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Michael P. Johnson *Editor*

Community-Based Operations Research

Decision Modeling for Local Impact and Diverse Populations

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The love and support of my wife, Karen, sons Devon and Langston, and my parents ensured that the days and nights of work on this project would yield an end-product worthy of them."

Foreword

While many in academia and business had explored (and sometimes exploited) what would eventually come to be known as operations research for decades before World War II, the interdisciplinary mathematical science has its formal origins firmly rooted in the war. Allied forces used operations research techniques to aid in the development of strategies, design of weapons and equipment, and efficient movement of supplies to troops. Many historians give a great deal of credit to operations research for the Allies' victory.

In the aftermath of the war, industry and business began using the operations research tools that were developed during the war. Scholastic programs and academic communities developed, and the young discipline gradually grew. Eventually social scientists found uses for operations research, and the discipline began expanding beyond applications that reduced costs, increased profitability, and generated material wealth and into applications that focused squarely on improving quality of life. Presently this discipline, which was born of necessity during the most devastating war in history, ironically finds itself ever more frequently called upon in efforts to resolve social problems and alleviate human suffering.

Ultimately the focus on using operations research to improve quality of life evolved into two distinct areas: responding to needs that arise from immediate unpredictable events (i.e., disaster preparedness and coordination of relief efforts), and addressing chronic systemic problems such as hunger, disease, poverty, and access to adequate healthcare (which, when done at the community level, has come to be known as community operational research in the UK, and, in the USA, as community-based operations research). These two areas feature efforts by operations researchers to address problems both through research and through hands-on initiatives.

Much of the early effort in community-based operations research focused on increasing the efficiency and effectiveness of public services. Notable examples of pioneering efforts included work on emergency response systems by Richard Larson; health care and medicine by Larry Wein and Judith Liebman; AIDS prevention by Edward Kaplan; forestry and natural resources by Andreas Weintraub;

sustainability by Luc Van Wassenhove; and criminal justice systems and policy by Alfred Blumstein. Inspired by these and other early efforts to use operations research to address issues that have impact at the community level, the operations research community has taken an increasing interest in community-based operations research problems over the past two decades. One recent example of tangible evidence that the operations research community has embraced community-based operations research was provided at the 2007 INFORMS Conference in Seattle, Washington. This conference featured an extremely well attended and enthusiastically received tutorial on community-based operations research that was given by Michael Johnson and Karen Smilowitz.

Community-based operations research problems are of intrinsic interest because of the potentially profound ramifications of their resolutions, but they are also appealing to many operations researchers because they are extremely challenging. The problems of community-based operations research are ill-defined and require the analyst to have a deep understanding of the associated political, social, cultural, and economic systems and how they interact. These characteristics have lead operations researchers working in this area to use systems-based approaches consistent with what was advocated by Russell Ackoff, Peter Checkland, and C. West Churchman in their early contributions to problem structuring methods.

While many operations researchers address community-based operations research problems through their research, others are working to resolve such problems through direct involvement in hands-on initiatives. For example, the Institute for Operations Research and the Management Sciences (INFORMS) and the International Federation of Operational Research Societies (IFORS) have established several activities through which these organizations' members can contribute to the resolution of community-based operations research problems. Many of these efforts focus on improving the quality of operations research education and applications. INFORMS publishes *INFORMS Transactions on Education* (*ITE*), a peer-reviewed academic journal devoted solely to issues in operations research education that is freely available online (www.informs.org/Journal/ITE). In addition to articles on issues in operations research education, *ITE* publishes teaching cases with accompanying teaching notes. The cases are freely available (so resource-poor instructors can provide their students with the URL rather than distribute printed copies), while the teaching notes are stored in a password protected site to prevent students from gaining access to these documents (instructors can contact INFORMS to request a password). By making the articles in *ITE* freely available, INFORMS actively addresses community-based operations research problems in a broad way by supporting improvement in operations research education, which results in improved applications of operations research at the community level.

INFORMS and IFORS also cosponsor an international education initiative through which annual teaching effectiveness colloquia are held in conjunction with operations research conferences in developing nations. These innovative colloquia are designed to improve the quality of operations research education and applications as well as foster the development of a worldwide network of operations research professionals (academics and practitioners) who are interested in operations research education and application issues. Through this initiative, colloquia have been held in conjunction with the Latin-Ibero-American Conference on Operations Research, Operations Research Society of South Africa Conference, Conference of the Association of Asian Pacific Operational Research Societies, Operations Research Practice in Africa, and the Operations Research Society of Eastern Africa Conference. The colloquia, which have attracted participants from 45 nations, have been held in Montevideo, Uruguay (2006); Cape Town, South Africa (2007); Cartagena, Colombia (2008); Jaipur, India (2009); Buenos Aires, Argentina (2010); and Nairobi, Kenya (2011). When participants in these colloquia take what they have learned back to their respective colleges and universities, they are indeed addressing problems at a community level. Again, through support of this initiative, INFORMS and IFORS actively address community-based operations research problems in a broad way by supporting improvement in operations research education and applications.

Such efforts are not limited professional societies. For example, the online version of the *Wiley Encyclopedia of Operations Research and Management Science* (http://www.wiley.com/WileyCDA/Section/id-380199.html), which was published in 2011, is available to operations researchers in developing nations for free or at a greatly reduced cost through Research4Life (http://www.research4life.org/). The online version of this eight volume, 6000+ page reference, which features several articles on community-based operations research and problem structuring methods, is updated quarterly to maintain the currency of the encyclopedia's content. Through the *Wiley Encyclopedia of Operations Research and Management Science*, Wiley actively addresses community-based operations research problems in a broad way by disseminating knowledge and supporting improvement in operations research education and applications in communities of developing regions.

These efforts have culminated in a need for a resource that focuses solely on community-based operations research. In *Community-Based Operations Research: Decision Modeling for Local Impact and Diverse Populations*, Editor Michael Johnson and the contributing authors have filled this need admirably. The chapters of this book summarize studies that generally extend what are considered to be mainstream operations research techniques in a straightforward manner, and so are very approachable. Strong emphasis is placed on the role that transnational and comparative research is likely to play in solving complex problems of public concern. The importance of interdisciplinary and cross-cultural approaches is also considered. The authors frequently reflect on the question of how to increase diversity of operations research academics and practitioners across broader geographies, application areas, and methodological specializations.

The discipline of operations research has much to offer society. We have become very good at using operations research tools to reduce costs, increase profitability, and generate material wealth, but the discipline is poised to contribute to society in a much broader way. While operations researchers have made several important contributions to applications that focus on improving quality of life, the discipline can and will do much more to contribute to the resolution of these problems. As the discipline moves forward in this area, it must continue to embrace and reflect the world's racial and ethnic diversity. Operations researchers working in this area must also continue to take critical, inclusive, and flexible approaches to the discipline.

I am excited to have the opportunity to read about the efforts of several of my colleagues to address challenging community-based operations research problems. This documentation of these colleagues' interactions with the political, social, cultural, and economic environments and integration of extremely important problem structuring methods will educate others in the operations research community who are interested in community-based operations research problems. I expect that the contents of this book will serve as an important step in our discipline's realization of its full potential with regard to community-based operations research problems.

Ruston, LA James J. Cochran

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Maria E. Mayorga is an Assistant Professor of Industrial Engineering at Clemson University. She received her Ph.D. in Industrial Engineering & Operations Research from the University of California, Berkeley. Dr. Mayorga has research and teaching interests in probability models and stochastic processes and optimization, with applications to healthcare systems engineering. Dr. Mayorga has authored over a two dozen publications in archival journals and refereed proceedings. Her research has been supported by the National Institutes of Health and BMW Manufacturing Co. among others. She is a member of INFORMS is a board member for the IIE Operations Research Subdivision. She has been the recipient of four best paper awards in several tracks of the IIE Research Conference.

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Natalie A. Privett is a recent addition to the Zaragoza Logistics Center as a post doctoral researcher. Dr. Privett completed her Ph.D. in Supply Chain Management at Stanford University in the department of Management Science and Engineering where her thesis was entitled, "Operations Management in the Non-Profit Sector," which included extensive work in supply chain modeling, public health, and analysis of public data sets. Dr. Privett's research spans both theoretical and empirical works, and focuses specifically on to improving nonprofit operations, public health, global health, and humanitarian relief. Building on her graduate work, Dr. Privett will continue to examine a variety of projects at the intersection of operations management and nonprofit sector applications. Her current research interests are in global health and humanitarian supply chains. Dr. Privett earned her undergraduate degree in Industrial Engineering from Texas A&M University and subsequently worked as an industrial engineer for Applied Materials before entering Stanford for graduate studies.

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Part I
Models and Analytic Methods

Chapter 1
Community-Based Operations Research: Introduction, Theory, and Applications

Michael P. Johnson

1 Introduction

1.1 Motivation for This Book

Operations research and the management sciences are disciplines that have their roots in quantitative analysis of real-world phenomena to support business tactics and strategy, military operations, and social policy interventions, among many other applications. A brief history of OR/MS is provided in Pollock and Maltz (1994). Many of the first examples of OR/MS that students encounter address services that have social impacts – think of the diet problem, estimates of waiting times at bus stops, and staffing models for public agencies. However, the majority of examples of OR/MS applications that students typically solve, and the ones that tend to define the profession, are drawn from the private sector: production planning, logistics and distribution of goods, call center management, portfolio optimization, and many others (see, e.g., the introductory examples in Winston & Venkataramanan, 2003).

This is a cause for concern, since goods and services provided by government and nonprofit organizations are a large part of the US economy: in 2005, of the 1.4 million nonprofit organizations known to the Internal Revenue Service, those nonprofits which reported their financial status to the IRS accounted for \$1.6 trillion in revenue and \$3.4 trillion in assets (Blackwood, Wing, & Pollock, 2008). Many aspects of our daily lives are defined by the quality of goods and services provided by not-for-profit means. Examples of these include education, public safety, human and social services, community and economic development, and environmental

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conservation and preservation. Increasingly, nonprofit organizations face severe challenges to delivering these goods and services, resulting from fiscal burdens transferred from state and local governments to nonprofits and foundations, a lack of knowledge about the mission and services of nonprofit organizations, and the increasing absence of nonprofits from the political process and public discourse (Delaney, 2011a, 2011b).

Many of these public goods and services have a local character: we may care more about the quality of our local school than ones across the city; we want emergency medical services to respond quickly to calls from our neighborhood first and foremost; we complain about waste or degraded environment that we experience nearby rather than in areas we do not often visit. A recent United Nations conference on local government and development goals emphasized the importance of decentralization of government resources and responsibility for local public services (United Nations Capital Development Fund, 2010); these trends are especially salient in the USA, with its strong tradition of federalism, performance management, and local autonomy. Social movements in the USA, and around the world, have increasingly focused on local organizing rather than national protests (Voss & Williams, 2009).

Moreover, we may care more about the impact of policies on groups of people who share our values, upbringing or racial or ethnic background, or who live in or near to our neighborhoods, as opposed to those who differ from us in various important ways.[1] Thus, there is a need for OR/MS applications that respond to public needs of a local nature and that reflect and are influenced by communities that define our daily lives.

However, a focus on publicly provided goods and services, especially those of a local nature, confronts the fundamental social concern of inequalities. For example, the Organisation for Economic Co-operation and Development (OECD) reports that the USA has the highest inequality and poverty rate across OECD countries with the exception of Mexico and Turkey; likewise, social mobility is lower, redistribution of income by the government plays a smaller role, and the distribution of earnings is greater than other OECD countries (OECD, 2008). Therefore, if we wish to ensure that society ensures that all members have an adequate quality of life, or a certain common level of access to opportunity, the problem of designing policies or prescriptions regarding provision of public goods and services of a local nature must account for populations that have differing levels of prosperity or political and social influence.

We refer to OR/MS applications that address provision of goods and services, or prescribe social policy actions, for which stakeholders are defined, in a spatial or social sense, as localized, or who are considered disadvantaged or underserved,

[1] The field of social network analysis is based on relationships between individuals and groups that share common beliefs, characteristics, or goals (Wasserman & Faust, 1994). The importance of social virtues and duties and participative decision making distinguishes the "communitarian" view of communities from the "liberal" view (Midgley & Ochoa-Arias, 2004b).

or for which issues of equity or social influence are important considerations, as examples of *community-based operations research* (CBOR). This definition differs somewhat from that provided in Johnson and Smilowitz (2007) in which it recognizes that "community" need not be tied exclusively or predominately to local neighborhoods. This subfield is an important area of inquiry because it provides those in the community of OR/MS as well as those in other fields the opportunity to develop theory and applications for research and practice that have the potential to improve the lives of individuals and communities in tangible ways. Moreover, such theory and applications can reflect multiple disciplinary perspectives and can adapt multiple methods in ways that are tailored for the problems at hand, and not necessarily to follow a given research tradition. Finally, CBOR can generate applications that reduce disparities in social inputs and outcomes across different groups using methods that are rooted in theory and evidence, and whose applications can be widely disseminated using appropriate modeling and information technology.

Methods in CBOR may vary widely, from traditional instances of prescriptive math models to a combination of qualitative and quantitative methods that may have much in common with related disciplines such as community planning, public health, and criminology. In addition, the design of specific recommendations for action may be less important than a deepened understanding about the social problem at hand, or the values and concerns of the stakeholders that may provide a basis for future efforts at prescriptive modeling.

This book, which contains 11 previously unpublished chapters, attempts to define the range of scholarly inquiry in this field, and to lay the groundwork for further research, teaching, and practice. One should immediately acknowledge the large literature in related fields of OR/MS, principally that of community operational research (Midgley & Ochoa-Arias, 2004a). Later in this chapter, we explore the similarities and differences between UK-style community OR and this novel rubric that reflects the social, political, and economic characteristics of the USA that has provided much of the theoretical and practice base of OR/MS. This book draws its inspiration from a recent paper (Johnson & Smilowitz, 2007), reprinted in this volume, that was an initial effort to define CBOR; later in this chapter we update many key findings from that paper.

