A MODEL FOR EFFECTIVE OPERATIONS MANAGEMENT INTEGRATING CONSTRAINED-OPTIMIZATION THEORY AND CUSTOMER CHOICE PATTERNS

by

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ABSTRACT

This study develops and empirically tests a model for effective operations management by integrating market-based objectives, decisions of operations managers, and operating system constraints. This study builds on the constrained-optimization theory of management science; is based on constructs from operations management (POM), econometrics, and marketing; uses a number of quantitative techniques (conjoint analysis, discrete-choice experiments, latent segment analysis, simulated annealing, and optimization); and enables managers to make better decisions regarding product/service design, process improvement, and production.

Empirical data for this study were collected from the customers and managers of the pizza delivery industry. First, discrete-choice experiments were used to identify choice patterns of customers in different market segments. Next, managers were asked to predict the choice patterns of customers. The managers also responded to a series of conjoint experiments and rated the relative difficulty in meeting customer demand under specific operating conditions. The managers also predicted the production cost. Finally, the information gathered from the empirical experiments was used in the optimal product design and optimal operating configuration design procedure.

This research contributes equally to POM, marketing, and management science academic and practitioner literatures because it incorporates market information into

product design and operating decisions and can be easily translated from theory to practice. The proposed model can be used as a constructive feedback in positioning operations according to market needs and operating constraints. The model identifies binding constraints in operating system. The managers can concentrate on breaking these binding constraints for effective implementation of continuous improvement or process reengineering projects. The proposed work contributes earlier work in product development by including cost of production into the analysis and identifies the operating configuration which facilitates the production of "profit-maximizing" product(s).

To Mitu and Pooja

Solving mathematical puzzles without worry concerning context can provide, for some, a satisfactory exercise. But the science and art of management calls for more. An application is when the context is understood, the theory is relevant and the decision process is influenced. Theory may become a waste of time for all but the theorists when there is no concern for relevance or application beyond the self-perpetuation of the club.

Shubik, 1987.

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CHAPTER 1

INTRODUCTION

1.1 Background

Many times, in the history of science, a situation arises in which the existing knowledge in a particular field or subject is no longer satisfactory. When this happens, often a movement is witnessed which can be described as a paradigm shift. Production and operations management (POM), a discipline encompassing the management of conversion processes, is currently experiencing a similar paradigm shift [37] [40] [93] [132]. Businesses all over the world are facing dynamic and intense global competition. This competitive environment has led both academics and practitioners to conclude that POM matters [25] [47] [70] [74] [121] [122]. It matters to the economy as a whole, and it matters to the individual businesses. The belief that POM is an important ingredient in corporate and national success has spurred the development of operations strategies in manufacturing and service firms seeking competitive advantage around the world [70] [71]. In the broadest sense, this movement can be summarized as a paradigm shift from cost-based competition to time and customer service-based competition [11] [125] [126].

Over the last 25 years, management researchers have emphasized the importance of effective operations management in improving the performance of a firm and have shown that production competence affects business performance [25] [114] [140]. A literature review on operations strategy suggests that proper strategic positioning or aligning of operations capabilities can significantly impact competitive strength and business performance of an organization [9]. Chase, Kumar, and Youngdahl [22] suggest that manufacturing managers should not view POM as activities far removed from customers and argue that factory-based customer service will be the next form of competition among manufacturers. Wheelwright and Hayes [145] developed a four-stage model of manufacturing operations' strategic role in the overall support of corporate goals. Their four stages -- internally neutral, externally neutral, internally supportive, and externally supportive -- categorize manufacturing in terms of its strategic importance and contribution to the firm. Chase and Hayes [21] have developed a similar four-stage (available for service, journeyman, distinctive competence achieved, world-class service delivery) model for service firms. The papers cited above are just a sample of a large number of published articles and books that highlight the importance of effective POM in improving the competitive position of a firm. With the development of the operations strategy paradigm, both academic researchers and practitioners are now beginning to agree that in order to meet market demands, the operations function of a firm must satisfy multiple and often conflicting objectives [20] [22] [64] [70] [109] [114]. These objectives can be broadly divided into the following customer-oriented dimensions: cost, product quality, service quality, delivery, and flexibility. However, often it is not possible to achieve the same amount of success in all operations objectives [19]. Managers have to make tradeoffs because of operating constraints [70] [119] [121] [122].

Management scholars have suggested several approaches to meet conflicting operations objectives in the presence of system constraints. For instance, Skinner [120] argues that a conventional factory attempts to do too many conflicting production tasks within one inconsistent set of manufacturing policies. He suggests the focused factory approach, which offers the opportunity to stop compromising each element of the production system and to build on competitive strengths. Similarly, the theory of constraints recommends concentrating on activities which help in achieving only one objective: making money now and in the future [46][47]. It suggests a five-step approach to identify and eliminate production bottlenecks (or binding constraints) for improving the performance of the firm: identify the system constraints; decide how to exploit the system constraints; subordinate everything else to the above decision; elevate the system constraints; if in the previous steps, a constraint has been broken, go back to the first step.

The continuous improvement philosophy approaches the challenge of improving operations' performance as a never-ending process of achieving small wins [19][113]. Though pioneered by US firms, this philosophy has become the cornerstone of the Japanese approach (called kaizen) to POM and is often contrasted with the traditional western approaches of relying on technological or theoretical innovations to achieve big win improvements [19][113]. Business process reengineering on the other hand recommends radical or breakthrough changes in a business process [60][61]. It begins with a clean sheet of paper and makes changes in the business processes involving operations management, product development, and customer service to increase the performance improvement rate several orders of magnitude higher than present [60][61].

The publications cited in the above paragraphs suggest several approaches -- strategic positioning and alignment of operations, production competence, focused factory, theory of constraints, continuous improvement, process reengineering -- to improve the performance of operations. At the same time, other POM and marketing researchers have focused their attention on reducing the gap between the marketing and operations functions of organizations to improve their competitive positions. For example, Crittenden [28] suggests that by working together, manufacturing and marketing can better appreciate each other's constraints and become more willing to make tradeoffs in their own functions. Deane, McDougall, and Gargeya [34] have illustrated the importance of the interaction between manufacturing and marketing decisions in predicting new venture firm success. Roth and Velde [110] presented a competitive service paradigm and argue that operations can be used as a success factor in marketing.

Other researchers have attempted to directly incorporate customer preferences in the design and development of new products by means of quality function deployment (QFD), also known as the house of quality approach [15][54][58][59][65]. Kim, Moskowitz, Dhingra, and Evans [78] present fuzzy multicriteria methodologies which allow the product designer to consider tradeoffs among various customer attributes, while considering the inherent fuzziness in the associated relationships.

There has also been a fair amount of research on the topic of optimal product design and market positioning of products. These publications attempt to identify the bundle of attributes for an existing product or a new product which maximizes market share or a profit function. Most of these articles utilize multidimensional scaling procedure or conjoint analysis-based customer preference data, identify the market segment of interest, and use a set of optimization or heuristic procedures to search for the best combination of attributes for the product. For example, Green and Krieger [54][56] have presented a variety of strategies for effective positioning of products in a target market segment, and Green, Carroll, and Goldburg [49] developed a general approach to product design optimization via conjoint analysis. Reviews of research on this topic are presented in Shocker and Srinivasan [116][117] and Green and Krieger [52][54].

1.2 The Purpose of This Study

The objective of this research is to develop a model for effective operations management by integrating market-based objectives, operating decisions, and operating system constraints. The model combines the essential elements of the production process with consumer evaluations and choices in the marketplace and enables managers to make better decisions regarding product or service design and production. The study also shows how the model can be applied to a particular service industry.

Specifically, the research reported herein builds on the constrained-optimization theory of management science (MS) and uses customer- or market-based criteria to identify and assign weights to different operations objectives. Identification of relative weights for market-based objectives will help in positioning operations according to customer demand patterns. Next, for given sets of customer demand patterns, binding and nonbinding constraints in operating system are identified. Since the binding constraints limit the performance of a system, operations managers can focus their attention on breaking these particular constraints to improve further the operating process. Finally, optimization procedures are used to identify the product and operating system configuration which maximizes profit in target market segments. Appendix A describes the constrained-optimization theory in detail. Several concepts of constrained-optimization theory are explained using a graphical solution procedure to a linear programming problem having two variables. The example shows why it is important to concentrate on breaking the binding constraints. Breaking binding constraints means somehow changing the characteristics of one or more binding constraints so that the performance of the system increases beyond the present optimum performance.

1.3 Scope of This Study

The following sections summarize the four parts of the research project and present the model for effective operations management. The first section describes how customers make tradeoffs and choose a product or a service. The importance of identifying gaps between customers' actual product/service choice patterns and operations managers' perceptions of customers' choice patterns is described in the second section. The third section presents a model of operating decisions based on managers' perceptions of customer choice patterns and operating system constraints. The fourth section describes the procedures utilized in identifying optimal product configurations for the target market segments. It also describes the approach used in identifying operating configurations which enable the production of customer-based optimal products. Finally, the fifth section integrates the ideas presented in the previous four sections.

The empirical data for this research were collected from a fast food industry (pizza delivery industry). The fast food industry is specifically chosen because it has the characteristics of both manufacturing and service businesses. The output of a fast food establishment contains tangible products in combination with intangible services. Hence, the tradeoff patterns of customers and the operating decisions of managers are influenced by a broad spectrum of variables.

For the sake of simplicity, in this dissertation the finished output is referred to as products. Even though service is not explicitly mentioned, it is implied as a part of the product.

1.3.1 Customer Choice Patterns

In order to meet customer demand in a dynamically changing competitive environment, it is important to listen carefully to the voice of the customer. Past research shows that customers choose from a set of alternatives, the product that has the highest utility for them [10][84][85]. After acquiring information and learning about the alternatives, consumers define a set of determinant attributes to use, and then compare products in a particular product class. The process by which customers compare products on sets of determinant attributes and make choices is complicated. Psychophysical judgments involve subjective perceptions of physical reality, in which individuals form impressions about the position of each considered product with respect to each determinant attribute based on a number of physical characteristics [10][84]. Figure 1.1 graphically shows a simplified model of the consumer decision-making process.

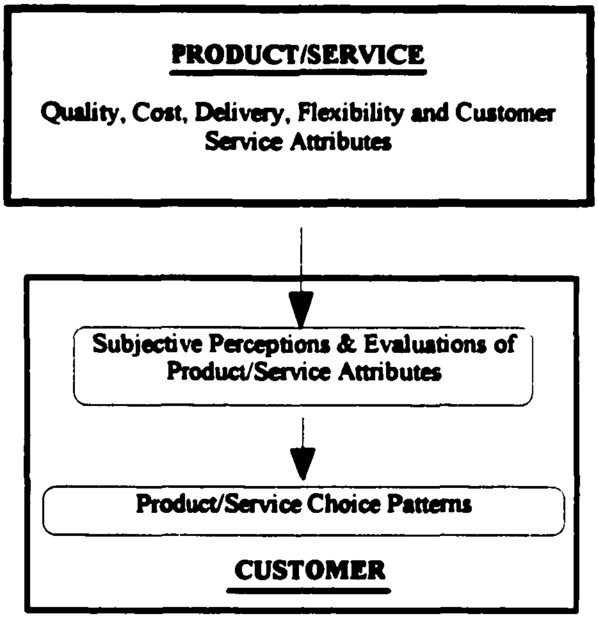

Figure 1.1: Customer decision-making process

After consumers form impressions of the positions of various alternatives on the determinant attributes, they make value judgments and combine information to form overall impressions of the products. In order to do so, they have to make tradeoffs among different product attributes. This evaluation process can be modeled as the integration of information about different determinant attributes to form an overall utility score for each product [7][8][10][84][85].

Understanding customer tradeoff or choice patterns for different product attributes will allow managers to design operations in a way which best meets customer demands. Hence, the first part of the proposed work involves understanding customer tradeoff patterns for a product. A number of publications in marketing research, transportation, and other social sciences have shown that discrete choice analysis (DCA) is the most effective methodology for identifying the tradeoff patterns in complex decision-making situations [10]. Therefore, in this research, DCA is used to identify customer tradeoff patterns for various product attributes.

The marketing-research and operations strategy literatures suggest that demand patterns can be better understood by using market segmentation analysis, which identifies groups of customers having similar tradeoff patterns [29][35][45][55]. In the past, a number of statistical and nonstatistical procedures have been used to segment customers based on their response to numerical scales. A recent study, however, identified a discrete-choice analysis-based latent structure (LS) procedure as the most effective market segmentation technique [98]. Therefore the LS procedure is used to identify market segments.

1.3.2 Managers' Perceptions of Customer Choice Patterns

Often operations managers do not interact closely with their firm's customers; hence, gaps may exist between their perception of customers' tradeoff patterns and the actual patterns. Similar gaps might exist between different functional departments of a firm [120]. Identifying such gaps is key to a successful process improvement, because it suggests how managers' perceptions are different from their customers. Smaller gaps imply a better understanding of customer needs. Therefore, the objective of the second part of this research is to identify the gaps between managers' perceptions of customer tradeoff patterns and customers' actual tradeoff patterns. Figure 1.2 shows the gap between the actual tradeoff patterns of the customers and the operations managers' perceptions of these tradeoff patterns. A statistical hypothesis testing procedure based on the DCA is used to identify the gap [130].

It is postulated that the tradeoff patterns of customers are based on their subjective evaluation of product attributes. Managers' perceptions of customer tradeoff patterns are also based on the same product attributes. The dashed line in Figure 1.2 shows that identifying the gap between customer choice and managers' perceptions can be a very constructive feedback mechanism and can help firms design and produce better products.

1.3.3 Operating Decisions

The operations function of an organization can be viewed as one very large constrained-optimization problem. In general, operations managers in a firm have to satisfy multiple (and often conflicting) objectives (product quality, service quality, cost,

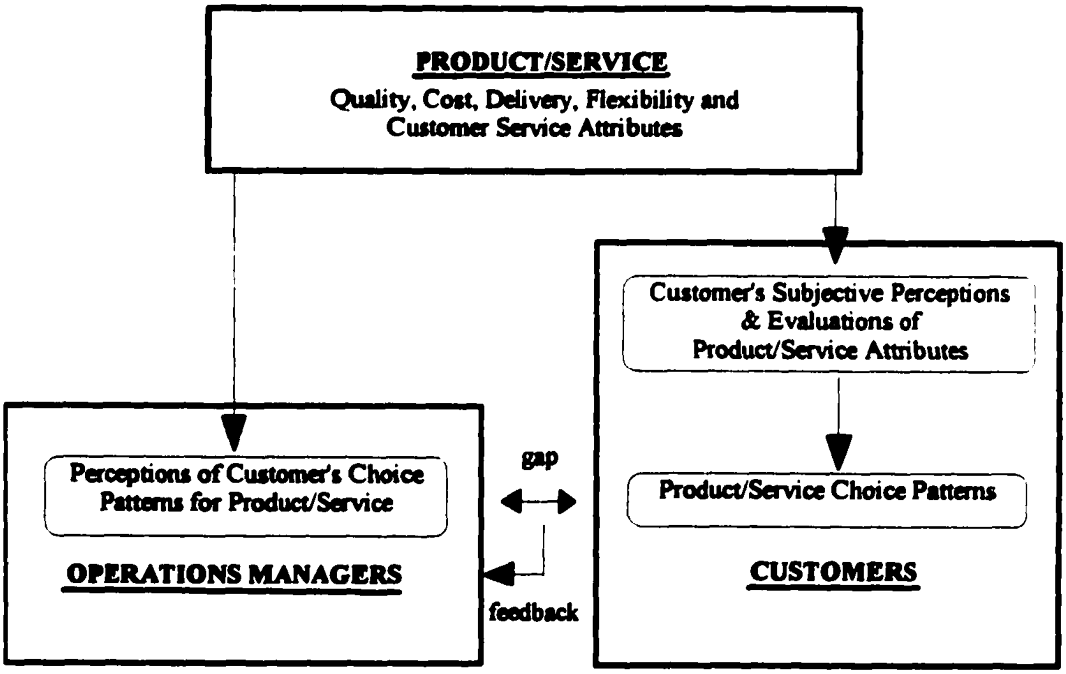

Figure 1.2: The gap between customers' actual tradeoff patterns and managers' perceptions of customer choice patterns

delivery, and flexibility) in the presence of operating system constraints [70]. These constraints limit operations managers' attempts to achieve a global optimum. The system constraints can either be binding or nonbinding, and can dynamically switch between binding and nonbinding as shown in Figure 1.3 [46][47].

An operations manager's objectives are based on his/her perceptions of customers' tradeoff patterns for different product attributes. Since only the binding constraints limit the objective, it is proposed that process reengineering, continuous improvement, or product development efforts should be directed towards breaking binding constraints. Efforts directed towards breaking nonbinding constraints will be wasted and hence the process reengineering, continuous improvement, or product development approach will not be effective. The dashed line in Figure 1.3 shows that breaking binding constraints will be effective and breaking nonbinding constraints will be ineffective.

It is also important to realize that different professional managers try to optimize the performance of their respective departments or subdepartments according to their background and training, while considering only a few objectives and/or a few constraints [120]. Also, not all objectives and system constrains are relevant to managers in different departments of a firm; hence, the end result might be a sum of several local optima which is usually worse than the global optimum.

The influence of operating constraints and customer choice patterns on managers' decisions is identified by conducting two sets of conjoint experiments [52][84][85]. In these experiments, the managers indicate the relative difficulty in meeting a given demand scenario under a specific operating condition.

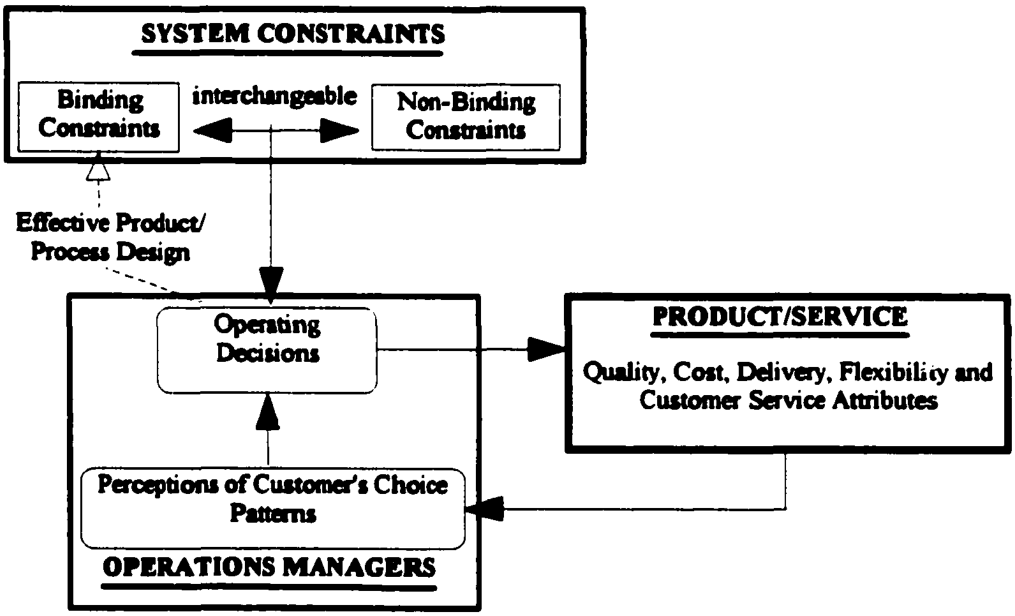

Figure 1.3: Operating decisions

The demand scenario contains information about customer choice patterns and total demand. The operating condition contains specific information about different operating variables (example -- supplier lead time, capacity of the facility, number of employees, wage rates). The managers also estimate the cost of producing products with the given operating configuration.

1.3.4 Optimal Product/Process Design

In the last 20 years or so, marketing research literature has witnessed an increasing interest in optimal product design models. Most of the past research have utilized conjoint analysis-based customer preference data at individual or at market segment level to identify optimal product or product lines configurations [44][49][56][116][117][128]. In most of these studies, products and customer preferences are represented by point locations in a multiattribute perceptual space. Customer preferences are also located in the same multiattribute space. The actual choice of a product or the probability of its selection depends on its proximity to the customer's ideal product location and its relative position with respect to the other alternatives. Generally, optimum search heuristics are utilized to identify the product configuration which maximizes a revenue or profit function or market share.

This study extends previous research by incorporating operating constraints and cost of production into the optimal product design procedures. Figure 1.4 shows a simplified diagram of the proposed approach. It shows that empirical data from both customers and operations managers are needed for identification of optimal product and

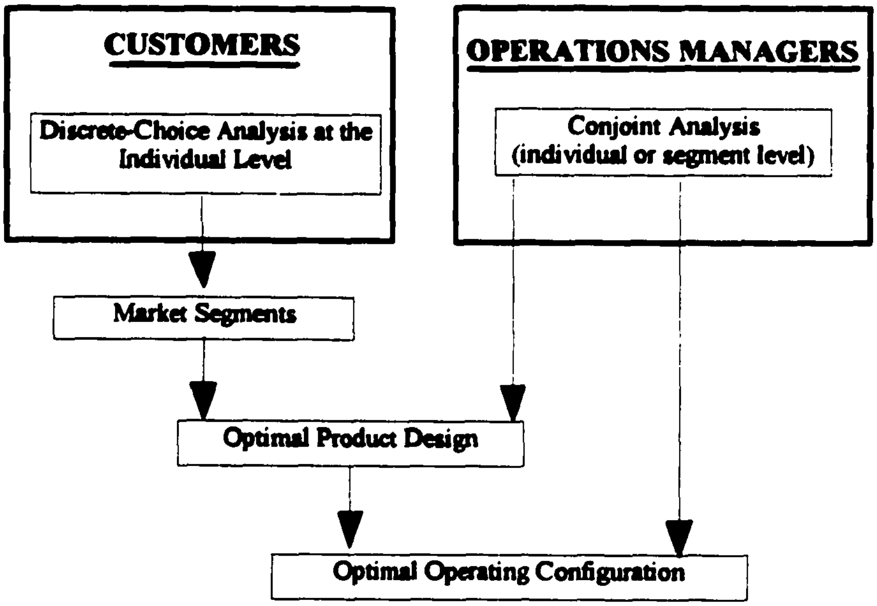

Figure 1.4: Optimal product/process design

operating configuration. The discrete-choice experiments are used to identify customer choice patterns for different product attributes. Cost of producing a product and operating difficulty, are estimated by data collected from the operations managers (section 1.3.3). Finally a nonlinear optimization procedure is used to find the products which maximize profit.

1.3.5 The Model for Effective Operations Management

Figure 1.5 connects the four parts of this research project described earlier and presents the model for effective and customer-based operations management. This figure combines actual customer choices of products and the operating decisions of operations managers. The model shows that actual customer choice patterns are a result of product quality, service quality, cost, delivery, and flexibility attributes of the product. It also shows that operations managers' perceptions of customer choice patterns are also based on the same attributes.

The operating decisions are based on managers' perceptions of customer choice patterns and the binding and nonbinding constraints present in the operating system. The dashed lines in Figure 1.5 suggest that managers can get constructive feedback from understanding customer choice patterns and can concentrate only on breaking binding constraints for process improvement and design of optimal product and operating configuration.

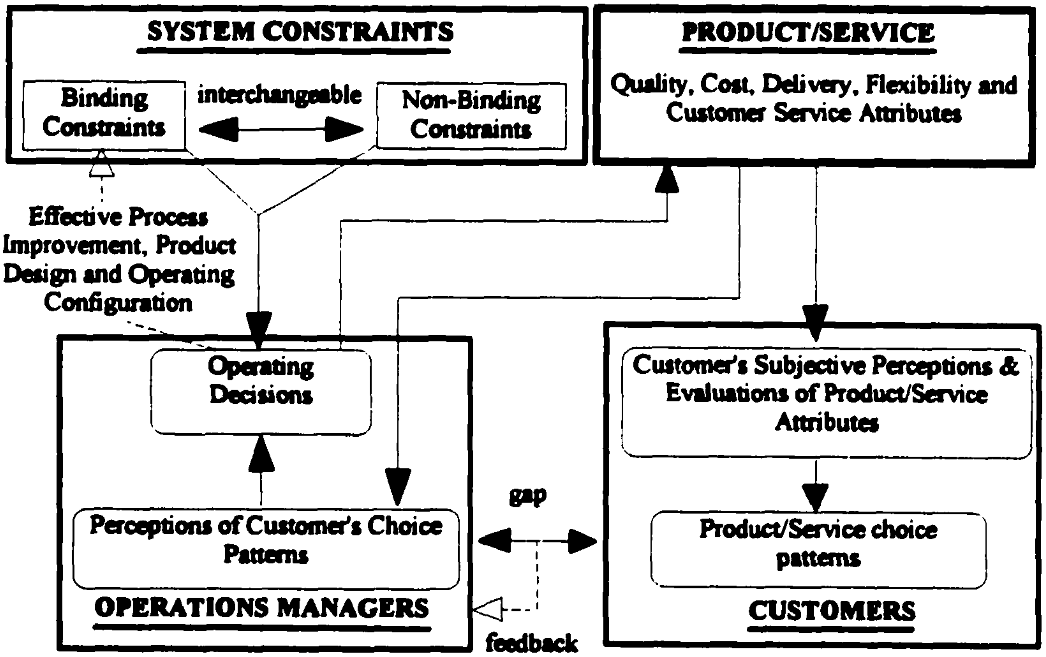

Figure 1.5: The model for effective operations management

1.4 Summary

A brief review of POM and marketing research literature presented in this chapter suggested the need for proper positioning of operating capabilities according to customer needs. A need for connecting operating information into optimal product/process design procedure was also recognized and a model for effective operations management was developed. This chapter also briefly discussed the empirical data collection and analysis procedure.

The remaining four chapters are organized in the following manner. Chapter 2 presents a detailed literature review of management science, manufacturing strategy, service operations strategy, product design, and process improvement literatures. Research questions, experimental design and data analysis procedures are presented in Chapter 3. Chapter 4 summarizes the results of analyzing data collected from the customers and the managers. Chapter 5 discusses the results with respect to the research questions, identifies limitations of the study, and provides directions for future research.

CHAPTER 2

LITERATURE REVIEW

This study builds on past research in several functional areas within business administration. This chapter presents a review of relevant literature in these fields. The chapter is divided into five sections. The first section presents a review of recent trends in management science (MS). A review of operations strategy literature in manufacturing and service industries is presented next. The third section reviews research on incorporating customer preferences/choice patterns into operating decisions. The fourth section reviews strategies for improving operating systems, including continuous improvement and process reengineering philosophies. The fifth section summarizes the literature review presented in the previous four sections.

All five sections review relevant literature and show how this work builds on and addresses the concerns of past research. For the sake of clarity, the study conducted by the author of this dissertation will be referred to as "the current research" in this chapter.

2.1 Management Science Philosophy

The current research builds on the constrained-optimization theory of management science. Recently, however, several articles have shown concern about the usefulness of

MS theories like constrained-optimization [1]. This section discusses the development of MS approaches and shows how the proposed work incorporates MS philosophy and addresses some of the concerns of leading MS philosophers. Churchman, Ackoff and Arnoff [24] defined MS as the application of scientific methods, techniques, and tools for optimization.

Following the success of MS tools during the World War II, a large number of industrial organizations started using those techniques to solve complex business problems. Several MS techniques like linear programming, dynamic programming, simulation, and project management have found wide applications in production planning, inventory control, capacity planning, resource allocation, transportation, scheduling and other business functions [41] [42]. In the current research, the constrained-optimization theory, the basis of several MS techniques, is used. Appendix A describes the concepts behind the constrained-optimization theory.

Turbab [136] and Thomas and DaCosta [134] conducted surveys of large corporations and found that nearly half of the companies had a special department that was engaged mainly in MS activities. Fabozzi and Valente [42] found that the most important area of application of mathematical programming techniques of MS was to POM. The results of the above mentioned and several other surveys show that MS techniques are extensively used to solve complicated business problems [6] [41] [42] [62] [80] [115] [134] [136].

Even though these surveys show that MS techniques are widely used in industry, in recent years, the academic literature has shown a growing concern about the future of

MS. Based on a literature review of articles published in *Harvard Business Review* and *Sloan Management Review*, Corbett and Wassenhove [27] concluded that either top level managers are not interested in MS literature and/or the MS research community is no longer paying attention to managerial literature. Several leading researchers believe that MS is being only used to solve narrow tactical problems and not the strategic problems of business organizations [1].

According to Ackoff [1], MS was originally a market-oriented profession, practiced by scientists and engineers in different disciplines to solve a variety of military and corporate problems. Because of the interdisciplinary nature of MS, these scientists used a variety of techniques to solve complex problems. Over time, operations researchers found that they could solve some types of recurring problems more effectively. Most of these problems evolved statistically stable systems in which human choice and purposeful behavior had virtually no role. The theories in MS that deal with human behavior are abstract and oversimplified and hence have little or no real applications. Therefore, Ackoff [1] believes that traditional MS tools are not helpful in solving complex and strategically important problems of today's businesses.

According to Corbett and Wassenhove [27], MS developed as management engineering in World War II. The goal of management engineering or the original management science was to solve the practical problems for which it was necessary to adapt existing tools or to use existing tools in innovative ways. The aim was to increase managers' understanding and thereby sharpen their intuition by eliminating irrational elements. In the 1950s and 1960s, MS rapidly expanded in theory and practice. As the outcome of this expansion, MS developed as management science and management consulting, in addition to management engineering. The goal of management science is to conduct fundamental research and develop new techniques. Management consulting solves someone's practical problems using existing standard MS methods. Corbett and Wessenhove [27] believe that in last 25 years, the original MS has expanded a lot in the management science and management consulting areas, but management engineering is left underdeveloped. According to Corbett and Wessenhove [27], virtually no research is being conducted to adapt the techniques developed by the fundamental research of management science in innovative ways to solve complicated problems of the present and future. Hence, they believe that the development of management engineering is essential if MS is to continue to be a useful science in the future.

Corbett and Wessenhove [27] suggest that MS scientists should use a new set of tools to address real problems. They suggest using MS in marketing terms as a means of providing value-added service to the client. Miser [96] suggests developing a more coherent and realistic view of science and professional practice. Pierskalla [106] states that MS must incorporate human behavior and should reach out to new areas of knowledge.

The current research addresses several of the concerns of leading MS researchers. The constrained-optimization theory, one of the MS approaches, in combination with several techniques new to the field of MS and POM are used to incorporate customer choice patterns in operating decisions. The current study is an attempt to integrate "new" tools with existing theories of MS. Issues related to complex human behavior are built into the techniques used. Binding and nonbinding constraints in the operating system are also identified through customer choice patterns. Additionally, the concepts presented in the proposed work can be easily translated from theory to practice.

2.2 Manufacturing and Service Operations Strategy

Research in operations strategy has identified several issues which should be carefully addressed if an operating system is to be improved to meet market demands. This section elaborates on the development of operations strategy concepts and explains how they relate to the current study. Most of the concepts in operations strategy emerged from detailed studies of manufacturing industries. Hence, a review of manufacturing strategy literature is presented first. Since almost every product has a service component attached to it and similarly almost every service has tangible product(s) attached to it, a review of service operations strategy is necessary to understand unique characteristics of services. Therefore, the second part of this section presents a literature review of service operations strategy. Finally, a review of literature related to operations objectives and competitive priorities is presented. Several of the constructs used in this study build on past research on operations objectives and competitive priorities.

2.2.1 Manufacturing Strategy

Manufacturing can give the firm a competitive advantage by improving operations to meet the needs of the market. Hence, for the last 25 years or so, managing manufacturing from a strategic point of view has captured the attention of researchers and practitioners alike. Broadly speaking, the literature describes the need for manufacturing strategy, explains how to integrate manufacturing strategy with corporate or business strategy, and analyzes competitive priorities in manufacturing. A detailed review of operations strategy literature is presented by Anderson, Cleveland, and Schroeder [9]. Swamidass [131] also compiled a bibliography of selected business strategy and manufacturing strategy publications. The following section presents a review of the articles that have had a significant impact on the development of manufacturing strategy.

Manufacturing strategy has received wide attention since the publication of Skinner's [119] landmark article in 1969. According to Skinner [119], top management had avoided involvement in manufacturing policy making because manufacturing had been dominated by technical experts and specialists. Skinner [119] argued that because companies fail to recognize the connection between the firm's business strategy and manufacturing strategy, the production system becomes noncompetitive. Skinner [119], for the first time, sketched out the relationship between business strategy and manufacturing strategy, called attention to tradeoffs in production system design, commented on the inadequacy of technical specialists in dealing with production tradeoffs, and suggested a strategic approach to manufacturing management.

Skinner [120] [121] [122] [123] in his subsequent publications elaborated on several of his ideas, most of which are still topics of active research in POM. He suggested that companies should concentrate on finding better ways to compete instead of concentrating on increasing productivity or reducing costs. He claimed that productivity improvement plans overemphasize short-term objectives and cost-cutting measures, thereby reducing a firm's competitive strength. Skinner [120] suggested the focused factory approach as a means of regaining competitiveness. The concept of the focused factory is based on the ideas that there are many ways to compete besides producing at low cost; that a factory cannot perform well on every yardstick; and that simplicity and repetition breed competence. Skinner [120] feels that a lot of companies attempt to do too many things within one plant. Additionally, professionals in different departments within a plant attempt to achieve goals that, although valid and traditional in their own fields, are often incompatible with the goals of other departments. Skinner [120] suggested developing an explicit statement of corporate objectives and strategy and translating them into manufacturing terminology.

