumes that the several response indicators are correlated, and seeks to divide the subsystem responses into a number of LCs such that the indicators are *conditionally independent* within each class. Conditional independence implies that the correlation between the indicators is no higher than "chance" correlation in any class. In order to determine the division of subsystem responses to LCs, the number of LCs must be defined a priori for model estimation. The division of subsystem responses is achieved using maximum likelihood estimation to estimate the conditional probabilities of each subsystem response given the LC, and the probability of each LC. A given model can be tested for conditional independence using the likelihood ratio Chi-squared test, $L^2 = 2\sum_i n_i \ln\left(\frac{n_i}{\hat{m}_i}\right)$, where n_i is the observed cell frequency in the cross-tabulation table, and $\hat{m}_i$ is the expected cell

Table 7.4 Correlation matrix for ten PVM responses

	Ingress			Roominess				Egress		
	Accept	Effort	Space	Head	Left	Knee	Room	Accept	Effort	Space
Ingress										
i_acceptable	1									
i_effort	0.828	1								
i_space	0.786	0.727	1							
Roominess										
Headroom	0.568	0.474	0.664	1						
Leftroom	0.244	0.265	0.259	0.223	1					
Kneeroom	0.273	0.294	0.249	0.193	0.522	1				
Roominess	0.562	0.527	0.660	0.774	0.549	0.444	1			
Egress										
e_acceptable	0.773	0.739	0.678	0.442	0.256	0.251	0.500	1		
e_effort	0.700	0.779	0.629	0.364	0.216	0.247	0.437	0.850	1	
e_space	0.682	0.669	0.824	0.526	0.290	0.238	0.580	0.786	0.744	1

frequency. The null hypothesis is that the indicators are conditionally independent within each LC. Another statistic to consider is the index of dissimilarity, Ds, given by $Ds = \sum_i \mathrm{abs}(n_i - \hat{m}_i)/(2M)$; this measure is the proportion of observations that would have to change cells for the model to fit perfectly, with a generally accepted criterion of $Ds < 0.05$. Among different models (i.e. different assumptions on the a priori number of LCs) which display conditional independence, and $Ds < 0.05$, the akaike information criterion (AIC), which is a function of likelihood and the number of classes [through the remaining degrees of freedom (df)], is used for model selection. It is given by $\mathrm{AIC} = L^2 - 2df$; the model with the lowest AIC is the preferred model, i.e., the model which balances goodness of fit with the number of model parameters.

LCA of PVM Data. For the PVM experiment, it is desired to understand the relationship among the ten responses collected for roominess, ingress, and egress as enumerated in Sect. 7.2. A correlation matrix is first estimated (Table 7.4), which indicates significant correlation among the responses for each subsystem.

The following conclusions can be drawn from the correlation matrix and coefficients, r:

(1) Responses for the three ingress questions are highly correlated ($r > 0.7$).
(2) Responses for the three egress questions are highly correlated ($r > 0.7$).
(3) Ingress responses are highly correlated to egress responses ($r > 0.6$).
(4) Headroom and leftroom are highly correlated to roominess ($r > 0.5$).
(5) Roominess and headroom are moderately correlated with ingress and egress ($r > 0.35$).

LCA is conducted for ingress, assuming the three ingress questions (i.e. acceptability, effort, and space) are indicators of each person's overall opinion of

Table 7.5 Model fit parameters for differing class number assumptions

LC	*LL*	*df*	L^2	AIC	*Ds*
1	−2,619.39	88	0.000	1,217.79	0.614
2	−2,209.27	76	0.000	421.55	0.384
3	−2,047.40	64	0.000	121.82	0.258
4	−1,969.79	57	0.001	−19.40	0.164
5	−1,944.48	50	0.712	−46.01	0.051
6	−1,942.11	42	0.592	−44.75	0.046
7	−1,936.82	44	0.964	−59.33	0.034
8	−1,936.54	38	0.880	−47.91	0.034
9	−1,937.36	26	0.279	−22.26	0.035
10	−1,937.45	19	0.053	−8.09	0.036

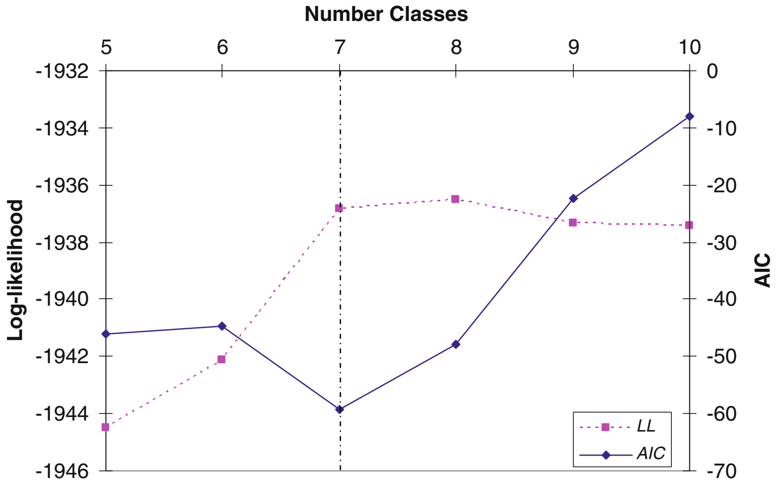


Fig. 7.4 Log-likelihood and AIC versus number of classes

the ingress quality. Different numbers of LCs, between 1 and 10, are assumed. The results of each of the ten models are shown in Table 7.5. Based upon the criteria given for L^2 and *Ds*, models with one to four LCs are not acceptable models (the five class model is borderline w.r.t. the *Ds* measure, but will be considered a viable model). The models with between 5 and 10 LCs are compared based on the log-likelihood (*LL*) and the AIC criteria in Table 7.5 and shown graphically in Fig. 7.4. The comparison indicates that increases in the number of classes beyond seven provides no further increase in the *LL*, while the AIC criterion indicates that the seven class model is preferred considering both the *LL* and the *df*.

The assignment of cases to the LCs is accomplished using a classification table, in which a case is assigned to the LC where it has the highest probability of belonging, as estimated by the conditional probability, π_i, of belonging to each

Table 7.6 Assignment of cases to latent classes

Response number	Ingress acceptability	Ingress effort	Ingress space	Latent class
101	1	2	1	1
103	1	3	2	2
105	2	3	2	3
108	2	3	3	4
110	3	3	3	5
115	3	4	4	6
120	4	5	5	7

Table 7.7 Ordered logit coefficient comparison of ingress measures

	Ingress measure				
	Acceptability	Effort	Space	Range	Latent class
HEL_Z	2.017	2.272	1.344	1.34 to 2.27	1.912
GRD_Z	−2.026	−2.261	−1.162	−2.26 to −1.16	−1.875
StoH	−1.124	−1.268	−0.731	−1.27 to −0.73	−0.985
HR_Z	2.270	1.745	2.703	1.75 to 2.70	2.196
HR_X	0.550	0.512	0.476	0.48 to 0.55	0.527
Stat	−2.814	−2.790	−4.954	−4.95 to −2.79	−3.150
Age	3.402	2.878	2.493	2.49 to 3.40	2.956
BMI	−2.382	−1.686	−2.003	−2.38 to −1.69	−2.158
ρ_0^2	0.1886	0.1873	0.1873		0.139

class. Example assignments of select cases of the three individual ingress responses to the seven LCs are shown in Table 7.6.

The LC is used as the response variable in the OL model, just as ingress acceptability, effort, or space are used. A comparison using the LC ingress measure versus the original three ingress measures is shown in Table 7.7 using OL models for comparison (numbers in the Table are OL β coefficients)

As seen in the models, the parameters in the LC model are within the max and min range of the parameters in the models using the three indicators as responses, indicating the LC is capturing the effect of all three of the ingress indicators. LCA was also conducted for the three egress responses, with a similar result to ingress: the preferred number of classes was found to be seven, with $L^2 = 0.99$, $Ds = 0.045$, and AIC $= -53.65$. LCA was used to create a model for all six ingress/egress responses, assuming ingress and egress responses are indicators of an overall opinion of the vehicle opening. This theory is supported by the fact that high correlation was found between ingress and egress responses; however, a model with an acceptable Ds measure is not identified with any number of assumed LCs. Therefore, it can be concluded that the three ingress responses are indicators of a respondent's opinion of ingress, whereas the three egress responses are indicators of egress opinion.

7.3.2 Understanding Factor Importance and Rating Style

7.3.2.1 Analysis of Variation of Rating Responses

Methodology. In the previous section, LC analysis was used to understand the relationship among responses, in situations in which multiple responses are assumed to be related to a single unobserved latent factor. In this section, methods are used to understand the relationship among the factors (product and human attributes), respondents, and the responses. In order to understand how the overall variance in the responses is partitioned among the explanatory variables, an ANOVA study is conducted. The ANOVA method was first formalized by Fisher in the 1920s [4] and remains a fundamental method in multivariate analysis. ANOVA analysis is an investigation of how the total sum of squares, SS_T, is decomposed into the sum of squares (SS) contributions from the model, SS_M, and the error, SS_E. The SS_M can be further decomposed to understand the influence of the individual product factors, SS_{TR}, and the individual human factors, SS_R, including the *block effect* attributable to individual respondents. The block effect is the portion of the respondent response not explained by the human factors, with the effect of different configurations and human attributes removed. It is realized in a model as a respondent-specific intercept (i.e. 24 unique intercepts). The magnitude of the sum of squares is a measure of the contribution of each factor and respondent, as well as the error, in explaining the variation in the responses (i.e. the ratings). ANOVA can be applied to the PVM experiment results to understand the contributions of the design factors, human factors, block effects, and errors to the total variation of the experimental responses.

ANOVA Analysis of PVM Data. The main effects ANOVAs for the ingress, egress (the LCs of Sect. 7.3.1 are used for the response), and the four roominess responses are shown in Table 7.8, including the partial sum of squares (PSS) and F value for each factor.

As seen in the ANOVA analysis, not every factor is statistically significant, as measured by the F-test (assuming significance at the 0.05 level). This finding serves as a guide to determine which factors to include in the random-effect OL models estimated for each response. The dominant product and human factors are in bold for each response. The analysis also demonstrates the importance of the respondent block effect. The magnitudes of the SS block effect versus the magnitude of the SS human factors are approximately equal, indicating that there is much heterogeneity in responses not captured by the human factors. This unexplained heterogeneity can be attributed to human or socio-economic attributes not recorded and therefore not included in the analysis (e.g. income, usage), or individual *rating styles*. It has been found in previous research that respondents often display distinct rating styles, such as rating systematically high or low, or displaying different scale usage, i.e., scale usage heterogeneity. Systematic high or low rating is related to the mean rating for a given person, μ_i, whereas scale usage heterogeneity is related to the standard deviation of the ratings for a given person,

Table 7.8 ANOVA for the six PVM responses

		Ingress		Headroom		Leftroom		Kneeroom		Roominess		Egress	
		PSS	*F*	*PSS*	*F*	*PSS*	*F*	*PSS*	*F*	*PSS*	*F*	*PSS*	*F*
SS_M	Model	1,501.4	17.42	1,311.8	27.91	605.1	12.88	369.3	7.86	700.5	14.90	1,269.8	27.01
SS_R	Gend	2.00	1.09	4.22	9.02	2.01	3.32	0.45	0.69	0.39	0.84	0.00	0.00
	Stat	27.27	4.96	**10.44**	7.44	**21.86**	12.06	9.03	4.56	**30.25**	21.57	16.40	3.64
	BMI	0.01	0.00	5.75	6.14	**18.66**	15.44	14.31	10.84	4.41	4.72	1.25	0.42
	Age	**79.56**	7.23	**17.24**	6.14	7.97	2.20	**48.81**	12.33	**25.48**	9.09	**95.77**	10.63
	Resp	356.01	10.22	98.63	11.09	72.76	6.34	131.52	10.49	145.36	16.37	340.74	11.94
SS_{TR}	HNG_X	4.92	1.34	0.36	0.39	2.47	2.05	1.65	1.25	0.62	0.67	10.69	3.56
	ROK_Y	1.06	0.29	0.35	0.37	**287.97**	238.3	**66.86**	50.66	46.36	49.59	6.71	2.23
	HEL_Z	**210.07**	57.28	3.22	3.44	1.87	1.55	31.30	23.71	3.55	3.80	**275.19**	91.61
	GRD_Z	49.27	13.43	0.36	0.38	1.93	1.60	0.57	0.43	0.74	0.80	75.03	24.98
	StoH	18.03	4.92	0.46	0.50	2.83	2.34	2.15	1.63	2.20	2.36	62.79	20.90
	HR_Z	**388.72**	105.9	**812.97**	868.1	18.10	14.98	4.97	3.76	**262.16**	280.4	**177.86**	59.21
	HR_X	46.13	12.58	1.66	1.77	0.92	0.76	3.21	2.44	3.00	3.21	17.30	5.76
	HR_Y	48.58	13.24	8.79	9.39	0.75	0.62	0.19	0.14	9.34	9.99	18.44	6.14
SS_E	Error	935.3		238.8		308.1		336.6		238.4		766.0	
SS_T	Total	2,436.6		1,550.6		913.2		705.9		938.8		2,035.8	

Values unshaded: significant at the 0.05 level

$\sigma_{u,i}$. Attempts have been made to identify these behaviors and control for them in the modeling process [5, 12]; however, in this work respondents were not given the same set of configurations (i.e. differing **E**) to evaluate due to the blocking (the full experiment contains four unique blocks) and each person is characterized by a different **S**, making comparisons of μ_i and $\sigma_{u,i}$ meaningless.

7.3.2.2 Analysis of Rating Style Using Hierarchical Clustering

Methodology. For the reasons presented in the previous subsection, a general method to control rating style must be developed, which does not assume respondents have evaluated the same set of configurations, and accounts for the influence of **S**. In the proposed method, the *block effect* will be used as a means of comparison among different respondents. The block effect is the portion of the respondent response not explained by the product or human factors, i.e., it removes the effect of varying **E** and **S** from the analysis. It is estimated in the modeling process as an individual-level intercept, β_n^0, or in a random-effects model as a distribution (typically Normal) of individual-level intercepts with mean zero, and variance τ, i.e. $\beta_n^0 \sim N(0, \tau)$. A challenge is using the block effect to understand both systematic rating bias, i.e., high rating style versus low rating style, but also scale usage heterogeneity, i.e., selective use of the provided scale. To address this issue, these two phenomena are investigated using a *Hierarchical Bayesian* (HB) approach to estimating the block effect for each person.

The method for using the block effect resulting from the HB analysis is as follows:

(1) Calculate the block effect for each person for each response using the HB approach.
(2) Use the block effect to calculate ratings *bias, bs_n,* and *scale usage, su_n,* for each person for each response.
(3) Perform factor analysis on *bias* and *scale usage* to determine if they are unidimensional and an indicator of rating style, or multidimensional, indicating a missing model parameter (**E** or **S**) or other uncontrolled factor in the experiment.
(4) Perform CA on unidimensional rating style terms (i.e. bias or scale usage) to understand the respondent clusters of similar styles (e.g. wide or narrow scale usage).

The key to this approach is the estimation of a *random* block effect for each respondent. In standard MLE, a *fixed* block effect (i.e. individual-level intercept) is estimated for each individual, β_n^0, which contains information about bias only; however, the hierarchical Bayes estimation method allows estimation of a *random* block effect for each person, β_{in}^0, which contains information about both bias and scale usage heterogeneity. In the proposed method, a three-level hierarchical prior is set for the random block effect as follows:

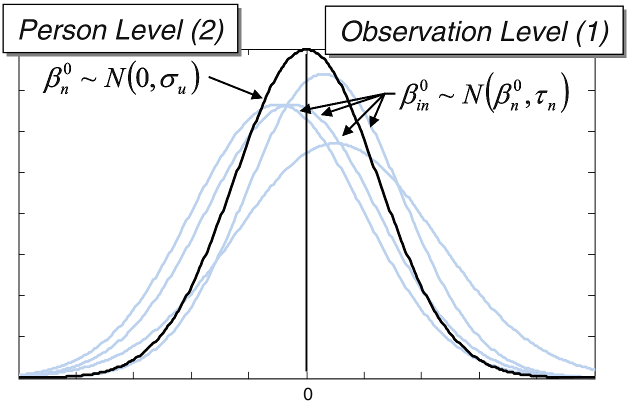


Fig. 7.5 Illustration of Bayesian priors for block effects

$$\text{prior} = \overbrace{p\left(\beta_{in}^0 | \beta_n^0, \tau_n\right)}^{\text{level1}} \overbrace{p(\tau_n) p\left(\beta_n^0 | \sigma_u\right)}^{\text{level2}} \overbrace{p(\sigma_u)}^{\text{level3}} \tag{7.1}$$

where $\beta_{in}^0 \sim N\left(\beta_n^0, \tau_n\right)$—(level 1), $\beta_n^0 \sim N(0, \sigma_u)$—(level 2), $\sigma_u \sim inv.gamma \left(k_3^0, \theta_3^0\right)$—(level 3).

The three levels indicated in the prior are the observation level (level 1), the person level (level 2), and the population level (level 3). This assignment of priors indicates that the block effect for each observation for each person (level *1*), β_{in}^0, is distributed normally, with mean β_n^0, and variance τ_n; the mean block effect for each person (level *2*), β_n^0, is normally distributed with mean zero and variance σ_u; the variance at the population level (level *3*), σ_u, follows an inverse gamma distribution, with specified parameters k_3^0 and θ_3^0. The hierarchical priors for levels 1 and 2 are illustrated in Fig. 7.5. The hierarchical prior relaxes the assumption of a fixed block effect for each person, and thus allows for understanding both the mean and variance of the block effect for each person. The mean $\left(\beta_n^0\right)$ provides information about rating *bias* and the variance (τ_n) provides information about the *scale usage*.

An issue with such an approach is that the random block term, β_{in}^0, is redundant with the similarly distributed Logistic error term, $\varepsilon_{in} \sim F(0, \sigma_\varepsilon)$, creating potential identification issues. This is overcome in the Bayesian method through the use of the prior which constrains the mean of the β_n^0, to be zero and places a limit on the variance τ_n through the inv. Gamma prior specification. Although this approach creates models which over-fit the data (i.e. very small error ε_{in}), the intent of such models is to estimate random block effects rather than to predict ratings.

In order to use the information to study rating style, the sign and magnitude of the mean block effect for each person, β_n^0, provides information on rating bias:

$$bs_n = \beta_n^0 - E\left(\beta_n^0\right) = \beta_n^0. \tag{7.2}$$

Table 7.9 Factor analysis for block mean and variance

	Bias bs_n	Scale usage su_n	
	Factor 1	Factor 1	Factor 2
Ingress	0.789		0.695
Headroom	0.793	0.420	
Leftroom	0.735	0.685	
Kneeroom	0.757	0.566	
Roominess	0.945	0.725	
Egress	0.744		0.783
Average correlation	0.629	0.234	
Cronbach's alpha	0.911	N/A	

A positive bs_n indicates a biased high rating style and negative bs_n indicates a biased low rating style compared to the population. To understand scale usage, su_n, a comparison is made between the variance of each individual's set of utilities including the block effect and the utilities with block effect omitted, i.e., the utility variance for the configurations rated by a respondent of a given **S**:

$$su_n = \mathrm{var}\left(W_n + \beta_n^0\right) - \mathrm{var}(W_n). \tag{7.3}$$

In this formulation, a positive value for scale usage, su_n, indicates wider scale usage, while a negative value indicates a narrower scale usage compared to the population of a given **S**.

Hierarchical Bayes Analysis of PVM Data. The hierarchical Bayes analysis is used to create models for each of the six responses (using the LC responses for ingress and egress), and the bias and scale usage is recovered for each respondent for each of the six responses. The bias bs_n and scale usage su_n for each person are investigated to determine if a systematic pattern exists for each person and for each of their six responses. Factor analysis is used to determine if bs_n and/or su_n are related to a single latent factor, i.e., the rating style, or if they are related to multiple latent factors, which would be indicative of a missing explanatory variable in the model. The number of latent factors for a given set of indicator variables is determined by the magnitude of eigenvalues of the covariance matrix: the general rule is that only factors with eigenvalues greater than 1.0 be retained [7]. In addition to the factor analysis Cronbach's alpha is also calculated, which is a measure of the reliability of indicators to a factor [3]. Cronbach's alpha is a confirmation that the variables are in fact indicators of a single factor, with a value greater that 0.7 generally used as the metric for unidimensionality. The results of the factor analysis conducted on the bias and scale usage for each of the six responses are shown in Table 7.9. The factor analysis conducted on the bias terms indicates that there is only one latent factor, consistent with the rating style hypothesis, while the analysis of scale usage terms indicates two latent factors, indicating scale usage is not related to an individual rating style. The Cronbach's alpha confirms that the bias indicators are related to a single factor with a high reliability of 0.91.

In the case of bias (bs_n), CA is used to identify the dominant rating styles of the respondents, i.e. systematically high or low raters. For the bias terms, CA is

Table 7.10 *k*-means cluster analysis of bias

	Ingress	Interior room				Egress	
id	LC	Headroom	Leftroom	Kneeroom	Roominess	LC	Cluster
Resp 1	6.726	6.034	4.812	7.035	6.849	10.450	2
Resp 2	−1.928	1.073	0.124	1.410	−4.780	−2.846	1
Resp 3	2.082	0.917	1.367	1.290	1.984	1.775	2
Resp 4	−2.211	−2.401	−2.132	−5.075	−2.481	−4.880	1
Resp 5	2.274	−4.292	−3.071	−0.312	3.464	4.473	2
Resp 6	3.128	10.380	3.181	11.120	6.782	2.186	1
Resp 7	0.640	2.749	2.033	1.415	−0.327	−0.444	1
Resp 8	6.022	2.767	2.997	2.121	3.728	3.080	2
Resp 9	1.482	−6.126	1.515	−5.421	−2.259	−1.126	1
Resp 10	0.523	0.605	−1.589	−0.844	−1.353	−0.047	1
Resp 11	−3.777	−0.264	0.044	5.468	−1.913	−6.355	1
Resp 12	0.743	1.350	−0.527	−0.141	1.956	0.856	1
Resp 13	0.347	−2.294	3.661	2.345	1.931	−1.827	3
Resp 14	1.034	−4.605	−4.708	−3.706	−3.308	2.583	2
Resp 15	−0.453	1.975	−0.992	2.367	0.838	2.701	3
Resp 16	0.096	1.424	2.201	5.937	6.395	2.631	2
Resp 17	1.502	−0.477	3.343	−5.648	1.412	1.475	1
Resp 18	−0.510	3.491	−0.080	−0.828	1.275	−0.796	1
Resp 19	−3.386	−6.550	−3.246	−4.579	−4.169	−4.461	1
Resp 20	−3.585	−4.207	−1.401	−4.582	−2.762	−3.193	1
Resp 21	−0.517	5.074	−2.220	−1.534	0.995	0.673	3
Resp 22	6.493	7.507	1.612	2.152	3.326	6.292	2
Resp 23	−2.561	−7.188	−8.716	−10.010	−8.894	−4.011	3
Resp 24	−2.940	−8.655	−2.681	−1.442	−6.107	−3.180	1

conducted using both the nonhierarchical *k*-means CA (assuming three clusters), and complete linkage hierarchical clustering (an a priori assumption of number of clusters is not required) to cluster similar rating styles. Because scale usage does not satisfy the hypothesis of indicating consistent respondent level rating styles, it is not further analyzed. The results of the *k*-means CA, with the bias cluster assignments, are summarized Table 7.10. The results of the complete linkage hierarchical clustering analysis (based upon a Euclidean distance measure) are shown in Fig. 7.6.

With respect to bias cluster classification, there is strong agreement between the *k*-means and hierarchical clustering, with the hierarchical method confirming the assumption of three unique clusters, and only three cluster classification discrepancies between the two methods. The three cluster model separates the respondents into groups in which each respondent's set of bias terms, bs_n, is close to zero (Neutral Raters), positive (High Raters), or negative (Low Raters).

With the cluster assignments identified for each respondent, a rating style variable, *styl*, can be defined and added as a respondent-level factor in the ANOVA analysis. The style variable is a categorical variable, i.e., [0, 1, 2], indicating the cluster assignment for each respondent. The result of adding the style factor is shown in Table 7.11. As seen, the random block effect (Resp) is significantly reduced

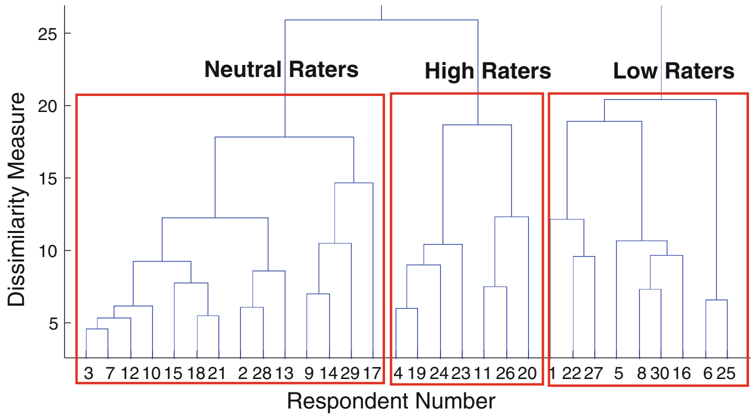


Fig. 7.6 Hierarchical complete linkage CA

Table 7.11 Inclusion of the rating style variable

	Ingress	Headroom	Leftroom	Kneeroom	Roominess	Egress
Model	1,501.35	1,311.83	605.13	369.31	700.45	1,269.80
Gend	11.01	15.41	5.82	1.83	11.84	23.07
Stat	22.50	4.52	5.52	2.22	2.68	37.62
BMI	8.25	4.82	16.99	8.75	0.74	14.35
Age	69.77	19.48	11.73	63.06	25.39	69.90
styl	69.37	23.05	19.58	45.70	51.07	61.27
Resp	143.66	56.47	61.54	95.02	61.51	106.85
HNG_X	4.92	0.36	2.47	1.65	0.62	10.69
ROK_Y	1.06	0.35	287.97	66.86	46.36	6.71
HEL_Z	210.07	3.22	1.87	31.30	3.55	275.19
GRD_Z	49.27	0.36	1.93	0.57	0.74	75.03
StoH	18.03	0.46	2.83	2.15	2.20	62.79
HR_Z	388.72	812.97	18.10	4.97	262.16	177.86
HR_X	46.13	1.66	0.92	3.21	3.00	17.30
HR_Y	48.58	8.79	0.75	0.19	9.34	18.44
Error	935.25	238.81	308.09	336.58	238.39	766.00
Total	2,436.59	1,550.64	913.22	705.89	938.84	2,035.80

compared to the values of Resp in Table 7.8, and the sum of squares contribution of the style factor is quite large, indicating that a significant portion of the unexplained random respondent effect can be attributed to the rating style of the respondent.

7.3.2.3 Ordered Logit Model with Rating Style

To better illustrate the use of the style factor, RE-OL models are estimated with and without inclusion of style variables in Table 7.12, illustrated using the LC Ingress response in Table 7.12. The OL model is described in Chap. 3, Sect. 3.3, and the style variable is determined in the previous subsection. For the modeling

Table 7.12 Comparison of ordered logit models for LC ingress

	Without style		With style	
	Coefficient	t-value	Coefficient	t-value
ROK_Y	0.324	1.91	0.320	1.89
HEL_Z	2.371	11.04	2.371	11.06
GRD_Z	−2.207	−7.40	−2.217	−7.42
StoH	−0.863	−4.00	−0.866	−4.02
HR_Z	2.822	13.33	2.818	13.32
HR_X	0.745	4.22	0.746	4.23
Gend	−0.380	−0.64	0.619	1.35
Stat	−0.313	−1.03	0.341	1.39
BMI	0.229	0.68	0.100	0.40
Age	−1.164	−1.44	0.408	0.64
$styl_H$			2.307	5.38
$styl_N$			1.611	2.04
σ_u	1.48		0.64	
ρ_0^2	0.184		0.194	

process, style is represented using two dummy variables for high rating style, $styl_H$, and neutral rating style, $styl_N$, to represent the three clusters of rating styles in the observed utility function:

$$W_{in} = \beta \cdot \mathbf{Z} = \beta^0 + \beta'\mathbf{E} + \beta'\mathbf{S} + styl_H + styl_N \tag{7.4}$$

Random respondent variation is reduced significantly with the inclusion of explanatory variables for ratings style: the fraction of unexplained variance at the respondent level, σ_u, reduces from 1.48 to 0.64 with the inclusion of style variables. In addition, the goodness of fit of the model, ρ_0^2 (a measure between 0 and 1), improves from 0.184 to 0.194. This indicates there is less unexplained ratings heterogeneity among respondents with inclusion of the style terms. The benefit of including the style term in the predictive model is a reduction in the variation of the block effect distribution, which results in smaller standard errors in the human/socio-economic model terms and improved understanding of the heterogeneity in rating responses. Assuming the population sampled in the experiment is representative of the population as whole, controlling for the rating style explicitly in the model will provide better predictions than those obtained by integrating over the respondent variance. Also, by knowing people have certain ratings styles, a pre-experiment calibration technique could be used to determine a respondent's rating style before the appraisal is conducted to ensure better consistency in rating style in future experiments [5].

7.3.3 Smoothing Spline Regression to Understand Response Behavior

Methodology. A general issue in preference modeling is an understanding of the functional relationship between the factors and responses. The functional relationship defined the form that the model attributes enter the model, for example as linear, quadratic, cubic (or higher) ordered terms, and whether factor interactions are included. As was noted in Chap. 6, it has been generally found that a human response to stimuli follows a power law relationship [13], which provides guidance for determining the form of the product factors in the model. However, in the case of human or socio-economic attributes, such a general theory does not exist. A general method to understand the relationship between the response and a factor is the use of SSR. SSR is similar to piecewise linear regression; however, the breakpoints are connected with polynomials as opposed to lines. SSR is used to better understand the relationship between response and factor, and decide upon the factor forms (e.g. linear, quadratic, cubic) to include in the subsequent RE-OL models. SSR can be used for both univariate (i.e. one factor) models and multivariate models (i.e. multiple factors), and therefore is classified as another tool of multivariate statistics. The smoothing spline models can be used directly, or can be used to provide guidance for determining factor forms to enter the model without the use of splines. It is desirable to replace the smoothing spline shapes with standard factor powers (i.e. quadratic, cubic) to manage model complexity, particularly when the resulting models are part of a system of models (i.e. Chaps. 8 and 9). In this section, smoothing spline linear regression models will be fit to the PVM data and the results will be used to provide guidance in determining factor forms for the OL modeling, in which the utility function is linear additive.

Analysis of PVM Data. With a set of responses determined in Sect. 7.3.2 and an understanding of the factor/response relationship determined in Sect. 7.3.3, the smoothing spline modeling process can be conducted. Plots of representative SSR relations from the PVM data are shown in Fig. 7.7a, b, and c (dashed lines represent 95% confidence intervals). These three plots represent the three dominant types of relationships found in the modeling process:

(1) *Linear Relationship*. As illustrated in Fig. 7.7a, using the SgRP to Ground factor (GRD_Z) as an example, many of the factors, both product and demographic, have a linear relationship with the rating response.
(2) *Power Law Relationship*. As illustrated in Fig. 7.7b, using the SgRP to Roof Z factor (HR_Z) as an example, several of the product factors exhibit a power law relationship. In such a relationship the rate of increase of the rating response decreases as the magnitude of the stimuli increases. This is important to capture in the modeling process and for the vehicle level optimization presented in Chap. 8 because increasing the magnitude of these dimensions, such as HR_Z, results in a diminishing rate of increase in the expected rating.
(3) *Critical Level Relationship*. As illustrated in Fig. 7.7c, using Seated Height as an example, several of the demographic attributes display a critical level relationship. In such a relationship, the rating response is constant over certain factor levels, such as very small or very large seated heights, but displays a linear (or higher) relationship over other levels of the factor, such as medium statures. It is important to capture such relationships in the modeling process, particularly if the model is to be used in optimization, since the demographics

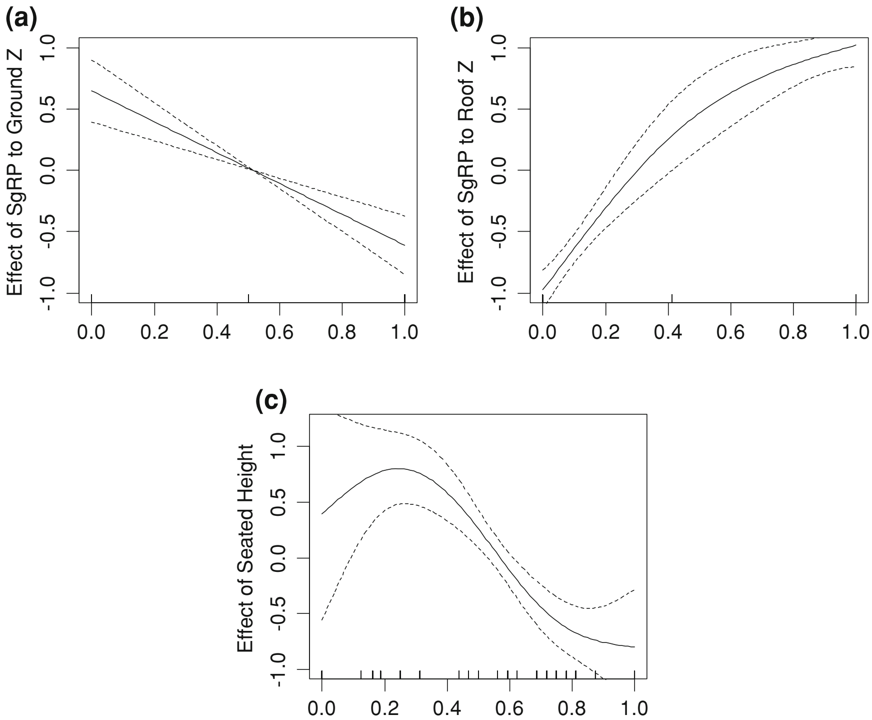


Fig. 7.7 Examples of linear, power law, and critical level attributes. **a** SgRP to Ground Z. **b** SgRP to Roof Z. **c** Seated height

of the target population for the product may fall in different portions of the plot (e.g. medium seated height), which will determine if a significant relationship exists.

With an understanding of the various relationships created using polynomial splines, a straightforward method is required to approximate these relationships in the RE-OL models described in Chap. 3, Sect. 3.3. The three behaviors identified can be approximated closely through combinations of linear, quadratic, and cubic terms. The linear relationship only requires a linear term, the power relationship a linear and quadratic term, and the critical level relationship a linear, quadratic, and cubic term (and thus can only be implemented for the demographic attributes). This method is utilized and demonstrated in a RE-OL model for the ingress rating response (using the LC ingress response created in Sect. 7.3.1). The results of the model are shown in Table 7.13.

Using the coefficients from Table 7.13, the effect of three factors shown in Fig. 7.7 (i.e. GRD_Z, HR_Z, Seated height) are plotted in Fig. 7.8, and compared to the SSR plots to determine if the proposed modeling approximations are close to the SSR results, and if the effects of the three factors are similar in the RE-OL model. In the plots of Fig. 7.8, the actual linear, quadratic, and cubic terms of the

Table 7.13 Random-effects ordered logit for LC ingress response

	Coefficient	t-value
$\mathrm{ROK_Y}$	0.29	1.71
$\mathrm{HEL_Z}$	6.95	2.83
$\mathrm{HEL_Z^2}$	−4.75	−1.92
$\mathrm{GRD_Z}$	−1.87	−6.03
StoH	−0.79	−3.58
$\mathrm{HR_Z}$	35.95	3.72
$\mathrm{HR_Z^2}$	−33.15	−3.45
$\mathrm{HR_X}$	5.43	1.81
$\mathrm{HR_X^2}$	−4.73	−1.57
$styl_H$	3.05	4.72
$styl_N$	1.41	2.04
Gender	1.25	1.61
Age	−5.02	−1.78
Age^2	5.12	1.61
BMI	1.37	1.88
Seated	832.33	1.68
Seated^2	−1,636.61	−1.66
Seated^3	805.13	1.65

factor are shown in the legend. In general, the shapes of the factor responses in the RE-OL model match the shapes of those in the smooth spline linear regression; however, the overall scale is different, since the linear regression model is on the scale of ratings, whereas the RE-OL model is on the scale of utility. Additional higher ordered terms were tested in the RE-OL model, but the relationships identified in the SSR were found to be applicable for the RE-OL, and thus no other higher ordered terms were found to be significant. Similar findings were made with the other collected PVM responses, i.e., headroom, leftroom, kneeroom, roominess, and egress. Based upon this study, SSR is an effective method for guiding the selection of terms to be included in the prediction model.

7.4 Methods for Modeling (Predicting)

The parametric OL (RE-OL) modeling as introduced in Chap. 3, Sect. 3.3 is first applied to the PVM data for predictive modeling of customer preference. In addition, other model forms are also investigated in this section to gain further insight into the data, and to confirm the OL modeling approach. *Data mining* or *machine learning* methods are investigated to determine if such methods can aid or replace traditional statistical modeling methods, such as the OL model. The data mining methods investigated in this work are classification methods, i.e., methods to predict the ratings class (i.e. 1–5 rating) based upon the attribute values. Two applicable approaches to classification data mining are investigated: a C4.5

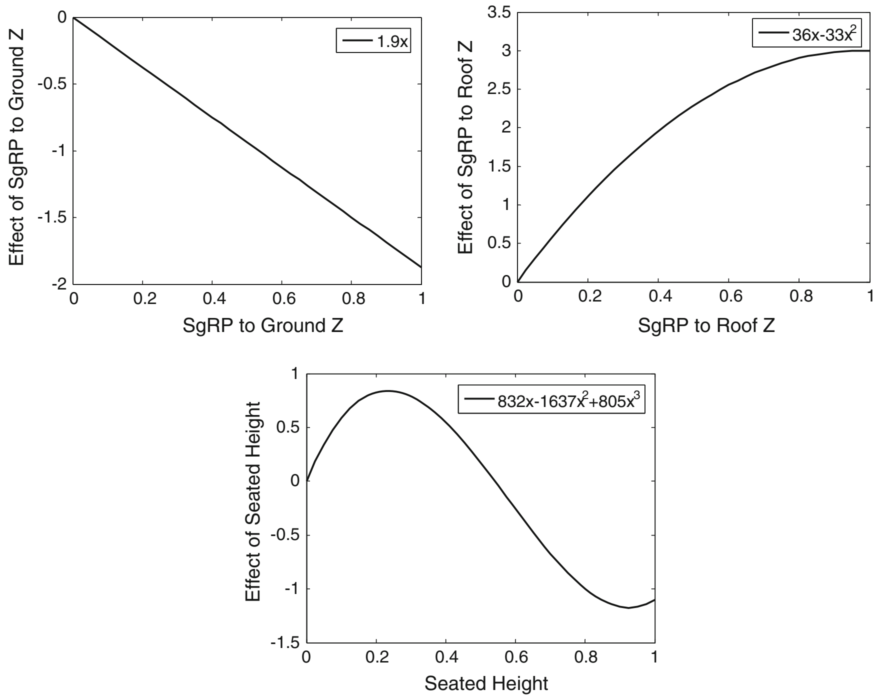


Fig. 7.8 Model factors using linear, quadratic, and cubic terms

Decision Tree and a Bayesian Network. The five classes to be estimated are the five (or four) ratings: 1, 2, 3, 4, 5. An issue to keep in mind with these approaches is that the mainstream implementation of the Decision Tree and Bayesian network is based upon the assumption that attribute values, **Z**, including both product attributes **E** and human attributes **S**, are *discrete* variables. This is not a significant issue for the PVM product factors, which only assume three levels and therefore can be considered discrete; however, they will be treated as nominal as opposed to interval (or ratio) level variables in these analyses. The demographic attributes are generally continuous interval level variables (except gender), and thus will be divided into discrete categories based upon their continuous values.

7.4.1 Random-Effects Ordered Logit Modeling

With the set of responses determined using LCA (Sect. 7.3.1), an understanding of the significant responses and the effect of rating style using ANOVA (Sect. 7.3.2.1) and CA (Sect. 7.3.2.2), and an understanding of the shape of the

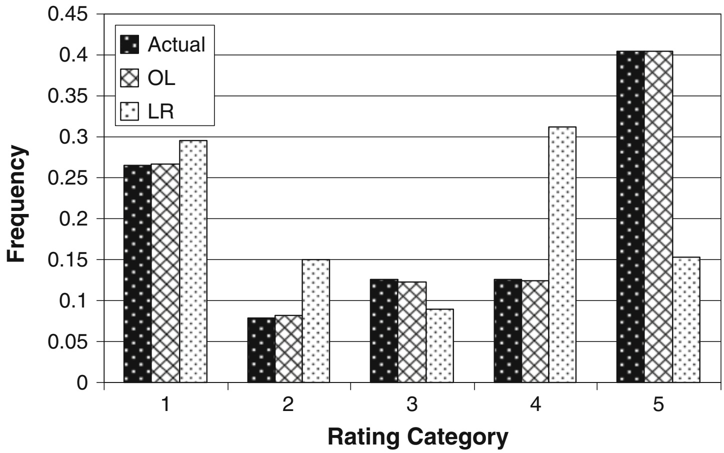


Fig. 7.9 Comparison of ordered logit and linear regression model fit

factor-response relationship using SSR (Sect. 7.3.3), RE-OL models can be fit to model the ordinal data, such as the rating responses or LCs resulting from a human appraisal experiment. The random-effect form of the model, which contains a random intercept to capture the block effect of the individual raters in an experiment (i.e. rating style), is used in this section to create preference models. Because the RE-OL model can be estimated using multiple factors to explain the response (i.e. the rating), RE-OL is classified as a multivariate statistical method.

7.4.1.1 Comparison of Ordered Logit to Linear Regression

Before fitting the OL models, a comparison is made to linear regression modeling to illustrate the benefits of OL modeling. As noted in Chap. 3, several key assumptions of the linear regression model are violated when the model is used to fit ordinal data (i.e. error does not have constant variance, the response is not a linear function of the factors, and the factors are bounded by the rating scale). However, linear regression models are fit to the survey data to demonstrate the differences and similarities between OL and linear regression modeling.

As an example, the PVM-based headroom model is estimated using linear regression by maximum likelihood estimation (MLE), instead of the more common least squares method, to allow comparison of the goodness of fit, ρ_0^2, measures. Using this approach yields $\rho_0^2 = 0.257$ for the linear regression (LR) model, compared to $\rho_0^2 = 0.364$ for the OL model, indicating the OL model better fits the data from the PVM-based survey. This is illustrated in the histogram of Fig. 7.9, comparing LR and OL predictions to the *actual* ratings distribution in the PVM survey. It can be seen in this figure that the distribution of ratings predicted by the OL model is much closer to the actual distribution in the data than the predictions from the linear regression model.

7.4.1.2 Random-Effects Ordered Logit Models and Interpretation

With confirmation that the RE-OL model is the proper model specification for the collected rating data, models are created with the specific task to include the effects of significant interactions. The two RE-OL models for the LC ingress and egress responses with significant terms, including interactions, are shown in Table 7.14 (OL cut-points omitted). RE-OL models for the roominess responses, i.e., headroom, leftroom, kneeroom, and roominess, are shown in Table 7.15 (OL cut-points omitted).

As seen in comparing among the models for ingress, egress and roominess, factors thought to be primarily associated with roominess, such as HR_Z, HR_X, and HR_Y, appear in the ingress–egress models, and factors thought to be associated with ingress, egress, such as HNG_X, appear in the roominess models. The reason for this could be two-fold: respondents' opinions of ingress, egress also influence their opinions of roominess, or the factors actually contribute to the ingress, egress or roominess experience directly. Different demographic attributes and demographic attribute interactions appear in the models. For example, gender, seated height, and age appear in the ingress model, whereas only age appears in the egress model. This could be explained by the fact that it is generally easier for respondents to exit the vehicle than enter the vehicle, and thus factors, such as seated height and anthropomorphic gender differences, do not influence the rating for egress as they do for ingress.

7.4.1.3 Effect of Explicitly Modeling Heterogeneity

The effect of including both systematic (**S**) and random heterogeneity (σ_u) on the rating predictions can be seen using a simple example in which the headroom model is re-estimated without **S**, without σ_u, and without both **S** and σ_u. The models estimated with different representations of heterogeneity are compared in terms of their ability to match the first four moments of the actual ratings distribution, as shown in Table 7.16.

A primary difference among the models can be seen in the goodness of fit, ρ_0^2, which increases as either systematic, random, or both, types of heterogeneity are included in the model. The effect of the improved model goodness-of-fit results in improved moment matching, as can be seen in the decreasing error in each moment as heterogeneity is more explicitly represented. An exception to this finding is the ability of each of the models to match the mean, since all models are unbiased estimates of the mean; improvements resulting from modeling heterogeneity are only seen in matching the higher moments. The improved model fit can be seen graphically using a comparison of histograms of the OL model without **S** and σ_u versus the OL with **S** and σ_u (i.e. RE-OL) in Fig. 7.10. It can be seen that the OL model without **S** and σ_u does a poor job of matching the actual ratings distribution, whereas the OL model with **S** and σ_u is much better at matching the actual ratings distribution.