There are a number of themes in recent academic research, discussed in more detail below, that provide direct motivation for this book. The first is the importance of *space, place, and community* in policy design and service delivery, a traditional motivation for OR/MS generally. Recent work emphasizing this dimension includes Grubesic and Murray (2010), Johnson, Turcotte, and Sullivan (2010), Mills (2009), and The Health Foundation (2010). A second motivating theme is a focus on *disadvantaged, underrepresented, or underserved populations* (which usually have a spatial and/or localized component as well), for example Cole (1994), Rawal et al. (2008), and Schweigman (2008). Also important are *international and transnational applications* that go beyond the use of traditional models in non-US contexts, such as Caulkins et al. (2008), Jehu-Appiah et al. (2008), and Schweigman (2008). In common with community OR, CBOR benefits from *multi-method, cross-disciplinary, and comparative* *approaches and appropriate technology* rooted in OR/MS (which are often especially suitable for locally focused problems). Examples of these include Bartolucci and Gallo (2010), Franco and Montibeller (2010), Hermans and Thissen (2009), Namen, Bornstein, and Rosenhead (2009), and Wenstop and Koppang (2009). Finally, the recent trend in quantitative and prescriptive modeling called *analytics* (Libertore & Luo, 2010) has much to contribute to CBOR as it supports a notion of generalized insight into problems of operations, uses a wide variety of quantitative methods, and is intended to support changes in policy and practice.

The themes described above and the recent literature illustrating them are certainly valued contributions to OR/MS. However, there is a need to address more fundamental questions regarding CBOR, and public-sector OR/MS generally that goes beyond most research currently available. First, is there a way to do OR that balances positivist and quantitative approaches that dominate US-style practice with a more critical and subjective approach to decision modeling, that accommodates a variety of qualitative and mixed-methods? Is rigorous OR compatible with motivating values of social change and social justice? Can we develop a theory of CBOR that can provide guidance simultaneously to researchers who seek principles guiding diverse applications and practitioners who seek specific guidance to solve difficult real-world problems? Finally, can CBOR, as we present it here, yield research outputs that will find exposure in the most prestigious research journals and academic programs and thus influence the understanding of CBOR within the discipline? This book presents diverse applications that provide a basis to address these questions regarding CBOR, and public-sector OR/MS in general.

1.2 The Historical Context of CBOR and Its Role Within OR/MS

There has been a long-lived debate over the proper role of OR/MS in addressing important societal problems. Of most interest to this book are three trends in OR/MS that precipitated major disagreements regarding the proper role of OR in society. The first trend, described by Pollock and Maltz (1994), is represented by the public service-oriented OR initiatives such as the "Operations Research in Public Affairs" program held at Massachusetts Institute of Technology in 1966, the Science and Technology Task Force of 1967 that initiated quantitative analysis of criminal justice problems, and the prevalence of quantitative analysis used in the prosecution of the Vietnam War. The second trend is the institutionalization of OR/MS within private-sector companies and the transition of OR/MS from a transformational technology to one that increasingly focused on mathematical analysis and incremental gains in efficiency (Jackson, 2004). The third trend, also described by Pollock and Maltz, is a societal disenchantment with quantitative methods that promised so much, yet seemed, with the increasingly unsuccessful Vietnam War and social unrest in America's cities as a backdrop, not to be delivering on their promise to improve society.

A classic paper in *Operations Research* by Russell Ackoff (1970) described a primarily qualitative study to improve a poor, minority neighborhood in Philadelphia that involved collaborations with local residents. This represented the start of Ackoff's progressive frustration with an OR/MS discipline that appeared to him to place undue emphasis on applied mathematics as against human processes, and stylized quantitative models versus a systems-learning approach (see Ackoff, 1979a, 1979b). Yet other researchers in the OR/MS field, such as C. West Churchman and Peter Checkland, shared Ackoff's beliefs in an alternative approach to OR/MS that would emphasize a broader understanding of "problems" and the social and political aspects of problem identification and solution, rather than a focus on theory-building and algorithm development for stylized mathematical representations of the real world. These decision problems would be viewed as part of a social system rather than a distinct entity that could be solved directly, as a consultant might (Checkland, 1981; Churchman, 1970). Kirby (2007) describes 30 years of disagreements between what could be called US-style OR, an increasingly mathematical and problem-focused approach, and an alternative, critical approach championed by researchers in the UK that closely examined the roles of power, class, and community in defining problems amenable to OR/MS models and methods, as well as the stakeholders who are affected by the problems and play a role in solving them.

Alternatives to traditional OR/MS are represented by community operational research (Midgley & Ochoa-Arias, 2004a), soft-OR and soft systems methodologies (Checkland, 1981; Churchman, 1979), and problem structuring methods (PSMs) (Rosenhead & Mingers, 2001). It is instructive to note that the US and UK experiences with a critical approach to OR diverged radically during the 1970s. This is due in large part to economic dislocations associated with the economic recession that affected UK residents in a larger and more fundamental way than Americans, as well as the larger role that socialist and Marxist political movements played in the UK as opposed to the USA (Kirby, 2007). While a relatively small but stable proportion of UK academics use community OR for research, hard-OR continues to dominate in applied research in the UK (Kirby, 2007).

We now briefly review other well-known variants of traditional OR/MS that are related to CBOR and which do not embody the critical perspective of the UK-based methods. Public-sector operations research, as indicated above, has played a role in OR/MS from the very beginning of the discipline. The standard reference in this area (Pollock, Rothkopf, & Barnett, 1994) tends to center on government and large nonprofit organizations as decision makers and use traditional prescriptive and quantitative decision models. A classic text on urban operations research by Larson & Odoni, 2007 focused on urban operations and logistics issues without a critical examination of the social processes that make urban problems different from those of others, nor does the text address the role of social policy in urban operations modeling. Policy modeling (e.g., Grass et al., 2010; Kaplan, 2008) uses stylized models from OR/MS, optimal control and other areas to estimate impacts of policy changes that incorporate time, uncertainty, and systems dynamics. Analytics

(Libertore & Luo, 2010) allows a more flexible notion of analytic and prescriptive methods for quantitative operations and planning problems, though typically motivated by and applied to private-sector issues.

The debate over the role that qualitative, critical, and community-oriented inquiry ought to play in OR/MS continues into the present. A letter to the editor of *OR/MS Today* (2009), in response to an editorial statement appearing in *Operations Research*, asserted that:

> . . .the issue is the way in which a recognized field of O.R. – sometimes referred to as "Soft O.R." or "problem structuring methods" (PSM) – is systematically ignored within the U.S. This field is now well-established and demonstrably successful within academic and practitioner communities elsewhere [1]. However, in many quarters of the U.S. operations research community, papers involving Soft O.R. are rarely, if ever, published in major journals. . .
>
> These methods have become widely accepted outside of the United States, and there is much evidence that they have been very successful in helping clients deal with complex, practical problems. However, they are virtually ignored within the United States, both in educational programs and in the major journals. . ..
>
> We are concerned that this is gradually causing a split across the worldwide O.R. community, particularly between the U.S. and Europe. . .
>
> We call on the American O.R. community to accept that Soft O.R. and PSMs are worthy contributions to effective O.R. interventions, and that they represent another valid, and valued, part of the O.R. discipline. . . (Ackerman et al., 2009)

In response, the editor of *Operations Research* asserted:

> The proliferation of journals in our field demands the clarification of the scope and mission of each journal. In my 2006 Editorial statement, I focused on a scope that is broad enough to cover both methodology and applications. . .
>
> Our objective is to serve the community by publishing high quality papers that are based on rigorous mathematical models and demonstrate potential impact on practice. . .
>
> Having worked on many practical problems, I have no doubt that mathematical models have limitations and that in many cases these methods need to be complemented, or replaced, by other techniques. Of course, there are many available methods to choose from and the techniques from "Soft O.R." may well be some of those. Indeed, there are various tools appropriate for dealing with "messy" problems, e.g., expert systems, business rules, management systems and other techniques of modern management. But when they are not based on rigorous mathematical models, *Operations Research* is not the appropriate outlet for such papers. (Simchi-Levi, 2009)

In response to this scholarly exchange regarding the role of qualitative methods within OR/MS, Mingers (2009) published an article in *OR/MS Today* introducing "soft OR" and related methods as well as relevant case studies to the US audience. A longer-form treatment of this topic has recently appeared (Mingers, 2011a).

Sodhi and Tang (2010) developed a model of the OR/MS "ecosystem" that is comprised of the core OR/MS community (researchers, educators and practitioners) and external entities that communicate with this community (end users, universities, funding agencies, and professional societies). They argue that an excessive focus on mathematical theory and analytical tools, combined with an unclear profile for OR/MS, the uncertain status of OR/MS in business schools, and uncertain employment prospects for those trained in OR/MS, among others, threatens the long-term viability of OR/MS as a discipline. The authors recommend that researchers move from examining stylized math models to engage the real world in significant practical problems, that academia reward researchers for doing so, and that educators increasingly train students to meet the needs of end users based in industry and government. These arguments are salient to CBOR, since CBOR problems and analytic methods, as we discuss below, are likely to be those that traditional US-style OR disdains, as seen in the *OR/MS Today* response to the letter to the editor. It is likely that CBOR would benefit from a change in values, research topics, and practice resources consistent with Sodhi and Tang's recommendations.

The importance of this debate for current research and practice in OR/MS is not clear. As we will demonstrate later in this chapter, the profile of CBOR in US degree-granting programs related to OR/MS and in top-tier journals, most based in the US, is rather low and has not increased by much since the review by Johnson & Smilowitz, 2007. However, the profile of CBOR in professional societies, especially the Institute for Operations Research and the Management Sciences (INFORMS), has increased somewhat since 2007. Thus, there is some evidence that there is modestly more interest in CBOR and related mixed-methods approaches within OR/MS in recent years than previously. The question remains: given the difficulty of addressing community-based problems in operations and strategy, is a rigorous mathematical basis for analysis the best or only way to do high-quality, cutting-edge research?

1.3 Chapter Outline

Section 2 of this chapter provides a more detailed survey of community operational research, which is the most direct motivation for this book. Section 3 presents a theory of CBOR that extends the traditional notion of OR/MS inquiry. Section 4 summarizes published work related to CBOR that has appeared since 2007. Section 5 provides an updated assessment of CBOR's profile within OR/MS across research, education, and practice. Section 6 contains a thematic summary of the 12 chapters within this volume. The last section concludes and identifies promising next steps for research within CBOR.

2 Community Operational Research: An Antecedent to CBOR

In this section, we summarize the most important aspects of community operational research. The many streams within community OR have been summarized well by Midgley and Ochoa-Arias (2004a) in their edited volume. Midgley and Ochoa-Arias (2004b) and Parry and Mingers (2004) asserted that the fundamental goals of community OR are to address the needs of low-income, mission-driven organizations, to build theory through engaged problem-solving, to redress societal imbalances by advocating for and solving problems of special interest to disadvantaged populations as against more-privileged classes, and to solve unusual problems for nonstandard clients using multiple analytic methods, including qualitative methods not necessarily prescriptive in nature, with a systems view of the problem at hand. In summary, community OR seeks to make change within communities through diverse methodologies, processes, methods, and techniques.

An important aspect of community OR is the importance placed on understanding the social context within which analysis is done. Jackson (2004) described six problem contexts by which all problems which may yield prescriptions based on analytic methods can be classified. "Mechanical-Unitary" denotes problems that have a single decision maker and which can be easily quantified and optimized, in other words, the sorts of problems, like production planning, crew scheduling, or queueing analysis, that are well studied and understood from the traditional context of US-based OR/MS. "Systemic-Unitary" problems are those associated with complex, probabilistic systems that can still be quantified in a way agreeable to stakeholders, for example a multi-period supply chain management decision model incorporating uncertainty that reflects the concern of a single decision maker. "Mechanical-Pluralist" problems reflect fundamental disagreements between participants about the nature of the problem, but which could be reduced to the Mechanical-Unitary problem if a single stakeholder's views dominate. An example of this problem is regional planning that addresses fundamental conflicts between land-use, transportation, and environmental sustainability between residents, businesses, planners, and politicians. "Systemic-Pluralist" problems have multiple stakeholders and address complex problems that cannot easily be reduced to those reflecting the needs of a single stakeholder. The long-running debates in the USA on health care reflect this view. Finally, "Mechanical-Coercive" and "Systemic-Coercive" problems serve the needs of the powerful, and specific solutions can be enforced through the power of the state, or corporations exerting market power. Military and national security problems are examples of these.

Midgley and Ochoa-Arias (2004b) explored, through the lens of political philosophy, the fundamental notion of "community" from which community OR problems originate and through which community OR findings are implemented. A "liberal" concept of community is based on autonomous individuals who assert their own rights above community cohesion. Such a community, associated with a traditional notion of capitalism, can result in consumerism and the dominance of corporations in establishing values, yielding social fragmentation and inequity. In contrast, a "communitarian" concept of community is based on social virtues and duties to individuals and the wider social group as opposed to individual rights, and leads to cooperative decision-making rooted in collective participation to generate shared values. The authors identify participation as central to enabling productive individual action in community OR, and specify three dimensions of participation: citizen power versus non-participation and tokenism; inclusion versus exclusion of human and nonhuman stakeholders, and critical versus consumerist participation. Finally, the authors discuss four kinds of communitarianism that are consistent with a productive application of community OR: participative democratic communitarianism, historical communitarianism, religious communitarianism, and green communitarianism.