The 1970s and 1980s saw the development of the manufacturing strategy paradigm. The research by Abernathy, Clark, Hayes, and Wheelwright built on earlier efforts of Skinner and emphasized how manufacturing can and should be used as a strategic competitive weapon [68] [69] [70] [71] [142] [143] [145]. The manufacturing strategy paradigm identified the ways in which the so-called five Ps (people, plants, parts, processes, and planning and control) of operations management can be analyzed as strategic and tactical decision variables [19]. The core idea behind these publications is the notion of manufacturing tradeoffs and the concept of factory focus.

According to Hayes and Wheelwright [70], a collective pattern of the following interrelated decisions determines the strategic capabilities of a manufacturing firm: capacity (amount, timing, type); facilities (size, location, specialization); technology (equipment, automation, linkages); vertical integration (direction, extent, balance); workforce (skill level, wage policies, employment security); quality (defect prevention, monitoring, intervention); production planning/materials control (sourcing policies, centralization, decision rules); and organization (structure, control/reward systems, role of staff groups). Although individual decisions are usually driven by, and in support of, specific products, markets, or technologies, the primary function of manufacturing strategy is to guide the business in putting together the set of manufacturing capabilities that will enable it to pursue its chosen competitive strategy over the long term.

In their subsequent publications, Hayes and Wheelwright [71] [145] identified four stages in manufacturing's strategic role in a corporation. The role of manufacturing is to minimize its negative potential in the internally neutral stage (the lowest stage). During the externally neutral stage (second stage), the firm follows the industry manufacturing practice. Manufacturing investments are screened for consistency with the business strategy during the internally supportive stage (third stage) of manufacturing's strategic role. Finally, a firm pursues a manufacturing-base competitive advantage in the externally supportive stage. These stages in manufacturing's strategic role outlined above fall along a continuum and suggest the path a company might follow as it seeks to enhance the contribution of its manufacturing function.

Hayes and Wheelwright [69] [70] proposed linking the manufacturing process with the product life cycle to match market requirements. They proposed a product and process matrix which suggests how to choose manufacturing processes to meet the demands of products in different stages of product life cycle.

Hill [74] provided an approach to manufacturing strategy that emphasizes the essential requirement of linking the marketing and manufacturing perspectives in order to determine the best strategies for the business as a whole. Hill's approach to manufacturing strategy serves to link the corporate objectives, marketing strategies, and manufacturing structure and infrastructure through the assessment of how different products win, qualify for, or lose orders in the market-place.

Mathe and Shapiro [90] suggest integrating service strategy into manufacturing strategy because the traditional definition of a product is no longer valid. Their definition of product comprises its physical aspects (the tangible product as determined by its production process -- the traditional definition of a product), the portfolio of services associated with the physical product, and the time dimension as the product and its services evolve over time, as customers needs change or as the tangible product deteriorates. Quinn, Doorley, and Paquette [109] make similar arguments about service-driven product strategy. Mathe and Shapiro [90] propose a service mix concept which is intended to identify and organize various combinations of services according to customer's needs for a given physical object or set of objects based on the different usage possibilities over a product's lifetime. Potts [107] suggests that manufacturing companies should concentrate on a product's service life cycle for generating additional profits.

Chase and Garvin [20] and Chase, Kumar, and Youngdahl [22] suggest that factory-based services will become the next form of competition among manufacturers and hence manufacturing executives should have a clear understanding of the service capabilities of their plants. Chase, Kumar, and Youngdahl [22] define information, problem solving, sales, and support as factory-based services and suggest that these services should be considered in developing manufacturing strategy. Chase and Garvin [20] propose that the factory can be used as a laboratory, consultant, showroom, or dispatcher to gain competitive advantage.

Lovelock [88] suggests that customer perceptions of value and quality are often strongly influenced by the customer service accompanying the core product. Creating an effective customer-service function that will enhance the firm's competitive posture requires a good understanding of the tasks to be performed, a clear definition of employee responsibilities, and attention to detail.

The articles cited in the previous paragraphs played a very effective role in the development of a manufacturing strategy paradigm. However, all these articles were based on case studies, and/or personal experiences of the authors. Recently, other researchers have attempted to verify the ideas of the manufacturing strategy paradigm using empirical data.

Schroeder, Anderson, and Cleveland [114] conducted a survey of manufacturing managers to identify the content of business and manufacturing strategy. They proposed interactive links between business strategy, manufacturing mission and distinctive competence, manufacturing objectives, and manufacturing policies. The results of this study indicate that business strategies typically are expressed in market or product terms.

Anderson, Cleveland, and Schroeder [9] proposed that a proper strategic positioning or aligning of operations capabilities can significantly affect competitive strength and business performance of an organization. Effective positioning and aligning of operations implies an organization designed within the context and purpose of the wider business.

Cleveland, Schroeder, and Anderson [25] proposed that production competence is a measure of the combined effects of a manufacturer's strengths and weakness in certain key performance areas and is related to manufacturing strategy. They defined production competence as manufacturing capability or set of capabilities that a firm possesses relative to its competitors and might wish to exploit in developing a competitive advantage. Cleveland, Schroeder and Anderson [25] identified the following nine key areas in which they believed strength or weakness could mean the success or failure of the business plan: adaptive manufacturing, labor cost-effectiveness, delivery performance, logistics, production economies of scale, process technology, quality performance, throughput and lead time, and vertical integration. The company's business performance was measured by combining manufacturing performance (measured by quality, cost, delivery, and flexibility), marketing performance (measured by market share and growth rate), and financial performance (measured by return on assets). Results of this exploratory empirical study indicated a potential relationship between business performance and production competence. Vickery, Dorge, and Markland [140] proposed a more comprehensive measure of production competence that assesses the level of support that manufacturing provides for the strategic objectives of the firm. They hypothesized that production competence is related to financial performance of the firm and tested it with empirical data from a sample of 65 firms in the furniture industry.

St. John and Young [124] were the first to use empirical tests the patterns of priorities and tradeoffs among operations managers. The results of their exploratory research suggest that day-to-day decision making within operations is not guided by the firm's competitive priorities. Their survey of 15 firms showed that agreement among operations managers on competitive priorities is related to agreement on long-run strategic tradeoff decisions and not to agreement on short-run tradeoffs. They also found that short-run actions of operations managers were often in conflict with stated competitive priorities.

The publications cited above suggest that there is a growing awareness of the importance of taking a strategic view of manufacturing, but there are still many unanswered research questions. It is not clear how manufacturing operations can be managed strategically or how manufacturing can move from Hayes and Wheelwright's first stage to their fourth stage. The focused factory concept and its derivative "plant-within-a-plant" idea show a lot of promise but are contradictory to the idea of expanding the role of the factory to include services.

The current study incorporates several concepts in manufacturing strategy described earlier. Understanding the tradeoff patterns of customers and operations managers will help in strategic positioning or aligning of operations. The current study identifies market segments (based on product and service attributes) which can be helpful to managers formulating an overall business strategy and consistent manufacturing and marketing strategies. The focused factory concept, as such, is not tested in this study, but actual customer tradeoff patterns and market segmentation analysis may be helpful to operations managers should they decide to follow the focused factory strategy. The relative weight of the service aspect of products is also analyzed in the current study. Statistical significance of these relative weights empirically test if customers indeed value services attached to primary products.

Past research in manufacturing strategy identified important constructs and made general recommendations. The results of the current research specifies which aspects of operations need change for process improvement or reengineering.

2.2.2 Service Operations Strategy

The empirical data for the current study are collected from a service industry (a fast-food industry); hence it is important to review the past research in service management. The literature review presented in this section shows that there has been a lot of theoretical work in the area of service management but only a relatively small number of theories have been empirically tested. Also some of the theories proposed by earlier researchers appear to be contradictory in nature.

Service industries have more than 70% of the total employment and account for more than 80% of the gross domestic product of the United States [39]. It has been predicted that the service sector will account for more than 88% of the workforce by the year 2001 [39]. Service industries represent a broad range of businesses, from professional service to retail sales to recreational activities. Broadly speaking, service encompasses all business activities, except for the production of goods. Services are generally characterized as having intangible output; immediate consumption; labor intensiveness; a high degree of customer contact; customer participation in the conversion process; and difficulty with quality, productivity, and performance measurement [39] [129].

The first volume of the *Journal of Operations Management* contained two articles emphasizing the need for future research in the area of service management. In one of the articles, Chase [17] reviewed and classified the topics covered in the four major research journals which had historically dealt most extensively with POM-related topics. Chase found that only 7% of the articles published were in the people/macro category, which includes topics such as service delivery systems. Buffa [14], in an another article, also raised the concern that more research is needed in service operations management. Buffa [14] stated that service systems are uncharted territory and virtually everything needs to be done.

The diversity of the service sector often makes it difficult to come up with managerially useful generalizations concerning the management of service organizations. Lovelock [86] classified services in five different two-by-two matrix forms and suggested how the specific nature of services in a particular class affects operations and marketing. Lovelock's classification scheme addresses the following questions: (1) What is the nature of the service act? (2) What type of relationship does the service organization have with its customers? (3) How much room is there for customization and judgment on the part of the service provider? (4) What is the nature of demand and supply for the service? and (5) How is the service delivered? Lovelock proposed that his classification scheme addressing the above five questions can help managers in obtaining a better understanding of their business. Additionally, by recognizing the common characteristics of their service business with other and often unrelated service businesses, the managers can identify ways to improve their own business.

Chase [16] proposed that if there is less direct customer contact in the service system, then the service system is more likely to operate at its peak efficiency. Conversely, the system is less likely to operate at its peak potential with high direct customer contact. Chase [18] proposed the "customer contact model" which classifies services on the degree of contact. Mersha [94] proposed a broadened definition of customer contact and differentiated between active and passive contact. Based on these distinctions, Mersha [94] extended the customer contact model and addressed several earlier concerns about this classification scheme.

Schmenner [112] expanded Chase's classification scheme and categorized services on two dimensions: labor intensity and customer interaction with service customization. Labor intensity is defined as the ratio of the labor cost incurred to the value of the plant and equipment. A high labor intensive business involves relatively small plant and equipment and considerable worker time, effort, and cost. The second dimension in the classification scheme combines two distinct concepts: customer interaction and customization. A service with a high level of interaction is one in which the customer can actively intervene in the service process. A service with high customization will work to satisfy an individual's particular preferences. The joint measure has a high value when a service exhibits both a high level of interaction and a high level of customization for the customers. He proposed a two-by-two service process matrix that classifies services as service factory, service shop, mass service, and professional service.

Levitt [81] [82], in one of the early works on service operations strategy, argued that since services are thought of in humanistic terms and manufacturing is thought of in technocratic terms, manufacturing is efficient and forward-looking, whereas services, in comparison, are primitive and inefficient. He further argued that if companies stop thinking of service in humanistic terms, they will be able to make drastic improvements in quality and efficiency. He suggested that service should be viewed as manufacturing in the field with a production line approach. Thomas [133], on the other hand, believes that because manufacturing has been the dominant economic force of the last century, most managers have been educated through experience and/or formal education to think about operations strategy in product terms. He believes that a large part of manufacturing experience is irrelevant to the management of service operations because services are very different from manufacturing. Thomas [114] recommends using economies of scale, proprietary technology, and service differentiation to build barriers in the service industry.

Lovelock [87] suggests an integrated approach to service management. He suggests using a combination of marketing, operations, and human resources perspectives for effective service operations management. Lovelock defines the marketing concept as creating relationships with specific types of customers by delivering a carefully defined service package of consistent quality that meets their needs and is perceived as offering superior value. He defines the human resource concept as recruiting, training, motivating, and retaining managers and other employees who can work together to balance the twin goals of customer satisfaction and operational effectiveness. The operations concept is defined as using specific operational techniques and strategies, executed by personnel with the necessary skills and supported by appropriate facilities, equipment, and information technology to create and deliver the specified service package to target customers, while consistently meeting quality and productivity standards. Key tools for examining service situations from this multifunctional perspective include identifying different types of service processes, analyzing of service systems, breaking down service products into core and supplementary elements, and flowcharting service delivery to establish linkages between front stage and back stage activities [87].

Sullivan [129] also advocates an integrated approach to service management. He suggests that POM researchers should include organizational behavior and marketing constructs and techniques to address service operations problems adequately. An interdisciplinary nature of service management was also recommended by Bowen and Cummings [12]. They propose that service management effectiveness affects and is affected by human resource management, strategic management, marketing, and operations management.

According to Lovelock [89], the challenge for service managers is to search for compatibility among the following four basic forces in a service business: (1) What does management want? (2) What do employees and suppliers want? (3) What do customers want, and (4) What is the organization actually capable of doing? Lovelock proposes that both operational efficiency and customer satisfaction are required to answer the above questions successfully. Hence, he suggests that operations and marketing should work together and learn to appreciate the other's perspective. He discusses the following 11 operational issues that are relevant to both marketing and operations managers: productivity improvement, make versus buy, facilities location, standardization versus customization, batch versus unit processing, facilities layout and design, job design, learning curve, management of capacity, quality control, and management of queues.

According to Davidow and Uttal [32], developing a service strategy is an essential step toward choosing an optimal mix and level of service for different customer sets. Customers will leave if they get too little service or the wrong kind of service, but the company will go broke or have a noncompetitive price if they provide too much. Hence, Davidow and Uttal [32] suggest using market segmentation analysis to determine service strategies for different segments of customers. They suggest that by segmenting markets, companies can better match supply and demand.

Heskett's [73] strategic service vision consists of the identification of a target market segment, development of a service concept to address targeted customers' needs, codification of an operating strategy to support the service concept, and design of a service delivery system to support the operating strategy. Heskett believes that the following elements are common to many of the successful service companies: close coordination between marketing and operations; a strategy built around elements of a strategic service vision; an ability to redirect the strategic service inward to focus on vital employee groups; a stress on the control of quality based on a set of shared value, peer group status, generous incentives, and, when possible, a close relationship with the customer; a cool appraisal of the effects of scale on both efficiency and effectiveness; the substitution of information for other assets; and the exploitation of information to generate new business.

Hart [64] advocates using unconditional service guarantee and suggests that it can be a very powerful strategy for service business. An unconditional service guarantee pushes the entire company to focus on the customer's definition of good service and not on any executive's assumptions. It sets clear performance standards and generates reliable data when performance is poor. It forces an organization to examine its entire service-delivery system for possible failure points and builds customer loyalty, sales, and market share.

Similar to Hayes and Wheelwright's [71] four-stage model for manufacturing organizations, Chase and Hayes [21] developed a four-stage model for strategic importance of service operations in a firm. The motivation behind this classification is to pinpoint the key elements that must be addressed in the strategy development process. This classification can also help position a firm's operations relative to its competitors and provide a current perspective and future vision that can be communicated to the company's employees. During the lowest strategic stage, available for service, service firms tend to consider their operations as necessary evils. These firms assume that if operations managers can do what they are supposed to do, without major disruptions, the firm will be profitable. Hence, management pays little attention to how other firms, whether direct competitors or not, design and manage similar service delivery systems. During the second stage, journeyman, the operations goal becomes not letting the competitors gain too much advantage. Hence, the firm begins to adopt industry practice in its operations. In a stage

3, distinctive competence achieved, senior management has a clear vision of what creates value in customers' eyes and hence operations is designed to deliver that value. To reach the fourth and the final stage, world class service delivery, the company must develop capabilities and credibility of its operations organization to the point where operations becomes proactive, forcing higher performance standards on the whole company, identifying new business opportunities, and helping redefine the firm's competitive strategy. Rather than simply investigating customer needs and attempting to fulfill them, stage 4 companies seek to create needs, establish expectations, and continually expand those expectations. They define the quality standards by which their competitors are judged.

Even though services have received a lot of attention by academicians and practitioners, so far only a handful of service operations management articles containing empirical data have been published in POM-related journals.

Roth and Velde [110] presented a competitive service strategy paradigm which explicitly considers the strategic role of service operations management as a competitive weapon. Their service strategy paradigm draws upon the prevailing manufacturing strategy literature in its definition of strategic operations choices and critical factors. Using a sample of 117 retail banks, the authors link competitive priorities with operations strategy contents of structure, infrastructure and integration choices. They empirically show that the patterns of operations choices vary by competitive priorities. Roth and Velde [110] propose that manufacturing strategy framework can be adopted in service delivery system design.

Davis [33] studied the tradeoff between customer waiting time and operations efficiency. He presented and applied a total cost model to a major fast-food chain, using data collected at several locations. This model has several implications in the design of a service system which is efficient and, at the same time, satisfies customer needs.

Lindsley, Blackburn, and Elrod [83] studied the tradeoff between time and product variety in the book distribution industry. They concluded that both time and variety are critical success factors. Hence, they recommended that managers should be aware of relative values of time and variety in their distribution strategy for better service management.

Haynes and Thies [72] linked the successful implementation of technology to three key factors. They recommend the following: (1) the process must be well defined and its characteristics must be identified before its implementation, (2) the goals of marketing and operations functions must be coordinated with respect to implementation strategy, and (3) technology implementation must consider the customers' needs and potential tangible benefits, so that customers will utilize the new system at volume levels that justify the initial expense of the technology implementation.

The above literature review suggests that in the last 15 years or so there have been many theoretical developments in the area of service operations management. Several researchers have proposed a variety of theories for effective service operations management. Lovelock [86], Chase [16], Mersha [94], and Schmenner [112] presented a number of service classification schemes and provided specific recommendations for effective operations management within a class of firms. Although these classification schemes have value, they cannot suggest how a particular firm in a given industry may achieve comparative advantage. On the other hand, the current work studies specific firms, identifies their strengths and constraints, and suggests a guideline for process improvement.

Some of the proposed theories in service operations management are contradictory in nature. For instance, Levitt [81] proposed a production line approach to services, whereas Thomas [133] believes that services should not be managed like a manufacturing operation. No large scale empirical studies support or discount either of these theories. The current research indirectly addresses the above issue by identifying weights for different operations objectives. For example, these market-based weights can indicate if traditional manufacturing-type variables like waiting time or cost are more important than the quality of customer service.

The multifunctional nature of service management is stressed by several authors [32] [73] [87] [129]. The current research builds on marketing and operations-based approaches to service management and uses an MS approach to optimize the process. Additionally, the affect of novel ideas like unconditional service guarantees on customer choice patterns can be easily tested by empirical experiments conducted in the current work.

2.2.3 Operations Objectives and Priorities

This section reviews the literature associated with objectives and competitive priorities of operations managers. An understanding of operations objectives and competitive priorities is essential for effective operations management, since they should be aligned with customers' choice patterns to better meet market demand.

Hayes and Wheelwright [70] identified cost or price, product quality, delivery performance (or dependability), and flexibility as the set of market-based performance measures for manufacturing. Cost is identified as the first competitive dimension but is not the only basis on which a business can compete. In some businesses the basis of a competitive advantage is superior product quality achieved either by providing higher product reliability and/or performance in a standard product. The third competitive dimension identified by Hayes and Wheelwright [70] is delivery performance. This objective includes delivery lead time and the reliability of delivery (% on-time delivery). Product and volume flexibility is identified as the fourth competitive dimension. A business that competes on the basis of product flexibility emphasizes its ability to handle difficult, nonstandard orders and takes the lead in development and introduction of new and innovative products. Volume flexibility emphasizes a firm's ability to accelerate or decelerate production very quickly and juggle orders so as to meet demands for unusually rapid delivery. According to Hayes and Wheelwright [70], firms have to make tradeoffs among these four dimensions to position themselves in the marketplace.

Ferdows and Meyer [38] studied tradeoffs among quality, cost, delivery, and flexibility objectives and argued that unless there is slack in the system, improvement in one of the objectives is possible only at the expense of the others. Hence, it will be difficult for a company which is operating its manufacturing system at industry standards to improve on two or more objectives simultaneously. Ferdows and Meyer's [38] sand-cone model is developed on the premise that excellence in manufacturing is built on a common set of fundamental principles which are easier to get in place starting with one particular type of activity and then pursuing other activities that expand and enrich this set of principles. The sand-cone model suggests improving quality first. When the efforts on quality improvement continue and expand, the company should also start focusing on dependability (delivery performance) of the production process. Next, when the previous efforts are expanded, managers should also pay attention to improving the flexibility of the process. Finally, after all the above three objectives are met, then direct attention to cost efficiency is justified.

Schroeder, Anderson, and Cleveland [114] conducted an empirical study to identify operations objectives. In response to an open-ended question, operations managers identified quality, delivery, cost, and flexibility as the top four operations objectives. The respondents, however, added capacity, volume, people concerns, nonunion status, trained workforce, productivity, inventory, equipment utilization, safety, and technical support also as operations objectives. On average, managers listed about six objectives each. Hence, Schroeder Anderson and Cleveland [114] believe that the Hayes and Wheelwright's standard list of four objectives (quality, cost, delivery, and flexibility) for operations is not adequate to describe practice.

Recently, it has been suggested that providing a package of customer service (in addition to primary product/service) should also be considered a manufacturing objective because competitive advantage can be gained by integrating service strategy in manufacturing [20] [22] [90]. Chase, Kumar, and Youngdahl [22] and Chase and Garvin [20] believe that operations objectives should contain factory-based services as an additional dimension of operations objectives. Hence, they suggest opening the technical core of manufacturing to customers by providing factory-based services. Information, problem solving, sales, and support are identified as four components of factory-based services. Quinn, Doorley, and Paquette [109] and Potts [107] also advocate using value-added services as operations objectives.

The management of quality in products and services recently has captured the attention of both practitioners and academicians. The teachings of quality gurus Deming, Crosby, Garvin, and others have started a new revolution, known as total quality management (TQM), in western industries. The TQM literature is rich and is full of theoretical articles, empirical results, case studies and implementation consequences. Because quality (both product and service) has been identified as a major operations objective, it is necessary to review the fundamental research in quality management which explores the meaning of quality itself. At the same time, presenting a detailed literature review of quality management is beyond the needs of this chapter. Therefore, the next few paragraphs present a review of two major research projects in quality management. The research by Garvin [43] and Parasuraman, Zeithaml, and Berry [102] [103] [104] explored the multidimensional nature of product and service quality, respectively, and provided a framework for quality management research.

According to Garvin [43] quality means pleasing the customer and not just protecting them from annoyances. Garvin proposed the following eight critical dimensions or categories of product quality: performance, features, reliability, conformance, durability, serviceability, aesthetics, and perceived quality.

Performance refers to a product's primary operating characteristics [43]. Garvin [43] defines features as bells and whistles of products -- the characteristics that supplement the basic functioning of a product. Reliability reflects the probability of a product malfunctioning or failing within a specified time period. Conformance is the degree to which a product's design and operating characteristics meet established standards. A measure of product life, durability has both economic and technical dimensions. Technically, durability is defined as the amount of use one gets from a product before it deteriorates. Alternatively, durability can also be defined as the expected cost, both dollars and inconvenience, of future repairs against the investment and operating expenses of a newer and more reliable option. Garvin [43] defined serviceability, the sixth dimension of product quality, as ease and speed of repair and courtesy and competence of repair personnel. The final two dimensions of quality are the most subjective. Aesthetics measures how a product looks, feels, sounds, tastes, smells, etc. Perceived quality measures a product or brand's reputation. It is a measure of customers' perceptions of product's quality.

Parasuraman, Zeithaml, and Berry (PZB) [102] defined service quality as a measure of how well the service level delivered matches customer expectations. PZB believe that delivering service quality means conforming to customer expectations on a consistent basis.

PZB [102] studied four service businesses (retail banking, credit card, securities brokerage, and product repair and maintenance) and developed a conceptual model for service quality. They conducted a series of focus group and executive interviews and concluded that a set of key discrepancies or gaps exists regarding executive perceptions of service quality and the tasks associated with service delivery to consumers. These gaps can be major hurdles in attempting to deliver a service which consumers would perceive as being of high quality. PZB [102] identified 10 determinants of service quality which form the basis of the gaps between executives and customers. These dimensions are reliability, responsiveness, competence, access, courtesy, communication, credibility, security, understanding/knowing the customer, and tangibles.

Reliability involves consistency of performance and dependability. It means that the firm performs service right the first time and honors its promises. Responsiveness concerns the willingness or readiness of employees to provide service. It involves the timeliness of service. Competence means possession of the required skills and knowledge to perform the service. It involves the knowledge and skills of the contact personal, support personnel, and the research capability in the organization. Access consists of approachability and ease of contact. It includes, for example, convenient hours and location of operation and waiting time to receive service. Communication means listening to the customers and keeping them informed in language they can understand. This means that a company might have to adjust its language for different customers -- increasing the level of sophistication with a well-educated customer and speaking simply and plainly with a novice. Credibility involves trustworthiness, believability, and honesty. It includes having customer's best interests at heart. Security means freedom from physical or financial danger, risks, or doubt. It also includes confidentiality of the service. Understanding/knowing the customer involves making an effort to understand a customer's specific requirements, for example, providing individualized attention and recognizing a regular customer. Finally, tangibles include the physical evidence of service (physical facilities, appearance of personnel, tools and equipment used to provide the service, physical representation of the service, and other customers in the service facilities). PZB [103] [104] in their subsequent publications developed a service quality survey instrument, SERVQUAL, to measure the customer's perceptions of service quality.

The articles cited in the previous paragraphs identify operations objectives as quality, cost, delivery, flexibility, and customer service. The theory of constraints (TOC), on the other hand, suggests that the goal of an industrial organization is to make money in the present and in the future [46] [47]. Hence, according to the TOC, the operations should be to continue performing activities that make money. This operations objective assumes that an organization can "make money" in the present and in the future only by keeping customers happy, by providing good service, by making high quality products, and so on.

The main logic behind the TOC approach is to achieve a global optimum by aligning operations towards one focused goal and then concentrating and breaking production bottlenecks (binding constraints) to improve processes. The TOC approach has been identified as an application of the constrained-optimization theory, which is also the main logic behind the current study [140].

The current study builds on previous research on operations objectives and priorities. The operations objectives identified by Hayes and Wheelwright [70]; Ferdows and Meyer [38]; Schroeder, Anderson, and Cleveland [114]; Chase, Kumar, and Youngdahl [22]; Chase and Garvin [20]; Quinn, Doorley, and Paquette [109]; Potts [107]; Roth and Velde [110]; Garvin [43]; and PZB [102] [103] [104] are the theoretical basis for the attributes used in the design of the discrete-choice and conjoint experiments. The current work identifies weights for operating variables based on the above objectives.

2.3 Incorporating Customer Preferences into Operating Decisions

One of the strengths of the current study is that it incorporates customer preferences into operating decisions. This idea is not new, however, and has been suggested and implemented in previous articles in marketing, operations management, and new product development. The approaches used to quantify customer choice patterns can be divided into two broad categories: first, incorporating customers into operating characteristics and, second, identifying customer tradeoff patterns for different product attributes. This section presents a brief review of both types of articles.

2.3.1 Quality Function Deployment

Quality function deployment (QFD) is a structured approach for integrating the voice of the customer into the product development process [59] [65] [138]. The purpose of QFD is to insure that customer requirements are factored into every aspect of the process from product planning to the production floor. QFD uses a series of matrices, which look like houses, to deploy customer input throughout design, manufacturing, and delivery of products. The main matrix relates customer choices and their corresponding technical requirements. Generally, additional features are added to the basic QFD matrix to broaden the scope of the analysis. Typical additional features include customer preference weights for different product attributes and competitive evaluations.

Generally, QFD uses four houses to present data [58] [59]. The first house, called the house of quality, links the voice of the customer to the design attributes. The voice of the customer is a hierarchical set of customer needs in which each need or set of needs is assigned a priority which indicates its importance to the customer. Design attributes are engineering measures of product performance. The second house of QFD links these design attributes to the actions the firm can take. The third house links actions to implementation decisions. The final house of QFD links the implementation decisions to production planning.

Griffin and Hauser [59] focused their research on identifying different ways of data collection to identify customer preferences. The results of their study indicate that approximately 90% or more of the customer needs can be identified by interviewing about 30 customers. The authors present a review of different techniques for collecting customer preferences about these needs.

Kim, Moskowitz, Dhingra, and Evans [78] presented a decision support system for QFD using fuzzy multicriteria methodologies. The relationships between the customer attributes and the engineering characteristics and among the engineering characteristics are typically vague and imprecise in practice because of the general fuzziness in the system

[78]. Hence Kim et al. [78] propose a fuzzy modeling approach to QFD by developing and illustrating various fuzzy, multiobjective models to aid a designer in choosing target values for engineering characteristics. These models allow the product designer to consider tradeoffs among various customer attributes, as well as to consider simultaneously the inherent fuzziness in the associated relationships.

Chakraborthy and Ghose [15] show the use and need of system-theory-related paradigms for developing quantitative and qualitative models for tracking product/process interactions in QFD. The basic idea behind their research is to construct a frontier of the engineering feature values using data envelopment analysis and to use this frontier to predict engineering feature values for the development of a new product.

The current research draws on the QFD literature cited above. Connecting customer choices to operating characteristics is based on basic concept behind QFD. The current work contributes to the QFD literature by incorporating operating constraints and customer choice patterns.

2.3.2 Optimal Product Design

Designing new products and modifying the attributes of existing products to satisfy the needs of customers in different market segments have captured the attention of several researchers in marketing and other disciplines. The current research extends the earlier work on the above topic by incorporating operating constraints and cost of production into the analysis. This section presents a brief review of relevant work on the topic of optimal product design. For a detailed review of the different aspects of product development, the reader is referred to the texts by Urban and Hauser [138] and Moore and Pessemier [98].

Previous work on optimal product design has extensively used multidimensional scaling technique and conjoint analysis based multiattribute data collected from the customers [117]. In the simplest version of these models, brand preferences for a particular consumer are assumed to be inversely related to increasing distance of the brands from the consumer's ideal point. It is assumed that consumer chooses the brand closest to his/her ideal point. Alternatively, it might also be postulated that the probability of selection of a particular brand by a consumer decreases as its distance from the consumer's ideal point increases. Most of the earlier work on the topic only used the above approaches (deterministic or probabalistic) to estimate the market share for existing products [48] [57] [67] [77] [99] [105] [116] [137]. The optimal product design problem however requires procedures not only for estimating the value of the objective function for each point location of interest but also for searching the multiattribute space systematically to find the location that results in the optimal objective function value.

Shocker and Srinivasan [117] formalized the problem of optimal product design by using multidimensional scaling technique derived multiattribute space of current brands and consumers' ideal points. Even though Shocker and Srinivasan suggested some possible solution strategies for both deterministic and probabalistic version of the problem, no specific algorithm was presented. Subsequently, several explicit solution techniques for deterministic version of Shocker and Srinivasan's [117] model were presented [4] [5]

[44] [147]. For example, Gavish, Horsky, and Srikanth [44] examined the problem of positioning a new product in an existing product class. They formulated the problem as a mixed integer nonlinear program assuming that both the consumer and the firm are involved in a two-stage decision process. The consumer first decides on the budget for the product class and second evaluates the subset of competing objects which have prices approximately equal to the budget constraint. The firm is assumed to identify a set of promising products positions in multiattribute space which would attract a large number of customers. It is then assumed to evaluate these product positions in terms of costs and resulting profits. Gavish, Horsky, and Srikanth [44] presented an exact algorithm for problems with small sample sizes and an efficient heuristic procedure for problems with large sample sizes.

A number of more recent publications have expanded the earlier work in optimal product design by considering probabalistic version of the problem or by attempting to incorporate cost or technological constraints in the formulation. For example, Houser and Simmie [66] characterized the problem as probabalistic in nature and explicitly considered cost and prices. However they did not discussed the actual problem of measuring the cost.

Zufryden [147] for the first time used conjoint analysis-based customer preference data for product design optimization. He formulated the problem as a zero-one integer programming model using conjoint analysis-based data. Zufryden's model assumes that the consumer compares the utility of the test product with that of one's current brand favorite and deterministically chooses the one with the highest utility. Zufryden however did not present any numerical examples of his approach nor any suggestions for implementation.

Green, Carroll, and Goldberg [49] presented a general approach to product design optimization via conjoint analysis. These authors developed a comprehensive system of programs, POSSE, consisting of procedures for carrying out the experimental design and stimulus construction, utility function estimation, deterministic or probabalistic choice simulation, objective function optimization, optimization, sensitivity analysis, and time path forecasting. Recently Green and Krieger [54] [56] have developed another product design and optimization model (SIMOPT) based on the similar ideas. They discuss strategies for modifying buyer perceptions, ideal-level preferences, and attribute importance that are attractive for a firm's existing product line. They then consider long-term strategies for modifying the current product's attribute levels.

Page and Rosenbaum [102] report the use of conjoint analysis in the design and development of new appliances. Their article contains detailed information about the design attributes, alternative product designs, market segments, and competitive positions of the firm and its competitors. They developed a simulation model that predicts the market share of alternative product-line configurations before the actual development of these products.

Sudharshan, May, and Shocker [128] compared several algorithms for optimal new product design. They tested the algorithms under a number of simulated market environments. They found that the algorithms developed by Albers [22] and Gavish, Horsky, and Brockhoff [44] outperform the other procedures.