Table 7.14 Ingress–egress RE ordered logit models

	Coefficient	t-value
LC ingress		
Gend	−33.53	−2.35
Seated	−786.25	−1.43
Seated^2	1,399.74	1.29
Seated^3	−632.79	−1.18
Age	−51.67	−3.33
Seated gend	35.65	2.37
Seated age	55.64	3.37
ROK_Y	0.28	2.18
HEL_Z	−16.75	−3.80
HEL_Z^2	−5.43	−2.01
GRD_Z	−1.75	−1.33
StoH	−4.09	−5.53
HR_Z	45.78	4.20
HR_Z^2	−47.01	−4.33
HR_X	1.07	5.48
HR_Y	7.71	2.12
HR_Y^2	−10.49	−2.99
ROK_Y HEL_Z	2.78	1.39
ROK_Y GRD_Z	−5.48	−2.52
ROK_Y HR_Y	4.84	2.97
HEL_Z GRD_Z	6.21	2.25
HEL_Z StoH	4.66	5.09
HEL_Z HR_Z	22.94	7.69
$styl_H$	2.16	4.72
ρ	0.155	
ρ_0^2	0.262	
LC Egress		
Age	−6.64	−1.26
Age^2	6.57	1.23
ROK_Y	3.53	2.27
HEL_Z	−11.52	−2.57
HEL_Z^2	−5.23	−1.79
GRD_Z	−0.74	−0.34
StoH	−4.27	−2.54
HR_Z	41.41	3.64
HR_Z^2	−41.13	−3.64
HR_X	1.48	1.05
$\text{ROK}_\text{Y} \cdot \text{HEL}_\text{Z}$	3.93	1.83
$\text{ROK}_\text{Y} \cdot \text{GRD}_\text{Z}$	−7.73	−1.95

(continued)

Table 7.14 (continued)

	Coefficient	*t*-value
$ROK_Y \cdot StoH$	−2.32	−1.28
$ROK_Y \cdot HR_X$	−3.17	−1.64
$HEL_Z \cdot GRD_Z$	6.77	2.4
$HEL_Z \cdot StoH$	5.74	6.04
$HEL_Z \cdot HR_Z$	12.89	4.34
$HEL_Z \cdot HR_X$	2.95	2.55
$styl_H$	2.70	6.12
ρ	0.214	
ρ_0^2	0.274	

Table 7.15 Roominess RE ordered logit models

	Coefficient	*t*-value
Roominess		
Seated	−11.08	−2.82
Age	−44.67	−2.99
Age^2	16.17	2.90
Seated age	30.42	2.10
ROK_Y	15.47	1.79
ROK_Y^2	−29.31	−3.53
HEL_Z	−2.33	−2.54
HR_Z	50.53	4.49
HR_Z^2	−57.09	−5.18
HR_Y	6.93	1.91
HR_Y^2	−6.25	−1.72
$ROK_Y\ HEL_Z$	−3.48	−2.26
$ROK_Y\ HR_Z$	28.76	6.34
$HEL_Z\ GRD_Z$	−5.11	−2.65
$HEL_Z\ HR_Z$	7.44	3.97
$styl_H$	2.51	5.07
ρ	0.216	
ρ_0^2	0.408	
Headroom		
Gend	6.65	2.81
Seated	901.88	2.03
$Seated^2$	−1,896.38	−2.16
$Seated^3$	990.29	2.28
Age	−16.52	−2.39
Age^2	18.07	2.67
BMI	2.13	2.06
Gend age	−10.23	−2.52
HNG_X	−2.76	−1.74
ROK_Y	1.63	2.04
HEL_Z	−7.72	−2.29

(continued)

Table 7.15 (continued)

	Coefficient	t-value
HR_Z	83.34	6.75
HR_Z^2	−74.99	−6.15
HR_Y	1.12	4.53
HNG_X ROK_Y	−3.92	−1.69
HEL_Z HR_Z	9.58	2.18
$styl_H$	2.17	3.51
ρ	0.251	
ρ_0^2	0.536	
Leftroom		
Seated	1,360.97	1.83
$Seated^2$	−2,694.32	−1.83
$Seated^3$	1,332.40	1.82
BMI	−8.49	−1.32
BMI^2	7.80	1.17
ROK_Y	4.84	16.40
GRD_Z	−0.45	−1.61
StoH	−0.47	−2.10
HR_Z	1.26	6.31
ρ	0.263	
ρ_0^2	0.307	
Kneeroom		
Age	−11.99	−1.66
Age^2	15.12	2.06
BMI	−1.31	−1.27
ROK_Y	2.95	4.64
HEL_Z	5.37	2.09
HEL_Z^2	−3.88	−1.51
HR_Z	0.59	2.81
HR_X	1.79	1.37
ROK_Y HR_X	−2.17	−1.12
$styl_H$	1.95	3.45
ρ	0.333	
ρ_0^2	0.225	

Table 7.16 Comparison of inclusion of heterogeneity in model

	OL without **S**		OL with **S**		RE-OL without **S**		RE-OL with **S**	
	Sample	Error (%)	Sample	Error (%)	Sample	Error (%)	Sample	Error (%)
Mean	3.321	−0.15	3.322	−0.14	3.315	−0.35	3.318	−0.25
Variance	2.049	−26.41	2.315	−16.86	2.203	−20.85	2.389	−14.20
Skewness	−0.109	−68.19	−0.249	−27.35	−0.168	−50.93	−0.264	−22.94
Kurtosis	1.178	−18.92	1.349	−7.11	1.276	−12.14	1.360	−6.36
ρ_0^2	0.380		0.483		0.518		0.536	

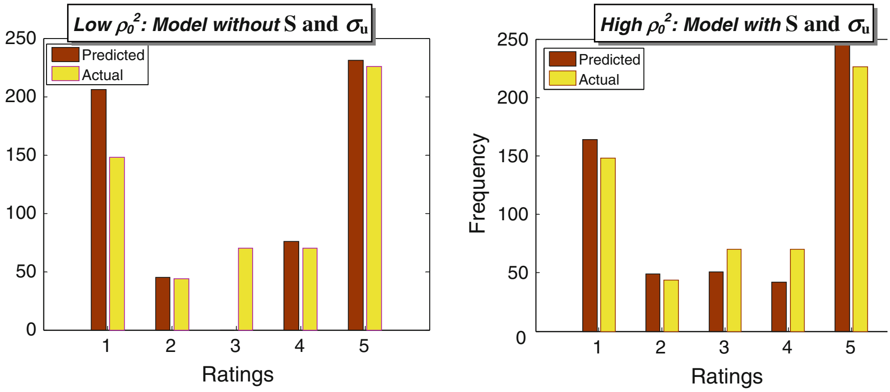


Fig. 7.10 Comparison of lowest to highest goodness-of-fit model

7.4.2 Decision Tree for Ratings Classification

A Decision Tree is created using the PVM dataset. A decision tree is created through a process in which a number of observations or cases, s, within a training data set, Tn, are *classified* into a number subsets with respect to a class variable (i.e. a response), R_p, based upon a rule concerning a "splitting" attribute value, **Z** (i.e. a product or demographic attribute). The tree building process continues to add branches until no further information can be gained. The decision tree is then pruned using a cost criterion to maximize the classification accuracy relative to the complexity of the tree [16]. The goal is to create a non-parametric model capable of predicting the class (rating) based on the value of the attributes. In this respect, a decision tree is similar to the OL model, in that the goal is to predict a rating based upon attribute values (e.g. HR_Z, Stature). Therefore, a decision tree can be viewed as a non-parametric alternative to the OL model.

The rule for selecting a splitting attribute is determined by selecting the attribute which maximizes the information gain for a given split, *gain*(*Z*), based on a measure of information, *info*:

$$\max\{gain(Z) = info(s) - info_Z(s)\}, \tag{7.5}$$

The average information, *info*(s), is expressed in the units of bits and can be calculated from the number of occurrences of a particular class R_p in s, given as *freq*(R_p, s):

$$info(s) = -\sum_{p=1}^{P}\left(\frac{freq(R_p, s)}{|s|}\right)\cdot\log_2\left(\frac{freq(R_p, s)}{|s|}\right)(\text{bits}). \tag{7.6}$$

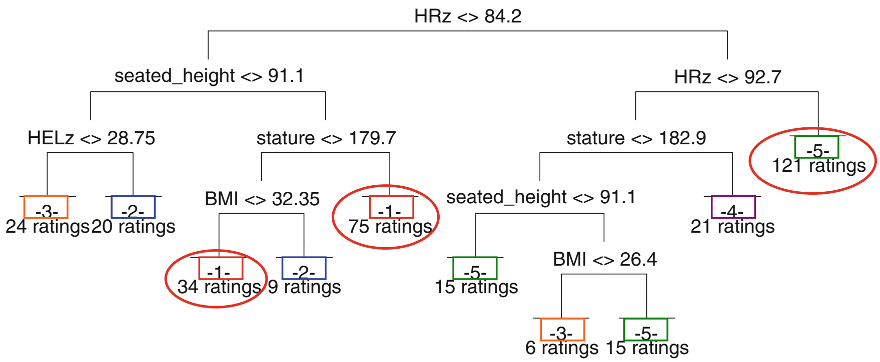


Fig. 7.11 C4.5 decision tree for headroom rating

Table 7.17 Summary statistics for the C4.5 Decision Tree

1	2	3	4	5	<– classified as
141	0	7	3	1	1
20	1	14	8	2	2
22	8	22	14	8	3
3	1	12	25	35	4
0	0	3	4	228	5
Correctly classified					417 (71.65%)
Incorrectly classified					165 (28.35%)
Root mean squared error					0.293
Kappa statistic					0.595

The average information is calculated over the entire training set, $s = Tn$, for the first split, and over number of cases at the root attribute for all subsequent splits. The information associated with a split on attribute **Z**, $info_Z(s)$, is given by:

$$info_Z(s) = \sum_{j=1}^{J} \frac{|s_j|}{|s|} \cdot info(s_j) \tag{7.7}$$

where s_j is a subset of cases created by performing J splits on attribute **Z**. The tree building process continues to add branches until no further information can be gained. The decision tree is then pruned using a cost criterion to maximize the classification accuracy relative to the complexity of the tree. As an example, a simplified decision tree is built for the *headroom* response as shown in Fig. 7.11 (variables un-normalized for clarity), and the model goodness-of-fit statistics are shown in Table 7.17. All units in the figure are *cm* except for BMI in standard units kg/m^2; the number in the box is the rating class, and the number below the rating class is the number of predicted observations belonging to each rating class based on the classification rule.

The decision tree can provide insights not gained readily in traditional parametric modeling methods, such as OL modeling. One such observation is that 85% of configurations receiving a rating of five occur when HR_Z (E_6) is at its maximum value, regardless of other product or demographic attribute values. This indicates that increasing HR_Z is a straightforward method for achieving a high headroom rating. While the HR_Z attribute is dominant in the ANOVA analysis, the decision tree provides information regarding how specific attribute values influence specific rating frequencies. Another interesting observation is that the combination of low values of HR_Z coupled with respondents of large seated height and overall stature account for the majority of the low ratings (69%). A more enlightening finding is that HR_Z at its minimum value coupled with high seated height, low stature, and low BMI account for 31% ratings of 1. This could possibly be explained by the seating position of low BMI respondents versus high BMI respondents, because low BMI respondents may position their seat differently in terms of lateral position and tilt angle, leading to a different experience of headroom for a given configuration for respondents of the same stature. This can be captured in a model through the inclusion of a BMI-seated height interaction term, which should be positive in sign. In conclusion, these findings indicate that HR_Z, BMI, seated height, stature and a BMI-seated height interaction are important variables in the parametric modeling process.

A decision tree was also conducted for *Ingress Effort*, as shown in Appendix 7A. As seen previously in the ANOVA analysis for ingress, there is not a dominant attribute in explaining ingress ratings, as for HR_Z in the headroom model. The tree indicates that ROK_Y, HEL_Z, GRD_Z, StoH, HR_Z, and HR_X are important to classifying the ratings, consistent with the OL model for ingress. Seated height and gender appear to be the most important demographic attributes, with age, stature and gender appearing to be less important. Interactions of seated height and gender and seated height and BMI should be tested in the modeling process. In general, large levels of HEL_Z (E_3) and HR_Z (E_6) lead to branches with high ratings for ingress, which is expected because these two variables control the vertical height of the door opening.

Decision trees can be created for the other attributes as well to better understand the relationship between factors and rating responses. The decision tree is useful for understanding important variables to consider in the modeling process, and can also point to trends not seen easily in a parametric modeling process. On the other hand, the decision tree does not account for individual rating styles, or allow for standard statistical interpretation of the factors, which are added to the model based upon the information gain criterion of Eq. (7.5). Another issue is that the decision tree does not provide continuous functions of the factors, but rather classifies based on threshold values of the factors (i.e. $<$, $>$), making it an inefficient tool to study the effect of changing attribute values upon ratings. Additionally, the hierarchical choice modeling approach to be developed in Chap. 8 relies upon the use of parametric models in the framework. Based upon the advantages and disadvantages of the decision tree, it is considered a preprocessing tool for the OL modeling process rather than a competing modeling methodology.

7.4.3 Bayesian Network for Ratings Classification and Associations

The use of Bayesian networks in analyzing and modeling the PVM data is presented in this subsection. The Bayesian network can be used in two distinct implementations, *supervised* and *unsupervised*. In the supervised implementation, the Bayesian network is used as a classifier in which attribute values are used to predict a class, e.g., a rating. In the unsupervised implementation, no assumption is made regarding responses (dependent variables) and factors (independent variables), but rather the network identifies dependent and independent variables. The two implementations of the Bayesian network will be investigated.

Supervised Bayesian Network. The supervised Bayesian network is a classifier in which a class R_i, such as a rating, is predicted based upon the conditional probability of the attribute $\mathbf{Z}$ values. In the supervised network, the class to be predicted is defined a priori. Therefore, the Bayesian network is used as a method to determine the probability of being in each class R_i, (i.e. each rating category) for each observation (i.e. each respondent), just as in the OL model. The probability of the class assuming a certain value R_i (i.e. rating of 1, 2, 3, 4 or 5), given a set of attribute values $\mathbf{Z}$, is determined using Bayes law:

$$\Pr\left[R = R_p | Z_1, \ldots, Z_J\right] = \frac{\Pr\left\{Z_1, \ldots, Z_J | R = R_p\right\} \cdot \Pr\left\{R_p\right\}}{\Pr\{Z_1, \ldots, Z_J\}} \tag{7.8}$$

The Bayes network uses the assumption of conditional independence. Conditional independence requires that each attribute, Z_j, is conditional only on the immediate, or parent, attributes and not upon the distant relative attributes (i.e. grandparents, great-grandparents, etc.). Using this assumption, the conditionally independent probabilities can be multiplied to find the joint probability of $\mathbf{Z}$:

$$\Pr\left\{Z_1, \ldots, Z_J | R = R_p\right\} = \prod_{j=1}^{J} \Pr\left\{Z_j | R, \mathrm{parents}\left(Z_j\right)\right\} \tag{7.9}$$

Using the assumption of conditional independence, Eq. (7.8) can be written (omitting the normalizing term $\Pr\{Z_1, \ldots, Z_J\}$):

$$\Pr\left[R = R_p | Z_1, \ldots, Z_J\right] = \Pr\left\{R_p\right\} \cdot \prod_{j=1}^{J} \Pr\left\{Z_j | R, \mathrm{parents}\left(Z_j\right)\right\} \tag{7.10}$$

Equation (7.10) demonstrates that the supervised Bayesian network is a form of non-parametric regression. The Bayesian network ratings predictions can therefore be directly compared to the OL regression predictions of Sect. 7.4.1:

$$\Pr[R = R_i | Z_1, \ldots, Z_J] = F\left(k_p - \beta'\mathbf{Z}\right) - F\left(k_{p-1} - \beta'\mathbf{Z}\right)$$

where F is the cumulative logistic distribution. An advantage of the Bayesian network is that no assumptions are made on the error distribution (i.e. logistic or normal distribution) because it is non-parametric. The rating predictions from both the Bayesian network and the OL model are compared in Fig. 7.12.

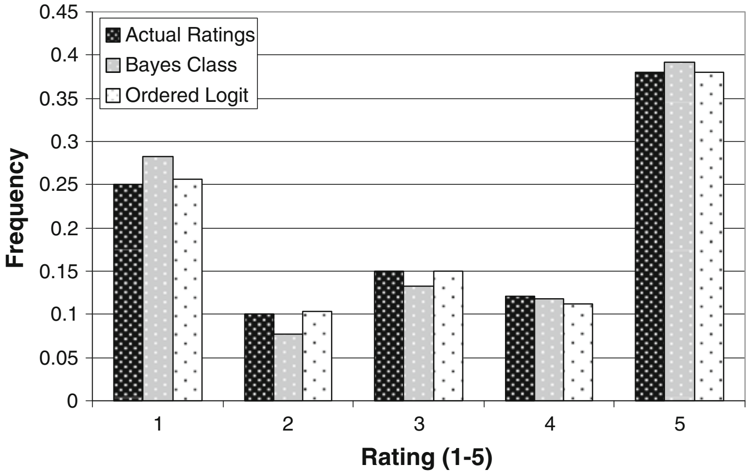


Fig. 7.12 Comparison of ratings predictions

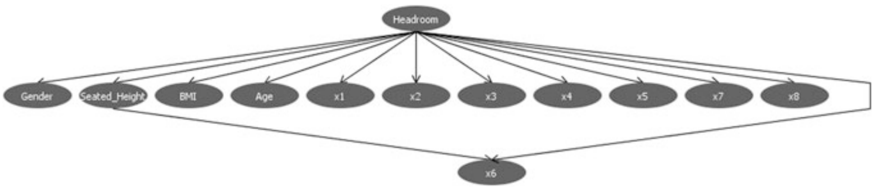


Fig. 7.13 Supervised Bayesian network graph for headroom

As seen in the histogram, the Bayesian network results in similar ratings classification to the OL model. The superior performance of the OL model can be attributed to the enforcement of the ordinal constraint (i.e. adjacent ratings are correlated), as opposed to the nominal assumption of the Bayesian network, and the discretizing of attributes to nominal categories in the Bayesian network. The Bayesian network also identifies the conditional relationships as shown in Fig. 7.13, with arrows going from the parent attributes to the child attributes. In this case the effect of E_6 (i.e. HR_Z) is conditional on the value of seated height, indicating that an interaction term of HR_Z-Seated Height should be investigated.

For datasets in this work (e.g. the PVM data) which are structured for RE-OL modeling and do not have missing values, the Bayesian network offers few advantages over OL modeling. Because the supervised Bayesian network is non-parametric and is a form of machine learning, like the decision tree, it can be viewed as a pre-processing tool to better understand relationships in the data.

Unsupervised Bayesian Network. As opposed to the supervised Bayesian network which can be viewed as an alternative to the OL model, the unsupervised Bayesian network is used to understand relationships in the data. In the unsupervised Bayesian network, no distinction is made between responses and factors with the goal of understanding the relationships within the data sets rather than predicting a class. For this

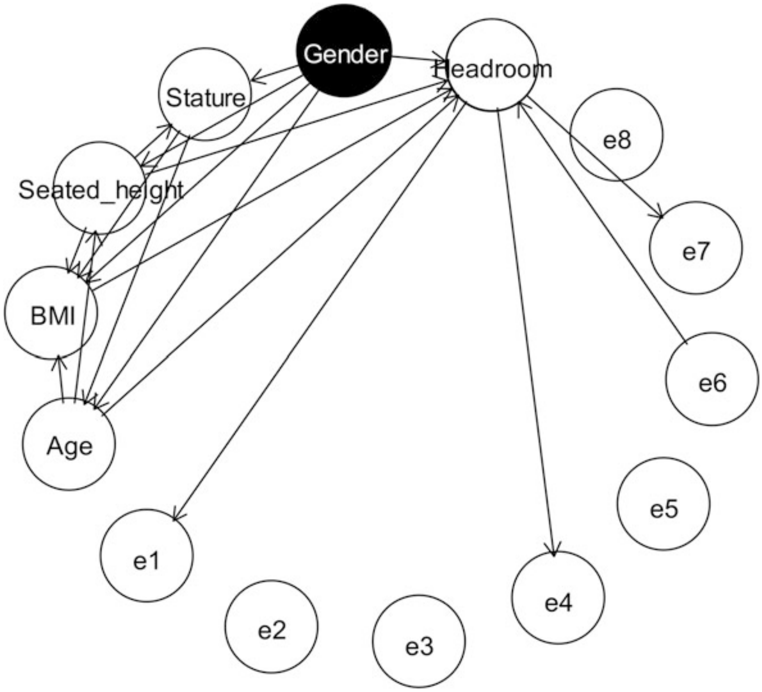


Fig. 7.14 Unsupervised Bayesian network including headroom

reason, the focus is upon identifying the joint distribution of attributes **Z** (in this case the rating response is considered another attribute) in terms of the conditional distributions:

$$\Pr[Z_1, \ldots, Z_J] = \prod_{j=1}^{J} \Pr\{Z_j | \text{parents}(Z_j)\} \tag{7.11}$$

An unsupervised Bayesian network for the PVM dataset (with only the headroom response included) is shown in Fig. 7.14, with the arrows going from parent to the child attributes.

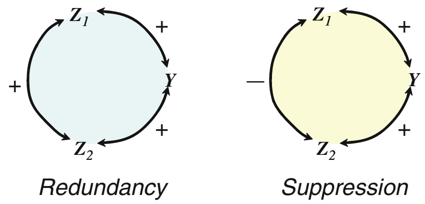
The joint distributions of attributes **Z** are expressed as the product of the conditional probabilities. The conditional probabilities identified to have parent attributes are as follows:

- [Headroom|Gender;Seated height;BMI;Age;E_6]
- [Age|Gender;Stature;Seated height;BMI]
- [Stature|Seated height;BMI]
- [Seated height|Gender;BMI]
- [BMI|Gender]
- [E_1|Headroom]
- [E_4|Headroom]
- [E_7|Headroom]

Table 7.18 Regression of age on other demographic attributes

Age	Coefficient	*t*-value
Gender	−0.364	0.00
Height	−0.232	0.03
Seated height	−0.610	0.00
BMI	0.177	0.00
Constant	0.985	0.00

Fig. 7.15 Correlation patterns creating redundancy and suppression



The relationships identified indicate that not all demographic attributes collected are independent, i.e., there are correlations among the demographics. For example, age is conditional upon the values of gender, height, seated height, and BMI, which can be confirmed using a regression analysis as shown in Table 7.18.

Such a regression is hard to interpret from the cause-effect standpoint as assumed in regression, since the prediction of age based upon other demographic attributes does not make intuitive sense. On the other hand, prediction of height based upon seated height and BMI is more plausible. In general, the unsupervised Bayesian network is identifying *correlations* within the data, which may or may not represent proper cause-effect regressions.

The issues created by correlation among demographic attributes in the modeling process are *redundancy* and *suppression*. Redundancy and suppression occur when certain correlation patterns are present among multiple independent (**Z**) and dependent variables (**Y**). An example of redundancy can be seen in Fig. 7.15 in which two **Z** and one **Y** are positively correlated. When redundancy is present and one of the **Z** is removed, the magnitude of the remaining **Z** increases. An example of suppression is also shown in the figure, in which two **Z** are positively correlated with the **Y**, but the two **Z** are negatively correlated with each other. When suppression is present and one of the **Z** is removed, the magnitude of the remaining **Z** may decrease or the sign may change. If there are more than two **Z**, the patterns are very difficult to diagram, and both redundancy and suppression may occur.

In the context of the hierarchical modeling framework, the predictive ability of a model is not hurt by redundancy or suppression, but these phenomena make it difficult to interpret the effect of the demographic attributes individually. Coefficient interpretation is important for model validation, ensuring that model coefficients match or can be explained from an understanding of the problem. Another issue is that in the hierarchical choice modeling approach developed in Chap. 8, multiple data sets may be merged (i.e. model fusion) with different combinations of redundancy and suppression, leading to issues in model estimation with the combined data.

Table 7.19 Factor analysis for collected demographic attributes

	Factor 1	Factor 2	Uniqueness
Gender	**−0.765**	−0.420	0.335
Height	**0.861**	−0.196	0.169
Seated height	**0.970**	−0.072	0.033
BMI	0.059	0.269	**0.929**
Age	−0.092	**0.724**	0.447

An approach to the problem is to assume the demographics are related to a smaller number of uncorrelated latent factors. Therefore, a latent variable analysis is conducted using the demographic attributes collected in the PVM appraisal. It is found that there are two significant factors. Using the iterated principle factor (IPF) method of solution and performing an orthogonal rotational (so that the 2 factors are uncorrelated) gives the result shown in Table 7.19.

The interpretation is that gender, height, and seated height are related to a latent factor called size, primarily vertical size. Factor 2 consists primarily of age, while BMI is primarily unique. A solution to incorporating latent variables in a model will be provided in Chap. 9 with the formulation of the latent variable approach to choice modeling. While the approach will be presented using latent variables for customer-desired attributes (**A**), the approach can also be used easily for the socio-demographic attributes (**S**) of this section.

7.5 Summary

Methods for the analysis of human appraisal experiments to understand and predict customer preferences for new or existing product designs were presented in this chapter. The methods employed are for the purpose of preprocessing data, reduction of data, capturing respondent heterogeneity, and creating RE-OL models to understand customer preferences and enable prediction of preferences for new product offerings. LCA is shown to be effective for combining several responses given by a customer during an appraisal into a smaller number of LCs related to their overall opinion of key product features. ANOVA analysis is used to understand the relative importance of the product and human attributes on the different rating responses provided in the survey. In these analyses, the respondent block effect, or unexplained respondent heterogeneity is found to be large. CA of the block effect is used to identify systematic ratings styles of the respondents, which explain a significant portion of the unexplained heterogeneity. Adding new variables to control for rating style in the modeling process significantly reduces the unexplained heterogeneity. The use of SSR is demonstrated to be an effective tool to understand the shape of the response-factor curve and guide the form of factors (i.e. linear, quadratic, cubic) to be introduced in the subsequent OL modeling.

With data preprocessing, response reduction, and an understanding of respondent heterogeneity, RE-OL models are estimated for each response. The importance of interactions and the benefits of explicitly modeling systematic heterogeneity and random heterogeneity are demonstrated in the ability of the distribution of the predicted ratings to match the actual distribution of ratings, an important feature of a model to be used to predict preferences for different populations and different designs. Machine learning methods from data mining are also applied to the PVM data. The decision tree provides additional insights into the relationship among the product factors, human factors, and rating responses not easily identified in the parametric OL model. The unsupervised Bayesian network provided insights into the relationships among the human factors not easily seen in methods, such as correlation analysis. The methods developed in this Chapter are crucial to not only understanding customer heterogeneity in human appraisal experiments, but also creating predictive models for use in the Bayesian Hierarchical Choice Model introduced next in Chap. 8.

7.6 Additional Resources for Computational Implementation

The following text provides a comprehensive overview of Multivariate Statistical methods:

- Johnson RA, Wichern DW (2007) Applied multivariate statistical analysis. 6th edn. Prentice Hall, Upper Saddle River, NJ

The following text provides a comprehensive introduction to data mining methods using the `Weka 3` code listed below:

- Witten IH, Frank E (2005) Data mining: Practical machine learning tools and techniques. Morgan Kaufmann, San Francisco, CA

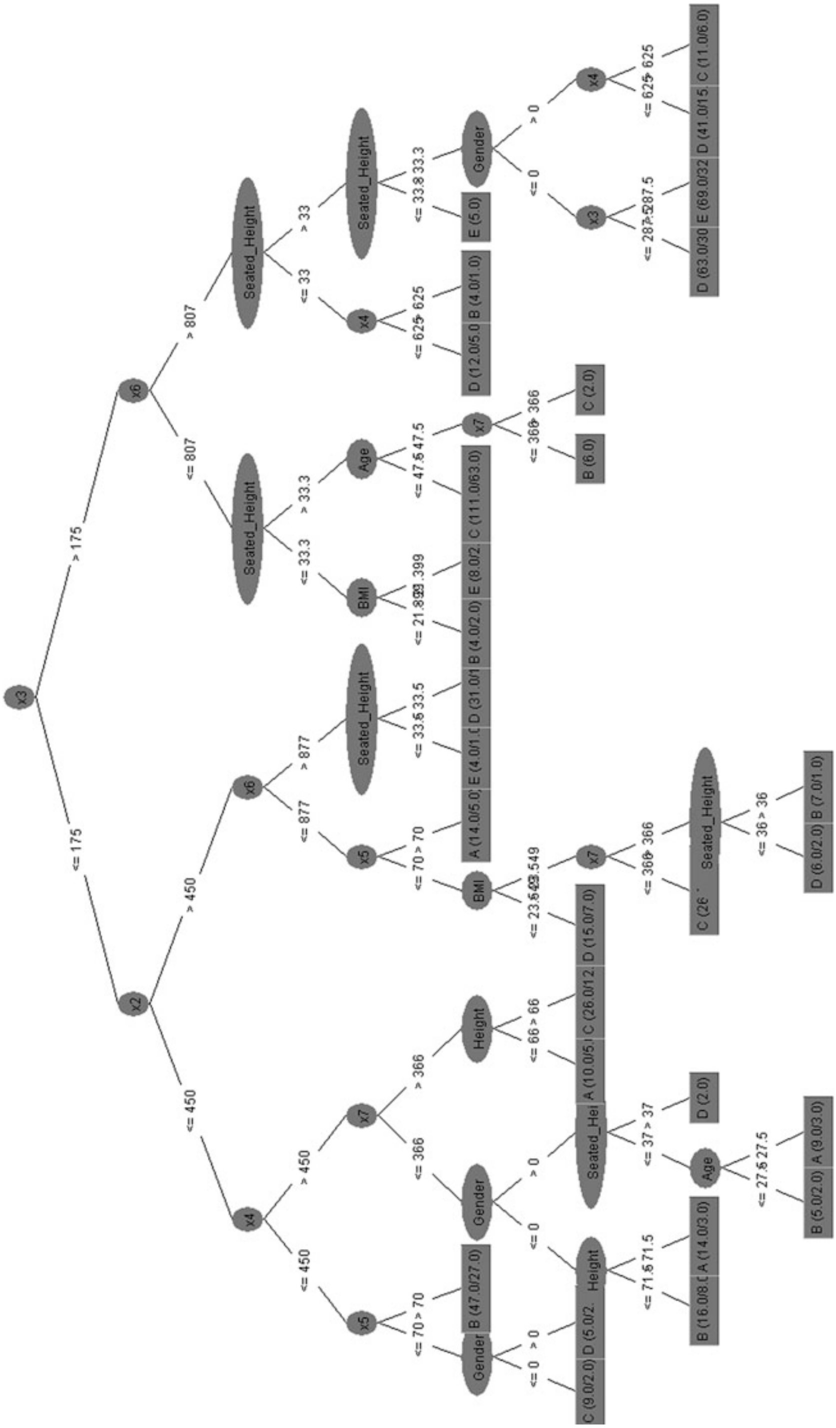
The following packages in R (http://www.r-project.org/) can be used to implement the techniques in this chapter:

- The package `poLCA` is available for LCA.
- The standard package `stats` contains the function `hclust` for hieararchical clustering and the function `kmeans` for *k*-means clustering.
- The standard package `stats` contains the function `anova` for ANOVA.
- The standard package `mgcv` contains the function `gam` for conducting SSR.
- The package `deal` is available for unsupervised Bayesian Networks

For general data mining techniques, such as the supervised Bayesian Network or the Decision Tree, the open source package `Weka 3` (http://www.cs.waikato.ac.nz/ml/weka/) is available.

Appendix A: C4.5 Decision Tree for Ingress Response

Decision Tree for Ingress Response is shown below:


x3
> 175
<= 175
x6
> 807
<= 807
x2
> 450
<= 450
Seated_Height
> 33
<= 33
> 33.3
<= 33.3
x4
> 625
<= 625
D (12.0/5.0
B (4.0/1.0)
E (5.0)
Gender
> 0
<= 0
x3
> 287.5
<= 287.5
D (63.0/30
E (69.0/32
D (41.0/15
C (11.0/6.0)
Age
> 47.5
<= 47.5
x7
> 366
<= 366
C (2.0)
B (6.0)
BMI
C (111.0/63.0)
E (8.0/2
B (4.0/2.0)
D (31.0/1
E (4.0/1.0
A (14.0/5.0
> 877
<= 877
> 33.5
<= 33.5
x5
> 70
<= 70
D (15.0/7.0)
C (26.0/12
A (10.0/5.
Height
> 66
<= 66
> 36
<= 36
D (6.0/2.0)
B (7.0/1.0)
> 37
<= 37
D (2.0)
> 27.5
<= 27.5
B (5.0/2.0)
A (9.0/3.0)
> 71.5
<= 71.5
A (14.0/3.0)
B (16.0/8.
B (47.0/27.0)
C (9.0/2.0)
D (5.0/2.

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Part III
Product Design Challenges

Chapter 8
Hierarchical Choice Modeling to Support Complex Systems Design

Nomenclature

A	Customer-desired attributes
β	Discrete choice or ordered logit model parameter for customer-desired attributes in a customer's utility function
C.S.	Choice share (aggregate product choice probability)
DS	Data set
E	Engineering attributes
ε_{in}	Random disturbance of customer choice utility of alternative i by customer n
η	"Excess" error variance in a specific data set
i	A configuration or alternative
k, k_p	Ordered logit cut points
μ	Scale factor in the MNL model
LL	Log-likelihood
n	A respondent
v	Random respondent heterogeneity distribution
R	Ratings
ρ_0^2	Model fit statistic for discrete choice and ordered logit models
S	Demographic attributes
PVM	Programmable vehicle model
u_{in}	True customer choice utility of alternative i by customer n
W_{in}	Observed part of the customer choice utility of alternative i by customer n
Z	Product and demographic attributes—explanatory variables in choice modeling

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_8,

In this chapter, we integrate the concepts of the previous chapters to develop a comprehensive hierarchical demand modeling approach for design of complex systems that typically consist of many subsystems and components. The hierarchical choice modeling framework utilizes multiple model levels corresponding to the complex system hierarchy to create a link between qualitative attributes considered by customers when selecting a product and quantitative attributes used for engineering design. The integrated Bayesian hierarchical choice modeling (IBHCM) approach utilizes choice data as well as other preference data, such as that collected using the human appraisals presented in Chaps. 6 and 7, to create a comprehensive choice model. To capture heterogeneous and stochastic customer preferences, the mixed logit (MXL) choice model is used to predict customer system-level choices, and the random effects ordered logit (RE-OL) model is used to model customer evaluations of system and subsystem-level design features. In the proposed IBHCM framework, both systematic and random customer heterogeneity are explicitly considered; the ability to combine multiple sources of data for model estimation and updating is provided using the Bayesian estimation methodology, and an integrated estimation procedure is introduced to mitigate error propagated throughout the model hierarchy. The new modeling framework is validated using several metrics and validation techniques for behavior models. The benefits of the IBHCM method are demonstrated in the design of an automobile occupant package, the same case study used in Chaps. 6 and 7.

8.1 Introduction to Hierarchical Choice Modeling in Complex System Design

Analytical techniques for modeling customer choice (or demand) were introduced in Chap. 3, and utilized in subsequent chapters to enable the Decision-Based Design paradigm for a variety of engineering problems. While the previous approaches are appropriate for relatively simple design artifacts, many issues remain in creating a demand model for a complex system. Modeling demand for a complex system is characterized by attribute hierarchies in model estimation, a wide variety of customer demographic descriptors, and data from multiple sources with varying degrees of richness (e.g., in-house marketing surveys, purchase data, exit interviews). The existing demand modeling approaches have assumed that product attributes in the choice model are quantitative, such as horsepower or fuel economy for an automobile or mass and power for an electric motor. However, many criteria used by customers to choose between complex engineering systems tend to be qualitative, such as comfort or styling attractiveness. Also, demand modeling approaches, typically used in engineering design do not adequately account for customer preference heterogeneity, i.e., each customer has a unique preference, and they do not consider multiple data sources to be used for model estimation.

Several challenges exist in creating a demand modeling methodology to support complex system design. As shown in Chap. 3, modeling customer heterogeneity in a complete manner is necessary to accurately capture the perception of a design for a given population segment. Another modeling challenge is that attributes considered by customers in a choice situation may be qualitative (e.g., comfort, styling attractiveness), and require mapping to physical, measureable design attributes at the multiple subsystem and component levels. While it may be possible to include all mapped quantitative component-level attributes in the product-level choice model, it is not realistic due to the sheer volume of such attributes and more importantly, may lead to issues with multicollinearity in model estimation. Additionally, the design of large artifacts is usually distributed over several teams, with separate human appraisal surveys conducted by different teams. In order to examine how customers trade-off between the different subsystem attributes when they make a purchase decision, it is necessary to combine data sources to simultaneously consider multiple feature-specific trade-offs. Estimating such pooled models is known as model fusion [1] or data enrichment [17] in the transportation literature.

To deal with the challenges presented, a *hierarchical choice modeling* strategy [11, 15] is introduced here**,** in which a top system-level discrete choice analysis model contains a reasonable set of system-level customer-desired attributes $\mathbf{A}$ (including price P). The lower level models establish the relationships between qualitative customer-desired attributes $\mathbf{A}$ as functions of quantitative engineering design attributes $\mathbf{E}$ at the subsystem and component levels and customer demographic attributes $\mathbf{S}$, i.e., $\mathbf{A} = f(\mathbf{E}, \mathbf{S})$. In order to ensure comprehensive modeling of systematic heterogeneity and thus minimize unexplained heterogeneity, taxonomy of $\mathbf{S}$ has been developed for model estimation (presented in Chap. 3, Fig. 3.1) in which the $\mathbf{S}$ are categorized as socio-economic, anthropometric, purchase history, or usage context attributes. The hierarchical approach uses customer *ratings* for qualitative attributes in the choice model, which are expressed in terms of quantitative engineering attributes through a hierarchy of ordered logit *linking* models (such as those estimated in Chap. 7, Sect. 7.6) for ratings prediction. The hierarchical approach ensures a more manageable model at each level, and mitigates the model estimation issues that accompany an all-in-one approach.

A comparison of the hierarchical and all-in-one choice modeling approaches is shown in Fig. 8.1.

To implement the approach, several issues must be addressed. A primary issue is the *need for a mechanism to mitigate error propagated* in the hierarchy, since models at each level of the hierarchy is estimated separately in the current implementation. This is a significant issue, because it is necessary to quantify uncertainty at the top-level choice model to enable decision making using the enterprise-level utility function U, and also to provide a mechanism to ensure that the model accurately captures customer preferences. Another issue identified for hierarchical modeling is the *challenge of data collection* to enable model estimation over the entire model hierarchy. As noted, in the design of a complex system, it is unrealistic to expect that the necessary data for the complete model

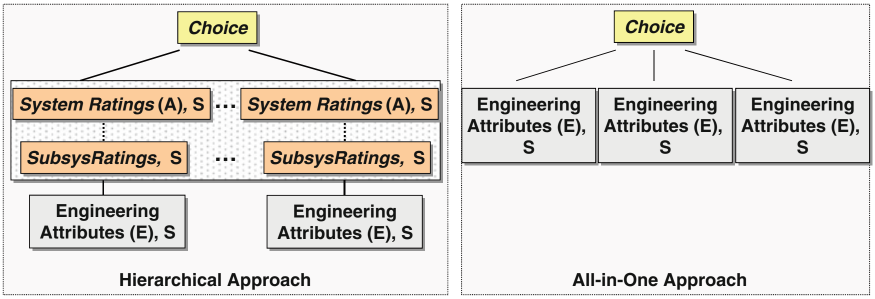

Fig. 8.1 Comparison of hierarchical to all-in-one approach

estimation process is present in a single data set. Another issue is that the need to capture both *systematic heterogeneity* (i.e., **S**) and *random heterogeneity* (i.e., random model parameters β_n) in the model hierarchy.

To address the issues described, a unified *IBHCM framework* is presented in this chapter to capture both systematic and random heterogeneity at all levels of the hierarchy, as well as to provide a method to estimate the predictive models from multiple data sources. An integrated multi-stage model solution methodology is introduced to mitigate error propagated through the model hierarchy and quantify uncertainty. The use of the Bayesian estimation method to estimate a complete hierarchy of random parameter or "mixed" models from a variety of data sources is also presented. Bayesian choice modeling has been applied primarily for estimating the MXL choice model to capture random heterogeneity [27], and has been developed for this purpose in a variety of product marketing contexts, such as to model repeated purchase behavior [21, 22]. Limited investigation of the use of Bayesian methods for combining multiple information sources has been conducted [6, 18], but not specifically in the choice modeling context. The automobile vehicle occupant packaging problem shown in Chaps. 6 and 7 is used to demonstrate the methodologies. The occupant packaging problem contains the proper level of complexity to demonstrate the features of the methodology.

8.2 Vehicle Occupant Packaging Design: A Motivating Example

In Chaps. 6 and 7, we introduced the vehicle packaging problem in the form of an experiment conducted on the programmable vehicle model (PVM) to understand user preferences for vehicle interior design. In this chapter, the example is expanded to include the larger problem of vehicle occupant packaging in the larger context of a complete vehicle design. Vehicle occupant package design is a multidisciplinary design activity that requires setting package design targets in

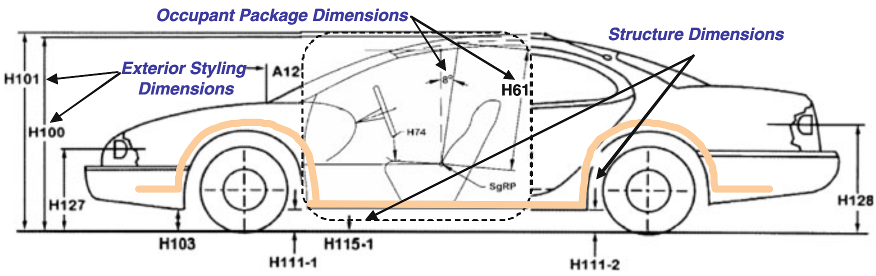

Fig. 8.2 Vehicle occupant packaging design trade-offs [23]

terms of standard society of automotive engineers (SAE) dimensions, in the presence of overall vehicle design considerations, such as structural, safety, and styling dimensions. Several approaches to capture the interaction of occupant packaging with other vehicle subsystems have been investigated in the literature [8, 19, 20, 25]. While these approaches consider specific interactions between occupant packaging attributes and select vehicle attributes, they do not consider the trade-offs among multiple vehicle attributes while simultaneously considering consumer preferences.

As shown graphically in Fig. 8.2, the vehicle package targets, represented by standard SAE dimensions, must be designed to best meet the needs of a demographically diverse target population, characterized by diversity in socio-economic attributes (e.g., age, income), anthropomorphic attributes (e.g., height, weight), expectations based on previous purchase history (e.g., vehicle brand, size), and intended usages (e.g., commuting, moving). Unlike other vehicle specifications, setting package targets has historically been heavily influenced by qualitative considerations, such as overall roominess of the occupant package. In addition, customer perceptions of the vehicle occupant package can be influenced by external factors, such as the market/product segment (SUV vs. midsize car) and the perceived status (luxury vs. economy) of the vehicle. Due to such complexity, targets for packaging attributes have traditionally been determined primarily through extensive benchmarking of competitive vehicles and experience, limiting the potential for optimization of a design for a given market segment. To address this issue, the IBHCM will be applied to this problem to demonstrate the benefits of a quantitative methodology for attribute target setting.

8.3 Preference Modeling for the Integrated Bayesian Hierarchical Choice Model

The key element in formulating the IBHCM is selection of model forms to be used at each level of the model hierarchy. An example of a model hierarchy for the occupant package design problem is illustrated in Fig. 8.3 for the vehicle

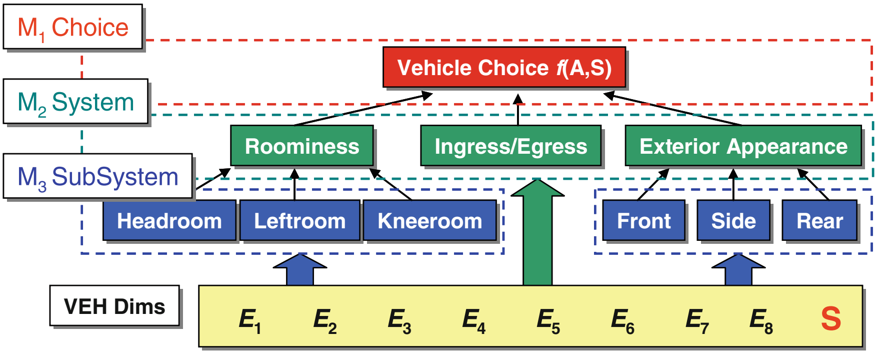

Fig. 8.3 Hierarchical choice modeling framework example for vehicle design

packaging design. This hierarchy represents a design problem in which a set of vehicle engineering attributes **E** (e.g., E_1–E_8 in the figure, see Chap. 7, Sect. 7.2 for description) influencing roominess, ingress/egress, and exterior appearance of the vehicle is mapped to attributes (**A**), customers consider in choosing a vehicle through a series of preference models, given by M_1, M_2, and M_3 in the figure. The **A** can be both quantitative $\mathbf{A}^{\mathrm{Quan}}$, such as horsepower, or fuel economy, which are linked to **E** through engineering analysis (i.e., physics-based or response surface models), and qualitative $\mathbf{A}^{\mathrm{Qual}}$, such as roominess or exterior styling, which are linked to **E** through *ordered logit ratings models*. While the vehicle problem is used to illustrate the hierarchy, the approach can be adapted to any complex engineering system design problem. Based upon the needs of the IBHCM approach, the following modeling approaches are used in the proposed hierarchy:

- M_1 (*choice*): Discrete choice analysis (DCA) MXL
- M_2, M_3 (*ratings*): RE-OL.

The MXL [22, 27] and RE-OL [9] models, introduced in Chap. 3, Sects. 3.2.4 and 3.3, respectively, are random parameter models, which capture the effect of system design attributes, as well as both systematic and random heterogeneity, in modeling customer choices or ratings. As noted in Chap. 3, **S** accounts for systematic taste heterogeneity. Random taste heterogeneity is accounted for using random model coefficients. This is achieved by allowing each individual person, n, to have his/her own set of model coefficients, β_n [27]. The specific forms of the observed utility, W_{in}, and the expressions for the choice and ratings probabilities are given in Chap. 3, Sects. 3.2.4 and 3.3, respectively. The method of Hierarchical Bayes estimation used for estimation of the model system is presented in Chap. 3, Sect. 3.4.2.

Bayesian estimation methods offer many advantages over classical methods in estimating the hierarchical choice model. Bayesian estimation differs from classical methods in that the posterior distribution of the parameters is identified in the solution process, as opposed to point estimates of the specified model parameters (i.e., β). Bayesian estimation uses Gibbs sampling to sample from the posterior

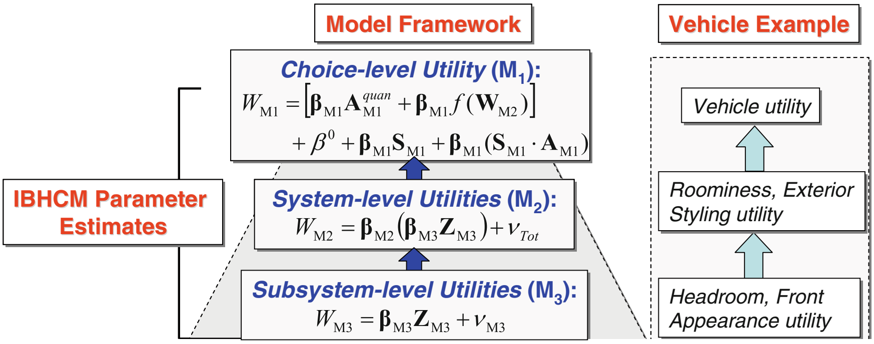

Fig. 8.4 Integrated bayesian hierarchical choice model

distribution. The Bayesian paradigm is also well aligned with the challenges of creating a design decision tool. Throughout the product design cycle and the product life, new information about demand may become available. This information may result from additional product surveys (SP) conducted or new actual purchase data (RP) acquired. With regard to actual purchase data, the growth of the internet, and the resulting growth in information, points to a future in which new information will be obtained at an almost continuous rate [28]. Incorporating this increased knowledge must be considered in the product planning phase and throughout the product life to ensure products to be competitive and profitable throughout the lifecycle in which they compete. Such considerations point to the use of a Bayesian methodology for estimating the choice model.

8.4 Integrated Bayesian Hierarchical Choice Modeling Approach

With models specified for use in each level of the model hierarchy, the general integrated model approach is formulated as shown in Fig. 8.4 with the vehicle design as an example. The theoretic advantages of this approach over alternative choice modeling approaches are as follows:

- Mitigate error and quantify uncertainty by propagating the distribution of $\boldsymbol{\beta}$ throughout the model hierarchy.
- Track the respondent effect for a single person throughout the model hierarchy.

The approach uses a propagation of cumulative respond-level utility, W (i and n subscripts omitted in this discussion), including cumulative respondent-level error ν_{Tot}, from the bottom level (M_3) to the top level (M_1) of the model hierarchy. The bottom-level subsystem utility, W_{M3}, is a function of engineering ($\mathbf{E}$) and demographic attributes ($\mathbf{S}$), given by $\mathbf{Z}$, ($\mathbf{Z} = \{\mathbf{E}, \mathbf{S}, \mathbf{E} \cdot \mathbf{S}\}$). The mid-level system utility, W_{M2}, is a function of utilities from the lower subsystem level. The top-level choice utility, W_{M1}, is a function of the quantitative customer-desired attributes, $\mathbf{A}^{\mathrm{Quan}}$, and qualitative customer-desired attributes, $\mathbf{A}^{\mathrm{Qual}}$, as well as demographic descriptors $\mathbf{S}$. The $\mathbf{A}^{\mathrm{Qual}}$ are functions of the system-level utilities given by $\mathbf{A}^{\mathrm{Qual}} = f(\mathbf{W}_{\mathrm{M2}})$. The $\mathbf{S}$ appear at both the bottom of the tree and top of the tree: the $\mathbf{S}$ at the bottom of tree capture the preference heterogeneity for the subsystem attributes while those at the top of the tree capture preference heterogeneity in the choice process. These multiple sets of $\mathbf{S}$ attributes can have overlaps but are often not identical due to the difference in responses of interest. The complete hierarchy of models uses integrated Bayesian estimation to fit model parameters (i.e., $\boldsymbol{\beta}$) in upper-level models to model predictions from lower-level models to minimize prediction error when using the system of models to make choice share predictions. The error in the system-level model, v_{Tot}, includes the cumulative respondent-level error from all subsystem-level models.

In order to realize the IBHCM approach illustrated in Fig. 8.4, heterogeneity must be captured throughout the model hierarchy, methods for utilizing sources of data associated with each model level must be developed, and a method of integrated estimation to mitigate error and quantify uncertainty throughout the hierarchy must be formulated.

8.4.1 Integrated Choice Model Formulation for Estimation

Using the mixed formulations for the M_1 level choice model (i.e., MXL) and the M_2 and M_3 level ratings models (i.e., RE-OL), the integrated formulation of the hierarchical choice model is derived. To quantify modeling error, the error distribution at each level of the model hierarchy must be accounted for in the final choice prediction. This problem has been solved for linear regression modeling, using instrument variable techniques. Specifically, two-stage least squares regression [16] has been used to account for error propagation in a two-level linear regression model system. The approach has been generalized by Lancaster [16] using Bayesian solution methods for linear regression systems with more than two models. In the approach of Lancaster, modeling error from the lower model level, denoted as $\mathrm{M}_{\mathrm{Low}}$, is propagated to the upper-level model, $\mathrm{M}_{\mathrm{Top}}$, such that the total error due to both models, $\varepsilon_{\mathrm{Tot}} = f\left(\varepsilon_{\mathrm{Low}}, \varepsilon_{\mathrm{Top}}\right)$, is estimated. However, the issue with applying this approach to the hierarchy of choice and ratings models is that the error terms are not estimated but rather specified. This causes the magnitude of the error variance to be confounded with the β terms (discussed in detail in the next section). This confounding occurs because only *differences* in utility matter in the choice/ratings model, and thus β and $\mathrm{Var}(\varepsilon)$ in each model cannot be separately identified [16, 27]. Thus, the method of finding the posterior distribution of $\varepsilon_{\mathrm{Tot}}$ developed for least squares regression cannot be applied directly for the IBHCM problem.