Taket and White (2000) examined partnership and participation across agencies to enhance policy development and decision making, and to enable group processes to become more participatory and democratic. Cross-national case studies contained in the book build on earlier research in PSMs and community OR (Taket & White, 1997) and support research and practice in public administration and public management as well as OR/MS.

These explorations within community OR are quite foreign to the traditional "hard-OR" presentation of the discipline. In various ways, all of these theories provide a useful foundation to the community OR applications presented in the remainder of the Midgley and Ochoa-Arias text and throughout the community OR literature. Why, then is there a need for a new sub-discipline called CBOR?

There is a useful role for elements of traditional "hard-OR" in community-focused applications that go beyond what has been achieved in community OR. In the USA, policy analysis is oriented toward policy prescriptions and social interventions based on evidence of potential effectiveness, efficiency, and equity (e.g., Bardach, 2005). There is a long tradition of quantitative decision modeling and decision support for public-sector applications whose best practices have been documented in prize competitions such as the INFORMS Edelman Awards and the practice-oriented scholarly journal *Interfaces*. Yet, as described above in the letters to the editor debate in *OR/MS Today*, many OR scholars are skeptical of models and methods that are not based on mathematical principles. A new view of OR/MS that is critical uses multiple methods and which is rooted in community participation for problem formulation and problem-solving can generate insights for theory and practice that judiciously adapts traditional perspectives and generates solutions that can change the notion of appropriate and useful OR prescriptions. In addition, the field of community OR, which, for all of its innovations, had been a minority movement among UK-based practitioners all along, appears to have lost some momentum recently as some of its highest-profile thinkers have migrated to other tasks. Finally, one cannot ignore the increased attention paid to community-oriented research and practice efforts that may be associated with the recent election of a US president whose professional roots lie in community organizing. In the next section, we present a theory of CBOR that incorporates the community OR perspective but is also consistent with traditional principles.

3 A Theory of CBOR

The usual representation of the steps associated with an OR/MS analysis (e.g., Winston & Venkataramanan, 2003, p. 5) consists of the following steps: problem formulation; observation of the system; design of a mathematical model of the problem; model verification; selection of decision alternatives; results presentation, and implementation. Libertore and Luo (2010) broadened this definition somewhat by proposing four collections of actions that comprise the practice of "analytics." The first consists of data collection, manipulation, and extraction. The second, model-based analysis, comprises visualization, predictive modeling, and optimization. The third set of actions focuses on insights derived from an understanding of events that have occurred in the system under study, estimation of future outcomes based on predictive models, and specification of future outcomes based on optimization models. The last set of actions addresses decisions made given current processes, changes to processes, and identification of new long-term strategies.

The theory of CBOR is based on four analytical steps distilled from the representations of the OR/MS and analytics processes listed above. The first step, *problem identification*, recognizes that situations which are not acceptable to stakeholders may not yield at first glance a statement of a problem to be solved, or may yield multiple problems whose statements may be contradictory or so messy as to defy representation in ways amenable to mathematical analysis. Determining what aspects of a system under consideration should be modified, and how, is an opportunity for a variety of problem structuring and values clarification methods, e.g., Keeney's value-focused thinking (Keeney, 1996), Checkland's soft systems methodology (Checkland, 2001), or facilitated modeling (Franco & Montibeller, 2010).

One's preferred method for problem identification should address the important role of place and neighborhood in determining the spatial extent of a problem to be solved. As an example, de Souza Briggs (2005) showed that place and neighborhood provide an entrée to economic mobility and social stability that serves as a contrast to a traditional focus on mobility and neighborhood change. In addition, CBOR must confront, where appropriate, race, ethnicity, class, gender, and other largely immutable community or social group identifiers associated with stakeholders affected by the problem under consideration. These may not, however, be associated with defined places or neighborhoods. Race and ethnicity, in particular, are so closely associated with social issues such as disparities in resources, social outcomes, and discrimination, among others (National Research Council, 2001a, 2001b), that they deserve close scrutiny to determine whether conventional OR/MS analysis neglects the perspectives and lived experiences of key stakeholder groups.

Institutions and organizations, both formal and informal, often serve as conduits by which problems can be identified and solved, and platforms from which solutions may be implemented. Especially in community-based analysis, researchers must pay attention to the crucial role played by the not-for-profit sector, including government, 501(c)(3) nonprofit organizations such as community development corporations, and other informal, "civic-sector" organizations whose financing, structure, social role, and understanding of problems and social values may be very different than those understood by analysts trained in the OR/MS tradition. Privett (this volume) and Vernis et al. (2006) provided important background on this important sector. Ignoring the role of geography, social groups and local organizations can lead to solutions in search of a problem, or solutions that do not address symptoms, such as disparities in social outcomes by race, class, or ethnicity, of larger social problems.

Problem identification through understanding the roles of personal and social values, the importance of place and neighborhood, the impact of social inequities, and the nature of institutions and organizations must necessarily culminate in an appreciation of a critical perspective upon the problem at hand, the societal context within which the problem is to be solved, and the nature of the analytic methods to be applied. Mingers (2000a), in a philosophical examination of OR/MS, endorsed "critical realism" as a way to accommodate the realist perspective of reality (as opposed to the widely discredited empiricist view) while allowing for interpretivist and subjective views of OR/MS, to support hard and soft approaches in OR/MS, and to recognize OR/MS's identity as a basically applied discipline. Mingers (2000b) approached critical thinking from a different perspective, that of undergraduate management education, but does so, through the lens of a new management course that embodies notions of critical action learning. This view, addressing critical thinking, critiques of traditional norms and processes, critiques of authority and critiques of objectivity, is key to formulating and solving socially relevant problems that is the core of CBOR.

The second step, *problem formulation*, is most closely associated with traditional OR/MS practice; methods such as value-focused thinking, soft systems methodology, and facilitated modeling can be applied here as well. This step has four characteristics that distinguish CBOR from other problem types. First, there are often multiple stakeholders; elements of the problem formulation such as decision variables, structural parameters, and so on may reflect multiple social groups and organizations. One example of multi-stakeholder analysis for problem formulation is "decision conferencing" (Phillips, 1989) in which groups, in workshop model, engage with a facilitator to perform real-time expert modeling. Second, this process ought to be collaborative: the conventional consultant-led approach, appropriately critiqued by Franco and Montibeller (2010), neglects the fact that stakeholders, who may know little of OR/MS, nevertheless may understand their social and cultural environment, neighborhood, and system very well.

Third, the problem formulation process should be evidence-based: analysts should do descriptive analysis that deepens understanding of problem context and develop parameters and indicators that link actions with outcomes. While descriptive analysis is a standard procedure for OR/MS, linking prescriptions with outcomes is not. Many public-sector applications have implied or explicit goals associated with improving social welfare, yet are limited in practice to conventional policy or practice interventions such as delivering meals more quickly to the homebound, or maximizing the number of clients in close proximity to a service facility.

It is often not at all clear that a change in an operational metrics or proxies such as reduced delivery time or distance-weighted demand above will have an appreciable impact on desired social outcomes such as reduced food insecurity or increased literacy, which are themselves approximations to more fundamental social outcomes such as improved health, or increased education performance or labor market participation. [The area of "policy modeling" (e.g., Kaplan, 2008) has, however, featured research that has taken special care to ground decision models in social science, public health, and other disciplines.] There is thus a role for public policy analysis and other domains in linking changes in social or physical environments and resources to beneficial population outcomes, and adapting these measures to quantities that can be represented by entities which can be manipulated in reasonable ways through decision models.

Finally, problem formulation for CBOR should explicitly address issues of equity, fairness, and ethics. As discussed earlier in this chapter, various measures of social inequity and economic disparities in the USA have increased in the first decade of the new millennium; any reasonable social intervention intended to improve the lives of individuals and communities should aspire, at least, to provide stakeholders with information about changes in the distribution of benefits to various stakeholders in the form of alternative measures of equity and fairness. While the social science literature on equity is extensive (LeClerc, McLay, and Mayorga, this volume, present a brief survey of this area), there is less attention paid in typical expositions of OR/MS fundamentals regarding the role of equity. LeClerc, McLay, and Mayorga, as well as Marsh and Schilling (1994) reviewed a wide variety of equity measures that can be incorporated in a straightforward way into decision models. Mingers (2011b) presented ethics in OR as a means to clarify the values and norms that motivate and frame the problem at hand, and to engage a wide variety of constituents in discussions that determine what solutions can be derived, and how that can be done.

The next step of the CBOR process is *problem solution*. "Solving" a CBOR problem can mean deriving a solution to a math optimization model, or evaluating the impact of different system configurations on queueing model performance measures, or even establishing consensus on changes to be made to a process, or common goals to be achieved. Great value can be provided to community members and community organizations simply by problem structuring and collaborative learning which enables community members to solve important problems in the best way they know how. Community operational research as developed and practiced in the UK provides many examples of problem solution distinct from optimal solutions to quantitative decision models.

CBOR problems can be solved through multiple research frameworks. Quantitative analysis, especially mathematical modeling, is commonly understood to be the *sina qua non* of operations research as well as analytics. However, other solution methods are possible. Case studies (Meredith, 1998; Yin, 2003) can document the impacts of changes in procedures or new operations or resource allocation decisions with or without an explicit mathematical model of the system under study. Action research (Burns, 2007) enables the researcher and the client to build theory, understanding, and best practices jointly. A central belief of CBOR, represented by the original chapters in this book, and also by the review of literature which follows, is that "hard-OR" and "soft-OR" methods are compatible and in fact essential for high-impact community applications. What is important is an understanding of the system, of the problem to be solved, and of the anticipated outcomes of the analysis.

Within quantitative analysis, alternative solution approaches are represented by heuristics, optimization, and hybrids of the two. The literature of quantitative solution methods in OR/MS is vast; it suffices here to note that CBOR/MS should account for available expertise, technology, and resources within the decision-maker's organization. Doing so may result in the decision to use a heuristic that is simple to explain and easy to implement as opposed to an optimization-based method or heuristic that requires understanding of OR/MS theory, models, and applications beyond that typically available in community-based organizations. However, it would be appropriate for a CBOR practitioner to present to the client the tradeoffs in terms of optimality, model complexity, and computing resources of alternative solution approaches, especially if the client expects to use the solution method on their own. The importance of spreadsheets as potentially transformational in disseminating OR/MS models and methods across underserved areas (Caulkins et al., 2008) should not be minimized; however, in some contexts, even spreadsheet-based analysis can tax the resources of some organizations, and OR/MS analysts should understand that an entirely qualitative presentation of decision problems and solutions can provide substantial insight and benefit to community-based organizations.

In principle, OR/MS analysis consists of iterative solutions, each coming closer to achieving the goals of a client. However, the consulting paradigm of OR/MS may obscure the importance of this process. In policy analysis generally, and public-sector OR/MS specifically, iterative analysis is understood to be fundamental to ensuring that answers derived are subject to public review and appropriately modified as new data, theory, or political concerns become available (Gass, 1994). This is especially true of CBOR/MS, in which community members, or community-based organizations play a central role in problem formulation, solution, and implementation. Again, we borrow from community operational research an understanding that building community capacity to solve progressively more challenging problems, or repeatedly solving problems of a recurring nature is central to the process of CBOR.

The last step we consider is *implementation*. As argued above, "solutions" to problems in CBOR may range from increased understanding of the problem under consideration, to agreement on objectives, goals, and metrics associated with solving a problem, to generalized insights on existing processes and strategies, to revised rules-of-thumb and procedures, to problem-specific policies akin to those derived from analytic solutions to multi-period problems, and to well-defined prescriptions associated with the values of decision variables arising from solutions to specific problem instances. In contrast to traditional private-sector OR, and consultant-style public-sector OR, the ultimate goal of CBOR is community change for the public good. This can be accomplished in three ways. *Theory-building* enables increased understanding of the relationships between problems, models, prescriptions, and real-world impacts. *Capacity-building* results in the increased ability of individuals and organizations to formulate models, solve problems, and change operations and strategy without the assistance of external analysts. *Social change* is associated with tangible improvements in quality of life of community members and increased ability of community members and local organizations which serve them to advocate for their needs more effectively and to better design and implement programs that meet those needs.

The four steps of CBOR proposed in this section – problem identification, formulation and solution, and implementation – though extended in various ways to address issues of equity, critical perspectives, multiple methods, iterative analysis and capacity-building, among others, represent only an initial effort to create a proper theory of CBOR. These steps do not, themselves, constitute a rigorous collection of principles, variables, and testable propositions leading to a deeper understanding of individual and organizational decision opportunities, methods, and implementation strategies, as well as evaluation of decision modeling impacts upon communities of interest (see, e.g., Von Evera, 1997). Development of such a theory is a topic for future research.

4 Recent Research Within CBOR

Johnson and Smilowitz (2007) reviewed journal articles and working papers whose methodological focus or substantive area appeared consistent with their definition of CBOR. They found approximately 52 papers which appeared over a range of 30 years that provided a diverse view of community-focused decision modeling. A review of the research literature from 2007 to the present reveals 32 CBOR-related journal publications, a significant increase in the rate of such work. (This review also includes three articles that are germane to this chapter which appeared before 2007 but were not included in the Johnson and Smilowitz article.) Using the same application area and methodology categories of Johnson and Smilowitz, we briefly review this recent literature and draw some conclusions about the state of the art of CBOR in peer-reviewed journals.

4.1 Applications

4.1.1 Human Services

There has been no recent CBOR work in public education, and only one application related to senior services and public libraries. Hare et al. (2009) developed a deterministic multi-state Markov model of home and community care services for the disabled in British Columbia to estimate the impact of an estimated doubling of the size of the senior population on HCC resources. The authors' model addresses home care and non-publicly funded care, as well as the impact of related changes in age and health status. Bayley et al. (2009) performed an empirical investigation of academic library operations for routine decisions related to physical space, collections, staffing requirements, services, and funding.