A number of articles have extended the ideas behind optimal product design to the selection of optimal product lines. These articles attempt to find an optimal subset of products which maximize an objective function based on market share or profit. For example, McBride and Zufryden [91] developed an integer programming approach to the optimal product line selection problem; Green and Krieger [51] developed a consumer-based approach to designing product line extensions; and Dobson and Kalish [36] addressed the problem of positioning and pricing a product line to maximize profits. Since the current research only addresses the problem of optimal product design and not the product line selection, the reader is referred to an article by Green and Kreiger [50] which presents a review of different models and heuristics for product line selection problem.

The current work builds on and extends the previous research in optimal product design. Even though several of the earlier models mention the importance of cost of production in the analysis, none have tried to estimate these costs. The optimal product design procedure developed in the current work, on the other hand, is based not only on the customer preference data but also on the cost of production data collected from the operations managers. Hence, one hopes that the current approach will be able to identify the product designs which maximizes profit. The current work further extends the work on optimal product design by incorporating operating constraints into the analysis. The operating configuration which can facilitate the production of a product with optimal design attributes is also identified.

2.4 Process Improvement

It is hoped that the current research will contribute to a firm's ability to utilize of resources for improving the operating process efficiently. This section reviews two major approaches for operating process improvement: the continuous improvement philosophy and business process reengineering. It is shown how the outcomes of the current work can contribute to these approaches.

2.4.1 Continuous Improvement

Continuous improvement (CI) is a philosophy that seeks to improve any and all factors that are related to the process of converting inputs to outputs [19][127]. It covers equipment, methods, materials, and people. A key part of the CI philosophy is the belief that improvement efforts should never stop. Even though CI originated in the United States, until recently it did not receive much attention from American managers [113]. Japanese companies, on the other hand, have used this approach to improve their processes for years. The term *kaizen*, Japanese for CI, is an essential element of operations management in Japanese companies [127].

Based on a review of several CI programs, Melcher, Acar, Dumont, and Khouja [92] identified essential features that differentiate CI systems from traditional systems. In a traditional system, management sees performance standards as essentially fixed by the constraints of technology and the existing organization. These constraints appear unbreakable without a major innovation in technology or production approach. In CI systems, management views the performance level of the firm as something to be continuously challenged and incrementally upgraded. CI uses a holistic analysis approach, focuses on the role of the workforce in problem identification, takes a long-term focus, and attempts to address root causes of problems. Generally, information flows in CI systems are both horizontal and vertical. Suggestions for improvements come from employees and flow upwards to management. Solutions are generally communicated horizontally for deployment in several departments within the firm.

According to Stevenson [127], successful continuous improvement systems must have both the support and involvement of management at all levels of the organization. Schroeder and Robinson [113] list five requirements for the success of CI programs. First, managers should understand that improvements require a learning period before they yield benefits. Second, labor and management must trust each other to generate the free flow of ideas that drive the CI effort. Third, a reward system must be instituted to promote interdepartmental cooperation. Fourth, continuous employee training is costly but a required element of CI programs. Finally, a CI program requires an efficient system to handle improvement ideas and administer the reward process.

In practice, CI plans range from very simple programs utilizing suggestion systems to sophisticated programs utilizing a variety of statistical tools. Generally a structured CI program includes the following three components: the plan-do-check-act (PDCA) cycle, problem structuring and analysis of the facts, and standardization [19].

The PDCA cycle, also known as the Deming Wheel, conveys the sequential and continual nature of the CI process [19] [126]. The plan phase of a CI process identifies problem areas in the process. The do phase deals with the implementation of the change.

The check phase deals with evaluating data collected during the implementation. Finally, during the act phase the improvement is codified as a standard procedure and replicated throughout the organization. This PDCA cycle continuous on to identify new problems after completing a cycle.

The outcomes of the current research can aid continuous improvement projects in several ways. An effective PDCA cycle starts with the identification of an important POM problem. Conjoint experiments conducted in the current work identify the weights for different operating constraints (or problems). Managers can focus their attention on breaking the binding constraints in their CI projects. The conjoint experiments can be repeated after the implementation of the solution to quantify the influence of that change. These future conjoint experiments will identify new binding constraints for the changed system and prompt a new PDCA cycle. In other words, the current work offers a systematic and scientific way of identifying problems and analyzing the effect of changing/breaking these constraints on market-based performance measures.

2.4.2 Business Process Reengineering

Business process reengineering (BPR) can be defined as the use of modern information technology to radically redesign business processes [60][61]. This well publicized definition of BPR has been revised and further expanded by a group of academic researchers and practitioners at the Boston University Manufacturing Electives Forum [96] as a radical or breakthrough change in a business process. Reengineered process designs seek dramatic orders of magnitude, as distinguished from incremental improvement in business value. Key value creation processes involving manufacturing operations include order fulfillment (the customer supply chain process), product development, order creation (selling and configuration), and customer service (post product delivery processes).

BPR, also known as business process innovation or business process improvement, has attracted increasing attention from both practitioners and academics. As an increasing number of companies have started to use reengineering for process improvement, several books and academic papers have begun to appear on the topic [60] [61] [63] [95]. This section presents the main ideas behind BPR and their relationship to the current study.

The explicit objective of BPR is to improve business value significantly [60] [61]. This effort generally begins with a clean sheet of paper, uses systematic, customer-oriented process analysis; and is managed as a project with definite start and end points. Reengineering is revolutionary in nature, with both significant expected payoffs and risks. Some researchers also believe that reengineering can create a negative impact on the organizational culture [96]. BPR generally starts with the recognition of the need for change. Both opportunity and crisis can be the needed driver for change [95].

BPR attempts to improve corporate performance by changing business processes, organization and human resources, and information technology. Built around new technologies and motivated workers, process reengineering begins with a commitment to a strategic vision from senior management. Its scope is vast and crosses multiple business functions.

BPR is based on the process view of the business. A process is defined as a structured, measured set of activities designed to produce a specified output for a particular customer or market. It implies a strong emphasis on how work is done within an organization. Taking a process approach implies adopting the customer's point of view. Processes are the structure by which an organization does what is necessary to produce value for its customers. Hence an important measure of a process is customer satisfaction with the output of the process. Since a process perspective implies a horizontal view of the business that cuts across the organization, adopting a process-orientated structure generally means deemphasizing the functional structure of the business [31].

According to Harrington [63], the main objective of BPR is to ensure that the organization has business processes that eliminate errors, minimize delays, maximize the use of assets, promote understanding, are easy to use, are customer friendly, are adaptable to customer's changing needs, provide the organization with a competitive advantage, and reduce excess labor.

Harrington [63] describes the five phases of BPR. The objective of the first phase called organizing for Improvement is to ensure success by building leadership, understanding, and commitment. This phase comprises establishing an executive improvement team, appointing an BPR campaign, providing executive training, developing an improvement model, communicating goals to the employees, reviewing business strategy and customer requirements, selecting the critical processes, appointing process owners, and selecting process improvement team members.

The objective of the understanding the process phase (second phase) is to understand all the dimensions of the current business process [63]. This objective is accomplished by defining the process scope and mission; defining the process boundaries; providing team training; developing a process overview; defining customer and business measurements and expectations for the process; flow diagraming the process; collecting cost, time, and value data; performing process walkthroughs; resolving differences; and updating process documentation.

Streamlining (third phase) attempts to improve the efficiency, effectiveness, and adaptability of the business process [63]. It provides team training, identifies improvement opportunities, eliminates bureaucracy, eliminates no-value-added activities, simplifies the process, reduces process time, error-proofs the system, upgrades and standardizes the equipment, automates and documents the process, and selects and trains the employees to accomplish the above goal.

Implementation of a system to control the process for ongoing improvement is accomplished during the measurements and controls (fourth phase) phase of BPR [63]. Finally, continuous improvement phase implements the CI process. The goals of the last two stages of BPR are achieved by developing in-process measurements and targets, establishing feedback systems, auditing the process periodically, defining and eliminating process problems, evaluating the impact of change on the business and on customers, benchmarking, and providing advanced training.

According to Cypress [30] BPR and MS share many common principles: a bias for overall optimization of business process performance and the organizations which perform them; an acknowledgment of the fundamental interactions among people, processes, and information technology; and a search for optimal solution strategies. Cypress [30] feels that the first generation of BPR currently used by most of the companies has led to significant improvement in corporate performance but is now reaching a plateau. This is happening because, even though the main objective of BPR is to achieve a global optimum, MS tools are not used in reengineering. Hence, Cypress [30] suggests using MS theories and optimization tools in combination with current BPR techniques to improve the process further.

Several of the conclusions of the MS approach (Appendix A) can be easily identified in the five-stage BPR approach described by Harrington [63]. For example, BPR attempts to identify critical processes or binding constraints, then to find a way to break these binding constraints by means of information technology and organizational changes. The effect of breaking the binding constraints is evaluated, and the process of continuous improvement is continued. Based on the above ideas, it is hoped that the outcomes of the current work will help in implementing effective BPR projects.

2.5 Summary

The current study builds on past research summarized in this chapter and takes an interdisciplinary approach to develop a model for effective operations management. This chapter presented a review of previous research in the areas of management science, manufacturing and service operations strategy, customer-based operations management, and process improvement.

The development and usefulness of MS theories and techniques were discussed also. Recently however, several leading MS researchers have shown concern about the future of MS. For example Ackoff [2] believes that MS is only being used to solve narrow tactical problems and not the strategic problems in business organizations. The current study addresses those issues by incorporating new mathematical techniques (conjoint analysis, discrete-choice experiments, latent segment analysis) within the existing MS paradigm and by taking a multidisciplinary approach to solve a complex business problem.

The detailed review of manufacturing and service operations strategy literature presented suggests that operations can provide competitive advantage to the company by aligning itself to meet market-based objectives. A review of publications addressing the issues related to the multidimensional nature of operations objectives (quality, cost, delivery, flexibility, and customer service) and priorities was also presented. The current study identifies the relative weights and statistical significance of the market-based objectives. Managers can use the results of the study to better position their operations.

The current study incorporates customer preferences into operating decisions and identifies the gap between customer choice patterns and managers' perceptions of customer choice patterns. The approach presented here builds on previous research in marketing research, quality function deployment, and related areas by integrating the voice of the customer into the elements of production process.

The current work extends earlier work in optimal product design by incorporating operating constraints and cost of production into the analysis. It not only identifies the product design which maximizes profit but also finds the operating configuration which facilitates the production of products with optimal design.

Finally, this chapter reviews two major approaches for operating process improvement-- continuous improvement philosophy and business process reengineering. It is suggested that the results of the current work will enable managers to utilize their efforts and company resources effectively for process improvement projects.

CHAPTER 3

RESEARCH DESIGN

This chapter builds on the theoretical base developed in the previous two chapters and explains the research design. The chapter is divided into five sections. The first section proposes and discusses research questions. The data collection procedures are explained in the second section. The approach employed in the development of discrete-choice and conjoint experiments is presented in the third section. The fourth section discusses data analysis procedures. Finally, the fifth section summarizes the main ideas presented throughout the chapter.

3.1 Research Questions

The literature review presented earlier suggests that customers choose a product from a set of alternatives that has the highest utility [10] [84]. After gathering information about the alternatives, customers use a set of determinant attributes to compare different products [10] [84]. Past research also suggests that customers form impressions of the positions of various alternatives on the determinant attributes, make value judgments, and combine information to form overall impressions of the products [7] [8]. A review of manufacturing and service operations strategy literature suggests that these determinant attributes can be broadly classified into the categories of product quality, service quality, cost, delivery, and flexibility [16] [25] [111]. In other words, these articles suggest that customers tradeoff quality, cost, delivery, flexibility, and customer service attributes in choosing a product. However there is virtually no published empirical study which explains how customers make tradeoffs between these attributes. The following research question proposes to investigate the customer tradeoff patterns for different product attributes:

3.1.1 Research Question I

How do customers tradeoff product quality, service quality, cost, delivery and flexibility attributes in choosing a product?

A review of operations strategy literature presented earlier suggests that managers' priorities should be driven by customer-based objectives for proper positioning or aligning of operations according to market needs [9]. However, often the operations function in an organization is far removed from the customers, and it is difficult for the managers to predict customer choice accurately because the operations managers do not always interact closely with the customers [120]. The following research questions explore the above issues:

3.1.2 Research Question II

What are managers' perceptions of customer tradeoff patterns for quality, cost, delivery, flexibility and customer service attributes of a product?

3.1.3 Research Question III

Are managers' perceptions of customer tradeoff patterns for product quality, service quality, cost, delivery, flexibility, and customer service attributes of a product the same as the customers' actual tradeoff patterns for those attributes?

The marketing-research and operations strategy literatures suggest that demand patterns can be better understood by segmenting the market and identifying customers having similar tradeoff patterns [29] [35] [45] [55]. Since the objective of this study is to develop a customer-based operations management model, it is important to identify the nature and relative sizes of customer groups with similar choice patterns. Therefore the following research question is relevant:

3.1.4 Research Question IV

What are the characteristics and relative sizes of customer groups with similar tradeoff patterns?

It is proposed that the operations function in an organization can be viewed as a large constrained-optimization problem with operations managers attempting to achieve market-based objectives. Earlier, it was suggested that an operations manager's ability to satisfy the market-based objectives depend on his/her perceptions of customer choice patterns and operating system constraints. It was also proposed that production cost is affected by customer demand patterns and operating constraints. The following research question investigates the above ideas:

3.1.5 Research Question V

How do customer tradeoff patterns and operating system constraints affect managers' ability to meet market demand?

3.1.6 Research Question VI

How do customer tradeoff patterns and operating system constraints affect production cost?

This study extends the earlier research in optimal product design by including production cost and operating constraints into the analysis. Specifically, the following research questions are investigated:

3.1.7 Research Question VII

How should the product quality, service quality, cost, delivery, and flexibility attributes associated with existing product and/or new products be changed to maximize the net profit obtained from all the products offered?

3.1.8 Research Question VIII

What operating configuration facilitates the production of profit-maximizing products?

3.2 Empirical Data Collection

The research questions presented earlier are based on the model for effective operations management presented in Chapter 1. The following section explains the data empirical collection procedure used to demonstrate the usefulness of the proposed model and explore the research questions for one service industry.

The data for this work are collected from the Pizza Delivery Industry. The pizza delivery industry is chosen because it has the characteristics of both manufacturing and service businesses. The tradeoff or choice patterns of customers in this industry are expected to be influenced by several operating variables (example -- waiting time, service reliability) in addition to cost and other product attributes (example -- types of pizza crust, food temperature).

The empirical work involved collecting data from both managers and customers of companies. The following section describes the data collection procedure.

3.2.1 Customer Data

The customer data collection procedure involved two phases. First, a small number of a random sample of customers were interviewed. There were two reasons for collecting this form of qualitative data. First, the academic literatures in operations management and marketing provide a detailed list of attributes (product quality, service quality, cost delivery, and flexibility) that customers consider when choosing products. However, it is possible that some of these attributes are not relevant for a particular type of product. Second, it is also possible that some unique characteristics of the Pizza Delivery Industry are not represented in the variables identified by previous research. Another reason for collecting qualitative data is to develop a "short-list" of the number and levels of attributes because the experimental designs are based on them.

Phase 2 consisted of collecting customers' responses to a set of discrete-choice experiments by a self-administered mail survey. Customer data ware collected from residents of the Salt Lake metropolitan area. The total population of this area is more than 500,000. Initially it was proposed that the study would utilize a telephone random digit dialing procedure developed by Waksberg [143]. However the Waksberg procedure was not used for the final data collection process because it was found to be very inefficient. Out of first 150 numbers generated by the Waksberg procedure, 108 yielded no response, and 14 were business establishments. Out of 28 residential numbers contacted, only 12 agreed to participate in the study. Therefore the Waksberg procedure was not used to contact any more customers.

The 1994-95 edition of the *Salt Lake City Regional Telephone Directory* contains 628 pages (numbers 201 through 828), and approximately 400 telephone numbers per page of residential telephone numbers. Five hundred telephone numbers were selected from the directory by using the following procedure: first, randomly select a page number between 201 and 628; second, randomly select a column number between 1 and 4; and third, select the telephone number from the top of the page (between 1 and 100).

Survey instruments along with a cover letter from the researcher, a forwarding letter from the chairperson, Department of Management, University of Utah and a self-addressed postage paid business reply envelope were mailed to 500 residential addresses selected from the telephone directory. Appendix B contains a copy of the data collection packet mailed to the customers.

3.2.2 Manager Data

The Salt Lake metropolitan area contains a large number of pizza delivery establishments. Table 3.1 presents a list of such businesses with two or more establishments in the Salt Lake Metropolitan area. Businesses with only one establishment were excluded from the study because they only deliver pizza in a limited area and/or charge extra for pizza delivery and/or offer gourmet pizzas. Since approximately 100 managers in the pizza delivery industry in Salt Lake Metropolitan area represent a small population, managers of all the establishments with two or more shops were contacted and invited to participate in the study.

A data collection packets mailed to the managers of establishments contained a cover letter from the researcher, a forwarding letter from the chairperson, Department of Management, University of Utah, a self- addressed postage paid business reply envelope, and two survey instruments (Appendix C). As an incentive for responding to the surveys, the researcher's cover letter promised to provide the managers a summary of results and included two cinema tickets (a $3 value).

3.3 Development of Discrete-Choice and Conjoint Experiments

The following section explains the attributes and the experimental design used in generating the survey instruments. Empirical data from the managers were collected by

Table 3.1: List of pizza delivery establishments in Salt Lake metropolitan area

Name of the Company	Number of Shops
Ambassador Pizza	11
Domino's Pizza	17
Free Wheeler Pizza	02
Godfather's Pizza	05
Pizza Hut	19
TOTAL	54

discrete choice and conjoint experiments. Customer data were collected only by a discrete choice experiment.

3.3.1 Design of Discrete Choice Experiments

Discrete choice analysis was used to identify customer tradeoff patterns for different product attributes and managers' perceptions of customer tradeoff patterns. Both sets of experiments contained the same attributes and were based on the same experimental design. A discrete choice analysis is an implementation of the multinomial logit model [10]. The subjects are asked to choose an alternative from a choice set containing two or more alternatives. The attribute levels of all the alternatives in a choice set are experimentally designed by the researcher. The choice task is repeated several times (based on experimental design used) and the data collected are used to estimate parameters for the multinomial logit model. Section 3.4 explains the multinomial logit model in detail.

The operations strategy literature suggests that market-based objectives can be classified into the following broad categories: product quality, service quality, cost, delivery and flexibility (product quality can be further divided into eight dimensions and service quality can be further divided into 10 dimensions. These dimensions of product and service quality are defined in Chapter 2). Even if one variable is used for every market-based objective, the number of variables in the experimental design will be more than 20. Such a large number of variables considerably increases the dimensionality of the experimental design. If the number of variables is large, then a large number of experimental profiles are needed to estimate accurately the effects of all variables. Therefore qualitative data collected from 15 randomly selected customers were used to generate a "short-list" of seven variables. These variables are price, discount on second pizza, promised delivery time, actual delivery time, pizza variety, pizza temperature, and unconditional moneyback guarantee.

Next a fractional factorial design procedure was used to generate a 16 profile orthogonal experimental design ($2^{7-3} = 2^4 = 16$ profiles) [27]. This experimental design can estimate all main effects and six selected two-way interactions. The design was assigned to the seven variables such that all two-way interactions between price, promised delivery time, actual delivery time, and pizza variety could be estimated. Management has control over these variables; hence any significant interactions among these variables will be a very useful information. The experimental profiles were generated assuming two levels for every variable. The attribute levels reflect the actual market values.

Table 3.2 presents the attributes, their two levels, and experimental design codes for all the variables. The experimental design matrix is presented in Table 3.3. The experimental design matrix presented in Table 3.3 was used to generate discrete choice experiments for customers and managers. In both the experiments the 16 profiles presented in Table 3.3 were paired with their respective "foldover" design. The attribute levels in a foldover design are the opposite of the original design. For example, the design code for all variables in the first profile is -1; therefore the foldover design code for all variables will be +1. The discrete choice experiment for customers asked them to choose

Table 3.2: Pizza delivery company attributes used to design discrete-choice experiments

Attribute	Design Code = -1	Design Code = +1
Price of First Large Pizza	$12	$18
Discount on Second Pizza	none	half price
Promised Delivery Time	20 minutes	40 minutes
Actual Delivery Time	same as promised	15 minutes late
Pizza Variety	1 type of crust	3 types of crust
Pizza Temperature	warm	steaming hot
Unconditional Money back Guarantee	no	yes

Table 3.3: Experimental design matrix for the discrete-choice experiments

Profile / Attribute	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Price of First Large Pizza	-1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	1	1	1	1
Discount on Second Pizza	-1	-1	-1	-1	1	1	1	1	-1	-1	-1	-1	1	1	1	1
Promised Delivery Time	-1	-1	1	1	-1	-1	1	1	-1	-1	1	1	-1	-1	1	1
Actual Delivery Time	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1
Pizza Variety	-1	1	1	-1	-1	1	1	-1	1	-1	-1	1	1	-1	-1	1
Pizza Temperature	-1	1	1	-1	1	-1	-1	1	-1	1	1	-1	1	-1	-1	1
Unconditional Money back Guarantee	-1	-1	1	1	1	1	-1	-1	1	1	-1	-1	-1	-1	1	1

between a company with attributes presented in Table 3.3, its foldover design company, or neither. The customers made 16 separate choices. The discrete choice experiment for managers was similar to the experiment for customers. However the managers were asked to predict the choice of their customers.

3.3.2 Design of Conjoint Experiments

The model for effective operations management (Figure 1.5) suggests that managers' ability to meet market needs and production cost depend on customer tradeoff patterns and operating system constraints. Therefore, customer choice patterns and the characteristics of the operating system (constraints) were used to design the conjoint experiment which estimated production cost and managers' perceptions of difficulty in meeting customer demands. Price, discount on second pizza, promised delivery time, actual delivery time, pizza variety, pizza temperature and money back guarantee were used to represent customer demand patterns (Table 3.2).

Based on qualitative information collected from five managers of different pizza delivery companies, seven operating variables were selected to represent operating system constraints. These variables are daily demand rate, customer order similarity, number of pizza delivery personnel, number of cooks and in-store employees, average wage rate, and supplier delivery frequency. Table 3.4 shows the operating system attributes and their levels. Again, the attribute levels reflect the actual market values.

An orthogonal fractional factorial design procedure was used to generate 32 experimental profiles with 14 attributes (Tables 3.2 and 3.4) [27]. The design allows the

Table 3.4: Operating system attributes used to design conjoint experiments

Attribute	Design Code = -1	Design Code = +1
Daily Demand Rate	200 pizzas/day	400 pizzas/day
Order Similarity	mostly small size orders	a mix of small and large size orders
Number of Pizza Delivery Personnel	3	7
Number of Cooks and In-Store Employees	3	7
Average Wage Rate	$5 per hour	$8 per hour
Pizza Preparation and Cooking Time	10 minutes	20 minutes
Supplier Delivery Frequency	once a week	every other day

estimation of all main effects and all two-way interactions between the following variables: price of first large pizza, actual delivery time, daily demand rate, number of pizza delivery personnel, number of cooks and in-store employees, and average wage rate. The experimental design matrix is presented in Tables 3.5 and 3.6.

3.4 Data Analysis Procedures

A number of techniques are utilized to analyze discrete choice and conjoint analysis-based data collected from managers and customers and to address the eight research questions. These techniques include logit regression for analyzing discrete choice data, a simulated annealing-based latent structure procedure for market segmentation, least square regression for analyzing conjoint data, and nonlinear optimization for optimal product/process design. The following section describes these techniques except the least square regression, because, in past, ordinary least square (OLS) regression has been used for numerous POM studies and therefore is well known.

3.4.1 Logit Regression

The appropriate statistical procedure for analyzing discrete choice-data collected from customers and managers is the logit regression procedure which is based on an econometric model called the multinomial logit model [10]. A multinomial logit model represents the probability of selecting an alternative from a possible choice set. The multinomial logit model is expressed as

Table 3.5: Experimental design matrix for the conjoint experiments (Profiles 1-16)

Profile / Attributes	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Price of First Large Pizza	-1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	1	1	1	1
Discount on Second Pizza	-1	-1	1	1	-1	-1	1	1	1	1	-1	-1	1	1	-1	-1
Promised Delivery Time	-1	1	1	-1	-1	1	1	-1	1	-1	-1	1	1	-1	-1	1
Actual Delivery Time	-1	-1	-1	-1	1	1	1	1	-1	-1	-1	-1	1	1	1	1
Pizza Variety	-1	-1	1	1	1	1	-1	-1	-1	-1	1	1	1	1	-1	-1
Pizza Temperature	-1	-1	1	1	1	1	-1	-1	1	1	-1	-1	-1	-1	1	1
Money back Guarantee	-1	1	-1	1	1	-1	1	-1	1	-1	1	-1	-1	1	-1	1
Demand Rate	-1	-1	1	1	-1	-1	1	1	-1	-1	1	1	-1	-1	1	1
Order Similarity	-1	1	1	-1	1	-1	-1	1	-1	1	1	-1	1	-1	-1	1
Number of Delivery Personnel	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1
Number of In-Store Employees	-1	1	1	-1	1	-1	-1	1	1	-1	-1	1	-1	1	1	-1
Average Wage Rates	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Pizza Cooking Time	-1	1	-1	1	1	-1	1	-1	-1	1	-1	1	1	-1	1	-1
Supplier Delivery Frequency	-1	-1	-1	-1	1	1	1	1	1	1	1	1	-1	-1	-1	-1

Table 3.6: Experimental design matrix for the conjoint experiments (Profiles 17-32)

Profile / Attributes	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
Price of First Large Pizza	-1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1	1	1	1	1
Discount on Second Pizza	1	1	-1	-1	1	1	-1	-1	-1	-1	1	1	-1	-1	1	1
Promised Delivery Time	-1	1	1	-1	-1	1	1	-1	1	-1	-1	1	1	-1	-1	1
Actual Delivery Time	-1	-1	-1	-1	1	1	1	1	-1	-1	-1	-1	1	1	1	1
Pizza Variety	1	1	-1	-1	-1	-1	1	1	1	1	-1	-1	-1	-1	1	1
Pizza Temperature	-1	-1	1	1	1	1	-1	-1	1	1	-1	-1	-1	-1	1	1
Money back Guarantee	-1	1	-1	1	1	-1	1	-1	1	-1	1	-1	-1	1	-1	1
Daily Demand Rate	-1	-1	1	1	-1	-1	1	1	-1	-1	1	1	-1	-1	1	1
Order Similarity	-1	1	1	-1	1	-1	-1	1	-1	1	1	-1	1	-1	-1	1
Number of Delivery Personnel	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1	-1	1
Number of In-Store Employees	1	-1	-1	1	-1	1	1	-1	-1	1	1	-1	1	-1	-1	1
Average Wage Rates	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Pizza Cooking Time	1	-1	1	-1	-1	1	-1	1	1	-1	1	-1	-1	1	-1	1
Supplier Delivery Frequency	1	1	1	1	-1	-1	-1	-1	-1	-1	-1	-1	1	1	1	1

$$P_{ij} = \frac{e^{\mu V_{ij}}}{\sum_{k=1,K} e^{\mu V_{kj}}} \tag{3.1}$$

where P_{ij} represents the probability of selecting an alternative i from the j^{th} choice set containing K possible choices [10]. V_{ij} in equation (3.1) represents the systematic utility of alternative i in choice set j. Utility can be defined as judgments, impressions, or evaluations that consumers form of products or services, taking all the determinant attribute information into account [85]. The multinomial logit model assumes that the errors are independent and identically distributed according to a Gumble distribution with a scale parameter μ [10]. The multinomial logit model assumes that the probability of selecting an alternative depends on the decision maker's perceptions of the relative attractiveness or utilities of the alternatives [10]. Representing a product or service as a bundle of its attributes and assuming an additive utility function, an alternative's utility can be calculated in the following manner:

$$V_{ij} = \sum_{l=1,L} \beta_l x_{ijl} \tag{3.2}$$

where x_{ijl} is the level of attribute l of alternative i in choice set j and β_l is the relative utility weight (part-worth utility) associated with attribute l [10]. The total number of attributes is L. There are a number of general approaches to finding β parameters; however, in practice the maximum likelihood estimation procedure is used most often. A maximum likelihood estimator is the estimated value of the β parameters for which the observed sample is most likely to have occurred [10]. Therefore the likelihood function for M subjects can be represented as

$$\mathcal{L} = \prod_{m=1,M} \prod_{i=1,I} \prod_{j=1,J} (P_{ij})^{Y_{ijm}} \tag{3.3}$$

$Y_{ijm} = 1$ if subject m chooses alternative I in choice set j

$Y_{ijm} = 0$ otherwise.

Several individual-level goodness-of-fit statistics can be calculated for the multinomial logit model. An asymptotic t-statistic (similar to a t-test in the OLS regression) can be calculated for estimated β parameters. Several likelihood ratio tests (similar to the F-test in OLS regression) can be used to test the overall model. A log-likelihood ratio test is based on the differences between the natural logarithm of the likelihood function (equation 3.3) under two conditions. First the likelihood ratio is calculated assuming equal probability of choosing all the alternatives in a choice set or assuming all β parameters to be zero. This natural logarithm of the likelihood (log-likelihood) value is represented as $\mathcal{LL}(0)$. Next, the likelihood ratio is calculated again, assuming the estimated β parameters. This log-likelihood value is called $\mathcal{LL}$(B). Then, the log-likelihood ratio test is defined as

$$\chi^2 = -2 \; [\; \mathcal{LL}(0) - \mathcal{LL}(B)] \qquad (3.4)$$

with the degrees of freedom equal to the number of β parameters [10]. Other goodness-of-fit measures called Akaike Information Criteria or AIC and Consistent Akaike Information Criteria or CAIC are defined in the following manner [10]:

$$\text{AIC} = -2 \; [\; \mathcal{LL}(B) - \text{number of } \beta \text{ parameters}] \qquad (3.5)$$

$$\text{CAIC} = -2 \; [\; \mathcal{LL}(B) - \text{number of } \beta \text{ parameters } (1 + \ln M)] \qquad (3.6)$$

For a "good" model both AIC and CAIC should be positive [10]. McFadden's ρ^2 and adjusted ρ^2 measures (similar to R^2 and adjusted R^2 in OLS regression) are defined in the following manner [10]:

$$\rho^2 = 1 - [\mathcal{LL}(B) / \mathcal{LL}(0)] \quad \text{and} \quad 0 \leq \rho^2 \leq 1 \qquad (3.7)$$

$$\text{Adjusted } \rho^2 = 1 - [\,(\mathcal{LL}(B) - \text{number of } \beta \text{ parameters}) \,/\, \mathcal{LL}(0)\,]$$
$$\text{and} \quad 0 \leq \text{Adjusted } \rho^2 \leq 1 \qquad (3.8)$$

For this study, the NTELOGIT program was used to estimate the β parameters [102]. NTELOGIT calculates the β parameters for an aggregate sample data using the maximum likelihood estimation procedure. The β parameters calculated for aggregate data are the same as the β parameters for the individual level data (equations 3.1, 3.2 and 3.3), but the aggregate $LL(B)$ and $LL(0)$ values are not the same as the individual level $LL(B)$ and $LL(0)$ values. This happens because errors at the individual level might get "canceled" at the aggregate level. For example, it is difficult to predict a person's choice with a multinomial logit model, but for a large group it is possible to predict the fraction of individuals choosing a particular alternative. Since the individual-level goodness-of-fit measures provide more complete information, a FORTRAN program was developed to calculate the individual level goodness-of-fit measures described above (equations 3.1 through 3.8) using β parameters estimated by the NTELOGIT. For the sake of comparison, the aggregate level McFadden's ρ^2 and adjusted McFadden's $\bar{\rho}^2$ measures calculated by NTELOGIT are also reported. Appendix D contains a copy of the FORTRAN program used to calculate the individual-level goodness-of-fit measures. The above procedure was used to estimate the tradeoff patterns of customers (Research Question I) and managers (Research Question II).

Research Question III suggests that there might be a gap between actual tradeoff patterns of customers and managers' perceptions of customer tradeoff patterns. In order to investigate this research question, the β parameters for the customers and managers need to be compared. However just comparing β for customers and managers will be erroneous because the multinomial logit model contains a Gumble scale parameter (μ), which might not be same for the two models. An appropriate statistical procedure for comparing two multinomial logit model is a Gumble scale hypothesis test procedure developed by Swait and Louviere [131]. This procedure first rescales the Gumble scale parameters and then compares the models using the following χ^2 statistic with L+1 degrees of freedom (L is the number of attributes) in the following manner:

$$\chi^2 = -2\,[\mathcal{LL}_\mu - (\mathcal{LL}_1 + \mathcal{LL}_2)] \tag{3.9}$$

where $\mathcal{LL}_1$ and $\mathcal{LL}_2$ are the log-likelihood values of the two multinomial logit models without any rescaling and $\mathcal{LL}_\mu$ is the log-likelihood value for the joint model with a rescaling parameter μ. NTELOGIT first finds the optimum scaling parameter μ and then tests two multinomial logit models by calculating the aggregate estimates for the three log-likelihood values specified in equation 3.9. In this study, however, the individual level estimates of the three log-likelihood values were used. The Gumble scale test based on the Individual level log-likelihood estimates are more conservative than the same test based on the aggregate level estimates.

3.4.2 Simulated Annealing-Based Latent Structure Procedure

As mentioned earlier, this study uses a latent structure procedure to identify the size and nature of different market segments. The latent structure procedure is a simultaneous segmentation and estimation methodology which maximizes the probability of on an individual belonging to a particular segment [99]. This procedure assumes that each individual belongs to one and only one segment.