To account for the error propagation in the hierarchical choice model, an error components interpretation of the random term is applied [27]. In the RE-OL model, the β^0 term is added to the utility expression to capture the random respondent effect. The β^0 term is the random intercept and is interpreted as the portion of the overall model error, which is attributed to individual respondents [9]. Thus, the part of the error attributed to respondent-level variation is observable, and we use a formulation analogous to that presented in Lancaster [16] for least squares regression, with modifications as required by the model form. The respondent-level error is propagated through all levels of ratings models (i.e., M_2 and M_3) and the total observed error for each system rating is quantified at the M_1 level choice model.

As shown in Eq. (8.1), the expected rating predicted by the ordered logit model is a function of the utility, W, with expected ratings predicted by the M_3 and M_2 level models expressed as a function of engineering and demographic attributes, $\mathbf{Z}$ ($\mathbf{Z} = \{\mathbf{E}, \mathbf{S}, \mathbf{E} \cdot \mathbf{S}\}$):

$$\begin{aligned} R_{\mathrm{M3}} &= f(W_{\mathrm{M3}}) = f\left(\beta^0_{\mathrm{M3}} + \boldsymbol{\beta}'_{\mathrm{M3}} \mathbf{Z}_{\mathrm{M3}}\right) \\ R_{\mathrm{M2}} &= f(W_{\mathrm{M2}}) = f\left(\beta^0_{\mathrm{M2}} + \boldsymbol{\beta}'_{\mathrm{M2}} \mathbf{R}_{\mathrm{M3}}\right). \end{aligned} \tag{8.1}$$

As seen in Eq. (8.1), the upper-level equation for R_{M2} is a function of expected ratings predicted by the lower-level model, $\mathbf{R}_{\mathrm{M3}}$. In order to enable the error term to be propagated through the model hierarchy, utility, W is propagated through the model hierarchy instead of the expected rating, R:

$$\begin{aligned} W_{\mathrm{M3}} &= \beta^0_{\mathrm{M3}} + \boldsymbol{\beta}'_{\mathrm{M3}} \mathbf{Z}_{\mathrm{M3}} \\ R_{\mathrm{M2}} &= f\left(\beta^0_{\mathrm{M2}} + \boldsymbol{\beta}'_{\mathrm{M2}} \mathbf{W}_{\mathrm{M3}}\right). \end{aligned} \tag{8.2}$$

Using utility instead of expected ratings allows an approach analogous to two-stage least squares regression to be used to estimate a total error term, given by v_{Tot}:

$$\begin{aligned} W_{\mathrm{M3}} &= \boldsymbol{\beta}'_{\mathrm{M3}} \mathbf{Z}_{\mathrm{M3}} + \overbrace{\beta^0_{\mathrm{M3}}}^{v_{\mathrm{M3}}} \\ W_{\mathrm{M2}} &= \beta^0_{\mathrm{M2}} + \boldsymbol{\beta}'_{\mathrm{M2}} W_{\mathrm{M3}} = \boldsymbol{\beta}'_{\mathrm{M2}}\left(\boldsymbol{\beta}'_{\mathrm{M3}} \mathbf{Z}_{\mathrm{M3}}\right) + \overbrace{\beta^0_{\mathrm{M2}} + \boldsymbol{\beta}'_{\mathrm{M2}}\left(v_{\mathrm{M3}}\right)}^{v_{\mathrm{Tot}}} \end{aligned}. \tag{8.3}$$

The posterior distribution of v_{Tot} thus captures the cumulative respondent-level error (β^0) from all preceding levels in the model hierarchy. The posterior distribution of v_{Tot} is sampled directly in the solution process, therefore simplifying model estimation. With this formulation, the predicted rating for each subsystem for each design alternative, i, for each person, n, is estimated for qualitative customer-desired attributes, $\mathbf{A}^{\mathrm{Qual}}$, appearing in the M_1-level choice model:

$$\mathbf{A}^{\mathrm{Qual}} = R_{\mathrm{M2}} = f(W_{\mathrm{M2}}) = f\left(\boldsymbol{\beta}'_{\mathrm{M2}} \boldsymbol{\beta}'_{\mathrm{M3}} \mathbf{Z}_{\mathrm{M3}} + \boldsymbol{v}_{\mathrm{Tot}}\right). \tag{8.4}$$

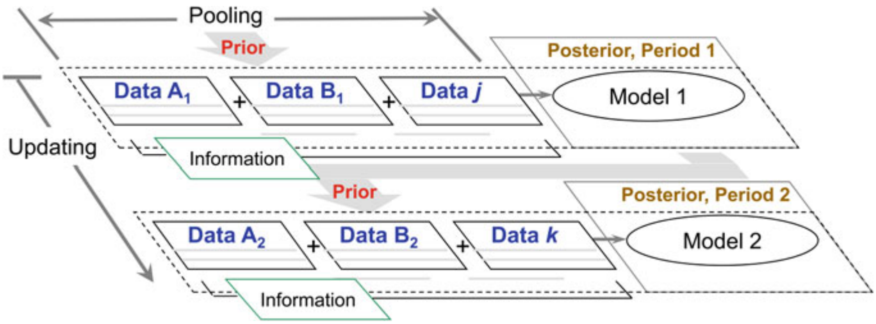

Fig. 8.5 Fusion and update of data in the hierarchical choice model approach

With expressions for each level in the model hierarchy and a method for integrated multi-stage model parameter estimation given in Eq. (8.3), the integrated choice framework is formulated. Because the models are estimated using an integrated, multi-stage procedure, β parameters from one model, such as the M_3 headroom model in the vehicle package design, can be correlated with β parameters in another model, such as the M_2 roominess model or the M_1 choice model. In the Bayesian estimation method, this correlation among model parameters at different levels of the hierarchy can be computed as demonstrated in Sect. 8.5.2. In creating a hierarchical choice model approach for a given design problem, it is necessary to ensure that the set of engineering attributes at the bottom of the model hierarchy characterizing customer-desired attributes at the top of the hierarchy be included in the modeling process. To help identify the set of engineering attributes related to customer-desired attributes, the product attribute function deployment (PAFD) method of Chap. 5 is recommended.

8.4.2 Integrated Choice Model Fusion and Updating

In addition to capturing heterogeneity, use of the IBHCM allows the models within the hierarchy to be estimated from several data sources. There are two methods to combine these multiple data sources: *fusion* is used when no single survey contains the complete information necessary to estimate all the desired model parameters, and *updating* is used when new information becomes available to update all model parameters. As illustrated in Fig. 8.5, fusion is associated with creating a model at a single time period from multiple data sources, whereas updating is associated with updating a model as new data becomes available.

The model fusion and update framework is based upon the Bayesian tradition of estimation, in which a *prior* distribution is assumed and the new data form the *information*, allowing estimation of a *posterior* distribution. The prior may be a non-informative prior and the information may be several fused data sets. The methodologies for model fusion and updating are described in this subsection.

Model Fusion. Whenever data from multiple surveys are fused (e.g., data sets labeled 1 and 2) to create a single model with pooled utility function W_{pooled}, the error variances in each of the datasets may in fact be different, thus violating the assumption of an independently and identically distributed (IID) error term in the resulting model. Differences in error variance affect the scale of the model parameters because only differences in utility matter in the utility function, and thus the scale of the utility function is set based on the variance associated with a given dataset. The scale is set by scaling the overall model error variance, $\text{var}(\varepsilon_{in})$, to a given value $\text{var}_S(\varepsilon_{ni}) = \sigma_k$ (e.g., $\sigma_k = \pi^2/6$,) by dividing W_{in}, and hence model parameters β, by a scale factor μ_k (e.g., $\mu_k = \text{var}(\varepsilon_{in})/(\pi^2/6)$) to achieve σ_k. Thus, the β parameters in a choice or ratings model are confounded with the scale factor (i.e., $\beta = \beta^*/\mu_k$) and cannot be separately identified (i.e., we cannot know β^* and μ_k separately). This presents an issue when estimating a choice model with multiple data sets in that the error variance, and thus μ_k, will differ for each of the k data sets. Hence, a method is needed to ensure the scale factors from all data sets are equal (i.e., $\mu_1 = \mu_2 = \mu_k$) to ensure β parameters estimated from different data sets are on the same scale in the pooled utility function, W_{pooled}.

A method to combine data from multiple sources using the MXL or RE-OL model is formulated in this section. To enable use of multiple data sets in the MXL methodology or the RE-OL method formulated in Chap. 3, a random term, η_k, of mean 0 and variance τ_k (i.e., $\eta_k \sim N(0, \tau_k)$) is assigned to each dataset-specific u_{in} to account for the different error variances associated with each dataset to enable a common model error term, ε_{in}. This is expressed as follows [4]:

$$u_{1,in} = W_{1,in} + \eta_1 + \varepsilon_{in}\; i \in 1,\; u_{2,in} = W_{2,in} + \eta_2 + \varepsilon_{in}\; i \in 2 \tag{8.5}$$

where η_1 and η_2 are the survey-specific error component terms, which are estimated together with the other model parameters (note: the η_k associated with the data set with the lowest error variance is set to 0 for model identification). These additional error terms, $\eta_1 \ldots \eta_k$, account for the differences in error variances in different data sets, and ensure that the overall common model error, ε_{in}, is IID (i.e., $\text{var}(\varepsilon_{1,in}) = \text{var}(\varepsilon_{2,in}) = \text{var}(\varepsilon_{in})$). This equivalence is achieved by allowing the additional error term, η_k, to contain the additional variance greater than the base variance, $\text{var}(\varepsilon_{in})$; for example:

$$\text{var}(\varepsilon_{2,in}) = \text{var}(\eta_2 + \varepsilon_{in}) = \text{var}(\eta_2) + \text{var}(\varepsilon_{in}),\; s.t.\; \text{var}(\varepsilon_{2,in}) > \text{var}(\varepsilon_{in}). \tag{8.6}$$

This approach therefore relies on the ability to separately estimate $\text{var}(\eta_1),\ldots,$ $\text{var}(\eta_k)$ such that the error variance associated with each data set is $\text{var}(\varepsilon_{in})$. To estimate the η_k, it is necessary that each survey, and thus each observed utility function W_1 and W_2, shares some common attributes, given by $\mathbf{A}_{\text{com}}$ or $\mathbf{S}_{\text{com}}$ to determine the survey-specific error component terms, based on the fact that model parameters for shared attributes indicate differences in model scale. Estimation of $\eta_1 \ldots \eta_k$ is enabled by the condition that the $\boldsymbol{\beta}$ parameters for shared attributes, $\mathbf{A}_{\text{com}}$ or $\mathbf{S}_{\text{com}}$, are equivalent and that $\eta_1 \ldots \eta_k$ are positive.

In the MXL and RE-OL approach, the pooled observed utility is simply the sum of W_1 and W_2 with a single set of common parameters, indicated by the subscript com (conditional on the fact that the η_k are appropriately included in the model estimation process):

$$W_{\text{pooled}} = \left(\boldsymbol{\beta}'_{\mathbf{A},1}\mathbf{A}_1 + \boldsymbol{\beta}'_{\mathbf{S},1}\mathbf{S}_1\right) + \left(\boldsymbol{\beta}'_{\mathbf{A},2}\mathbf{A}_2 + \boldsymbol{\beta}'_{\mathbf{S},2}\mathbf{S}_2\right) + \boldsymbol{\beta}'_{\mathbf{A},\text{com}}\mathbf{A}_{\text{com}} + \boldsymbol{\beta}'_{\mathbf{S},\text{com}}\mathbf{S}_{\text{com}}. \tag{8.7}$$

Model Updating. The Bayesian framework provides a convenient means for updating the hierarchical model as new data becomes available, for example as new model year surveys are conducted for an automobile. In this case, the current model parameters are the *prior* distribution and the new survey is the *information* necessary to calculate the new *posterior* distribution of the model parameters. Updating can be useful when the initial model is estimated using survey data acquired from prototype hardware. In Bayesian estimation, model parameters (including ordered logit cut points **k**) are updated according to the ratio of variances in the prior distribution versus that in the information (i.e., vehicle) data set [13]. Therefore, the prototype based model can be updated with the limited vehicle survey to both update the model parameters, $\boldsymbol{\beta}$, to account for the influence of actual vehicle preferences, and to update the cut points, **k**, to ensure that OL model rating predictions are reflective of actual vehicle ratings.

8.5 IBHCM for the Vehicle Packaging Design Problem

8.5.1 Data and Model Hierarchy for the Vehicle Packaging Design Problem

Vehicle occupant package design is used as an example to demonstrate the use of the IBHCM in system design. The focus is to present the features and benefits of the hierarchical choice modeling approach in an illustrative manner, rather than completing a comprehensive design optimization of the entire vehicle package. The scope of the case study is restricted to the driver's occupant package. The IBHCM framework and vehicle dimensions for this problem are shown in Fig. 8.3. The vehicle dimensions considered are the eight dimensions used in the PVM human appraisal experiment described in Chaps. 6 and 7:

(1) E_1: Hinge position in X (HNG_X)
(2) E_2: Rocker position in Y (ROK_Y)
(3) E_3: Heel position in Z (HEL_Z)
(4) E_4: Ground position in Z (GRD_Z)
(5) E_5: Sill position in Z (StoH)

(6) E_6: Roof position in Z (HR_Z)
(7) E_7: Front Header position in X (HR_X)
(8) E_8: Side Rail position in Y (HR_Y)

The eight dimensions fall into the following categories: dimensions associated with the vehicle door opening (HEL_Z, GRD_Z, and StoH), those associated with the headroom (HR_Z, HR_Z, and HR_Y) and those associated with the occupant package length (HNG_X) and width (ROK_Y). The dimensions are varied to produce unique vehicle configurations presented to the survey respondents. Additionally, four demographic attributes **S** are considered: gender, stature (height), income, and age. The **E** and **S** used in the case study are determined using an initial screening experiment to determine the set which influences customer preferences.

Models to be estimated. The hierarchical model used to model customer choices and preferences for the occupant package *roominess* and *ingress/egress* used in the case study is the random parameter IBHCM described in Sect. 8.4. This model links the preferences for roominess and ingress/egress at the choice level with the vehicle variables which determine the roominess and ingress/egress design (i.e., E_1–E_8). This model estimation is presented later in this section. RE-OL M_2 and M_3 level models linking the vehicle variables to the preferences for exterior styling are also created. For these models, a height-to-width ratio variable, $(GRD_Z + HR_Z)/ROK_Y$, called H/W, and a height-to-length variable, $(GRD_Z + HR_Z)/HNG_X$, called H/L are created to capture the finding that respondents view styling in terms of the ratio of dimensions, rather than the absolute dimensions. Also, HEL_Z, GRD_Z, and StoH are expressed in terms of the Step Height to the driver's door, as $GRD_Z - HEL_Z$ + StoH. The exterior styling M_2 and M_3 models, estimated using an integrated multi-stage approach, are shown in Table 8.1. In summary, the IBHCM model links the preferences for roominess and ingress/egress, as well as exterior styling, at the choice level with the vehicle design attributes which determine the roominess and ingress/egress design (i.e., E_1–E_8).

Human appraisal experiments and surveys. Three data sets are available for model estimation: two clinical studies—an interior packaging-based survey ($\boldsymbol{DS}_1$) and an exterior styling-based survey ($\boldsymbol{DS}_2$)—and a combined roominess, ingress, and egress ($\boldsymbol{DS}_3$) study performed on the Ford PVM. The interior and exterior clinical surveys were conducted on four vehicles in the full-size luxury segment, and contain both *rating* and *choice* data. In the interior package survey, 73 respondents are asked to rate package attributes at both subsystem (e.g., overall roominess, ingress/egress) and component levels (e.g., head room, knee room) for four vehicles. They are also asked to choose the vehicle they intend to purchase from a set of four vehicles. In the exterior survey, the same 73 respondents are asked to rate exterior appearance attributes and to make a purchase choice among the same set of vehicles. In addition to the packaging attributes, demographic attributes $\mathbf{S}_1$ and $\mathbf{S}_2$ (age, income, stature, gender) are recorded. Five vehicle attributes are included in the M_1 choice model: (1) roominess (*Room*), (2) ingress (*Ing*), (3) quality of materials (*Q Mat.*), (4) exterior styling (*Ext*), and (5) willing to

Table 8.1 Exterior M_2 and M_3 models

	Coefficient			*t*-value
M_3: Front appearance				
H/W	−0.799			−10.15
Gend	−0.304			−3.65
Age	0.318			1.95
M_3: Side appearance				
H130	−0.219			−2.19
H/L	−0.732			−8.07
Gend	−0.262			−3.08
Age	0.281			1.75
M_3: Rear appearance				
H/W	−0.840			−10.52
Gend	−0.318			−3.69
Age	0.644			3.61
M_2: Exterior appearance				
Front	0.45			19.59
Side	0.66			8.76
Rear	0.35			13.35
Variance–covariance matrix of random effects				
Front (M_3)	0.99			
Side (M_3)	0.90	0.98		
Rear (M_3)	0.86	0.93	1.07	
Exterior (M_2)	0.69	0.76	0.72	0.83

pay (*W to P*). The attribute values are in the form of ratings on a 1–10 scale for each attribute for each respondent. The following demographic descriptors (**S**) are used in the M_1 model: (1) gender, (2) stature (i.e., height), (3) income, (4) age.

The Ford PVM, described in Chaps. 6 and 7, is a computer controlled vehicle model, which can simulate a large number of vehicle configurations, and hence is efficient for gathering preference data. A comprehensive combined roominess, ingress, and egress human appraisal was conducted using the PVM, consisting of 30 respondents each *rating* 18 vehicle configurations. Because the PVM is specific to interior configurations and not representative of a complete vehicle, vehicle choice data was not collected and an M_1 level model cannot be estimated from data set $\boldsymbol{DS_3}$. The appraisal was designed using the optimal experiment design method for human appraisals of Chap. 6, Sect. 6.4. In the designed experiment**,** the eight engineering attributes of Fig. 8.3 and three demographic attributes were varied as described in Chap. 7, Sect. 7.2. The PVM data is used to estimate M_2 and M_3 level roominess, ingress, and egress RE-OL models in the hierarchy.

RE-OL Model updating. An issue to address is that the M_2 and M_3 data is collected using the PVM, while the resulting model estimated is used for predicting ratings for actual vehicle designs. The PVM lacks vehicle-specific features and styling. This is important because PVM-based ratings models will

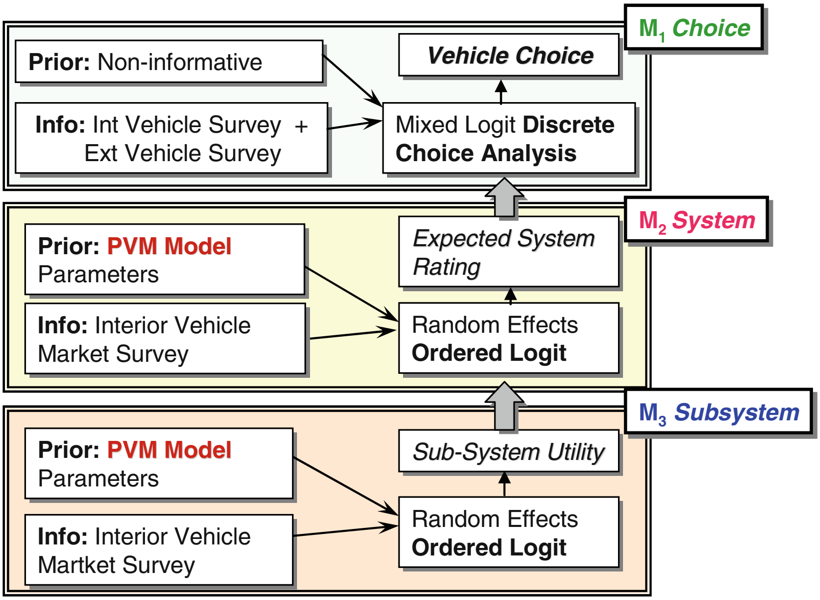

Fig. 8.6 Integrated bayesian hierarchical choice model in vehicle example

not include the influence of customer *perceptions* created by unique styling and layout features, in addition to the influence of the purely dimensional PVM features. Using actual vehicles to gather survey data for model estimation is challenging, because it is difficult to achieve the necessary factor randomization and variation to achieve efficient model parameter estimates [10]. However, the IBHCM approach can be utilized for updating the PVM-estimated ordered logit model with limited actual vehicle survey data from market clinical studies (following Sect. 8.4.2) to include the influence of vehicle styling features in the model and ensure the predicted ratings are relative to the actual vehicles, which is described next.

IBHCM Formulation. The model hierarchy and the use of the multiple data sets in the model estimation are shown in Fig. 8.6. As discussed, models estimated with the PVM data ($\boldsymbol{DS}_3$) form the prior distribution at the M_2 and M_3 model levels, while the interior ($\boldsymbol{DS}_1$) and exterior ($\boldsymbol{DS}_2$) vehicle market surveys, conducted on actual vehicles from market clinical studies, are the information sources at all three model levels in Bayesian analysis. Choice surveys were not conducted using the PVM, and therefore only the market surveys are available for M_1 model-level estimation. Because we have no prior information on the model parameters at the M_1 level, a non-informative prior is used for this level. In Bayesian estimation, the mean of the posterior distribution of model parameters is dominated by the source, i.e., the prior distribution or the information source, with the smallest estimator variance, given by σ_0^2 for the prior distribution and σ_1^2/n for the information source (n is the number of observations) [26]. Therefore, the information source will dominate as the number of observations in the information increases, reducing the influence of prior information based on prototype hardware.

8.5.2 *IBHCM Estimation for the Vehicle Packaging Design Problem*

In order to illustrate the benefits of the IBHCM approach, four versions of the hierarchical choice model are estimated. The alternative model versions use fixed (i.e., no random heterogeneity) versus random coefficients, and separate versus integrated model estimation in these combinations:

- *Scenario* 1: Fixed parameters, each model individually estimated (SEP).
- *Scenario* 2: Fixed parameters, integrated approach (INT).
- *Scenario* 3: Random parameters, each model individually estimated (SEP).
- *Scenario* 4: Random parameters, integrated approach (INT) (as in Sect. 8.4).

In Scenarios 1 and 3, each of the three models (M_1, M_2, and M_3) is estimated independently, whereas Scenarios 2 and 4 utilize the integrated estimation; however, only Scenario 4 utilizes the full error propagation method described in Sect. 8.4.1. Additionally, *Vehicle 4* is the vehicle under design, and thus is the only vehicle in the choice set linked to the M_2 and M_3 level models. The IBHCM was estimated using *WinBUGS* [24], interfaced with *R-Project* [12] for data pre- and post-processing.

The results (i.e., model β parameters) of the 4 model scenarios are shown in Table 8.2. The variance and variance–covariance matrices for the two random effects models are shown in Table 8.3. For the Random SEP model, covariance between parameters in different models cannot be estimated since each model is estimated separately. In the Random INT model, covariance can be estimated between parameters in different models. All variance–covariance values in the M_2 and M_3 models are significant at greater than the 99% confidence level. While significant covariance was found among the parameters in the M_3 and M_2 level models, significant covariance was not found between the ratings models at the M_3 and M_2 levels and the parameters in the M_1 level model. Studies of the M_1 level choice model indicated that the covariance between M_1 model parameters is statistically insignificant, and thus a diagonal variance matrix can be specified to aid in convergence.

Table 8.2 Results of four model scenarios

	Fixed SEP		Fixed INT		Random SEP		Random INT	
	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
M_3: Headroom								
ROK_Y	1.53	8.26	1.50	8.10	1.55	8.53	1.60	6.74
GRD_Z	−0.19	−0.97	−0.18	−0.89	0.11	0.54	0.09	0.46
HR_Z	4.02	18.80	3.90	16.81	4.64	19.91	4.67	16.05
HR_Y	1.36	9.01	1.29	8.50	1.67	10.43	1.67	10.97
Stat	−2.16	−6.84	−2.20	−7.23	−3.27	−8.00	−3.13	−7.92
BMI	1.46	4.84	1.53	5.23	1.76	4.56	1.62	4.43
Age	−0.84	−3.47	−0.87	−2.71	−1.18	−3.72	−1.07	−3.67
M_3: Leftroom								
ROK_Y	3.48	16.83	3.45	18.27	3.54	17.16	3.51	18.16
GRD_Z	−1.53	−8.24	−1.64	−9.77	−1.44	−7.67	−1.37	−8.00
StoH	0.28	1.63	0.25	1.59	0.27	1.55	0.29	1.51
HR_Z	1.72	10.30	1.63	9.65	1.71	10.59	1.69	9.87
Stat	−2.17	−6.88	−2.13	−6.15	−3.17	−8.07	−3.07	−8.62
BMI	−1.21	−4.33	−1.08	−3.90	−1.87	−5.29	−1.78	−5.07
Age	−0.36	−1.44	−0.32	−1.22	−0.63	−2.03	−0.30	−0.92
M_3: Kneeroom								
ROK_Y	1.38	9.62	1.44	8.88	1.36	8.98	1.36	8.55
HEL_Z	1.01	6.70	1.03	6.62	1.05	6.93	1.04	6.80
StoH	−0.36	−2.22	−0.34	−2.32	−0.34	−2.06	−0.38	−2.24
HR_Z	0.81	5.04	0.86	5.51	0.84	5.06	0.88	4.82
Stat	−1.40	−4.52	−1.38	−4.41	−1.02	−2.37	−1.67	−4.25
BMI	−1.01	−3.55	−1.06	−4.19	−1.42	−4.13	−1.42	−4.25
Age	1.02	4.13	0.92	3.56	1.70	5.15	1.08	3.50
M_2: Roominess								
Head	0.38	6.93	0.27	2.90	0.52	9.53	0.21	2.02
Left	0.48	6.50	0.39	2.50	0.66	7.63	0.42	1.32
Knee	0.59	8.00	−0.18	−1.15	0.58	7.47	−0.53	−1.23
M_2: Ingress/egress								
ROK_Y	0.83	5.39	0.86	5.55	0.80	5.26	0.81	5.77
HEL_Z	1.86	10.31	1.93	12.81	1.87	10.56	1.85	10.91
GRD_Z	−2.03	−10.83	−2.09	−11.53	−2.26	−11.57	−2.23	−12.67
StoH	−2.79	−14.97	−2.79	−15.32	−2.83	−15.30	−2.84	−16.53
HR_Z	1.87	10.23	1.81	11.46	1.86	9.95	1.88	10.90
Stat	−2.28	−6.82	−2.03	−5.98	−2.92	−7.41	−2.87	−8.06
Age	−1.04	−3.53	−1.01	−3.88	−1.75	−4.83	−1.66	−6.68
Gend	−0.09	−0.60	−0.01	−0.04	−0.31	−1.11	0.02	0.10
M_1: Choice model								
Roominess	0.53	4.11	0.90	1.30	1.17	4.45	1.90	2.30
Ingress/egress	0.43	3.75	0.44	0.95	1.25	2.99	1.10	2.74
Quality materials	0.41	3.90	0.51	4.82	1.45	4.05	1.30	3.14
Exterior appearance	1.48	5.22	1.52	4.87	2.68	3.70	2.69	5.03

(continued)

Table 8.2 (continued)

	Fixed SEP		Fixed INT		Random SEP		Random INT	
	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value	Coefficient	*t*-value
Willing to pay	0.39	2.06	0.34	1.65	0.87	1.83	0.89	1.49
Gend·Alt2	0.03	0.06	−0.10	−0.18	0.35	0.37	0.09	0.12
Gend·Alt3	−0.03	−0.05	−0.01	−0.02	0.11	0.12	0.08	0.11
Gend·Alt4	−0.24	−0.43	−0.31	−0.62	−0.37	−0.39	−0.35	−0.48
Stat·Alt2	−0.54	−0.54	−1.57	−1.52	−2.02	−1.08	−3.09	−1.96
Stat·Alt3	−0.89	−0.79	−1.14	−0.99	−2.34	−1.31	−3.11	−2.17
Stat·Alt4	−0.18	−0.16	0.00	0.00	−1.77	−1.00	−1.16	−0.77
Inc·Alt2	0.87	0.77	−0.01	−0.01	1.59	0.77	−0.06	−0.04
Inc·Alt3	0.23	0.20	0.00	0.00	0.84	0.43	0.45	0.31
Inc·Alt4	−0.17	−0.13	−1.18	−1.18	1.51	0.67	−1.16	−0.75
Age·Alt2	0.93	0.94	2.16	2.06	2.34	1.44	3.76	1.97
Age·Alt3	0.71	0.71	1.22	1.10	1.72	1.10	3.16	1.70
Age·Alt4	1.29	1.24	1.51	1.75	2.33	1.49	3.00	1.57
$\eta_{\text{packaging}}$	1.31	2.44	0.98	3.28	1.27	2.26	0.95	3.67

8.6 Validation of the Integrated Bayesian Hierarchical Choice Model

The IBHCM is validated both to ensure convergence of the model as well as to test the fit of the model and its ability to accurately predict choices within the data set. The four model scenarios presented in Sect. 8.5.2 are used for comparison purposes.

8.6.1 IBHCM Convergence

Convergence of the monte carlo markov chains (MCMC) is assessed to determine if the posterior distribution is stationary and thus is a reasonable approximation of the actual posterior distribution. The most popular practical measure of MCMC convergence is the Gelman–Rubin $\hat{R}$ statistic [3]. In order to test for convergence, at least two chains must be utilized and two intermediate measures must be determined to calculate the $\hat{R}$ statistic. A measurable quantity of the each iteration of each chain for each model parameter is defined as $\boldsymbol{\omega}$. The first measure is the *between-chain* variance, B, and the second measure is the *within-chain* variance, W, as illustrated in Fig. 8.7. The expressions for B and W are given in Eq. (8.8) as:

Table 8.3 Variance–covariance matrix for random effects models

Random SEP		Random INT					
M_2 and M_3 Variance (-covariance) matrices							
Headroom (M_3)	1.94	Headroom (M_3)	3.96				
Leftroom (M_3)	2.31	Leftroom (M_3)	3.54	5.40			
Kneeroom (M_3)	2.16	Kneeroom (M_3)	3.26	4.35	4.64		
Roominess (M_2)	1.99	Roominess (M_2)	3.32	3.86	3.71	4.05	
Ingress/egress (M_2)	1.15	Ingress/egress (M_2)	3.08	3.52	3.22	3.35	3.94
M_1 Variance (-covariance) matrices							
Roominess	0.93	Roominess	1.29				
Ingress/egress	2.00	Ingress/egress	−0.10	1.19			
Quality materials	1.54	Quality materials	−0.08	−0.21	1.38		
Exterior appearance	1.00	Exterior appearance	–	–	–	0.98	
Willing to pay	1.61	Willing to pay	–	–	–	0.09	1.81

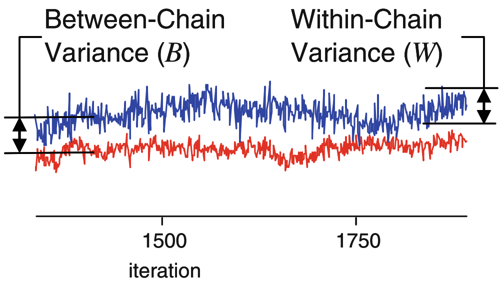

Fig. 8.7 Example of between versus within-chain variance

$$
\begin{aligned}
B &= \frac{r}{m-1}\sum\nolimits_{k=1}^{m}\left(\bar{\omega}_k - \bar{\omega}\right)^2 \\
W &= \frac{1}{m(r-1)}\sum\nolimits_{j=1}^{r}\sum\nolimits_{k=1}^{m}\left(\omega_{jk} - \bar{\omega}_k\right)^2,
\end{aligned}
\tag{8.8}
$$

where m is the number of parallel chains, r is the number of realizations of each chain, $\bar{\omega}$ is the overall mean value of all m r realizations, $\bar{\omega}_k$ is the mean of the r realizations of chain k, and ω_{jk} is the jth realization of chain k.

Using the measures B and W, the $\hat{R}$ statistic is defined as:

$$
\hat{R} = \sqrt{\frac{(1 - 1/r)W + (1/r)B}{W}}
\tag{8.9}
$$

The within-chain variance, W, will initially be small as the sampler will not fully explore the state space, whereas the between-chain variance, B, will initially be large before the j chains have converged to the posterior distribution. Therefore, $\hat{R}$ will initially be large, but will converge to 1.0 as the j chains converge to the

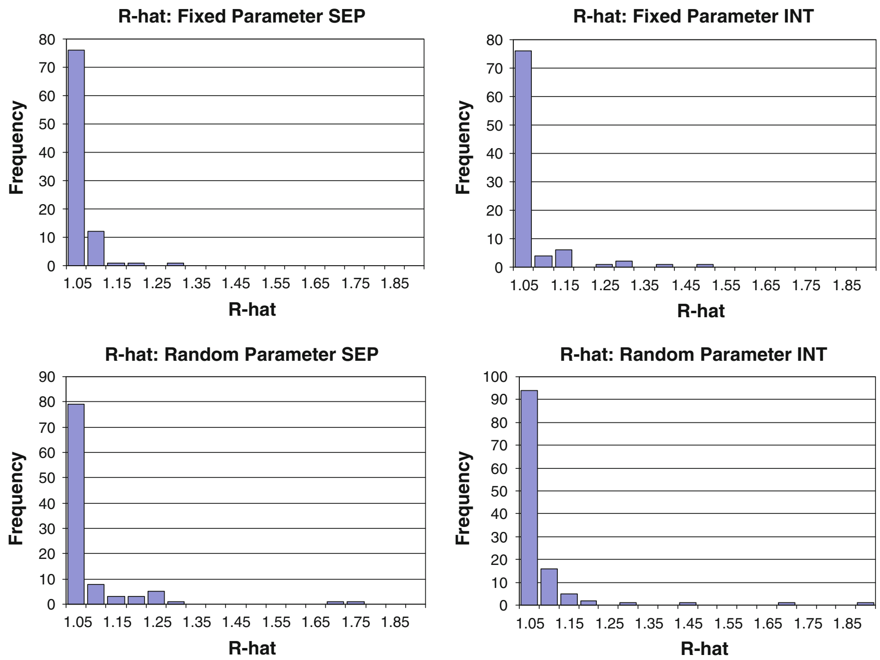

Fig. 8.8 *R*-hat statistic distribution for parameters in each model scenario

posterior distribution [16]. While there is no formal definition for acceptable convergence, it is recommended by Gelman–Rubin that a value of $\hat{R}$ of less than 1.2 is a reasonable measure of convergence for a chain [7].

Histograms of $\hat{R}$ for each of the model parameters (i.e., b, Σ) are shown in Fig. 8.8. As seen in the figures, each of the models generally converged with $\hat{R}$ less than 1.2; however, each of the models has a few (less than 5%) of the chains with $\hat{R}$ greater than 1.2. These outliers have been investigated and found to be related either to the ordered logit cut points, or the variance components, and not the model parameters in the utilities functions (i.e., β). The cut points ($\mathbf{k}$) have more difficulty in converging, possibly due to the ordinal constraint upon them.

8.6.2 IBHCM Model Fit and Prediction Tests

Unlike physics-based models, model validation for behavioral models is challenging in that a physical experiment may be difficult to conduct to validate the model. Validation must be done utilizing the same data available for model estimation in most situations. As a first step, magnitudes and signs of model parameters (β) are verified to agree with the understanding of the problem

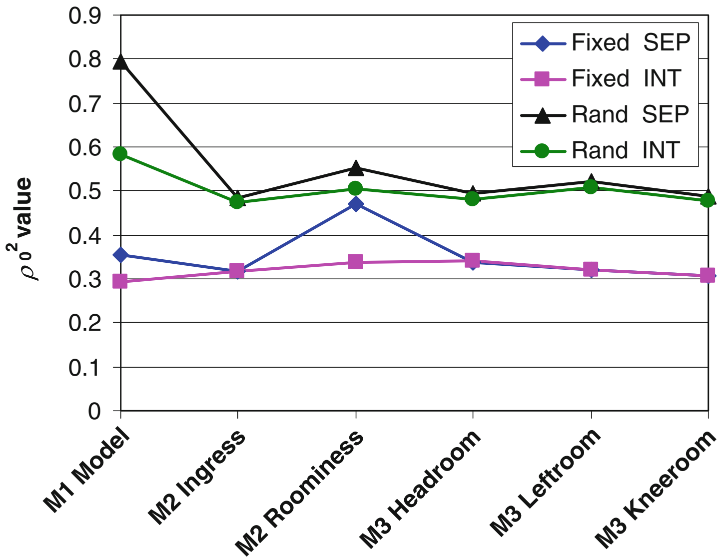

Fig. 8.9 Comparison of model ρ_0^2 for four models

(e.g., customers should, on average, prefer greater roominess). In this study, formal validation is conducted primarily by comparing the model estimated using the IBHCM approach to the other three less rigorous scenarios presented in Sect. 8.5.2. The following validation techniques are used for behavioral models:

- *Goodness-of-Fit Measures*. Goodness-of-fit measures based upon the log-likelihood of the converged model, such as the likelihood ratio index ρ_0^2 [21], are measures of how well the estimated model predicts actual *individual* choices in the data set. Higher values of ρ_0^2 indicate better model fit [27].
- *Choice Share/Segment Prediction Tests*. Due to the hierarchical nature of the model, prediction errors in the lower-level models propagate to the choice level model, creating inaccuracies in choice prediction. Therefore, a test is conducted to determine overall vehicle choice share prediction accuracy, as well as a test of predictions on specific segments of the choice, for example predictions on several segments of human stature [2].
- *Confirmation of Effect of Modeling Heterogeneity*. The effect of including systematic and random heterogeneity in the model is shown.

Goodness-of-fit. The ρ_0^2 statistic for each of the sub-models (i.e., M_3, M_2, M_1) within each overall hierarchical model is calculated and plotted in Fig. 8.9. Significantly higher ρ_0^2 values are achieved using the random parameter models versus the fixed parameter models. This is expected as the random parameter model captures random taste heterogeneity in addition to the systematic taste heterogeneity of the fixed parameter models. The inclusion of random

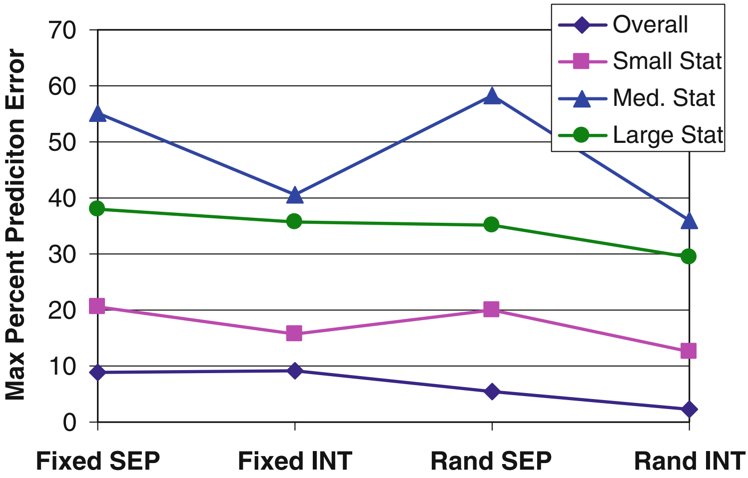

Fig. 8.10 Prediction error comparison

heterogeneity provides the largest improvement in the M_1 level choice model, indicating that there is much taste variation at the choice level not accounted for by the inclusion of **S** in this model. Additionally, the models estimated separately have better goodness-of-fit statistics than the INT estimated models. This is due to the fact that the parameters in the INT models are fit to models in which the response is predicted by another model in the hierarchy, as opposed to the actual responses.

Choice share predictions. The models are compared based upon the error in choice share (*C.S.*) predictions for the four different vehicles in the choice set. Fig. 8.10 shows a plot of the *maximum* choice share prediction error among the four vehicles (labeled *Overall*) for each of the four model scenarios. The error for both fixed parameter models is relatively high; however, the integrated formulation approach successfully minimizes the error of the vehicle under design. Introducing random parameters has the effect of more evenly distributing the error among the *C.S.* predictions, thus reducing the maximum choice share errors. The integrated estimation with random parameters has a similar effect as the fixed parameter INT estimation in that it significantly reduces the error of the vehicle under design (Veh. 4), but also lowers the *C.S.* prediction error for the other vehicles as well.

A *C.S.* prediction test was conducted for three segments of human stature (small, medium, large). In this test, the data set is segregated into the three segments of stature and the prediction error is quantified for each segment. This test is recommended because it is typical to have relatively small data sets in designed choice experiments due to the expense in conducting choice experiments [2], thus making it infeasible to have separate training and test data sets. The results of the Stature market segmentation test are also shown in Fig. 8.10 (labeled *Small*, *Med.*, and *Large Stat*).

Table 8.4 Effect of including random and systematic heterogeneity in the model

	Vehicle 1 *C.S.*	Vehicle 2 *C.S.*	Vehicle 3 *C.S.*	Vehicle 4 *C.S.*	
Initial *C.S.*	0.141	0.380	0.180	0.299	
Attribute change	+ Ing	+ Room	+ Room	+ Q Mat.	
	+ Ext	+ Ext	+ Ext	+ W to P	ρ_0^2
Model 0	0.418	0.830	0.814	0.489	0.056
Model 1	0.270	0.588	0.383	0.416	0.350
Model 2	0.260	0.595	0.395	0.407	0.381
Model 3	0.318	0.592	0.411	0.466	0.678
Model 4	0.313	0.600	0.429	0.472	0.806

As seen, the prediction errors for the segment subsets are generally lower for models using the integrated estimation method (Scenarios 2 and 4) versus the separate estimation (Scenarios 1 and 3). This improvement in predictive capability justifies the small loss in model goodness-of-fit seen in Fig. 8.9. The lowest prediction error is consistently achieved with the random parameter INT model (Scenario 4). The errors are tested to determine if they are outside the 95% confidence interval for the choice share estimates. The 95% confidence intervals for each segment choice share are calculated using the binomial proportion confidence interval [2]. It is found that choice share predictions from the Fixed SEP and Rand SEP models for medium stature segment for Vehicle 3 are outside the 95% confidence interval, further justifying the use of the INT estimation approach.

Modeling heterogeneity. The non-linear choice versus utility curve implies that the model with the best representation of heterogeneity and the least restrictions on the choice probabilities (i.e., IIA) will provide the best estimate of the choice share for a design change or the introduction of a new design. To demonstrate this concept, a comparison among five DCA models (i.e., M_1 level only models) estimated for the set of four competing vehicles in $\boldsymbol{DS}_1$ and $\boldsymbol{DS}_2$ is provided. The five choice models estimated are as follows:

- *Model* 0: Aggregate Logit model estimated using average vehicle ratings.
- *Model* 1: MNL model with no demographics (no **S**).
- *Model* 2: MNL model with demographics included (**S**).
- *Model* 3: MXL model with no demographics (no **S**).
- *Model* 4: MXL model with demographics included (**S**).

The five models are estimated, resulting in initial choice shares for each of the four vehicles of [0.141, 0.380, 0.180, 0.299]. Case studies are conducted in which various hypothetical changes to the design of each of the vehicles are made individually, which are assumed to increase the respondent ratings by two points (e.g., rating 4 increases to 6) for each change. The effects of the design changes upon the choice share of the changed vehicle are shown in Table 8.4 for each of the four cases investigated. For example, the Ingress (*Ing*) and Exterior Styling (*Ext*) ratings are increased (+) for Vehicle 1 (*Veh. 1*) in the first case study, with the

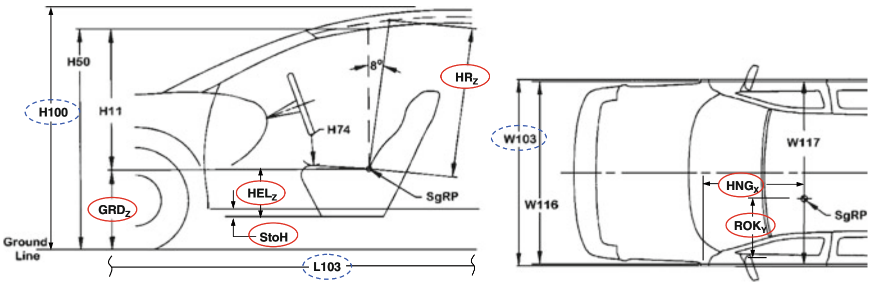

Fig. 8.11 Relationship among vehicle packaging dimensions [23]

predicted choice share (*CS.*) estimated using each model (Model 0–Model 4) for the improved design shown in the respective row.

The ρ_0^2 metric indicates that the MXL with **S** model (model 4) has the best fit, while the aggregate model has the worst fit. Considering only the aggregate logit model in comparison to the four other models for each case, it is seen that the aggregate model always overestimates the effect of a design change. The reason the aggregate model overestimates the choice share improvement is the S-shaped u_{in} versus $\Pr_n(i)$ curve: the aggregate model does not account for individuals at the tails of the curve whose $\Pr_n(i)$ does not change significantly with an increase in W_{in}. In the first case study using Vehicle 1, the models without **S** tend to overestimate the effect of the change for a given model type (i.e., MNL and MXL), while the MNL models underestimate the effect of the change versus the respective MXL models (i.e., with **S** and without **S**). Other patterns of over- or underestimation can be seen in the studies for Vehicles 2–4. The differences in prediction between the MNL and MXL models can be explained primarily by the relaxation of the IID property of the MNL model when using the MXL model. The difference in predictions between models with and without **S** can be explained by the increased heterogeneity in W_{in}, resulting from better modeling of individual-level utility with inclusion of **S**.

8.7 Case Study: Vehicle Occupant Package Design Optimization

A vehicle package optimization formulation is used to demonstrate the benefits of the estimated IBHCM in setting package design targets. The package optimization problem is to select the HNG_X, ROK_Y, HEL_Z, GRD_Z, StoH, and HR_Z dimensions to maximize choice share for Vehicle 4, of the four vehicles in the clinical survey, while meeting vehicle-level requirements (i.e., fuel economy, weight). The height, a function of GRD_Z and HR_Z, is limited by the overall vehicle height, given by H100, assumed to have a limit of 58 inches. Also, it is assumed that the weight of the vehicle

Table 8.5 Vehicle choice share optimization problem

Given

a) Vehicle dimensions (L103, W103, H100) for vehicle 4

b) Preference models for M_1, M_2, and M_3

c) Models for fuel economy and weight

d) Target market demographics (**S**)

FIND:

Dimensions: HNG_X, ROK_Y, HEL_Z, GRD_Z, StoH, HR_Z

To MAXIMIZE

Choice share, Q, for vehicle 4

Subject to:

$H100 \leq 58$ in.

Fuel economy f(engine size, L103, W103, H100, weight) $\geq$ 24.0 mpg

Weight $= f(L103, W103, H100) \leq 3{,}500$ lbs

Relationships:

$L103 = 165.4 \text{ in} + HNG_X$

$W103 = 41.8 \text{ in} + 2\ ROK_Y$

$H100 = 2.0 \text{ in} + GRD_Z + HR_Z[\cos(8 \text{ deg})]$

Table 8.6 Optimization results for the package design

Attribute	Starting value	Optimum value	
		Random INT	Fixed INT
HNG_X	29.5 in	31.5 in	30.3 in
ROK_Y	16.1 in	15.4 in	16.1 in
HEL_Z	12.2 in	13.0 in	13.0 in
GRD_Z	22.0 in	21.6 in	21.6 in
StoH	5.6 in	5.3 in	5.3 in
HR_Z	32.2 in	36.3 in	33.6 in
Fuel economy	24.2 mpg	24.2 mpg	24.0 mpg
Weight	3,480 lb	3,460 lb	3,475 lb
Vehicle height	56.9 in	56.7 in	55.2 in
Choice share	32.65%	40.07%	41.97%

is limited to 3,500 lbs maximum for overall performance reasons, and that the fuel economy must be at least 24 mph to meet federal standards. The six dimensions to be optimized are shown in Fig. 8.11 (solid line oval), as well as the overall vehicle dimensions, which will be used in the constraint functions (dashed line oval).