There has been, however, an upswing in publications in humanitarian logistics, which we now define to include disaster planning. Altay and Green (2006) reviewed OR applications to disaster response across four life-cycle categories and identify disaster recovery as a particularly ripe area for research. Cole (1995) used a social accounting matrix to investigate disaster preparedness to estimate the direct and indirect costs of damage-causing events, with a particular focus on small localities as opposed to the usual national or state-level analysis. He applies his model to the Caribbean island of Aruba and estimates potential disaster impacts such as water or oil interruption. Mills (2009) described the efforts of the Louisiana State University GIS Clearinghouse Cooperative to develop geographic information systems applications that provide a way to measure disaster recovery across dimensions such as intent to return, actual return, and quality of life. These applications are intended to provide information to residents as well as researchers using lower-cost technology wherever possible to support spatially informed decisions by individuals and communities. Lee et al. (2009) examined how to dispense medical countermeasures in the face of a large-scale public health emergency where thousands of sick or injured people need medical attention. They designed a program called RealOpt that allows users to simulate, on a large scale, locations for dispensing-facility setup, facility layout design, staff allocation, and disease propagation analysis. Real Opt has been distributed to 1,000 health departments and was used successfully during an Anthrax drill in Georgia in 2005.

4.1.2 Community Development

Since 2007, there appear to have been no CBOR applications in transportation, only one in housing, but five that wholly or in part address community and urban planning, and one more that addresses elements of the latter two categories. These latter papers are mostly applied to environmental planning, which did not receive much emphasis in the previous review. Johnson, Turcotte, and Sullivan (2010) developed a multi-objective mathematical programming model to design strategies for acquiring and redeveloping foreclosed housing in urban areas to balance social objectives of aggregate social benefits, development costs that incorporate scale economies associated with clustered units, as well as equity, while accounting for limited financial resources. This model his applied to a small city in Massachusetts and demonstrates alternative development paths that show useful variation in decision and criterion space. Ewing and Baker (2009) developed an excel-based decision support application to support technology choice in construction of environment-friendly buildings. Their decision theoretic model accommodates multiple criteria, multiple stakeholders, and significant tradeoffs between short-term and longer-term investments.

Within community and urban planning, Cole (1994) applied the social accounting matrix model introduced earlier in this review to determine the income and employment impact of individual projects on a lower-income community in the city of Buffalo, New York. His analysis revealed that the East Side neighborhood represents a locus of disinvestment, with African-American residents particularly not benefiting from local investments. In a later paper (Cole, 2002), he used the same method to assess alternative development strategies for the Chinese Yellow River Delta region that address flooding and instability in the region, impact of pollution emissions in the water, and competition for the available land. Evaluating four development scenarios, he accounted for the environmental costs of economic development as well as the cost of restraints for environmental preservation. Foote et al. (2007) applied a new method called boundary critique to the problem of management of ongoing water shortages in a small town in New Zealand. By addressing the issue of inclusion, exclusion, and marginalization of people and issues, the authors demonstrate how PSMs can be applied in novel ways to define the problem context from multiple conflicting viewpoints and to develop workshops that achieved consensus on water conservation strategies. Mills (2009), described above, clearly has a focus on community and urban planning and development rooted in local participation and appropriate spatial technologies. Wang and Zou (2010) described an urban planning spatial decision support system that uses spatial data mining methods to identify new trends in urban economic development and opportunities for underground developments such as subways that would not conflict with existing infrastructure. The authors propose novel mixes of high-rise and low-rise residential developments that would preserve living spaces for long-time residents.

4.1.3 Public Health and Safety

Recent research in CBOR in the area of public health and safety has been focused almost entirely on public health applications, with no work done in emergency services and only single applications in criminal justice, hazardous and undesirable facilities, and food security, which had received much more emphasis in the earlier CBOR review. We discuss these latter applications first. Grubesic and Murray (2010) discussed, as in this volume, the problem of determining, through spatial optimization models, the likely allocation of sex offenders subject to certain residency and saturation limits. These models are used to test the extent to which sex offender residency rules provide for separation of offenders and vulnerable populations while allowing offenders to integrate into society. Model results indicate that these rules tend to concentrate and isolate potentially dangerous individuals in areas that have more vulnerable populations, less law enforcement capacity, and fewer community resources to oppose such allocations. Schweigman (2008) applied operations research methods to food security in sub-Saharan Africa and finds opportunities for productive applications to a large-scale problem at the intersection of demography, agriculture, and politics if modeling activities are integrated in an interdisciplinary approach in interaction between farmers, policy makers at the local level, and researchers.

In the area of public health, Baltussen et al. (2010) discussed recent literature on the application of multicriteria decision analysis (MCDA) on ranking of health priorities, both within the context of specific health interventions and for more generalized policy design. They suggest that the use of such models could be expanded to set national priorities through methods such as focus groups that might provide the basis of a multi-country database on health interventions that address local preferences. de Vericourt and Lobo (2009) used the example of eye hospitals in India to investigate the optimal allocation of resources in an organization between profit-generating and free services. They suggest that a threshold value of resources below which all resources should go toward profitable ventures is most efficient, accounting for the importance of free services to the organizational mission. When such a threshold is incompatible with organizational mission, organizations can alternatively structure the pricing of their for-profit ventures to cover nonprofit activities according to total resource availability, but with less optimal results. Hare et al. (2009), reviewed above, used Markov models to estimate demands on services for British Columbians with acute, chronic, palliative, or rehabilitative health care needs as a result of predicted increases in the size of the elderly population. Jehu-Appiah et al. (2008) used MCDA to set priorities for the Ghana Ministry of Health while considering both efficiency and equity. They find that interventions targeting serious diseases, vulnerable populations, or that are cost effective are more likely to be chosen. The study found that using such an analysis was a step forward for the transparency and accountability of the ministry. Kramer et al. (2009) used decision analysis to control the spread of malaria in Tanzania that considered the five critical challenges to controlling vector-borne diseases. In particular, this analysis addresses the presence of multiple actors at multiple scales and recognizes the impact of interactions between the environment, individuals, and communities, as opposed to a traditional focus on the disease vector or treatment of the disease itself.

The Health Foundation (2010) used multicriteria benefit–cost decision conferencing with high stakeholder involvement to choose health interventions that give the highest impact in life expectancy, lifetime quality of health, and lowered infant mortality. Application of this method to an isolated, disadvantaged, and underserved region enabled stakeholders to choose three interventions that were most affordable yet most likely to make a substantive difference. Silva and Johnson (2009) applied hierarchical facility location-allocation models to propose reconfigurations of the primary health system in the urban and rural portions of Davao City, Philippines, that increase population coverage, reduce travel distances, and reduce system costs through fewer facilities.

In US applications, Rawal et al. (2008) observed that blacks and Hispanics use children's mental health services less often than Caucasians. Using data from the Illinois Department of Children and Family Services and information from a standardized assessment screening tool of patients, they predict hospitalizations based on multiple medical criteria, so that more children who need such services actually access them, reducing the incidence of racial disparities in psychiatric hospital admissions. Motivated by large and increasing gaps in breast cancer mortality rates between black and white women, Sheppard et al. (2010) performed interviews with a racially diverse set of breast cancer patients and health care providers to understand barriers to usage of an effective therapy. They found that cultural identity, relationships and expectations, and cultural empowerment were significant factors in improving communication about and increasing participation in effective cancer treatment regimen. This results in the design of alternative intervention strategies, a community-based decision support mechanism.

The application area reviews above reveal two areas of emphasis absent in the 2007 review: underserved populations, especially racial and ethnic minorities (Cole, 1994; Rawal et al., 2008; Sheppard et al., 2010), and developing countries (Jehu-Appiah et al., 2008; Kramer et al., 2009; as well as Caulkins et al., 2008, though the latter paper focuses on methods of disseminating OR in Africa rather than particular applications). Finally, we observe a single example CBOR focused specifically on nonprofit management (de Vericourt & Lobo, 2009a, 2009b).

5 Methods

The current review takes a more expansive view of analytic methods associated with CBOR than the 2007 review; there appears to have been a relative explosion of new tools for decision making in community-oriented contexts.

5.1 Qualitative Methods

As discussed above, Foote et al. (2007) developed the notion of "boundaries" that determine what information is relevant and what is superfluous when applying PSMs to the needs of marginalized groups. This method allows the use of multiple interventions that accommodate diverse values and institutional critiques. Bartolucci and Gallo (2010) addressed world and regional peace and freedom as an OR/MS ethical responsibility and apply system dynamics models, combination logic functions, Boolean optimization, and multicriteria clustering to humanitarian logistics and management, conflict analysis and prevention, and sustainable development. Hermans and Thissen (2009) focused on the roles that stakeholders play in defining and solving problems. They address networks of actors, perceptions, and beliefs about the environment within which a problem is to be solved, internal motivations ("values") of actors, and the resources available to actors to realize their objectives. Their survey of recent applications along these dimensions includes methods in network analysis, preference elicitation, stakeholder analysis, conflict analysis, transactional analysis, discourse analysis, and cognitive mapping. They assess tradeoffs between practical usability and analytic quality among these different methods.

In an introduction to a special issue on the topic of ethics and operations research, Le Menestrel and Van Wassenhove (2009) discussed the role that ethics plays in designing operations research studies, the importance of recognizing value conflicts in OR, and the question of whether the core focus on efficiency as a performance metric in OR methods ignores diversity of values and limits the practical utility of OR studies. One paper in that collection by Wenstop and Koppang (2009) focuses particularly on the role that emotions play in conflicts intended to be resolved through OR methods. Based on the recent results in neuroscience, the authors develop five ethical rules for OR analysis of value conflicts that address engagement of researchers with decisions to be analyzed, the fundamental, as opposed to instrumental, role of stakeholders, and an increased focus on the consequences of decisions. Mingers (2011b) discussed the role that a particular process called "discourse ethics" plays in operations research, particularly soft-OR (and by extension CBOR), in examining morals that underlie questions regarding what ought to be done in a particular problematic situations, and the societal norms that dictate how fundamental rights can shape the formulation of decision problems. He argues that discourse ethics can support debate and discourse among the widest possible set of stakeholders and decision makers, and can address pragmatic, ethical, and moral issues that encompass the diversity of problems addressed by OR.

5.2 Quantitative Methods

Kaplan (2008) reviewed many applications of policy analysis, a collection of tools to analyze policy-relevant problems using stylized representations of the real world, and adaptations of methods such as queueing models and optimal control to derive practical insights into policy-relevant problems with local impact. As discussed earlier in this chapter, Libertore and Luo (2010) summarized the analytics movement, a superset of traditional OR analysis, to leverage large amounts of operational data to generate practice insights based on descriptive and prescriptive models and especially to develop changes to high-impact actual business processes. Although the authors' examples are drawn mostly from the private sector, analytics has the potential to revolutionize government and nonprofit service design and delivery through a focus on data, processes, and implementation that goes far beyond traditional prescriptive mathematical modeling.

5.3 Mixed Methods

We end our review of the recent CBOR literature by revisiting the debate between quantitative and qualitative methods in OR and multiple approaches to combining diverse analytical methods. As discussed previously, Kirby (2007) addressed the historical evolution of "soft" OR approaches, initially as an alternative to classical "hard" OR, and eventually as a complement to less rigid and more adaptive forms of standard OR techniques. Mingers (2001) explained how multiple methods can enable analysts to flexibly address multiple phases of a project, from understanding the problem from the perspective of stakeholders, analysis to understand and explain the current situation, assessment of proposed explanations, and actions to bring about changes. Multiple methods also allow analysts to productively intervene in situations comprising aspects that can be observed and modeled, aspects that are socially constituted, and aspects that reflect individual beliefs and values. Namen, Borstein, and Rosenhead (2009) applied robustness analysis, a method that combines a qualitative and subjective understanding of a problem from the perspective of stakeholders and a quantitative approach to identifying sequences of decisions that may yield desirable outcomes. This method incorporates the competing concepts of "robustness," i.e., fraction of acceptable configurations, or sequences of decisions, that are achievable, and that of "debility," the fraction of unacceptable or undesirable configurations achievable after an initial decision. The authors apply this method to a community-based malnutrition problem in a Brazilian community. A most-preferred solution involving sustainable community food production balances robustness and debility. The discussion of a critical approach to OR earlier in this chapter (Mingers, 2000a, 2000b) is also salient here, as these critical approaches accommodate multiple views of the problem and multiple methods to solve it.

This review of recent literature that we classify as CBOR indicates that there are multiple opportunities for decision modeling applications across application areas and analytical methods that address the needs of diverse stakeholders, values, social contexts, data types, and decision frameworks. It is encouraging to note the increasing rate of CBOR-related publications in recent years.

6 CBOR's Profile Within Research, Education, and Practice

Johnson and Smilowitz (2007) reviewed articles published between 2002 and 2007 in top-tier disciplinary journals within OR/MS and found that the presence of papers that could be classified as CBOR was very low. They also reviewed top-ranked undergraduate and graduate programs in the fields of business, industrial engineering/operations research, and public policy and found, as of 2007, very few courses that appeared to have substantial CBOR content. We have revisited this analysis for the years 2007–2010 and expanded our scope to address the presence of CBOR in OR/MS practice.

6.1 Research

Johnson and Smilowitz found only four articles in four main industry journals by 2007. This work was expanded using a list of the 28 top-ranked relevant journals in OR/MS compiled by Josephine E. Olson at the University of Pittsburgh (Olson, 2000). A review of eight of these journals, judged most likely to have CBOR-related articles from 2007 to 2010,[2] as well as a new journal (*Decision Analysis*) not on the list at the time it was created yielded only a single article out of 3,404 articles published during this time whose topic coverage approximates the criteria for CBOR provided at the start of this chapter (though six others have the potential to support CBOR-related extensions). We note the contrast between this count, and the 32 CBOR-related journal articles, discussed in the previous section, which have appeared between 2007 and 2010. It appears that CBOR, though increasing in popularity in recent years, has not had a commensurate presence in top-tier journals in OR/MS.