If U_n represents the probability that an individual belongs to segment n, then the likelihood function (3.3) can be modified as

$$\mathcal{L} = \prod_{m=1,M} \sum_{n=1,N} U_n \prod_{i=1,I} \prod_{j=1,J} (P_{ijn})^{Y_{ijm}} \tag{3.10}$$

where P_{ijn} represents the probability of selecting alternative i in the choice set j assuming that the individual belongs to segment n. Equations 3.1 and 3.2 can be modified for calculating P_{ij} by using a segment level probability estimate (P_{ijn}) in the following manner

$$P_{ij} = \sum_{n \in 1,N} U_n P_{ijn} = \sum_{n \in 1,N} U_n \frac{e^{V_{ijn}}}{\sum_{k \in 1,K} e^{V_{kjn}}} \tag{3.11}$$

and

$$V_{ijn} = \sum_{l=1,L} \beta_{ln} x_{ijl} \tag{3.12}$$

The likelihood function represented by equation 3.10 does not have a closed form solution and therefore it is solved iteratively. Each iteration consists of two steps. First, β parameters are estimated for the segments assuming some segment membership. Once the parameters have been estimated, the probability of membership in segment n, based on observed data, is calculated. In the second step, the individuals are reassigned to the segment that maximizes their probability of being in a segment. Then new β values are calculated and people are relocated to the segments. This procedure is repeated until the segment membership stabilizes and the likelihood function (equation 3.10) is maximized. The procedure described above will be referred to as the basic latent structure (BLS) procedure.

Since BLS is an iterative procedure the final solution depends on the starting solution. The individuals are reassigned according to the β values calculated in the previous iteration; therefore it is possible that the global optimum might not be obtained even after a large number of BLS iterations. In the past, simulated annealing (SA), a systematic random search procedure, has been found to be very effective in getting a near global optimum solution in a variety of optimization problems [80].

The basic ideas behind SA are based on a physical process known as annealing, which means the cooling of metal in a heat bath. If solid material is heated past its melting point and then cooled back into a solid state, the structural properties of the cooled solid depend on the rate of cooling. The SA algorithm simulates such cooling process by a probability function. SA has been applied to a number of POM problems [13] [17] [77] [114] [136]. Therefore a SA heuristic-based latent structure procedure (SALS) was developed to further improve the solutions obtained by the BLS procedure. Table 3.7 presents an overview of the SALS procedure. Simulated Annealing allows the BLS procedure to assign customers from several starting points. Because SA sometimes prefers a current worse solution over the previous solution (step 9 in Table 3.7), the BLS procedure searches a larger region in the solution space and hence has a better chance of finding the global optimum solution. Therefore this study uses the SALS procedure for the market segmentation analysis.

Table 3.7: Simulated annealing-based latent structure procedure (SALS)

Step	Procedure
1	Randomly assign customers to the segments.
2	Select t, α and number of iterations
3	Reassign customers according to BLS procedure, calculate β values and the likelihood function value ($\mathcal{LL}_1$). Copy the solution to the INCUMBENT solution.
4	Randomly reassign a few (from 5% to 50%) customers. Calculate new β values and likelihood function values ($\mathcal{LL}_2$). This is a TRIAL solution.
5	Calculate $\delta = \mathcal{LL}_1 - \mathcal{LL}_2$
6	If $\delta < 0$ then copy the TRIAL solution to the INCUMBENT solution.
7	If likelihood function value corresponding to the INCUMBENT solution > likelihood function value for the BEST solution then copy the INCUMBENT solution to the BEST solution.
8	If $\delta \geq 0$ then generate a uniformly distributed random number X between 0 and 1.
9	If $X < e^{-\delta/t}$ then copy the TRIAL solution to the INCUMBENT solution.
10	Repeat steps 4 through 9 N-SAME-T number of times.
11	$t = \alpha * t$
12	Repeat steps 4 through 11 N-REDUCE-T number of times.
13	Stop.

Chapter 4 provides the results of the market segmentation analysis using SALS and also explains how Simulated Annealing parameters t, α, N-SAME-T and N-REDUCE-T were selected. Appendix E contains a FORTRAN code of the SALS procedure.

3.4.3 Optimal Product/Process Design Procedure

An overview of the optimal product/process design (OPPD) approach developed in this study was presented earlier in Figure 1.4. This approach combines customer choice and market segment information collected from the customers and production cost and operating difficulty information collected from the managers to identify profit maximizing product and process attributes. The OPPD approach presented in this section assumes that the management of a particular company (say Company Z) can change one or more product attribute(s) and/or one or more operating system attribute(s). It also assumes that the product attributes of the competitors of Company Z do not change.

As shown in Figure 1.4, the OPPD approach involves identification of relative weights of product attributes for customers in different market segments. The relative weights (or part-worth utilities) are estimated by a multinomial logit model developed for customers and the number, sizes and natures of market segments are identified by the SALS procedure. As shown in Figure 1.4 conjoint analysis-based data collected from the managers are used to calculate production cost and operating difficulty. Next, profit maximizing product and process attributes are identified by a grid search procedure. The OPPD approach can be formulated for a company (say Company Z) as a nonlinear optimization problem in the following manner:

Maximize:

$$M * MS_t * (P_t - C_t) \tag{3.13}$$

Subject to:

$$MS_t = \sum_{n=1,N} S_n \frac{e^{VM_{nt}}}{\sum_{t \in 1,T} e^{VM_{nt}}} \tag{3.14}$$

$$\sum_{n=1,N} S_n = M \tag{3.15}$$

$$VM_{nt} = \sum_{l=1,L} \beta_{ln} X_{lt} \qquad \forall\, n,t \tag{3.16}$$

$$C_t = \sum_{l=1,L} \phi_{lt} X_{lt} + \sum_{q=1,Q} \psi_{qt} Y_{qt} \tag{3.17}$$

$$D_t = \sum_{l=1,L} \xi_{lt} X_{lt} + \sum_{q=1,Q} \lambda_{qt} Y_{qt} \tag{3.18}$$

$$D_t\,min \le D_t \le D_t\,max \tag{3.19}$$

$$X_{lt}\,min \le X_{lt} \le X_{lt}\,max \qquad \forall\, l \tag{3.20}$$

$$Y_{qt}\,min \le Y_{qt} \le Y_{qt}\,max \qquad \forall\, q \tag{3.21}$$

where

P_t = price of product offered by Company Z

X_{lt} = product attribute l of company t

Y_{qt} = operating system attribute q of Company Z

are the decision variables and

M = total market size

Ms_t = market share of Company Z

C_t = operating cost for Company Z

S_n = size of market segment n

N = total number of market segments

T = total number of companies

Vm_{nt} = utility of company t in market segment n

L = total number of product attributes

β_{ln} = weight of product attribute l in market segment n

Q = total number of operating system attributes

ϕ_{lt} = weight for product attribute l in production cost function for Company Z

D_t = operating difficulty for Company Z

ψ_{qt} = weight for operating attribute q in cost function for Company Z

ξ_{lt} = weight for product attribute l in operating difficulty for Company Z

λ_{qt} = weight for operating attribute p in operating difficulty for Company Z

are the input variables.

The objective function (equation 3.13) maximizes the total profit for Company Z by finding profit per product (P_t - $\dot{C}_t$) and by multiplying it by the expected number of products sold in a market of size M. The market share for Company Z, MS_z is calculated by applying multinomial logit model to the actual number of alternatives (number of companies offering products) available to the customers. Since products offered by different companies may have different price, quality, and other attributes, their utility will not be same for the customers. In other words, customers in different segments might prefer products from different companies. Equation 3.14 calculates the expected market share for Company Z by adding the expected market share per segment weighted by segment sizes. Equation 3.15 ensures that the sum of the segment sizes equals the total market size. The utility for all the companies in different market segments (equation 3.16) is calculated by the logit regression equation incorporating actual attributes of the companies and estimated β parameters for all the segments.

Equations 3.17 and 3.18 represent production cost and operating difficulty for Company Z. These models are developed by collecting conjoint analysis-based data collected from the managers. The managers rate the operating difficulty on a scale (1 = lowest difficulty level; 10 = highest level) and estimate the production cost for given customer demand patterns and operating condition. Each manager responds to 32 experimentally designed profiles represented in Tables 3.5 and 3.6. The data collected from all the managers in Company Z are combined, and the OLS regression is used to develop a production cost and an operating difficulty model.

The model for effective operations management presented in Chapter 1 suggests that the ability to meet customer demand depends on the operating difficulty or constraints levels. In other words, the model suggests that the optimal product and operating attributes will change if the operating difficulty level changes. Hence equation 3.19 puts an upper and a lower bound for operating difficulty level. The OPPD model can be optimized for different lower and upper D_z bounds (D_z min and D_z max) and hence the effective operations management model can be tested. Finally equations 3.20 and 3.21 constrain the product attributes (X) and operating attributes (Y) based on their possible ranges.

CHAPTER 4

RESULTS

This chapter presents the results and analysis of empirical data collected from managers and customers of the Pizza Delivery Industry. The chapter is divided into six sections. The first section presents the results of customer choice data. The second section describes the managers' perceptions of customer choice patterns. The third section compares customer choice patterns with managers' perceptions of customer choice patterns. The market segmentation results are presented next. The fifth section develops production cost and operating difficulty models. Finally, the sixth section presents the results of the optimal product/process design procedure.

4.1 Analysis of Aggregate Customer Choice Data

Customer choice survey instruments were mailed to 500 randomly selected customers in the Salt Lake metropolitan area. Fifty-six surveys were returned because of incomplete address or because the resident had moved to a new location without any forwarding address. Sixteen individuals returned the survey unanswered because they either don't eat pizza or because they didn't want to participate in the study. One hundred and forty-five surveys were returned out of which 17 were less than 25% complete and hence were not considered. Therefore the effective response rate was 31.1%.

Table 4.1 presents the results of the logit regression for customer choice data. The regression coefficients represent the relative weights or part-worth utilities of the attributes. Table 4.1 shows that all the attributes are statistically significant. The numerical signs for price, promised delivery time, and actual delivery time are negative, which means the that probability of selecting a pizza delivery company decreases if there is an increase in the value of any of the above attributes. The numerical signs for all the other attributes are positive. This means the probability of selecting a company will increase if they offer discount, more variety, steaming hot pizza, or a money back guarantee. In other words, the results of this experiment show that customer choice of pizza delivery company depends on the product quality (variety, pizza temperature), service quality (promised and actual delivery time, money-back guarantee), cost (price), delivery (promised and actual delivery time), and flexibility (variety) -based attributes. The numerical signs for the attribute parameters are as expected.

Table 4.1 shows that relative weight for price is highest followed by pizza temperature, pizza variety, money back guarantee, discount, and delivery time. A high weight for price and low weight for discount suggests that a company might be able to increase its market share and profit by reducing price and discount at the same time. It is interesting to note that pizza temperature has the second highest weight. Currently most of the companies do not deliver steaming hot pizza. This suggests that there is an opportunity to increase market share and profit by delivering steaming hot pizza.

Table 4.1: Multinomial logit main effects model for all customers

Variable	β
Price of a Large Pizza	-0.614 *
Half Price for Second Pizza	0.222 *
Promised Delivery Time	-0.179 *
Actual Delivery Time	-0.125 *
Pizza Variety	0.273 *
Pizza Temperature	0.341 *
Money back Guarantee	0.236 *
Intercept	0.726 *
Individual level $LL(0)$	-2249.957
Individual level $LL(B)$	-1770.358
-2 [$LL(0)$ - $LL(B)$] (χ^2 with 8 d.f.)	959.198 *
AIC	3524.716
CAIC	3634.349
Individual level ρ^2	0.213
Individual level ρ^2 (adjusted)	0.209
Aggregate level ρ^2	0.871
Aggregate level ρ^2 (adjusted)	0.858

* P value < 0.05

Table 4.1 also presents several goodness-of-fit statistics. The likelihood ratio for this model is 959.198 which is χ^2 distributed with 8 degrees of freedom and is statistically significant at the 5% level. The aggregate ρ^2 is 0.87 and adjusted ρ^2 is 0.86, which means the multinomial model can predict the aggregate customer choice patterns very well. The individual level ρ^2 is 0.213 an adjusted ρ^2 is 0.209 which means that approximately 21% of an individual customer's choice can be accurately predicted by the choice model. The individual level ρ^2 value reported above also suggests that the model fits the data well [10]. The individual level ρ^2 is low relative to the aggregate level ρ^2 simply because it is a very difficult to predict a person's exact choice pattern.

The experimental design for the customer choice experiment can estimate six two-way interactions between price, promised delivery time, actual delivery time, and pizza variety. Therefore, another multinomial logit model was developed which contained the seven main effects, six interactions, and an intercept. Table 4.2 presents the results of "main effects and six two-way interactions" model for all customers. However none of the interactions were statistically significant at the 5% level. Comparing the $\mathcal{LL}$(B) values from Table 4.1 and Table 4.2, it is clear that the "main effects and selected interactions" model does not improve the solution over the "main effects only" model. The difference in the log-likelihood value for the two models is only 2.538 which is statistically not significant (χ^2 with 6 degrees of freedom). Therefore only the "main effects" model (Table 4.1) is used for subsequent analysis.

The multinomial logit model for the customers of Company Z is presented in Table 4.3. This model was developed for 56 customers who ordered pizza from Company Z.

Table 4.2: Multinomial logit main effects and selected interactions model for all customers

Variable	β
Price of a Large Pizza	-0.611 *
Half Price for Second Pizza	0.214 *
Promised Delivery Time	-0.176 *
Actual Delivery Time	-0.122 *
Pizza Variety	0.287 *
Pizza Temperature	0.338 *
Money back Guarantee	0.221 *
Price X Promised Delivery Time	0.054
Price X Actual Delivery Time	0.097
Price X Pizza Variety	0.108
Promised Delivery Time X Actual Delivery Time	-0.087
Promised Delivery Time X Pizza Variety	-0.022
Actual Delivery Time X Pizza Variety	-0.007
Intercept	0.745 *
Individual level $LL(0)$	-2249.957
Individual level $LL(B)$	-1772.896
$-2\,[LL(0) - LL(B)]$ (χ^2 with 14 d.f.)	954.122 *
AIC	3572.972
CAIC	3709.649
Individual level ρ^2	0.216
Individual level ρ^2 (adjusted)	0.206
Aggregate level ρ^2	0.878
Aggregate level ρ^2 (adjusted)	0.856

* P value < 0.05

Table 4.3: Multinomial logit model for customers of Company Z

Variable	β
Price of a Large Pizza	-0.318 *
Half Price for Second Pizza	0.009
Promised Delivery Time	-0.032
Actual Delivery Time	-0.040
Pizza Variety	0.131 *
Pizza Temperature	0.197 *
Money back Guarantee	0.356 *
Intercept	0.922 *
Individual level $LL(0)$	-984.357
Individual level $LL(B)$	-851.443
$-2\,[LL(0) - LL(B)]$ (χ^2 with 8 d.f.)	265.828 *
AIC	1718.886
CAIC	1783.292
Individual level ρ^2	0.135
Individual level ρ^2 (adjusted)	0.127
Aggregate level ρ^2	0.550
Aggregate level ρ^2 (adjusted)	0.524

* P value < 0.05

The model fits the data very well. The model is statistically significant at the 5% level. It is interesting to note that money back guarantee and price have high coefficient values but discount is not statistically significant. Additionally, promised delivery time and actual delivery times are not significant. Pizza temperature and pizza variety have the second and third highest coefficients, respectively; however Company Z currently does not deliver steaming hot pizza. Therefore by offering steaming hot pizza and more variety Company Z can increase the utility for its customers and increase its market share and profit. The ρ^2 value for the customers of Company Z is 0.135 which is lower than the ρ^2 value for all the customers (ρ^2 = 0.213). This result suggests that the data collected from the customers of Company Z is less homogeneous than the data collected from all the customers. In other words, the above result shows that not all customers Company Z for the same reason.

4.2 Analysis of Discrete-Choice Data Collected from Managers

Survey instruments were mailed to the managers of all the pizza delivery establishments listed in Table 3.1 in April 1995. Regional corporate managers of all the pizza delivery companies were contacted and requested to participate in the study. However, only one national pizza chain (Company Z) agreed to participate in the study. Only five completed discrete-choice surveys were returned by the end of May 1995. Therefore another set of survey instruments were sent to the managers of Company Z in June 1995 through the regional corporate manager. A follow-up letter was mailed to the managers of other pizza delivery establishments in June 1995 requesting them to respond to the survey. Finally, a total sample size of 23 was obtained. However four surveys were less than 25% complete and were not considered. Of the 19 usable surveys 11 managers were from Company Z. Therefore the effective response rate is 38%.

The multinomial logit model developed for data collected from all managers is presented in Table 4.4. The goodness-of-fit statistics presented in Table 4.4 suggest that the model fits the data well and is statistically significant at the 5% level. Except pizza variety, all other attributes are statistically significant at the 5% level (the p-value for pizza attribute is slightly more than 0.05). In other words, according to the managers, pizza variety is not significantly related to customer choice for pizza delivery companies at the 5% level. It is also interesting to note that pizza temperature has a high β value for the manager model (Table 4.4) even though none of the companies deliver "steaming hot" pizza. The numerical value of the coefficient for promised delivery time (0.44) is much higher than the coefficient for the actual delivery time (0.17). This suggests that managers perceive that the influence of promised delivery time is higher than the influence of the actual delivery time on customer choice for a pizza delivery company.

The results of the multinomial logit model developed for the managers of Company Z are summarized in Table 4.5. The likelihood ratio of 94.052 (χ^2 distributed with 8 d.f.) suggest that the model is statistically significant at the 5% level. Table 4.5 shows that except pizza variety all variables are significantly related to managers' perceptions of customer choice at the 5% level. Again it is interesting to note that the numerical value of the pizza temperature is the highest . The numerical value of promised delivery time is the second highest followed by price, discount and actual delivery time.

Table 4.4: Multinomial logit model for all managers

Variable	β
Price of a Large Pizza	-0.559 *
Half Price for Second Pizza	0.441 *
Promised Delivery Time	-0.404 *
Actual Delivery Time	-0.171 *
Pizza Variety	0.160
Pizza Temperature	0.460 *
Money back Guarantee	0.259 *
Intercept	1.488 *
Individual level $\mathcal{LL}(0)$	-333.978
Individual level $\mathcal{LL}(B)$	-253.907
-2 [$\mathcal{LL}(0)$ - $\mathcal{LL}(B)$] (χ^2 with 8 d.f.)	160.142 *
AIC	523.814
CAIC	570.925
Individual level ρ^2	0.240
Individual level ρ^2 (adjusted)	0.216
Aggregate level ρ^2	0.726
Aggregate level ρ^2 (adjusted)	0.676

* P value < 0.05

Table 4.5: Multinomial logit model for managers of Company Z

Variable	β
Price of a Large Pizza	-0.368 *
Half Price for Second Pizza	0.328 *
Promised Delivery Time	-0.523 *
Actual Delivery Time	-0.262 *
Pizza Variety	0.197
Pizza Temperature	0.537 *
Money back Guarantee	0.225 *
Intercept	1.744 *
Individual level *LL*(0)	-193.356
Individual level *LL*(B)	-146.330
-2 [*LL*(0) - *LL*(B)] (χ^2 with 8 d.f.)	94.052 *
AIC	276.66
CAIC	347.026
individual level ρ^2	0.243
Individual level ρ^2 (adjusted)	0.202
Aggregate level ρ^2	0.671
Aggregate level ρ^2 (adjusted)	0.597

* P value < 0.05

The following section presents a comparison of customer choice models (Tables 4.1 and 4.3) and managers' perceptions of customer choice models (Tables 4.4 and 4.5) using the Gumble scale hypothesis testing procedure. The choice model for all customers is compared with the choice model for all managers. Next, the choice models for customers and managers of Company Z are compared.

4.3 Customer Models Compared to Manager Models

Table 4.6 summarizes the results of comparing choice models for all customers with choice models for all managers. The individual-level log-likelihood values were used to calculate χ^2 which is 26.05 and is statistically significant at the 5% level. Therefore the null hypothesis of equal parameters with varying Gumble scale parameters is rejected. In other words, this test shows that the managers' perceptions of customer choice patterns are not the same as the customers' actual choice patterns.

The results presented in Table 4.6 might be biased because 11 out of 19 (58%) managers were from Company Z but the actual proportion of managers working for Company Z is less than 35%. Hence another test was conducted only for the managers and the customers of Company Z. The results of this test are presented in Table 4.7. The χ^2 statistic for this test is 21.226 (with 9 d.f.) which is statistically significant at the 5% level. Hence it can be concluded that the managers' perceptions of customer choice or tradeoff patterns are not same as customers' actual choice or tradeoff patterns for Company Z. One might argue that the results presented in Tables 4.6 and 4.7 show the gap between what customers "say they do" and what managers think customers do which

Table 4.6: Summary report for Gumble scale hypothesis test for all customers and managers

Parameter	Estimated Value
Optimum μ	1.1834
$\mathcal{LL}$(B) for All Customer Model = $\mathcal{LL}_1$	-1770.358
$\mathcal{LL}$(B) for All Manager Model = $\mathcal{LL}_2$	-253.907
$\mathcal{LL}$(B) for Joint Model After Rescaling = $\mathcal{LL}_\mu$	-2037.29
$-2\ [\mathcal{LL}_\mu - (\mathcal{LL}_1 + \mathcal{LL}_2)]$ (χ^2 with 9 d. f.)	26.05 ($p < 0.05$)

Table 4.7: Summary report for Gumble scale hypothesis test for customers and managers of Company Z

Parameter	Estimated Value
Optimum μ	1.3835
$\mathcal{LL}$(B) for All Customer Model = $\mathcal{LL}_1$	-851.443
$\mathcal{LL}$(B) for All Manager Model = $\mathcal{LL}_2$	-146.330
$\mathcal{LL}$(B) for Joint Model After Rescaling = $\mathcal{LL}_\mu$	-1008.386
$-2\ [\mathcal{LL}_\mu - (\mathcal{LL}_1 + \mathcal{LL}_2)]$ (χ^2 with 9 d. f.)	21.226 ($p < 0.05$)

is not same as the gap between what customers "actually do" and what managers think customers do. However the market segmentation results show that the customer models predict market share with very small error. Therefore it is reasonable to assume that what customers "say they do" is the same as what customers "actually do." In other words there is indeed a gap between customer tradeoff patterns and managers' perceptions of customer tradeoff patterns.

The results presented in Tables 4.6 and 4.7 support the model for effective operations management (Figure 1.5) and suggest that customer feedback is necessary for proper positioning of operations according to market needs.

The following section presents summarized results of the market segmentation analysis. The discrete choice data collected from all customers was used by the SALS procedure to develop segment-level multinomial logit models.

4.4 Market Segmentation Results

The simulated annealing-based latent structure (SALS) procedure for market segmentation requires four parameters for the simulated annealing heuristic: t, α, N-SAME-T and N-REDUCE-T. These parameters are used in the following manner: e^{-t} is used to calculate the initial probability of accepting a worse solution; t is reduced by a factor α after completing N-SAME-T number of iterations; N-REDUCE-T represents the number of times t is reduced by α. For this study, the SALS procedure was implemented for two different t values: 1.0 and 5.0. The α was fixed to 0.91, N-SAME-T was fixed to 100 and N-REDUCE-T was fixed to 10. Prior to selecting the above values several other "trail" values were used. A higher t value makes the probability of accepting a worse solution very small; hence the SALS procedure is essentially reduced to the BLS procedure. The values of α, N-SAME-T and N-REDUCE-T are similar to other POM studies with simulated annealing [13] [136].

The SALS procedure was used to develop two- through five-segment models. Additional higher order models were not developed because the total sample size was only 128, which means some segments might have a very few (<15 or so) individuals. The statistical reliability of such a segment might be suspect.

Table 4.8 presents the results of the two-segment model. The χ^2 statistic is statistically significant at the 5% level. Additionally Table 4.8 shows that the individual level ρ^2 value is 0.34 which is higher than aggregate model (presented in Table 4.1) $\hat{\rho}$ value of 0.21. Hence it can be concluded that the two-segment model improves on the aggregate model. All the attributes are statistically significant for segment 2a but actual delivery time and pizza temperature are not significant for segment 2b. Table 4.8 shows that segment 2a consists of approximately 67% of customers and has high weight for pizza temperature and pizza variety. In other words segment 1 appears to be a "high quality." Segment 2b appears to be a represent the "price sensitive" group of customers. The coefficients for price, discount, and money back guarantee have the three highest numerical values.

Table 4.9 summarizes the results of the three-segment model. The model is statistically significant at the 5% level and improves the fit with respect to the two segment model (ρ^2 value of 0.38). The coefficients for pizza variety, price, and discount are the

Table 4.8: Two-segment model

Variable	Segment 2a Size = 85	Segment 2b Size = 43
Price of a Large Pizza	-0.264 *	-2.120 *
Half Price for Second Pizza	0.213 *	0.622 *
Promised Delivery Time	-0.154 *	-0.733 *
Actual Delivery Time	-0.133 *	-0.127
Pizza Variety	0.404 *	0.338 *
Pizza Temperature	0.513 *	0.233
Money back Guarantee	0.317 *	0.517 *
Intercept	0.486 *	0.846 *
Goodness for Fit Statistics:		
Individual level LL (0)	-2249.957	
Individual level LL (B)	-1478.39	
-2 [LL (0) - LL (B)] (χ^2 with 17 d.f.)	1543.1 *	
AIC	2924.78	
CAIC	3144.045	
Individual level ρ^2	0.343	
Individual level ρ^2 (adjusted)	0.336	

* P value < 0.05

Table 4.9: Three-segment model

Variable	Segment 3a Size = 44	Segment 3b Size = 42	Segment 3c Size = 42
Price of a Large Pizza	-0.301 *	-0.570 *	-2.249 *
Half Price for Second Pizza	0.442 *	0.049	0.416 *
Promised Delivery Time	-0.191 *	-0.103	-0.609 *
Actual Delivery Time	-0.174 *	-0.136 *	-0.21
Pizza Variety	0.716 *	-0.093	0.198
Pizza Temperature	0.240 *	1.037 *	0.207
Money back Guarantee	0.141 *	0.741 *	0.681 *
Intercept	0.408 *	0.473 *	0.361 *

Goodness of Fit Statistics:	
Individual level *LL* (0)	-2249.957
Individual level *LL* (B)	-1402.28
-2 [*LL* (0) - *LL* (B)] (χ^2 with 26 d.f.)	1695.4 *
AIC	2756.56
CAIC	3085.458
Individual level ρ^2	0.376
Individual level ρ^2 (adjusted)	0.366

* P value < 0.05

three highest for the customers in segment 3a. All attributes are statistically significant for segment 3a. Pizza temperature, money back guarantee, and price are the three most important attributes for customers in segment 3b. Discount, promised delivery time, and pizza variety are not significant for segment 3b. It appears that segment 3a and 3b emerge from segment 2a (from 2 segment model; Table 4.8) because the size of segment 3c is approximately the same as segment 2b. The three largest attribute utilities for segment 3c are price, discount, and money back guarantee. The three most important attributes for segment 2b (Table 4.8) were also price, discount, and the money back guarantee.

Table 4.10 presents the four-segment model. The log-likelihood ratio for the model is 1769.05 which is χ^2 distributed with 32 degrees of freedom and is statistically significant at the 5% level. The ρ^2 value is 0.39 and therefore this model improves on the three segment model presented in Table 3.9. The nature and size of segment 4b remain similar to segment 2b and 3c. In other words, it appears that the "price sensitive" group of customers remains together in segment 4d. Actual delivery time, pizza variety, and pizza temperature are not significant for customers in segment 4d. Twenty-three percent of customers are in segment 4a. Pizza variety, price, and discount appear to be the three most important factors for customers in segment 4a. All attributes except pizza temperature, are statistically significant for segment 4a. However, pizza temperature, price and actual delivery time appear to be the three most important factors for segment 4b. Segment 4c consists of 16% of the customers. Only four attributes, money back guarantee, promised delivery time, pizza variety, and pizza temperature are statistically significant for segment 4c.

Table 4.10: Four-segment model

Variable	Segment 4a Size = 30	Segment 4b Size = 37	Segment 4c Size = 20	Segment 4d Size = 41
Price of a Large Pizza	-0.975 *	-0.467 *	-0.119	-2.287 *
Half Price for Second Pizza	1.169 *	0.003	-0.007	0.341 *
Promised Delivery Time	-0.053	-0.032	-0.410 *	-0.465 *
Actual Delivery Time	-0.687 *	-0.399 *	0.102	-0.206
Pizza Variety	1.323 *	0.251 *	0.282 *	0.161
Pizza Temperature	0.071	1.055 *	0.303 *	0.174
Money back Guarantee	0.365 *	0.376 *	0.449 *	0.862 *
Intercept	0.722 *	0.348 *	0.032	0.458 *
Goodnes of Fit Statistics:				
Individual level *LL* (0)	-2249.957			
Individual level *LL* (B)	-1365.43			
-2 [*LL* (0) - *LL* (B)] (χ^2 with 35 d.f.)	1769.1 *			
AIC	2794.86			
CAIC	3105.39			
Individual level ρ^2	0.393			
Individual level ρ^2 (adjusted)	0.378			

* P value < 0.05

The five-segment results are presented in Table 4.11. The χ^2 (with 40 d.f.) value of 1930 suggests that the model is significant at the 5% level. This model improves the four-segment model even further (ρ^2 value is 0.43). The "price sensitive" customers remain together in segment 5e (approximately 31%). Price, discount, and money back guarantee are the three most important factors for customers in this group. Price and discount are also important for customers in segment 5a. However for segment 5a, actual delivery time is equally important. Pizza temperature and price are the two most important factors for segment 5b which consists of approximately 20% of the customers. Money back guarantee and promised delivery time are the two most important factors for segment 5c which consists of 18% of the customers. Segment 5d is made up of approximately 14% of the customers who are quality sensitive.

Several conclusions can be drawn from the market segmentation results presented in Tables 4.8 through 4.11. The overall fit of the multinomial logit model increases as the number of segments increase. The ρ^2 value increased from 0.21 for the aggregate model to 0.43 for the five-segment model. Therefore predictions based on the five-segment model should yield better results.

Table 4.12 presents the actual attributes of pizza delivery companies specified in Table 3.1. The researcher contacted the managers of these five companies and asked them about their price, discount, variety, and money back guarantee. The promised and actual delivery time were calculated from the customer data. The average promised and actual delivery time were calculated for the customers who have ordered pizza from these companies. Next, expected market shares for these companies was calculated by the

Table 4.11: Five-segment model

Variable	Segment 5a Size = 21	Segment 5b Size = 26	Segment 5c Size = 23	Segment 5d Size = 18	Segment 5e Size = 40
Price of a Large Pizza	-0.626 *	-0.988 *	-0.344 *	-0.187	-2.383 *
Half Price for Second Pizza	0.846 *	0.364 *	0.026	0.299 *	0.745 *
Promised Delivery Time	-0.145	-0.364 *	-0.464 *	-0.024	-0.913 *
Actual Delivery Time	-0.686 *	-0.162	0.014	0.224	-0.05
Pizza Variety	0.466 *	0.289 *	0.146	1.703 *	0.286 *
Pizza Temperature	0.344 *	1.659 *	0.338 *	0.463 *	0.396
Money back Guarantee	0.276 *	0.232	0.891 *	0.112	0.513 *
Intercept	-0.232	0.277	0.732 *	-0.245	0.694 *
Goodness of Fit Statistics:					
Individual level ll (0)	-2250				
Individual level ll (B)	-1284.7				
-2 [ll (0) - ll (B)] (χ^2 with 44 d.f.)	1930.4 *				
AIC	2649.48				
CAIC	3037.64				
Individual level ρ^2	0.429				
Individual level ρ^2 (adjusted)	0.411				

* P value < 0.05

Table 4.12: Market share calculations based on actual pizza attributes

Attribute Value	Ambassador Pizza	Domino's Pizza	Free-Wheeler Pizza	God-father's Pizza	Pizza Hut
Price of a Large Pizza	$13	$14.35	$13.60	$16.10	$14.00
Discount on the Second Pizza	half price	half price	none	half price	half price
Average Promised Delivery Time	33 mins	31 mins	40 mins	32 mins	32 mins
Average Actual Delivery Time	39 mins	31 mins	40 mins	33 mins	35 mins
Pizza Variety	1 type of crust	3 types of crust	1 type of crust	2 types of crust	3 types of crust
Pizza Temperature	warm	warm	warm	warm	warm
Money back Guarantee	yes	yes	yes	yes	yes
Market Share (2 segment model)	0.1922	0.2926	0.0701	0.1355	0.3095
Market Share (3 segment model)	0.2301	0.2627	0.1109	0.1183	0.278
Market Share (4 segment model)	0.1923	0.2968	0.1056	0.1075	0.2969
Market Share (5 segment model)	0.2137	0.2999	0.0545	0.1077	0.3252
Actual Market Share (number of shops)	0.2037	0.3148	0.037	0.0926	0.3518

aggregate, two-, three-, four- or five-segment multinomial logit. Table 4.12 also presents a measure of the actual market share for these pizza delivery companies. The actual market share calculation is based on the relative number of pizza delivery establishments per company. This assumption was judged to be reasonable because all of the establishments deliver approximately 200 pizzas per week day. It is clear from Table 4.12 that a five-segment model predicts the market share very accurately.