The optimization problem is summarized in Table 8.5. The optimization is conducted using both the INT random parameter model, and the INT fixed parameter models to compare the difference in results between the two approaches. While the choice model captures customers' trade-offs among interior and exterior attributes, it is necessary to mathematically express the relationships between packaging dimensions and other vehicle design performances (e.g., weight, fuel economy) to capture vehicle-level design trade-offs. Data to estimate regression models is collected for a total of 77 vehicles from the automotive website Edmunds.com [5], based on the segment of the vehicles in the occupant-based packaging survey $\boldsymbol{DS}_1$. From Kumar [14], fuel economy is modeled as a function of weight, engine size, and width/length ratio, and the weight is expressed as a function of vehicle dimensions as summarized in Table 8.5.

The results of the optimization are shown in Table 8.6, with the current values of the six dimensions to be optimized listed under starting value.

The initial choice share estimated using the hierarchical choice model is 32.65%. The optimization converges with the final optimum values for the six dimensions listed in the table, leading to a choice share increase to 40.07% using the Rand INT model versus 41.97% for the Fixed INT model. The final values of fuel economy, weight, and vehicle height are also presented below, with $\mathrm{GRD_Z}$ and StoH reaching the lower constraint on their values. The optimum values of the variables and the maximum choice share solution are different when using the fixed parameter model. Because the goodness-of-fit of the random parameter model (shown in Sect. 8.6.2) is significantly higher than the fixed parameter model, the choice share prediction accuracy is higher for the random parameter model.

8.8 Summary

The IBHCM framework presented in this chapter utilizes multiple model levels to create a link between qualitative attributes considered by customers when selecting a product and quantitative attributes used for engineering design. This new framework addresses the shortcomings of previous methods while providing a highly flexible modeling framework to address the needs of complex system design, such as the vehicle design problem considered in this work. In the proposed framework, both systematic and random customer heterogeneities are explicitly modeled at all levels of the model hierarchy. The importance of including a complete representation of customer heterogeneity in the model framework is clearly demonstrated using the vehicle occupant packaging design example. The ability to combine multiple sources of data for model estimation and updating is significantly expanded over previous methods. A comprehensive method to mitigate error propagated throughout the model hierarchy is presented and its effectiveness demonstrated. Using the vehicle occupant package design, the modeling approach is validated using several metrics and techniques, demonstrating the ability of the new approach to better capture heterogeneous customer preferences and mitigate error propagated.

The integrated Bayesian hierarchical choice model, formulated for model updating and model fusion, can be incorporated into the overall DBD framework for demand estimation. Initially, at time $t = 0$, the prior information and the evidence are combined to estimate the $\boldsymbol{\beta}$ parameters of the choice model (including M_1, M_2, and M_3 levels), which together with an estimate of the total market size, $D(t)$, enables estimation of Q. After initial estimation, the demand model can be updated in future time periods as more information becomes available, as preferences change, or a combination of both information and preference change, using the Bayesian framework.

The hierarchical choice modeling approach presented in this chapter will make possible the realization of a comprehensive Decision-Based Design framework for complex systems, in which a hierarchy of systems and subsystems exist, as well as multiple sources of survey data over different time periods. Using this method, detailed design decisions can be made on a single or multiple subsystems, or for the entire system.

8.9 Additional Resources for Computational Implementation

The following resources provide a general treatment of Bayesian techniques for model estimation:

- Gelman A, Carlin JB, Stern HS, Rubin DB (2004), Bayesian Data Analysis, Vol 25. Texts in statistical science. Chapman and Hall/CRC, Boca Raton, FL
- Congdon P (2003), Applied Bayesian Modelling. John Wiley and Sons Inc, Chichester, West Sussex (very useful for modeling in WinBUGS as described below).

The following text provides a comprehensive treatment of choice modeling using Bayesian techniques:

- Rossi PE, Allenby GM, McCulloch R (2005), Bayesian Statistics and Marketing. John Wiley and Sons, Ltd., Hoboken, NJ

The following resources are available for estimating hierarchical Bayes choice models:

- The `bayesm` package (which is a companion to the Rossi et al. book) is available in R for estimating choice and ordered probit models using the Bayes paradigm.
- `WinBUGS` (http://www.mrc-bsu.cam.ac.uk/bugs/winbugs/contents.shtml) is available for estimating general models using MCMC (Gibbs) sampling. Various types of choice and ordered logit models can be specified and solved in `WinBUGS` (see the Congdon reference for a comprehensive treatment of the topic). The `R2WinBUGS` package in R is available to link R with `WinBUGS`, enabling the use of R for data processing and `WinBUGS` for model estimation.

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Chapter 9
Latent Variable Modeling

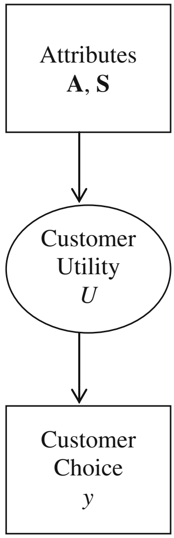
Nomenclature

A	Customer-desired product attributes
α	Measurement model coefficients
β	Choice model coefficients
γ	Structural model coefficients
η	Error in the structural model
I	Indicators
L	Latent variable
LF	Likelihood function
P	Product price
Q	Product demand
S	Customer sociodemographic attributes
$\sum$	Variance of error terms
U	Enterprise utility
u_{in}	True utility of alternative i by customer n
υ	Error in the measurement model
W_{in}	Deterministic part of the utility of alternative i by customer n
y	Choice
ε	Random unobservable part of the utility in the choice model

In this chapter, we again consider the problem of selecting attributes to appear in the discrete choice analysis model, but in this case latent variable modeling is used to consider the customer attitude and perception in the choice model more comprehensively than in previous chapters. The latent variable approach better captures psychological factors that affect the purchase behavior of customers. The chapter begins by describing the need for latent variables in a demand model, and then follows with the formulation and estimation of the integrated latent variable demand model. A case study is presented for a vehicle engine design problem, the

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_9,

Fig. 9.1 Standard discrete choice model



same as presented in Chap. 4 (case study 2). The advantages and disadvantages of the latent variable model approach are discussed.

9.1 The Need for Considering Latent Variables in Demand Models

In the demand modeling approach presented thus far, the demand is modeled as a function of key customer-desired attributes **A**, that relate product attributes to the specific customer desires, customer socio-demographic attributes **S**, price P, and time t. As illustrated in Chap. 8, the **A** can be quantitative measures (e.g., horsepower, fuel economy) or qualitative measures (e.g., comfort, roominess) quantified using a system of ratings. As illustrated in Fig. 9.1, a standard discrete choice model enables prediction of the customer's choice y by assuming that the customer maximizes his or her underlying utility U which is thought of as a function of **A** and **S**. Note that the customer utility U is treated as an intermediary variable that is unobserved and cannot be measured directly.

However, it is possible that customers do not compare products on a well-defined, specific product attribute basis, but rather on a more abstract level which is difficult to quantify using the methods presented in previous chapters. *A customer does not purchase a product for what it is but for what it does in the customer's mind*. For example, a vehicle can be described by customer-desired attributes like engine size, number of seats, etc., but what the customer really cares about is what the vehicle can do for him/her, i.e., transportation, status, convenience, etc. The way customers view and value a product depends on the customer's experience and knowledge. It is likely that the customer-desired attribute as perceived by the customer differs from the attribute's literal engineering meaning and level. Conceptually we can think that the lists of facts are interpreted and weighed by the customer when deciding what alternative to purchase. This weighing and interpretation can be related to the customer's attitude and perception. The customer's attitude is an indication of how important customer attributes are to the customer, e.g., price, safety, reliability, etc. The customer's attitude reflects the customer's needs, values, and capability. This attitude is formed over time, and affected by experience and external factors that include socio-demographic characteristics [1]. Perceptions relate to the customer's believed or estimated customer-desired attribute levels, such as performance, ease of use, service, image, etc., of the product. It is commonly assumed that the customer's choice is based on the *perceived customer attribute* levels rather than the customer attribute levels themselves. In the standard discrete choice model, this is thought to be captured by the random disturbance ε (epsilon) of the customer utility function, but this is a simplistic treatment. Behavioral researches have stressed the importance of cognitive workings inside the black box (i.e., the customer's brain) on choice behavior [1]. According to McFadden [11] there are errors in a customer's perception that arise from the way information is stored, retrieved, and processed. It is expected that considering the customer's perception and attitude explicitly in the demand model helps explain part of the random disturbance ε of the customer utility and so enhances the demand model's predictive capability.

In Chap. 8, we assumed that a customer rating of a system attribute could capture the customer attribute toward system- and subsystem-level attributes. This assumption was justified based on the fact that the surveys used to collect the rating data were carefully designed using the methods of Chap. 6 and that the system attributes surveyed were well aligned with attributes considered by customers in a choice situation based on previous experience or analysis. However, in cases where the perception of customer-desired attributes by survey respondents is not well understood from previous analysis, the latent variable approach introduced in this chapter provides a means to capture these perceptions. Models with latent variables can capture the cognitive workings inside the black box by modeling the customer's perception. Latent variable modeling [4, 10] is a technique that can capture the customer's attitude and perception through the use of psychometric data. Psychometric data is obtained through asking survey questions related to the customer's attitude and perception toward the product design. For instance, psychometric survey questions ask the customers to indicate how satisfied or dissatisfied they are with respect to customer attributes on a rating scale. An example of a latent variable model is provided in Fig. 9.2, in which we use questions of J.D. Power's vehicle quality survey (VQS) as examples of indicators.

A latent variable model captures psychological factors, i.e., the customer's attitude and perception, as latent variables $\boldsymbol{L}$, which are, like utility, unobservable. These latent variables influence the customer's behavior, which cannot be

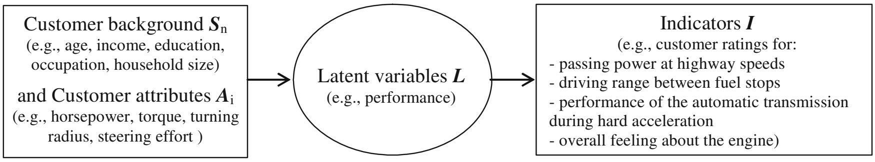


Fig. 9.2 Example of a latent variable model

measured directly but can be measured by observing indicators $\boldsymbol{I}$ of these psychological factors (such as, responses to survey questions regarding individual's attitude or perceptions). The latent variables can be modeled as a function of the customer background **S** and attributes **A**. Just as customer utility can only be measured indirectly by studying a customer's purchase behavior, the customer's perception and attitude cannot be measured directly either. However, questions can be developed to elicit the customer's perception of product aspects like image, cost, performance, etc. The answers to these questions give an *indication* of the level of the latent variable similar to the customer purchase choice indicating the level of the customer utility. It should be noted that the indicators are the "effects" *caused* by the latent variable, and just like the customer's choice in the discrete choice model, indicators are not an input but an output.

By combining the latent variable model and the discrete choice model we obtain the integrated latent variable discrete choice model, see Fig. 9.3. The integrated model can model the influence of the customer's attitude and perception on purchase behavior. The integrated model employs the latent variables $\boldsymbol{L}$ as *additional predictors* to help predict the customer's utility U and customer choice y.

The inclusion of psychometric data through latent variables in the discrete choice model facilitates a more realistic capturing of the customer purchase behavior and hence, an increased predictive accuracy of the choice model. Latent variable modeling is related to factor analysis and structural equation modeling in that similar analysis techniques are used. Keesling [8], Joreskog [7], Wiley [13], and Bentler [2] have contributed to the latent variable theory by developing the structural and measurement equation framework and methodology for specifying and estimating latent variable models [1].

Different approaches for including indicators of psychological factors into choice models have been developed. Koppelman and Hauser [9] included indicators directly into the customer utility function in the form of attribute ratings, which is the basis of the approach followed in Chap. 8. Phrashker [12] proposed to first fit the latent variables to indicators and subsequently to include the fitted latent variables in the customer utility function [12]. However, these approaches have their shortcomings. For example, indicators are not a direct measure of customer utility. Rather, they reflect the perception and attitude of the customer, while the customer's perception and attitude are influenced by the customer's background and the product description. Ben-Akiva extended the above approaches by formulating a general treatment of the inclusion of latent variables in discrete choice models [1].

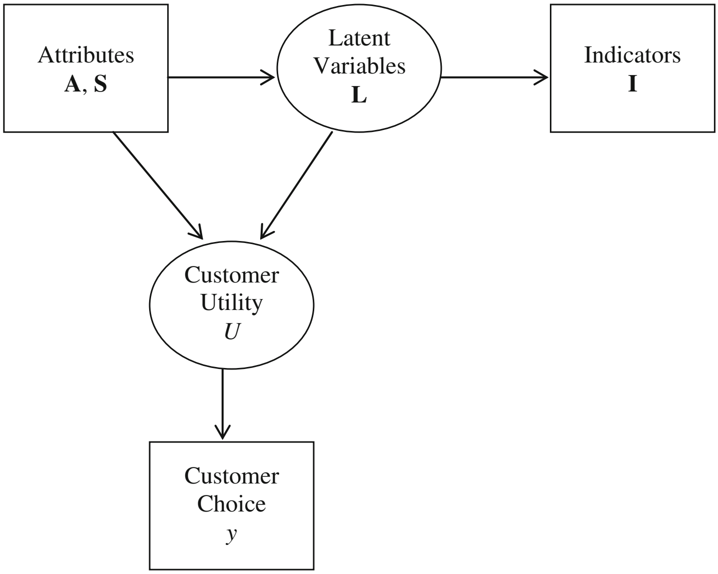


Fig. 9.3 Integrated latent variable model

Theory and application of latent variable modeling seem to be limited to binomial choice situations, i.e., buy/not-buy or chose alternative “A” or chose alternative “B” decisions. However, many realistic choice settings involve more than those choice situations. Therefore, there is a need to extend the latent variable discrete choice model to multinomial choice situations. This work extends the integrated latent variable discrete choice modeling approach as proposed by Ben-Akiva for application in engineering design decision-making and extends the approach to include multinomial choice situations. The integrated latent variable program is tested for the vehicle engine design case study in Sect. 9.3.

9.2 Integrating Latent Variable Models into Demand Models

In this section we present the structure of the integrated latent variable discrete choice model, which consists of a latent variable model and a discrete choice model. Our formulation of latent variable modeling is limited to continuous latent constructs and indicators. Corrective procedures have been developed to facilitate consideration of discrete indicator variables [1] using the ordered probit model, which is related to the ordered logit model introduced in Chap. 3 and used in Chap. 8 for rating data. The approach presented here can therefore be extended for discrete rating (i.e., indicator) data using the ordered logit model for the measurement model; however, additional computation cost is incurred due to the need to estimate both a *structural* and a *measurement* model, as will be described in the next section.

9.2.1 Incorporation of Latent Variables as Attributes in Choice Models

Implementing the integrated latent variable modeling approach involves the following 5 steps: (1) Determine what customer-desired attributes **A** and customer socio-demographic attributes **S** to consider. (2) Assess how many and what latent variables $\boldsymbol{L}$ to consider given **A** and **S**. (3) Identify for each latent variable sufficient (i.e., 4 or more) indicators $\boldsymbol{I}$ that measure the level of that latent variable. (4) Determine the structural equations and the measurement equations for the latent variable model and for the choice model. (5) Determine the likelihood function and fit the integrated latent variable model. These five steps are detailed next.

Step 1 is explained in Chap. 3 for standard discrete choice modeling and will not be repeated here. Regarding Steps 2 and 3, in Chap. 4 we discussed specific customer desires that are considered by customers when deciding what product to purchase. At the detailed level the specific customer desires are translated into customer-desired attributes **A**, which are measurable quantities so that a link with engineering design can be established and further cascaded down to the design options **X**. At the high level, the specific customer desires can be grouped into top-level customer desires such as performance, durability, reliability, ease of use, service, image, cost, etc. These top-level customer desires can be thought of as the latent variables. An alternative approach to determine how many and what latent variables to consider is to use principle component analysis [6] of the available data. The number of principle components that result from this analysis are an indication of the number of latent variables that capture as much of the variance present in the data as possible. Principle component analysis can also give an indication of the attributes and indicators that link to a particular latent variable. This approach is demonstrated in the example section of this chapter in Sect. 9.3. Step 4, identification of the structural equation and measurement equations is detailed next. The integrated model with coefficients is presented in Fig. 9.4.

The latent variable model consists of two parts, a *structural model* and a *measurement model*. The structural model models the latent variables **L** as a function of the customer-desired attributes **A**, and the socio-demographic attributes **S** and consists of one equation per latent variable. A structural model equation is presented in Eq. (9.1), where the indices for the latent variables, customer-desired attributes, and socio-demographic attributes are omitted. The random disturbance η is often assumed normally distributed with variance 1 for identification, an issue to be explained later in this section [10].

$$\boldsymbol{L} = \gamma_1 \mathbf{A} + \gamma_2 \mathbf{S} + \eta. \tag{9.1}$$

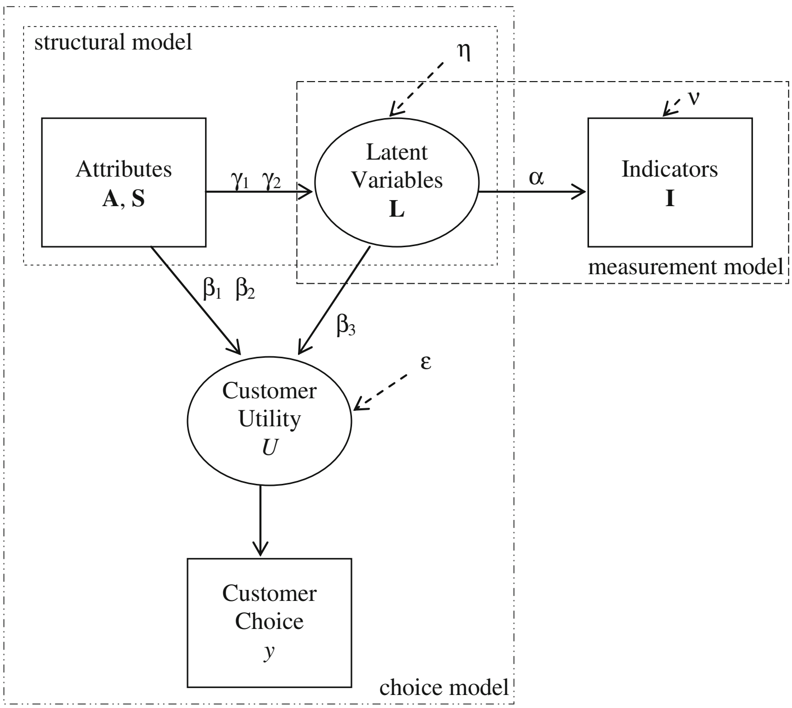


Fig. 9.4 Integrated latent variable model with structural model and measurement model

Similarly, we can write the structural equation for the customer utility U and random disturbance ε, which is assumed distributed extreme value with mean 0 and variance $\pi^2/6$ for logit choice models, which is shown in Eq. (9.2) (other choice models may assume different distributions for ε).

$$U = \beta_1 \mathbf{A} + \beta_2 \mathbf{S} + \beta_3 \boldsymbol{L} + \varepsilon. \tag{9.2}$$

Note, that the functional form of the structural equations is not prescribed but is often assumed additive. Additionally, we remark that not all customer-desired attributes **A** and socio-demographic attributes **S** need to be linked with the latent variables $\boldsymbol{L}$ and similarly, not all **A** and **S** are necessarily linked directly to the customer utility U. The measurement model measures the relationship between the latent variables $\boldsymbol{L}$ and the indicators $\boldsymbol{I}$. The measurement model contains one equation per indicator as shown in Eq. (9.3).

$$I = \alpha L + \upsilon \tag{9.3}$$

The random disturbance v is often (but not necessarily) assumed to be normally distributed and is an indication for the model fit, i.e., v is an indication of how well the measurement equation explains the variance found in the observed indicator values. The measurement equations may also contain socio-demographic attributes or other variables available within the integrated model, such as the choice indicator y, in addition to the latent variables as explanatory variables. Such a measurement model specification can capture systematic response biases. For instance, when a customer provides indicator values in addition to choice, including the chosen alternative as an attribute in the measurement equations results in exaggerated indicator values, which can be indicative of justification bias [1]. The choice model is strictly speaking also a measurement equation in that choice y can be seen as an indicator of the customer's utility U. As with discrete choice modeling, the relationships should be causal, i.e., the paths should be econometrically justifiable.

Combining Eqs (9.1–9.3), and the choice model forms the integrated discrete choice latent variable model. *Latent variable models are estimated by minimizing the discrepancy between the covariance matrix of the observed data and the covariance matrix predicted by the latent variable model as a function of the unknown model parameters.* The maximum likelihood technique or Bayesian methods can be used to estimate the model parameters. An *ad hoc* approach to fitting the latent model and the choice model is to estimate a latent variable model first, and then estimate the choice model extended with the latent construct. However, Ben-Akiva showed that such a sequential approach may lead to inconsistent coefficient estimates. The integrated model, consisting of the discrete choice model and the latent variable model should be estimated simultaneously for consistent and efficient estimates, which will be shown to require the integration of a multidimensional integral [1]. When fitting the integrated model, it is necessary to ensure that the integrated latent variable model is identified, which is explained next.

Identification of Latent Variable Models

Identification is an issue with latent variable models. Latent variable models can be underdetermined, just-determined, or overdetermined. Underdetermined models have no unique solution, while overdetermined models are desirable [10]. Therefore, it is necessary to assure that a latent variable model is not underdetermined. A good practice is to have at least four indicators per latent variable. Further, for each latent variable, one path should be fixed (i.e., constrained to a preselected value) or the variance of the latent variable should be fixed. A general rule for identification of latent variable models is that the number of unknown parameters should be less than the number of unduplicated variances and covariances in the observed covariance matrix of the data considered. That is, the unknown parameters should be less or equal to $p(p + 1)/2$ for p observed variables. However, satisfying this rule is necessary but not sufficient. It is possible that some parts of the model are still unidentified, which needs to be checked. When using maximum likelihood estimation, identification can be confirmed by using different starting points, which should yield the same estimated model parameters. Another method is to use the obtained latent variable model to generate synthetic data (indicator values and choice data) using Monte Carlo sampling and then to use this synthetic data to again fit the latent variable model parameters. If the latent variable model is identified then the parameter estimates of the two models should be comparable within a reasonable margin of accuracy [1]. Identification is less of a concern when using Bayesian estimation techniques because prior distributions can be specified to constrain the movement and spread of parameters in model estimation [3]. In the following section we derive the likelihood function that can be employed to fit integrated multinomial latent variable models.

9.2.2 Development of the Likelihood Function of the Integrated Multinomial Model

A likelihood function of the integrated latent variable model with a multinomial logit choice model for estimation of multinomial choice data is derived in this section. We consider the integrated approach in this work in which both the latent variable model and the choice model are estimated simultaneously based on maximum likelihood estimation (optimization) or Bayesian methods. The generic likelihood function (LF) for the integrated model as presented in Ben-Akiva [1] is shown in Eq. (9.4).

$$\begin{aligned} \mathrm{LF} &= f\left(y, I|Z; \alpha, \beta, \gamma, \Sigma_\varepsilon, \Sigma_v, \Sigma_\eta\right) \\ &= \int_L \underbrace{\Pr(y|Z, L; \beta, \Sigma_\varepsilon)}_{\substack{\text{choice} \\ \text{model}}} * \underbrace{g\left(L|Z; \gamma, \Sigma_\eta\right)}_{\substack{\text{structural} \\ \text{model}}} * \underbrace{h(I|Z, L; \alpha, \Sigma_v)}_{\substack{\text{measurement} \\ \text{model}}} \, dL \end{aligned} \tag{9.4}$$

where $Z = (\mathbf{A}, \mathbf{S}, P)$ and L are latent variables.

Equation (9.4) shows how the likelihood consists of the integration of the choice model over the distribution of the latent variables $\boldsymbol{L}$, including the indicators $\boldsymbol{I}$, which is the joint probability of the observed variables y and indicators $\boldsymbol{I}$, given the attributes $\mathbf{Z}$ (which includes $\mathbf{A}$, $\mathbf{S}$, and P) and unknown parameters α, β, γ, and the variances of the random disturbances Σ_ε, Σ_η, and Σ_v. Using Eq. (9.4), Ben-Akiva derived the likelihood function for binary logit choice, shown in Eq. (9.5) [1].

$$\mathrm{LF} = \int \int_L \left[\frac{1}{1 + \exp(-y[\beta_1 Z + \beta_2 L])}\right] * \prod_{k=1}^{nl} \frac{1}{\sigma_{\eta_k}} \phi\left[\frac{L_k - Z\gamma_k}{\sigma_{\eta_k}}\right] * \prod_{r=1}^{ni} \frac{1}{\sigma_{v_r}} \phi\left[\frac{I_r - L\alpha_r}{\sigma_{v_r}}\right] dL \tag{9.5}$$

where nl and ni indicate the number of latent variables and indicators respectively, ϕ represents the standard normal density function (pdf), and σ represents the standard deviation of the random error of the latent variables and the indicators. The likelihood is obtained by integrating the density function over the latent variables $\boldsymbol{L}$. The binary choice expression can be extended to multinomial choice (i.e., Multinomial Logit) for a choice set C_n by substituting the following expression for the choice probability in Eq. (9.4):

$$\Pr(y_i|Z,L;\beta,\Sigma_\varepsilon) = \frac{\exp(y_i[\beta_1 Z_i + \beta_2 L_i])}{\sum_{j\in C_n}\exp\left(\beta_1 Z_j + \beta_2 L_j\right)} \tag{9.6}$$

With expressions available for the likelihood function, the integrated model can be estimated.

Solution Techniques

One issue we face when fitting an integrated latent variable model is that the number of parameters to be estimated increases quickly with the increasing number of variables. The potential number of parameters that need to be estimated is shown in Eq. (9.7) as can be seen in Fig. 9.4.

$$n = l(a + s + i + 2) + a + s + i, \tag{9.7}$$

where n indicates the number of parameters to be estimated and a, s, l, i indicate the number of coefficients to be estimated for customer-desired attributes, socio-demographic attributes, latent variables, and indicators, respectively. When assuming that the variance of the latent variables is fixed to one for identification, the potential number of parameters to be estimated reduces to:

$$n = l(a + s + i + 1) + a + s + i \tag{9.8}$$

In Eq. (9.8) it is assumed that all possible paths need to be estimated. However, in practice, many parameters will be constrained to 0. Based on our experience, a reasonable estimate of the number of parameters is: $n = 2\ (a + s + i) + l$. The number of parameters to be estimated poses a heavy computational burden when compared to the computational effort required for fitting a choice model only, which requires estimation of $a + s$ parameters. In addition to the number of parameters to be estimated, the integrated latent variable approach requires simulation of the variance of the latent variables.

Two methods are available for estimating the model as discussed in Chap. 3: (1) Maximum likelihood estimation (MLE) and (2) Hierarchical bayes (HB). In the MLE approach, the likelihood function of Eq. (9.4) is maximized using optimization methods to find the values of the model parameters (i.e. α, β, γ, ν, η, ε). While this approach is the most direct and can reach convergence quickly, the likelihood function has many local maxima and requires simulation of the double integral using numerical methods (i.e., Monte Carlo simulation). The HB method overcomes the optimization challenges; however, the HB method requires the specification of prior distributions for model parameters. The priors can be used advantageously, however, to help with the identification issues described in the previous section by placing a constraint on the magnitude and dispersion of the model parameters [3]. The HB method also allows for more freedom in estimating error terms and better understanding model parameter distributions. This can be extended to estimating random parameter models, such as using the mixed logit model as the choice model. In this work, we will utilize the HB estimation method following the approach of Congdon [3].

9.3 Case Study: Integrated Latent Variable Model for Vehicle Engine Design

Using the same vehicle engine design problem considered in Chap. 4, we demonstrate an implementation here of the choice modeling latent variable modeling approach. The choice alternatives are the same 12 trims of seven vehicle models of the midsize car market segment in the example problem of Chap. 4. The integrated latent variable model is implemented using the five steps laid out in Sect. 9.2.

Step 1. Determine what Attributes to Consider

A set of ten customer-desired attributes is used that relate to the price, reliability, engine performance, fuel economy, and to the vehicle's size such that a description of the whole vehicle is obtained.

Step 2. Identify the Latent Variables

This step consists of determining the number of latent variables that will be considered in the integrated model, and subsequently identifying the latent variables themselves. In the literature, there are no specific guidelines for how latent variables should be identified. In our view, the number of latent variables depends on the number of top-level customer desires (presented in Chap. 4) that can be identified. One approach is to ask customers how they reach their purchase decisions, what aspects of the product they consider. The customer-desired attributes **A** used for this case study, which encompasses a description of the vehicle make and model, are mainly financial data, reliability indices, engine performance, and vehicle dimensions that can be grouped into three categories: *cost, performance, and comfort*. Therefore, we consider these as three possible latent variables.

Another approach, suggested in [10], to determine how many and what latent variables to include in the latent variable model, is to analyze the data using factor analysis. Factor analysis often facilitates a reduction of the number of variables of a data set by transferring the data set to a new set of variables, called factors, that are a linear combination of the existing variables. Factor analysis [6] aims to identify underlying linear constructs (i.e., components) that reproduce the correlation matrix of the observed data by capturing as much of the variability found in the observed data as possible. Equation (9.9) shows how the new variables (F_i) are a combination of the variables A of the existing data set.

$$F_i = \delta_{i1}A_1 + \delta_{i2}A_2 + \delta_{i3}A_3 + \ldots + \delta_{in}A_n \tag{9.9}$$

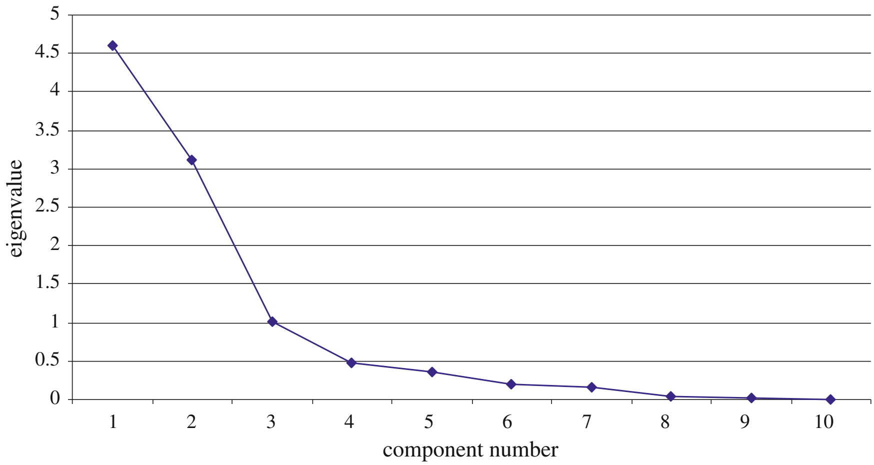


Fig. 9.5 Scree plot of customer attributes used for example study

The factor analysis approach is iterative in that it determines the δ-coefficients (called factor loadings) by first finding the factor F_1 that explains the most variance of the data, then the factor F_2 that explains the second largest amount of variance, etc. The factor loadings represent the correlation between the factor and the variable. Hence, the square of a coefficient δ_{in} indicates the amount of variance of variable A_n is explained by factor F_i. The eigenvalues of the factors can be thought of as a measure of how much variance of the data each component explains. The larger the factor's eigenvalue, the more variance is explained by that component. The complete set of factors explains 100% of the variance found in the observed data. However, the goal is to obtain a reduced set of factors that captures the data variance well. A rule of thumb, known as the Kaiser-Guttman rule [10], is to only consider the factors with an eigenvalue larger than one. Another approach is to graph the eigenvalues in order of magnitude as shown in Fig. 9.5. This approach, known as Scree plot analysis, considers the data as a mountain with debris at its foot. Figure 9.5 shows the Scree plot of the ten attributes used for this example. The mountain contains the valuable components of the data (high eigenvalues), these components are retained, and the debris at the foot is considered rubble and therefore omitted. Given the Scree plot, our earlier assumption of using three latent variables is quite reasonable, though the eigenvalue of the third component is just slightly larger than one.

Factor analysis can be employed as exploratory analysis to help determine the number of latent variables and the composition of the latent variables, i.e., to indicate the attributes that are associated with a particular latent variable. The factor loadings indicate the statistical relationship between the attributes and latent variables on one side and the relationships between the latent variables and the indicators on the other side. Good predictive capability of the latent variable model, and thus the integrated model, *requires that these relationships are not just* *statistically significant but also causal*. In this particular example the factor loadings do not match with our common-sense understanding of causal relationships. Therefore, in this example, factor analysis is only used to determine the number of latent variables. The factor analysis can be seen as an exploratory analysis in which the observed data is explored and a hypothesis is formed, while the latent variable model can be seen as a confirmatory analysis. That is, the coefficient estimates of the latent variable model can be used to confirm the coefficients hypothesized by the factor analysis. Factor analysis is done separately for the attributes and for the indicators. The next task is to identify preferably at least four indicators per latent variable, which is detailed in Step 3.

Step 3. Identify Indicators for Each Latent Variable

In this step we determine the indicators that measure each latent variable that we identified in the previous step, i.e., cost, performance, and comfort. It would be ideal to hypothesize indicators that can measure each latent variable. A survey can then be developed and conducted to obtain the data for the indicators. However, in this example we use existing survey data for the indicators, which necessitates an assumption explained below.

Indicator Data for the Integrated Latent Variable Model

For this example we consider data from a J.D. Power VQS study as possible indicators. Like choice data, the indicator values should be at individual customer level. The survey used in the VQS study asks respondents (existing car buyers) questions about how they rate their vehicles qualities. The VQS questionnaire considers eight aspects of the car at vehicle level, e.g., engine/transmission, cockpit, ride and handling, HVAC (heating, ventilating, air conditioning), comfort, sound system, seats, and vehicle styling. Each of these aspects at vehicle level is incorporated into multiple questions concerning details of that aspect, which each customer is asked to rate on a linear scale ranging 1–10. For engine/transmission these are: *sound while idling*, *sound at full throttle acceleration*, *performance during rapid acceleration*, *smoothness during hard acceleration*, *passing power at highway speeds*, *range between fuel stops*, *fuel economy*, *overall transmission performance*, etc. These ratings provided by the customers are used as indicator values in the latent variable model. The linear rating scale used in the VQS questionnaire does not require a tradeoff among attributes, thus it seems reasonable to assume that the VQS customer ratings are free of interaction effects. However, the brand image and halo-effect (customer is excited about the new purchase) may taint the ratings customers give to the vehicle they purchased. In Sect. 9.1 this is called justification bias and an approach to account for it is presented there.

J.D. Power's VQS study only asks vehicle owners to rate their own vehicle and not any other vehicles. Since in our case study there are 12 vehicles considered in the choice set this implies that for each respondent the ratings (i.e., indicators) of the remaining 11 vehicles are not available. Ideally we should have ratings of each

Table 9.1 Latent variable attributes and indicators for vehicle demand modeling

Latent variable (***L***)	Attribute (**A**)	Indicator (***I***) (J.D. Power VQS rating)
L_1 performance	A_4 engine horsepower	I_1 engine performance during rapid acceleration
	A_5 engine torque	I_2 engine fuel economy
	A_6 fuel economy	I_3 engine overall feeling
	A_{10} vehicle mass	I_9 vehicle overall feeling
L_2 comfort	A_7 front head room	I_4 convenience and comfort-front leg room
	A_8 front leg room	I_5 convenience and comfort-front head room
	A_9 trunk space	I_6 seats overall feeling
	A_{10} vehicle mass	I_7 convenience and comfort-overall feeling
		I_8 convenience and comfort-cargo space
		I_9 vehicle overall feeling

customer for each vehicle in the choice set. This issue is bypassed by assuming that customers of similar age, income, education, gender, and ethnicity act and behave the same and thus would rate in a similar way such that we can use their ratings to complete the ratings of the vehicles considered in the choice set. Given that the ratings (indicators) for each of the vehicles are obtained from vehicle owners, we assume that there is no need to account for justification bias. Once the latent variable model is fitted, the model can be used to predict the indicator levels, i.e., the customer ratings as a function of **A** that describe the vehicle and the **S**. Although predicting customer ratings is not a primary consideration in our case study, customer ratings are used by J.D. Power to determine the Automotive Performance, Execution And Layout (APEAL) score, which is an important measure for vehicle manufacturers.

Given the shortage of indicator data related to cost/price we drop the latent variable for cost and retain two latent variables, performance and comfort. Two latent variables are reasonable given that the eigenvalue of the third factor (cost) is close to one. The indicators and customer attributes identified for each latent variable are shown in Table 9.1. Each customer attribute and indicator is considered for its causal relevance to each latent variable.

An important issue in latent variable modeling is "identification" discussed in Sect. 9.2. In this example, each latent variable in our case study is measured by at least four indicators. Further, the number of data entries of the observed data covariance matrix, computed as $p(p+1)/2$, where p denotes the number of observed variables (20 in this example), exceeds the number of unknown parameters (i.e., γ, α, and β coefficients and the variances of the indicators, v). A latent variable model is called overidentified when the number of unknown parameters is exceeded by the number of (observed) variances and covariances of the covariance matrix. Overidentification is a good thing, but, does not guarantee identification of the latent variable model. That is, identification should be checked, using the procedure presented and demonstrated in Sect. 9.2. We will address techniques for ensuring identification in Step 5. The complete integrated latent variable model as specified is shown in Fig. 9.6, where A_1, A_2, and A_3 represent MSRP-price, VDI (dependability index), and the binary variable USA/imp (domestic vs. import).

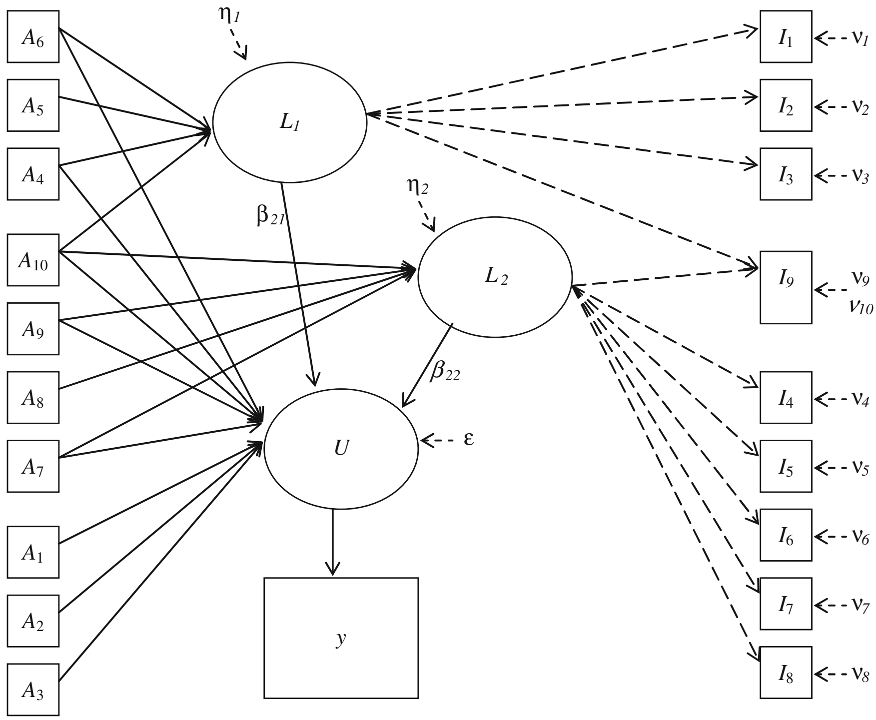


Fig. 9.6 Complete integrated latent variable model for vehicle engine design example

We have now determined the indicators and attributes for our example model. The next step is to form the structural equations and the measurement equations.

Step 4. Determine the Structural Equations and the Measurement Equations

In this step we form the structural equations and the measurement equations for the latent variable model and for the choice model. The two structural equations are presented in Eq. (9.10). Note that the indices for the choice alternative are omitted. Socio-demographic attributes (**S**) are not considered in this example, and therefore an index for respondent is not required in this example. That is, each respondent is assumed to have the same taste (β-coefficient) in the choice model.

$$\begin{aligned} \text{performance} &= \gamma_{11}\text{horsepower} + \gamma_{12}\text{torque} + \gamma_{13}\text{fuel\_economy} + {}_{14}\,\text{vehicle\_mass} + \eta_1 \\ \text{comfort} &= \gamma_{21}\text{front\_headroom} + \gamma_{22}\text{front\_legroom} + \gamma_{23}\text{trunkspace} + \gamma_{24}\text{vehicle\_mass} + \eta_2 \end{aligned} \tag{9.10}$$

The structural equation for the customer utility U_1 is presented in Eq. (9.11). Note that the index for choice alternative i is omitted.

$$\begin{aligned}\mathrm{U} = {} & \beta_{11}\text{price} + \beta_{12}\text{vdi} + \beta_{13}\text{Usa/imp.} + \beta_{14}\text{horsepower} + \beta_{15}\text{fuel\_economy} + \ldots \\ & \ldots + \beta_{16}\text{front\_headroom} + \beta_{17}\text{trunkspace} + \beta_{18}\text{vehicle\_mass} + \ldots \\ & \ldots + \beta_{21}\text{performance} + \beta_{22}\text{comfort} + \varepsilon\end{aligned} \tag{9.11}$$

The measurement equations in Eq. (9.12), omitting the indices for the choice alternatives are:

$$\begin{aligned}\text{performance\_during\_rapid\_acceleration} &= \alpha_{11}\text{performance} + v_1 \\ \text{engine\_fuel\_economy} &= \alpha_{12}\text{performance} + v_2 \\ \text{engine\_overall\_feeling} &= \alpha_{13}\text{performance} + v_3 \\ \text{front\_legroom} &= \alpha_{21}\text{comfort} + v_4 \\ & etc.\end{aligned} \tag{9.12}$$

Finally, the multinomial choice model, which can also be considered as a measurement equation, is given by Eq. (9.13).

$$y_{in} = \frac{e^{W_i}}{\sum_{j=1}^{C_n} e^{W_j}} \tag{9.13}$$

where y_{in} represents the probability that respondent n chooses alternative i from a set containing C_n alternatives. In this case the choice set contains the 12 vehicles.

Step 5. Estimate the Integrated Latent Variable Model

The model is solved using the Hierarchical Bayes methods [3, 5]. The model is formulated in WinBUGS, which utilizes the Gibbs method to sample from the posterior distribution, while data are handled using *R*. Equations (9.1–9.3) are coded into WinBugs and the posterior distributions of α, β, γ, v, and η are found (the variance of the choice model, ε, is set to $\pi^2/6$ as described earlier). For identification, α_{11} and α_{21} are set deterministically to 1.0 to determine the scale of the $\boldsymbol{\alpha}$ coefficients, and the prior distributions of the $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ coefficients are specified as $\sim N(1, 1)$ to aid in identification, as recommended in Ref. [3]. Additionally, all data are normalized on the range [0, 1] so that model parameters can be compared based upon magnitude. The model is fit using a reduced data set consisting of 160 vehicle purchases to lessen the computational requirements. In addition to the integrated latent variable (LV) model, a multinomial logit model (i.e., not a latent variable model but a traditional choice model) is estimated in STATA and used as a reference for comparison. It employs the same customer-desired attributes that are used for the integrated LV model, except that the latent variables Performance and Comfort are not included [thus omitting customer-desired attributes A_5 (engine torque) and A_8 (front leg room) from the choice model]. The estimated market shares from both model approaches are presented in Table 9.2. The model estimation results for both models are summarized in Table 9.3.

Table 9.2 Comparison of market share estimate

Vehicle ID	Observed market share (%)	MNL only (%)	Integrated LV (%)
1	5.00	6.17	5.37
2	3.75	6.08	5.52
3	6.25	5.40	6.04
4	3.75	2.82	2.91
5	5.00	6.20	6.20
6	8.75	11.60	11.45
7	11.25	7.11	7.97
8	11.25	8.07	8.47
9	3.75	8.28	6.83
10	26.25	24.52	25.28
11	11.25	10.47	10.12
12	3.75	3.28	3.85

As shown in Table 9.2, the latent variable matches the actual market shares more closely than the traditional MNL model. This is an indicator that the latent variable model better fits the actual data. The results in Table 9.3 show that the integrated latent variable model provides a better model fit than the multinomial logit choice model estimated by STATA as quantified by the improved ρ^2 (0.0692 vs. 0.0781) for the choice models. In the integrated LV model, the latent variables $L_1 = \mathit{Performance}$ and $L_2 = \mathit{Comfort}$ are significant at the 95 and 90% levels, respectively, indicating that capturing customers' perception and attitude in the choice model further explains the choice process. For the Integrate LV model, we can further examine the $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}$ coefficients. The γ_{11}–γ_{14} coefficients indicate that horsepower, torque, fuel economy, and vehicle mass all are significant in explaining L_1, performance; however, horsepower is significantly less important than the other three attributes (i.e., the **A**). Also, L_1 has a negative sign (β_{21}) in the choice model. The lesser importance of horsepower in the "performance" measure indicates that the perception of "performance" by customers is perhaps different from an engineering-driven definition of performance that would be more closely associated with horsepower. Also, the negative sign of performance in the choice model may indicate that the particular customer base used to estimate the model tends to purchase vehicles on other criteria, such as price, VDI, and/or comfort. The γ_{21}–γ_{24} coefficients indicate that front head room, front leg room, trunk space, and vehicle mass are all significant in explaining L_2, comfort; however, trunk space is negatively correlated with comfort. This can be explained by the fact that for a give vehicle class, vehicles with more trunk space may achieve the space at the expense of interior room or interior configuration, thus sacrificing vehicle comfort as perceived by actual customers. The coefficients in the measurement model, α_{12}–α_{14} and α_{22}–α_{26}, are all close to 1.0 and are all statistically significant. This is to be expected as the indicators of Eq. (9.12) were preselected using factor analysis and the scale of the coefficients was set by specifying $\alpha_{11} = \alpha_{21} = 1.0$. Regarding the error terms, the covariance of L_1, performance, and L_2, comfort,

Table 9.3 Results summary for the integrated latent variable model

	MNL only		Integrated latent variable	
	Coefficient	Std Error	Coefficient	Std Error
β_{11} *(price)*	−5.896	1.088	−6.365	1.118
β_{12} *(vdi)*	2.238	0.925	2.655	0.930
β_{13} *(USA/imp)*	2.952	0.814	3.462	0.809
β_{14} *(horsepower)*	3.761	0.701	4.118	0.770
β_{15} *(fuel economy)*	2.224	0.877	2.760	0.972
β_{16} *(front head room)*	2.583	0.581	2.615	0.602
β_{17} *(trunk space)*	0.339	1.164	0.772	1.192
β_{18} *(vehicle mass)*	10.570	2.276	11.760	2.364
β_{21} *(Performance)*			−1.691	0.712
β_{22} *(comfort)*			1.552	0.896
Log-likelihood	−370.087		−366.5615	
Rho-squared	0.0692		0.0781	
Additional coefficients in the structural and measurement models				
Structural models coefficients				
γ_{11} *(horsepower)*			0.096	0.031
γ_{12} *(torque)*			0.323	0.033
γ_{13} *(fuel economy)*			0.388	0.015
γ_{14} *(vehicle mass)*			0.379	0.019
γ_{21} *(front head room)*			0.174	0.011
γ_{22} *(front leg room)*			0.352	0.015
γ_{23} *(trunk space)*			-0.147	0.021
γ_{24} *(vehicle mass)*			0.920	0.020
Measurement models coefficients				
α_{11} *(performance)*			1	0
α_{12} *(performance)*			0.855	0.006
α_{13} *(performance)*			1.001	0.004
α_{14} *(performance)*			1.074	0.009
α_{21} *(comfort)*			1	0
α_{22} *(comfort)*			0.956	0.005
α_{23} *(Comfort)*			0.953	0.005
α_{24} *(comfort)*			0.949	0.004
α_{25} *(comfort)*			0.950	0.006
α_{26} *(comfort)*			1.061	0.006
Errors for the structural and measurement models				
η_{11}			0.060	0.003
η_{12}			0.045	0.002
η_{21}			0.045	0.002
η_{22}			0.058	0.002
$v_1 - v_{10}$			0.041–0.216	

is given by η_{11}–η_{22}. As seen, there is significant correlation in the two latent variables, possibly because both variables are a function of vehicle mass. The errors in the ten indicator models, labeled as v_1–v_{10} in Table 9.3 (only the range is shown for convenience), indicate that the errors in the indicator models are well controlled, as indicated by the range of 0.041–0.216. This corresponds to R^2 (i.e., coefficient of determination) values ranging from 0.512–0.994 for the ten indicator models. In summary, the example clearly demonstrates how the integrated latent variable approach can be implemented and its potential benefits by explicitly considering the customer's perception and attitude. Additionally, we can understand how the customer-desired attributes are related to the customer perceptions through the estimation results.