6.2 Education

Johnson and Smilowitz argued in 2007 that CBOR had a low profile in the academic community. They conducted a survey of the top 25 industrial engineering undergraduate programs, top 25 business undergraduate programs, top 10 industrial engineering graduate programs, and the top 25 business graduate programs, based on the 2007 rankings of US News and World Report, and found that only one graduate industrial engineering program and only one undergraduate business program offered a class with content that addresses CBOR. An update of these schools in 2010 showed little change. However, since 2007, four undergraduate industrial engineering programs have added courses that resemble public sector-OR, but three undergraduate engineering schools seem to have eliminated OR from the curriculum altogether. Mingers (2009) observed that there is very little coverage of soft-OR in U.S. curricula.

6.3 Practice

INFORMS has many societies and sections associated with disciplinary and application area interests of its members. Before 2008, there was only one section with interests related to CBOR: the section on Public Programs and Processes. In 2008, INFORMS worked with members to create a new section from Public Programs and Processes, and two newly proposed groups with overlapping mandates: the Community of OR for Public Service Efforts, and the Section on Humanitarian Applications. The resulting group, the Section on Public Programs, Services and Needs, has greatly increased its membership, number of sponsored sessions at recent INFORMS conferences, and presentations with CBOR content.

[2] *Operations Research*, *Management Science*, *Manufacturing and Service Operations Management*, *Decision Analysis*, *European Journal of Operational Research*, *Mathematics of Operations Research*, *Mathematical Programming*, *Journal of the American Statistical Association*, *Annals of Operations Research.*

In addition, in 2009 INFORMS inaugurated the "Doing Good with Good OR – Student Paper Competition," which emphasizes student-led research using OR/MS methods, considered broadly, which has significant societal impact. INFORMS has also inaugurated a Governmental/Non-Profit Task Force whose mission is to identify projects and partners in the not-for-profit sector that have the potential to leverage the expertise of the INFORMS membership. Finally, the INFORMS journal *Operations Research* is preparing a special issue titled "OR for the Public Interest," and its journal *Interfaces* will publish a special issue titled "Humanitarian Applications: Doing Good with Good OR" to be published in 2011.

In contrast, the older subfields of community OR and soft OR have had significant profiles in non-US-based journals, universities, and professional societies. Journals such as *Omega*, *European Journal of Operational Research*, and *Journal of the Operational Research Society* have published papers on primarily by community OR, soft OR, and related areas since the 1970s; authors such as Rosenhead and Mingers (2001), Midgley and Ochoa-Arias (2004a), and Taket and White (2000) have published books on these topics. Initiatives such as the Community OR Unit at Lincoln University, the Centre for Community OR at University of Hull (later merged with the Centre for Systems Studies), and the PSMs Study Group at the University of Warwick have provided scholarly support for this topic. In addition, Cochran (2011) has several entries on various topics within soft-OR and application areas related to CBOR (though neither CBOR nor COR are addressed directly in this encyclopedia).

While CBOR continues to have a low profile in top-tier academic journals and in top-ranked OR/MS degree programs, an increased emphasis on public-sector research and applications within the largest OR/MS professional society provides hope that CBOR, and public-sector applications in general, will achieve increased visibility in research journals and education programs in years to come.

7 Book Chapters

The 12 chapters to follow in this book, emphasize a number of distinct themes across their diverse application areas. In this section, we summarize these contributions according to thematic category and then discuss the extent to which these chapters reinforce the motivating themes of this book which were introduced at the start of this chapter.

7.1 Models and Analytic Methods

This book places special emphasis on research that develops new ways of abstracting real-life organizations, systems and processes into models, and designs and/or adapts novel analytic methods by which such models may yield prescriptions or policies that are relevant to practice.

"Community-Based Operations Research," by Michael Johnson and Karen Smilowitz (first published in 2007) is an initial effort to place a name on OR/MS applications that emphasize issues of place and space, of minorities and disadvantaged groups, and of the role of community in identifying, formulating, and solving problems and implementing solutions derived from them. This tutorial paper develops a theory of CBOR, presents a hypothetical CBOR application to urban public education, and reviews the scholarly research in the field defined as CBOR starting in the early 1970s. The authors then discuss two actual CBOR applications and emphasize the linkages between the applications and key elements of CBOR. The first application is a mathematical programming model for the design of delivery routes for donated food to food pantries that balances concerns of efficiency and equity. The second application is a spatial decision support system providing guidance for low-income families who seek to relocate using rental housing vouchers, based on analysis of typical clients' ability to do elementary spatial analysis and analysis of decision alternatives, culminating in a prototype Web-based SDSS.

"Operations Management in Community-Based Nonprofit Organizations," by Natalie Privett builds theory, identifies applications and makes links to other disciplines in exploring how the basic metaphor of operations management and logistics – the supply chain – can be applied to the nonprofit sector. This chapter is divided into topics that correspond to three portions of the supply chain. The first, supply – or inputs – is represented by fundraising, earned income, and foundation grants. The second, nonprofit production – or activities – is organized according to objectives, coordination and centralization, and production processes by which services are provided to client populations. The last category, consumers and markets of nonprofit goods and services, provides insight into the role that supply and demand play in decisions regarding resource acquisition, service design and collaboration and competition, and how the work of nonprofit organizations can be quantified and evaluated using principles of performance measurement. The chapter concludes by summarizing the similarities and differences between for-profit supply chains and nonprofit organizations providing goods and services for the public good, and identifies some promising areas of future research, including the role of risk, multiple organizational objectives, and the interplay between for-profit and nonprofit organizations and services.

"Modeling Equity for Allocation in Public Resources" by Philip Leclerc, Laura McLay, and Maria Mayorga provides a theoretical foundation for consideration of equity as a co-equal criterion for allocating public resources along with traditional concerns of effectiveness and efficiency. The authors define equity as addressing three elements: the resources to divide between recipients, the sets of recipients by which resources will be divided, and time periods across which resources are provided. By closely examining how stakeholder perspectives change over time, they define a fundamental distinction between the equity of the resource allocation process (*ex ante* equity) and the equity of the outcomes produced by the process (*ex post* equity), and show that allocations that may be ex ante equitable may not be ex post equitable, and vice versa. These concepts are illustrated using an example from emergency medical services in which uncertainty plays a fundamental role in service delivery time and patient survival. The authors then provide illustrative mathematical formulations of equity objectives and discuss issues of mathematical tractability and incorporation into multi-objective mathematical programs. They recommend that other researchers extend this work through a systematic analysis of equity objectives that would extend the foundational work of Marsh and Schilling (1994), investigation of the implications of use of equity as a constraint rather than an objective in math programming models, incorporation of process equity in operations research models, development of a "toolbox" of a core set of equity functions of broad applicability to OR/MS, and investigation of how equity can be incorporated into a wide range of applications apart from EMS.

7.2 Facility Location and Spatial Analysis

CBOR finds a natural home in the areas of facility location and spatial analysis. Goods and services are often provided to localized populations through spatially fixed sites such as libraries, health centers, and schools. Since many services, and the facilities by which they are provided, have spatial extent, issues of the spatial distribution of client populations and proximity of clients to service providers, and the ways in which both are measured, and the policy implications of both, are of importance. We note that each of the papers discussed below also address concerns of disadvantaged and/or stigmatized or under-represented groups as well as service delivery.

"Spatial Optimization and Geographic Uncertainty: Implications for Sex Offender Management Strategies," by Alan Murray and Tony Grubesic, is related to their recent (2010) work on decision models for measuring the spatial impacts of rigorous enforcement of laws relating to allowed residential locations for persons convicted of serious sexual offenses. Here, though, the authors examine the nature of measurement itself in geographic information systems and discuss the impact upon residential prescriptions for sex offenders of uncertainty in approximating proximity and physical location within GIS. In reaction to four categories of such uncertainty – object geometry, data precision, distance measurement, and proximity interpretation – the authors propose improvement of data and/or model quality along each of these dimensions, as well as changing the language of statues themselves. By doing so, policy analysts, law enforcement, and offender advocates can ensure that laws are designed and enforced effectively and fairly.

"Locating Neighborhood Parks with a Lexicographic Multiobjective Optimization Method," by Jorge Sefair, Adriana Molano, Andrés Medaglia, and Olga Sarmiento, turns the focus directly to spatial decision modeling. The authors address the question of identifying and assembling land parcels in urbanized areas into parks to meet minimum threshold requirements of parkland per resident motivated by documented benefits of proximity of residents to parks, green spaces, and recreation. This is a discrete multi-objective facility location problem, the objectives being geographic coverage, level of, and proximity of parks to, positive and negative local externalities, number of beneficiaries, physical accessibility, and total cost, subject to limits on the total size of the park as well as of component parcels. The authors apply an ε-constraints approach as well as a priori lexicographical ordering of decision criteria based on consultations with planners to measure and control the deviation of objective values from best-possible values across various feasible solutions. These methods are applied to urban park planning in Bogotá, Columbia; it is demonstrated that the model instances can be designed with an acceptable level of technical difficulty, solutions generated that clearly show variations in performance across multiple objectives, and spatial and policy impacts of alternative park infrastructure strategies illustrated in insightful and innovative ways.

"Using GIS-Based Models to Protect Children from Lead Exposure," by Douglas Hastings and Marie Lynn Miranda, represents the strongest link to the themes of minority and disadvantaged groups and service delivery. Given the significant negative health impacts upon children of exposure to even very low levels of lead, primarily associated with lead-based paint in the home, the authors introduce a model to measure levels of childhood residential lead exposure. This model uses GIS to assemble spatial data on residential parcels and associates with these parcels data on documented risk factors for childhood lead exposure as well as actual geocoded blood surveillance data. These data are used in a regression model to forecast lead exposure at the parcel level; model results are displayed using GIS to provide public policy and public health insights unavailable through other display or description methods. This forecasting model, appropriately validated, has been used by organizations to design localized lead poisoning prevention strategies such as targeted blood screening, lead paint abatement and educational programs, and community outreach. The authors, though focused on public health implications of their model, provide suggestions for decision modeling applications that can enable users to make policy decisions for public health interventions that balance multiple decision criteria.

7.3 Minorities and Disadvantaged Groups

A central motivation for CBOR, as for community operational research, is the role that decision modeling can play in designing policies and prescriptions that affect the lives of individuals and communities who, by virtue of socioeconomic disadvantage, political marginalization, or stigmatization on the basis of race, ethnicity, class, or other personal or group characteristics, are not traditionally the focus of public-sector OR/MS. The papers in this section are motivated most strongly by the lived experiences of disadvantaged groups and are intended to improve outcomes for these groups.

Lee Stenson's "A Model for Hair Care In the African American Community" is motivated by the fact that hair care, a service reflecting conflicting cultural values of beauty and assimilation, is simultaneously a fundamental pillar of minority communities and often time-consuming and expensive. Using queuing models, Stenson investigates the ways that operations of hair care salons serving African-American populations be improved so as to increase throughput and revenue to operators and reduce the cost, in time and money, to patrons. Surveys of hair care salon owners and observations of actual salon operations enable the author to apply discrete event simulation to a stylized representation of a hair care salon with performance parameters that reflect real-world operations. The author recommends that salon operators reduce the practice of "stacking" customers who arrive in close time proximity, partition services provided according to processing times, and hire assistants, to maximize profits and throughput. The author also recommends that clients consider choosing hair styles that require less processing time and maintenance. These recommendations have significant cultural and policy significance: in the USA generally, minority women's hair styles that communicate values of cultural assimilation are the most expensive and time consuming. Also, minority women serving in the armed forces have limited access to hair care salons that provide culturally appropriate services.

"A Modeling Approach to Evaluating 'At Risk' Youth and Communities," by B. Jacob Loeffelholz, Richard Deckro and Shane Knighton, addresses another marginalized group in America: youth at risk for membership in street gangs. The authors adapt Ishikawa, or cause-and-effect diagrams to classify risk factors for street gang membership based on the voluminous social science literature on this subject and create stylized profiles of "at-risk" youth. On the basis of these risk factor hierarchies, the authors apply Keeney's (1996) value-focused thinking methodology to identify specific measures for individual-level risk factors and calibrate single-dimensional value functions to translate levels of risk factors into scores which are then aggregated into weighted risk scores. The authors adapt this methodology to community-level factors associated with gang activity and similarly compute weighted risk scores by which communities at highest risk for gang activity can be identified. The goal of this modeling exercise is to design gang prevention programs with the greatest likelihood of reducing gang activity, as well as identifying risk factors for individuals and communities of gang affiliation that may support other social service interventions.

"Fair Fare Policies: Pricing Policies that Benefit Transit-Dependent Riders," by Kendra Taylor and Erick Jones, focuses on another disadvantaged population: minorities and persons of low income who are most likely to depend on mass transit to meet their transportation needs, and least likely to purchase high-discount transit passes that require significant initial cash outlays. Motivated by increased investments by mass transit systems in "smart card" systems for automated fare collection as well as fare increases intended to reduce operating deficits that can disproportionately affect transit-dependent patrons, the authors propose pricing schemes that can ensure that even patrons who do not purchase expensive multi-ride discount plans pay little or nothing for additional rides that would have been free under transit pass schemes. Using research on price elasticity of transit fares and cross-fare elasticity between various transit products, the authors solve a nonlinear program to determine the optimal increase in the price of various fare products, and the increase in all prices, to maximize revenue subject to limits on demand levels for a new "best fare" product and overall increases in fares. The authors apply their model to real-world transit data and demonstrate that a new fare policy with benefits especially for the transit-dependent can result in increased revenues, and may attenuate decreases in ridership as compared to outcomes for conventional fare increases without such fare products.