An interesting result was observed regarding the market segmentation techniques SALS and BLS. It was observed that the BLS procedure sometimes does not converge to a solution and hence SALS was essential for market segmentation. Another interesting result was that approximately 33% of the customers always remain in the "price sensitive" segment. All the other segments emerge from segment 2a of the two-segment model.

4.5 Operating Cost and Difficulty Results

The model for effective operations management presented earlier suggests that the operations managers' abilities to satisfy market needs depend on the customer choice patterns and operating constraints. The model also suggests that production cost depends on the same customer and operating variables. Therefore two conjoint experiments were conducted to test the above ideas.

Fourteen managers from Company Z responded to 32 profile conjoint experiments by estimating production cost and operating difficulty. Follow-up letters were sent to the managers of the other companies. However only five other managers responded to the survey instrument. Several managers were also contacted by telephone and requested to respond to the survey instrument without any success. The main reason for non-participation was the proprietary nature of production cost information. Hence only the data collected from the managers of Company Z were analyzed by the OLS regression.

Fourteen managers of Company Z responded to the 32 profile conjoint experiments and estimated operating difficulty on a scale 1 to 10 (1 = least difficult; 10 = most difficult). Of the possible 448 (14 x 32) responses, only 428 were obtained because of a few incomplete surveys. Table 4.13 presents the operating difficulty model for the managers of Company Z based on 428 responses. The regression model is statistically significant at the 5% level, R^2 is 0.37 and the adjusted $\hat{R}$ is 0.35. Six variables are statistically significant at the 5% level. They are promised delivery time, actual delivery time, daily demand rate, number of cooks and in-store employees, number of pizza delivery personnel, and pizza preparation and cooking time. The numerical signs for the daily demand rate and pizza preparation and cooking time are positive. Therefore the operating difficulty level increases with an increase in demand rate or with an increase in pizza preparation and cooking time. The numerical signs for the other statistically significant variables are negative. Overall, it appears that the variables related to the demand volume and speed of delivery determine operating difficulty.

The OLS regression output for the production cost estimation is summarized in Table 4.14. Four of fourteen managers of Company Z did not complete this part of the survey. The regression is statistically significant at the 5% level, the R^2 is 0.18, and the adjusted R^2 is 0.14. Only four variables are statistically significant at the 5% level. They are daily demand rate, number of pizza delivery personnel, number of cooks and in-store

Table 4.13: Operating difficulty model for Company Z

Parameter	Estimated Value
R^2	0.369
Adjusted R^2	0.347
Standard Error	2.45
F-Ratio (d.f. 14, 413)	17.21 *
Price of a Large Pizza	-0.084
Half Price for Second Pizza	-0.049
Promised Delivery Time	-0.600 *
Actual Delivery Time	-0.319 *
Pizza Variety	0.04
Pizza Temperature	0.149
Money back Guarantee	0.053
Daily Demand Rate	0.840 *
Order Similarity	-0.092
Number of Pizza Delivery Personnel	-1.346 *
Number of Cooks and In-Store Employees	-0.270 *
Average Wage Rate	0.007
Pizza Preparation and Cooking Time	0.507 *
Supplier Delivery Frequency	0.126
Intercept	6.604 *

* P value < 0.05

Table 4.14: Production cost model for managers of Company Z

Parameter	Estimated Value
R^2	0.177
Adjusted R^2	0.137
Standard Error	144.85
F-Ratio (d.f. 14, 287)	4.4101 *
Price of a Large Pizza	3.723
Half Price for Second Pizza	3.722
Promised Delivery Time	-1.176
Actual Delivery Time	6.863
Pizza Variety	13.573
Pizza Temperature	12.998
Money back Guarantee	2.671
Daily Demand Rate	-23.756 *
Order Similarity	8.327
Number of Pizza Delivery Personnel	17.990 *
Number of Cooks and In-Store Employees	30.253 *
Average Wage Rate	45.188 *
Pizza Preparation and Cooking Time	-2.285
Supplier Delivery Frequency	7.739
Intercept	617.651 *

* P value < 0.05

employees, and the average wage rate. A relatively lower R^2 value suggests that several other variables affect product cost.

The experimental design used for the conjoint experiments was capable of estimating the two-way interactions between the following variables: price of first large pizza, actual delivery time, daily demand rate, number of pizza delivery personnel, number of cooks and in-store employees, and average wage rate. However none of these interactions were statistically significant for either production cost model or the operating difficulty model.

Overall, the production cost and operating difficulty results show that a customer-based variable and several operating variables determine production cost and operating difficulty in the pizza delivery industry. These results will be used in the optimal product/process design procedure described in the following section.

4.6 Optimal Product/Process Design Results

The five-segment customer choice model was used in the OPPD procedure because it predicts the market share better than the other models. The production cost and operating difficulty model for Company Z, estimated in section 4.5 was also required. A nonlinear optimization procedure was used to find the optimal level of product and operating process attributes at various difficulty levels [110]

The nonlinear optimization procedure finds the market share and profit for several different levels of product and process attributes. The current implementation assumed the following attribute ranges: price $12 to $18; half price for the second pizza either available or not available; promised delivery time 20 to 40 minutes; actual delivery time either on-time to 15 minutes late; pizza available with 1, 2, or 3 crusts; pizza temperature either warm or hot; money back guarantee either available or not available; the daily demand rate between 200 and 400; and the order either all small sizes or a mix between small and large sizes. The other operating attributes were number of delivery personnel from 3 to 7, number of cooks and in-store employees from 3 to 7, average wage rate from $5 to $8 per hour, pizza preparation and cooking time 10 to 20 minutes, and supplier delivery frequency either once a week or every other day. The total market size was fixed to 1000 pizzas per day.

The profit calculation (equation 3.13) will change if a company offers discount for the second pizza. Therefore for accurate profit calculation it is necessary to estimate the actual proportion of customers who order two pizzas at a time. The researcher asked the regional manager of Company Z and was informed that the number of customers who order two or more pizzas at a time varies according to the time of the day, location of the shop, and day of the week. However no estimate of order size was provided by Company Z. Therefore, the OPPD procedure was implemented assuming all customers order one pizza at a time.

Table 4.15 presents the optimal results. The nonlinear optimization procedure was implemented by a spreadsheet program called QuattroPro [110]. The table shows the optimal profit, market share and cost for a difficulty range. It is clear from Table 4.15 that the profit increases and production cost decreases as the operating difficulty level increases. The management science philosophy presented in Appendix A is consistent with

Table 4.15

Optimal product/process design results

Difficulty Level	2.5	3	3.5	4	4.5	5	6	7	8	9	10
Optimum Profit ($)	2460.1	3655.7	4263.0	4849.3	5238.7	5598.2	5911.7	6094.6	6165.7	6277.8	6349.4
Market Share (%)	22.1	52.8	57.3	61.4	64.2	65.5	67.3	67.8	68.0	68.3	68.5
Cost ($/Pizza)	6.8	6.9	6.9	6.9	6.8	6.2	5.8	5.5	5.4	5.2	5.1
Price ($)	18.0	13.8	14.3	14.8	14.9	14.7	14.5	14.5	14.4	14.4	14.4
Discount on Second Pizza	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Promised Delivery Time (mins)	40.0	35.4	26.8	20.0	20.0	20.0	20.0	20.0	20.0	20.0	20.0
Actual Delivery Time (mins)	55.0	50.4	41.8	32.6	20.7	21.8	20.0	20.0	20.0	20.0	20.0
Pizza Variety (Types of crust)	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0	3.0
Pizza Temperature	hot	hot	hot	hot	hot	hot	hot	hot	hot	hot	hot
Moneyback Guarantee	no	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Daily Demand Rate	200.0	200.0	200.0	200.0	200.0	200.0	287.0	400.0	400.0	400.0	400.0
Order Similarity	mix	mix	mix	mix	mix	mix	similar	similar	similar	similar	similar
Number of Drivers	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	6.0	4.0	3.0
Number of Cooks	7.0	7.0	7.0	7.0	7.0	3.0	3.0	3.0	3.0	3.0	3.0
Average Wage Rate ($)	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0	5.0
Pizza Cooking Time (mins)	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.5	13.7	10.3	13.5
Supplier Delivery Frequency/week	once	once	once	once	once	once	once	once	once	once	once

this result which suggests that by "breaking" binding constraints higher objective function values can be obtained. Hence if a company is able to operate at the higher difficulty level, it should obtain higher profit.

Figure 4.1 shows the increase in optimal profit level with the increase in the difficulty level. This figure shows that profit increases with decreasing rate with increase in the difficulty level. Figure 4.1 shows that relatively big increase in profit if difficulty level increases from 3.0 to 5.0 but a relatively small increase in profit when difficulty level changes from 7.0 to 9.0. The market share corresponding to optimum profit as a function of operating difficulty is presented in Figure 4.2. The market share changes are similar to changes in profit.

Figure 4.3 shows the changes in operating cost with respect to operating difficulty. The cost does not change when difficulty level increases from 2.5 to 4.0. The operating cost decreases with the decreasing rate when difficulty level increases from 4.0 to 10.0.

Overall the OPPD results show that market-based and operating attributes are necessary for optimal product design. The results show that operating difficulty has an effect on optimal product and process attributes and that profit increases if a firm manages to operate at the higher difficulty level.

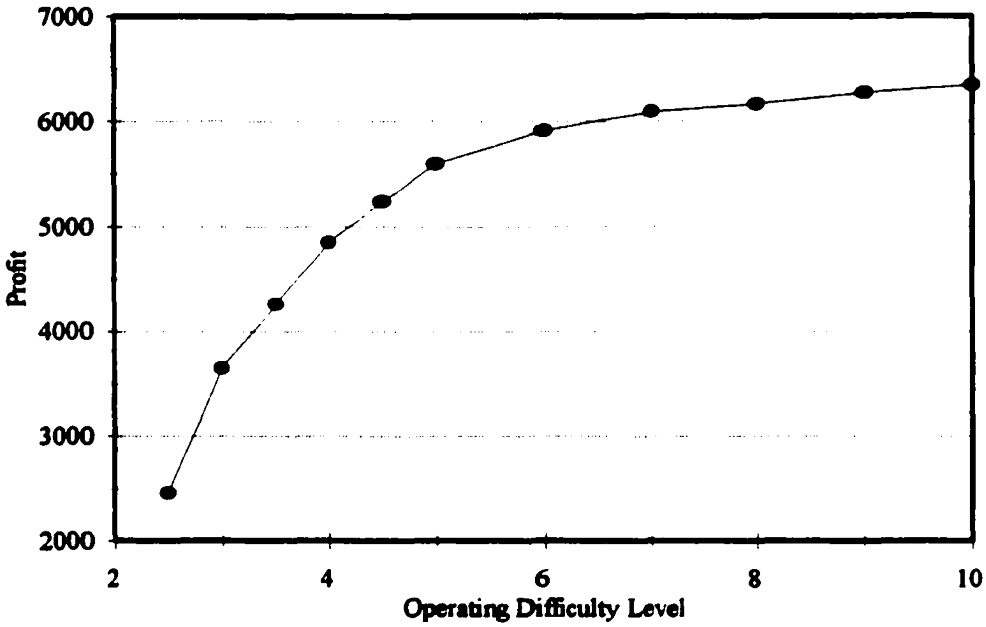

Figure 4.1:Optimum profit and operating difficulty

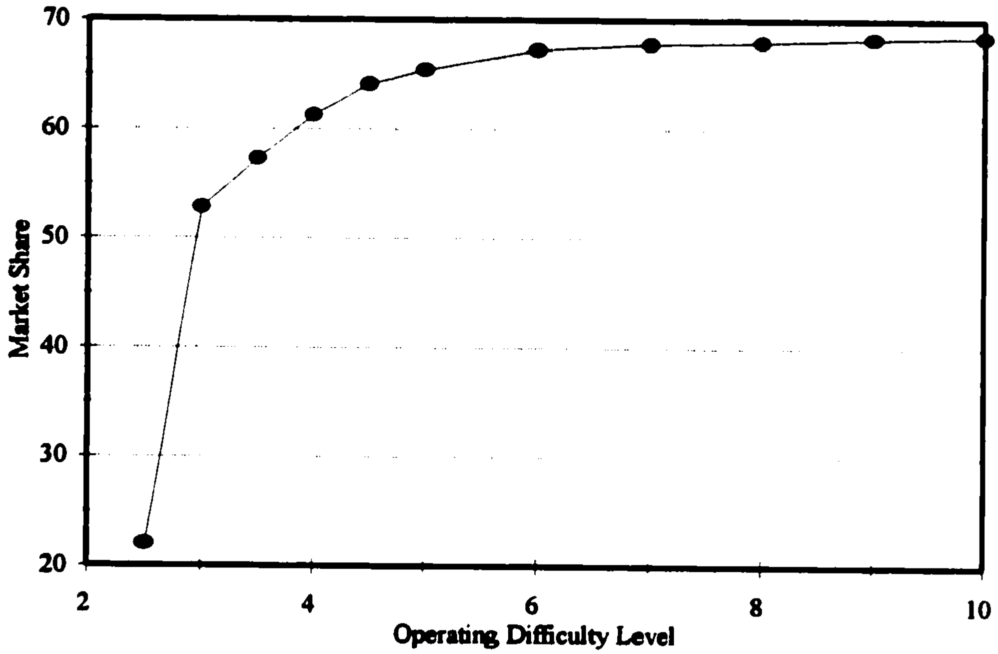

Figure 4.2: Market share and operating difficulty

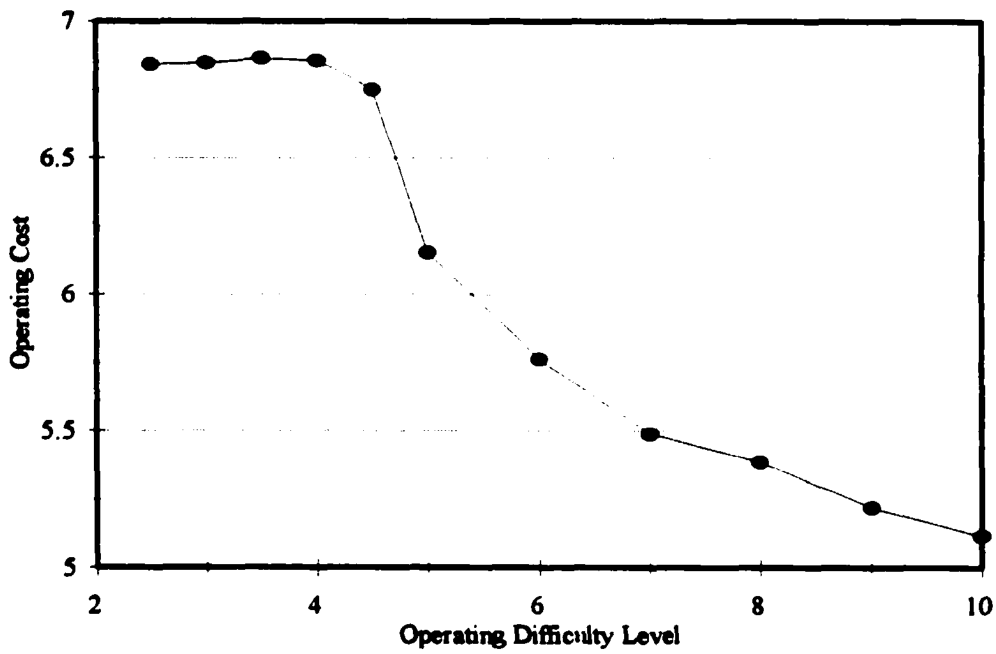

Figure 4.3: Operating cost and operating difficulty

CHAPTER 5

CONCLUSIONS

This chapter discusses the results presented earlier, draws conclusions and provides directions for future research projects. First the experimental results are discussed with respect to the eight research questions. Second, the contributions of this study to the academic and practitioner literatures are presented. Finally limitations of the study are presented with possible directions for future research.

5.1 Discussion

Eight research questions were presented in Chapter 3. The research questions were based on the model for effective operations management presented in Chapter 1. The following sections discuss the results with respect to these eight research questions.

5.1.1 Customer Choice Patterns

Based on past research in POM and marketing, research question I suggested that customer tradeoff patterns depend on product quality, service quality, cost, delivery, and flexibility attributes of a product. Seven attributes were selected to represent product quality (pizza variety and pizza temperature), service quality (money back guarantee, actual delivery time), cost (price of a large pizza, discount for the second pizza), delivery (promised delivery time, actual delivery time), and flexibility (pizza variety) attributes in the pizza delivery industry. Tables 4.1 and 4.2 presented the results of customer tradeoff data for 128 randomly selected customers. These results support the ideas presented by research question I which states that customers tradeoff quality, cost delivery and flexibility attributes. All seven attributes were found to be statistically significant. A similar result obtained for the customers of one company is presented in Table 4.3. The goodness-of-fit statistics showed that the models fits the data very well.

Hence, based on discrete choice data collected from randomly selected customers, it can be concluded that customer tradeoff patterns for pizza delivery industry depend on product quality, service quality, cost, delivery, and flexibility attributes. The results show that a pizza delivery firm's utility increases with a decrease in price; promised and actual delivery time, and an increase in discount, pizza variety, pizza temperature; and a money back guarantee. As mentioned earlier, pizza temperature was found to be statistically significant even though none of the companies offer steaming hot pizza.

The numerical sign for attribute coefficients are consistent with intuitive reasoning. For example, customer choice for a product almost always increases for a decrease in price and increase in quality. The strength of the study is the multinomial logit model which can predict customers' choices. The model shows both the relative weight and direction of the influence of a product attribute on customer choice which in turn determine market share (and hence profit). Hence, the effect of changing one or more attributes can be easily evaluated, and the model can be used as a decision-support tool by the managers.

5.1.2 Managers' Perceptions of Customer Tradeoff Patterns

The managers of pizza delivery establishments were asked to predict the tradeoff patterns of their customers. Table 4.4 presented the results for all managers and Table 4.5 presented the results for the managers of one specific company. The models are statistically significant and fit the data well. Therefore, it can be concluded that the managers' perceptions of customer tradeoff depends on product quality, service quality, cost, delivery, and flexibility attributes. It is, however, interesting to note that pizza variety is not significant at the 5% level. Therefore it can be concluded that the managers do not feel that customer choice for a pizza delivery is influenced by variety.

The multinomial logit model for the managers of Company Z presented in Table 4.5 shows that absolute value of weight for promised delivery time is much higher than absolute weight for actual delivery time. In other words, the managers believe that customer choice for a pizza delivery company can be influenced by reducing the promised delivery time but actually delivering the pizza late. However, past research suggests that providing late service will reduce the likelihood of selecting the company again [101]. In other words, multinomial logit models presented in Tables 4.4 and 4.5 show that managers perceptions of customer tradeoff patterns might not be the same as the actual customer tradeoff patterns.

5.1.3 Comparison Between Customer and Manager Model

The model for effective operations management presented in Figure 1.5 and research question III suggests that there is a gap between actual customer tradeoff patterns and managers' perceptions of customer tradeoff patterns. A Gumble scale hypothesis testing procedure was used to test if indeed the two models are different from each other. Two tests were conducted: first, a test for all customers and all managers, and, second, a test for the customers and managers of a specific company. The results presented in tables 4.6 and 4.7 show that multinomial logit models for the customers are not same as the models for the managers.

In other words, the results show that operating decisions based on "what managers think customers want" will not be effective. For example, the absolute weight for pizza price is higher than that of pizza temperature for the customers of Company Z (Table 4.3). However, the managers of Company Z perceive the weight for pizza temperature to be higher than the weight for price (Table 4.5). Hence the decisions based on managers' perceptions of customer tradeoff patterns might not result in an expected increase in sales. The Gumble scale hypothesis test result suggests that there is indeed a gap between customer tradeoff patterns and managers' perceptions of customer tradeoff patterns. Hence, constructive feedback from customers is essential for evaluating any changes in operations and for effective product/process design or improvement.

5.1.4 Customer Groups with Similar Tradeoff Patterns

Research question IV proposed the need for identification of customer groups with similar tradeoff patterns. A simulated annealing-based latent structure (SALS) procedure was developed to identify size and nature of market segments (or customer groups with similar tradeoff patterns). This procedure maximizes the probability of a customer being in a particular market segment.

The results presented in Tables 4.8 through 4.11 show that the SALS procedure can be successfully used to identify customer groups with similar tradeoff patterns. The SALS procedure developed in this study is based on the basic latent structure (BLS) procedure developed by Moore, Gray-Lee, and Louviere [98]. The BLS procedure solves the segmentation problem from one starting point but the SALS procedure solves it for several starting points based on a probability distribution function (Table 3.6). Therefore, the SALS procedure has a very high probability of identifying the best combination of customer groups. Additionally, BLS is an iterative procedure; therefore if a bad starting point is used to start assigning customers, the β values might not converge. It is also possible that for a particular starting point, the solutions might not improve even after a large number of BLS iterations. Since the SALS procedure is based on multiple starting points, it overcomes the above limitations of the BLS procedure.

Tables 4.12 compared expected market segments based on the SALS results to the actual market segments of five pizza delivery companies. All the models predict actual market share very well. The accuracy of the prediction, however, increases when the number of segments is increased from 2 to 3, 4 and 5. This result should be expected for any good segmentation technique because the number of parameters in the multinomial logit model increases with the increase in number of segments. For example, the two segment model has 17 parameters (eight β values each for segments 2a and 2b and one parameter for the size of the segments); the five-segment model, on the other hand, has 44 parameters (eight β values each for segments 5a, 5b, 5c, 5d, and 5e and four parameters for the size of the segments). Hence the five-segment model should be used as a decision support tool because its predictions are most accurate.

Tables 4.8 through 4.11 presented the weights and statistical significance of attributes for different market segments. It is interesting to note that approximately 33% of the customers always remain in the same segment. The tradeoff patterns of customers in this segment (2b, 3c, 4d, or 5e) are very sensitive to the price of pizza. The other segments in 3, 4, and 5 segment models emerge from segment 2a. The size and nature of the segments are different from each other as expected. For example, the three most important attributes for segment 5a are discount, actual delivery time, and price; for segment 5b they are pizza temperature, price, and discount/promised delivery time; for segment 5c they are money back guarantee, promised delivery time, and price; for segment 5d they are pizza variety, pizza temperature, and discount; and for segment 5e they are price, promised delivery time, and discount.

Overall, however, it appears that the cost of pizza in some form (price, discount, money back guarantee) is important for customers in all segments. Not all the other attributes (delivery time, variety, temperature) are important for all the segments. This is a very valuable piece of information for the managers because (based on the nature of a segment), they can design specific products to meet the needs of customers in a particular segment.

The market segmentation results show that the delivery time is statistically significant for most of the segments. Therefore an effective utilization of labor resources is a must for improving operating performance. The delivery time can be hypothesized to depend on several other operating variables (number of pizza delivery personnel, pizza preparation and cooking time, the size of the pizza delivery area). In other words, by improving the design of the service delivery system, pizza delivery time should be reduced which will lead to an increase in sales.

Pizza temperature and pizza variety were found to be important for all segments. Therefore, a firm's utility will increase if they offer more variety and/or steaming hot pizza. Currently steaming hot pizza is not offered by any company. The model predicts a significant market share gain from investing in pizza delivery containers which can keep pizzas steaming hot until delivered.

Overall, the market segmentation results provide very valuable information for designing a pizza delivery system. They provide constructive feedback to the managers for improving operations.

5.1.5 Operating Difficulty

The model for effective operations management and research question V suggests that managers' abilities to meet market needs depends on operating constraints. The OLS regression model developed for conjoint analysis-based data collected from operations managers of Company Z is statistically significant and hence supports the proposed model for effective operations management.

Table 4.13 shows that the number of pizza delivery personnel, the number of cooks and in-store employees, and pizza cooking and preparation time (representing operating constraints) are statistically significant. It appears that operating variables related to the ability to deliver pizza on time determine operating difficulty. Hence, efficient labor scheduling appears to be necessary for effective process improvement.

It is interesting to note that supplier delivery frequency is not significant. In other words, the managers do not perceive the raw material delivery every other day to be more helpful in meeting demand than raw material delivery once a week. This result is surprising because the pizza delivery establishments deliver approximately 200 pizzas per day during the weekday and approximately 400 pizzas per day during the weekends. Hence, a once a week supplier delivery frequency will require storing enough raw material for approximately 1800 pizzas. Perhaps the pizza delivery stores have large storage areas and the managers do not feel the need to get fresh supplies every other day.

The following market-based variables are statistically significant: promised delivery time, actual delivery time, and daily demand rate. These variables also represent the influence of a manager's ability to deliver pizza on time on operating difficulty level. For example, if the demand rate increases from 200 to 400 or if delivery time is reduced from 40 minutes to 20 minutes, it will be more difficult for the managers to satisfy the needs of the customer.

The managers do not perceive pizza variety, pizza temperature, and pizza order similarity to be related to operating difficulty. This is also a very interesting result because it suggests that manager can provide a higher quality pizza (for example, more variety) without increasing operating difficulty.

The OLS regression model presented in Table 4.13 connects the customer tradeoff patterns and operating constraints with managers' abilities to meet market needs. The results suggest that the managers should focus on both the operating and customer-based attributes for effective operations management.

5.1.6 Production Cost

Research question VI suggests that production cost is a function of market-based and operating variables. Table 4.14 presented the production cost model for all the managers of Company Z. The overall OLS regression model was statistically significant at the 5% level. However coefficients for only four variables were significant. They are daily demand rate, number of pizza delivery personnel, number of cooks and in-store employees, and the average wage rate. The variables related to delivery time and other attributes are not perceived as determinants of production cost.

The R^2 for the production cost model is only 0.18. The model is based on data collected from several managers; therefore, it is possible that the managers had no agreement on the determinants of production cost. It is also possible that many determinants of production cost were not included in the experimental design. The overall model however is statistically significant and shows that some product and operating attributes are related to production cost. Therefore this model was used for the optimal product/process design (OPPD) procedure.

5.1.7 Optimal Product/Process Design

Research questions 7 and 8 concentrate on identifying profit maximizing product and operating attributes levels. Assuming that all product and operating attributes can be changed within the prespecified range, optimal attribute levels were identified (Table 4.15).

The results show that the total profit increases as the operating difficulty level increases. The result is consistent with the constrained optimization theory of management science (Appendix A) which suggests that the objective function value can be increased by breaking the binding constraints. Hence this result supports the model for effective operations presented earlier and suggests that operations managers should focus on breaking the binding constraints for effective product design and process improvement. If managers can organize the operation such that it functions efficiently at the high difficulty level, a higher profit can be obtained. Consider a simple example: Table 4.15 shows that seven delivery personnel and seven in-store employees represent a low difficulty level for a daily demand rate of 200 and three delivery personnel and three in-store employee represent high difficulty level for demand rate of 400. The total profit for the low difficulty level is $2460 and is $6349 for the high difficulty level. However, in order to get higher profit, the managers will have to design the service delivery system more efficiently because the number of employees is lower and the demand rate is higher. In other words, the OPPD results provide a guideline for managers for designing profit maximizing products and operating system attributes.

The results also show that production cost decreases as the difficulty level increases. At the high difficulty level managers have to use production resources effectively and hence the production cost declines. This is very valuable information for managers. Often operations are organized as cost centers. Hence if the operating system is designed efficiently such that it can operate at the high difficulty level, the product cost will be reduced.

The attribute levels for all variables do not change when difficulty level is increased. For example, in Table 4.15 pizza variety, pizza temperature, discount, and supplier delivery frequency remained the same for the four difficulty levels. This result suggests that not all variables need to be changed when the operating system is re-designed to operate at a higher difficulty level.

The OPPD procedure finds the optimal attribute levels within the prespecified range. Therefore if a particular attribute (for example, pizza delivery time) cannot be changed, the procedure will find the best combination of other attributes at the specified difficulty level.

The results presented in Table 4.15 assume that the attributes of other companies do not change when Company Z changes its attributes. However, the mathematical formulation of the OPPD procedure is very flexible in nature and any changes in the attributes of other companies can be easily incorporated. For example the market share calculation can be adjusted if one company always reduces the price by the same amount as Company Z, or always offers the same discount. The OPPD procedure will take such changes into account through the market share calculation and then find the best combination of attributes.

5.1.8 Summary

Based on past research in POM, management science, and marketing, a model for effective operations management (Figure 1.5) was proposed. This study demonstrated the use of several aspects of the proposed model for one service industry; the pizza delivery industry. The results show that product quality, service quality, cost, delivery, and flexibility-based attributes determine customer choice or tradeoff patterns for pizza delivery companies. It was shown that there is a gap between customer tradeoff patterns and managers' perceptions of customer tradeoff patterns. The study developed a procedure for market segmentation (the SALS procedure) which predicts market share very accurately. Finally, production cost and operating difficulty models were developed for the operations managers which were used in the optimal product/process design procedure.

5.2 Contributions of This Study

The research presented in this thesis was interdisciplinary in nature building on several streams of literature within business administration. This section summarizes the contributions of this study to operations strategy, quality function deployment, optimal product design, management science, and marketing literatures.

5.2.1 Contribution to Operations Strategy Literature

Past research in operations strategy has focused on improving the strategic importance of operations in a firm by effectively managing available tradeoffs [71]. A number of theoretical articles have presented various tradeoff decisions made by operations managers. These decisions include identifying the relative importance of operations objectives (product quality, service quality, cost, delivery, and flexibility) and identifying the relative importance of various operating variables for product/process design and importance. The operations strategy literature also focuses on finding ways to position operations capabilities according to market needs.

The proposed model combines the above themes in operations strategy by connecting customer tradeoff (or choice patterns) with operating constraints. Several aspects of the model were tested for one specific service industry. For example, past research in operations strategy had suggested that customer choice depends on quality, cost delivery and flexibility variables; however no empirical work had been published [71]. This study empirically tests how customers in one service industry tradeoff product quality, service quality, cost, delivery, and flexibility-based attributes.

A number of published articles had argued about improving the service component of a product for increasing market share. This study used two variables to test such an approach. The variable actual delivery time measures service reliability by measuring delay in delivering pizza with respect to promised delivery time. Another variable, money back guarantee, is similar to warranty for a tangible product. These variables were found to be statistically significant for the aggregate models and for several segments. In other words, this study empirically tested the value of the service component attached to a tangible product.

Several POM articles published in the last 10 years or so have argued that operations capabilities should be aligned according to market needs if operations management is to become a competitive weapon in a firm. However, none of the articles suggest how to position operating capabilities. This study proposed that the gap between customer tradeoff patterns and managers' perceptions of customer tradeoff patterns can be used as constructive feedback for positioning operating according to market needs. Using Gumble scale hypothesis testing this study showed that such a gap indeed exists and that managers' perceptions of customer tradeoff patterns are not same as customers' actual tradeoff patterns.

Several articles have emphasized the need for effective operations management in the service industry. These articles classify services and present a list of managerially important activities for different groups. However none of the articles emphasize how operations can improve for a particular company in a given industry. This study contributes to the service operations strategy literature by identifying the attributes that determine operating difficulty in one industry. The managers can focus their efforts on improving the performance of these attributes for effective service operations management.

This study proposed and showed that managers' abilities to meet customer needs depends not only on customer demand patterns but also on operating variables. Production cost was also shown to be related to marketing and operating variables. These results provide insight into the complex issue of effective coordination between marketing and operations functions of a firm. It shows that both marketing and operating issues are important for successfully satisfying customer needs. In other words, this study provides empirical support to an integrated approach to service operations management proposed by Lovelock, Sullivan, Husket, and other researchers.

A lot of research has been done on customer waiting time and its effect on customer satisfaction [33]. This study further emphasizes impact of waiting time. The customer-based utility of a company decreases if waiting time (promised delivery time) is increased or service reliability (actual delivery time) is reduced. The model shows how the number of customers for a company will increase in given market segments if waiting time or service reliability is changed. Hence the relative weight of waiting time it can be used as input to a simulation model which evaluates different service delivery configuration and/or labor schedules.

The results of this study contribute to the knowledge of operations management by testing past theories/ideas. They provide directions for improving operations effectively. Both continuous improvement and business process reengineering approaches can benefit from the approach proposed in this research. Continuous improvement philosophy is a holistic approach and focuses on problem identification and continuously working towards a solution. The model for effective operations management identifies important customer-based and operating variables which need attention. For example, the results for Company Z showed the variables related to pizza delivery time were the determinants of operating difficulty. Therefore the management can focus their attention on improving labor schedules to effectively address the problem. In other words, the results for this study can be used as a starting point for implementation of a process improvement approach. The results also provide a starting point for process reengineering because it identifies the determinants of operating cost and difficulty. Hence the process reengineering efforts should be directed towards the processes dependent on statistically significant operating and product-base variables.

5.2.2 Contributions to Quality Function Deployment Literature

Quality function deployment (QFD) provides a structured approach for integrating customer preferences into product design process. QFD uses a series of matrices, which look like houses (called the House of Quality) to integrate customer requirements throughout design, production, and delivery of products. This study contributes to the QFD literature by developing effective methodology for identifying relationships between product and operating attributes.