A comparison of the Integrated LV approach presented in this chapter and the integrated bayesian hierarchical choice model (IBHCM) of Chap. 8 can be made. Both methods utilize ratings in a choice model to understand customers' perceptions of product design attributes, as opposed to a quantitative engineering measure of the attribute. A fundamental difference is that the integrated LV approach considers the ratings to be indicators of underlying latent perceptions, whereas the IBHCM considers the ratings to be direct measures of customers' perception of a defined choice attribute, such as comfort or roominess. Because the LV approach does not assume direct knowledge of the latent choice attributes, it requires additional analysis to determine the latent variables to include in the choice model specification (e.g., preliminary factor analysis) and a greater computation burden in estimating the choice model (i.e., estimation of $\boldsymbol{\alpha}$, γ, $\boldsymbol{\beta}$, $\boldsymbol{v}$, $\boldsymbol{\eta}$). The IBHCM reduces the computational burden by identifying the choice attributes a priori, and linking the survey and collecting rating data on these attributes directly; however, the assumption that choice attributes can be determined a priori may be difficult to achieve and validate. Also, as discussed in this chapter, ratings are not a true model input: they are technically an output measure resulting from the latent perception. In summary, the integrated LV model is a more rigorous treatment for including customer perception in the choice model; however, the computation and data collection burdens may make the approach prohibitive for a complex system design, making the IBHCM an attractive and reasonable approximation for large-scale engineering design activities.

9.4 Summary

In this chapter we present an extension of the discrete choice method, presented in Chap. 4, with latent variables to facilitate the consideration of the customer's attitude and perception in the demand model. The latent variable approach better captures psychological factors that affect the purchase behavior of customers than conventional discrete choice modeling. The latent variable discrete choice model is extended for use for multinomial choice. Hierarchical Bayes methods, implemented in WinBUGS, are used to estimate demand models that consist of an integration of the latent variable model and the multinomial logit choice model. The advantage of this approach is the potential for enhancing predictive accuracy of the demand model through consideration of the customer's perception and attitude, and a better representation of hierarchy of attributes, which facilitates the design of complex engineering systems. An advantage of using latent variables is the possibility of considering more variables in the demand model, enabling a more detailed description of design alternatives. The more detailed design alternative description facilitates better guidance of engineering design decision making. An additional primary benefit of using latent variables is that perceptual attributes which are difficult to quantify such as the customer's loyalty toward a product or their opinion of the "innovativeness" of the product, can be explicitly considered in the demand model, giving more accurate demand predictions. The improved accuracy of a choice model with latent variables will lead to a better understanding of customer acceptance, and hence a more accurate estimation of customer demand, for a product.

9.5 Additional Resources for Computational Implementation

An introduction to the use of latent variables in choice modeling is mentioned in Ref. [1]. Congdon P (2003) Applied bayesian modelling provides a comprehensive treatment of Bayesian estimation of a latent variable model, with examples in WinBUGS [3].

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Chapter 10
A Choice Modeling Approach for Usage Context-Based Design

Nomenclature

A	Customer-desired product attributes
β	Coefficients in customer's choice utility function
CV	Conventional vehicle
DCA	Discrete Choice Analysis
DOE	Design of experiment
ε_{in}	Random disturbance of customer choice utility of product i by customer n
HEV	Hybrid electric vehicle
M	Non-engineering attributes
MNL	Multinomial logit
P_{in}	Choice probability for product i and customer n
PHEV	Plug-in hybrid electric vehicle
S	Customer profile attributes
$\mathbf{S_W}$	Preference-related customer profile attributes
$\mathbf{S_Y}$	Performance-related customer profile attributes
u_{in}	Customer choice utility of product i by customer n
U	Usage context attributes
$\mathbf{U_W}$	Preference-related usage context attributes
$\mathbf{U_Y}$	Performance-related usage context attributes
$\breve{\mathbf{U}}$	Usage context scenarios
UCBD	Usage context-based design
W_{in}	Observed (deterministic) part of the customer choice utility of product i by customer n
X	Engineering design options or variables
Y	Engineering performance
$\mathbf{Y_r}$	Performance of service results
$\mathbf{Y_t}$	Performance of transformation

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_10,

Usage context-based design (UCBD) is an area of growing interest within the design community. Usage context is defined as all aspects describing the context of product use that vary under different use conditions and affect product performance and/or consumer preferences for the product attributes. In this chapter, we propose a choice modeling framework for UCBD to quantify the impact of usage context on customer choices and exploit the rich contextual information existing in product usage. We start by defining the taxonomy for UCBD. By explicitly modeling usage context's influence on both product performances and customer preferences, a step-by-step choice modeling procedure is proposed to support UCBD. Two case studies, a jigsaw example with stated preference data and a hybrid electric vehicle (HEV) example with revealed preference data, demonstrate the needs and benefits of incorporating usage context in choice modeling.

10.1 Introduction to Usage Context-Based Design

As discussed in Chap. 3, customer choice (demand) modeling is becoming prevalent in engineering design research for designing products or product families. Capturing heterogeneous choice behavior is achieved using disaggregate demand modeling methods, with the probabilistic discrete choice analysis (DCA) method being the most widely used approach in engineering design. While previous works have laid the foundation for modeling the heterogeneity in customers' choice behavior, the potential of disaggregate choice modeling in engineering design has not been fully realized due to an overreliance on marketing and demographic attributes (gender, age, income, etc.) to approximate the complex drivers behind heterogeneous customer choice. Existing choice modeling methods lose their effectiveness and fail to offer insights into *why* choices were made, because of the limited scope of customer attributes included in the model. For this reason, it is necessary to investigate the reasons behind and the situations under which a product is being *used* to fully understand and model heterogeneous choice behavior. Hence, we must delve into a more proactive modeling approach to discover driving factors underlying customers' choices by taking into account the *usage context* of a product. Here, the usage context of a product is defined as *all aspects describing the context of product use that vary under different use conditions and affect product performance and/or customer preferences for the product attributes*. The usage context may also have a significant impact on the product performance, which is not considered in existing methods that simply treat product performance as "constant" across all customers and usage contexts in choice modeling.

Marketing researchers were among the first to recognize the importance of product usage context. As Belk [2] pointed out, *use situation* has "a demonstrable and systematic effect on current behavior". Dickson [7] proposed a person-situation (*usage context* in our terminology) framework in which the market is explicitly segmented into groups of customers within usage situations. More recently, De la Fuente and Guillén [6] studied the usage suitability of household cleaning products and their influences on purchase behavior. Although the existing literature illustrated the significance of usage context in the customers' choice process, the linkage between usage context and product performance as well as product design is missing, which calls for an innovative way to explicitly model usage context's impact with analytical methods.

In this chapter, we present the founding principles underlying a choice modeling approach to UCBD, where usage context is considered as a critical part of the driving factors behind customers' choice, in addition to customer sociodemographic attributes and product design attributes. We first provide a review of usage context influence, based on the literature from both market research and engineering design (Sect. 10.2). A taxonomy for UCBD is presented in Sect. 10.3 by defining the important terms and their relations. Next, we discuss how the taxonomy is integrated into a step-by-step choice modeling procedure to support UCBD, which captures the impact of usage context by explicitly modeling its influence on both product performances and customer preferences (Sect. 10.4). Findings from both a jigsaw case study with stated preference data (Sect. 10.5) and a HEV case study with revealed preference data (Sect. 10.6) demonstrate the needs and benefits of incorporating usage context in choice modeling. Conclusions and future work are summarized at the end.

10.2 Literature On Usage Context Studies

10.2.1 Usage Context Literature in Market Research

Marketing researchers have long been interested in understanding and conceptualizing the underlying factors behind customer behavior [9, 22, 26]. Belk [2] laid out the definition of *use situation* as follows: "all those factors particular to a time and place of observation, which do not follow from knowledge of personal (intra-individual) and stimulus (choice alternative) attributes, and which have a demonstrable and systematic effect on current behavior." Belk later proposed a revised stimulus-organism-response (S-O-R) paradigm [3] in which the stimulus is divided into an object and a situation, or *usage context* in our terminology. Relating to Belk's S-O-R paradigm, we propose here a UCBD influence diagram as illustrated in Fig. 10.1.

In the context of UCBD, *object* refers to product and *situation* refers to usage context. Both usage context and product act as stimulus to a customer, which leads to his/her choice behavior. Besides the conceptualization, Belk's [3] categorization of five groups of situational characteristics (named *usage context attributes* **U** in this work) serves as the foundation for developing and classifying the usage context attributes for choice modeling; more details on this subject will be provided in Sect. 10.3.

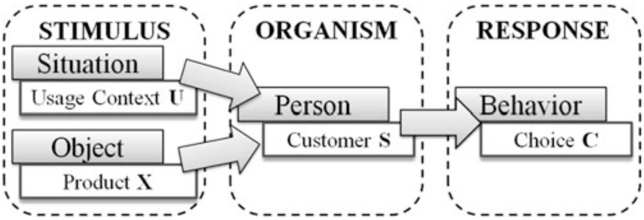

Fig. 10.1 UCBD influence diagram based on Belk's S-O-R paradigm

The need for considering situational (usage contextual) variables in market segmentation was first recognized in the 1980s. Dickson [7] pointed out that usage situation is overlooked in market segmentation and presented a person-situation segmentation framework in which the market is explicitly segmented into groups of customers within usage situations. The work by Christensen et al. [5] recommends ending the common practice of segmenting customers based on their demographics and replacing it with ways that reflect how customers actually live their lives. The "substitution in use" (SIU) approach by Stefflre [30] was developed based on the premise that customers think about product category instances within their functional roles in various possible usage contexts. As a further validation of this premise, in a more recent case study of snack foods, Ratneshwar and Shocker [25] showed that products which do not belong to the same category could be considered as comparable in certain usage contexts, highlighting the need for constructing different choice set alternatives based on customer profile and usage context. More recently, De la Fuente and Guillén [6] analyzed customer perceptions with regard to the suitability of household cleaning products to anticipated usage contexts, as well as their influences on purchase behavior. In the case of multiple-usage-context scenarios, Berkowitz, Ginter and Talarzyk [4] suggested aggregating an individual's given usage situation demand weighted by the situation's frequency of occurrence or importance, which provides a guideline for handling the multiple-usage case detailed in Sect. 10.4. While their approach demonstrated the influence of usage suitability on customer choice, the linkage between usage context and product performance, as well as product design is absent.

10.2.2 Usage Context Literature in Engineering Design

Even though the study of usage context in customer behavior has been prevalent for years, it had not been applied to engineering design unit the 1990s. In Ulrich and Eppinger's product design and development book [31], the need for designers to envision a product's "use environment" in identifying customer needs is emphasized. Methods have been suggested to observe a product in use as a way of gathering raw data from customers. Green et al. define product usage context as a combination of application and environment in which a product will be used

[12–14]. A broader concept of *product design context* is constructed, consisting of three contexts that influence customer preferences: *usage context*, *customer context* and *market context*. Their work supports the idea that context can be differentiated based upon functional attributes, indicating a link between engineering parameters and perceived usefulness, which occurs under the influence of different usage contexts. Most recently, study on usage context attributes of HEVs [17] suggested that usage context should be treated as an additional dimension of the customer characterization process to reflect their preference heterogeneity.

Previous works on usage context are mainly focused on qualitative analysis to support concept generation. However, the benefits of understanding usage context have great potential in an analytical design process as well. Through a choice model, we can understand the impact that usage context has on product performance and customer preferences, and therefore optimize product design to maximize the customer demand, or profit contributed by the product. In this chapter, we present a comprehensive choice modeling framework for UCBD to quantitatively incorporate usage context into the product design process. In the following sections, taxonomy for UCBD is first provided and is followed by a presentation of the four-phase choice modeling procedure, illustrated with two case studies.

10.3 Taxonomy in Usage Context-Based Design

To establish a common foundation for choice modeling in UCBD, we devote this section to defining taxonomy by following the established classification in the market research domain and the specific needs associated with product design. To illustrate the taxonomy, the design of a jigsaw for cutting wood is used as an example throughout this section.

Usage context attributes U refer to the characteristics or attributes used to describe the usage context. Associated with this taxonomy is the definition of "usage context". Belk [2] stated that use situation includes all factors that influence the customer behavior at a given time and place, except for the customer profile and product attributes. Unlike Belk, Green et al. [12] narrows down the scope of "usage context" to two major aspects, the *application* context and the *environment* context, and limits the influence of usage context to customer preferences only. Usage context in real life varies significantly across product categories. In our approach, its influence on customer behavior includes the impact on product performance, choice set, and customer preference. Hence, we define the usage context as *all aspects describing the context of product use that vary under different use conditions and affect product performance and/or customer preferences for the product attributes*. This definition emphasizes two concepts key to our approach. First, usage context covers all aspects related to the use of a product, but excludes customer profile (demographic attributes) and product attributes, which will be defined later on in this section. Second, usage context influences customer behavior through product performance, the choice set, as well as customer preference.

One consideration to note is that, under many circumstances, it is difficult to draw a clear distinction between the customer profile and usage context as separate sources of influence on customers' choice. In some cases, customer profile attributes may also seem like a usage context attribute, or vice versa. For example, a customers' purchase history can be regarded either as a customer attribute or as a usage context. As a guideline, we refer to customer profile attributes as those stable characteristics of a customer that do not vary over a set of usage contexts, while those temporal, transitory characteristics of a customer that do vary over usage contexts belong to the area of usage context. In other words, these usage context attributes change from application to application or from environment to environment over time. For example, the skill of the customer to successfully accomplish a cutting task using a power tool, brand loyalty, and positive or negative experiences with a particular brand [11], are considered as *customer profile attributes*, since they are more stable over time than the *usage context attributes*.

Specific to the choice modeling process, we can divide usage context attributes $\mathbf{U}$ into *performance*-related and *preference*-related, according to the way in which they impact customer behavior. These usage context attributes $\mathbf{U}$ can be either continuous or discrete. While performance-related attributes $\mathbf{U_Y}$ influence product performance $\mathbf{Y}$, preference-related attributes $\mathbf{U_W}$ have an impact on the choice set and customer preference. In some cases, performance-related and preference-related usage context attributes are not mutually exclusive. For example in using a jigsaw, if the saw is to be used for cutting outdoors, the density of saw dust experienced by the user may be different than if the saw were used indoors (performance impact), whereas the user may prefer a bright saw color for outdoor use so that the saw will be easily identified if placed on the ground (preference impact). Whether a usage context attribute is related to performance or preference can be determined by prior knowledge of experienced users or by the observations of products being used. Prior knowledge of a usage context attribute's influence on preference can be used to reduce the complexity of estimating a choice model, and hypothesis testing of a usage context attribute in the choice model estimation process can be used to confirm this knowledge.

Usage context scenarios $\breve{\mathbf{U}}$ refer to the most common combinations of usage context attributes $\mathbf{U}$ describing common usage scenarios, which can be identified through surveys and data analysis techniques such as cluster analysis. Identifying common usages can significantly simplify the data collection process compared to surveying all factorial combinations of usage context attributes $\mathbf{U}$. In addition to the situation that each customer has one primary usage scenario, there are cases that multiple-usage scenarios need to be considered. The idea of usage importance indices, denoted as F, emerges from the need for considering multiple-usage scenarios, where a single product is used under a series of different usage scenarios. In this case, multiple usage scenarios are weighted by their usage importance indices in the range of [0 1]. Equation (10.1) shows that the usage context attributes $\mathbf{U}$ and usage importance indices F together define the usage context scenario $\breve{\mathbf{U}}$.

$$\breve{\mathbf{U}} = (\mathbf{U}, F) \tag{10.1}$$

The usage importance indices can be either specified by a user, or determined based on the observations of user choices under multiple-usage scenarios. In the former case, a user is asked to provide the best estimate of the importance of a particular usage in the survey. In the latter situation, the survey questionnaire is designed to identify the importance indices through choice model estimation.

Customer profile attributes S includes all stable or permanent aspects of customer profile attributes impacting customer choice behavior, for example, *gender*, *age*, *income bracket*, etc. In the choice modeling of UCBD, customer profile attributes $\mathbf{S}$ may have a direct impact on customers' preference and therefore may influence their choices. Similar to usage context attributes, customer profile attributes $\mathbf{S}$ can be categorized into performance-related $\mathbf{S_Y}$ and preference-related $\mathbf{S_W}$ to differentiate their impact. For example, household income belongs to $\mathbf{S_W}$, as it is expected to have a large impact on customers' sensitivity on price: the more they earn, the less they care about the price. On the other hand, skill level of the customer operating a jigsaw is considered as a performance-related $\mathbf{S_Y}$, because jigsaw performances vary when operated by a beginner, intermediate, or experienced user.

Customer-desired product attributes A are defined as key product characteristics that influence customers' choices in selecting a product. In a market survey, customers are usually asked to rate these customer-desired product attributes. They include not only engineering performances $\mathbf{Y}$, but also non-engineering attributes $\mathbf{M}$.

Engineering performance $\mathbf{Y}$ refers to all performance-related engineering attributes. Since $\mathbf{Y}$ plays a critical role in the engineering design process, engineering performance $\mathbf{Y}$ is our focus in this work. In the jigsaw example and other similar cases, engineering performance $\mathbf{Y}$ is further divided into *performance of service results* and *performance of service delivery* or transformations. The performance of service results $\mathbf{Y_r}$ represents the measures of the end performances of the resulting service, such as cutting precision, planarity, etc. On the other hand, the performance of service delivery or transformations $\mathbf{Y_t}$ represents the measures of the performances related to the delivery of the service, such as linear speed, noise, vibration, safety conditions, etc. The performances of the service delivery are no longer visible in the results once it has been delivered.

Non-engineering attributes $\mathbf{M}$ include all non-engineering aspects of customer desired attributes, for example, price, brand, esthetics and other common marketing measures. Price is one of the most influential non-engineering attributes

M in customers' choice. In practice, price can enter the utility function as a single term, or can be scaled by income or log income to reflect the connection between income and price sensitivity, as shown in the case study.

Product choice set J_n is defined as a group of product alternatives customers consider during their choice procedure. Simonson [29] showed that choices are made in the context of a consideration set, i.e., a choice set. Since only differences in utility matter due to the nature of choice models, the selection of a product choice set exhibits great impact on customer choice. Methods for determining the appropriate choice set considering usage context are described in Sect. 10.4.

Product design variables X describe the engineering decisions involved in product design. In the jigsaw case, blade tooth height, stroke frequency, step distance between two teeth, etc., all belong to the product design variables **X**.

10.4 Choice Modeling Framework in Usage Context-Based Design

In order to capture the impact of usage context and utilize usage context information in a design process, a framework for choice modeling in UCBD is presented next. Our discussion follows the general sequence of the major phases for implementing the choice modeling framework as introduced in Chap. 3.

Phase I Collect usage context information and identify usage context attributes **U**. (*usage context identification*)

Phase II Collect customer choice data together with choice set information J_n, customer profile **S** and their usage context attributes **U**. In a stated preference survey, a choice experiment representing different combinations of customer profile and usage context is designed where each respondent makes the selection among a choice set for given usage scenarios. For revealed preference data collection, all data from real customer purchases are recorded. (*data collection*)

Phase III Create a physics-based model or a human-appraisal-based ordered logit model for predicting engineering performance **Y** as a function of usage context attributes $\mathbf{U_Y}$, customer profile $\mathbf{S_Y}$, and design variables **X**. (*linking performance with usage context and customer profile*)

Phase IV Create a choice model for market share and demand estimation (*choice model estimation*)

In the rest of this section, details for each phase are provided.

Phase I: Usage context identification. A successful product design requires an understanding of customers' needs so that the products produced will match customers' interest. Similarly, in the proposed choice modeling framework for UCBD (Fig. 10.2), we start with a survey through which important usage context

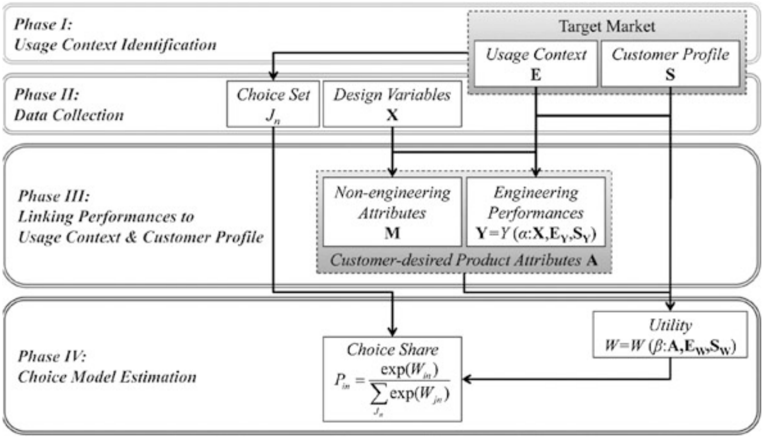

Fig. 10.2 The choice modeling for usage context-based design

Table 10.1 Five categories of usage context

Usage context type	Jigsaw example
Physical surroundings	Location of cutting, Accessibility of an outlet, Availability of workbench, Distance to do-it-yourself (DIY) stores
Social surroundings	Presence of children, neighbors
Temporal perspective	Expected process duration, Lifetime of similar cutting tools in possession, Estimated time needed to purchase the tools in a nearby DIY store
Task definition	Material properties, Board thickness, Minimal linear speed, Maximal vibration level, Noise and safety conditions, Accuracy requirements
Antecedent states	Set of saw tools already in possession, New life conditions or projects, Cash at disposal

attributes and common usage context scenarios among target customers are identified. Widely used survey methodologies include focus groups, one-on-one interviews of experienced users, and observations of the product being used [31].

Following Belk's classification [3], usage context can be categorized into five types: *physical surroundings*, *social surroundings*, *temporal perspective*, *task definition*, and *antecedent states*. In Table 10.1, we use the jigsaw example to illustrate how the usage context attributes can be defined by following these five basic categories. It should be noted that based on Belk's classification, the scope of the usage context attributes is beyond the act of using the product, but also includes the context of purchase.

Physical surroundings are the most apparent characteristics of a usage. These characteristics include geographic location, weather condition, lighting, and other physical characteristics of a usage, as well as the distance to do-it-yourself (DIY) stores when the new tool is needed. In the case of using a jigsaw for cutting a board, the location where the operation must take place (indoor/outdoor), the accessibility of a power outlet, the availability of a workbench are typical examples of physical surroundings.

Social surroundings provide additional information about the social situation of a usage. Whether another person is present, his/her influence on the user and other social characteristics belong to this category. For instance in cutting a board, one may prefer a jigsaw to a circular saw often used under these conditions, for reasons of safety and noise because of the presence of children nearby.

Temporal perspective refers to those aspects of the purchasing situation or to those of a given usage, which are specific for a given range of time. For instance, the expected process (cutting task) duration may be a reason for preferring a circular saw to a jigsaw or a powerful jigsaw to a more basic one (faster linear speed). The age and expected lifetime of the cutting tools in possession are also deciding factors to determine how to upgrade the set of cutting tools in order to complete a set of cutting tasks. In terms of purchase situation, the time and emergency aspect for buying a new tool in a surrounding DIY store may also be determining under certain circumstances.

Task definition covers all features that explain the purpose of the purchase. For instance, one must consider the type of material to cut (wood, steel, etc.), the specification of the cut (blind or not, straight or wiggly, orthogonal or inclined), the properties of material (cutting hardness which is physically proportional to the material density), the thickness of the board to cut (beyond a certain thickness, the cut is impossible), the minimal linear speed that is acceptable when the user delivers the maximal amount of pushing arm forces and wrist torques, the maximal vibration level that is tolerable, or the admissible noise and minimal safety conditions.

Antecedent states define a dimension of usage, which is antecedent to the purchase. The factors for a new jigsaw acquisition may be the set of saw tools one already possesses (circular, chain, panel, bow, miter, etc.) and their respective age and expected remaining lifetimes, a new life condition or project (moving from an apartment to a house, or a house remodeling), and the cash at one's disposal.

The above-mentioned five categories of usage context attributes can be used as a checklist in the process of determining the potential usage context attributes. For stated preference surveys, as will be demonstrated in the jigsaw case study (Sect. 10.5), a user survey is used to collect the set of primary usage context attributes $\mathbf{U}$. For problems with a large number of usage context attributes $\mathbf{U}$, a cluster analysis becomes essential to reduce the possible combinations of usage context attributes $\mathbf{U}$ to a manageable size, and focus the study on a set of common usage context scenarios $\breve{\mathbf{U}}$, i.e., the most common combinations of usage context attributes $\mathbf{U}$.

Phase II: Data collection. Due to the nature of data collection, surveys can be divided into Stated Preference (SP) [21] and Revealed Preference (RP) [27]. SP refers to choice experiments where respondents are presented with a set of simulated product options from which they make a choice. This approach is attractive for model building because a high level of control can be exercised over the collected data, resulting in a data set optimized for choice modeling. However, SP data does not represent real purchase behavior and such surveys require significant time and additional cost to administer, thus resulting in a limited size and quality [23] dataset. For these reasons, it is sometimes desirable to utilize actual purchase data and customer satisfaction surveys collected.

In a stated preference survey, a choice experiment is conducted in which customers are asked to make a choice among several available alternatives under given usage context scenarios. Since the number of products available is usually much larger than the number of products a customer can use and compare in a choice experiment within a reasonable amount of time, an optimal experimental design can be applied to reduce the number of products in the choice set to a feasible level. For example, a nested design of experiments (DOE) on $(J_n|\mathbf{S}, \mathbf{U})$ can be applied to find the optimal set of choice alternatives for respondents based on their customer profile $\mathbf{S}$ and usage context $\mathbf{U}$. The D-optimal experiment design algorithm for human-appraisal surveys introduced in Chap. 6 [19] can be used to select the products to include in the choice set for the best model estimation.

A try-it-out survey is highly recommended for collecting SP data, in which customers are asked to use the products under given usage scenarios, rate the performances, and make a choice of one of the products. There are many advantages to conducting a try-it-out survey: first, hands-on experience is very important as it often simulates a real purchase process better for products that are typically tested prior to purchase; second, customers experience the product under certain usage contexts, which ensures the relevance; and third, assessments of the product performance reflect customers' perceived product performance. On the other hand, the try-it-out survey often requires more resources than a paper survey, where photos (or images) and data specification sheets are commonly used to present the products.

As for the revealed preference survey, all interesting product attributes, the customer profile, the usage context, and the choice set considered by each customer are recorded, together with the purchase decisions. RP data has the advantage in that it reflects customers' real choice behavior; however, RP data may present issues with collinearity, endogeneity, and lack of randomization. An examination of the information matrix from choice model estimation could identify the possible orthogonality issues in RP data. In some cases, customers' ratings of product performances are also collected in RP surveys to capture customers' perceived product performances. Such level of detail is required to model the impact of usage context on product performance and customer preference as introduced next.

Phase III: Linking performance with usage context and customer profile. This is a unique phase for UCBD applications in which product performances $\mathbf{Y}$ are formulated as a function of performance-related usage context attributes $\mathbf{U_Y}$, performance-related customer profile attributes $\mathbf{S_Y}$, and product design variables $\mathbf{X}$, as shown in Eq. (10.2):

$$\mathbf{Y}_{in} = Y(\alpha : \mathbf{U}_{\mathbf{Y}n}, \mathbf{S}_{\mathbf{Y}n}, \mathbf{X}_i) \tag{10.2}$$

where the coefficients α can either be established by a physics-based model or determined through a human-appraisal-survey-based regression model. The physics-based model is constructed based on the physical relations. Taking the jigsaw design as an example, a system of equations can be derived to calculate the translational force and the torque on the user's wrist to assess the user's comfort level during the cutting process as a function of wood type and thickness as well as of admissible force and torque depending on the user experience [33]. The second approach utilizes rating data given by customers in a human-appraisal survey and builds a regression model to predict the ratings of performances $\mathbf{Y}$. While the physics-based model saves the time and cost of a survey, a human-appraisal survey can be used to assess either quantitative or qualitative performance perceived by the customers. Such surveys can be integrated into the try-it-out survey for choice modeling, as described in Phase II. The ordered logit model [24] is used for modeling the discrete rating data in the HEV case study in this chapter.

Phase IV: Choice model estimation. As shown in Fig. 10.2, in Phase IV a predictive model of demand Q is established using DCA introduced in Chap. 3. In DCA, the individual's (n) true choice utility, u, for a design alternative, i, consists of an observed part W, and an unobserved random disturbance ε (unobserved utility):

$$u_{in} = W_{in} + \varepsilon_{in} \tag{10.3}$$

As shown in Eq. (10.4), the observed or deterministic part of utility W_{in} is expressed as a function of customer-desired product attributes $\mathbf{A}$, usage context attributes $\mathbf{U}$, customer profile attributes $\mathbf{S}$.

$$W_{in} = W(\beta : \mathbf{A}_{in}, \mathbf{U}_{\mathbf{W}n}, \mathbf{S}_{\mathbf{W}n}). \tag{10.4}$$

where $\mathbf{A}_{in}$ denotes the customer-desired product attributes of respondent n, alternative i, $\mathbf{U}_{\mathbf{W}n}$ and $\mathbf{S}_{\mathbf{W}n}$ denotes the preference-related customer profile attributes and usage context attributes of respondent n. The coefficients β are estimated based on the data collected in Phase III. From the observed utility, W_{in}, the probability P_{in} of an individual i choosing a given alternative n can be estimated. By following the information flow in the four-phase diagram (Fig. 10.2), we can see clearly how product design variables $\mathbf{X}$, together with the definitions of usage context $\mathbf{U}$ and customer profile $\mathbf{S}$, are first mapped to product performance

Y (Eq. 10.2), then to deterministic utility W (Eq. 10.3), and finally to the probability of choice P_{in}, which can be aggregated to the total market share based on predictions for a population. This flow creates a mathematical link between product design decisions, represented by **X**, to customer demand, represented by P_{in}.

Furthermore, using the choice model created based on predominately single-usage surveys, the choice prediction can be expanded to multiple-usage cases using Eq. (10.5).

$$W_{in} = W(\beta : \mathbf{A}, \breve{\mathbf{U}}_{\mathbf{W}n}, \mathbf{S}_{\mathbf{W}n}) = \sum_{k} W(\beta : \mathbf{M}, \mathbf{Y}^k, \mathbf{U}^k_{\mathbf{W}n}, \mathbf{S}_{\mathbf{W}n}) \cdot F^k$$

where

$$\mathbf{Y}^k_{in} = Y(\alpha : \mathbf{U}^k_{\mathbf{Y}n}, \mathbf{S}^k_{\mathbf{Y}n}, \mathbf{X}_i) \tag{10.5}$$

where k is indicator of different usage scenarios. Here we assume that the terms resulting from each usage context are independent from each other, and that the utility function for the multiple-usage case can be calculated as a weighted sum of individual usages, as Berkowitz suggested in [4].

10.5 Case Study 1: Jigsaw Example

In this section, the design of a jigsaw is used to demonstrate the implementation of the usage context-based choice modeling approach with stated preference data. The jigsaw is a common power tool for cutting wood. Under different usage contexts, the jigsaw performances, as well as the customers' preferences for the saw, change. The choice set considered in the user survey is formed by a few representative jigsaw products in the market. The four phases of choice modeling for UCBD are illustrated with the hypothetical saw design and a few representative attributes for demonstration. A choice model is built and estimated on synthetic survey data generated using a few key assumptions about customer preferences. Results are discussed which demonstrate the proposed framework.

- **Phase I: Usage context identification**

Phase I is completed with three tasks: *collect usage information*, *identify common usage contexts through cluster analysis*, and *identify usages context attributes*. We start with a user survey in which questions about primary usages are asked. It should be noted that the primary usage context is not limited to the most frequent usage context, and can be defined by the user. In some cases, for instance, a saw is expected to accommodate the most-demanding usage context. As described in Sect. 10.4, five categories of usage context can be used as a guideline for determining the usage context attributes. Figure 10.3 shows a small

Please answer the following question by choosing the best description of your primary saw usage context.
1. The woods you are cutting are:
soft medium hard
2. The working environment of your cutting is:
indoor outdoor
…

Fig. 10.3 Sample user survey questionnaire for phase I

Table 10.2 Common usage contexts identified from cluster analysis

No	Working environment U_1	Wood type U_2	Usage context description
1	0	1	Indoor cutting for soft wood
2	1	2	Outdoor cutting for medium wood
3	0	2	Indoor cutting for medium wood
4	1	3	Outdoor cutting for hard wood

portion of the sample user survey questionnaire as an example. A few typical usage context questions for a jigsaw user would include wood type, working environment, etc.

In this case study, we select *wood type* and *working environment* as two usage context attributes $\mathbf{U}$ for demonstration purpose; wood type (it amounts to wood density) is considered as a performance-related attribute $\mathbf{U_Y}$ that influences product performance $\mathbf{Y}$, while both wood type and working environment are treated as preference-related attributes $\mathbf{U_W}$ with an impact on customer preference. The *wood type* attribute is coded as 1 for soft, 2 for medium, and 3 for hard, while the *working environment* attribute is coded as 0 for indoor and 1 for outdoor. Based on the survey data of common usages, cluster analysis is performed. For our case study, indoor cutting for soft wood, outdoor cutting for medium wood, indoor cutting for medium wood, and outdoor cutting for hard wood are identified to be the most common usages (Table 10.2) based upon the results from a k-means clustering analysis [15] on the hypothetical survey data with two usage context attributes, *working environment* and *wood type*, and k (number of clusters) = 3.

- **Phase II: Data collection**

Various human-appraisal experiments can be utilized to collect customers' preferences under different usage contexts as described in Sect. 10.4. The question lies in how to minimize the number of surveys to cover the various attributes included in choice modeling. Here we assume that each respondent is surveyed for more than one usage context (but only one primary usage context at a time in the

Table 10.3 Sample DOE of customer survey

Experimental runs #	Gender	Income (k)	Skill level	Usage scenario	Product in J_n
1	0	70	1	1	1
2					3
3					4
4					5
5				2	2
6					5
7					7
8					8
9				3	2
10					5
11					6
12					7
13				4	1
14					3
15					4
16					6
1	1	100	2	1	2
2					3
3					4
4					5
5				2	1
6					5
7					7
8					8
9				3	2
10					5
11					6
12					8
13				4	2
14					3
15					4
16					7

choice experiment). We also assume that all respondents have some level of experience with the product and are able to differentiate between the different usage contexts described in the survey questionnaire. Eight jigsaw products available in the market are considered, but only four products that are most relevant for a given usage context form the choice set J_n in each choice experiment. Table 10.3 shows a sample DOE of the customer survey for 2 respondents, each with 16 experimental runs. Three customer profile attributes are included: *gender* (0 for male and 1 for female), *income* (annual income in \$1,000s), and *skill level* (1 for elementary user, 2 for experienced user, and 3 for professional user). For example, respondent 1 is assigned with four choice experiments under usage scenario 1, 2, 3, 4, respectively. Under usage scenario 1, products 1, 3, 4, and 5 are

Table 10.4 List of attributes and design variables included in jigsaw case study

Customer-desired product attributes **A**		
M	Price	
Y_{t1}	Advance speed S_a	
Y_{t2}	Comfort level P_{comfort}	%
Usage context attributes **U**		
U_1	Working environment	Indoor, outdoor
U_2	Cutting board wood type	Soft, medium, hard
Customer profile attributes **S**		
S_1	Income	Uniform dist., [50 k, 150 k]
S_2	Gender	Male, female
S_3	Skill level	1, 2, 3
Product design variables **X**		
H_d	Blade tooth height	
F	Stroke frequency	
A	Blade translation	
s	Step distance between teeth	

chosen as choice alternatives, as shown in the last column of Table 10.3, while products 2, 5, 7, and 8 are chosen to form a choice set for respondent 1 under usage scenario 2. Beyond the DOE approach, the choice set can also be selected based on the products' suitability. The suitability of a product depends on customer profile **S** and usage context attributes **U**. It can be assessed using physics-based models. For example, a product resulting in over-the-limit wrist force is considered not suitable.

The synthetic data are simulated with 500 respondents, 4 choices alternatives, and 4 usage contexts (8,000 observations in total) based on a few key assumptions about customer preferences. The suggested questionnaire for respondent 1 in customer survey is shown in Appendix A. As each choice experiment has a different choice set, the products listed in the questionnaire might be different for each respondent.

Table 10.4 presents four categories of attributes considered for choice modeling, including three customer-desired product attributes **A** (*price*, *advance speed*, and *comfort*), two usage context attributes **U** (*working environment*, and cutting board *wood type*), three customer profile attributes **S** (*income*, *gender*, and *skill level*), together with four design variables **X** (*blade tooth height*, *stroke frequency*, *blade translation*, and *step distance between teeth*).

It should be pointed out that the experimental design is not unique, and can be designed based on the number of respondents who are available [16, 19]. For example, when there are a large number of respondents, fewer choice experiments can be used for each respondent than in experiments with fewer respondents. Pairing the usage contexts to customers' primary usages is recommended, as it yields a better understanding of the influence of usage context attributes. If a two-stage (customer) decision making process is considered (i.e., first the choice set is selected followed by the specific product), the survey can be designed for predicting the choice set for each customer first.

- **Phase III: Linking performances with usage context and customer profile**

In this study, the link between product variables $\mathbf{X}$, performance-related usage context attributes $\mathbf{U_Y}$, performance-related customer profile attributes $\mathbf{S_Y}$, and engineering performance $\mathbf{Y}$ (Eq. 10.1), is established using a series of physics-based equations based on the functional principles of the jigsaw [32, 33]. Both engineering performances $\mathbf{Y}$ considered in this study, the advance speed S_a and comfort level P_{comfort}, belong to Y_t (performance of transformation). The advance speed S_a is calculated as follows:

$$S_a = \frac{2H_d f \cdot A}{s} \tag{10.6}$$

where H_d is the blade tooth height, f is the stroke frequency, A is the blade translation, and s is the step distance between two teeth. All variables in the equation (H_d, f, A and s) are product design variables $\mathbf{X}$; usage context doesn't influence this particular performance. The comfort level P_{comfort} is associated with the required wrist torque with respect to user' maximum wrist capability, as shown in the following equation:

$$P_{\text{comfort}} = 1 - \left|\frac{M_w}{M_{w-\max}}\right| \tag{10.7}$$

where $M_{w-\max}$ is the maximal wrist torque that can be delivered by the user (depending on the gender and skill level), while the wrist torque M_w is a function of product design variables and usage context attributes, as shown in Eq. (10.8).

$$M_w = F_a\left(H_w + \frac{T_c}{2}\right) + F_c L_w + F_f H_w - (d + L_w)F_r \tag{10.8}$$

H_w and L_w describe the position of the wrist, while d describes the location of the reaction force on the jigsaw slider, all of which are elements related to the product design. The usage context attribute T_c is the thickness of the board being cut, and F_f and F_r, which are both functions of the friction factor between the jigsaw and wood. F_a captures the force of the advancing blade on the wood, while F_c describes the force of the cutting blade. Hence, $M_w$is a function of both product design variables $\mathbf{X}$ and usage context attributes $\mathbf{U_Y}$ (i.e., wood type), while $M_{w-\max}$ is modeled as a function that depends on customer profile attributes $\mathbf{S_Y}$. Details of the above physics-based equations can be found in references [32, 33].

Table 10.5 Multinomial logit model estimation results in jigsaw case study

Attributes	Coefficient	Standard error	P > |z|
Y_{t1}	5.39	1.42	0.00
Y_{t2}	27.30	1.98	0.00
M/S_1	−35.86	1.76	0.00
$S_2{*}Y_{t2}$	4.13	1.51	0.01
$S_3{*}Y_{t1}$	7.42	0.49	0.00
$U_1{*}Y_{t2}$	−4.94	1.62	0.00
$U_2{*}Y_{t1}$	4.06	0.49	0.00

- **Phase IV: Choice model estimation**

The goodness-of-fit of the estimated multinomial logit model, measured by the rho squared is 0.82 with a log likelihood of −500.76. The coefficients the estimators, standard errors, and the significance of their Z values are provided in Table 10.5. The price Y is divided by the income S_1, as customers with higher income are expected to be less sensitive to the price. The sign of the M/S_1 coefficient shows that price has a negative impact on the utility function. The coefficients of Y_{t1} and Y_{t2}, are both significant, showing that both performances are important in users' choice. Therefore, in-service and service performance results must be considered in the jigsaw design. The coefficient for $S_2{*}Y_{t2}$ is significantly positive, which indicates that the female users tend to care more about the comfort than male users do. This is important to consider in the design process if the intended market for the saw has a sizable female population. Similarly, the coefficient for $S_3{*}Y_{t1}$ is significantly positive, meaning that skilled users care more about the advance speed during cutting, compared with amateur users. As for the interactions between performance Y_{t1} and usage context variable U_1 (indoor/outdoor) and performance Y_{t2} and usage context variable U_2 (wood type), both coefficients are statistically significant, which indicates that both U_1 and U_2 belong to the category of preference-related usage context variable $\mathbf{U_W}$. Moreover, the negative sign suggests that Y_{t2} (comfort) is less important when users are cutting outdoors ($U_1 = 1$), while the positive sign indicates that advance speed is more critical when users are cutting hard wood ($U_2 = 3$). This again provides direction in the design process: for example, if the intended market for the saw are users cutting soft to medium woods (e.g., framing materials), then advance speed is not more important in the design than if the intended market is for those cutting hard woods (e.g., hardwood flooring). The results from this case study are consistent with the general trend in customer preferences assumed in data generation.

With the estimated choice model, future demand of a target market (including target customers and target usages) can be projected. Here we take the prediction of a single user' choice probability as an example to illustrate the difference between single usage and multiple usage scenarios. Considering the following two scenarios as shown in Table 10.6 for a female user with \$70 k annual income and skill level 3:(1) Single-usage: she uses the product solely under single usage 1,

Table 10.6 Usage importance index f for choice prediction

	Usage 1 (%)	Usage 2 (%)	Usage 3 (%)	Usage 4 (%)
Single usage	100	0	0	0
Multiple usage	30	0	0	70

Table 10.7 Predicted choice probability under different usage scenarios for eight products

P (%)	1	2	3	4	5	6	7	8
Single usage	0.4	75.2	24.2	0.0	0.0	0.2	0.0	0.0
Multiple usage	0.4	44.1	55.4	0.0	0.0	0.1	0.0	0.0

indoor cutting for soft wood; (2) Multiple usage: she uses the product under usage 1, indoor cutting for soft wood, with 30% relative importance and usage 4, outdoor cutting for hard wood, with 70% relative importance.

The weighted sum prediction formulation in Eq. (10.5) is used to evaluate the utilities of the eight products under both the single-usage scenario and the multiple-usage scenario. The resulting choice probabilities *P* are summarized in Table 10.7.

In the single-usage case, the most preferred product 2 has a choice probability of 75.2%. However, in the multiple-usage case for the same user, product 3 has the highest choice probability of 55.4%, while the choice probability of product 2 (44.1%) is the second highest. It is interesting to note that the preference rank order of products may change when the usage scenario is different. Similar approach can be applied to forecast the choice probability of a group of target customers each with different usage scenarios by aggregating individual's choice probability over a target population.

10.6 Case study 2: Hybrid Electric Vehicle Example

Alternative fuel vehicles have drawn increasing attention in the past few years, because of their potential to reduce greenhouse-gas emissions and utilize renewable energy sources [1, 8, 28]. However, understanding customer choices of alternative fuel vehicles is challenging because their preference construction process involves many aspects beyond traditional engineering considerations, which calls for a comprehensive modeling framework to incorporate usage context into engineering design. Taking HEVs as an example, vehicle performances, such as mileage per gallon (MPG), often depend highly on their usage contexts, while customers' attitudes toward new technology, especially "green" products, are strongly influenced by their intended usage. In this section, a HEV case study is used to illustrate the proposed usage context-based choice modeling framework. Different from the jigsaw problem, the revealed preference data collected by JD Power and Associates for both HEVs and conventional vehicles (CVs) is utilized for model estimation. It should be noted that in the current study, the impact of HEV policies and other purchase incentives is not considered.

- **Phase I: Usage context identification**

Two usage context attributes are considered for HEV choice modeling: a *local/highway indicator* and *average miles driven daily*. While both attributes are treated as preference-related attributes $\mathbf{U_W}$, the local/highway indicator is also considered as a performance-related attribute $\mathbf{U_Y}$ in MPG calculation, as detailed later. The local/highway indicator is assessed based on the combined MPG published by US Environmental Protection Agency [10] and the estimated MPG given by survey respondents. The indicator is a continuous parameter, ranging from 0 for pure local driving to 1 for pure highway driving. It is assumed that the local/highway indicator reflects the general driving condition a respondent faces, therefore the vehicle usage context. The local/highway driving condition not only greatly impacts vehicles' performances, e.g., MPG, but is also expected to influence customers' choice preference for hybrid vehicles. The other usage context attribute considered is *average miles driven daily*, a commonly used descriptor of customers' travel pattern. The data is derived from the recorded miles driven in the first three months in the J.D. Power and Associates data. This is an important usage context attribute in designing new HEV and future plug-in hybrid electric vehicles (PHEV), as average miles driven daily strongly influence the target performance of the batteries.

- **Phase II: Data collection**

The vehicle quality survey (VQS) conducted by J.D. Power and Associates belongs to the revealed preference data because the customer satisfaction survey is strictly about the new vehicles respondents purchased instead of hypothetical design alternatives. In the 2007 VQS, vehicle purchase data from 90,000 nation-wide respondents on over 300 vehicles in the market are collected, including data for 11 HEV models. Further, respondents' demographic attributes and their usage patterns are recorded in the questionnaire. For model estimation, data collected from 8,025 respondents, who reported their vehicle choice sets, are selected. The attributes and design variables included in the choice model are summarized in Table 10.8.

There are 288 car models covered in the data set, each of them is chosen by at least one respondent. Fifteen customer-desired product attributes (**A**) are selected including *price*, *vehicle origin*, *vehicle size*, *vehicle type*, MPG, *HEV indicator*, and nine rating scores given by the respondents. The attribute "price" is the money respondents paid excluding tax, license, trade-in, and etc. Since the VQS only provides price for the purchased vehicles, the price data for other vehicles considered are estimated from a linear regression model based on vehicle make and model, and customers' geographic locations. As shown in the third column in Table 10.8, vehicle origins are categorized as domestic, European, Japanese, and Korean; vehicle sizes are grouped into compact, midsize, large, and premium;

Table 10.8 List of attributes and design variables included in HEV case study

Customer-desired product attributes A		
A_1	Price	Price paid, excluding tax, license, trade-in, etc
A_2	MPG	Mileage Per Gallon under usage
A_3	Vehicle origin	Domestic/European/Japanese/Korean
A_4	Vehicle size	Compact/midsize/large/premium
A_5	Vehicle type	Mini/car/SUV/minivan/van/MAV/pickup
A_6	Hybrid electric vehicle	1 for hybrid, 0 for conventional
A_{exterior}	Exterior attractiveness rating	Discrete rating on a scale from 1 to 10
A_{interior}	Interior attractiveness rating	
A_{storage}	Storage and space usage rating	
A_{audio}	Audio rating	
A_{seats}	Seats rating	
A_{hvac}	HVAC rating	
A_{dynamics}	Driving dynamics rating	
A_{engine}	Engine and transmission rating	
A_{safety}	Visibility and safety rating	
Usage context attributes U		
U_1	Local/highway indicator	0—local, 1—highway
U_2	Average miles driven daily	Unit: miles
Customer profile attributes S		
S_1	Gender	1 for male, 2 for female
S_2	Age	Age
S_3	Income	Household income last year
S_4	Children	Number of children under 20 living in the household
S_5	Education	Level of education completed
Product design variables X		
X_1	Exterior dimensions	Vehicle length/width/height (unit: in)
X_2	Vehicle weight	Unit: lbs
X_3	Interior dimensions	Front head/shoulder/hip/leg room (unit: in) Rear head/shoulder/hip/leg room (unit: in)
X_4	Storage capacity	Luggage capacity Cargo capacity
X_5	Engine specifications	Engine size Number of cylinders
X_6	Performance	Horsepower Torque
X_7	MPG targets	Target mileage per gallon level under city/highway condition

vehicle type includes mini, car, sport utility vehicles (SUV), minivan, van, multi-activity vehicles (MAV), and pickup. The *HEV indicator*, coded as 1 for hybrid vehicles, and 0 for conventional vehicles, reflects customers' attitude toward new hybrid technology. Nine aspects of a vehicle, including exterior attractiveness, interior attractiveness (as stated by the average purchaser), storage and space usage, audio/entertainment/navigation system, seats, heating ventilation and air conditioning, driving dynamics, engine and transmission, and visibility and driving safety, are rated on a scale of 1–10, 10 being the most satisfactory. These discrete ratings are included in the choice modeling procedure, as they are considered to be a good measure of customers' perceived vehicle performance (quality).