7.4 Service Delivery

CBOR, like most of OR/MS, addresses the delivery of services as well as physical goods. Public-sector OR/MS has traditionally emphasized delivery of services, such as emergency medical service, transportation, natural resources, and education which are often not traded in conventional markets, or for which there are significant positive or negative externalities. CBOR's focus on service delivery includes in addition impacts on disadvantaged, localized, or traditionally under-studied populations and an emphasis on equity.

"Decision Making for Emergency Medical Services," by Hari Rajagopalan, Cem Saydam, Hubert Setzler, and Elizabeth Sharer, is a review of recently published research on ambulance relocation models to improve response times and thereby patient survival rates. The authors explore improved methods to forecast calls for EMS service that incorporate uncertainty regarding the time and location of such calls, and, given better demand forecasts, decision models for deploying and redeploying EMS servers to balance proximity to call locations and the need to reduce fatigue and improve morale of EMS employees. The authors use data from Mecklenburg County, NC, to demonstrate novel forecasting models using artificial neural networks, and two competing ambulance location models: the Dynamic Available Coverage Location Model (DACL) and Minimum Expected Response Location Problem Model (MERLP). ANNs provide benefits over conventional models because of modest modeling assumptions and applicability to complex data patterns. In addition, while DACL determines the minimum number of servers (ambulances) that are needed to cover demand given a time standard threshold, MERLP additionally minimizes the total overall travel distance for a fleet of ambulances. The authors' results are shown to have promise for urbanized communities showing significant changes in demand levels, and for extensions that address equity and variable service levels for especially vulnerable populations.

"Capacity Planning for Publicly Funded Community Based Long-Term Care Services," by Feng Lin, Nan Kong, and Mark Lawley, develops an optimal control model for allocation of elderly persons to alternative long-term care (LTC) services: home and community-based services (HCBS) and institutional care, in particular, nursing homes. This is done by making assumptions about the rate of transitions from the overall population of older public insurance beneficiaries

(Medicare) to the two LTC alternatives, and the rate of transitions from the larger population of beneficiaries to the status of death and between the two LTC services, as well as the death state. The optimal control model minimizes the sum of fixed and variable costs associated with LTC options subject to balance equations on the rate of change of levels in the four categories and a boundary condition. Results based on Medicaid recipients in the state of Indiana demonstrate that a substantial increase in the capacity of the HCBS system from the base case results in modest decreases in annual expenditures.

"Educational Costs and Efficiency of Illinois Schools: A Nonparametric Analysis," by J.S. Flavin, Ryan Murphy and John Ruggiero, is an application of the well-known data envelopment analysis method to public education. To the usual DEA technology description of discretionary inputs such as labor and capital transformed into outputs such as performance on standardized tests and drop-out rates, the authors incorporate nondiscretionary inputs such as parental education or involvement, poverty, income, and minority status. These nondiscretionary inputs define "environment levels" that affect efficiency: a more adverse environment requires higher expenditures to create a given level of output. The authors develop a teacher price index from a first-stage DEA model that maximizes reductions in observed expenditures consistent with observed production allowing variable returns to scale; they then calibrate a regression model in which the dependent variable is the teacher price index and independent variables are nondiscretionary inputs. Parameter estimates from this regression are used as weights on the values of nondiscretionary inputs to create an overall environmental index; this index is used in a third-stage DEA model that accounts for the impact of favorable environments upon observed efficiency. This model is applied to data on elementary school districts in Illinois. The authors identify substantial inefficiency and show that environmental costs are driven by teacher prices, as well as student composition and socioeconomic conditions.

7.5 Relation of Book Chapters to Motivating Themes

The introduction to this chapter identified six themes which have motivated the development of this book: the importance of space and place in policy design and service delivery, a focus on underserved, under-represented or disadvantaged populations, international and transnational applications, multi-method, cross-disciplinary and comparative approaches and appropriate technology, the role of community in collaborative decision modeling and the potential positive impact of analytics on community-based applications. These themes are intended to strike a balance between the traditional focus of US-style OR/MS on mathematical rigor and a focus on stratified decision contexts [the "mechanical-unitary" type of OR/MS application as defined by Jackson (2004)], and more expansive notions of decision makers, stakeholders, community and analytic methods as represented primarily by community OR, soft-OR, and problem structuring/facilitated modeling methods that are more popular outside of the USA.

The contributions to this book can be classified into three levels of emphasis on these motivating themes. The themes of multi-method, cross-disciplinary and comparative approaches and appropriate technology and underserved, under-represented or disadvantaged populations receive a high level of emphasis, being a focus of 7 and 9 of the 12 chapters, respectively. In contrast, the themes of space and place and analytics are an important component of Chaps. 5 and 3, respectively, yielding a medium level of emphasis. Finally, the lowest level of emphasis in this volume are the themes of international and transnational applications and the community's role in collaborative decision modeling, which are addressed in detail in only Chaps. 2 and 1, respectively.

Based on previous discussion, these results perhaps should not be surprising. It will lie to future researchers to remedy this deficit in research emphasis.

8 Summary and the Future of CBOR

CBOR is a sub-discipline of OR/MS that is rooted in diverse research traditions, which may serve as a "middle-ground" between "hard-OR" and "soft-OR," thus appealing to US-style adherents of OR/MS, and which derives its research rigor from theory-building and testing, novel methods of data gathering and analysis, and an emphasis on demonstrable, tangible social impacts and creative development of appropriate decision technologies. This chapter has demonstrated that CBOR has matured significantly since the 2007 introduction to the field. CBOR is gaining increased prominence in the research literature and in professional practice; it is hoped that its presence in top-tier journals and educational programs will improve similarly in the coming years. The theory of CBOR, though quite preliminary at this time, provides a framework for innovative research that crosses disciplinary boundaries and places increased emphasis on the role of stakeholders, analysts, and decision makers to develop decision models that are rooted in expansive notions of community and decision making.

This chapter acknowledges that certain thematic areas of CBOR, such as international and transnational applications and the community's role in collaborative decision modeling are not reflected in the CBOR research literature to the level of others such as interdisciplinary approaches and the role of underserved and disadvantaged populations. We also acknowledge that there are relatively few published applications, especially at top-tier journals, that address all or even most of the characteristics of CBOR described earlier in the chapter.

There are substantial opportunities for research in the decision sciences that is community-engaged and action-oriented, that leverages a current interest in analytics to draw stronger links with work in social sciences, public management, and community and urban planning, and which addresses comparative and trans-national approaches to explore impacts across sectors, communities, regions, and countries. Current work by this author in the areas of multi-method modeling models for foreclosed housing acquisition and development (Johnson, Keisler et al., 2010), and neighborhood-level investment policy design to address municipal shrinkage (Johnson, Hollander & Hallulli 2011) are examples of research in CBOR that may serve to broaden the field and increase links between traditional US-style OR and alternative approaches.

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Chapter 2
"Community-Based Operations Research"*

Michael P. Johnson and Karen Smilowitz

1 What is Community-Based OR?

1.1 Introduction

There are many public-sector problems in the U.S. of interest to researchers and practitioners whose origins and solutions have a strong local or community flavor and reflect concern with individual life outcomes. Such problems include poverty, food security, urban education, criminal justice and human services. Indicators of the severity of these problems are numerous. The U.S. poverty rate, about 12.6% in 2005, has not decreased sig\nificantly over the past three years despite growth in multiple economic indicators. Moreover, the poverty rate for African-Americans and Hispanics remains about three times that of non-Hispanic whites (U.S. Census Bureau 2006). Performance of public and private elementary and secondary school students on a national measure of academic achievement has shown only modest improvements between 1999 and 2004, with white, non-Hispanic students two to three times more likely to score at the highest levels (National Center for Educational Statistics 2006). Unemployment rates for African American males without college education have increased dramatically over the past 15 years, with rates two

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to three times that of whites; incarceration rates for African-Americans in their late 20s are about six times that of whites (Western 2006, Bureau of Justice Statistics 2006). The number of U.S. households with at least moderate housing burdens (at least 30 percent of income) rose from 31 to 34 million between 2001 and 2004, while average commute times increased at greater rates for lower-income families than for higher-income families (Joint Center for Housing Studies 2006).

Research on social issues such as those described above has traditionally been descriptive in nature, and concentrated within the social sciences, urban planning and related disciplines; they have tended to receive somewhat less attention from disciplines such as operations research/management science whose models and methods tend to be more prescriptive. We assert that an adaptation of previously identified domains of OR/MS, which we denote as "community-based operations research", is well-positioned to provide models and analytic methods that can provide guidance to individuals, government and non-governmental organizations that seek to address these problems. In this article, we describe the characteristics of problems that fall within the scope of community-based OR, develop a taxonomy of problem areas, provide a review of related OR/MS research literature and explore two case studies of community-based OR applications. Finally, we identify some next steps for research and practice in this area.

The scope of this paper is largely limited to the United States, as American political and social values, and demographic and economic characteristics may differ from other developed countries in certain ways relevant to community-based OR. We focus on the last 30 or so years of research and applications, the scope of time within which 'public-sector operations research' has become a well-defined domain. We define 'operations research/management science' broadly to include prescriptive decision models as well as descriptive models that are directly applicable to decision modeling. Evidence to support the presence of community-based OR comes primarily from refereed journal articles, published books and conference proceedings, though working papers are cited if they provide primary evidence of recent research activity in a given domain.

1.2 Defining Community-Based Operations Research

Fundamentally, community-based OR addresses public-sector problems, that is, problems in which the primary outcome measure to be optimized is not a direct representation, or proxy for, shareholder benefit and in which the outputs are subject to public scrutiny (see, e.g. Pollock and Martz 1994, p. 6). Community-based OR is a subfield of public-sector OR (see e.g. Pollock, Rothkopf and Barnett 1994, Larson and Odoni 1981) that emphasizes most strongly the needs and concerns of disadvantaged human stakeholders in well-defined neighborhoods. Within these neighborhoods, localized characteristics vary over space and exert a strong influence over relevant analytic models and policy or operational prescriptions. There are three important implications of this definition that distinguish community-based OR from other areas of public-sector OR.

First, our focus on human stakeholders implies a fundamental interest in human versus physical resources, as might be represented by decision models for natural resources management, energy policy, and, to a lesser extent, infrastructure design. Second, our focus on disadvantaged, underserved or vulnerable populations recognizes that these groups may have distinct social or political preferences, are less able to use political influence to adapt public policies to their own needs, and may suffer stigma that may impede access to resources, expertise and tools associated with state-of-the art decision models or policy interventions. Third, our focus on "place" implies that models should account for community-level characteristics, like socio-economic status, that are salient to decision models and which vary over space in systematic ways. For example, suppose a public library branch location model does not distinguish between demands originating from neighborhoods that differ according to socio-economic status. Then a poor and non-poor neighborhood with equal levels of demand may be treated equally by the model, even if relative travel costs are higher, and marginal benefits from access to recreational and educational resources greater, for residents of poor neighborhoods as compared to non-poor neighborhoods.

Community-based OR has its roots in a classic article by Ackoff (1970) describing community-engaged problem-solving in a distressed, mostly African-American community in Philadelphia. This amalgam of analysis, action and advocacy received the greatest attention in the United Kingdom during the 1980s and 1990s as 'community operational research' (Jackson 1988, Parry and Mingers 1991, Taket and White 1994), though some attention has been given to this sort of OR practice and theory in the US (e.g. Bajgier *et al*. 1991). An important goal of this article is to respond to Parry and Mingers' statement that "[v]ery little has been published on Community OR, and as a result it is unclear how much as been achieved" (1991, p. 580). These authors demonstrated that much of the work in community OR appeared to consist of student projects and community outreach that might be classified now as 'capacity-building', rather than applications based on analytic models intended to provide specific policy and operational guidance to decision-makers in a way that extends existing theory and methods. Most of the applications of community-based OR described in this paper have occurred since Parry and Mingers' article, and address the methodological concerns noted above.

Certain public-sector problems are not amenable to community-based OR. As mentioned previously, many social problems, such as criminal offending, low-quality housing or inadequate access to retail food outlets, exhibit symptoms that vary across neighborhoods. These problems may also have important regional or national characteristics that are aggregates of individual outcomes, for example high incarceration rates, residential segregation or adverse health outcomes related to food insecurity. In turn, these high-level characteristics may be associated with regional or national-level policy failures, such as ineffective national drug enforcement policy, inadequate funding for affordable housing, or insufficient incentives for grocery stores to locate in underserved communities. An important area of public-sector OR, referred to by Kaplan (2008) as *policy modeling*, uses stylized models inspired by problems of a local nature that may generate important insights regarding regional or national-level policy design. Policy modeling has yielded novel and influential insights in drug policy (see e.g. Rydell, Caulkins and Everingham 1996), crime policy (see e.g. Blumstein, Rivara and Rosenfeld 2000) and public health (see e.g. Kaplan and Merson 2002). Community-based OR, though quite distinct from policy modeling, can complement policy modeling by generating solutions associated with direct and rapid improvements in individual and neighborhood-level outcomes.

We may summarize the defining characteristics of community-based OR problems as follows. They tend to have *multiple stakeholders and multiple decisionmakers* (Gass 1994, Bardach 2000). We enumerate typical stakeholder and/or decisionmaker groups as follows. Donors are government, non-profit, or for-profit organizations whose direct or in-kind contributions support service provision. Clients are individuals, families or organizations who benefit directly from service provision. Non-client residents are individuals, families or organizations who benefit indirectly or not at all from service provision but who may nevertheless pay for it through taxes. Service providers are government or non-profit organizations who design, implement and manage service provision strategies. Local government enforces laws, administrative rules and codes that define the legality of various initiatives. As we have emphasized, key stakeholders and decisionmakers are *localized* and often economically or socially *disadvantaged*. Therefore, tradeoffs between efficiency, effectiveness and equity are essential. In contrast to other private- and public-sector OR models, limiting focus to a single decisionmaker, stakeholder or objective function type may obscure important aspects of the problem at hand.