The discrete-choice approach can be used to identify relative weights for product attributes from the customer's point of view. The discrete-choice weights provide more information than a ranking or a rating scale because discrete-choice weights are based on the multinomial logit model. Therefore the effect of changing a particular attribute level on expected sales level can be identified. For example if β represents the relative weight for an attribute which has been changed from X1 to X2 then the customer utility for the product will change by $e^{\beta(X1 - X2)}$. The rating or ranking scores only inform the relative importance of the attributes; however, no additional analysis can be performed. Additionally, a rating scale in QFD considers only one attribute at a time and therefore only provides absolute importance of an attribute which is not the same as relative importance of an attribute with respect to others. For example, the rating scale can inform that both price and delivery time are important for the pizza delivery industry but it cannot calculate the relative importance of one over the other. Since the discrete choice weights are based on a multinomial logit model the relative weights of attributes can be easily calculated by $e^{\beta 1 X} / e^{\beta 2 Y}$, where X and Y represent levels of two attributes and β1 and

$\beta 2$ represent their corresponding discrete-choice weights.

The house of quality uses a matrix which connects customer attributes with operating attributes. The correlations between the two sets of variables are represented in the matrix. This matrix provides very valuable information but does not provide any causal information. For example, the house of quality can inform that pizza delivery time is correlated to the number of pizza delivery personnel. However it cannot predict delivery feasibility or delivery cost if delivery time and/or the number of pizza delivery personnel are changed. This study shows that conjoint analysis can be successfully used to connect customer preferences with operating variables. The OLS regression model for production cost and operating difficulty not only shows the relative weight of different attributes but can also predict product feasibility and cost if one or more attributes are changed. Additionally, conjoint studies with large number of profiles can be used to calculate selected two-way interactions between the attributes, in addition to the main effect of the variables. In other words, this study shows that the use of conjoint analysis in a house of quality matrix might provide more information than just using correlation.

5.2.3 Contributions to Optimal Product Design Literature

Past research in optimal product design has used conjoint analysis based customer preference data to identify product characteristics which satisfy the needs of customers in a particular market segment. Most of these attempt to find the product configurations which maximize market share. A few studies have incorporated variable cost in the optimal product design formulation; however, no attempt has been made to estimate production cost as a function of product or operating attributes. Additionally, none of the formulations explicitly consider market segmentation results in the optimal product design procedure.

This study contributes to optimal product design literature by addressing several of the issues above. The study shows that production cost can by estimated by a conjoint analysis with product and operating attributes as independent variables. Therefore the study shows how to identify the attribute levels which maximize profit, not just the market share. Additionally, the results show that optimal product design changes with changes in operating difficulty. In other words, this study finds the attribute level for products which are best under specific operating conditions.

This study, for the first time, uses discrete choice analysis-based data in the optimal product design procedure. The advantage of using such a procedure is that market share for a particular product configuration can be estimated very accurately by using the multinomial logit model. This study also uses the latent structure procedure for identifying market segments which further increase the accuracy of market share calculations.

The main strength of the optimal product design formulation presented in this study is its flexible nature. The approach can find the best combination of attributes levels within possible ranges. The formulation can be easily modified from finding one optimal product to finding optimal product line configuration by representing product variety as one of the attributes.

5.2.4 Contributions to Management Science Literature

Recently several articles have shown concern about the usefulness of management science (MS) theories in the future [3]. Several researchers believe that purposeful human behavior is not included in most of the published MS research [27] [96]. Some MS philosophers also feel that the management engineering component of MS (innovative use of MS theories) is lagging behind.

This research addresses some of the above concerns by building on the constrained-optimization theory of MS. The approach uses the constrained-optimization theory in combination with a customer's actual tradeoff patterns. Therefore purposeful human behavior is built into the study.

The study uses simulated annealing (an optimization heuristic) in combination with econometric models (latent structure procedure, multinomial logit model) for identification of the market segments. Additionally a grid search optimization procedure identified optimal product/process attributes. Therefore the study contributes to the MS literature by the innovative use of constrained-optimization theory and by combining optimization procedures with customer tradeoff patterns.

5.2.5 Contributions to Marketing Literature

This study contributes to marketing literature by extending the scope of customer research into design and improvement of operations. Since the approach presented in this dissertation is interdisciplinary in nature, building on past research in operations management and marketing, both functional areas benefit from the integrated approach.

One of the objectives of marketing research is to identify customer needs. This study finds what customers prefer and then identifies the product configurations that will satisfy customer preferences. Additionally, conjoint analysis has been used for several marketing applications. This study showed that conjoint analysis can be used to integrate marketing and operating variables.

A specific contribution to marketing research is the development of the SALS procedure for market segmentation. The SALS procedure improves the BLS procedure developed recently by Moore, Gray-Lee, and Louviere [97]. It has been shown that the BLS procedure is better that several other market segmentation approaches. Therefore the SALS procedure is a definite contribution to marketing research literature.

The above sections have shown that the research reported in this dissertation contributes to the knowledge of business administration. However, this study is not free from limitations. The following section elaborates on these limitations and provides directions for future research.

5.3 Limitations and Directions for Future Research

The objective of this study was to develop and empirically test an approach for effective operations management by integrating market-based variables and operating characteristics. The study does provide valuable insights into the complex process of business management and does have several limitations which should be addressed in future research projects. This section elaborates on several of these limitations.

The usefulness of the proposed model for effective operations management was demonstrated for only one industry. It is possible that results are different for other manufacturing and service businesses. For example, identification of customer-based attributes might not be easy for professional services because of customized demand patterns. Implementation of such an approach will be equally difficult for manufacturing operations because interdependence of resources are often very complicated. Therefore one conjoint experiment trying to integrate different aspects of manufacturing might not work. Hence the scope of the model, experimental design, data collection procedure, and analysis schemes needs to be extended to obtain generalizable results.

The customer sample size for this study was very small (128 customers and 25 managers); hence the reliability of some results might be low. Therefore, future research projects should be conducted with larger sample sizes. Additionally, the response rate from the customers and the managers are 31% and 38% respectively. However non-response bias tests were not performed. Future projects should either perform non-response bias analysis and/or identify ways for increasing the response rate.

The study proposed that customers tradeoff product quality, service quality, cost, delivery and flexibility attributes in choosing a product or service. Several of these constructs are multidimensional in nature; however only seven attributes were used in the experimental design. Future research should include more product attributes the avoid the possibility of missing important attributes. Detailed qualitative data collection by interviewing customers or by focus groups or by other similar means might be needed to identify all relevant attributes.

The experimental design used in data collection was based on two levels for every attributes. Such an experimental design reduces the number of profiles needed in data collection but assumes a linear relationship between the attribute and the dependent variable. It is not possible to identify any higher order relationships between the variables with a two-level experimental design. For example, it is possible that the true relationship between customer choice is and delivery time is quadratic in nature and customer choice for company is not effected by a 5 minutes change in delivery time but is strongly effected by a 20 minutes change. The experimental design used in this study cannot identify such nonlinear relationships.

The experimental design used was capable of estimating a selected number of two-way interactions between the attributes; however none of the interactions estimated were statistically significant. This result suggests that the correct set of variables was not used in the experimental design for identifying interactions. The interrelationships between the attributes should be closely studied before designing experiments in future research projects.

The conjoint analysis-based data collected from operations managers were used to develop an operating cost model. However the R^2 for the model was very low, suggesting that several variables affecting production cost were not present in the model. The accurate production cost calculation is essential because of its use in the identification of optimal product and process attribute levels. Hence, future projects should identify other attributes affecting production cost.

The conjoint design profiles used for developing production cost and operating difficulty models were capable of estimating a selected number of two-way interactions.

However none of the estimated interactions were statistically significantly suggesting that the wrong set of variables was used in experimental design for estimating interactions.

One of the objectives of the study was to identify binding constraints in the operating systems; however the question of how to break these constraints is not addressed. In other words, the approach provides the answer to "what to change for process improvement" but does not provide any guideline to "how to implement" these changes. For example, this study identified pizza delivery time related variables to be significantly related to operating difficulty. However the approach cannot provide guidelines for how to efficiently reduce the delivery time. Therefore, future research should be directed towards implementing continuous improvement or process reengineering projects and break the binding constraints followed by an evaluation of the performance of the remodeled operations. Then the empirical experiments can be repeated to compare the performance of remodeled operations with respect to the original operating configuration.

This study does not incorporate the accounting implications of breaking the binding constraints. Because of interdependence of resources in a firm, it is possible that some additional constraints might be hidden behind the apparent binding constraints. Hence, future research should incorporate financial/accounting implications of changing the operating system.

The OPPD procedure calculates market share for the companies with given attribute levels, but in order to estimate the profit, the size of the market information is essential. Information about the size of the market is needed for calculating daily demand rate. Daily demand rate is an independent variable in production cost and operating difficulty models. Therefore future analyses should try to identify market size.

Empirical studies with large sample sizes and broadly-designed conjoint and discrete-choice experiments across different industries should result in more generalizable results. Conjoint analysis and discrete-choice experiments are based on fractional factorial design of experiments. Hence, only the main effects and a limited number of interaction effects of the independent variables on the dependent variables could be identified. Future research projects with more general designs and larger sample sizes should be undertaken to overcome this limitation.

APPENDIX A

CONSTRAINED-OPTIMIZATION THEORY

Management science (MS) is commonly described as a scientific approach to decision making that involves the operations of organizational systems. In particular, the process begins by carefully observing and formulating the problem and then constructing a scientific model that attempts to abstract the reality. It is then hypothesized that this model is a sufficiently precise representation of the essential features of the situation, so that the conclusions obtained from the model are also valid for the real problem.

Another characteristic of MS is its broad viewpoint. Since MS adopts an organizational point of view, it attempts to resolve the conflicts of interest among the components of the organization in a way that is best for the organization as a whole [75]. In other words, the MS approach is a search for global optima. Detailed discussion of MS philosophy can be found in the texts by Churchman, Ackoff, and Arnoff [24]; Ackoff & Sasieni [3]; Ackoff and Rivett [2]; and Hillier and Lieberman [75], among others.

The MS approach uses the following steps in problem solving and decision making:

1 Identify and define the problem.

2 Determine the set of alternative solutions.

3 Determine the criteria that will be used to evaluate the alternatives.

4 Evaluate the alternatives.

5 Choose an alternative.

6 Implement the selected alternative.

7 Evaluate the results and determine if a satisfactory solution has been obtained.

The above steps are fairly general in nature. Different management scientists might disagree on the exact steps described above, but they will all agree on the same focal theme: identification and selection of the alternative which results in best objective.

The constrained-optimization (CO) philosophy of MS is based on a total system's approach. A CO model represents the causal relations between one or more objectives and the factors that change the attainment of objectives (also known as constraints). Usually, a set of mathematical equations models the objectives and constraints. Forty years or so of advancement in MS has led to the development of algorithms and heuristic procedures to solve a variety of problems represented by CO.

Since the CO approach is based on a model of the true system, it is important to have a very good representation of the system of analysis. This implies a clear definition of the system's objective(s). It is also important to identify all variables (at least all the important ones) affecting the performance of the system. Identification of correct causal relationships between variables is also necessary. Additionally, all constraints, their interrelations, and their relation with the objective function need to be represented in the model [75]. In theory, the objective and the constraints can take any functional form. It is also possible to model stochastic or probabilistic systems.

A simple example might be helpful in explaining some conclusions of the CO approach. Figure A.1 shows the Linear Programming (or LP, one type of CO) representation of product-mix problem. Straight lines C1, C2, and C3 represent three constraints (capacities of three machines) present in the system. The Line OF represents the objective function (a profit function, in this case). Graphical solution of this LP problem shows that corner point A represents the optimal solution.

The simple LP problem illustrated in the previous paragraph can be used to understand several conclusions obtained in the CO approach of system analysis:

1 There are two type of constraints: binding and nonbinding. Constraints C1 and C2 represent binding constraints and C3 represents a nonbinding constraint in Figure A.1.

2 Binding constraints limit the attainment of the objective and hence should be utilized as much as possible. For example, constraints represented by C1 and C2 in Figure A.1 should be utilized as much as possible. If C1 and C2 are not utilized completely then the profit obtained will be less than the optimal profit.

3 Nonbinding constraints should not be utilized completely. If a nonbinding constraint is utilized entirely, then a part of its utilization will not contribute anything to the objective function. For instance, corner point A requires full utilization of C1 and C2 but only partial utilization of C3. Since A represents the best value of objective function in the feasible solution space, additional utilization of C3 will not generate more profit than point A.

4 Only by considering all constraints simultaneously can the best solution be

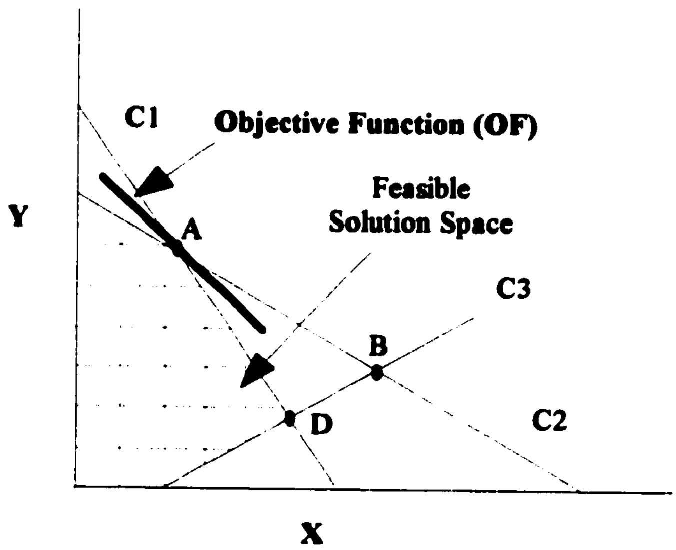

Figure A.1: Linear programming (graphical method) obtained. Considering a few constraints at a time will only give rise to local optima which might or might not be same as the global optimum. In fact, summing of local optima is never better than and usually worse than the global optimum. For example, only considering C1 and C2 will give the same solution (point A), but by considering C1 and C3, the result will be E (out of feasible solution space); by considering C2 and C3, the result will be B (out of feasible solution space).

5 It is implicitly assumed that all interdependence of variables, resources, and objective is represented in the model.

6 Variability in the system can and should be modeled. The example problem (Figure A.1) is deterministic in nature, but it is possible to model stochastic systems. Several procedures attempt to obtain near-optimal solutions for stochastic problems.

7 Further improvement in the system's performance can only be achieved by breaking the binding constraints. Breaking nonbinding constraints will not change the performance of the system. Hence, in this LP example, additional profit (more than A) can only be obtained by breaking C1 or C2. This can be done either by changing the slope or the intercept or both for lines C1 and/or C2. For example if it is possible to completely remove C1 then the new optimal solution will be represented by point B. Point B represents a profit higher than point A. On the other hand, removing or changing constraint C3 will not always increase or decrease the profit of the system. It is possible, however, for C3 to change the performance of the system in some special cases; for example, if C3 is changed so

much that it intersects C1 at point A. This change in C3 would have completely changed the system and now C3 would be a binding constraint. But, as long as C3 is a non-binding constraint, performance of the system cannot be changed by changing C3.

Conclusion (7) above is consistent with the continuous improvement philosophy of POM. This philosophy argues that an organization should always attempt to improve by identifying ways by which performance can be improved, but this does not mean that changing any characteristic of the system will improve the performance. For example, one may want to improve profit of the plant represented in Figure A.1. Will it help if one makes the resource represented by C3 more efficient? If one does, then it will finish the same task in say Q% utilization and Q < present utilization, but does that change the position of point A (maximum profit point)? The answer is that it does not. However, a more efficient C1 and/or C2 will move point A in a direction (away from the origin) which will increase the profit.

This brief review of MS philosophy shows that an accurate CO model cannot only help achieve the best performance currently but also act as a guideline to change and improve the process. The advantage of using the CO approach is actually even more broad. Even if it is not possible to get an accurate mathematical model of the system, the general problem-solving steps identified earlier will help achieve better performance.

APPENDIX B

CUSTOMER DATA COLLECTION PACKET

[ON UNIVERSITY OF UTAH LETTERHEAD]

Dear Friend,

The quality of many services is thought by many consumers to have reached a critically low point. Tonight Show host Jay Leno recently remarked that when he reminded a supermarket cashier that she had forgotten to say "Thank you," she replied, "It's printed on your receipt."

Perhaps an important reason for poor quality of services is that few people who experience poor service get an opportunity to provide constructive feedback. As a result, information of great value to service providers is lost and poor service is perpetuated. To do our small bit to counter this phenomenon, we at the David Eccles School of Business, University of Utah are conducting a study of *Pizza Home Delivery Industry*. The results of this study will be used to provide constructive feedback to the managers so that they can improve their operations to better meet consumer needs.

The study involves understanding choice patterns of several randomly selected consumers like yourself. Therefore we request you to respond to all the sections of this survey. It will take you about 10 to 15 mins to complete the survey.

We assure you of complete confidentiality. You will not be identified under any circumstances. You will notice that there are no serial numbers and/or identification marks on the survey.

This project has been approved by the Institutional Review Board (581-5382) and has been endorsed by the Department of Management (581-7415) at the University of Utah. Please feel free to contact them if you need any clarifications regarding this study. Please contact the Project Director if you wish to receive a copy of the results.

Thank you for your help.

Sincerely,

ROHIT VERMA

This information will ONLY be used to compare groups of consumers with different demographic characteristics.

1 **Age** ________ **years** 2 **Your Sex** ____ **Male** ____ **Female**

3 **Your Education**

___ Less than High School
___ High School
___ Some College
___ 4-Year College Degree
___ Masters
___ Doctorate

4 **Are You**

___ Employed Full Time
___ Employed Part Time
___ Not Employed Outside Home
___ Currently Unemployed
___ Retired
___ Full-Time Student

5 **How Many People Live In Your Household?** __________

6 **Pretax Yearly Household Income**

___ Less than $15,000
___ $15,000 to $30,000
___ $30,000 to $45,000
___ $45,000 to $60,000
___ $60,000 to $80,000
___ $80,000 to $100,000
___ More than $100,000

7 **How Often Do You**

	in Last 6 Months	Approximate number of Pizzas/Order
Get Pizza Home Delivered		
Get Pizza Delivered at Work		
Get Pizza Delivered for Parties, etc.		
Go To a Dine-In Restaurant For Pizza		
Carry-Out Pizza Meals		

5 How Often Have You Ordered Pizza From These Companies (at Home, at Work, for Parties etc)

	in Last 6 Months	Number of Pizza/Order	Price of a Large Pizza	Promised Delivery Time	Actual Delivery Time
Ambassador Pizza					
Domino's Pizza					
Free Wheeler Pizza					
Godfather's Pizza					
Pizza Hut					
Other?					

The following pages contain 16 choice sets of pizza delivery companies. Assuming you are "In the Mood for Pizza" and that you want your pizza delivered, please choose the pizza delivery company from which you would like to order pizza. For the sake of simplicity, the choice sets contain information about only some of the attributes of the companies. Assume that all other attributes (not specified) are same for both companies. For example, even though the choice sets show the price of large pizza only, you can assume that both companies also offer small, medium, and large size pizzas at prices lower than their large pizzas.

The following example illustrates a possible response:

Choice Set	Company #1	Company #2	
Price of First Large Pizza	$12.00	$18.00	
Discount on Second Pizzas	none	1/2 price	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	15 mins. late	same as promised	
Pizza Variety	1 type of crust	3 types of crust,	
Pizza Temperature when delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Would Order Pizza From		✔	Neither?

In the above example a consumer decided to order pizza from Company #2.

The following pages contain 16 similar choice sets. Please use you own criteria to choose pizza companies. *Remember there are no right or wrong answers.*

Please respond to all the choice sets because incomplete response makes the data analysis very difficult. The profiles of pizza companies are generated by a scientific procedure and therefore it is necessary to receive your response to all the choice sets.

Choice Set #1	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	yes	no	
I Would Order Pizza From =>>>			Neither?

Choice Set #2	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Would Order Pizza From =>>>			Neither?

Choice Set #3	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	yes	no	
I Would Order Pizza From ==>>>			Neither?

Choice Set #4	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	no	yes	
I Would Order Pizza From ==>>>			Neither?

Choice Set #5	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	yes	no	
I Would Order Pizza From ==>>>			Neither?

Choice Set #6	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Would Order Pizza From ==>>>			Neither?

Choice Set #7	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	yes	no	
I Would Order Pizza From ==>>>			Neither?

Choice Set #8	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Would Order Pizza From ==>>>			Neither?

Choice Set #9	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	yes	no	
I Would Order Pizza From ==>>>			Neither?

Choice Set #10	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	yes	no	
I Would Order Pizza From ==>>>			Neither?

Choice Set #11	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	can be up to 15 mins late	same as promised	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	yes	no	
I Would Order Pizza From ==>>>			Neither?

Choice Set #12	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	no	yes	
I Would Order Pizza From ==>>>			Neither?

Choice Set #13	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	no	yes	
I Would Order Pizza From ==>>>			Neither?

Choice Set #14	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	yes	no	
I Would Order Pizza From ==>>>			Neither?

Choice Set #15	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	no	yes	
I Would Order Pizza From ==>>>			Neither?

Choice Set #16	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Would Order Pizza From ==>>>			Neither?

THANK YOU FOR YOUR HELP

Please Return the completed survey in the enclosed postage paid return envelope.

APPENDIX C

MANAGER DATA COLLECTION PACKET

[ON UNIVERSITY OF UTAH LETTERHEAD]

Thank you for participating in the University of Utah Research Project on the Pizza Industry. The results of this study will be used to provide constructive feedback to the managers and for academic research.

The success of this project depends of you and others like you who have been randomly selected to represent the Pizza Industry Managers in the Salt Lake Valley. Therefore we request you to respond to all the sections of this survey. It will take you about 10 to 15 mins to complete the survey. *There are no right or wrong answers to any questions.*

***We assure you of complete confidentiality.* You will not be identified under any circumstances. We will combine your response will several other managers like yourself and analyze the combined data (you will notice that there are no serial numbers and/or identification marks on the survey).**

Please respond to all the sections of the survey because the data analysis becomes very difficult for an incomplete response. If you wish to receive a copy of the results or need any other information regarding this project please feel free to contact us.

Thank you very much for your help.

Sincerely,

ROHIT VERMA

This information will ONLY be used to compare groups of managers with different demographic characteristics.

1 **Your Age _____ years**

2 **Your Sex ____ Male ____ Female**

3 **Your Education** ___ **Less than High School** ___ **High School**
___ **Some College** ___ **College Degree**
___ **Masters** ___ **Doctorate**

4 **Your Total Work Experiance in the Pizza Industry ______ years**

5 **About the Company were you currently work**

Name:____

Total # of Employees During the Weekdays ______________

Total # of Employees During Weekends ________________

Wage Rates (please complete the following table)

Wage Rate/Hour	# of Employees
between $4.00 to $5.00	
between $5.00 to $6.00	
between $6.00 to $8.00	
between $8.00 to $10.00	
between $10.00 to $15.00	
more than $15.00	

Average # of Pizzas Sold on a Typical Weekday _____________
Average # of Pizzas Sold on a Typical Weekend Day _________
Approximate Pizza Preperation Time ______________________
Approximate Pizza Delivery Time _________________________
Supplier Delivery Frequency ____________________________
Your Work Experiance In This Company __________________

The Following pages contain 16 choice sets of Pizza Delivery Companies. Each set contains the profiles of two pizza delivery companies.

Assuming that YOUR CUSTOMERS are "In the Mood for Pizza" and that they want the pizza delivered, please choose the pizza delivery company from which you think the customers would like to order pizza. For the sake of simplicity, the choice sets contain information about only some of the attributes of the companies. Assume that all other attributes (not specified) are same for both companies. For example, even though the choice sets show the price of large pizza only, you can assume that both companies also offer small, medium and large size pizzas at prices lower than their large pizzas.

Note: If you think your customers won't like any of the two pizza delivery companies in a particular choice set, then choose neither.

The following example illustrates a possible response:

Choice Set	Company #1	Company #2	
Price of First Large Pizza	$12.00	$18.00	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	15 mins. late	same as promised	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature when delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Think My Customers Would Order Pizza From		✔	Neither?

In the above example a manager thinks that his/her customers would order pizza from Company #2.

The following pages contain 16 similar choice sets.

Please respond to all the choice sets because incomplete response makes the data analysis very difficult. The profiles of pizza companies are generated by a scientific procedure, and therefore it is necessary to receive your response to all the choice sets.

Choice Set #1	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	yes	no	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #2	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #3	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	yes	no	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #4	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	no	yes	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #5	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	yes	no	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #6	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #7	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	yes	no	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #8	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	no	yes	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #9	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	yes	no	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #10	**Company #1**	**Company #2**	
Price of First Large Pizza	**$12**	**$18**	
Discount on Second Pizza	**none**	**1/2 price**	
Promised Delivery Time	**20 mins**	**40 mins**	
Actual Delivery Time	**up to 15 mins late**	**same as promised**	
Pizza Variety	**3 types of crust**	**1 type of crust**	
Pizza Temperature When Delivered	**warm**	**steaming hot**	
Money Back Guarantee	**yes**	**no**	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #11	**Company #1**	**Company #2**	
Price of First Large Pizza	**$18**	**$12**	
Discount on Second Pizza	**none**	**1/2 price**	
Promised Delivery Time	**40 mins**	**20 mins**	
Actual Delivery Time	**up to 15 mins late**	**same as promised**	
Pizza Variety	**1 type of crust**	**3 types of crust**	
Pizza Temperature When Delivered	**warm**	**steaming hot**	
Money Back Guarantee	**yes**	**no**	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #12	**Company #1**	**Company #2**	
Price of First Large Pizza	**$18**	**$12**	
Discount on Second Pizza	**1/2 price**	**none**	
Promised Delivery Time	**40 mins**	**20 mins**	
Actual Delivery Time	**same as promised**	**up to 15 mins late**	
Pizza Variety	**1 type of crust**	**3 types of crust**	
Pizza Temperature When Delivered	**steaming hot**	**warm**	
Money Back Guarantee	**no**	**yes**	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #13	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	1/2 price	none	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	no	yes	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #14	Company #1	Company #2	
Price of First Large Pizza	$18	$12	
Discount on	1/2 price	none	
Promised Delivery Time	20 mins	40 mins	
Actual Delivery Time	same as promised	up to 15 mins late	
Pizza Variety	1 type of crust	3 types of crust	
Pizza Temperature When Delivered	warm	steaming hot	
Money Back Guarantee	yes	no	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #15	Company #1	Company #2	
Price of First Large Pizza	$12	$18	
Discount on Second Pizza	none	1/2 price	
Promised Delivery Time	40 mins	20 mins	
Actual Delivery Time	up to 15 mins late	same as promised	
Pizza Variety	3 types of crust	1 type of crust	
Pizza Temperature When Delivered	steaming hot	warm	
Money Back Guarantee	no	yes	
I Think My Customers Would Order Pizza From =>>>			Neither?

Choice Set #16	**Company #1**	**Company #2**	
Price of First Large Pizza	**$12**	**$18**	
Discount on Second Pizza	**none**	**1/2 price**	
Promised Delivery Time	**20 mins**	**40 mins**	
Actual Delivery Time	**same as promised**	**up to 15 mins late**	
Pizza Variety	**1 type of crust**	**3 types of crust**	
Pizza Temperature When Delivered	**warm**	**steaming hot**	
Money Back Guarantee	**no**	**yes**	
I Think My Customers Would Order Pizza From **=>>>**			**Neither?**

THANK YOU FOR YOUR HELP

Please Return the completed survey in the enclosed postage paid return envelope.

The Following pages contain 32 situations of pizza delivery companies. Each situation contains the profile of a pizza delivery company and customer demand pattern.

(1) Estimate the cost of producing and delivering the pizza specified
(2) Estimate the relative difficulty in meeting customer demand in the specified situation (1 = Very Easy; 10 = Very Difficult).

For the sake of simplicity, the situations contain information about only some of the attributes of the companies. Assume that all other attributes (not specified) are same for all the companies. For example, even though the situations show the price of large pizza only, you can assume that all companies also offer small, medium and large size pizzas at prices lower than their large pizzas.

The following example illustrates a possible response:

Pizza Attributes	
Price of First Large Pizza	$12
Discount on Additional Pizzas	None
Promised Delivery Time	40 mins
Actual Delivery Time	same as promised
Pizza Variety	3 types of crust
Pizza Temperature when delivered	warm
Money Back Guarantee	no
Operating System Attributes	
Daily Demand Rate	approximately 200 pizzas/day
Order Similarity	A Mix of Small and Large Size Orders
Number of Pizza Delivery Personnel	7
Number of Cooks & Other In-Store Employees	3
Average Wage Rate For All Employees	$8
Pizza Preparation & Cooking Time	10 mins
Supplier Delivery Frequency	every other day
Under the given operating condition, what will be the cost of delivering a pizza specified above =>	$7.00
What will be the relative difficulty in meeting customer demand under the given condition? 1 = Most Easy; 10 = Most Difficult	6

In this example a manager thinks that cost of producing a delivering a pizza is $7.00 and operating difficulty is 6.