Meanwhile, *gender*, *age*, *household income*, *number of children under age* 20 *living together* and *education level*, are included as five customer profile attributes **S**. Among the set of **S**, critical preference-related attributes $\mathbf{S_W}$ will be identified through choice modeling in Phase IV. All five **S** attributes are considered in the ordered logit regression for predicting the performance rating scores, as will be shown in Phase III.

- **Phase III: Linking performances with usage contexts and customer profile**

Different from the jigsaw example in which physics-based modeling can be used to establish the relationship between performance and usage context attributes, in the HEV example, respondent survey data is used to create the relationship as shown in Eq. (10.2) by using the ordered logit modeling method [20] for nine customer-desired product attributes (**A**) in the form of ratings. Here the ratings are used to represent product performances **Y**. Seven high level engineering design variables **X** are used in this case study, including *exterior dimension*, *interior dimension*, *performance*, MPG *targets*, etc. The obtained ordered logit models are also used to predict the ratings of other vehicle designs in the choice set as customers only rate the vehicles they purchase. This limitation of the rating data in VQS may cause ownership bias in model estimation and potentially lead to inaccurate estimates of some coefficients due to the missing heterogeneity in owners' ratings. Further details for implementing the ordered logit model based on the VQS data by JD Power and Associates can be found in [18]. In addition to the design variables **X**, customer profile $\mathbf{S_Y}$ such as *gender*, *age*, etc., are included to capture customers' heterogeneity in rating. The coefficients estimators are later used for what-if-scenario analysis to forecast potential market share for targeting customer and usage attributes.

Furthermore, the impact of usage context (local/highway indicator U_1) on the vehicle performance (A_2, MPG) is represented in the following equation:

$$A_2 = \frac{1}{\frac{1-E_1}{\mathrm{MPG_{city}}} + \frac{E_1}{\mathrm{MPG_{highway}}}} \tag{10.9}$$

where $\mathrm{MPG_{city}}$ and $\mathrm{MPG_{highway}}$ belong to the product design variables **X** listed in Table 10.8.

Table 10.9 Selected coefficients of MNL with **U** and MNL without **U** for HEV

Attributes	MNL without **U**			MNL with **U**		
	Coefficients	Standard error	Significant with p value	Coefficients	Standard error	Significant with p value
A_1/S_3	−0.0003	0.0000	c	−0.0004	0.0000	c
A_2	/	/		−3.1080	0.0846	c
A_2_city	0.0456	0.0139	c	/	/	
A_2_highway	−0.0791	0.0141	c	/	/	
$U_1{*}A_2$	/	/		5.9454	0.1697	c
$U_2{*}A_2$	/	/		0.0002	0.0003	
A_3_European	1.9353	0.0900	c	2.1886	0.1045	c
A_3_Japanese	0.2314	0.0505	c	0.5161	0.0576	c
A_3_Korean	1.2617	0.0904	c	1.3313	0.1065	c
A_4_Large	−0.5636	0.0907	c	−0.9111	0.1024	c
A_4_Medium	0.0907	0.0534	b	−0.1376	0.0601	a
A_4_Premium	−0.2496	0.0780	c	−0.3136	0.0888	c
A_5_MAV	−0.9746	0.0782	c	−1.3558	0.0847	c
A_5_Mini	0.6717	0.1312	c	1.3347	0.1568	c
A_5_Minivan	−0.6733	0.1393	c	−0.9826	0.1607	c
A_5_Pickup	1.6354	0.1973	c	1.4446	0.2227	c
A_5_SUV	−0.0632	0.0971		−0.2733	0.1115	a
A_5_Van	1.2458	1.2891		0.8806	1.3755	
A_6_d_hybrid	2.8933	0.5878	a	57.0667	2.4840	c
$U_1{*}A_6$_d_hybrid	/	/		−105.8431	4.8316	c
$S_5{*}A_6$_d_hybrid	0.2875	0.1213	c	0.1686	0.0846	a
A_{exterior}	0.0593	0.0340	c	0.0407	0.0385	
A_{interior}	0.4835	0.0174	c	0.4585	0.0190	c
A_{storage}	0.5804	0.0146	c	0.6253	0.0175	c
A_{audio}	0.1741	0.0312	c	0.1421	0.0355	c
A_{seats}	0.1636	0.0373	c	0.1046	0.0424	a
A_{HVAC}	0.1242	0.0340	c	0.1285	0.0391	c
A_{dynamics}	0.2362	0.0380	c	0.1640	0.0433	c
A_{engine}	0.2565	0.0301	c	0.3061	0.0343	c
A_{safety}	0.0999	0.0384	b	0.0455	0.0437	

[a] Significant with p value <= 0.05
[b] Significant with p value <= 0.01
[c] Significant with p value <= 0.001

- **Phase IV: Choice model estimation**

In Phase IV, as a result of choice modeling, interactions between customer-desired product attributes **A**, usage context attributes **U**, and customer demographics **S** are explicitly modeled in the utility function. The coefficients for all attributes and their interactions based on a multinomial logit model estimation (MNL with **U**) are listed in Table 10.9, together with the estimation results from a

Table 10.10 Model statistics of MNL without **U** and with **U**

Multinomial logit model	Without **U**	With **U**
Log likelihood at zero	−11,125.01	−11,125.01
Log likelihood at convergence	−6,178.62	−4,825.26
ρ^2	0.4203	0.5663

multinomial logit model without usage context attributes (MNL without **U**) as a comparison.

From the results of the MNL including **U** attributes in modeling, we note that the coefficient for price/income is negative as expected. Only two customer profile attributes, *household income* and *education level*, are statistically significant as preference-related attributes $\mathbf{S_W}$. A positive estimator for $U_1{*}A_2$ indicates that the usage context attribute U_1 (local/highway indicator) has a positive impact on customers' preference on MPG measure. In other words, people primarily driving on highways tend to care more about the MPG value, in addition to the utility increase experienced by the change in MPG. Moreover, the attitude toward HEV itself has a fairly large coefficient estimator of 57.0667, which shows that people driving locally tend to favor HEV. Similarly as we expected, highway drivers do not prefer HEVs, as shown in the negative coefficient estimator of the U_1 and HEV indicator interaction ($U_1{*}A_6$). This finding presents an opportunity to design a HEV, which performs well in highway driving to help overcome this issue. On the other hand, most coefficients from the MNL without modeling **U** have the same sign as the ones in MNL with **U**, but they are very different in magnitude, as the usage heterogeneity is not explicitly modeled. Inclusion of usage context will help designers more specifically target the vehicle design to the usage contexts of the intended market for the vehicle.

Goodness-of-fit measures based upon the log likelihood of the converged model, such as the likelihood ratio index ρ^2 (also known as pseudo R-square); reflect how well the estimated model predicts actual individual choices in the data set. Higher values of ρ^2 indicate better predictions of the choices. As shown in Table 10.10, a significantly higher log likelihood of −4,825.26 and subsequently ρ^2 value of 0.5663 are achieved using the MNL model with usage context attributes **U** versus the MNL model without **U**. This implies that introducing the usage context attributes in choice modeling has captured the systematic taste heterogeneity of customers under different usage contexts. This is important for designers so that they may best understand the preferences and usage contexts of the intended users.

Cross-validation. For cross-validation of a choice model, the original data are divided into 5 subsets of samples. For each of the five cross-validation tests, a choice model is trained on 4 subset samples and later validated using the remaining hold-out sample. The likelihood ratio index ρ^2 values and hit rates (percentage of correctly predicted choices) are calculated and averaged out, as listed in Table 10.11.

Table 10.11 Fivefold cross-validation results for choice modeling of HEVs

Test	MNL without **U**		MNL with **U**	
Measure	ρ^2 (%)	Hit rate (%)	ρ^2 (%)	Hit rate (%)
1	58.72	67.41	68.10	75.76
2	57.10	66.60	66.87	76.20
3	56.10	66.42	65.61	74.02
4	56.35	65.67	65.84	74.14
5	55.77	66.79	65.98	75.20
Average	56.81	66.58	66.48	75.07

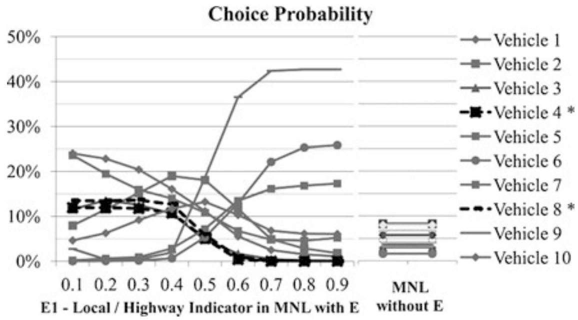

Fig. 10.4 Choice probability of target population under different usage contexts (a Hybrid electric vehicle)

On average, the likelihood ratio index ρ^2 shows an over 17% improvement from 56.81% in the MNL without **U** to 66.48% in the MNL with **U**. The hit rate, though not theoretically consistent with random utility theory, is another commonly used measure of the prediction accuracy of an estimated model at the individual level. It is calculated by dividing the number of correctly predicted choices by the total number of respondents. Similar to ρ^2, the hit rate increases from 66.85% in the MNL without **U** to 75.07%, which shows that usage context greatly influences customers' choice and should be modeled explicitly.

What-if-scenario analysis. With the formulations described above and choice model results from MNL with **U**, a prediction model can be built to forecast the customers' choice. For example, a target population of 260 customers is simulated with the customer profile distribution drawn from the hybrid owner pool in VQS 2007 data set. Assuming that they are choosing a new vehicle to purchase from a random choice set of 4 car models selected from 10 car models available in the market. The ten car models, among which two (vehicle 4 and vehicle 8) are HEVs, are selected based on their popularity in the choice set of customers who considered at least one HEV. The choice set of each customer can also be predicted using statistical learning or data mining methods with existing market data. Since not all customers would consider a HEV when they shop for a new car, we assume that 40% of customers would include HEVs in their choice set, while the rest of them would not. Additionally, we consider a series of nine different usage contexts: a uniformly distributed *local/highway indicator* with 0.2 range and mean value from 0.1 to 0.9 (with 0.1 interval), while average *miles driven daily* matches with the original dataset. Aggregated choice probability in target population calculated using our proposed framework is summarized in Fig. 10.4.

In Fig. 10.4, the solid lines (conventional vehicles) and dashed lines (HEVs) on the left hand side show the predicted choice probability by MNL with **U**, while the gray lines on the right hand side represent the constant choice probability predicted by MNL without **U**. For instance, when the target population, on average, drives 40% under local conditions, the HEV 4 and vehicle 8 have the predicted choice probabilities of 10.72 and 12.64%, respectively in MNL with **U**, as opposed to the constant 7.32 and 8.11% in MNL without **U**. According to the prediction from the MNL with **U**, their predicted market shares gradually decrease, as U_1 increases. When U_1 is less than or equal to 0.3, conventional vehicle 1 has the largest market share, closely followed by conventional vehicle 5. When U_1 increases to 0.5, the predicted choice probabilities change significantly, as shown in the middle of the figure. Each car model has its niche in the market. Similarly, when U_1 is larger than or equal to 0.6, conventional vehicle 9 becomes the dominant car model, as it has the highest choice probability. This suggests that customers with extreme driving conditions (U_1 close to 0 or 1) have stronger or clearer preferences for a specific car model, which is consistent with our experience. In comparison, the predicted dominant vehicle choice by the MNL without **U** turns out to be conventional vehicle 2 with a choice probability of 16.51%, which is significantly different from the one predicted by the MNL with **U**. Since the missing usage information plays a key role in customers' choice, as demonstrated earlier, and it is natural to expect that customers make distinctive decisions when usage context changes, the MNL with **U** better models the choice process. Accurately predicting the choice probabilities (i.e., market share) for a given vehicle design, customer population and set of usages is an important tool for vehicle designers to tailor the vehicle design to the target market as closely as possible.

10.7 Conclusion

In this chapter, we present a choice modeling framework for UCBD to quantify the impact of usage context on customer choices. Previous works have illustrated the importance of considering usage context in design, but did not present a systematic and quantitative approach to choice modeling. The primary focus of this chapter is the development of a systematic UCBD taxonomy and a step-by-step procedure to quantitatively assess the impact of usage context on product performance and customer preferences.

Taxonomy for UCBD is first defined by following the established classification in the market research domain and the needs associated with choice modeling. The step-by-step procedure for creating choice models in UCBD is then presented. To facilitate the identification of usage contexts in Phase I, it is recommended to elicit the usage context attributes from five categories of product usages including *physical surroundings*, *social surroundings*, *temporal perspective*, *task definition*, and *antecedent states*. In Phase II data collection, both the methods of Stated Preference and Revealed Preference surveys are presented to account for the choices respondents make conditional on the given usage context, which allows us to examine simultaneously the influence of product design, customer profile, usage context, and their interactions, on customer choices. Furthermore, Phase III is a unique step in a quantitative UCBD process in which the influence of usage context and customer profile on product performance is analytically modeled. Additionally, in Phase IV, usage context enters into an individual's choice utility function directly to capture its influence on product preferences. In Phases III and IV of modeling, both customer profile attributes $\mathbf{S}$ and usage context attributes $\mathbf{U}$ are further classified into performance-related $\mathbf{S_Y}$, $\mathbf{U_Y}$ and preference-related $\mathbf{S_W}$ and $\mathbf{U_W}$ to differentiate their impact on product performance and customer preferences, respectively. The usage context choice modeling approach in this chapter represents a significant expansion of traditional choice modeling approaches in the design literature.

Two case studies, a jigsaw design example with synthetic stated preference data and a HEV example with real revealed preference data, illustrate the proposed modeling framework. Both case studies follow the four-phase modeling procedure. The jigsaw case study emphasizes usage context identification, data collection with stated preference surveys, and the use of physics-based modeling to capture the impact of usage context on performance. Additionally, details of the modeling steps (Phases III and IV) are reported in the HEV case study based on the revealed preference survey data that reflects customers' real choices and the use of ordered logit modeling for predicting customer ratings for system attributes. Results from both examples demonstrate the impact of usage context upon customer preference as well as product performance. A set of validation tests are included for the HEV case study, which demonstrate the necessity of expanding a traditional choice modeling framework to include usage context for improved model predictive capability. What-if-scenario analysis in the HEV example showed that predicted choice share in the target market changes in response to the change of performance ratings in distinctive usage contexts for given vehicle designs, which illustrates the potential of the proposed choice modeling framework in supporting engineering product design.

Appendix A: Sample Survey Questionnaire for Try-It-Out Survey (User 1, Usage Scenario 1)

Assume that you are in the market for a new saw. The four choices you have are shown as follows:

Product	1	3	4	5
Picture				
Type	Jigsaw	Jigsaw	Jigsaw	Jigsaw
Amperage (A)	5	6.4	5.5	6.5
Speed range high (SPM)	3,000	2,800	3,200	3,100
Height (in)	10	4.6	13.63	4.5
Weight (lbs)	5.8	10	9.39	10
Price ($)	39.97	97.99	69.00	119.00
…				

(1) Given the primary usage of *cutting soft wood indoor*, please try these products out and rate their performance on a scale from 1 to 5 (5 being the highest) in the following table:

Product	1	3	4	5
Advance speed				
Comfort				
…				

(2) Please make a choice among these four products (which product would you like to purchase? You may not make a selection if you are not happy with any of these products).

____

(3) Please tell us a little bit about yourself:

- Are you:

☐ Male ☐ Female

- What is your skill level in terms of saw usage?

☐ Beginner ☐ Intermediate ☐ Experienced

(4) Which one of the following groups best describes your household's total annual income before taxes?

☐ Under \$50,000 ☐ \$50,000–59,999 ☐ \$60,000–69,999
☐ \$70,000–\$79,999 ☐ \$80,000–89,999 ☐ \$90,000–99,999
☐ \$100,000–\$109,999 ☐ \$110,000–119,999 ☐ \$120,000–129,999
☐ \$130,000–\$139,999 ☐ \$140,000–149,999 ☐ \$150,000 or more
…

(5) Please tell us about your saw usage (up to three usages scenarios):

Usage scenario 1 (Primary Usage):

- Do you use saws?

☐ Outdoor ☐ Indoor

- Do you use saws to cut?

☐ Soft wood ☐ Medium wood ☐ Hard wood

…

Usage scenario 2:

- Do you use saws?

☐ Outdoor ☐ Indoor

- Do you use saws to cut?

☐ Soft wood ☐ Medium wood ☐ Hard wood

…

Usage scenario 3:

- Do you use saws?

☐ Outdoor ☐ Indoor

- Do you use saws to cut?

☐ Soft wood ☐ Medium wood ☐ Hard wood

…

Please tell us about the importance of these three usages in percentage:
Usage scenario 1: %
Usage scenario 2: %
Usage scenario 3: %

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Chapter 11
A Decision-Based Design Approach to Product Family Design

Nomenclature

$\mathbf{A}$	Customer-desired product attributes
$\mathbf{A}_{\mathrm{eng}}$	Customer-desired product attributes related to engineering performance
$\mathbf{A}_{\mathrm{ent}}$	Customer-desired product attributes related to enterprise product planning
C	Total product cost
$\mathbf{E}$	Engineering design attributes
$E(U)$	Expected value of enterprise utility
P	Product price
Q	Product demand
$\mathbf{S}$	Customer demographic attributes
U	Enterprise utility
V	Selection criterion used by the enterprise (e.g., profit, revenues, etc.)
W_{in}	Deterministic part of the utility of choosing alternative i by customer n
$\mathbf{X}$	Design options
$\mathbf{X}_{\mathrm{d}}$	Engineering design options
$\mathbf{X}_{\mathrm{ent}}$	Enterprise planning options
$\mathbf{Y}$	Exogenous variables (represent sources of uncertainty in market)
t	Time interval for which demand/market share is to be predicted
u_{in}	True utility of choosing alternative i by customer n
ε_{in}	Random unobservable part of the utility of choosing alternative i by customer n

In this chapter, we present an extension of the DBD approach to product family design. Products that share a common platform but have specific features and functionality required by different sets of customers form a product family. In product family design, achieving the commonality of the platform for minimizing producer's cost is a competing objective with meeting the variability of

W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8_11,

consumer preference. The Decision-Based Design approach is employed here for complex decision makings in product family design. First, we introduce the market segmentation grid (MSG) to help understand the different product variants needed, and then introduce the nested logit (NL) model to estimate demand considering product segmentation. We next create a product family formulation of DBD for making complex decisions in optimal product line positioning optimal "commonality" decisions, and optimal levels of engineering design attributes. We demonstrate the method using a case study for the design of a family of universal electric motors.

11.1 Introduction to Product Family Design

In an effort to meet the diverse needs of today's highly competitive global marketplace better, many companies are utilizing product families and platform-based product development to increase variety, shorten lead times, and reduce costs [14]. In general terms, a product family refers to a set of products that have been derived from a common product platform to satisfy a variety of market niches [36]. Individual members of the product family normally share common parts and subassemblies. Platforms, in the most general sense, are intellectual and material assets shared across a family of products, and their use helps minimizing manufacturing complexity without compromising the ability to satisfy a variety of customer requirements. In addition to improving economies of scale and scope, a product platform can facilitate customization by enabling a variety of products to be quickly and easily developed to satisfy the needs and requirements of distinct market niches [34].

Most existing product family design approaches [7, 10, 11, 24, 25, 33, 38] are targeted at identifying the optimal commonality decision while meeting prespecified performance goals. It should be noted, however, that while increasing commonality may reduce costs, it might also compromise the performance of some of the products in the family. Our aim is to integrate market considerations with manufacturing and product development considerations in platform-based product family design. NL [44], a demand modeling approach that recognizes the dissimilar impacts of competition in different market segments, is integrated within a design optimization model to make decisions on *product line positioning*[1] to determine appropriate *platform leveraging strategies* while simultaneously exploring the cost savings benefits of increased commonality. Demand models

[1] Product positioning is usually defined in marketing terms as developing a product and associated marketing mix that (a) is 'placed' as close as possible in the minds of target customers to their ideal in terms of important features and attributes, and (b) clearly differentiates it from the competition. Product line positioning refers to similar efforts for the entire product line. Here, product line positioning decisions are those that determine the optimal number of products in the line and their corresponding production volumes along with the appropriate market niches for each product in the line.

help not only in calculating production costs (as a function of production volume) more accurately but also in estimating revenues (as a function of market share). In recognition of the increasing importance of market considerations in product development, some recent developments [17, 20, 27, 28, 31] have included the use of a demand model as part of an enterprise-driven approach to the design of product families. However, these developments have only dealt with the problem of product line positioning in a limited way. Either an arbitrary number of products is assumed for the product family [27, 31] or an enumeration-type methodology is used to determine the optimal number of product variants [20]; commonality considerations are usually ignored in the interests of simplicity [15], but in reality, commonality can impact demand both positively and negatively. For instance, commonality in the cockpit has helped fuel demand for Airbus aircraft [1], but too much commonality often leads to a lack of product distinctiveness [35], which hurts sales, and it can also lead to cannibalization of one's own product line as products start to compete with themselves [12, 16]. An example can be found in the automotive industry: Volkswagen reportedly saved 1.5 billion USD per year due to lots of commonality among their four brands: Volkswagen, Audi, Skoda, and Seat [2, 43]; however, too much commonality caused considerable confusion and dramatically hurt sales as people were buying lower end models instead of higher end models [29]. Volkswagen has since set out to overhaul their brands to make them more distinct and improve sales [30]. In order to determine an acceptable level of performance loss in platform-based product development, it is important to consider product performance in the context of market considerations (i.e., competitors' products and customer preferences). Also, current approaches do not adequately examine the impact of competition or how new products added to a product family compete with existing products in the family.

The novel market-driven product family design (MPFD) methodology [18] presented in this chapter attempts to overcome the limitations of existing approaches and offers a comprehensive strategy to deal with the product family design problem. It helps to make decisions on (1) product line positioning, (2) commonality (i.e., deciding which parts and processes are to be shared among different products in the family), and (3) the optimal configuration of design variables for each product in the family. These decisions are based on engineering and manufacturing feasibility and economic considerations estimated from a demand model that predicts market performance as a function of product characteristics and market conditions (e.g., customer demographics, competition). The proposed methodology provides a framework to examine the impact of adding new products/removing existing products to/from the family. Unlike most existing approaches that assume a single platform, the method introduced also deals with the problem of determining the optimal number of product platforms for the product family [40]. The rest of the chapter is organized as follows. First, background on the MSG, a technique used to articulate platform leveraging strategies is provided. Details of the proposed MPFD methodology are presented in Sect. 11.3. Section 11.4 discusses the case study that demonstrates the utility of the proposed methodology, while the approach is summarized in Sect. 11.5.

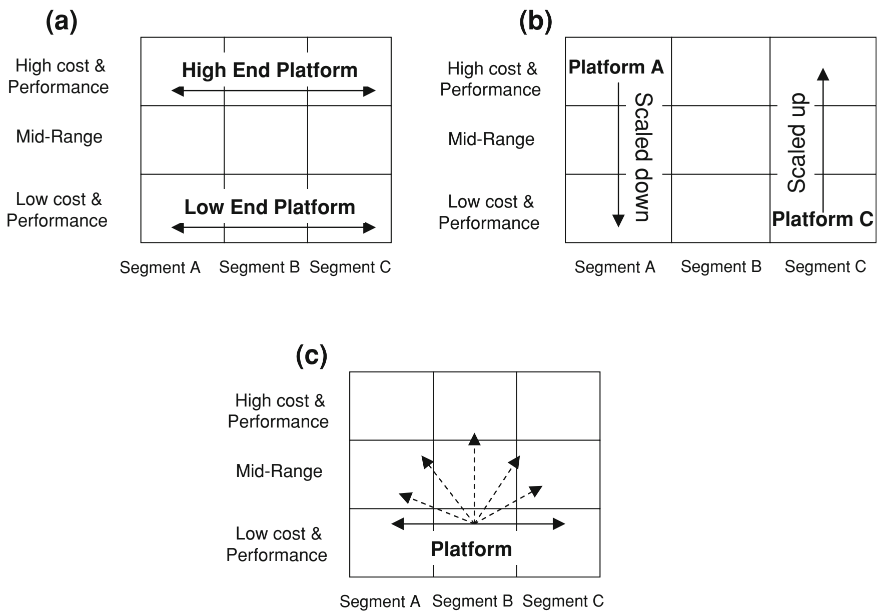


Fig. 11.1 Platform leveraging strategies are illustrated using the market segmentation grid (Adapted from [26]). **a** Horizontal leveraging. **b** Vertical leveraging. **c** Beachhead approach

11.2 Market Segmentation Grid

The widespread use of market segmentation is the inevitable consequence of the increase in competition and the global nature of today's market place. A variety of data-driven approaches have been proposed in the literature [21, 42] to formally segment the market, including Conjoint Analysis [5, 9, 13, 46], clustering [23] and neural networks [41]. However, the focus of this study is on adding rigor to a more qualitative approach that has been gaining ground in the past decade, namely, the MSG [26]. It should be noted that the MSG is used for product differentiation and not for the segmentation of the customer-population. In recent years, the MSG has become the *de facto* method to visualize product differentiation and platform leveraging strategies in the product family design community [22].

Meyer and Lehnerd [26] introduced the MSG shown in Fig. 11.1 to more clearly articulate platform leveraging strategies in a given market. In a MSG, the total market for a product family is defined through a matrix of market niches that identify particular user groups and price/performance tiers. Market segments are plotted horizontally in the grid while price/performance tiers are plotted vertically—the intersection of each price/performance tier with each market segment defines a specific market niche. The horizontal leveraging strategy illustrated in Fig. 11.1a is one in which subsystems and/or manufacturing processes are leveraged across different market segments within the same price or performance tier. The vertical leveraging strategy, see Fig. 11.1b, scales key platform subsystems and/or manufacturing processes across price/performance tiers within a market segment. The advantage of this strategy is the capability of the company to leverage its knowledge about a particular market segment without having to develop a new platform for each price/performance tier. The beachhead approach shown in Fig. 11.1c combines horizontal leveraging with vertical leveraging to develop an effective, low-cost platform with efficient processes. It is able to scale-up the performance characteristics of the platform for low-end users to the mid-end and high-end users, as well as be applied to different market segments. In the product family literature, MSGs have only been used as visual aids to arrive at the appropriate platform leveraging strategy. In this work, the effectiveness of the MSG is enhanced by mathematically expressing the product positioning decisions and platform leveraging strategies in the MSG, and including it directly in the optimization formulation. The proposed approaches also recognizes that all products in the market may not compete equally, and products in a given market segment compete more closely with each other than with products in other market segments. The segmentation in the market, as illustrated in the MSG, is modeled using the NL technique as introduced in Sect. 3.2.3.

11.3 The Market-Driven Product Family Design Methodology

The proposed MPFD methodology seeks to integrate market considerations with traditional product family design issues (e.g., commonality, manufacturing cost) to design the most profitable product families unlike traditional product family design methods which mostly focus on the cost benefits. The MPFD methodology (see Fig. 11.2) consists of the following four steps: (1) creation of the MSG, (2) estimation of the NL demand model and building a choice simulator program, (3) construction of models for product performance and cost, and (4) optimization of the product family by maximizing profit. Each of the steps is performed sequentially, but steps (2) and (3) can be accomplished in parallel if desired. A short discussion on each of the MPFD steps follows.

11.3.1 Creation of the Enhanced Market Segmentation Grid

Data on the existing market is required to create an "enhanced" MSG that includes information not only about the market segments and the performance/price tiers but also about the competitors in each niche (i.e., the market segment and performance/price combination). Collecting market data involves gathering sales data ideally at

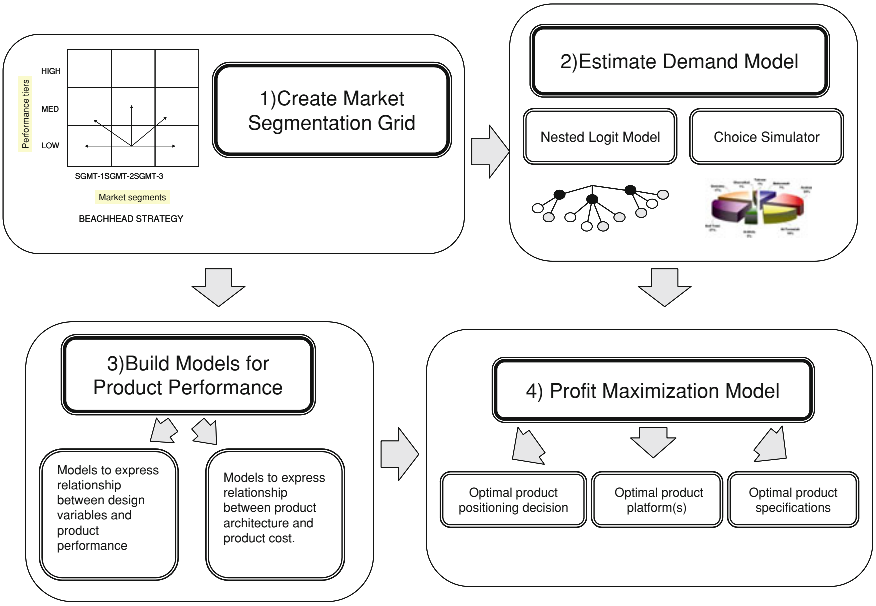


Fig. 11.2 The MPFD methodology to design platform-based product families

the level of the individual customer in order to determine the choice set available to each individual customer as well as incorporate biases associated with demographics (e.g., age, income). Information on the performance characteristics of competitors' products in the market must also be collected and can be usually obtained from product catalogs. An important consideration is the choice of the performance attribute to include in the grid as the vertical axis of the MSG. The use of "Differentiating Attributes" (DA), defined in [35] as "characteristics that customers deem important in distinguishing between products," is adopted for this purpose. For example, interior noise level is a DA for automobiles; customers generally expect different values of this DA for different kinds of vehicles, such as audible cues from the engine in sporty vehicles but near silence in luxury vehicles [34]. In this work, DAs are assumed to be identical to the customer-desired attributes (**A**) described earlier. Developing the MSG in this step is independent from developing the product design details and building product performance models (Step 3), and it is this aspect of the proposed methodology that enables the seamless integration of the market analysis with the engineering modeling activities.

11.3.2 Estimation of the Nested Logit Demand Model

The information in the MSG has to be converted into an equivalent choice tree representation before the estimation of the NL model. As introduced in Sect. 3.2.3, by using NL modeling, products in each market segment are grouped under a

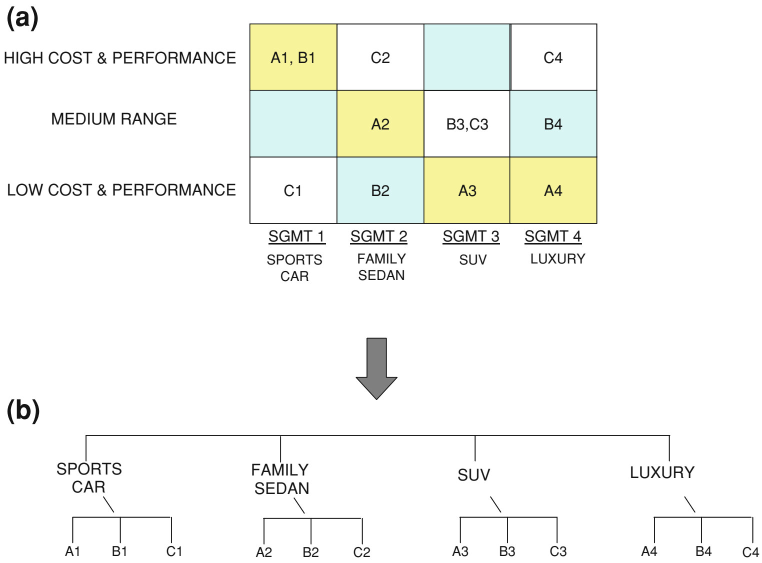


Fig. 11.3 A MSG and its equivalent choice tree representation. **a** Market segmentation grid. **b** Equivalent decision (choice) tree representation

separate nest in an NL choice tree representation similar to the one shown in Chap. 3 which is then followed by the estimation of the NL model by determining the values of the unknown β's and scale parameter (μ) for each of the nests (i.e., segments). A hypothetical vehicle market is used to describe this procedure. The MSG consists of four market segments along the horizontal axis (corresponding to sports, family sedan, SUV, and luxury segments) and three performance/cost tiers on the vertical axis, leading to 12 niches in all (see Fig. 11.3a). For simplicity, horsepower is used as the performance measure along the vertical axis. The grid is populated with cars from three manufacturers: A, B, and C. Consider the tree representation of the grid in Fig. 11.3b in which the cars under each segment are grouped together in a nest. This representation is used to group cars that compete more closely with each other and enable the use of the NL technique. Such a choice tree representation may also be used to simulate the customer's decision-making process, i.e., customers may choose among different vehicle segments before choosing among the different vehicles in each segment.

The next step involves the estimation of the NL demand model. Each nest in the NL model corresponds to a particular market segment. The demand model used in this work, establishes the relationship between the customer-desired attributes, $\mathbf{A}$, the socioeconomic and demographic attributes, $\mathbf{S}$, price, P, and the demand, Q, i.e., $Q(\mathbf{A}, \mathbf{S}, P)$. In order to aid engineering decision-making, customer-desired attributes ($\mathbf{A}$) are replaced by corresponding engineering attributes $\mathbf{E}$ in the model, where $\mathbf{E}$ are any *quantifiable product properties* that are used in the engineering product development process. Estimating a NL demand model is similar to estimating a MNL model as introduced in Sect. 3.2.2, except that the scale parameter (μ) corresponding to each of the nests has to be estimated. As discussed earlier, the values of the scale parameters help to evaluate the validity of the nesting structure and also serve as a measure of the "within-segment" competition.

Once the NL demand model is estimated, it can be used repeatedly to estimate the impact of design changes or the effect of adding/removing products from the line using a *choice simulator* program. A choice simulator is a computer program that simulates the demand model and uses the market data as inputs to estimate changes in market share for each product as a function of engineering attributes, customer demographic attributes, and price values (i.e., **E**, **S**, and P). One challenge in building a choice simulator for the product family optimization problem is the complexity introduced due to the addition of multiple products into the market simultaneously—new products encoded in the product line positioning decision have to be grouped with similar competitors' products in corresponding market segments and the data set has to be updated in each optimization iteration.

11.3.3 Construction of Models for Product Performance and Cost

Building models for product performance functions **E**(**X**) involves building models that represent the relationship between engineering attributes **E** and design options **X** (which includes decisions on size, shape, material, etc.) through engineering analysis. These relationships can be expressed through analytical models, finite element models, simulation models, meta modeling techniques, etc. Similarly, cost is modeled as a function of the design options (**X**). The cost model is used to evaluate the benefits of different commonality decisions (i.e., shared parts and processes between different product variants in the product family). In this work, the total cost (C) is expressed in terms of material cost (C_M), labor cost (C_L), repair and warranty costs (C_R), design costs (C_D), and overhead costs (C_O). Material cost is expressed in terms of production volume V, design options **X**, and manufacturing attributes **Mf**. Examples of manufacturing attributes (**Mf**) are tooling and fixturing specifications, production plans and schedules, and inventory control schemes. The repair/warranty costs (C_R) are expressed as a function of the product's reliability, which in turn is expressed as a function of **X** and operating conditions **O** (e.g., temperature, pressure). These two models can be used to *make trade-offs between cost and performance*, in conjunction with the demand model.

11.3.4 Optimization of the Product Family

The product family design optimization problem primarily involves the determination of the (1) optimal product line positioning decision, which involves choosing the optimal number of product variants in the family and the market niches they should target, (2) optimal "commonality" decisions (i.e., the number of platforms in the family and the design variables that should be shared by product variants assigned to each of the platforms), and (3) optimal levels of engineering design attributes (**E**), and corresponding design options for each product in the family. In this work, the problem is formulated as an all-in-one problem to make these decisions simultaneously and solved in a single stage using an iterative procedure. In each iteration, a random binary string that has information on (i) product line positioning decisions as well as (ii) commonality decisions is supplied to the profit maximization model. The "product line positioning" substring (i.e., the part of the binary string that is used to make the product line positioning decision) not only sets bounds on the performance variable used to define tiers along the vertical axis (e.g., power in the case of electric motors) but also has an impact on the market share garnered by each "new" product since the product line positioning substring decides the targeted market segment and therefore the competitors' products which have the biggest impact on the market shares for each "new" product.

Figure 11.4 illustrates how a binary string can be used to represent product line positioning decisions. Consider a MSG with three segments and three performance tiers forming a (3 × 3) grid. A 1D binary string whose size corresponds to the number of the cells in the MSG is used to represent such a grid. The "1"s in the string and the crossed cells in the grid correspond to the decisions to introduce products in corresponding market niches. Similarly, the "0"s in the string and uncrossed cells correspond to decisions to not launch products in the corresponding niche. Competitors' products represented in the MSG in Fig. 11.4 by shaded cells are not represented in the string. Consider segment two (corresponding to column 2 in the MSG): the two crossed squares indicate that the firm is considering launching two new products in that segment while the two shaded boxes represent competitors' products in the corresponding niches. In all, four products compete for market share in this segment. It should be noted that competitors' products are not numerically encoded in the binary string (the corresponding blocks in the binary string are only shaded for ease of understanding), and only a one time conversion of the competitors' products in the grid to equivalent nodes in the NL tree is necessary.

Figure 11.5 illustrates how product line positioning and product commonality decisions can be simultaneously encoded in a numeric string. The string is essentially divided into two parts: the first part of the numeric string corresponds to the *product line positioning* decision, and the second part is used to store *commonality* decisions. Each product is by an ordered pair (market tier, market segment). For example, Product 1: (3,1) indicates that Product 1 is from market

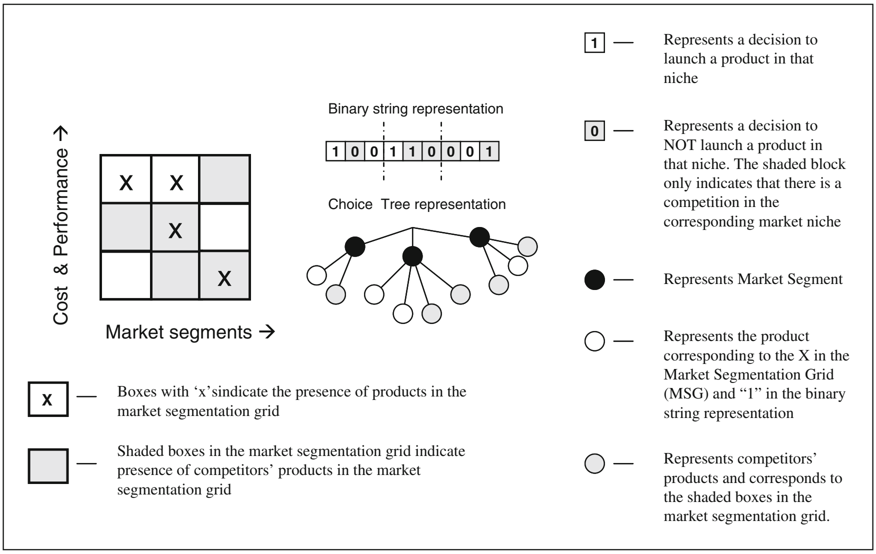


Fig. 11.4 Equivalent MSG, binary string, and NL tree representations or a given product line positioning decision

segment 1 and market tier 3. Assuming each of the products in the family has three design variables (say x_1, x_2, x_3), then each product is represented by a 4-bit commonality substring. The first bit represents the *platform index*, and the following three bits are binary *commonality decision variables*, which indicate if the corresponding design variable is common across all the products sharing the platform.

For example, if the third commonality decision variable is 1, then it indicates that the design variable x_3 is being shared. From Fig. 11.5, it is clear that Products 1:(3,1) and 2:(2,2) share Platform 1 and Products 3:(1,3) and 4:(3,3) share Platform 2. Products 1 and 2 share Design Variable 2, and Products 3 and 4 share Design Variable 3. It should be noted that the *product line positioning* and *commonality substrings* together express *the platform leveraging strategy*. In this manner, existing products can be represented in the string by fixing the values of the bits corresponding to the (tier, segment) pairs to "1" during the optimization. Including the existing product(s) in the formulation can help when redesigning and/or repricing that product (i.e., determining optimal levels of **E**, and P). Cost savings due to sharing parts and production infrastructure and parts with existing products can also be explored.

The product family design problem is formulated as shown in Fig. 11.6. The formulation captures the key product family design decisions considered in this work. The set of design options corresponding to product is represented as $\mathbf{X}_{ij}$. N represents the number of market tiers in each market segment, and S represents the number of market segments. X_{ijk} represents the kth variable corresponding to product

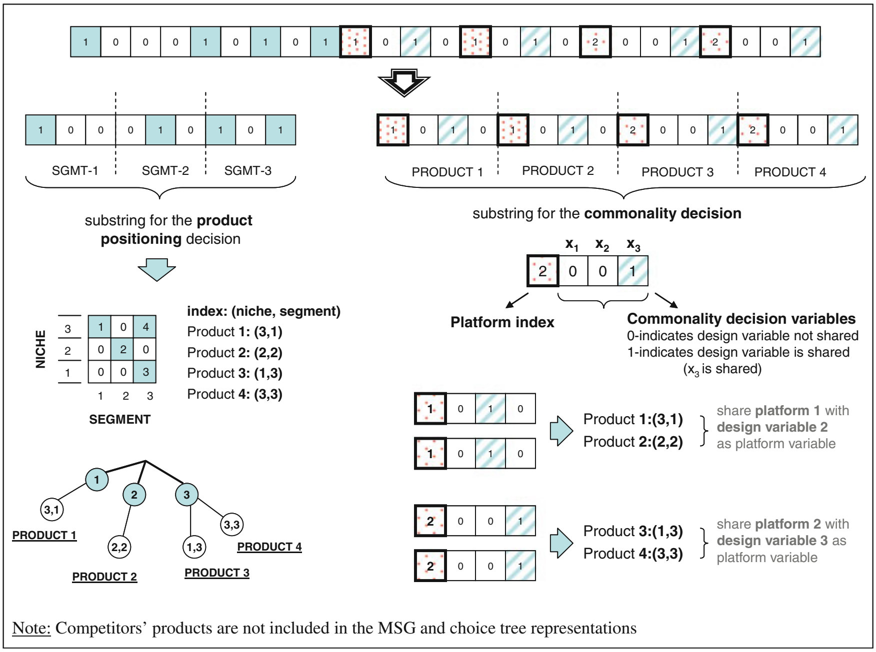


Fig. 11.5 String representation of product line positioning and commonality decisions

$\mathbf{E}_{ij}$ corresponds to performance characteristics of the product. $\mathbf{E}_{ij}$ can be expressed as a function of design options $\mathbf{X}_{ij}$ using relationships $\mathbf{r}$. Design constraints are expressed as $\mathbf{g}(\mathbf{X},\mathbf{E}) \leq \mathbf{0}$. The market segment-specific variable bounds for design options of all products $\mathbf{X}_{ij}$ in segment j are represented by $\mathbf{LB}_j$ and $\mathbf{UB}_j$ while $\Pi_{\mathbf{G}_1,\mathbf{G}_2}$ corresponds to the profit with respect to binary string $\mathbf{G}$:[$\mathbf{G}_1$,$\mathbf{G}_2$].

Product line positioning decisions are represented by $\mathbf{G}_1$ while commonality decisions are expressed using $\mathbf{G}_2$. It is expressed as a function of demand Q_{ij}, price P_{ij}, the demand and price values for product (i,j), and cost C. While a description of the different cost components was provided earlier, it should be noted that both $\mathbf{G}_1$ and $\mathbf{G}_2$ have a direct impact on cost since $\mathbf{G}_1$ decides the number of product variants and the production volumes of different products in the family while $\mathbf{G}_2$ decides which of the $\mathbf{X}$'s are shared between different products.

11.4 Case Study: Design of a Family of Universal Electric Motors

The design of a family of universal motors is used to demonstrate the implementation of the proposed methodology. Motivated by Black and Decker's case study reported in [19] an example problem involving the design of a family of

Given

a) Market data

Sales data of different products, buyer-specific information (e.g., age, income)

b) Demand model

Demand as a function of product attributes and buyer-specific information. Includes estimates for utility function coefficients ($\boldsymbol{\beta}$), scale parameters ($\boldsymbol{\mu}$), etc.; $\mathbf{Q}$ **(E,S,P)**

c) Models for Product Performance

Analytical and Simulation models expressing relationship between $\mathbf{E}_{ij}$ and $\mathbf{X}_{ij}$

$\mathbf{E}_{ij} = \mathbf{r}(\mathbf{X}_{ij}) \quad i \leq N, j \leq S$

d) Cost models

Models for different cost components; material cost ($\mathbf{C}_M$), labor cost ($\mathbf{C}_L$), design cost ($\mathbf{C}_D$), repair/warranty costs ($\mathbf{C}_R$), overhead costs ($\mathbf{C}_O$), etc.

$$\underset{\mathbf{G}_1,\mathbf{G}_2,\mathbf{X},\mathbf{M},\mathbf{O}}{C} = \sum_{i \leq N, j \leq S} \left(C_M\left(Q_{ij}, \mathbf{X}_{ij}, \mathbf{Mf}\right) + C_L\left(Q_{ij}, \mathbf{X}_{ij}, \mathbf{Mf}\right) + C_R\left(\mathbf{X}_{ij}, \mathbf{O}_{ij}\right)\right) + C_D + C_O$$

Find

a) Product Positioning substring (G1)

Contains information on number of products, and market niches corresponding to each of them.

b) Commonality substring (G2)

Contains information on the number of platforms, the products sharing each platform, and platform composition (i.e., which design variables to share in each platform)

c) Design Options (X)

Choice of shape, size, material, etc., represented by $\mathbf{X}_{ij}$, the vector of all design variables X_{ijk} corresponding to product (i,j)

Maximize

a) Profit

$$\underset{\mathbf{G}_1,\mathbf{G}_2,\mathbf{X}}{\Pi} = \sum_{i,j} Q_{ij}\left(\mathbf{E}_{ij}, \mathbf{S}, P_{ij}\right) P_{ij} - C$$

Satisfy

b) Design constraints

Relationships between **E** and **X**, and between different **X**

$\mathbf{g}(\mathbf{X}_{ij}, \mathbf{E}_{ij}) \leq \mathbf{0}; \qquad i \leq N, j \leq S$

$\mathbf{LB}_j \leq X_{ijk} \leq \mathbf{UB}_j; \qquad \forall X_{ijk} \in \mathbf{X}_{ij}, i \leq N, j \leq S$

Fig. 11.6 Formulation for profit maximization-based product family design

universal electric motors was first used in [39] and subsequently used by a number of researchers in the community as reviewed in [36]. Existing formulations of the universal electric motor product family design problem are briefly discussed in the

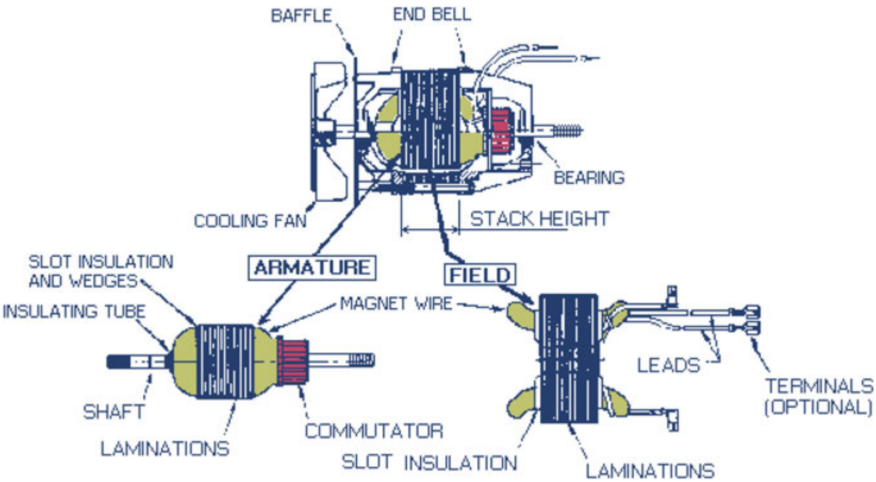


Fig. 11.7 Universal motors schematic (*Source* [39])

next section. This is followed by discussions on the enhancements to the universal electric motor product family design problem, with special emphasis on market and manufacturing considerations. The section concludes with a discussion on the results and interpretations associated with the case study.