As for UK-style community OR, successful community-based OR models and applications require substantial *stakeholder participation* in problem definition, solution and implementation (Bajgier *et al.* 1991, Taket and White 1994). This is incompatible with the conventional 'consultant' view of OR modeling in which a dispassionate expert becomes immersed in a problem domain, formulates and solves an appropriate analytical model and presents a range of recommendations to decisionmakers.

Accountability, a traditional focus of public administration generally (Heinrich 2003; see also Gates 2006) is especially important for community-based OR for determining the social impact of model solutions. Many important community-based services, targeted as they are on disadvantaged populations, generate relatively low levels of user fees and rely disproportionately on support from non-governmental organizations. In turn, these donors may want service providers to demonstrate that they have achieved significant client and system outcomes—but these are difficult to measure and communicate, as compared to process outputs. The implications of this criterion are twofold: there is an increased need for researchers to design effectiveness measures that can be easily implemented in community OR models, and there is an increased need for practitioners to work closely with funders to justify the support received.

Finally, there is a general tension between *uniqueness* and *generalizeability* that affects how community-based OR models and applications are viewed by disciplines that might take an interest in them. The greater the programmatic and spatial specificity of a given application and the focus given to community engagement, the greater is the resemblance of community-based OR to domains at the intersection of community planning, community organizing and social work. As Kaplan (2008) observes, this view of community-based OR may have led Ackoff (1979) to become disenchanted with the prospects of 'traditional' OR as a vehicle for making significant changes in society. The greater the generality of the model and the application, the greater is the resemblance of community-based OR to decision modeling applications whose contribution is primarily technical and methodological, or those, like policy modeling, that take a regional or national focus, decreasing the likelihood of direct, relatively rapid benefits to community stakeholders. Our belief is that, all else equal, the long-term impact of community-based OR is likely to be greatest if emphasis is placed on models that provide specific, theory-based guidance to local decisionmakers that can be easily replicated in different application contexts.

1.3 Sample Application: Public School System Design

An example of an application that captures many of the characteristics of community-based OR described above is that of an urban public school district facing declining enrollment, increasingly rigorous educational quality targets and revenue shortfalls that must simultaneously decide on a set of schools to close and to combine, academic programs to relocate and students to reassign (see e.g. Mar Molinero 1988 and Johnson 2006a). Table 2.1 demonstrates the various dimensions along which community-based OR can help decisionmakers and stakeholders collaborate to generate specific recommendations for policy and operational guidance.

Results indicate that this problem is rich, in terms of opportunities for community engagement, mathematical modeling complexity, data requirements and multi-stakeholder decision support. A traditional OR approach to this application might emphasize sophisticated, high-quality solution algorithms for a somewhat stylized representation of the underlying problem, perhaps using simulated data, and a focus on efficiency and possibly effectiveness measures. A community-based OR approach might instead result in a model that captures the local environment more fully, and incorporate equity and effectiveness explicitly, thus implying greater difficulty in optimal solution procedures. However, this approach might also result in heuristic solution algorithms and strategies for model formulation and policy implementation that emphasize qualitative methods more typical of UK-style community OR.

1.4 A Taxonomy of Community-Based OR Applications

There is no concise, standard classification of public-sector service areas known to us (a comprehensive list of service areas is available on the U.S. Blue Pages, www.usbluepages.org). For the purposes of this article, we classify community-based OR

Table 2.1 Example Community- Based OR Application: Urban Public School Closings

Attribute	Description
Localized focus	A school closing policy may differentially affect low-performing schools, and disadvantaged neighborhoods, as compared to schools and neighborhoods overall. Therefore, generic modeling constructs may not capture the most challenging aspects of urban public education policy.
Multiple conflicting objectives	Efficiency: direct dollar savings in fixed and variable costs Effectiveness: changes in student educational performance Equity: changes in average school travel times across neighborhoods; changes in levels of racial, ethnic or class segregation across and within schools.
Multiple stakeholders	Donors: local school district, Federal government, local foundations. Clients: families whose children attend public schools. Non-client residents: households without school-age children, or whose children attend non-public schools. Service provider: local board of education.
Role of disadvantage	Racial and ethnic minorities, which tend to be economically disadvantaged and segregated, may constitute a majority of students enrolled in public schools, while not necessarily a majority of the voting population, or cadre of professional analysts, funders or political leaders.
Accountability	Cost savings are a direct consequence of school closings; improved educational outcomes are not. Educational outcomes may even worsen over the short term as the system re-equilibrates. School closing decisions could be based, in part, on conventional measures such as standardized test scores—or, alternatively, on more sophisticated measures that identify the 'value added' by schools. But specifying the latter might be controversial and expensive.
Lack of resources	Local boards of education may have no analysts with experience in OR/MS models and methods, and few hardware or software resources to solve the challenging models that arise in developing school closing strategies.
Uniqueness versus generalizeability	Too much focus on local attributes shifts emphasis to politics, community organizing and educational administration rather than a more generic model that can incorporate issues relevant to many different cities.

Problem description: Johnson (2006a)

application areas in four broad categories: human services, community development, public health and safety, and nonprofit management. *Human services* consist of: services to senior citizens, humanitarian (e.g. post-disaster) logistics, public libraries and literacy, public education and family supportive services. Family supportive services include e.g. foster care, income-based benefits such as food stamps and public assistance and need-based benefits such as mental health/mental retardation, drug/alcohol treatment and homeless services.

Community development consists of housing, community/urban planning and transportation. In turn, housing can be classified as low- and moderate-income housing, often provided through government subsidies, and affordable, mixed-income and workforce housing, often provided through zoning ordinances or private initiative as well as direct government support. Community and urban planning can address conventional economic development of distressed or isolated communities as well as pre-disaster planning and post-disaster reconstruction.

Public health and safety addresses health care, criminal justice, emergency services, hazardous/undesirable facility location, and correlates of chronic diseases associated with individual deprivation or social externalities, such as food insecurity, or proximity to environmental hazards. Finally, *nonprofit management* addresses general issues in management of community-based or community-oriented service providers. In Section III we will review selected research literature in these three broad application areas.

Table 2.2 displays a variety of community-based OR application areas according to multiple attributes such as geographic/ temporal scope, performance/outcome metrics and modeling/computational complexity. Where there are multiple examples of published OR applications in a particular category, we emphasize the application we believe has the strongest community orientation.

Notice that community-based OR problems can be operational, tactical or strategic in nature; that analytical methods from logistics and multi-criteria decision analysis/decision theory tend to dominate, and that there are multiple outcome measures of interest, some of which may require knowledge of economics to quantify (e.g. net social benefit), others of which may require close examination of stakeholder values (e.g. equity).

1.5 What is Community-Based OR's Profile within the Profession?

We conclude this introductory section by assessing the visibility of community-based OR with the OR/MS community. Community-based OR appears to have a low profile within top-tier disciplinary OR/MS journals. A review of articles published between 2002 and 2007 whose topics appear consistent with our definition of community-based OR yields 4 papers in *Operations Research* out of 401,[1] or 1%, and no papers in *Management Science*, *Transportation Science* or *Information Systems Review*.

Community-based OR also appears to have a low profile within academic degree programs that intersect OR/MS. A scan of curricula of top schools as according to

[1] Three of these papers appeared in a special 50th anniversary edition of *Operations Research* comprised of specially commissioned retrospectives.

Table 2.2 Community-Based OR Application Areas

Attributes								
Application Areas	Example Application(s)	Entity	Geographic/ Temporal Scope	Performance/ Outcome Metrics	Relevant Methods	Modeling/ Computational Complexity	Political/ Social Controversy	Example Application
Food security	Distribution of donated food from warehouse to local pantries	Government, NGO*	Regional; strategic/ tactical/ operational	Percentage food outlet needs met; resource utilization	Vehicle routing, inventory theory	High	Low	Lien, Iravani and Smilowitz (2007)
Senior services	Design and location of site-based senior services (meals-on-wheels, recreational facilities)	Government, NGO	Regional; strategic/ tactical/ operational	Total cost; percentage of demands met	Location-allocation, vehicle routing	Moderate to high	Moderate	Johnson, Gorr and Roehrig (2005)
Humanitarian logistics	Location of staging areas for post-disaster delivery of supplies; routing and scheduling of supply shipments	Government, NGO	Nation, region; strategic/ tactical/ operational	Total cost, lives saved	Location-allocation, vehicle routing, inventory theory	High	Moderate	Campbell *et al.* (2008)
Affordable/ subsidized housing	Location of "project-based" housing; potential allocations of households using "tenant-based" subsidies; decision support for individual household relocation	Government, NGO, public-private partnerships	Region, neighborhood, individual; strategic/ tactical / operational	Net social benefit; percentage of demand met; equity	Location-allocation; cost-benefit analysis; multi-criteria decision models	Moderate	High	Johnson (2005)

Public education	Opening/ closing/ resizing/ reconfiguring buildings and services; demand forecasting; performance evaluation; student transportation	Government	Region; strategic/ tactical/ operational	Net social benefit; percentage of demand met; equity	Location-allocation; forecasting; data envelopment analysis; districting; vehicle routing	High	High	Mar Molinero (1988)
Criminal justice	Location of community corrections centers; facilitating prisoner re-entry into communities	Government, NGO	Region, neighborhood; tactical	Net social benefit; equity	Location-allocation; forecasting	Moderate	High	Johnson (2006)
Urban and regional development	Post-disaster reconstruction; design of community redevelopment initiatives; site selection and parcel acquisition	Government, NGO, public-private partnerships	Region, neighborhood; strategic/ tactical	Net social benefit; equity; sustainability; spatial desirability	Location-allocation; districting; project selection; multi-criteria decision models; decision analysis	High	High	Patz, Spitzner and Tammer (2002)
Public health	Location/service design of health centers; blood distribution; design of public health initiatives	Government, NGO	Region, neighborhood, individual; strategic/ tactical/ operational	Net social benefit, equity, lives saved	Location-allocation; vehicle routing; inventory theory; stochastic	High	High	Kaplan (1995)

(continued)

Table 2.2 (continued)

Attributes

Application Areas	Example Application(s)	Entity	Geographic/ Temporal Scope	Performance/ Outcome Metrics	Relevant Methods	Modeling/ Computational Complexity	Political/ Social Controversy	Example Application
					processes; decision theory			
Public libraries/ literacy	Location/service design	Government	Region, neighborhood; strategic/ tactical/ operational	Social cost, physical access	Location-allocation, scheduling	Moderate	Low	Mandell (1991)
Undesirable facility location	Waste dumps, power plants, human services	Government, NGO	Region, neighborhood; strategic/ tactical	Net social benefit, equity	Location-allocation, multi-criteria decision models	Moderate	High	Murray *et al.* (1998)
Emergency services	Location of fire, police and EMS stations; dispatching, routing and staffing	Government	Regional, neighborhood; strategic/ tactical/ operational	Total cost, lives saved, crime averted, equity	Location-allocation, queueing theory, decision theory, vehicle routing	High	High	Bodily (1978)

*NGO = "non-governmental organizations", e.g. community development organizations, social service agencies, churches the 2007 rankings of *U.S. News and World Report* (http://www.usnews.com/usnews/edu/) indicates that: within the top 25 undergraduate industrial engineering/operations research programs, none appear to offer courses that address community-based OR; within the top 10 graduate industrial engineering/operations research programs, only one offers one or more courses whose content includes community-based OR. Within the top 25 undergraduate business programs, only one appears to offer one or more courses that address community-based OR; a similar result holds for the top 25 graduate programs in business. Finally, within the top 25 graduate programs in public affairs, only three offer courses with significant OR/MS content, and of these only one school's OR/MS course offerings appear to address community-based OR.

We acknowledge that much important work in OR/MS that intersects community-based OR is done outside of business schools, departments of industrial engineering and unpublished, or published in non-OR/MS flagship journals. For example, *pro bono* OR consulting and applications, as advocated by Woolsey (1998) and McCardle (2005), often address problems of interest to public-sector organizations. However, we believe that a greater emphasis on community-based OR in education, research and practice may increase the professional returns to those who work in this area. We make specific suggestions in this regard in the final section.

2 Literature Review

In the years since the Parry and Mingers (1991) survey of community OR, a number of papers have appeared that address the authors' concerns. In the review that follows, we focus on studies in OR/MS and related fields that address analytic methods, public or nonprofit management, localized needs, equity concerns or disadvantaged/underserved populations with a bias towards model-based prescriptions.

2.1 Analytic Methods

2.1.1 Quantitative methods

We know of no conventional quantitative modeling methods from OR/MS that cannot be applied to community-based OR problems. We draw attention particularly to Erlenkotter's (1977) examination of an extension of the uncapacitated fixed-charge facility location models to account for price-sensitive demands. He shows that a conventional private-sector objective of profit maximization is equivalent to marginal-cost pricing, while a public-sector objective of total social benefit maximization yields revenues that do not cover total costs. A 'quasi-public' variant of this problem ensures non-negative profits. This analysis reinforces our emphasis on community-based OR models that optimize measures of equity that may balance less desirable social net benefit measures.

2.1.2 Qualitative methods

Qualitative methods provide a valuable complement to traditional approaches. UK-style community OR draws heavily from methods such as 'soft systems methodology' (see e.g. Checkland 1987) that focus on systems analysis and qualitative methods for learning *about* the problem. Community-based OR, in addition, accommodates methods such as 'value-focused thinking' (Keeney 1992) that assists modelers in formulating decision problems that are closely-aligned with stakeholder values and amenable to analytical methods that yield specific prescriptions.