Pizza Attributes	**Situation 1**	**Situation 2**
Price of First Large Pizza	**$12**	**$18**
Discount on Second Pizza	**1/2 price**	**1/2 price**
Promised Delivery Time	**40 mins**	**40 mins**
Actual Delivery Time	**can be up to 15 mins late**	**same as promised**
Pizza Variety	**1 type of crust**	**1 type of crust**
Pizza Temperature When Delivered	**steaming hot**	**warm**
Money Back Guarantee	**no**	**no**
Daily Demand Rate	**200 pizzas/day**	**400 pizzas/day**
Order Similarity	**Mostly Small Size Orders**	**Mostly Small Size Orders**
Number of Pizza Delivery Personnal	**7**	**7**
Number of Cooks & In-Store Employees	**7**	**3**
Average Wage Rate	**$8**	**$8**
Pizza Preperation & Cooking Time	**20 mins**	**10 mins**
Supplier Delivery Frequency	**Once a Week**	**Once a Week**
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 3	Situation 4
Price of First Large Pizza	$18	$18
Discount on Second Pizza	none	none
Promised Delivery Time	40 mins	20 mins
Actual Delivery Time	same as promised	up to 15 mins late
Pizza Variety	3 types of crust	1 type of crust
Pizza Temperature When Delivered	steaming hot	steaming hot
Money Back Guarantee	yes	no
Daily Demand Rate	200 pizzas/day	400 pizzas/day
Order Similarity	Mostly Small Size Orders	Mostly Small Size Orders
Number of Pizza Delivery Personnal	3	3
Number of Cooks & In-Store Employees	3	7
Average Wage Rate	$8	$5
Pizza Preperation & Cooking Time	20 mins	20 mins
Supplier Delivery Frequency	Once a Week	Once a Week
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 5	Situation 6
Price of First Large Pizza	$12	$18
Discount on Second Pizza	none	none
Promised Delivery Time	40 mins	40 mins
Actual Delivery Time	same as promised	up to 15 mins late
Pizza Variety	1 type of crust	1 type of crust
Pizza Temperature When Delivered	warm	steaming hot
Money Back Guarantee	yes	yes
Daily Demand Rate	200 pizzas/day	400 pizzas/day
Order Similarity	Small & Large Size Orders	Small & Large Size Orders
Number of Pizza Delivery Personnal	7	7
Number of Cooks & In-Store Employees	7	3
Average Wage Rate	$5	$5
Pizza Preperation & Cooking Time	20 mins	10 mins
Supplier Delivery Frequency	Once a Week	Once a Week
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 7	Situation 8
Price of First Large Pizza	$12	$12
Discount on Second Pizza	none	1/2 price
Promised Delivery Time	20 mins	40 mins
Actual Delivery Time	same as promised	up to 15 mins late
Pizza Variety	1 type of crust	1 type of crust
Pizza Temperature When Delivered	steaming hot	warm
Money Back Guarantee	yes	yes
Daily Demand Rate	400 pizzas/day	400 pizzas/day
Order Similarity	Mostly Small Size Orders	Mostly Small Size Orders
Number of Pizza Delivery Personnal	7	3
Number of Cooks & In-Store Employees	7	3
Average Wage Rate	$8	$5
Pizza Preperation & Cooking Time	10 mins	20 mins
Supplier Delivery Frequency	Every Other Day	Every Other Day
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 9	Situation 10
Price of First Large Pizza	$18	$12
Discount on Second Pizza	1/2 price	1/2 price
Promised Delivery Time	20 mins	20 mins
Actual Delivery Time	up to 15 mins late	same as promised
Pizza Variety	3 types of crust	3 types of crust
Pizza Temperature When Delivered	warm	warm
Money Back Guarantee	yes	no
Daily Demand Rate	200 pizzas/day	200 pizzas/day
Order Similarity	Mostly Small Size Orders	Mostly Small Size Orders
Number of Pizza Delivery Personnal	7	3
Number of Cooks & In-Store Employees	7	7
Average Wage Rate	$5	$8
Pizza Preperation & Cooking Time	10 mins	20 mins
Supplier Delivery Frequency	Once a Week	Every Other Day
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 11	Situation 12
Price of First Large Pizza	$18	$12
Discount on Second Pizza	1/2 price	1/2 price
Promised Delivery Time	20 mins	20 mins
Actual Delivery Time	same as promised	same as promised
Pizza Variety	1 type of crust	3 types of crust
Pizza Temperature When Delivered	steaming hot	steaming hot
Money Back Guarantee	no	yes
Daily Demand Rate	200 pizzas/day	400 pizzas/day
Order Similarity	Small & Large Size Orders	Mostly Small Size Orders
Number of Pizza Delivery Personnal	7	7
Number of Cooks & In-Store Employees	3	3
Average Wage Rate	$5	$5
Pizza Preperation & Cooking Time	20 mins	20 mins
Supplier Delivery Frequency	Every Other Day	Once a Week
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 13	Situation 14
Price of First Large Pizza	$18	$12
Discount on Second Pizza	none	none
Promised Delivery Time	20 mins	20 mins
Actual Delivery Time	same as promised	up to 15 mins late
Pizza Variety	3 types of crust	3 types of crust
Pizza Temperature When Delivered	warm	steaming hot
Money Back Guarantee	yes	yes
Daily Demand Rate	400 pizzas/day	200 pizzas/day
Order Similarity	Small & Large Size Orders	Small & Large Size Orders
Number of Pizza Delivery Personnal	3	3
Number of Cooks & In-Store Employees	3	7
Average Wage Rate	$5	$5
Pizza Preperation & Cooking Time	10 mins	20 mins
Supplier Delivery Frequency	Every Other Day	Every Other Day
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult >>		

Pizza Attributes	Situation 15	Situation 16
Price of First Large Pizza	$18	$12
Discount on Second Pizza	1/2 price	none
Promised Delivery Time	40 mins	40 mins
Actual Delivery Time	same as promised	up to 15 mins late an be
Pizza Variety	1 type of crust	3 types of crust
Pizza Temperature When Delivered	steaming hot	steaming hot
Money Back Guarantee	yes	no
Daily Demand Rate	200 pizzas/day	200 pizzas/day
Order Similarity	Mostly Small Size Orders	Mostly Small Size Orders
Number of Pizza Delivery Personnal	3	7
Number of Cooks & In-Store Employees	7	3
Average Wage Rate	$5	$5
Pizza Preperation & Cooking Time	10 mins	10 mins
Supplier Delivery Frequency	Every Other Day	Every Other Day
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult >>		

Pizza Attributes	Situation 17	Situation 18
Price of First Large Pizza	$18	$12
Discount on Second Pizza	none	1/2 price
Promised Delivery Time	40 mins	40 mins
Actual Delivery Time	can be up to 15 mins late	same as promised
Pizza Variety	1 type of crust	3 types of crust
Pizza Temperature When Delivered	warm	steaming hot
Money Back Guarantee	no	no
Daily Demand Rate	200 pizzas/day	400 pizzas/day
Order Similarity	Small & Large Size Orders	Small & Large Size Orders
Number of Pizza Delivery Personnal	3	3
Number of Cooks & In-Store Employees	7	7
Average Wage Rate	$8	$5
Pizza Preperation & Cooking Time	10 mins	10 mins
Supplier Delivery Frequency	Every Other Day	Once a Week
Estimated Pizza Cost		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 19	Situation 20
Price of First Large Pizza	$18	$12
Discount on Second Pizza	none	none
Promised Delivery Time	20 mins	20 mins
Actual Delivery Time	up to 15 mins late	up to 15 mins late
Pizza Variety	1 type of crust	3 types of crust
Pizza Temperature When Delivered	warm	warm
Money Back Guarantee	yes	no
Daily Demand Rate	200 pizzas/day	400 pizzas/day
Order Similarity	Mostly Small Size Orders	Small & Large Size Orders
Number of Pizza Delivery Personnal	7	7
Number of Cooks & In-Store Employees	3	3
Average Wage Rate	$8	$8
Pizza Preperation & Cooking Time	20 mins	20 mins
Supplier Delivery Frequency	Every Other Day	Once a Week
Estimated Pizza Cost		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	**Situation 21**	**Situation 22**
Price of First Large Pizza	**$12**	**$18**
Discount on Second Pizza	**none**	**none**
Promised Delivery Time	**40 mins**	**20 mins**
Actual Delivery Time	**same as promised**	**same as promised**
Pizza Variety	**1 type of crust**	**3 types of crust**
Pizza Temperature When Delivered	**steaming hot**	**steaming hot**
Money Back Guarantee	**no**	**no**
Daily Demand Rate	**400 pizzas/day**	**200 pizzas/day**
Order Similarity	**Small & Large Size Orders**	**Small & Large Size Orders**
Number of Pizza Delivery Personnal	**3**	**7**
Number of Cooks & In-Store Employees	**3**	**7**
Average Wage Rate	**$8**	**$8**
Pizza Preperation & Cooking Time	**20 mins**	**10 mins**
Supplier Delivery Frequency	**Every Other Day**	**Once a Week**
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 23	Situation 24
Price of First Large Pizza	$18	$18
Discount on Second Pizza	1/2 price	1/2 price
Promised Delivery Time	40 mins	40 mins
Actual Delivery Time	up to 15 mins late	up to 15 mins late
Pizza Variety	3 types of crust	3 types of crust
Pizza Temperature When Delivered	warm	steaming hot
Money Back Guarantee	no	yes
Daily Demand Rate	200 pizzas/day	400 pizzas/day
Order Similarity	Small & Large Size Orders	Small & Large Size Orders
Number of Pizza Delivery Personnal	3	7
Number of Cooks & In-Store Employees	3	7
Average Wage Rate	$5	$8
Pizza Preperation & Cooking Time	20 mins	20 mins
Supplier Delivery Frequency	Once a Week	Every Other Day
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 25	Situation 26
Price of First Large Pizza	$12	$12
Discount on Second Pizza	1/2 price	1/2 price
Promised Delivery Time	20 mins	20 mins
Actual Delivery Time	up to 15 mins late	up to 15 mins late
Pizza Variety	1 type of crust	1 type of crust
Pizza Temperature When Delivered	warm	steaming hot
Money Back Guarantee	no	yes
Daily Demand Rate	400 pizzas/day	200 pizzas/day
Order Similarity	Small & Large Size Orders	Small & Large Size Orders
Number of Pizza Delivery Personnal	7	3
Number of Cooks & In-Store Employees	7	3
Average Wage Rate	$5	$8
Pizza Preperation & Cooking Time	10 mins	10 mins
Supplier Delivery Frequency	Every Other Day	Once a Week
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 27	Situation 28
Price of First Large Pizza	$18	$12
Discount on Second Pizza	1/2 price	none
Promised Delivery Time	20 mins	20 mins
Actual Delivery Time	same as promised	same as promised
Pizza Variety	1 type of crust	1 type of crust
Pizza Temperature When Delivered	warm	warm
Money Back Guarantee	yes	no
Daily Demand Rate	400 pizzas/day	200 pizzas/day
Order Similarity	Small & Large Size Orders	Mostly Small Size Orders
Number of Pizza Delivery Personnal	3	3
Number of Cooks & In-Store Employees	7	3
Average Wage Rate	$8	$5
Pizza Preperation & Cooking Time	20 mins	10 mins
Supplier Delivery Frequency	Once a Week	Once a Week
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 29	Situation 30
Price of First Large Pizza	$18	$12
Discount on Second Pizza	none	1/2 price
Promised Delivery Time	40 mins	40 mins
Actual Delivery Time	same as promised	same as promised
Pizza Variety	3 types of crust	3 types of crust
Pizza Temperature When Delivered	warm	warm
Money Back Guarantee	no	yes
Daily Demand Rate	400 pizzas/day	200 pizzas/day
Order Similarity	Mostly Small Size Orders	Small & Large Size Orders
Number of Pizza Delivery Personnal	7	7
Number of Cooks & In-Store Employees	7	3
Average Wage Rate	$5	$8
Pizza Preperation & Cooking Time	20 mins	10 mins
Supplier Delivery Frequency	Every Other Day	Every Other Day
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

Pizza Attributes	Situation 31	Situation 32
Price of First Large Pizza	$18	$12
Discount on Second Pizza	1/2 price	none
Promised Delivery Time	20 mins	40 mins
Actual Delivery Time	up to 15 mins late	up to 15 mins late
Pizza Variety	3 types of crust	3 types of crust
Pizza Temperature When Delivered	steaming hot	warm
Money Back Guarantee	no	yes
Daily Demand Rate	400 pizzas/day	400 pizzas/day
Order Similarity	Mostly Small Size Orders	Mostly Small Size Orders
Number of Pizza Delivery Personnal	3	3
Number of Cooks & In-Store Employees	3	7
Average Wage Rate	$8	$8
Pizza Preperation & Cooking Time	10 mins	10 mins
Supplier Delivery Frequency	Every Other Day	Once a Week
Estimated Pizza Cost?		
What will be the relative difficulty in meeting customer demand under the given operating condition? 1 = Most Easy 10 = Most Difficult =>>		

APPENDIX D

PROGRAM FOR LOG-LIKELIHOOD ESTIMATION

```
c       THIS PROGRAM CALCULATES LOGLIKELYHOOD VALUES
c       INPUT: CHOICE PATTERNS & ESTIMATED BETA WEIGHTS
        dimension cdata(130,50), x(50,20)
        dimension beta(5,20), yl(5,50), rl(5)
        dimension rloglike(5)
        open(20,file='cust.att')
        open(21,file='cdata.dat')
        open(23,file='beta.in')
        write(5,*) 'Number of Segments = ?'
        read(5,*) nseg
        read(5,*) nd
        nsub = 19
        no = 48
        nd1 = nd-1
        do 101 i = 1,nsub
        read(21,901) id, (cdata(i,j),j=1,48)
901     format(i3,48f1.0)
101     continue
        do 102 i = 1,no
        read(20,*) (x(i,j),j=1,nd)
102     continue
        do 105 i = 1,nseg
        read(23,*) (beta(i,j),j=1,nd)
105     continue
        ncs = 16
        nco = 3
        do 52 i = 1,5
        rl(i) = 0
        do 53 j = 1,50
        yl(i,j) = 0
53      continue
52      continue
        do 41 k = 1,nseg
        do 42 i = 1,no
        do 43 j = 1,nd1
        yl(k,i) = yl(k,i) + x(i,j) * beta(k,j)
43      continue
        j = j + 1
        yl(k,i) = yl(k,i) + beta(k,j)
```

```
      do 44 i = 1,no
      yl(k,i) = exp(yl(k,i))
44    continue
      i = 0
      do 45 i1 = 1,ncs
      sum = 0
      do 46 i2 = 1,nco
      i = i + 1
      sum = sum + yl(k,i)
46    continue
      i = i - 3
      do 47 i2 = 1,nco
      i = i + 1
      yl(k,i) = yl(k,i) /sum
47    continue
45    continue
41    continue
      do 48 isub = 1, nsub
      do 49 iseg = 1, nseg
      rl(iseg) = 0
      do 50 ino = 1,no
      rl(iseg) = rl(iseg) + alog(yl(iseg,ino))*cdata(isub,ino)
50    continue
49    continue
      if (nseg.eq.5) then
      am = amax1(rl(1),rl(2),rl(3),rl(4),rl(5))
      endif
      if (nseg.eq.4) then
      am = amax1(rl(1),rl(2),rl(3),rl(4))
      endif
      if (nseg.eq.3) then
      am = amax1(rl(1),rl(2),rl(3))
      endif
      if (nseg.eq.2) then
      am = amax1(rl(1),rl(2))
      endif
      if (nseg.eq.1) then
      am = rl(1)
      endif
      do 51 k = 1,nseg
      if (rl(k).eq.am) then
              k1 = k
      endif
51    continue
c      seg(isub) = k1
      rloglike(k1) = rloglike(k1) + rl(k1)
      total = total + rl(k1)
48    continue
      write(5,*) total, (rloglike(i),i=1,nseg)
      stop
      end
```