A schematic of a universal motor is shown in Fig. 11.7, which is the same product considered in Chap. 4, Sect. 4.4. As shown in the figure, a universal motor is composed of an armature and a field, which are also referred to as the rotor and stator, respectively. The armature consists of a metal shaft and slats (armature poles) around which wire is wrapped longitudinally as many as a thousand times. The field consists of a hollow metal cylinder within which the armature rotates. Additional details on universal motors can be found in [3]. The objective of the design problem is stated as

> Design a family of ten universal electric motors that satisfies a variety of torque and power requirements by scaling a common motor platform

Similar to the original Black and Decker case study, the aforementioned work seeks to find the optimal product family assuming a prespecified product platform. Individual products in the family share identical values for all motor design variables except stack length (L) and current drawn by the motor (I). The motor design variables that are of interest are tabulated in Table 11.1. The terminal voltage V_t is fixed at 115 V to correspond to standard household voltage. A mathematical model for the design of a universal electric motor [39] relates the design variables [N_c, N_s, A_{wa}, A_{wf}, r, t, I, L] to the performance measures Power (P), Torque (T), Mass (M), and Efficiency (η).

Table 11.1 Universal motor design variables and bounds

Variable	Description
N_c	Number of wire turns on the motor armature (turns); $(0 \leq N_c \leq 1,500)$
N_s	Number of wire turns on each field pole (turns); $(0 \leq N_s \leq 500)$
A_{wa}	Cross-sectional area of the armature wire (m^2); $(0.01 \times 10^{-6} \leq A_{\mathrm{wa}} \leq 1.0 \times 10^{-6})$
A_{wf}	Cross-sectional area of the field wire (m^2); $(0.01 \times 10^{-6} \leq A_{\mathrm{wf}} \leq 1.0 \times 10^{-6})$
r	Radius of the motor (m); $(0.01 \leq r \leq 0.10)$
t	Thickness of the motor (m); $(0.0005 \leq t \leq 0.10)$
I	Current drawn by the motor (A); $(0.1 \leq I \leq 6.0)$
L	Stack length (m); $(0.01 \leq L \leq 0.1)$

Table 11.2 Universal motor design constraints

Name	Constraint
Magnetizing intensity, H	$H \leq 5{,}000$ A turns/m
Feasible geometry	$t < r$ (m)
Power, P	$P = 300$ W
Torque, T	$T = \{0.05, 0.1, 0.125, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.50\}$Nm
Efficiency, η	$\eta \geq 0.15$
Mass, M	$M \leq 2.0$ kg

The solution to the universal motor product family design problem should also satisfy the set of constraints given in Table 11.1. The constraint on magnetic intensity (H) ensures that the magnetic flux within each motor does not exceed the physical flux carrying capacity of steel. The constraint on feasible geometry ensures that the thickness of the stator (t) does not exceed the radius (r) of the stator; the thickness of the stator is measured from the outside of the motor inward. The required output power (P) is taken as 300 W, and the ten torque values (T) for the motor family range from 0.05 to 0.50 Nm, and there are minimum expectations for efficiency and mass of each of the motors. The product family design objectives are to *minimize mass* (M), and *maximize efficiency* (η) of each of the motors in the family while sharing the prespecified platform variable.

Most of the aforementioned approaches require specifying the universal electric motor platform a priori. Some researchers do not impose this restriction and attempt to *optimize* the choice of platform variable(s) using a variety of formulations: the variation-based method [33], penalty functions [25], sensitivity analysis, and cluster analysis [8] and a genetic algorithm-based approach [38]. However, these approaches only seek to minimize loss in motor performance (i.e., motor efficiency and mass) due to the commonality decisions without modeling manufacturing and market considerations explicitly (Table 11.2).

11.4.1 Description of the "Enhanced" Universal Electric Motor Product Family Design Problem Formulation

In order to model the market for universal motors, in addition to achieving an understanding of different market segments for the universal motor, data on the size of the market, specifications of competitors' products, and market shares of different competitors' products needs to be collected. The product platform decisions also require an understanding of the manufacturing process and associated cost components. Discussions on the universal electric motor market and the manufacturing cost model used for the product family design follow.

11.4.1.1 Description of the Hypothetical Universal Electric Motor Market

The high performance characteristics and flexibility of universal electric motors have led to a wide range of applications [41], especially in household use where they are found in products, such as electric drills and saws, blenders, vacuum cleaners, and sewing machines. A hypothetical market for universal motors is assumed to comprise manufacturers of products that use the universal electric motor. Our aim is to demonstrate the impact of market considerations on product family design. Towards this end, hypothetical market data for universal electric motors is constructed for the study. A description of the resulting MSG follows.

A MSG with four market segments—household/kitchen appliances, power tools, cordless power tools, and garden/lawn tools—is presented in Fig. 11.8. *Power* and *Cost* are used as the DA for defining tiers within each segment with the understanding that motors with higher power cost more. It should be noted that the overlap between the power bounds for adjacent tiers in a segment implies competition among universal electric motors from different tiers in the same segment. As illustrated in Fig. 11.8, the segment for *household/kitchen appliances* includes (manufacturers of) blenders, vacuum cleaners, washing machines, and gas-heated dryers. The *power tools* segment includes drills, various types of saws (e.g., band saw, circular saw, and jigsaw), sanders, and fastening tools. The *cordless power tools* segment includes approximately the same product mix as the power tools segment except for the fact that the motors used in these devices are required to run on battery-operated (DC) power supply. Finally, the *garden/lawn tools* segment includes string and hedge trimmers, garbage disposal units, yard blowers and lawn mowers. The distinguishing characteristic of the motors in each segment is included under each of the segments in the MSG representation. The motors used in household appliances tend to operate at *higher speeds* while motors used in power tools are characterized by *higher torque* requirements. The motors in the cordless power tools segments share the higher torque characteristic. In addition, they are also required to be *lighter and more efficient* since they need to be portable and operate on a battery-operated power supply. Finally, the motors in the garden

Fig. 11.8 Market segmentation grid for universal motor product family

Table 11.3 Results of demand model estimation for the universal motor market

Parameter	Price (P)	Power	Efficiency (η)	Mass (M)	Scale parameters for each market segment			
					μ_1	μ_2	μ_3	μ_4
Coefficient	−0.011	0.0031	0.71	−0.51	0.29	0.25	0.5	0.5

tools segment are characterized by *higher power* requirements and tend to be bigger and heavier.

In all, data for 23 motor manufacturers and 40 industrial customers (device manufacturers) was generated for the hypothetical universal electric motor market, and a segment-wise listing of product offerings is provided in Appendix A.1. The size of the market is assumed to be 40,000 motors, and demand is assumed to be uniform across all the industrial customers (i.e., 1,000 motors each). The industrial customers are assumed to choose among different motors based on the motor's attributes [i.e., Price P, Power (P: $\mathbf{E}_1$), Efficiency (η: $\mathbf{E}_2$), and Mass (M: $\mathbf{E}_3$)]. Customers in each segment are assigned the same order quantity to simplify the analysis.

A number of NL demand models were estimated and on the basis of behavioral interpretations and goodness of fit estimates, the model in Table 11.3 was chosen for further consideration. The model coefficients (for attributes $\mathbf{A}$ = Price, Power, Efficiency, and Mass) have signs consistent with current understanding of preference behavior for different motor attributes. For example, price has a negative coefficient, and efficiency has a positive coefficient, implying that manufacturers prefer cheaper and more efficient motors.

The values of all scale parameters are between [0 1], which justifies the nesting structure (i.e., the use of different nests for each market segment) that is employed. As discussed earlier, the value of the scale parameter associated with a particular market segment provides an indication of the level of competition among the different product offerings in that segment. All the scale parameters have fairly low values, indicating that the within-segment competition is significant in all four segments. This means that whenever a new product is introduced into one of the four market segments (say power tools segment), the market shares of the existing products change but the market shares of the products in the remaining segments (i.e., Segments 1, 3, and 4) remain relatively unaffected. μ_1 and μ_2 have lower values than μ_3 and μ_4, indicating that the "within-segment" competition in Segments 1 and 2 (i.e., household appliances and power tools segments) are higher than the "within-segment" competition in Segments 3 and 4 (i.e., cordless power tools and garden tools segments). The estimation of the demand model is followed by building the choice simulator so that the market considerations can be integrated into the product family optimization problem. The choice simulator program requires the product line positioning string (see Fig. 11.5) and the performance specifications (i.e., Price, Power, Efficiency, and Mass) of each motor in the string as inputs. In turn, it calculates the market share both in terms of revenue as well as actual quantities for each of the motors in the market.

The demand model also helps to demonstrate the roles of competition and segmentation (on the market shares of individual motors) in the market. Figure 11.9 illustrates the difference in market share of the existing products (corresponding to products with serial numbers 1–23 in the figure) before and after the introduction of a new product (Product 24) in Segment 2, in Fig. 11.11a and b, respectively. The product line positioning decision under consideration involves introducing a single new product in the "high-power/high-cost" niche in the *power tools* segment [i.e., in (tier, segment) $\equiv$ (3,2)] with the specifications given in Table 11.4. While the introduction of Product 24 (code: NEW) in Segment 2 takes away significant market share from the other products in the segment (i.e., Products 10–14), the market share of each product in the remaining segments (segments corresponding to household appliances, cordless power tools, and garden tools) are relatively unaffected. This indicates that the "within-segment" competition in the *power tools* segment is significant, and products in that segment compete much more closely with each other for market share, than they do with products from other segments (e.g., household appliances, garden tools).

SEGMENT 1			SEGMENT 2			SEGMENT 3				SEGMENT 4		
sl no	code	Q_j	sl no	code	Q_j	sl no	code	Q_j	%	sl no	code	Q_j
1	A11	189.7	10	B21	459.1	15	A31	1268.0	13.2	20	B41	1483.0
2	C11	841.1	11	C21	760.9	16	C31	1375.0	14.3	21	C41	1492.0
3	C12	1057.0	12	C22	962.3	17	C32	2290.0	23.8	22	C42	3078.0
4	B11	1255.0	13	A21	965.9	18	C33	2713.0	28.2	23	B42	3784.0
5	B12	1176.0	14	B22	4112.0	19	B31	1967.0	20.5			
6	B13	2204.0										
7	C13	2413.0										
8	A12	2090.0										
9	B14	2085.0										
13310.8			7260.2			9613.0				9837.0		

(a) Market share distribution for existing market

SEGMENT 1			SEGMENT 2			SEGMENT 3				SEGMENT 4		
sl no	code	Q_j	sl no	code	Q_j	sl no	code	Q_j	%	sl no	code	Q_j
1	A11	176.6	10	B21	152.9	15	A31	1180.0	13.2	20	B41	1362.0
2	C11	783.0	11	C21	253.4	16	C31	1280.0	14.3	21	C41	1389.0
3	C12	983.8	12	C22	320.5	17	C32	2132.0	23.8	22	C42	2865.0
4	B11	1169.0	13	A21	321.7	18	C33	2526.0	28.2	23	B42	3522.0
5	B12	1095.0	14	B22	1370.0	19	B31	1831.0	20.5			
6	B13	2052.0	**24**	**NEW**	**7103.0**							
7	C13	2246.0										
8	A12	1946.0										
9	B14	1941.0										
12392.4			9521.5			8949.0				9138.0		

(b) Market share distribution after introduction of product 24 in segment 2

Fig. 11.9 Impact of competition and market segmentation for the universal motor market. **a** Market share distribution for existing market. **b** Market share distribution after introduction of product 24 in segment 2

Table 11.4 Performance specification of product NEW: (3,2)

Parameter	Price P ($)	Power (W)	Efficiency η (%)	Mass M (kg)
Values for product NEW	48.52	700.0	89.5	1.32

11.4.1.2 Description of the Cost Model for the Universal Motor Case Study

The cost model is established to help to demonstrate the benefits of commonality (i.e., shared components, processes, etc.) among different products in the family. Here, the *manufacturing cost* is expressed as a function of *motor design variables* (**X**) *and the manufacturing processes*, and commonality in the design variables and processes are shown to lead to reduction in cost. Information from various motor manufacturer web sites and insights provided by Simpson et al. [39] were used to arrive at the cost model. In general, motor manufacturing cost is determined by two parameters:

- *motor size* determined by motor radius (r), motor thickness (t) and stack length (L), and
- *motor windings* determined by number of turns in the armature and stator windings (N_c and N_s) and the cross-sectional areas of the armature and stator wires (A_{wa} and A_{wf})

Table 11.5 Segment-specific bounds for the universal motor product family

Market segment	Primary distinguishing feature(s)	Constraints
Segment 1 (Household appliances)	Higher Speed	$T \geq 0.05$ (Nm)
Segment 2 (Power tools)	Higher torque (T) Higher efficiency (η)	$T \geq 0.10$ (Nm)
Segment 3 (Cordless power tools)	Higher efficiency (η) Battery power supply Lighter	$\eta \geq 30$ (%) $T \geq 0.10$ (Nm) $M \leq 1.5$ (kg) $V_t = 35$ (V)
Segment 4 (Garden/lawn tools)	Higher power heavier	$M \leq 3.0$ (kg) $T \geq 0.05$ (Nm)

<u>Given</u>

a) Market data

sales data of different product offerings in segments 1: household appliances, 2: power tools, 3: cordless tools, and 4: garden/lawn tools

b) Demand model (refer to table 3)

coefficients of the utility function, scale parameters for nests corresponding to different market segments ; Q {Price (P), Power, Efficiency (η), Mass (M)}

c) Models for Product Performance

mathematical model expressing relationship between **Power**, **Efficiency**, and **Mass** of motor in terms of motor design variables **X**:{N_c, N_s, A_{wa}, A_{wf}, r, t, I, L}; see (Simpson et al., 2001)

d) Cost models

models for different cost components (see cost model description in Appendix)

<u>Find</u>

a) Product Positioning substring (**G₁**)

the number of products, and the appropriate market niche to position each of them

b) Design options (**X**) for each of the motors in the family

values of N_c, N_s. A_{wa}, A_{wf}, r, t, I, and L

<u>Maximize</u>

a) Profit $\sum_{1=i}^{n} P_i \times Q_i\left(P_i, \mathrm{Power}_{(i)}, \eta_i, \mathbf{M}_i\right) - C(\mathbf{Q}, \mathbf{X})$

<u>Satisfy</u>

a) Design constraints

Relationships between **E** and **X,** and between different **X** , listed in [39]

Segment-specific bounds for performance attributes (**E**) and design variables (**X**) in section V

Fig. 11.10 Universal electric motor product family design optimization problem

The stator manufacturing involves *core manufacturing*, *coil winding,* and *finishing*. Equipment cost, fixturing costs, and setup costs in *core manufacturing* operations are primarily decided by motor size. The cost of *motor winding* is mostly decided by the motor winding variables (i.e., N_c, N_s, A_{wa}, A_{wf}). *Finishing* involves lacing and forming operations. The former is usually manual, and the latter is dependent on motor size variables. The most cost-intensive operations involve core manufacturing, and therefore it is considerably more expensive to manufacture motor variants with "different" sizes [i.e., different radii (r), thickness (t), and stack length (L)], than to produce motor variants with "different" motor windings [i.e., different (N_c, N_s, A_{wa}, A_{wf})].

The cost model used here is intended to reflect that; however, values used for equipment cost, fixturing and setup costs are only indicative—as reported in [5], "exact cost estimates are not necessary as long as the relative magnitudes are in order". In addition to motor components, the cost models also include descriptions for the motor casing (the cost of which is again dependent on motor size) and the motor fan, which is a function of the power output and efficiency of the motor. The cost model used in this work establishes the relationship between the design variables **X** and the total production cost C. The relationship between commonality and associated (manufacturing) cost is embedded in the cost model used here. The cost model thus penalizes "unique" fixturing and setup costs. The model assumes that motor variants with design variables falling within a certain narrow range can be manufactured with the same setup and fixtures. Therefore, for any two motor variants to share the same set of manufacturing processes (and hence minimize unique fixturing and setup costs), it is not necessary for them to have "identical" values for the corresponding design variables; the corresponding design variables for the two motor variants are only required to fall within the same range. Additional details on the cost model are included in the Appendix A.2.

11.4.1.3 Description of the Analytical Model for the Universal Motor Case Study

A mathematical model that expresses the relationship between the design variables **X**: [N_c, N_s, A_{wa}, A_{wf}, r, t, I, L] and the performance measures Power, Torque (T), Mass (M), and Efficiency (η) can be found in Chap. 4, Table 4.2. Variable bounds for the design variables and the constraints that govern the relationships between the design variables and the performance measures are as specified in Tables 4.1 and 4.2. Details on how segmentation of the universal electric motor market is expressed through additional constraints are provided in Table 11.5.

11.4.2 Description of the Optimization Problem for the Universal Motor Product Family Design

The general formulation of the product family design problem was presented in Fig. 11.6. The formulation specific to the universal electric motor product family is presented in Fig. 11.10. The most important difference from the generalized formulation in Sect. 11.3.4 is the absence of the commonality substring ($\mathbf{G}_2$) in the formulation.

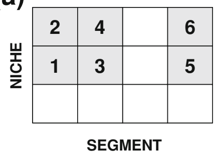
Due to the combinatorial and nonlinear nature of the formulation, the product line positioning problem within product family design is known to be a NP-hard optimization problem [4, 32]. In order to reduce computational effort, commonality is enforced through the cost model for the universal electric motor product family. Here, the cost model is expressed purely as a function of the motor design variables $\mathbf{X}$: [N_c, N_s, A_{wa}, A_{wf}, r, t, I, L] and manufacturing processes. In the cost model used here, the production volume for each motor variant i is assumed to be the same as its market demand Q_i for simplicity.

11.4.3 Results and Interpretations

The product family design formulation considered here is a NP-hard optimization problem. In each optimization iteration, a different product line positioning decision is considered, and the corresponding product family is optimized based on this decision. Ideally, $2^{3\times4} = 4{,}096$ product product lines corresponding to the (3×4) universal motor MSG have to be considered; however, in order to reduce the computational effort, some restrictions were imposed on the product line positioning string. Since products in the same market segment (nest) compete more closely with each other, each segment was allowed to have at most two products to prevent the "new" products from cannibalizing each others' market share. Also, only a maximum of six products is considered for the family. These restrictions reduce the number of total product line positioning combinations to 1,996. The problem was solved using the Optimization Toolbox in Mathworks' MATLAB® [6]

Unlike the aforementioned existing formulations that require the product variants sharing a platform to have identical values for the platform variables, the definition of platform in this work is driven by manufacturing and cost considerations. Earlier in the discussion of the case study, it was established that motor size [expressed through variables motor radius (r), motor thickness (t), and stack length (L)] has the largest effect on the manufacturing cost; motor size has not only an impact on the *core manufacturing* processes but also on *coil winding* and *finishing* operations. In the cost model used in this work (see details in Appendix A.2), motor variants that have motor design variables with similar (not necessarily identical) values share fixturing and setup costs. For example, the cost model does not distinguish between motor radii (r) that are different by less than 2 mm, thicknesses (t) that are different by less than 1 mm, and stack lengths (L) that are different by less than 5 mm. Consequently, in the following discussions, the definition of the platform is narrowed further to describe only those design variables related to motor size [i.e., motor radius (r), motor thickness (t), and stack length (L)]. The platform leveraging strategies presented here only indicate if the motor sizes of the different motor variants sharing the platform were similar enough to share manufacturing resources.

(a)

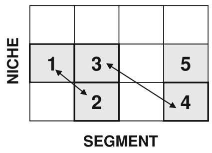


Revenue: $ 967219.6

Profit: $ 65997.16

#	Price ($)	Power (W)	η (%)	Mass (kg)	Q_j
1	30.36	450	84.9	0.93	2215
2	30.36	600	89.2	1.03	3369
3	46.31	550	88.1	0.92	3143
4	46.31	650	89.9	1.13	3870
5	54.12	750	89.1	1.53	3864
6	54.12	850	88.5	2.00	3970

(b)



Revenue: $746143.7

Profit: $ 301629.3

#	Price ($)	Power (W)	η (%)	Mass (kg)	Q_j
1	37.43	550	87.0	0.94	2379
2	47.64	550	87.4	0.91	2662
3	54.20	626	88.2	1.03	3265
4	61.79	625	88.1	1.03	2834
5	68.78	750	86.1	1.57	2591

Fig. 11.11 Comparisons of product line positioning decisions from revenue and profit-based optimization. **a** Best case scenario obtained for revenue optimization (DESIGN:REV_BEST). **b** Best case scenario obtained for profit optimization (DESIGN: PROFIT_BEST)

In order to study the impact of commonality on the different product variants in the universal electric motor family, two variations of the formulation given in Fig. 11.10 are solved. First, cost considerations are excluded, and the problem was formulated as a revenue-based optimization problem. The results obtained were then compared to those obtained using the original profit-based optimization formulation in Fig. 11.10. Figure 11.11 illustrates comparisons between the product line positioning decisions and platform leveraging strategies obtained using the revenue-based and profit-based product family design optimization, respectively. Figure 11.12 presents similar comparisons with respect to the design (i.e., the values of design variables **X**) of the different motor variants in the family. The results presented in Fig. 11.11a and b should be seen in conjunction with the product offerings displayed in Fig. 11.8. It is observed that the product line resulting from revenue-based formulation has six products while the profit-based formulation yields only five products for the optimal product line. Revenue-based optimization positions all of the products in the medium and high-power tiers in all the segments, avoiding the low-power/low-price niche altogether. These are reasonable results since cost considerations are not included, and higher prices translate to higher revenues. Also, as shown in Fig. 11.11a in each segment, the products in the high price and medium price tiers have the same price, which is

(a)

	N_c	N_s	$A_{wa}(mm^2)$	A_{wf} (mm^2)	r (cm)	t (mm)	I (Ampere)	L (cm)
1	125.67	100.00	0.37	0.37	4.00	10.00	5.50	2.00
2	118.09	100.00	0.53	0.53	4.00	5.51	5.85	2.00
3	100.00	100.00	0.65	0.65	4.07	1.43	6.29	2.00
4	100.00	100.00	0.72	0.72	4.39	1.21	6.80	2.00
5	100.00	100.00	0.94	0.94	5.36	0.86	8.36	2.00
6	100.00	100.00	1.00	1.00	5.71	0.79	8.90	2.00

(b)

	N_c	N_s	$A_{wa}(mm^2)$	A_{wf} (mm^2)	r (cm)	t (mm)	I (Ampere)	L (cm)
1	125.79	100.00	0.36	0.38	4.00	10.00	5.49	2.00
2	100.00	100.00	0.35	0.35	4.00	10.00	5.47	2.00
3	100.00	100.00	0.52	0.53	4.00	1.50	6.17	2.00
4	100.00	100.00	0.46	0.55	4.00	1.49	6.17	2.00
5	100.00	100.00	0.56	0.65	5.00	3.49	7.58	2.00

Fig. 11.12 Comparisons of motor designs obtained using revenue- and profit-based optimization. **a** Design for best case scenario obtained for revenue-based optimization (DESIGN: REV_BEST). **b** Design for best case scenario obtained for profit-based optimization (DESIGN: PROFIT_BEST)

lower than that of comparable products in the existing market. This indicates that the higher power motors are being sold at below their actual cost,[2] which is an expected result since this formulation does not include costs, and selling higher power motors at prices below their cost would increase revenues by capturing higher market share.

Apart from the difference in the number of products, there are several important differences between the product lines in Fig. 11.11a and b. When the (quantity-wise) market shares of the two product lines are compared, the total market share (computed by adding the demand Q_j for each of the product variants in the family) of the product family from the revenue-based formulation is about 50% of the total market (i.e., 40,000 motors) whereas the market share of the product family from the profit-based formulation is only about 30% of the total market. However, the revenues corresponding to the two product lines are comparable, even considering that the profit-based line has one fewer product. Also motor variants 1, 3, and 5 in

[2] It is reasonable to assume that the motor in the high-power niche is likely to cost more to produce than the motor in the medium-power niche. It can also be seen from Fig. 11.11a that in each segment, the higher power motor weighs more than the medium-power motor which suggests that more material (e.g., thicker windings) was used to produce the motor with the higher power rating.

the two formulations can be compared directly since they are positioned in identical (performance tier, market segment) pairs in both the formulations. It can be observed that motor variants 1, 3, and 5 in the profit-based formulation are more expensive than their revenue-based formulation counterparts. These are indications that the products in the revenue-based formulation are under-priced. Significantly, the profit-based formulation does not position any product in the high-price/high-power tier of any of the market segments. This is most likely due to commonality considerations; higher power motors tend to be larger (e.g., higher values for motor radius) and require more material (e.g., thicker and longer motor windings), making it more challenging to make them similar (i.e., common) to motors with lower power rating without sacrificing efficiency and adding mass.

The platform leveraging strategy is indicated in Fig. 11.11b by the line segments connecting product variants that share a platform (i.e., motor variants with similar but not necessarily identical values for the design variables related to motor size). The product designs listed in Fig. 11.12 are used to arrive at the platform leveraging strategies illustrated in Fig. 11.11. For example in Fig. 11.12b, Motors 1 and 2 have identical values for radius (r) and stack length (L), and very similar values for motor thickness (t). Therefore the cells corresponding to Motors 1 and 2 are joined by a line segment.

For the profit-based optimization, Motors 1 and 2 share one manufacturing platform and Motors 3 and 4 share another manufacturing platform (since they have similar values for the motor size variables) while Motor 5 incurs unique fixturing and setup costs. Since cost considerations were not included in the revenue-based product family during the optimization, there is no platform leveraging between the products. Interestingly, the *cordless power tools* segment (Segment 3) is avoided altogether, by solutions from both formulations. In the case of the profit-based formulation, this is because producing a motor for the *cordless power tools* segment would make it difficult to respect commonality considerations. Motors for the *cordless power tools* segment need to operate on a battery-operated power supply (i.e., $V_t = 36$ V) and hence need to carry larger current to achieve the rated output power. While such motors could be produced within the same design considerations by using thicker windings, etc., it would be very hard to make them light enough to meet the weight constraint for that segment and still be of a similar size to the other motors in the family. In the case of the revenue-based formulation, the absence of any products in the *cordless power tools* segment is most likely due to the fact that the number of motors in the line is restricted to six, and the other segments are more profitable. Finally, financial criteria need to be used to choose between the two product lines. The revenue-based formulation (see Fig. 11.11a) results in higher revenues than the profit-based formulation (see Fig. 11.11b). However, when the manufacturing cost is calculated for the motors chosen by revenue-based formulation, the profit earned by the revenue-based formulation is only roughly 20% of the profit earned by the profit-based formulation. This is primarily due to the fact that the products in the profit-based formulations are platform-based and are therefore cheaper to produce; hence, the product family design from the profit-based formulation needs to be chosen. The view that manufacturing and market considerations are central to the product family design formulation is well supported in practice. For example, Black and Decker's decision to choose stack length as the *scaling variable* [39] in their motor family is not optimal when considering motor performance in isolation. The decision is much sounder when manufacturing considerations are included; it is easier to manufacture different motor variants that vary only in stack length since only the number of laminations in the stack needs to be varied.

11.5 Summary

Today's marketplace is a "buyers' market", and many manufacturers are faced with an ever-increasing demand for differentiating their products from those of competitors. More companies are adopting platform-based product development and product family design in order to increase the variety of their product offerings while keeping costs low. Designing product families requires not only engineering knowledge for platform decisions, but also an understanding of the impact that the platform will have on manufacturing and marketing. Relatively few of the existing optimization-based approaches to product family design include a demand model in the formulation, and those that do, do not provide a realistic examination of how different product offerings from a firm compete with its other products and with competitors' products in the same market segment.

A novel MPFD methodology based on the principles of Decision-Based Design is presented in this chapter to model product platform and product line positioning considerations simultaneously. It is shown how the segmentation in the market can be modeled using the NL technique which demonstrates the dissimilar impacts of competition on the market shares of products in different market segments. One of the main features of the methodology is the use of MSGs not just as visual tools as in current practice, but also as part of the product family optimization formulation. This is accomplished by mathematically expressing the product line positioning decisions and the platform leveraging strategies in the MSG. This allows us to determine the optimal product line positioning decision and corresponding platform leveraging strategy simultaneously. The design of a family of universal electric motors is used to demonstrate the MPFD methodology. Data for a hypothetical market is created, and a cost model that captures the relationships between motor design variables and shared manufacturing processes is developed. Solutions for (i) revenue-based optimization (which includes only the product line positioning problem) and (ii) profit-based optimization (which includes both the product line positioning problem and the product platform problem) are compared. The results show that there is a strong need to consider performance, as well as cost and market considerations simultaneously in order to make rational and economic decisions.

Appendix A: Supporting Material to the Universal Motor Product Family

A.1. Product Offerings in the Hypothetical Universal Motor Market

Nine products compete for market share in Segment 1; Segments, 2 and 3 have five products each, and Segment 4 has four products. Each product is also represented by a 3 bit alphanumeric code in the table. Also listed are values of the performance attributes, i.e., Price P, Power (P:$\mathbf{E}_1$), Efficiency (η:$\mathbf{E}_2$), and Mass (M:$\mathbf{E}_3$), for each of the 23 products in the market. Customers are assumed to be appliance-manufacturers. The first bit is a letter and corresponds to the supplier; this is followed by the segment index and product index numeric bits. For example, A12 represents a motor by company A in Segment 1. It also tells us that this is the second product introduced by A in that segment (Table A.1).

A.2. Description of the Cost model Used for the Universal Motor Product Family

The total product cost C is divided into total material cost (C_{mat}), labor cost (C_{labor}), total fixturing and setup costs (C_{fxtr}), and investment costs (C_{fixed}).

$$C = C_{\text{mat}} + C_{\text{labor}} + C_{\text{fxtr}} + C_{\text{fixed}} \tag{A.1}$$

In the cost expressions presented below, the subscript 'i' is used to represent the motor variant 'i', and the total number of motor variants in the family is assumed to be 'n'. The production volume for motor variant 'i' is assumed to be Q_i, the market demand for motor variant 'i'. Also, it should be noted that two additional components, a steel casing and a cooling fan, are included in the cost calculations for the motor assembly. The expressions for material cost are as below.

$$\begin{aligned} C_{\text{mat}} &= \sum_{i=1}^{n} C_{\text{mat}(i)} \\ C_{\text{mat}(i)} &= C_{\text{steel\_parts}(i)} + C_{\text{fan}(i)} + C_{\text{windings}(i)} \end{aligned} \tag{A.2}$$

In the above expression, $C_{\text{steel\_parts}(i)}$ represents the sum of the material costs incurred due to the steel parts in the motor (armature laminations, stator laminations, and the casing); $C_{\text{fan}(i)}$ represents the cost of the fan used in the motor variant 'i', and $C_{\text{windings}(i)}$ represents the material costs incurred due to the stator and armature windings. The expression for cost of steel parts $C_{\text{steel\_parts}(i)}$ is included below. In the following expressions, $M_{\text{component}}$ represents the mass of the component under consideration.

Table A.1 Product offerings in the hypothetical universal motor market

Segment	Sl no	Product	Price ($)	Power (W)	η	Mass (kg)
1	1	A11	60	600	47	1.42
1	2	C11	39	550	51	1.14
1	3	C12	33	500	53	0.97
1	4	B11	30	480	56	0.91
1	5	B12	29	450	57	0.82
1	6	B13	18	420	63	0.79
1	7	C13	17	400	66	0.7
1	8	A12	15	370	64	0.65
1	9	B14	9	300	71	0.56
2	10	B21	66	640	48	1.6
2	11	C21	61	600	52	1.36
2	12	C22	57	570	55	1.26
2	13	A21	51	520	58	1.23
2	14	B22	34	470	61	0.91
3	15	A31	70	450	66	0.65
3	16	C31	65	420	68	0.61
3	17	C32	45	360	70	0.54
3	18	C33	33	300	72	0.5
3	19	B31	25	180	76	0.46
4	20	B41	91	840	37	1.61
4	21	C41	84	760	42	1.45
4	22	C42	62	710	45	1.32
4	23	B42	60	600	47	1.42

$$C_{\text{steel\_parts}(i)} = \left(M_{\text{casing}(i)} + M_{\text{stator}(i)} + M_{\text{armature}(i)}\right) \times Q_i \times C_{\text{steel}} \tag{A.3}$$

where the mass of the casing is dependent on the motor radius.

$$M_{\text{casing}(i)} = \begin{cases} \left(\pi(25^2 - (25-2)^2) \times L_{\max} + 2 \times \pi \times 25^2 \times 2\right) \times 10^{-6} \times \rho_{\text{steel}} & \text{if } 0.00 < r_i \leq 0.02 \text{ m} \\ \left(\pi(45^2 - (45-2)^2) \times L_{\max} + 2 \times \pi \times 45^2 \times 2\right) \times 10^{-6} \times \rho_{\text{steel}} & \text{if } 0.02 < r_i \leq 0.04 \text{ m} \\ \left(\pi(65^2 - (65-2)^2) \times L_{\max} + 2 \times \pi \times 65^2 \times 2\right) \times 10^{-6} \times \rho_{\text{steel}} & \text{if } 0.04 < r_i \leq 0.06 \text{ m} \\ \left(\pi(85^2 - (85-2)^2) \times L_{\max} + 2 \times \pi \times 85^2 \times 2\right) \times 10^{-6} \times \rho_{\text{steel}} & \text{if } 0.06 < r_i \leq 0.08 \text{ m} \\ \left(\pi(105^2 - (105-2)^2) \times 10^{-6} \times L_{\max} + 2 \times \pi \times 105^2 \times 2\right) \times 10^{-6} \times \rho_{\text{steel}} & \text{if } 0.08 < r_i \leq 0.10 \text{ m} \end{cases}$$

where ρ_{steel} = 7800 kg/m^3; $L_{\max}$ = 0.10 m.

$$M_{\text{stator}(i)} = \pi \cdot \left(r_{\text{i}}^2 - (r_i - t_i)^2\right) \cdot L_i \cdot \rho_{\text{steel}} \text{ and } M_{\text{armature}(i)} = \pi \cdot \left(r_{\text{i}}^2 - t_i - l_{\text{gap}}\right)^2 \cdot L_i \cdot \rho_{\text{steel}}$$

Table A.2 Nomenclature of terms used for fixturing and setup costs (*note* values used for fixturing and set up cost here are hypothetical)

Term	Definition
C_r	Cost of fixturing/setup cost per unique motor radius variant; ($)
n_r	Number of motor variants with different motor radii. Motor radii (r_i) are considered different if they differ by more than 2 mm
C_t	Cost of fixturing/setup cost per unique motor thickness variant ($)
n_t	Number of motor variants with different motor thickness. Motor thicknesses are considered different if they differ by more than 1 mm
C_L	Cost of fixturing/setup cost per unique motor stack length variant; ($)
n_L	Number of motor variants with different stack lengths. Motor stack lengths are considered different if they differ by more than 5 mm
C_{wa}	Cost of fixturing/setup cost per unique armature winding variant ($)
n_{wa}	Number of motor variants with different cross-sectional area for armature windings. Armature windings are considered different if the cross-sectional areas differ by more than 0.1 mm^2
C_{wf}	Cost of fixturing/setup cost per unique stator winding variant. $2.5 \times 10^3 \times n_{\text{wf}}$ ($)
n_{wf}	Number of motor variants with different cross-sectional area for stator windings. Stator windings are considered different if the cross-sectional areas differ by more than 0.1 mm^2

The expression for fan cost for motor 'i' is expressed as

$$C_{\text{fan}(i)} = P_{\text{fan}(i)} \times C_{\text{fanpower}} \times Q_i \tag{A.4}$$

where

$$P_{\text{fa}(i)} = 0.5 \times (1 - \eta) \times P_{\text{input}(i)}$$
$$C_{\text{fanpower}} = 0.1\ ^{\$}\!/_{\text{W}}$$

The cost of the windings depends on the diameter of the windings used. Higher diameter (or lower gauge) wires are necessary in high-power applications and tend to have better and more expensive insulation since high-power motors also typically mean higher heat losses. Here, it is assumed that the motor winding wire is bought from suppliers as opposed to being drawn in-house. The rate for motor winding wire ($C_{\text{rate\_wndg}(i)}$) is based on those used by Bulk Wire, a division of Powerwerks, Inc. The cost of windings is split into the cost of stator ($C_{\text{stat\_wndg}}$) and rotor windings ($C_{\text{rot\_wndg}}$) and is expressed as

$$\mathrm{C_{windings(i)}} = \left(\mathrm{C_{stat\_wndg(i)}} + \mathrm{C_{rot\_wndg(i)}}\right) \times \mathrm{Q_i} \tag{A.5}$$

where

$$C_{\text{stat\_wndg}(i)} = (2 \cdot L_i + 4(r_i - t_i)) \cdot 2 \cdot N_{s(i)} \times A_{\text{wf}(i)} \times \rho_{\text{copper}} \times C_{\text{rate\_wndg}(i)}$$
$$C_{\text{rot\_wndg}(i)} = \left(2 \cdot L_i + 4 \cdot \left(r_i - t_i - \mathrm{l_{gap}}\right)\right) \cdot N_{c(i)} \times A_{\text{wa}(i)} \times \rho_{\text{copper}} \times C_{\text{rate\_wndg}(i)}$$

and

$$C_{\text{rate\_wndg}(i)} = \begin{cases} 36.01\ (\$/\text{kg}) & \text{if}\ \ 0.00 < A_{\text{wf}(i)}, A_{\text{wa}(i)} \leq 0.128\ \text{mm}^2 \\ 34.61\ (\$/\text{kg}) & \text{if}\ \ 0.128 < A_{\text{wf}(i)}, A_{\text{wa}(i)} \leq 0.205\ \text{mm}^2 \\ 32.89\ (\$/\text{kg}) & \text{if}\ \ 0.205 < A_{\text{wf}(i)}, A_{\text{wa}(i)} \leq 0.324\ \text{mm}^2 \\ 32.01\ (\$/\text{kg}) & \text{if}\ \ 0.324 < A_{\text{wf}(i)}, A_{\text{wa}(i)} \leq 0.519\ \text{mm}^2 \\ 31.12\ (\$/\text{kg}) & \text{if}\ \ 0.519 < A_{\text{wf}(i)}, A_{\text{wa}(i)} \leq 1\ \text{mm}^2 \end{cases}$$

While the cost expressions so far listed here generally imply that higher performance motors are also more expensive, they do not capture the relationships that reward commonality between the product variants in the universal motor product family. The fixturing and setup cost C_{fxtr} is used for this purpose and is expressed as shown below. The definitions of the terms used in the expression for C_{fxtr} are provided in Table A.2.

$$C_{\text{fxtr}} = C_r \times n_r + C_t \times n_t + C_t \times n_t + C_{\text{wa}} \times n_{\text{wa}} + C_{\text{wf}} \times n_{\text{wf}} \tag{A.6}$$

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Chapter 12
Multilevel Optimization for Decision-Based Design

Nomenclature

$\mathbf{A}$	Customer-desired attributes
$\mathbf{A}_{\mathrm{eng}}$	Customer-desired attributes related to engineering performance
$\mathbf{A}_{\mathrm{ent}}$	Customer-desired attributes related to enterprise product planning
AIO	All-in-one
ATC	Analytical target cascading
ATS	Analytical target setting
C	Total product cost
DBD	Decision-based design
DCA	Discrete choice analysis
$\mathbf{E}$	Engineering design attributes
$E(U)$	Expected value of enterprise utility
$\mathbf{E}^*$	Utopia target of $\mathbf{E}$
$\mathbf{E}^D$	Achievable product performance
MDO	Multi-disciplinary design optimization
MNL	Multinomial logit
P	Product price
Q	Product demand
RP	Revealed preference
$\mathbf{S}$	Customer demographic attributes
SP	Stated preference
$\mathbf{T}^U$	Targets of $\mathbf{E}$ set by the enterprise product planning problem
U	Enterprise utility
V	Selection criterion used by the enterprise (e.g., profit, revenues, etc.)
W_{in}	Deterministic part of the utility of choosing alternative i by customer n
$\mathbf{X}$	Design options
$\mathbf{X}_{\mathrm{d}}$	Engineering design options
$\mathbf{X}_{\mathrm{ent}}$	Enterprise planning options
$\mathbf{Y}$	Exogenous variables (represent sources of uncertainty in market)

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DOI: 10.1007/978-1-4471-4036-8_12,

t Time interval for which demand/market share is to be predicted
u_{in} True utility of choosing alternative i by customer n
ε_{in} Random unobservable part of the utility of choosing alternative i by customer n

In the previous chapters, decision-based design (DBD) has been used to model the interaction between enterprise product planning and engineering product development in a single optimization problem and solved using an all-in-one (AIO) approach. Such an approach may not be practical in a typical industry design environment, due to the organizational and computational complexities involved. In this chapter, we present a hierarchical multilevel optimization approach, based on the principles of DBD and the concept of analytical target cascading (ATC), to integrate enterprise-level product planning with engineering-level product development. A search algorithm that coordinates the multilevel optimization solution process is presented. Such an algorithm systematically explores the engineering attribute space that may consist of a number of disconnected feasible domains due to engineering constraints. A case study that involves the design of an automotive suspension system is used to illustrate the effectiveness of the approach.

12.1 Introduction to Multidisciplinary Design Optimization and Multilevel Optimization

Enterprise-driven design approaches like DBD consider product development efforts in the context of other enterprise goals (e.g., economic considerations like profit, revenues, market share). In contrast, many common engineering design methods focus only on aspects of the design process as their names suggest, i.e., design for cost, design for manufacture, etc., therefore leading to suboptimal results when considering the total economic benefit. The use of enterprise-driven approaches is facilitated by use of models for product-demand, as explained in Chaps. 1–4. DBD is a collaborative design approach that recognizes the substantial role that decisions play in design and in other engineering activities. It advocates a single criterion optimization approach to design while considering the interests of both the producer and the customer (e.g., profit, market share) under the presence of uncertainty, and the risk-attitude of the producer. In this chapter, a multilevel optimization approach, based on the principles of DBD and the concept of ATC, to integrate enterprise-level product planning with engineering-level product development, is presented. *The argument in favor of a decomposed approach to DBD is that a decomposed approach is not only better suited for handling computational complexities associated with the design of large systems, but it also reflects the hierarchical organizational structure and decision making in most manufacturing firms*. Before introducing the decomposed DBD approach, a short review of the multidisciplinary design optimization (MDO) literature and the multilevel-optimization formulation is first provided.

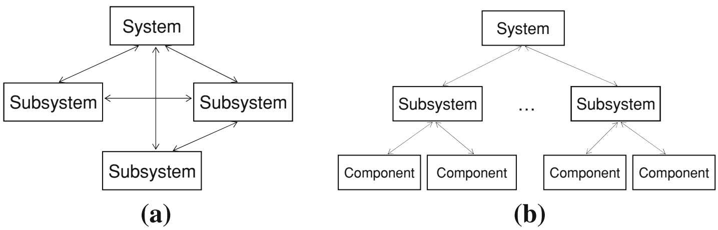


Fig. 12.1 Decomposition of a complex system. **a** Non-hierarchical decomposition, **b** hierarchical decomposition

Designing a large-scale artifact typically involves multidisciplinary efforts in marketing, product design, and production. Solving the optimization problem using an all-in-one approach is often practically infeasible in such situations due to computational and organizational complexities. Methods that have been proposed for decomposing the full optimization problem into a set of smaller subproblems based on discipline are referred to as MDO approaches. Optimization by decomposition, while alleviating the problem of having to deal with a large number of design variables and constraints at the same time, is made necessary by a number of factors. The decomposed approach helps enable simultaneous multidisciplinary optimization wherever possible and also addresses organizational needs to distribute the work over several groups of engineers/analysts. It should be noted that the decomposition of the system into manageable subsystems could be either hierarchical or non-hierarchical (Fig. 12.1), and a brief discussion on each type follows.

12.1.1 Non-Hierarchical Decomposition

Historical evolution of engineering disciplines and the complexity of the MDO problem suggest that disciplinary autonomy is a desirable goal in formulating and solving MDO problems. In MDO, several design architectures have been developed to support collaborative multidisciplinary design using distributed design optimization, e.g., Concurrent Subspace Optimization (CSSO) [18], Bi-Level Integrated System Synthesis (BLISS) [14, 15], Collaborative Optimization (CO) [3, 4], and Analytical Target Cascading (ATC) [9, 10, 12]. A comprehensive review of the MDO architectures is provided in Kroo [11]. It should be noted that the choice of the MDO formulation to a design problem largely depends on whether the problem follows the hierarchical or non-hierarchical characteristics of decision flow. In most of the MDO approaches listed above, a complex engineering problem is non-hierarchically decomposed along disciplinary or other user-specified boundaries into a number of subproblems. Then they are brought into multidisciplinary agreement by a system-level coordination process. The non-hierarchical MDO infrastructure is better suited to capture the interrelationships between multiple engineering disciplines in

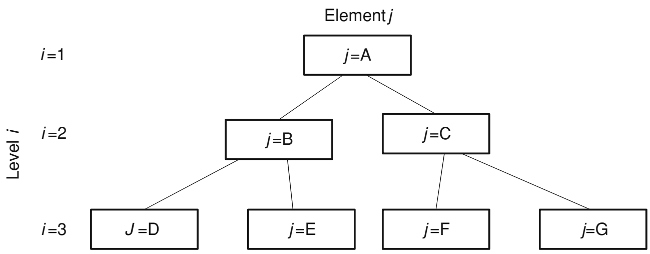


Fig. 12.2 Example of a hierarchically partitioned optimal design problem

engineering-level product development; however, a hierarchical approach such as the ATC is more appropriate in an enterprise-driven product design scenario where the enterprise decision making is often done at a higher level to set up targets for engineering product development. Compared to the bi-level optimization formulations for engineering level product development, the multilevel hierarchical modeling facilitated by the ATC approach better represents a multi-layered organizational decision making infrastructure. A brief introduction to ATC is provided below; the reader is directed to Kim et al. [9] for a more detailed exposition of the method.

12.1.2 Hierarchical Decomposition

The ATC approach decomposes the original engineering problem hierarchically at multiple levels, and operates by formulating and solving a minimum deviation optimization problem (to meet targets) for each element in the hierarchy. Target cascading is a system design approach enabling top level design targets to be cascaded down to lower levels of the modeling hierarchy. A key difference between ATC and most of the MDO formulations, including CO [3] is that, with ATC, the original problem is decomposed hierarchically at multiple levels, while the interconnections between the multiple subsystems at each level are considered and coordinated at one level above.

The ATC problem Pij associated with the jth element at the ith level of the hierarchy (see Fig. 12.2) is formulated in Eq. (12.1). Responses $\hat{\mathbf{R}}_{ij} = \left[\tilde{\mathbf{R}}_{ij}, \mathbf{R}_{ij}\right]^T = \mathbf{r}_{ij}\left(\mathbf{R}_{(i+1)k_1}, \ldots, \mathbf{R}_{(i+1)k_{c_{ij}}}, \mathbf{x}_{ij}, \mathbf{y}_{ij}\right)$ are computed by means of analysis and/or simulation models. The vector of all optimization variables is $\hat{\mathbf{x}} = \left[\mathbf{x}_{ij}, \mathbf{y}_{ij}, \mathbf{y}_{(i+1)k_1}, \ldots, \mathbf{y}_{(i+1)k_{c_{ij}}}, \mathbf{R}_{(i+1)k_1}, \ldots, \mathbf{y}_{(i+1)k_{c_{ij}}}, \varepsilon_{ij}^{\mathbf{R}}, \varepsilon_{ij}^{\mathbf{y}}\right]^T$ and $\mathbf{x}_{ij}$ is the vector of local design variables. $\tilde{\mathbf{R}}_{ij}$ corresponds to responses linked to local targets and $\mathbf{R}_{ij}$ corresponds to responses linked to cascaded targets. $\varepsilon_{ij}^{\mathbf{R}}$ and $\varepsilon_{ij}^{\mathbf{y}}$ are the tolerance variables for ensuring consistency of suboptimization problems. Superscripts $(\cdot)^U$

and $(\cdot)^L$ denote values passed down and up from the upper and lower levels, respectively. The vector $\mathbf{T}$ denotes local targets and $\mathbf{g}_{ij}$ and $\mathbf{h}_{ij}$ are local design constraints. Weights $\mathbf{w}$ are assigned to the deviation terms in the objective and the convergence behavior of the ATC process can be altered by adjusting the weights.

$$
\begin{aligned}
P_{ij} : \min_{x_{ij}} \; & \mathbf{w}_{ij}^{\tilde{\mathbf{R}}} \left\| \tilde{\mathbf{R}}_{ij} - \mathbf{T}_{ij} \right\| + \mathbf{w}_{ij}^{\mathbf{R}} \left\| \mathbf{R}_{ij} - \mathbf{R}_{ij}^{U} \right\| + \mathbf{w}_{ij}^{\mathbf{y}} \left\| \mathbf{y}_{ij} - \mathbf{y}_{ij}^{U} \right\| + \varepsilon_{ij}^{\mathbf{R}} + \varepsilon_{ij}^{\mathbf{y}} \\
& \text{subject to} \\
& \sum_{k \in C_{ij}} \left\| \mathbf{R}_{(i+1)k} - \mathbf{R}_{(i+1)k}^{L} \right\| \leq \varepsilon_{ij}^{\mathbf{R}} \\
& \sum_{k \in C_{ij}} \left\| \mathbf{y}_{(i+1)k} - \mathbf{y}_{(i+1)k}^{L} \right\| \leq \varepsilon_{ij}^{\mathbf{y}} \\
& \mathbf{g}_{ij}(\hat{\mathbf{R}}_{ij}, \mathbf{x}_{ij}, \mathbf{y}_{ij}) \leq \mathbf{0} \\
& h_{ij}(\hat{\mathbf{R}}_{ij}, \mathbf{x}_{ij}, \mathbf{y}_{ij}) = \mathbf{0}
\end{aligned}
\tag{12.1}
$$

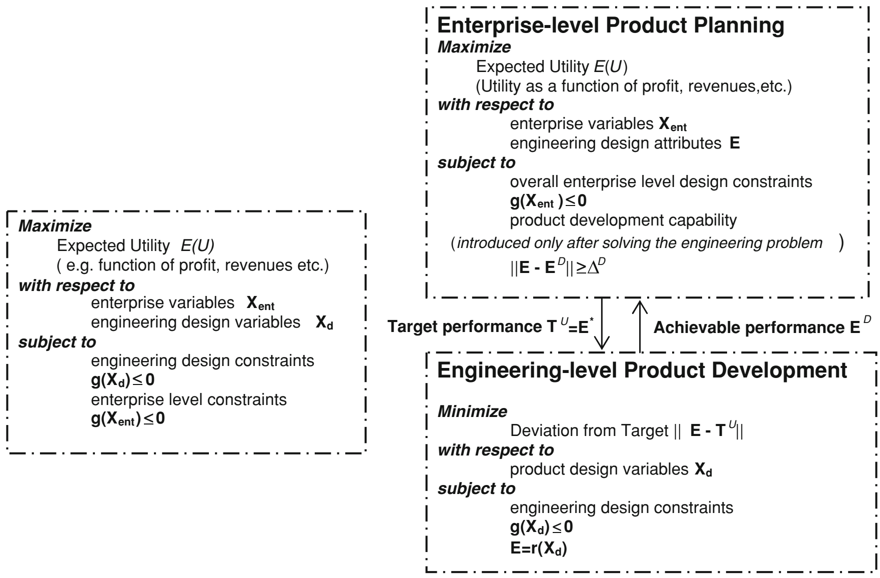
Here, a multilevel optimization approach based on the principles of DBD is proposed. The enterprise-level product planning and engineering-level product development problems are solved independently. A Target Exploration algorithm, first proposed in Kim et al. [8] is used to co-ordinate the solution and the product development problem is itself solved using ATC [9, 10, 12]. Further details are provided below.

12.2 A Multilevel Optimization Approach to Decision-Based Design

The existing implementation of the profit-driven DBD approach presented in the earlier chapters seeks to integrate *enterprise product planning* and *engineering product development* by using an AIO approach and solving as a single optimization problem. In a typical product design scenario, teams designing components get their performance targets (e.g., weight, size) from subsystem teams who in turn get their targets from system teams. Also, a typical design problem for a large artifact would involve hundreds of variables and constraints. An AIO approach is not advisable in such a design environment because it would not only reflect the design situation inaccurately but make the optimization problem overwhelmingly difficult.

12.2.1 Multi-Level Optimization Formulation to DBD

Figure 12.3 illustrates the difference between the AIO approach and the multilevel optimization formulation to DBD. The AIO approach in Fig. 12.3a treats the problem of maximizing the expected value of enterprise-level utility $E(U)$ as a



(a) All-In-One approach **(b)** Hierarchical approach

Fig. 12.3 Comparison between AIO and hierarchical approach to DBD

single optimization problem, where the decisions on product planning and product development are made simultaneously. Figure 12.3b illustrates the proposed decomposed multilevel framework, reflecting interaction between enterprise-level product planning and engineering product development. Following the "target cascading" paradigm [7, 9, 10, 12] for hierarchical decision making in industrial settings, engineering product development is viewed as a process for meeting the targets set from the enterprise level.

Using a multilevel optimization formulation, at the upper level, the enterprise-level product planning problem maximizes the expected utility $E(U)$ with respect to the engineering design attributes $\mathbf{E}$ and the enterprise variables $\mathbf{X}_{\mathrm{ent}}$. Decisions made on the optimal levels of engineering design attributes $\mathbf{E}$, represented as $\mathbf{E}^*$, are then used as targets or $\mathbf{T}^U$, passed to the lower level engineering product development process. The objective of the lower level engineering product development is to minimize the deviation between the performance target $\mathbf{T}^U$ and the achievable product performance response $\mathbf{E}$ while satisfying the engineering feasibility constraints $\mathbf{g}$, with respect to engineering design options $\mathbf{X}_{\mathrm{d}}$. Restrictions on cost can be considered either as constraints or targets in engineering-level product development. The equation $\mathbf{E} = \mathbf{r}(\mathbf{X}_{\mathrm{d}})$ stands for the engineering analysis models that capture the relationship between engineering design attributes and design options. The achievable product performance $\mathbf{E}^D$ is then transferred to the enterprise-level problem.

It should be noted that the optimization problem at the engineering development level can be further decomposed and solved using multilevel optimization. Based on the nature of decomposition, either non-hierarchical or hierarchical, different multilevel optimization (MDO) formulations can be used. The ATC approach decomposes the original engineering problem hierarchically at multiple levels, and operates by formulating and solving a minimum deviation optimization problem (to meet targets) for each element in the hierarchy. As shown in Fig. 12.3, the proposed approach models the enterprise-level problem and the engineering-level problem as two separate problems in a multilevel optimization formulation. The enterprise product planning sets the targets for the engineering product development problem corresponding to the maximum utility. Under a multilevel design framework, an ideal product development scenario is when the targets corresponding to the optimal enterprise utility would lead to an engineering design matching the targets perfectly. In most engineering design cases, it is uncommon to meet the utopia target perfectly due to the tradeoff nature of multiple attribute target values or physical feasibility (i.e., no feasible design is available to meet the targets perfectly). If the engineering feasible domain is disconnected in the space of performance attributes (i.e., multiple, discrete feasible designs are available), the task becomes more challenging.

12.2.2 Target Exploration Algorithm

Disconnected feasible performance domains often occur in the design of complex systems where multiple engineering disciplines are involved and each discipline seeks distinctly different design alternatives in downstream engineering development. For example, the vehicle suspension design case study illustrates a case where a vehicle manufacturer attempts to maximize the enterprise utility based on two disconnected feasible target performance domains imposed by suppliers of suspension components. In such cases where the feasible domain is disconnected, the engineering design with the minimum deviation from the attribute targets (i.e., the design which is a converged solution from the multilevel optimization) may not correspond to the maximum possible utility value and a new set of targets for the engineering problem need to be assigned. To explore this disconnected feasible target space, there is a need for a search algorithm that can systematically explore attribute targets to lead the engineering product design process to finding a feasible and optimal design in the enterprise context. Here, a search algorithm, first proposed in Shi et al. [13], is used to guide the enterprise-level decision maker to assign alternative targets so that the enterprise maximizes net revenue and the suppliers achieve targets as closely as possible. The adjustment of targets set at the enterprise level may shift the enterprise utility value away from its original utopia value. In return, however, a better (i.e., corresponding to higher enterprise-level utility) feasible design can be obtained satisfying the engineering constraints that may exist in other disconnected feasible domain. While the details on the

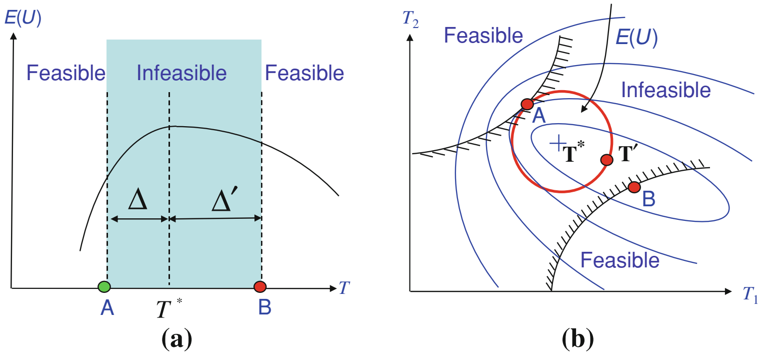


Fig. 12.4 Utilities with engineering feasible domain imposed. Points *A* and *B* are both engineering local optima with the minimum deviation from the target. The deviation for the point *A* is smaller, but the corresponding utility is not higher than that of point *B* (Kim et al. 2005). **a** One-dimensional case, **b** two-dimensional case

algorithm are available in Shi et al. [13], some of the important features are presented here. Figure 12.4 illustrates one-dimensional and two-dimensional cases where the (feasible) minimum deviation from the utopia target does not match the best available utility. Points *A* and *B* are both engineering local optima with the minimum deviation from the target in each of the feasible space. The deviation for the point *A* is smaller, but the corresponding utility is not higher than that of point *B*. Note that these plots represent the engineering target (attributes **E**) domain instead of the design option space. The original enterprise level utility optimization problem is:

$$\begin{aligned} P^0_{\mathrm{ent}}: \quad & \max_{\mathbf{X}_{\mathbf{ent}}} E[U(\mathbf{T}, \mathbf{X}_{\mathrm{ent}})] \\ s.t. \quad & g(\mathbf{X}_{\mathrm{ent}}) \le 0 \end{aligned} \tag{12.2}$$

where the objective is to maximize the expected utility $E(U)$, a function of engineering design attributes **E** and enterprise level variables $\mathbf{X}_{\mathrm{ent}}$. The optimal value of engineering design attributes $\mathbf{E}^*$ obtained from model in Eq. (12.2) are assigned as the utopia targets $\mathbf{T}^*$ for engineering development. The engineering problem then finds an optimal response to the utopia target with the minimum deviations (see formulation in Fig. 12.4b).

To enable the move from one feasible domain to another, a circular inequality constraint (Fig. 12.4b) is imposed in the enterprise problem based on the achievable engineering response E^D, and the enterprise DBD problem is re-solved, as shown in Eq. (12.3). The physical meaning of the additional constraint is that it imposes a minimum geometric distance from the utopia target so that the enterprise problem is forced to find an alternative target for the engineering problem. The idea of adding the constraint is to explore targets at new domains that may potentially lead to feasible designs with a better value for expected utility. The points inside the circular constraint are ruled out because they are infeasible (otherwise they should be identified as solution in the previous iteration as their deviations from the utopia target is less). Note that, for the discussion on the solution of the enterprise level product planning problem, engineering design attributes **E** are referred to as targets **T**. The modified enterprise problem P'_{ent} based on the engineering design E^D generates a new target $\mathbf{T}'$ for the engineering problem. Based on the new target, the engineering problem finds point B as the optimum with the minimum deviation from the new target $\mathbf{T}'$. Point B is farther from the original utopia target; however, the corresponding utility is higher than that of point A. As a result, point B is selected as the optimal engineering design that has a better utility value.

$$\begin{array}{ll} P'_{\text{ent}}: & \underset{\mathbf{T},\mathbf{X}_{\text{ent}}}{\text{Max}}\ E[U(\mathbf{T},\mathbf{X}_{\text{ent}})] \\ s.t. & \\ C_{\text{aux}}: & ||\mathbf{T}-\mathbf{E}^D|| \geq \left|\frac{\alpha}{\phi}\right|\Delta \text{ where } \Delta = ||\mathbf{T}^* - \mathbf{E}^D|| \end{array} \tag{12.3}$$

To avoid returning to the previous solution, additional slope information is utilized to adjust the radius of the restricted feasible domain in the enterprise problem. Hence, $\left|{}^{\alpha}/_{\phi}\right|\Delta$ is used instead of Δ. Here, α and ϕ are the gradients of the utility function with respect to the current response $\mathbf{E}^D$ and new target $\mathbf{T}'$. The proposed iterative procedure is terminated as soon as an engineering level design is found with a better utility; the goal of the algorithm is to explore the target space of engineering design attributes **E** until a feasible engineering design with a better enterprise utility is identified. The proposed algorithm does not attempt to find the global optimum; instead it explores the engineering feasible domain to find an alternative feasible design with a better utility if it exists in a disconnected feasible domain.

The multilevel framework presented in Fig. 12.3b shares a number of features with the ATC representation of the product planning and product development subproblems in Michalek et al. [12]. However, there are important differences. While the ATC formulation in Michalek et al. [12] treats the enterprise problem as deterministic, uncertainty and designer's risk attitude into the formulation are incorporated by using expected utility $E(U)$ as the optimization criterion for the enterprise problem. In Michalek et al. [12], the product planning problem not only considers the optimization of the enterprise level objective (e.g., profit) but also attempts to minimize the deviation between achievable engineering design attributes and targets set by marketing. In this approach, enterprise and engineering objectives are treated separately in product planning and product development problems. Expected utility is the only optimization criterion at the enterprise level and the ATC approach is used only for the engineering product development problem. Such an approach not only preserves the essential distinction between product planning and product development functions but also results in far fewer iterations between the enterprise and engineering level problems, compared to Michalek et al. [12]. In fact, the engineering level problem needs to be resolved only if the design space is disconnected and the enterprise level targets are adjusted by the product planning problem.

12.3 Case Study: Automobile Suspension Design

An automotive suspension system design problem is used to demonstrate the multilevel approach. The assumptions made for the case study and the rationale behind including the various engineering design attributes **E** to represent customer-desired attributes **A** in the demand model are first explained. Details on demand model estimation and the design of the suspension system obtained using the multilevel optimization framework are then provided.

12.3.1 Multilevel Optimization Formulation of the Suspension Design Problem

Here, the enterprise-driven DBD approach is applied to the design of a suspension system of a mid-size car. In this discussion, it is shown: (1) how the problem can be solved using a multilevel optimization formulation and (2) how the demand model is created to provide linking between enterprises planning and engineering development. The enterprise product planning of vehicle and engineering product development of the suspension system are treated as hierarchical decision making activities, and the suspension design problem is viewed as a hierarchical design problem by itself and solved using the ATC approach. The ATC formulation for the suspension system is based on that in Kim et al. [10]. The schematic of the multilevel decision-based suspension design model is illustrated in Fig. 12.5. Here, targets for front and rear suspension stiffnesses, represented as K_{sf} and K_{sr} ($T^U = E^*$, the top level suspension system attributes), are set by solving the enterprise level DBD product planning problem. These targets are then used to guide the subsystem engineering development of front and rear suspensions. By solving the problems at the subsystem level, the targets for front and rear coil spring stiffness (K_{Lf} and K_{Lr}) are identified to guide the engineering development at the component level (i.e., front and rear coil spring designs). Below, an overview of the ATC model for the chassis system of an automobile aimed at establishing vehicle ride and handling targets, which was originally used in Kim et al. [10] is included.

A schematic of the information flow in the vehicle design problem structure is provided in Fig. 12.5. Each block indicates an optimal design model where design decisions are made to achieve minimum deviation from the targets. Each design model calls one or more analysis models to evaluate the current design. System-level analysis models for the front and rear suspensions are multibody-dynamics models of short long arm (SLA) suspensions [5]. Based on the solution to the enterprise-level profit-maximization problem, the stiffness targets for the system-level engineering problems are set. For example, once an optimal value for the overall suspension stiffness (K_{sf} for the front suspension) is found at the enterprise problem, that value becomes a target value at the subsystem-level engineering

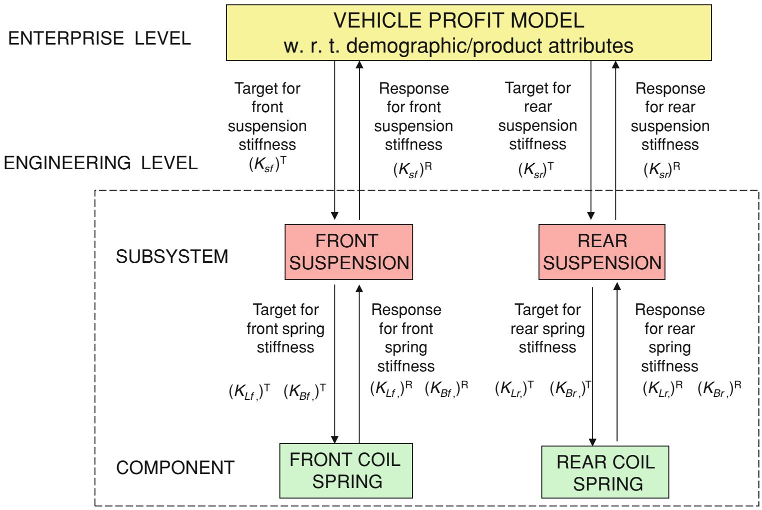


Fig. 12.5 Schematic of multilevel decision-based suspension design model

problem, in which the suspension design variables (coil spring stiffness K_{Lf}, bending stiffness K_{Bf}, suspension travel Z_{sf}, and free length L_{of}, for the front suspension) are altered to achieve a suspension configuration and with a stiffness as close to the cascaded target value as possible. Coil spring stiffness and bending stiffness values (K_{Lf} and K_{Bf}, respectively, for the front suspension) are then cascaded to the component level as targets. The spring subsystem variables (wire diameter d_{f}, coil diameter D_{f} and pitch p_{f}, respectively, for the front suspension) are optimized to achieve minimal deviation from the targets assigned for the coil spring stiffness.

Once the vehicle design targets are cascaded down to the lowest level, the resulting design information must then be passed back to higher levels, up to the top level. In general, it will not be possible to achieve the target values exactly in each design problem, due to constraints and variable bounds or due to lower level responses. For example, the front suspension stiffness obtained from the system-level optimization problem might not match the target value from the vehicle level due to constraints on coil spring free length and stiffness. Similarly, upon cascading the desired coil spring stiffness to the coil spring component design problem, packaging or fatigue constraints might result in spring stiffnesses deviating from the specified target value. This iterative process, working in both a top-down and a bottom-up fashion, leads to a consistent design or uncover potential incompatibilities among overall system responses, targets, and element parameters. The reader is referred to Kim et al. [10] for additional details on the mathematical formulation of the ATC model for the design of the suspension system.

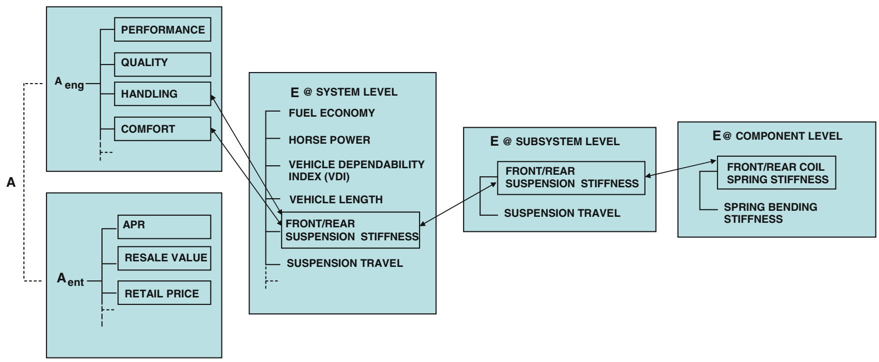


Fig. 12.6 Examples of customer-desired attributes **A** and engineering design attributes **E** in the automotive suspension design case study. The *arrows* represent the correlations utilized in the current case study

12.3.2 Demand Model for Mid-Size Car Segment

A multinomial logit (MNL) demand model is estimated to study the impact of front and rear suspension characteristics and other important vehicle level product attributes (e.g., engine performance, ride quality, and comfort) on customers' choices of a mid-size car. This case study is developed using market data provided by the power information network group (PIN) at J.D. Power & Associates. Data on the vehicle attributes are from Ward's automotive yearbook [2]. The statistical software package STATA [16] is used to estimate the multinomial choice model coefficients based on the maximum likelihood criterion. For choice set selection in demand modeling, 12 vehicles (7 models and 12 trims) from the mid-size segment are used to represent the entire market for mid-size cars. Examples of customer-desired attributes **A** and engineering design attributes **E** considered in the suspension design case study, are presented in Fig. 12.6. Customer-desired attributes **A** belong to system level attributes. They are grouped into engineering-related customer attributes $\mathbf{A}_{eng}$ and non-engineering or enterprise-related customer attributes $\mathbf{A}_{ent}$. Examples of $\mathbf{A}_{eng}$ considered for demand modeling in the case study is performance, quality, comfort, and handling. Relationship between $\mathbf{A}_{eng}$ and engineering design attributes **E** is illustrated in Fig. 12.6. Fuel economy and horse power are examples of engineering design attributes that are related to performance while vehicle length and suspension stiffnesses are related to vehicle handling. Front and rear suspension stiffnesses also influence customers' view of comfort. In this work, to facilitate engineering decision making, the engineering design attributes **E** at the system level are modeled directly as the inputs of the demand model. Figure 12.6 also illustrates the cascading of engineering design attributes from vehicle system level to subsystem level, then to component level in suspension design. It should be noted that transfer relationships need to be established between the performances—attributes at different levels of the hierarchy. For example, front/rear suspension stiffness is a performance attribute at the subsystem level and its target is identified as a design variable in system-level optimization. Front/real coil spring stiffness is a performance attribute at the component level; its target is identified through optimization at the subsystem level.

The demand model also considers various non-engineering oriented design attributes $\mathbf{A}_{\text{ent}}$. APR of the auto loan and resale value, which are grouped under $\mathbf{A}_{\text{ent}}$ coincide with the enterprise planning options $\mathbf{X}_{\text{ent}}$ for the case study. It should be noted that all design attributes unrelated to the suspension design, (e.g., horsepower and fuel economy) are assumed to be constant. As a result of MNL analysis, demand Q is expressed as a function of demographic and product attributes such as income, age, retail price, resale value, vehicle dependability index (VDI: a quality measure, expressed in terms of defects per 100 parts), annual percentage rate (APR) of the loan, fuel economy, vehicle length, front suspension stiffness, and rear suspension stiffness. For the estimation of the demand model (customer) utility biases due to excluded variables are measured using alternative specific constants and alternate specific variables [1, 17]. They measure the "average preference" of an individual relative to a "reference" alternative. One important consideration when evaluating MNL models is that demographic variables related to the customer's age and income can only be included as alternative specific variables. The income terms in the demand model capture the interaction of the customer's income with different vehicle alternatives. Eleven income variables were estimated, each corresponding to a particular vehicle alternative, and income variable 1, corresponding to vehicle alternative 1, was used as reference. It is anticipated that the income variables corresponding to more expensive cars will have positive signs since people with higher incomes are likely to view expensive cars more favorably.

Table 12.1 includes results of the demand model estimation and observations on the model estimation results follow. Negative signs of retail price, VDI, APR, and vehicle length mean that customers prefer lower values for these variables, i.e., customers prefer cheaper cars, lower interest rates, fewer defects, and cars that facilitate easy parking. Positive sign for fuel economy means that customers prefer higher gas mileage and positive signs for the suspension stiffnesses mean that stiffer suspensions are preferred. Typically, a stiffer suspension generally translates to better handling and load-carrying abilities but also results in a harsher ride. Hence, the current choice model indicates that customers (in the present data set) "value handling characteristics more than ride quality." The statistical goodness of fit of the different MNL models developed for this purpose is evaluated using likelihood estimates. While choosing the final model, statistical goodness-of-fit measures and the capability of the model to reflect contemporary understanding of customer behavior (e.g., signs and magnitudes of the coefficients of attributes like fuel economy, horse power in the utility function should be consistent with the expectation) were the primary considerations.

Table 12.1 Results of estimation of the multinomial logit model

Attribute type	Description	Coefficient	t-value	95% confidence interval
Demographic attributes	Income × vehicle 2	0.13	6.41	(0.09, 0.18)
Income variables capture the interaction between customers' income and vehicle type. (e.g., income × vehicle 2 captures the interaction between income and mid size vehicle 2)	Income × vehicle 3	0.01	0.48	(−0.03, 0.05)
	Income × vehicle 4	0.06	2.57	(0.01, 0.11)
	Income × vehicle 5	−0.10	−4.20	(−0.15, −0.05)
	Income × vehicle 6	−0.08	−3.37	(−0.13, −0.03)
	Income × vehicle 7	0.07	2.99	(0.02, 0.11)
	Income × vehicle 8	0.08	3.22	(0.03, 0.12)
	Income × vehicle 9	0.08	3.25	(0.03, 0.14)
	Income × vehicle 10	0.19	9.38	(0.15, 0.23)
	Income × vehicle 11	0.05	2.29	(0.01, 0.10)
	Income × vehicle 12	0.04	1.18	(−0.02, 0.10)
Demographic attributes Variable captures interaction between age and country of origin of product.	Interaction between customers' age and country of origin of product	0.13	12.37	(0.11, 0.15)
Product attributes	Retail price	−1.57	−4.14	(−2.31, −0.82)
	Resale value	2.15	2.54	(0.49, 3.80)
	Vehicle dependability index	−1.69	−1.49	(−3.92, 0.53)
	Annual percentage rate (APR)	−1.05	−1.34	(−2.58, 0.49)
	Fuel economy	0.64	1.51	(−0.19, 1.46)
	Vehicle length	−0.60	−0.5	(−2.95, 1.74)
	Front suspension stiffness (K_{sf})	1.75	3.11	(0.65, 2.85)
	Rear suspension stiffness (K_{sr})	0.88	1.28	(−0.47, 2.24)

12.3.3 Solving the Suspension Design Problem Using Multilevel Optimization

Although the focus in this study is on suspension system design, it is necessary to compute the net profit of producing the whole vehicle to formulate the utility optimization model at the enterprise level. In the previous vehicle chassis design example by ATC [10] the targets for the chassis system design are given based on experience, i.e., fixed target values. In the current formulation the targets are set based on maximizing the enterprise utility, i.e., profit of a firm. Based on the targets, ATC cascades top level design targets to system, subsystem, and components. In the current example only front and rear vehicle suspension subsystems and spring components are included in the hierarchy for simplicity.

In this work, the net profit in Eq. (12.4) is used for this purpose. Price of a vehicle P is assumed to be constant or unchanged from the current design, C_{susp} represents the unit cost for the suspension system and C_0 is the unit cost for the rest of the vehicle system, respectively. In this work, C_0 is assumed to be constant, since changes in only suspension parameters will be made. The suspension system cost is assumed to be linearly proportional to the suspension stiffnesses (Eq. 12.5). In the context of design, among the engineering design attributes in the demand model, only front/rear suspension stiffnesses are considered as variables, while the rest of the vehicle attributes are set constant at the baseline values. It is also assumed that the competitors will not change their designs. Uncertainty is captured in the cost variables a_{f} and a_{r}, considered as the exogenous variables $\mathbf{Y}$ in the DBD framework (see Chap. 4). The suspension cost variables a_{f} and a_{r} are both defined as normally distributed variables, with mean $\mu_{\mathrm{a}} = 0.05\,[\$\ /\mathrm{kNm}^{-1}]$ and standard deviation $\sigma_a = 0.005\,[\$\ /\mathrm{kNm}^{-1}]$. For the current study, values for a mid-sedan size, $P = \$20{,}000$, $C_0 = \$18{,}100$ are used.

$$\Pi = Q \times \left(P - C_{\mathrm{susp}} - C_0\right) \tag{12.4}$$

$$\Pi = Q \times (P - a_{\mathrm{f}} k_{\mathrm{sf}} - a_{\mathrm{r}}\, k_{\mathrm{sr}} - C_0) \tag{12.5}$$

Also, a logarithmic function of profit Π, consistent with the principles of utility theory [6], is used as the enterprise utility $U(\Pi)$, to account for the risk averse nature of the firm. Then the enterprise level objective is to maximize the expected utility $E(U)$ where

$$E(U) = \int U f(V)\mathrm{d}V.$$

In this work, the enterprise planning problem is formulated as an unconstrained optimization problem. The expected utility function indicates that softer front suspension and stiffer rear suspension lead to the highest utility (see Fig. 12.7; Table 12.2). In Fig. 12.7, the shaded regions in the target performance space indicate a disconnected feasible domain for the suspension design. The two shaded regions in the figure represent two suspension design options (i.e., softer versus stiffer front/rear suspension designs) available to the designer. For example, the suspension manufacturing supplier provides two alternatives for suspension design and the vehicle producer adjusts their product planning decision based on the availability of engineering designs. When applying the proposed multilevel optimization algorithm utopia targets $\mathbf{T}^*$ ($k_{\mathrm{f}} = 30.2\,[\mathrm{kN/m}]$, $k_{\mathrm{r}} = 19.5\,[\mathrm{kN/m}]$, corresponding to an expected utility 14.27 and average profit \$80,460), are assigned for the suspension design problem after solving the original DBD at the enterprise level. Design A with the minimum deviation ($k_{\mathrm{f}} = 25\,[\mathrm{kN/m}]$, $k_{\mathrm{r}} = 19.5\,[\mathrm{kN/m}]$

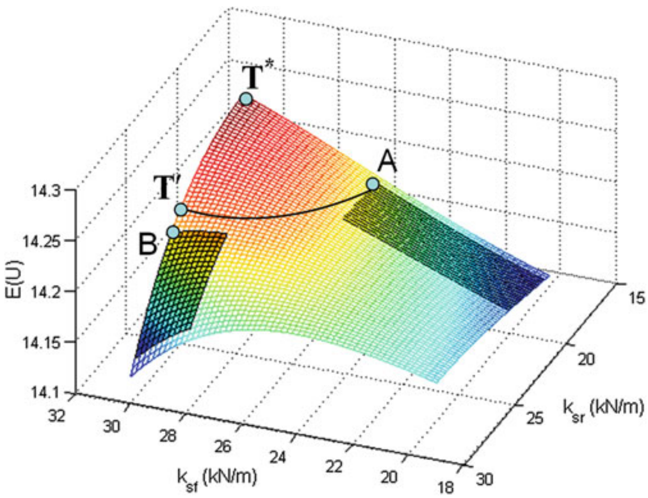


Fig. 12.7 Vehicle demand model: profit change with respect to suspension stiffness changes. The *shaded areas* represent disconnected feasible suspension design domain. After the engineering design A is found, a geometric limiting constraint (*solid circle*) is added in the utility space to find an alternative target $\mathbf{T}'$ to explore another disconnected feasible space

with expected utility 14.215 and average profit −$8,935, i.e., loss) is found after solving the multilevel optimization using ATC at the engineering development level. Based on the design A, an additional geometric constraint (see [8]) is added at the enterprise level, which assigns an alternative target $\mathbf{T}'(k_\mathrm{f} = 30.2\,[\mathrm{kN/m}],\ k_\mathrm{r} = 24.83\,[\mathrm{kN/m}]$ with expected utility 14.241 and average profit $26,722) to the suspension design problem.

Based on the new target $\mathbf{T}'$, the ATC finds design B ($k_\mathrm{f} = 30.2\,[\mathrm{kN/m}],\ k_\mathrm{r} = 26\,[\mathrm{kN/m}]$ with the improved expected utility 14.218 and average profit $23,064) with the minimum deviation. The corresponding expected utility for design B is higher than that of design A. Design B is selected as the final design with a better enterprise level utility value. Table 12.2 summarizes the iteration process using the proposed multilevel optimization algorithm. Detailed suspension designs at the subsystem and component level are summarized in Tables 12.3, 12.4, 12.5, 12.6. For example, front suspension design model takes coil spring stiffness, spring free length, and torsional stiffness as inputs to the suspension model and returns suspension stiffness and suspension travel as outputs. Among the inputs, coil spring stiffness is cascaded to the front coil spring design model as a target. Based on the coil spring target from the suspension model, the coil spring design at the component level takes wire diameter, coil diameter, and pitch as inputs and returns actual coil spring stiffness and spring bending stiffness as outputs.

Table 12.2 Iteration history: maximizing expected utility with vehicle suspension design change (see Fig. 12.7)

Iteration	Target for front suspension stiffness $(K_{sf})^T$ (N/mm) T_1^*	Target for rear suspension stiffness $(K_{sr})^T$ (N/mm) T_2^*	Desired Profit ($)	Desired $E[U]$	Response for front suspension stiffness $(K_{sf})^R$ (N/mm)	Response for front suspension stiffness $(K_{sr})^R$ (N/mm)	Profit achieved ($)	$E[U]$
1	30.2	19.5	80460	14.272	25.0 (point A)	19.5 (point A)	−8935	14.215
2	30.2	24.83	26722	14.241	30.2 (point B)	26 (point B)	23064	14.218

Here, the value of profit has been computed for the mean values of a_f and a_r

Table 12.3 Front suspension design

Front suspension subsystem design	Type	Optimal value	Lower bound	Upper bound
Coil spring stiffness K_{Lf} (N/mm)	Input	117.53	30	160
Spring free length L_{0f} (mm)	Input	372.9	300	650
Bending stiffness K_{Bf} (N-m/deg)	Input	30.0	20	85
Suspension stiffness K_{sf} (N/mm)	Output	30.2	19	30.2
Suspension travel Z_{sf} (m)	Output	0.1	0.05	0.1

Table 12.4 Rear suspension design

Rear suspension subsystem design	Type	Optimal value	Lower bound	Upper bound
Coil spring stiffness K_{Lr} (N/mm)	Input	80.1	30	160
Spring free length L_{0r} (mm)	Input	410.3	300	650
Bending stiffness K_{Br} (N-m/deg)	Input	58.7	20	85
Suspension stiffness K_{sr} (N/mm)	Output	25.8	19	30.2
Suspension travel Z_{sf} (m)	Output	0.1	0.05	0.1

Table 12.5 Front coil spring design

Front coil spring design	Type	Optimal value	Lower bound	Upper bound
Wire diameter d_f (m)	Input	0.014	0.005	0.03
Coil Diameter D_f (m)	Input	0.074	0.05	0.20
Pitch p_f	Input	0.04	0.04	0.10
Coil spring stiffness K_{Lf} (N/mm)	Output	124.9	–	–
Spring bending stiffness K_{Bf} (N-m/deg)	Output	16.1	–	–

Table 12.6 Rear coil spring design

Rear coil spring design	Type	Optimal value	Lower bound	Upper bound
Wire diameter d_r (m)	Input	0.02	0.005	0.03
Coil Diameter D_r (m)	Input	0.14	0.05	0.20
Pitch p_r	Input	0.05	0.05	0.10
Coil spring stiffness K_{Lr} (N/mm)	Output	84.5	–	–
Spring bending stiffness K_{Br} (N-m/deg)	Output	33.2	–	–

12.4 Summary

A DBD-based multilevel optimization approach that integrates enterprise-level product planning with engineering-level product design is presented. To ensure preference consistency when solving decomposed enterprise and engineering problems, a search algorithm is employed to systematically explore the product attribute targets set at the enterprise level to lead the engineering product development to feasible and optimal designs in the enterprise context. The vehicle design example captures the disjoint nature of the product performance targets and manufacturing limitations. With the current algorithm the final optimal design is a better design in maximizing the profit of a firm as well as meeting the feasibility requirements imposed in the vehicle suspension design specifications. The MNL model is used to estimate the demand model which is in turn used to calculate the profits (i.e., the enterprise level objective) as a function of the design decisions, for the vehicle case study. The decomposed approach presented provides a systematic way to resolve the organizational and computational complexities involved in integrating design efforts across the enterprise. It is shown how customer preferences for product attributes can be translated into the market share of a product and used to guide the engineering product development process by setting up the targets for engineering design attributes. An effort is made to clearly distinguish between the various types of product attributes that are commonly used in an enterprise-driven design situation; some attributes are more relevant to customer desires, while others are used by engineers alone; some depend on engineering design options while others are more related to enterprise planning options.

Conventionally the product development tries to match the utopia target with the minimum deviation. In cases where the utopia target is unattainable, the minimum deviation design may not correspond to the highest possible enterprise utility if the design space is disconnected. An automotive suspension design case study was presented to demonstrate the effectiveness of our approach. The case study uses the customer data for the mid-size sedan market and the demand model demonstrates the impact of the suspension variables on customer choices. The proposed multilevel optimization model is potentially the most useful during the early stages of a design process when the iterative process can be used to revise, negotiate, and validate design targets by engineering design and the enterprise-planning groups.

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Chapter 13
Closure

13.1 Summary of the Decision-Based Design Approach

An enterprise-driven Decision-Based Design (DBD) approach to support decision making for designing engineered products and systems is presented in this book, with an emphasis on methods for integrating heterogeneous consumer preference into engineering design. DBD acknowledges that decision making is the fundamental construct of engineering design and that decision theory, and its underlying mathematical principles must be followed for making rigorous design decisions. When seen as a decision making process, the product development process can be viewed as alternative generation, followed by alternative selection. By examining the limitations associated with the existing multicriteria design selection methods, we show that a single-criterion enterprise-driven DBD approach is appropriate to unambiguously select the preferred alternative in a rigorous manner.

The strength of enterprise-driven DBD is its realization of the economic notion that the immediate purpose of the producer of products is not to satisfy just what customers want, but to sell the product for a price that will make it worthwhile to continue production. A product is designed and produced for a market where buyers and sellers meet, i.e., product design should consider the actual market mechanism that determines its success or failure in the market place. Thus, where Marshall showed that the forces of demand (i.e., customer) and supply (i.e., producer) simultaneously determine a product's price [6], in this book we extend this for engineering design to: *the forces of demand and supply simultaneously determine a product's design and price.* As such, DBD facilitates the integration of engineering design and business decision making.

The specific tools and methodologies required to implement the DBD approach in engineering design practice are presented in this book, with an emphasis on methods for modeling heterogeneous consumer preferences in the form of demand (choice) modeling. In addition to introducing the fundamentals of discrete choice analysis and variants of choice models (Chap. 3), specific challenges of integrating choice models into DBD are addressed in this book with methods to:

DOI: 10.1007/978-1-4471-4036-8_13,

- Identify both engineering and customer attributes (Chap. 5),
- Collect and analyze customer preference data (Chaps. 6 and 7),
- Handle a hierarchy of sub-systems and product attributes (Chap. 8),
- Represent customer preference heterogeneity in a complete manner (Chap. 8),
- Combine multiple sources of data and update models (Chaps. 8 and 11),
- Capture customer perceptual attitudes (Chap. 9),
- Consider the effect of usage context (Chap. 10),
- Design individual products as well as product families (Chap. 11), and
- Implement multidisciplinary optimization methodologies (Chap. 12).

References to computational tools are provided throughout the book to enable readers to implement the methodologies using open-source software.

13.2 Advancing Research in Decision-Based Design

It should be evident to the reader that DBD is a collaborative design paradigm that requires interaction and integration of multiple disciplines of among others engineering design, manufacturing engineering, industrial design, marketing, and management in an enterprise. Hence, research in DBD is inherently interdisciplinary, at the intersection of multiple fields, such as design theory, decision theory, complex systems design, market research, operations research, project management, economic theory, cognitive science, psychology, and information technology.

Looking toward future research opportunities in DBD, we can learn from the vision statement from the *ED 2030: Strategic Planning for Engineering Design* [15] which includes the following: *In 2030, designers will work synergistically within design environments focused on design not distracted by the underlying computing infrastructure. Designers will interact in task-appropriate, human terms and language with no particular distinction between communicating with another human team member or online computer design tools. Such environments will amplify human creativity leading towards innovation-guided design. Future design tools and methods will not only support analysis and decision making from a technological point of view, but will also account for psychological, sociological, and anthropological factors based on fundamental understanding of these factors and their interaction. Instead of just designing products and systems, designers will be concerned with design of the total experience. Design of system of systems will supercede the design of individual systems. This will lead to reduced uncertainty in engineering design and greater confidence in the design process.* And Furthermore, *Design will go from incremental changes and improvements to great bold advances. Therefore design will be an exciting activity full engaging our full human creative abilities.*

Several implications to the future of DBD research can be derived from the above vision statement. First, as product design involves both physical artifacts and human

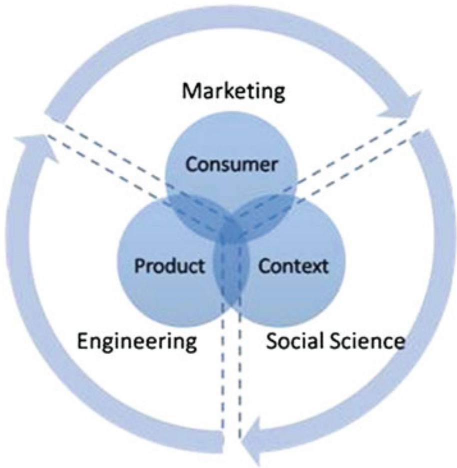

Fig. 13.1 Connections among engineering, marketing and social science domains

participants (designer as well as customers), one top challenge in DBD research is to understand the interface between the socio-technical aspects in design. As shown in Fig. 13.1, designing a product customers want requires not only a good understanding of the interface between customer and product, but also a deep understanding of the context of customer preference and how customers make their choices. To make rigorous decisions for product design, it is necessary to consider factors beyond the traditional engineering domain, including customer perception, emotion, usage context, and social influence. While this book takes a deep dive into the integration of engineering and marketing domains, the intersection and interaction with the domain of social science is not explored. Quantitative methods in social science research, such as agent-based [12] and network simulations [8], can be naturally integrated into the analytical choice modeling approach presented in this book; however, it remains a research topic of how to best integrate the quantitative DBD approach with qualitative methods widely used in social science research, such as ethnographic observations and interviews for gathering user needs and understanding customer choice behavior [5].

Second, as design is fundamentally a team-based, multi-player, human decision making process, the scope of design can be broadened to not only include designing the artifact, but also the design organization itself. Beyond modeling designer and customer preferences, DBD research has the potential to be extended to address organization design issues, such as how to formulate incentives in an organization, by introducing theories from the field of mechanism design [2, 7, 10]. Mechanism design (sometimes called reverse game theory) is a field in game theory, which is concerned with solution concepts for a class of private information games. In these games, a "designer" (enterprise decision maker) chooses the game structure rather than inheriting one, and the game is usually solved by motivating agents (multiple players in a design organization) to disclose their private information.

Third, while the DBD approach presented in this book is focused on the design alternative selection stage of an engineering design process, there is the need to better understand the role of DBD in alternative generation: namely how can the value-driven DBD approach further enhance design creativity in generating useful design concepts? In addition to *incremental innovations* [4], which are capable of creating competitive advantages for a firm in existing markets, new methods are needed for implementing the DBD approach to *break through innovation*, in which a (radical) technological break through creates a brand new market, with no immediate competitors and potentially high profits.

Fourth, implementing the DBD approach requires a comprehensive approach to cost modeling which also captures the uncertainty of such a (cost) model in a rigorous manner. While we presented a discussion of cost modeling, rigorous methods which search product databases or utilize previous design project data to estimate future costs of a new design need to be developed to aid in creating trustworthy cost models for assessing the economic benefit of a product design.

Finally, the DBD approach can be used to address product design challenges in an area of great attention in product design today and in the foreseeable future: *sustainable design*. As noted in the comprehensive review of sustainable life cycle design by Ramani et al. [13], design decisions made early in the product life cycle can have a large impact on the sustainability of a product over its life cycle, from the product's manufacture, to its in-service use, to its end of life recovery and disposal (or remanufacture). This points to the need for a rigorous decision making approach for sustainable product design. The DBD framework can be used to manage the tradeoff among the sustainability of the product, the acceptance of the product by the market, and the profit margin of the enterprise. Products which are optimized for sustainability but do not meet the needs of customers (e.g., automobiles with limited range, electronics with difficult end-of-life customer disposal processes) or producers (e.g., high manufacturing costs, high warranty expenditures), will not be successful in the marketplace and will hinder adoption of green practises in product design. The choice model can be used to assess customer acceptance of sustainable designs, while the cost model captures the producer's investment in sustainable practises.

It is worth noting that the engineering design and innovation (EDI) program at US National Science Foundation supported two workshops in 2010 related to designing complex engineering systems, one on engineering system design [11] and the other on multidisciplinary design optimization [17]. The common research themes emerged from these workshops are equally relevant to the future challenges in DBD research.

13.3 Advancing Research in Choice Modeling

Associated with DBD research, many challenges and research opportunities exist for modeling consumer choice behavior. The first is the ongoing challenge of validation of discrete choice models and quantifying the uncertainty of these models. While a validation of the theoretic underpinnings of DBD is presented in

Chap. 2 and case studies are provided in each chapter to validate the applicability of the methods to real design situations, ongoing validation of choice models in real design contexts is required to uncover unforeseen issues, which may hamper adoption and require future development work. Quantifying the uncertainty of a behavior model, like a choice model, is not a trivial task, with many potential sources of uncertainty existing, such as preference variation due to market dynamics, demand model misspecification, choice context uncertainty, response variability, variation in engineering design model parameters, and sampling errors associated with the estimation procedure [14].

Another challenge is understanding the attributes customers consider in a choice process and the change in customer preference over time. While we have presented methods to understand these attributes, such as the PAFD method (Chap. 5) to elicit customer-desired product attributes and the latent variable method (Chap. 9) to capture perceptual attitudes, there is still a need for a comprehensive method to uncover the actual attributes considered in a choice process. Methods, such as text mining to search social networking sites with product discussions, may yield good results in this area. A related challenge is to understand the change in consumer preferences over time. As noted in Chap. 3, a dynamic form of the choice model is possible by allowing the model attribute parameters to be a function of time, i.e., $\beta(t)$ (introduced in Chap. 3 Sect. 3.5.7). While this approach is possible with choice data over several time periods, the collection of such data and the model implementation provide challenges. With respect to data collection, preferences may change quickly and it may be difficult to establish a trend. Text mining of social networking sites may result in a method to capture these trends in a timely fashion. Also, Kano found that attributes change over time from *excitive* to *proportional* to *must be* [3], which could be used as a framework for modeling changes of preferences over time. With respect to model implementation, it can be a challenge to determine which preferences are changing significantly with time as well as the form of the function used to model the trend. Also, care must be taken with respect to the error term in a dynamic model to ensure the error meets the assumption of the model type as described in Chap. 3.

Another issue is to incorporate market forecasts into the DBD framework. As explained in Chap. 3 Sect. 3.5.7, the estimated market share for a given design artifact is given by the product of the *choice share* for the given artifact times the total *market size* for the given product category. The choice share for a given design artifact can be estimated using the choice model; however, forecasting the total market size (over a given timeframe) requires alternative methods. Market forecasting has been addressed in certain markets, such as for electronics and other high technology products [1]; however, a general approach for market size forecasting is required for accurate demand forecasts from the DBD method. Text mining methods may be utilized for this task to determine which product categories are trending on internet search or social network sites, indicating an increasing market size trend.

A general challenge of discrete choice analysis is the computational implementation of the methods. While we have utilized `R` and `WinBUGs` for estimating the models, the techniques used and the computational expense for some of the advanced methods, such as the Integrated Bayesian Hierarchical Choice Model (Chap. 8), the Latent Variable Approach (Chap. 9), and the Product Family Design method (Chap. 11), may present challenges to those new to DBD and choice modeling techniques.

Another challenge is better capturing the influence of competitor's actions in response to the design actions of a given enterprise. The response may be in the form of a price change and/or design change by competitors which may reduce the demand forecasted by the choice model [9, 16]. Research questions are whether the potential competitor actions should influence the design decisions, how to capture uncertainty in these potential competitive actions, and how to address the computational challenges of integrating these considerations in the DBD framework.

Finally, the challenge of pedagogy must be addressed. While we believe this book to be a significant step toward presenting the DBD framework in a rigorous yet understandable manner, the topic is still best taught at the graduate level to students with a strong background in design optimization and statistics or mathematics. It remains a challenge to determine how to implement the DBD concept into an undergraduate curriculum and see their use in student design projects, such as senior capstone design courses or extra-curriculum design activities.

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DOI: 10.1007/978-1-4471-4036-8,

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W. Chen et al., *Decision-Based Design*,
DOI: 10.1007/978-1-4471-4036-8, © Springer-Verlag London 2013