APPENDIX E

SIMULATED ANNEALING BASED LATENT STRUCTURE

PROCEDURE FOR MARKET SEGMENTATION

```
c       THIS PROGRAM USES SIMULATED ANNEALING HEURISTIC AND
c       LATENT STRUCTURE ALGORITHAM TO ASSIGN CUSTOMERS IN
c       DIFFERENT MARKET SEGMENTS
c       *******************************************************
        dimension seg(130),cdata(130,50),x(50,20)
        dimension freq(5,50),beta(5,20),vll(5),vi(5)
        dimension segb(130),betab(5,20),vllb(5),vib(5)
        dimension sego(130),betao(5,20),vllo(5),vio(5)
        dimension segsize(5),group(50)
        double precision tone, ttwo
        open(11,file='cust.att')
        open(7,file='cdata.dat')
        open(9,file='segdata.dat')
        open(14,file='cmd.fil')
        open(15,file='group.in')
        open(21,file='five.out')
        open(22,file='lsstep.out')
        open(23,file='five1.out')
        open(24,file='five2.out')
        open(25,file='five3.out')
        open(26,file='five4.out')
        open(27,file='five5.out')
        write(5,*)
        write(5,*) 'Give IBIG and NREP'
        read(5,*) ib,nr
        write(5,*) '!!!!!!!!!! P L E A S E   W A I T !!!!!!!!!!'
        nseg = 5
        nsub = 128
        no = 48
        nd = 8
        nd1 = nd-1
        do 101 i = 1,nsub
        read(7,901) id, (cdata(i,j),j=1,48)
901     format(i3,48f1.0)
101     continue
        do 102 i = 1,no
```

```
      read(11,*) (x(i,j),j=1,nd)
102   continue
      call asgnseg(nseg,nsub,seg)
      vitb = -25000000
      temp = 5
      call freqseg(nseg,nsub,seg,cdata,freq)
      call model(nseg,no,nd,freq,x,beta,vll)
      call ls(nsub,nseg,no,nd,seg,cdata,freq,x,beta,vll,vi,vit)
      call csolu(sego,betao,vllo,vio,vito,seg,beta,vll,vi,vit)
      do 106 ibig = 1,ib
      do 105 nrep = 1,nr
      CALL GETTIM (IHR, IMIN, ISEC, I100)
      CALL GETDAT (IYR, IMON, IDAY)
      TONE =
          DFLOAT(86400*IDAY+3600*IHR+60*IMIN+ISEC)+DFLOAT(I100)/100.
      call new(nsub,nseg,no,nd,seg,cdata,freq,x,beta,vll,vi,vit)
      write(22,*) 'IBIG = ', ibig, ' NREP = ',nrep
      write(22,*) vitb,vito,vit
      if (vit.gt.vitb) then
        call csolu(segb,betab,vllb,vib,vitb,seg,beta,vll,vi,vit)
      endif
      delta = vito - vit
      if (delta.lt.0) then
        call csolu(sego,betao,vllo,vio,vito,seg,beta,vll,vi,vit)
      else
        call random(rand)
        rprob = exp(-delta/temp)
        if (rand.lt.rprob) then
          call csolu(sego,betao,vllo,vio,vito,seg,beta,vll,vi,vit)
        else
          call csolu(seg,beta,vll,vi,vit,sego,betao,vllo,vio,vito)
        endif
      endif
      write(22,*) vitb,vito,vit
      write(22,*) '************'
      write(5,*) 'IBIG =', ibig, '  NREP = ',nrep
      CALL GETTIM (IHR, IMIN, ISEC, I100)
      CALL GETDAT (IYR, IMON, IDAY)
      TTWO =
DFLOAT(86400*IDAY+3600*IHR+60*IMIN+ISEC)+DFLOAT(I100)/100.
      write(5,*) 'Time = ', ttwo-tone
      write(5,*)
105   continue
      temp = 0.91 * temp
106   continue
      do 107 ii = 1,nsub
      iseg = segb(ii)
      segsize(iseg) = segsize(iseg) + 1
107   continue
      write(21,*) 'Segment Size and Beta Weights'
      do 108 ii = 1,nseg
      write(21,903) segsize(ii), (beta(ii,jj),jj=1,nd1)
```

```
108     continue
903     format(f4.0,1x,14(f5.2,1x))
        write(21,*)'Total and Individual LL Values'
        write(21,904) vitb, (vio(ii),ii=1,nseg)
        write(21,*)
        write(21,*) 'Segment Members'
        write(21,*)
904     format(6(f10.2,1x))
        write(21,*) (segb(ii),ii=1,nsub)
        call freqseg(nseg,nsub,segb,cdata,freq)
        read(15,*) (group(i),i=1,48)
        i = 1
        do 110 j = 1,no
        write(23,905) freq(i,j), (x(j,k),k=1,nd), group(j)
905     format(10f4.0)
110     continue
        i = 2
        do 120 j = 1,no
        write(24,905) freq(i,j), (x(j,k),k=1,nd), group(j)
120     continue
        i = 3
        do 130 j = 1,no
        write(25,905) freq(i,j), (x(j,k),k=1,nd), group(j)
130     continue
        i = 4
        do 140 j = 1,no
        write(26,905) freq(i,j), (x(j,k),k=1,nd), group(j)
140     continue
        i = 5
        do 150 j = 1,no
        write(27,905) freq(i,j), (x(j,k),k=1,nd), group(j)
150     continue

        stop
        end
c       ************************************************************
        subroutine csolu(segb,betab,vllb,vib,vitb,seg,beta,vll,vi,vit)
        dimension seg(130),beta(5,20),vll(5),vi(5)
        dimension segb(130),betab(5,20),vllb(5),vib(5)
        do 81 i = 1,130
        segb(i) = seg(i)
81      continue
        do 82 i = 1,5
        do 83 j = 1,20
        betab(i,j) = beta(i,j)
83      continue
82      continue
        do 84 i = 1,5
        vllb(i) = vll(i)
        vib(i) = vi(i)
84      continue
        vitb = vit
```

```
      return
      end
c     **********************************************************
c     **********************************************************
      subroutine new(nsub,nseg,no,nd,seg,cdata,freq,x,beta,vll,vi,vit)
      dimension seg(130),cdata(130,50),freq(5,50)
      dimension x(50,20),beta(5,20),vll(5),vi(5)
      real*8 chis
      call random(rand)
      iasgn = 42 + rand*112
      do 71 i = 1,iasgn
      call random(rand)
      randno = rand * nsub
      isub = randno + 1
      call random(rand)
      randno = rand * nseg
      iseg = randno + 1
      seg(isub) = iseg
71    continue
      call freqseg(nseg,nsub,seg,cdata,freq)
      call model(nseg,no,nd,freq,x,beta,vll)
      call ls(nsub,nseg,no,nd,seg,cdata,freq,x,beta,vll,vi,vit)
      return
      end
c     **********************************************************
c     **********************************************************
      subroutine ls(nsub,nseg,no,nd,seg,cdata,freq,x,beta,vll,vi,vit)
      dimension seg(130),cdata(130,50),freq(5,50)
      dimension x(50,20),beta(5,20),vll(5),vi(5)
      dimension yl(5,50),rl(5), ssize(5)
      real*8 chis
      integer nsub,nseg,no,nd,nd1,ncs,nco
      nd1 = nd-1
      ncs = 16
      nco = 3
      do 40 iter = 1,1
      vit = 0
      vlt = 0
      do 52 i = 1,5
      ssize(i) = 0
      rl(i) = 0
      vll(i) = 0
      vi(i) = 0
      do 53 j = 1,50
      yl(i,j) = 0
53    continue
52    continue
      do 41 k = 1,nseg
      do 42 i = 1,no
      do 43 j = 1,nd1
      yl(k,i) = yl(k,i) + x(i,j) * beta(k,j)
43    continue
```

```
42        continue
          do 44 i = 1,no
          yl(k,i) = exp(yl(k,i))
44        continue
          i = 0
          do 45 i1 = 1,ncs
          sum = 0
          do 46 i2 = 1,nco
          i = i + 1
          sum = sum + yl(k,i)
46        continue
          i = i - 3
          do 47 i2 = 1,nco
          i = i + 1
          yl(k,i) = yl(k,i) /sum
47        continue
45        continue
41        continue
          do 48 isub = 1, nsub
          do 49 iseg = 1, nseg
          rl(iseg) = 0
          do 50 ino = 1,no
          rl(iseg) = rl(iseg) + alog(yl(iseg,ino))*cdata(isub,ino)
50        continue
49        continue
          am = amax1(rl(1),rl(2),rl(3),rl(4),rl(5))
          do 51 k = 1,nseg
          if (rl(k).eq.am) then
                  k1 = k
          endif
51        continue
          seg(isub) = k1
          vi(k1) = vi(k1) + rl(k1)
48        continue
          call freqseg(nseg,nsub,seg,cdata,freq)
          call model(nseg,no,nd,freq,x,beta,vl1)
c          write(5,*) 'ITERATION = ',iter
          do 54 ijk = 1,nseg
          vit = vit + vi(ijk)
          vlt = vlt + vl1(ijk)
54        continue

c          do 801 i10 = 1,nsub
c          iiseg = seg(i10)
c          ssize(iiseg) = ssize(iiseg) + 1
c801        continue
c          do 802 i10 = 1,nseg
c          write(5,702) ssize(i10), (beta(i10,jj),jj=1,nd1)
c702        format(f4.0,2x,7(f8.4,1x))
c802        continue
c          write(5,*)
c          write(5,*) vit,vlt
```

```
40      continue
        return
        end
c       ***********************************************************
c       ***********************************************************
        subroutine model(nseg,no,nd,freq,x,beta,vll)
        dimension beta(5,20),vll(5),b(20)
        dimension x(50,20),freq(5,50)
        real*8 chis
        integer nseg,nd,nd1,no
        nd1 = nd - 1
        open(9,file='segdata.dat')
        open(14,file='cmd.fil')
        do 31 i = 1,nseg
        rewind 9
        rewind 14
        do 32 j = 1,no
        write(9,30) freq(i,j), (x(j,k),k=1,nd)
30      format(9f4.0)
32      continue
        rewind 9
        rewind 14
        n9 = 9
        call flog(n9,b,chis)
        do 33 j = 1,nd1
        beta(i,j) = b(j)
33      continue
        vll(i) = chis
31      continue
        return
        end
c       ********************************************************
c       ***********************************************************
        subroutine freqseg(nseg,nsub,seg,cdata,freq)
        dimension seg(130),cdata(130,50),freq(5,50)
        integer nsub,nseg
        do 11 i = 1,5
        do 12 j = 1,50
        freq(i,j) = 0
12      continue
11      continue
        do 13 i = 1,nsub
        j = seg(i)
        do 14 k = 1,48
        freq(j,k) = freq(j,k) + cdata(i,k)
14      continue
13      continue
        return
        end
c       *********************************************************
c       *********************************************************
```

```
      subroutine asgnseg(nseg,nsub,seg)
      dimension seg(130)
      integer nseg,nsub
      do 1 i = 1,nsub
      call random(rand)
      randno = rand * nseg
      irandno = randno + 1
      seg(i) = irandno
1     continue
      return
      end
c     ***********************************************************

      SUBROUTINE FLOG(NREAD1,B1,LRCHIS)
      PARAMETER (NVARMAX=270, NALTMAX=24)
      DIMENSION B1(11)
      REAL*8 ZPZ(NVARMAX*(NVARMAX-1)/2),Z(NALTMAX,NVARMAX),
     +       BETA(NVARMAX-2),ZTOT(NVARMAX-1),XPB(NALTMAX),
     +       PHAT(NALTMAX),TOLEPS,CVGEPS,LRCHIS,LRCH1,
     +       RBUF(NVARMAX)
      INTEGER VARPTR(NVARMAX),SWEPT(NVARMAX-1),ALTPTR(NALTMAX),CMDUNT,
     +        DATUNT,ALTMAX,NVARS,JGRP,JFRQ,DFERR,NZPTR(NVARMAX),
     +        PAGENO,LOGUNT,LSTUNT,PAGSIZ,ROWPAG,COLPAG,NDEL,
     +        DMASK(NVARMAX),NSETS
      CHARACTER*8 VARNAM(NVARMAX),DELNAM(NVARMAX),RJVNAM(NVARMAX)
      CHARACTER*127 ERRMSG
      CHARACTER*512 DATFMT
      LOGICAL ERROR,CONVRG,COVMAT,COVR4T,POISON
      DATA CMDUNT,LOGUNT,LSTUNT/14,6,6/,
     #     TOLEPS,CVGEPS,MAXITR/1.D-10,1.D-6,20/,
     #     PAGSIZ,ROWPAG,COLPAG/58,53,6/

      DATUNT = NREAD1
  200 ITER  = 0
      LOGUNT = 6
      LSTUNT = 6
      ERROR = .FALSE.
      ALTMAX = NALTMAX
      DO 300 K=1, NVARMAX-1
         SWEPT(K) = 1
  300 CONTINUE
      NVARS = 0
      NDEL=0
      DO 310 K=1, NVARMAX-2
         BETA(K)=0.0D0
  310 CONTINUE

      CALL CMDINP(CMDUNT,DATUNT,DATFMT,NVARMAX,
     #            NVARS,VARNAM,VARPTR,BETA,ERROR,ERRMSG,
     #            LOGUNT,LSTUNT,PAGSIZ,ROWPAG,COLPAG,COVMAT,
     #            COVR4T,POISON,NDEL,DELNAM,DMASK)
        IF (ERROR) GO TO 900
```

```
c       write (6,*) '  Commands input ...'

 100  CALL WCSSP(DATUNT,DATFMT,VARPTR,ALTMAX,NVARS,RBUF,BETA,ZPZ,
     #           LRCHIS,DFERR,Z,ZTOT,XPB,PHAT,ALTPTR,POISON,ERROR,
     #           ERRMSG,NZPTR,NDEL,DMASK,LRCH1,NSETS)
        IF (ERROR) GO TO 900

c       write (6,*) '  WCSSP returned successfully.'

      CALL UPDATE(ZPZ,BETA,NVARS,VARPTR,TOLEPS,CVGEPS,MAXITR,
     #            ITER,CONVRG,SWEPT,ERROR,ERRMSG)
        IF (ERROR) GO TO 900

c       write (6,*) '  UPDATE returned successfully.'

C        IF (LOGUNT.NE.6) WRITE (6,110) ITER,LRCHIS
C        WRITE (LOGUNT,110) ITER,LRCHIS
 110      FORMAT ('0',5X,'ITERATION: ',I3,
     #               ', LOG-LIKELIHOOD VALUE: ',F16.8)
C        WRITE (LOGUNT,111)
 111      FORMAT ('0',5X,'CURRENT BETA VALUES:'/)
C        WRITE (LOGUNT,114) (BETA(JJ),JJ=1,NVARS-2)
 114      FORMAT (8X,E13.7,1X,E13.7,1X,E13.7,1X,E13.7,1X,E13.7)

        IF (.NOT. CONVRG) GO TO 100

      CALL REPORT(ZPZ,NVARS,VARNAM,VARPTR,LRCHIS,LRCH1,DFERR,
     #             LSTUNT,PAGENO,B1)
c print covariance matrix in regular format
      IF (COVMAT) THEN
        CALL PRTMAT(ZPZ,NVARS,RJVNAM,VARNAM,VARPTR,
     #               LSTUNT,ROWPAG,COLPAG,PAGENO,PAGSIZ)
      ENDIF
C      WRITE(LSTUNT,'(''1'')')
c print covariance matrix in R4TN format
      IF (COVR4T) THEN
        write (lstunt,*) '   '
        write (lstunt,*) '   '
        write (lstunt,*) ' Covariance Matrix in format for R4TN '
        write (lstunt,*) '   '
        WRITE (LSTUNT,*) '***********'
        WRITE (LSTUNT,'(I6,I12)') NVARS-2,NSETS
        DO 171 JJ=1,NVARS-2
          WRITE (LSTUNT,*) BETA(JJ)
  171   CONTINUE
        WRITE (LSTUNT,*) '***********'
        DO 172 I=3,NVARS
          WRITE (LSTUNT,*) ( ZPZ((I-1)*(I-2)/2+J-1), J=3,I)
  172   CONTINUE
        WRITE (LSTUNT,*) '***********'
      ENDIF
      GOTO 910
```

```
 900  WRITE (LOGUNT,*) '      '
      WRITE (LOGUNT,'(6X,A72)') ERRMSG
      IF (LOGUNT.NE.6) THEN
         WRITE (*,'(1X,A72)') ERRMSG
      ENDIF

 910  CONTINUE
C      CLOSE (DATUNT,STATUS='KEEP')
C      IF (LOGUNT.NE.6) THEN
C         CLOSE (LOGUNT,STATUS='KEEP')
C      ENDIF
C      IF (LSTUNT.NE.6) THEN
C         CLOSE (LSTUNT,STATUS='KEEP')
C      ENDIF

C      IF(.NOT.ERROR) GO TO 200
C      CLOSE(CMDUNT,STATUS='KEEP')
      RETURN
      END

C---------------------------------------------------------------------
C     COMMAND INPUT SUBROUTINE                                         *
C                                                                      *
C      CAROL GILBERT                                 6/17/86           *
C---------------------------------------------------------------------

      SUBROUTINE CMDINP( CMDUNT,DATUNT,FORMAT,NVMAX,
     #                NV,VARNAM,VARPTR,BETA,ERROR,ERRMSG,
     #                LOGUNT,LSTUNT,PAGSIZ,ROWPAG,COLPAG,COVMAT,
     #                COVR4T,POISON,ND,DELNAM,DMASK)
*
*
      LOGICAL ERROR,TEST,COVMAT,LSTPTR,LOGPTR,GRPSET,FRQSET,BETSET
      LOGICAL NODATA,COVR4T,POISON
      INTEGER CMDUNT, DATUNT, LOGUNT, LSTUNT,PAGSIZ,ROWPAG,COLPAG,
     #        VARPTR(1), K, NV, ND, DMASK(1)
      CHARACTER*1 BUFARR(512),CHR
      CHARACTER*8 VARNAM(1),STATS(7),KEYWRD,GRPVAR,
     #            FRQVAR,DEVICE,DELNAM(1)
      CHARACTER*20 PTRNAM
      CHARACTER*512 FORMAT,BUFSTR
      CHARACTER*127 ERRMSG
      REAL*8 BETA(1)
*
      EQUIVALENCE(BUFSTR,BUFARR)
*
      ERROR=.FALSE.
      TEST=.TRUE.
      LSTPTR=.FALSE.
      LOGPTR=.FALSE.
      COVMAT=.FALSE.
      COVR4T=.FALSE.
```

```
      POISON=.FALSE.
      GRPSET=.FALSE.
      FRQSET=.FALSE.
      BETSET=.FALSE.
      NODATA=.TRUE.
      NV=0
      ND=0
      IO=0
*
*
C      OPEN (14 ,FILE='CMD.FIL')
C      OPEN (15 ,FILE='DAT1FIL')
      REWIND (14)

      GO TO 101
*
*
* KEYWORD
  101 READ(CMDUNT,'(A8)')KEYWRD
      CALL UPCASE(7,KEYWRD)
C     WRITE(*,*) 'processing ',KEYWRD
      IF(KEYWRD.EQ.'COMMENT ')GO TC 101
      IF(KEYWRD.EQ.'NVARS   ')GO TO 110
      IF(KEYWRD.EQ.'VARNAMS ')GO TO 120
      IF(KEYWRD.EQ.'FORMAT  ')GO TO 130
      IF(KEYWRD.EQ.'GROUP   ')GO TO 160
      IF(KEYWRD.EQ.'FREQVAR ')GO TO 170
C      IF(KEYWRD.EQ.'LIST    ')GO TO 180
C      IF(KEYWRD.EQ.'LOG     ')GO TO 200
      IF(KEYWRD.EQ.'STATS   ')GO TO 210
      IF(KEYWRD.EQ.'NDELETE ')GO TO 220
      IF(KEYWRD.EQ.'DELETE  ')GO TO 230
      IF(KEYWRD.EQ.'BETAS   ')GO TO 240
      IF(KEYWRD.EQ.'STOP    ')GO TO 250
      IF(KEYWRD.EQ.'EXECUTE ')GO TO 260
      IF(KEYWRD.EQ.'CVGEPS  ')GO TO 270
      ERROR=.TRUE.
      ERRMSG=' UNRECOGNIZED KEYWORD: '//KEYWRD
      RETURN
*
*
* BRANCHING TO APPROPRIATE ACTION BASED ON KEYWORD
*
* NVARS
  110 BACKSPACE(CMDUNT)
      READ(CMDUNT,'(8X,I4)')NV
      IF((NV.GT.NVMAX).OR.(NV.LT.1))GO TO 112
      GO TO 101
  112 ERROR=.TRUE.
      ERRMSG=' NUMBER OF VARIABLES IS TOO BIG, OR LESS THAN 1'
      RETURN
*
```

```
* VARNAMS
  120 BACKSPACE(CMDUNT)
      IF(NV.EQ.0) GO TO 125
      READ(CMDUNT,'(8X,A8,1X,A8,1X,A8,1X,A8,1X,A8,1X,A8,1X,A8,1X,A8)',
     #              ERR=127)(VARNAM(I),I=1,NV)
      TEST=.FALSE.
      GO TO 101
  125 ERROR=.TRUE.
      ERRMSG=' NVARS MUST APPEAR BEFORE VARNAMS IN COMMAND FILE'
      RETURN
  127 ERROR=.TRUE.
      ERRMSG=' COMMAND FILE VARIABLE NAME READ ERROR'
      RETURN
*
* FORMAT - Extended FORMAT to 511 characters - ber 89.06.05
*
  130 BACKSPACE(CMDUNT)
      K = 0
      DO 132 I=1,512
         BUFARR(I)=' '
  132 CONTINUE
  133 READ(CMDUNT,'(8X,72A1)',ERR=136)(BUFARR(K*72+J),J=1,72)
      READ(CMDUNT,'(A8)')KEYWRD
      BACKSPACE(CMDUNT)
      IF(KEYWRD.NE.'        ')THEN
         FORMAT=BUFSTR
         GO TO 101
      ENDIF
      K = K + 1
      IF (K .LE. 6) GOTO 133
  136 ERROR=.TRUE.
      ERRMSG='FORMAT STATEMENT IS INCORRECT. MUST BE LESS THAN 504 CHAR
     &ACTERS AND IN ( ).'
      RETURN
*
* GROUP
  160 BACKSPACE(CMDUNT)
      IF(TEST)GO TO 166
      GRPVAR='        '
      READ(CMDUNT,'(8X,A8)')GRPVAR
      GRPSET = .TRUE.
      DO 165 I=1,NV
  165 IF(GRPVAR.EQ.VARNAM(I))GO TO 167
      ERROR=.TRUE.
      ERRMSG=' IN COMMAND FILE, GROUP NAME DOES NOT MATCH ANY VARNAM (C
     +HECK DELETED VARIABLE LIST)'
      RETURN
  166 ERROR=.TRUE.
      ERRMSG=' IN COMMAND FILE VARNAMS MUST APPEAR BEFORE GROUP AND FREQ
     &VAR'
      RETURN
  167 JGRP=I
```

```
      GO TO 101
*
* FREQVAR
  170 BACKSPACE(CMDUNT)
      IF (TEST)GO TO 166
      FRQVAR='        '
      READ(CMDUNT,'(8X,A8)')FRQVAR
      FRQSET = .TRUE.
      DO 175 I=1,NV
  175 IF(FRQVAR.EQ.VARNAM(I))GO TO 179
      ERROR=.TRUE.
      ERRMSG=' FREQVAR DOES NOT MATCH ANY VARNAME (CHECK DELETED LIST)'
      RETURN
  179 JFRQ=I
      GO TO 101
*
* LIST
C  180 CONTINUE
C      BACKSPACE(CMDUNT)
C      DATFIL=
C     +'                                                                '
C      READ(CMDUNT,'(8X,A64)',ERR=182) DATFIL
C      LSTUNT=15
C      OPEN (15 ,FILE='DAT1FIL')
C      GOTO 101
C  182 ERROR=.TRUE.
C      ERRMSG=' LIST FILE NAME INPUT ERROR'
C      RETURN
*
* STATS
 210  BACKSPACE(UNIT=CMDUNT)
      READ (UNIT=CMDUNT,FMT='(8X,A8,7(1X,A8))') (STATS(I),I=1,7)
      DO 212 I=1,7
        CALL UPCASE(7,STATS(I))
        IF(STATS(I) .EQ. 'COVBETA') COVMAT=.TRUE.
        IF(STATS(I) .EQ. 'COVR4TN') COVR4T=.TRUE.
        IF(STATS(I) .EQ. 'POISSON') POISON=.TRUE.
 212  CONTINUE
      GOTO 101
*
* NDELETE - discard unwanted variables on input - ber 88.06.14
*
  220 BACKSPACE(CMDUNT)
      IF((NV.EQ.0)) GO TO 221
      READ(CMDUNT,'(8X,I4)') ND
      WRITE(6,*) 'NDELETE=',ND
      WRITE(6,*) '     '
      IF((ND.GT.NV-2).OR.(NV.LT.1))GO TO 222
      GO TO 101
  221 ERROR=.TRUE.
      ERRMSG=' NVARS must appear before NDELETE'
      RETURN
```

```
  222 ERROR=.TRUE.
      ERRMSG=' Number of variables to delete must be between 1 and NVAR
     +S-2'
      RETURN
*
* DELETE - Names of unwanted variables to be deleted on input - ber 88.0
*
  230 BACKSPACE(CMDUNT)
      IF ((ND.EQ.0)) GO TO 238
      IF (GRPSET.OR.FRQSET) GO TO 237
      READ(CMDUNT,'(8X,A8,1X,A8,1X,A8,1X,A8,1X,A8,1X,A8,1X,A8,1X,A8)',
     #              ERR=239)(DELNAM(I),I=1,ND)
      DO 234 I=1,NV
         DMASK(I) = I
  234 CONTINUE
      DO 231 I=1, ND
         DO 232 J=1, NV
            IF (VARNAM(J) .EQ. DELNAM(I)) THEN
               DO 233 K=J+1, NV
                  VARNAM(K-1) = VARNAM(K)
                  DMASK(K-1) = DMASK(K)
  233          CONTINUE
               NV = NV - 1
               GOTO 231
            ENDIF
  232    CONTINUE
         WRITE(*,*) 'WARNING, unable to delete ',DELNAM(I),
     +              ' NOT in VARNAMS list, execution continues ...'
         ND = ND - 1
  231 CONTINUE
      GO TO 101
  237 ERROR=.TRUE.
      ERRMSG=' DELETE must appear before GROUP and FREQVAR'
      RETURN
  238 ERROR=.TRUE.
      ERRMSG=' NDELETE must appear before DELETE and after NVARS'
      RETURN
  239 ERROR=.TRUE.
      ERRMSG=' DELETE read error'
      RETURN
*
* BETAS - Specify starting values for coefficients MFF 25 Aug 89
*
  240 BACKSPACE(CMDUNT)
      IF((NV.EQ.0)) GO TO 241
      READ (CMDUNT,'(8X,D13.7,1X,D13.7,1X,D13.7,1X,D13.7,1X,D13.7)'
     &     ,ERR=242)  (BETA(J),J=1,NV-2)
      BETSET=.TRUE.
      GO TO 101
  241 ERROR=.TRUE.
      ERRMSG=' NVARS must appear before BETAS'
      RETURN
```

```
  242 ERROR=.TRUE.
      ERRMSG=' BETA value input error from Command File'
      RETURN
*
*  STOP      ****  Added 14 Nov. 1969  MFF
*
  250 CONTINUE
      ERROR = .TRUE.
      ERRMSG = ' End of Command File reached    '
      RETURN
*
*  CVGEPS    ****  Added 1 Dec. 1992  MFF
*
  270 BACKSPACE(CMDUNT)
      READ(CMDUNT,'(8X,D13.5)') CVGEPS
      IF((CVGEPS.LT.1.D-40).OR.(CVGEPS.GT.1))GO TO 271
      GO TO 101
  271 ERROR=.TRUE.
      ERRMSG=' CVGEPS VALUE OUT OF RANGE'
      RETURN
*
* EXECUTE      ****   Changed 14 Nov. 1989   MFF
*
  260 CONTINUE
C       IF (NODATA) THEN
C         ERROR=.TRUE.
C         ERRMSG=' No DATAFIL statement in Command File'
C         RETURN
C       ENDIF
      VARPTR(1)=JGRP
      VARPTR(2)=JFRQ
      JV=0
      DO 264 JB=1,NV-2
        IF(.NOT. BETSET) THEN
          BETA(JB)=0.D00
        ENDIF
        JV=JV+1
        IF((JV.EQ.JGRP).OR.(JV.EQ.JFRQ))THEN
         JV=JV+1
        ENDIF
        IF((JV.EQ.JGRP).OR.(JV.EQ.JFRQ))THEN
         JV=JV+1
        ENDIF
        VARPTR(JB+2)=JV
  264 CONTINUE
*
*
      RETURN
*
*
      END
```

```
C***********************************************************************
C   WCSSP  (WEIGHTED, CENTERED SUMS OF SQUARES AND PRODUCTS)           *
C    INPUTS:                                                           *
C     DATUNT  = UNIT NUMBER OF DATA FILE                               *
C     DATFMT  = DATA FORMAT                                            *
C     VARPTR  = VECTOR OF POINTERS TO GROUP,FREQ,X(1),...,X(BETDIM)    *
C     ALTMAX  = MAXIMUM NUMBER OF ALTERNATIVES IN ANY GROUP            *
C     NVARS   = NUMBER OF VARIABLES (INCLUDING GROUP AND FREQ)         *
C     BETA    = CURRENT PARAMETER VECTOR                               *
C    OUTPUTS:                                                          *
C     ZPZ     = WEIGHTED Z'Z IN TRIANGULAR STORAGE MODE                *
C     DFERR   = DEGREES OF FREEDOM FOR ERROR                           *
C     NSETS   = NUMBER OF CHOICE SETS IN DATA FILE                     *
C    WORK ARRAYS:                                                      *
C     Z       = WORK AREA FOR DATA SUBMATRIX                           *
C     ZTOT    = WORK AREA FOR RUNNING TOTALS                           *
C     XPB     = WORK AREA FOR X'BETA                                   *
C     PHAT    = WORK AREA FOR FITTED PROBABILITIES                     *
C     ALTPTR  = WORK AREA FOR ALTERNATIVE POINTERS                     *
C     NZPTR   = WORK AREA FOR NONZERO ELEMENT POINTERS                 *
C    ERROR REPORTS:                                                    *
C     ERROR   = ERROR FLAG  (LOGICAL)                                  *
C     ERRMSG  = ERROR MESSAGE ASSOCIAGED WITH ERROR FLAG                *
C***********************************************************************

      SUBROUTINE WCSSP(DATUNT,DATFMT,VARPTR,ALTMAX,NVARS,RBUF,BETA,
     #                 ZPZ,LRCHIS,DFERR,Z,ZTOT,XPB,PHAT,ALTPTR,POISON,
     #                 ERROR,ERRMSG,NZPTR,NDEL,DMASK,LRCH1,NSETS)
      LOGICAL EOD,ERROR,POISON
      INTEGER NVARS,VARPTR(NVARS),ALTMAX,DATUNT,DFERR,ALTPTR(ALTMAX),
     #        ALTERN,BETDIM,IZOLD,IZ,IZPZ,IALT,JZ,JGRP,JFRQ,
     #        JC,JR,JB,JCOL,JROW,JCBASE,NALT,NZPTR(NVARS),NNZ,
     #        NDEL,DMASK(NVARS),NREAD1,NSETS
      REAL*4 GROUP,LSTGRP
      REAL*8 ZPZ(NVARS*(NVARS-1)/2),Z(ALTMAX,NVARS),BETA(NVARS-2),
     #       ZTOT(NVARS-1),XPB(ALTMAX),LRCHIS,LRCH1,RFACT,
     #       PHAT(ALTMAX),PTOT,FTOT,FHAT,ZROW,ZCOL,WTOT,RBUF(NVARS)
      CHARACTER*512 DATFMT
      CHARACTER*127 ERRMSG

*     INITIALIZE
        DATUNT=9
        REWIND (DATUNT)
        EOD = .FALSE.
        GROUP = -9999.
        ALTERN =  0
        IZOLD = 0
        BETDIM = NVARS - 2
        JGRP = VARPTR(1)
        JFRQ = VARPTR(2)
        DFERR = -BETDIM
        LRCHIS = 0.D00
```

```
      LRCH1= 0.0D00
      NREAD = NVARS + NDEL
      NSETS = 0

      DO 90 IZPZ = 1,NVARS*(NVARS-1)/2
        ZPZ(IZPZ) = 0.D00
 90   CONTINUE

*     FILL DATA BUFFER UNTIL GROUP NUMBER CHANGES
 100  LSTGRP = GROUP
      IZ = MOD(IZOLD,ALTMAX)+1
C***********************************************************************
C     Add the capability to delete unwanted variables from input stream
C                                                   - BER 89.06.04
C***********************************************************************

C
C     Read the entire dataline, delete the unnecessary data
C
      IF (NDEL .GT. 0) THEN
         READ (DATUNT,12,END=110,ERR=110) (RBUF(J),J=1,NREAD)
   12 FORMAT (9F4.0)

         DO 105 J=1,NVARS
            Z(IZ,J) = RBUF(DMASK(J))
 105     CONTINUE
      ELSE
C
C     Use all the data, DELETE option NOT specified, avoid unnecc. proce
C
C        WRITE(*,*) 'Before read ... '
         READ (DATUNT,12,END=110,ERR=110) (Z(IZ,J),J=1,NVARS)
C        WRITE(*,*) 'After read, IZ = ',IZ
      ENDIF

C       IF NOT AT END OF DATA FILE THEN
          GROUP = Z(IZ,JGRP)
C         IF (MOD(INT(GROUP),10000).EQ.0) WRITE(6,*) 'Processing ',GROUP
c         WRITE (6,*) 'Processing ',GROUP
          IF (LSTGRP .EQ. GROUP) THEN
            IZOLD = IZ
            ALTERN = ALTERN+1
            IF (ALTERN .GT. ALTMAX) THEN
              ERROR = .TRUE.
              ERRMSG = ' Problem in DATAFILE: Too many alternatives'
              RETURN
            END IF
            ALTPTR(ALTERN) = IZ
            GO TO 100
          END IF
          GOTO 120
C       ELSE (AT END OF DATA FILE)
```

```
 110      EOD = .TRUE.
C       END IF

*-----------------------------------------------------------------------
*     INCREMENT Z'Z MATRIX
 120  IZOLD = IZ
      NALT = ALTERN
      IF (NALT .GT. 0) THEN
        NSETS = NSETS + 1
        DFERR = DFERR + NALT - 1
        PTOT = 0.D00
        FTOT = 0.
        WTOT = 0.D00

        DO 125 JZ = 1, NVARS
          ZTOT(JZ) = 0.D00
 125    CONTINUE

        DO 140 IALT = 1, NALT
          IZ = ALTPTR(IALT)
          XPB(IALT) = 0.D00
          JB  = 0
          DO 130 JB = 1,BETDIM
            JZ=VARPTR(JB+2)
            XPB(IALT) = XPB(IALT) + Z(IZ,JZ)*BETA(JB)
 130      CONTINUE
          PHAT(IALT) = DEXP(XPB(IALT))
          PTOT = PTOT + PHAT(IALT)
          FTOT = FTOT + Z(IZ,JFRQ)
 140    CONTINUE

        LRCH1=LRCH1 + RFACT(FTOT,POISON) - FTOT*DLOG(FLOAT(NALT))
        LRCHIS=LRCHIS + RFACT(FTOT,POISON)
        DO 190 IALT = 1, NALT
          IZ = ALTPTR(IALT)
          PHAT(IALT) = PHAT(IALT)/PTOT
          FHAT = FTOT*PHAT(IALT)
          LRCHIS = LRCHIS - RFACT(Z(IZ,JFRQ),POISON)
     +                  + Z(IZ,JFRQ)*DLOG(PHAT(IALT))
          LRCH1 = LRCH1 - RFACT(Z(IZ,JFRQ),POISON)
          Z(IZ,JFRQ)= XPB(IALT) +Z(IZ,JFRQ)/FHAT -1.
          WTOT = WTOT + FHAT

          JCBASE = -1
          NNZ = 0
          DO 180 JC = 2, NVARS
            JCOL = VARPTR(JC)
            JCBASE = JCBASE + JC - 2
            ZCOL = Z(IZ,JCOL)*FHAT
            IF (ZCOL .NE. 0) THEN
              NNZ = NNZ + 1
              NZPTR(NNZ) = JC
```

```
              ZTOT(JCOL) = ZTOT(JCOL) + ZCOL
              DO 170 JNZ = 1, NNZ
                JR = NZPTR(JNZ)
                JROW = VARPTR(JR)
                IZPZ = JR + JCBASE
                ZPZ(IZPZ) = ZPZ(IZPZ) + Z(IZ,JROW)*ZCOL
 170          CONTINUE
            END IF
 180      CONTINUE
 190    CONTINUE

        JCBASE = -1
        DO 210 JC = 2, NVARS
          JCOL = VARPTR(JC)
          JCBASE = JCBASE + JC - 2
          ZCOL = ZTOT(JCOL)/WTOT
          DO 200 JR = 2, JC
            JROW = VARPTR(JR)
            IZPZ = JR + JCBASE
            ZPZ(IZPZ) = ZPZ(IZPZ) - ZTOT(JROW)*ZCOL
 200      CONTINUE
 210    CONTINUE

      END IF
*-----------------------------------------------------------------------
      IF (.NOT. EOD) THEN
        ALTERN = 1
        ALTPTR(ALTERN) = IZOLD
        GO TO 100
      ELSE
        RETURN
      END IF
      END
C**********************************************************************
C  UPDATE                                                             *
C    UPDATES THE BETA VECTOR.                                         *
C    INPUTS:                                                          *
C      ZPZ            (MODIFIED)                                      *
C      BETA           (MODIFIED)                                      *
C      NVARS                                                          *
C      VARPTR                                                         *
C      TOLEPS, CVGEPS  TOLERANCE AND CONVERGENCE EPSILONS             *
C      MAXITR          MAXIMUM NUMBER OF ITERATIONS                   *
C      ITER            (MODIFIED)                                     *
C    OUTPUTS:                                                         *
C      CONVRG  .TRUE. WHEN BETA CONVERGES                             *
C      ERROR,ERRMSG                                                   *
C**********************************************************************
      SUBROUTINE UPDATE (ZPZ,BETA,NVARS,VARPTR,TOLEPS,CVGEPS,
     #                  MAXITR,ITER,CONVRG,SWEPT,ERROR,ERRMSG)
      INTEGER NVARS,VARPTR(NVARS),MAXITR,ITER,SWEPT(NVARS-1),JPIVOT
      REAL*8 ZPZ(NVARS*(NVARS-1)/2),BETA(NVARS-2),TOLEPS,CVGEPS,
```

```
     #DELTA,MODDLT
      LOGICAL CONVRG,ERROR
      CHARACTER*127 ERRMSG

      CONVRG = .FALSE.
      ITER = ITER + 1

      DO 100 JPIVOT =  2,NVARS-1
        CALL SWEEP(ZPZ,NVARS-1,JPIVOT,SWEPT,TOLEPS,ERROR,ERRMSG)
        IF (ERROR) RETURN
 100  CONTINUE

c     write (6,*) '    UPDATE: Step 1.....'

C   TEST FOR CONVERGENCE
      MODDLT = 0.D00
      DO 110 JB = 1, NVARS-2
        DELTA = BETA(JB)
        JZPZB = JB*(JB+1)/2+1
        JZPZV = JZPZB + JB
        BETA(JB) = -ZPZ(JZPZB)
        DELTA = (DELTA-BETA(JB))**2/ZPZ(JZPZV)
        MODDLT = MODDLT + DELTA
 110  CONTINUE
      MODDLT = DSQRT(MODDLT/(NVARS-2))

c     write (6,*) '    UPDATE: Step 2.....'

      IF (MODDLT .LE. CVGEPS) THEN
        CONVRG = .TRUE.
      END IF

      IF (ITER .GT. MAXITR) THEN
        CONVRG = .TRUE.
        ERROR  = .TRUE.
        ERRMSG = 'MAXIMUM ITERATIONS EXCEEDED.'
      END IF

      RETURN
      END


      SUBROUTINE SWEEP(Z,IORDER,IP,SWEPT,EPS,ERROR,ERRMSG)
C*****************************************************************
C REVERSIBLE UPPER TRIANGULAR SWEEP FROM J.H. GOODNIGHT,         *
C THE SWEEP OPERATOR: ITS IMPORTANCE IN STATISTICAL COMPUTING    *
C                                                                *
C GEORGE WOODWORTH   6/3/85                                      *
C*****************************************************************
      DOUBLE PRECISION Z(1),EPS,B,C,D
      INTEGER SWEPT(1)
      LOGICAL ERROR
```

```
      CHARACTER*127 ERRMSG
      IZP = IZADR(IP,IP)
      D = Z(IZP)
      IF (D .LT. EPS) THEN
        ERROR = .TRUE.
        ERRMSG = 'DESIGN MATRIX IS SINGULAR.'
        RETURN
      ENDIF

      DO 100 IR = 1, IORDER
        IF (IR .NE. IP) THEN
          IZB=IZADR(IR,IP)
          B = Z(IZB)/D
          IF (IR .GT. IP) THEN
            B = SWEPT(IR)*SWEPT(IP)*B
          ENDIF
          DO 90 IC = IR, IORDER
           IF (IC .NE. IP) THEN
             IZC = IZADR(IC,IP)
             C = Z(IZC)
             IF (IC .LT. IP) THEN
               C = SWEPT(IC)*SWEPT(IP)*C
             ENDIF
             IZ = IZADR(IR,IC)
             Z(IZ) = Z(IZ) - B*C
           ENDIF
   90      CONTINUE
        ENDIF
  100 CONTINUE

      DO 200 IR = 1, IORDER
        IF (IR .NE. IP) THEN
          IZ = IZADR(IR,IP)
          Z(IZ) = Z(IZ)/D
          IF (IR .LT. IP) THEN
            Z(IZ) = - Z(IZ)
          ENDIF
        ENDIF
  200 CONTINUE

      Z(IZP) = 1/D
      SWEPT(IP) = -SWEPT(IP)

      RETURN
      END

      FUNCTION IZADR(I1,I2)
C------------------------------------------------------------------
C RETURNS ROW-MAJOR UPPER TRIANGULAR ADDRESS FOR ROW I1, COL I2.
C
C GEORGE WOODWORTH   6/3/85
C------------------------------------------------------------------
```

```
      IR=MIN0(I1,I2)
      IC=MAX0(I1,I2)
      IZADR=IR+(IC*(IC-1))/2
      RETURN
      END
*
*
      SUBROUTINE REPORT(ZPZ,NVARS,VARNAM,VARPTR,LRCHIS,LRCH1,
     #                  DFERR,LSTUNT,PAGENO,B11)
*
      CHARACTER*8 VARNAM(NVARS),VAR
      INTEGER VARPTR(NVARS),DFERR,LSTUNT,PAGENO
      REAL*8 ZPZ(NVARS*(NVARS-1)/2),LRCHIS,LRCH1,MODCHI,COEF,SE,T
      REAL*8 RHOSQ, RHOSQB
      DIMENSION B11(11)
*
*WRITE FRONT PAGE HEADINGS

      PAGENO=1
C      WRITE(LSTUNT,120) PAGENO
  120   FORMAT('1',//10X,' MULTINOMIAL LOGISTIC REGRESSION',16X,
     #                  'PAGE ',I1)
C      WRITE(LSTUNT,122)VARNAM(VARPTR(2))
  122   FORMAT(/10X,'DEPENDENT VARIABLE: ',A8)
C      WRITE(LSTUNT,132)
  132   FORMAT(/10X,'VARIABLE',5X,'  COEFFICIENT',5X,'  STD ERROR ',
     #             5X,'      T     ')
*
* WRITE PARAMETER ESTIMATES
      ICOUNT=13
      DO 150 J=3,NVARS
        ICOUNT=ICOUNT+1
        K=(J-1)*(J-2)/2 + 1
        L=J*(J-1)/2
        VAR=VARNAM(VARPTR(J))
        COEF=-ZPZ(K)
        SE=DSQRT(ZPZ(L))
        T=COEF/SE
        B11(J-2)=COEF
C        WRITE(LSTUNT,142)J-2,VAR,COEF,SE,T
  142     FORMAT(6X,I3,2X,A8,6X,E13.6,5X,E13.6,5X,F10.4)
        IF (ICOUNT.EQ.66) THEN
          PAGENO=PAGENO+1
C          WRITE(LSTUNT,146) PAGENO
  146       FORMAT('1',//10X,' MULTINOMIAL LOGISTIC REGRESSION',16X,
     #                    'PAGE ',I1)
C          WRITE(LSTUNT,148)
  148       FORMAT(/10X,'VARIABLE',5X,'COEFFICIENT',5X,'STD ERROR ',
     #                  5X,'    T     ')
          ICOUNT=11
        ENDIF
  150 CONTINUE
```

```
C  WRITE STATISTICS

      IF (ICOUNT .GT. 57) THEN
        PAGENO=PAGENO+1
C         WRITE(LSTUNT,154) PAGENO
  154   FORMAT('1',//10X,' MULTINOMIAL LOGISTIC REGRESSION',16X,
     #                     'PAGE ',I1)
      ENDIF
C        WRITE(LSTUNT,156)
  156   FORMAT (//10X,'STATISTICS',/)
C        WRITE(LSTUNT,158) LRCH1
  158   FORMAT(15X,' L(ZERO):          ',F8.2)
C        WRITE(LSTUNT,159) LRCHIS
      RCHIS=LRCHIS
  159   FORMAT(15X,' L(BETA):          ',F8.2)
      MODCHI=-2.0D0*(LRCH1-LRCHIS)
C        WRITE(LSTUNT,160) MODCHI,NVARS-2
  160   FORMAT(15X,' -2(L(0)-L(B)):  ',F8.2,'      D.F.: ',I5)
      RHOSQ=1.0D0-(LRCHIS/LRCH1)
      RHOSQB=1.0D0-((LRCHIS-NVARS+2)/LRCH1)
C        WRITE(LSTUNT,161) RHOSQ
  161   FORMAT(15X,' RHOSQ:            ',F8.5)
C        WRITE(LSTUNT,162) RHOSQB
  162   FORMAT(15X,' ADJUSTED RHOSQ: ',F8.5)
      ICOUNT=ICOUNT+9

      RETURN
      END

      SUBROUTINE PRTMAT(M,NVARS,RJVNAM,VARNAM,VARPTR,
     *   LSTUNT,ROWPAG,COLPAG,PAGENO,PAGSIZ)
C     *****************************************************************
C     *  PRINT A LOWER TRIANGULAR MATRIX                              *
C     *    M      : ADDRESS OF MATRIX TO BE PRINTED                   *
C     *    NVARS  : NUMBER OF VARIABLES (N OF PARMS +2)               *
C     *    VARNAM : VECTOR OF VARIABLE NAMES                          *
C     *    VARPTR : ADDRESSES OF VARIABLES IN VARNAM ARRAY            *
C     *                                                               *
C     *    LSTUNT : UNIT NUMBER OF LIST FILE                          *
C     *    ROWPAG,COLPAG : ROWS/COLS PER PAGE                         *
C     *    PAGENO : PAGE NUMBER OF PREVIOUS PAGE                      *
C     *    PAGSIZ : PHYSICAL PAGE SIZE (NUMBER OF LINES)              *
C     *                                                               *
C     *****************************************************************

      INTEGER FSTROW,NVARS,VARPTR(NVARS),LSTUNT,ROWPAG,COLPAG,PAGENO
      INTEGER PAGSIZ,NROWS
      INTEGER ROWBAS,COLBAS,ROWMAX,COLMAX,LNG,LSTCOL,TOTLNS,HDRLNS
      REAL*8 M(1),MAXM
      CHARACTER*8 VARNAM(NVARS),PAGNAM,RJVNAM(NVARS)
      CHARACTER*10 STR
      CHARACTER*20 MATFMT
```

```
      HDRLNS=6
      NROWS=NVARS-2
      FSTROW=3
      MAXM=0.D00
      DO 80 I=FSTROW,FSTROW+NROWS-1
        DO 70 J=FSTROW, I
          MAXM = DMAX1(MAXM,DABS(M( (I-1)*(I-2)/2+J-1 )))
 70     CONTINUE
 80   CONTINUE
      IF (MAXM .LT. 1.D-6) MATFMT='(6X,A8,10(1X,G10.0))'
      IF (MAXM .LT. 1.D00) MATFMT='(6X,A8,10(1X,F10.8))'
      IF (MAXM .GE. 1.D00) MATFMT='(6X,A8,10(1X,F10.7))'
      IF (MAXM .GE. 1.D01) MATFMT='(6X,A8,10(1X,F10.6))'
      IF (MAXM .GE. 1.D02) MATFMT='(6X,A8,10(1X,F10.5))'
      IF (MAXM .GE. 1.D03) MATFMT='(6X,A8,10(1X,F10.4))'
      IF (MAXM .GE. 1.D04) MATFMT='(6X,A8,10(1X,F10.3))'
      IF (MAXM .GE. 1.D05) MATFMT='(6X,A8,10(1X,F10.2))'
      IF (MAXM .GE. 1.D06) MATFMT='(6X,A8,10(1X,F10.1))'
      IF (MAXM .GE. 1.D07) MATFMT='(6X,A8,10(1X,F10.0))'
      IF (MAXM .GE. 1.D08) MATFMT='(6X,A8,10(1X,G10.0))'

      DO 90 I=FSTROW,FSTROW+NROWS-1
        CALL RJNAME(VARNAM(VARPTR(I)),RJVNAM(VARPTR(I)))
 90   CONTINUE

      ROWBAS=FSTROW-1
      COLBAS=FSTROW-1

      TOTLNS=PAGSIZ
100   ROWMAX=MIN(ROWBAS+ROWPAG,FSTROW+NROWS-1)-ROWBAS
      COLMAX=MIN(COLBAS+COLPAG,FSTROW+NROWS-1)-COLBAS

      IF (PAGSIZ-TOTLNS-2 .LT. ROWMAX+HDRLNS) THEN
        PAGENO=PAGENO+1
        CALL NTOSTR(PAGENO,STR,LNG)
        PAGNAM='PAGE '//STR(1:LNG)
        WRITE (LSTUNT,'(''1''/13X,10A11)')
     *     ('           ',J=1,COLPAG-1), PAGNAM
        TOTLNS=0
      ELSE
        WRITE (LSTUNT,'(1X)')
        WRITE (LSTUNT,'(1X)')
        TOTLNS=TOTLNS+2
      ENDIF

      WRITE (LSTUNT,
     * '(''      MULTINOMIAL LOGISTIC REGRESSION,  '',
     *   ''COVARIANCE MATRIX OF PARAMETER ESTIMATES''/)')

      WRITE (LSTUNT,'(14X,10(3X,A8))')
     *  (RJVNAM(VARPTR(J)),J=COLBAS+1, COLBAS+COLMAX)
```

```
      WRITE (LSTUNT,'(''       --------'',10A11)')
     *  ('-----------',J=1,COLMAX)

      TOTLNS=TOTLNS+HDRLNS

C*****************************************************************
C    I IS THE VARIABLE NUMBER, 1=GROUP, 2=DEPENDENT (FREQENCY) *
C                              3 THRU NVARS=INDEPENDENT         *
C    HOWEVER, THE M ARRAY IS ADDRESSED AS FOLLOWS:              *
C      ROW,COL=1 IS THE DEPENDENT VARIABLE                      *
C      ROW,COL=2 THROUGH NVARS-1 ARE THE INDEPENDENT VARS IN    *
C        THE ORDER THEY APPEAR ON THE VARIABLE LIST.            *
C      VARPTR(I) POINTS TO THE NAME OF THE ITH ROW,COL          *
C*****************************************************************

      DO 110 I=ROWBAS+1,ROWBAS+ROWMAX
        LSTCOL=MAX(0,MIN(I,COLBAS+COLMAX)-COLBAS)
        IF (LSTCOL .GT. 0) THEN
          WRITE(LSTUNT,MATFMT) VARNAM(VARPTR(I)),
     *      (M( (I-1)*(I-2)/2+J-1 ),
     *        J=COLBAS+1,COLBAS+LSTCOL)
          TOTLNS=TOTLNS+1
        ENDIF
 110  CONTINUE

      ROWBAS=ROWBAS+ROWPAG
      IF (ROWBAS .GE. FSTROW+NROWS-1) THEN
        COLBAS=COLBAS+COLPAG
        ROWBAS=COLBAS
      ENDIF
      IF (ROWBAS .LT. FSTROW+NROWS-1) GOTO 100

      RETURN
      END

      SUBROUTINE NTOSTR(NUMBER,STRING,LENGTH)
      INTEGER NUMBER,N,Q,R,LENGTH
      CHARACTER*10 DIGITS,STRING
      DATA DIGITS/'0123456789'/
      STRING='ZZZ'
      LENGTH=3
      N=NUMBER
      LENGTH=0
 100  IF ((N .LE. 0) .OR. (LENGTH .GE. 10)) GOTO 105
        LENGTH=LENGTH+1
        Q=INT(N/10)
        R=N-10*Q
        STRING(11-LENGTH:11-LENGTH)=DIGITS(R+1:R+1)
        N=Q
        GOTO 100
 105  CONTINUE
      DO 110 I=1, LENGTH
```

```
        STRING(I:I) = STRING(10-LENGTH+I:10-LENGTH+I)
110   CONTINUE
      RETURN
      END

      SUBROUTINE RJNAME(LJUST,RJUST)
      CHARACTER*8 LJUST,RJUST
      INTEGER LNG

      LNG=8
100   IF ((LJUST(LNG:LNG) .NE. ' ') .OR. (LNG .EQ. 0 )) GOTO 110
      LNG=LNG-1
      GOTO 100

110   RJUST='        '
      IF (LNG .GT. 0) RJUST(9-LNG:8)=LJUST(1:LNG)

      RETURN
      END


      SUBROUTINE UPCASE(LEN,LETTER)

      INTEGER LEN
      CHARACTER*1 UCASE(26),LCASE(26)
      CHARACTER*1 LETTER(LEN)

      DATA UCASE/'A','B','C','D','E','F','G','H','I','J','K','L','M'
     +          ,'N','O','P','Q','R','S','T','U','V','W','X','Y','Z'/
      DATA LCASE/'a','b','c','d','e','f','g','h','i','j','k','l','m'
     +          ,'n','o','p','q','r','s','t','u','v','w','x','y','z'/

      DO 100 N=1,LEN
        DO 110 J=1,26
          IF(LETTER(N).EQ.LCASE(J)) LETTER(N)=UCASE(J)
110     CONTINUE
100   CONTINUE
      RETURN
      END

      REAL*8 FUNCTION RFACT(VAL,POISON)
      REAL*8 VAL
      LOGICAL POISON

      RFACT=0.0D0
      IF (.NOT.POISON.AND.VAL.GT.1.5D0) THEN
        DO 100 N=2,INT(VAL+0.5D0)
          RFACT=RFACT+DLOG(FLOAT(N))
100     CONTINUE
      ENDIF
      RETURN
      END
```

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