2.2 Human Services

2.2.1 Senior services

Bartholdi et al. (1983) develop a heuristic vehicle routing strategy for home-delivered meals (HDM, aka "Meals on Wheels") that can be implemented easily by the resource-constrained organization using earlier work on space-filling curves. Wong and Meyer (1993) use geographic information systems (GIS) to locate HDM kitchens and design delivery routes to minimize total travel distance. Gorr, Johnson and Roehrig (2001) develop an interactive, optimization-based spatial decision support system (SDSS) for HDM kitchen location, catchment area design and vehicle routing for the needs of nonprofit managers seeking incremental or dramatic changes to service strategies. Johnson, Gorr and Roehig (2005) design and implement hierarchical facility location models to locate facilities that provide daytime congregate services to senior citizens that address, respectively, minimizing distance-based costs and maximizing utility using current local data on senior centers and demands for services.

2.2.2 Humanitarian logistics

Haghani and Oh (1996) consider operational transportation problems for a fixed distribution network and develop a model of the distribution process. Jia, Ordonez and Dessouky (2007) introduce network design models for large-scale emergency medical service in response to terrorist attacks. Balcik and Beamon (2005) study distribution network design for relief chains managed by non-governmental organizations. Campbell, Vandenbussche and Hermann (2008) explore various objective functions for the local distribution of supplies after a disaster. To ensure equity and efficiency, two objectives are considered: minimizing the maximum arrival of supplies and minimizing the average arrival of supplies. Beamon and Kotleba (2006) design a stochastic inventory control model that determines optimal order quantities and reorder points for a long-term emergency relief response.

2.2.3 Public libraries and literacy

Mandell (1991) presents multiple models of equity and effectiveness, and applies them to the problem of book acquisition for public libraries. Francis *et al.* (2006) develop models to assist a large suburban library system to manage its vehicle fleet and optimize operations under budget constraints. The objective function balances travel time incurred by the delivery agency and the service benefit to the libraries served. A similar, smaller interlibrary loan system in Ohio, studied in Min (1989), differs from the current example in that all libraries are visited daily.

2.2.4 Public education

Thanassoulis and Dunstan (1994) shows how data envelopment analysis (DEA) can be used to guide secondary schools to improved performance through role-model identification and target setting in a way that recognizes the multi-outcome nature of the education process and reflects the relative desirability of improving individual outcomes. The approach presented in the paper draws from a DEA-based assessment of the schools of a local education authority carried out by the authors. Mar Molinero (1988) develops recommendations for school closures in a region with declining school-age population using techniques to measure the similarity of school catchment areas that are input to a multidimensional scaling analysis that identifies socio-economic characteristics of these areas. Recommendations to close high-cost, low-performing schools that serve most-disadvantaged regions are contrasted with political opposition from local communities that seek to preserve local educational opportunities. Bowerman (1995) formulates a multi-objective model for urban school bus routing that addresses efficiency and equity jointly, and develops a two-phase approach combining student clustering and route generation. Taylor, Vasu and Causby (1999) describe forecasting models for school attendance and optimization models for public school locations and attendance boundaries which reflect detailed knowledge of school administrators, elected representatives and planners. These models address the need for racial balance across schools to minimize the need for busing, and have increased the confidence of community stakeholders in the school planning process, as measured by decreased political opposition to siting plans and increased passage rate of funding referenda.

2.3 Community Development

2.3.1 Housing

Kaplan (1986), Kaplan and Amir (1987) and Kaplan and Berman (1988) formulate and solve math programs related to production scheduling problems to design policies for relocating families in public housing communities undergoing renovations to minimize total development time while ensuring that as few families as possible are displaced from public housing into private markets. Kaplan (1987) uses queuing theory to evaluate the impacts of race-based versus non-race-based tenant assignment policies in public housing on levels of racial segregation and waiting times for available units. Forgionne (1996) describes a decision support system for assessing the army's needs for on-base new construction or off-base leased housing, determined in part by estimates of the level of off-base affordable housing available to its personnel.

Johnson and Hurter (2000) generate alternative potential allocations of households using rental vouchers to Census tracts across a county to jointly optimize measures of net social benefit and equity, subject to constraints on programmatic and political feasibility. Estimates of dollar-valued impacts of subsidized housing are derived from models adapted from housing economics that use observations of actual households. Johnson (2007a) solves a multiobjective model for location of project-based affordable renter- and owner-occupied housing to optimize social efficiency and equity measures. Objective functions and structural parameter values are derived from discussions with nonprofit housing providers. Johnson (2007b) estimates structural parameters for math programming-based models for affordable housing design using microeconomic models of the firm and of the consumer, and statistical methods such as forecasting and factor analysis. Observations of housing units, households and housing projects are provided by community-based non-profit housing developers.

Johnson (2005) presents a Web-accessible prototype of a SDSS for individual housing mobility counseling using multiple decision models and reflecting the needs of housing clients, counselors and landlords. Johnson (2006b) provides a research framework for a professional-quality housing counseling SDSS and provides evidence derived from field research that typical subsidized housing program participants can make productive use of quantitative decision models. Both of these papers are discussed in greater detail in Section III.

2.3.2 Community/urban planning

Norman and Norman (2001) evaluate case studies of public art installations in Japan and the UK to support the concept of centralized, model-based decisionmaking in the provision of public amenities. Patz, Spitzner and Tammer (2002) develop decision models to design land use strategies in a European context, allowing especially for existing historic buildings and districts. Jung *et al.* (2007)

develop a planning model for post-disaster reconstruction planning in urban areas inspired by Hurricane Katrina which struck the U.S. Gulf Coast in 2005. In this model, small neighborhoods are aggregated into districts that share the same land-use designation (e.g. human use or passive use) in order jointly optimize measures of environmental protection, social impacts and spatial integrity.

2.3.3 Transportation

Vlahos, Khattak, Manheim and Kanafani (1994) develop a framework for computer-aided transportation planning that accommodates multiple, possibly antagonistic, stakeholders for the purposes of presentation, analysis and judgment. A case study of this methodology emphasizes how community-based participants can collaborate with government and elected officials in developing a controversial transportation strategy. Murray and Davis (2001) use community-level data on socio-economic status, public transport access and public transport need to determine differential impacts on communities of alternative public transit investments.

2.4 Public health and safety

2.4.1 Public health

Kaplan (1995) estimates changes in HIV infection rates associated with an experimental needle exchange program using maximum likelihood change point models and continuous-time Markov processes. Both models are estimated using observations of the HIV status of used needles provided by injection drug users. Aaby *et al.* (2006) present models to improve pre-contagion planning for clinics that dispense medications and vaccines using discrete-event simulations, queuing models and capacity planning models. Griffin, Sherrer and Swann (2006, 2008) have developed a decision model based on the maximum covering facility location problem to identify centroids of U.S. counties at which community health centers may be sited in order to maximize the weighted demand for CHC services, subject to constraints on funds available for fixed and variable costs and facility capacities. Their model qualifies as "community-based" in two ways: first, the care with which they have analyzed available health care data to impute localized measures of health services demand, especially for medically underserved populations, and second, evidence provided that recommendations are fairly insensitive to smaller spatial units of analysis such as Census tracts. They find significant improvements in a variety of performance measures, including total encounters, cost per encounter and number of uninsured persons served.

Models to address food insecurity include Chou, Teo and Zheng (2005) and Lien, Iravani, and Smilowitz (2007). Chou, Teo and Zheng study a bread delivery problem where unsold bread from bakeries is delivered by volunteers to needy families. In their problem, demands are fixed and supply is random. They show how incorporating flexibility, meaning allowing volunteers to deliver to multiple families, can reduce the amount of wasted bread. Lien, Iravani, and Smilowitz develop mathematical models and solution methods for perishable food distribution from donors to agencies that address that address vehicle routing problems (assigning donors and agencies to routes and sequencing stops within each route) and inventory allocation problems (determining the amount to distribute to each agency). In contrast to cost-minimizing objectives, which can lead to inequitable solutions, a novel service-based maximin fill-rate objective incorporates fairness and agency sustainability, though at the cost of more complex modeling and solution techniques. This latter paper is discussed in greater detail in Section III.

2.4.2 Criminal justice

Brown and Liu (2003) develop crime forecasts to support tactical operations, in particular the presence and intensity of local 'hot spots' using a multivariate prediction model that relates the features in an area to the predicted occurrence of crimes through the preference structure of criminals. Xu and Chen (2004) use link analysis techniques based on shortest-path algorithms to identify networks of offenders in areas such as narcotics violation, terrorism, and kidnapping and find differing levels of effectiveness depending on the shortest-path search strategy. Johnson (2006) develops decision models to select sites for community corrections centers using multiobjective math programming and multicriteria decision analysis. These models reflect field research with stakeholders and propose siting strategies that account for neighborhood-level amenities that may be associated with successful re-entry to civilian life as well as concerns regarding potential re-offending. Blumstein (2007) offers a comprehensive review of OR/MS applications to law enforcement and criminology, focused on policy modeling but reflecting close examination of community-level dynamics that motivate more stylized analytical approaches.

2.4.3 Emergency services

The literature on fire and emergency medical services provision is extensive and long-lived; Swersey (1994) provides a comprehensive review. Models for location of emergency services facilities (e.g. Walker 1974, Marianov and ReVelle 1991, Hogan and ReVelle 1986), and end-user applications (RAND Fire Project 1979) though innovative in applying set covering models, maximum covering models and backup coverage models, typically do not address community-level or equity issues explicitly. However, Schilling *et al.* (1979) formulated a multiple-objective maximum-covering-based model for fire station location that balances population coverage, property value coverage and area coverage, i.e. the equity/efficiency/effectiveness objectives defined as key to community-based OR applications. The police sector design problem, in which a study area is partitioned into regions with equal service characteristics, has been dominated by queuing models such as the Larson's (1974, 1975) hypercube model. Bodily (1978) applied multi-attribute utility theory to the hypercube model to incorporate preferences of citizens interested in service equity, police officers interested in workload equalization, and administrators interested in system efficiency.

2.4.4 Hazardous/undesirable facilities

The process by which undesirable, obnoxious or hazardous facilities are located, and prescriptive models for doing so, contain elements of commonality with community-based OR. Kleindorfer and Kunreuther (1994) provide a comprehensive overview of this domain and describe a detailed process for facility siting that incorporates community concerns. Gregory *et al.* (1991) present policies by which community stakeholders can be fairly compensated for accepting location of undesirable facilities.

There are a variety of mathematical programming-based models for hazardous facility siting in which local community concerns and equity objectives are central. Ratick and White (1988) formulate a model that balance measures of facility location costs, political opposition as a function of the population within a risk radius of a facility, and equity, an increasing function of the number of communities perceived by any particular community as bearing equivalent risks associated with proximity to a facility. Erkut and Newman (1992) extend the scale opposition factor within the model of Ratick and White by representing equity as a continuous (rather than discrete) function that increases in the distance between population centers, as well as decreasing in facility size. Murray, *et al.* (1998) choose locations for undesirable facilities to maximize the total population that is outside the 'impact radius' of sited facilities, or, in a variant, maximize the total weighted population that is within the impact radius of at most one facility.

Merkhofer and Keeney (1987) use decision theory to choose sites for a nuclear waste repository while addressing community concerns, while Erkut and Moran (1991) apply Analytic Hierarchy Process for location of municipal landfills, addressing explicitly a wide range of community-level factors that influence final rankings.

2.5 Nonprofit Management

Baker Werth (2003) describes the development of a decision support division within a county human services agency to support strategic management and accountability services for local government. de Vericourt and Lobo (2009) model of a non-profit's decision to partake in for-profit activities. For-profit activities often generate future revenue for non-profit work at the expense of current resources. They show that under certain conditions the optimal investment decision in for-profit activities is of threshold type.

2.6 Lessons Learned

The past 15 years has seen a significant growth in research that is consistent with our definition of "community-based operations research". Increasingly, OR/MS researchers are aware of the need to incorporate socio-economic and political concerns directly into their planning models, rather than assert, as Gregg and Mulvey (1988) do in a stochastic programming model of facility location applied to library closings, that "political factors can be incorporated by means of user intervention (p. 90)." The models discussed in this section also reflect a desire to apply detailed understanding of stakeholder needs to quantitative models which can yield actionable, policy-relevant prescriptions. These efforts stand in contrast to some research outputs associated with UK-style "community operational research" and early US efforts in this domain that focused more on community engagement and community efficacy. Finally, many of the models discussed in this section cross disciplinary boundaries, for example adapting models from other domains for purposes of decisionmaking, or using research evidence outside of OR/MS to justify model-building efforts. However, more needs to be done to ensure that novel and innovative community-focused planning models are implemented in the field and their impacts on stakeholder groups evaluated rigorously. In this sense, the record of real-world impacts represented by models of the type presented in Larson and Odoni's *Urban Operations Research* (1981) serve as a benchmark for community-based OR.

3 Applications

3.1 Food Security

In 2005, thirty-six million Americans suffered from hunger (U.S. Department of Agriculture 2005). Twenty-five million of these Americans rely on America's Second Harvest (ASH) and their network of pantries, shelters and soup kitchens for food (America's Second Harvest 2005). The largest suppliers to these agencies are regional and local food banks. Food banks are large-scale distribution centers which collect, store and distribute food. Much of this food is donated by various sources of surplus food (e.g., supermarkets and grocery chains). According to the U.S. Department of Agriculture (1997), about 96 billion pounds of food are wasted each year in the United States. The goal of American's Second Harvest and the agencies in their network is to match surplus food with those in need. This matching is a large-scale distribution and inventory management problem that occurs each day at thousands of non-profit agencies across the country. Much research has been conducted on related supply chain problems in commercial settings where the goal of such systems is either to maximize profit or minimize cost. Little work, however, has been conducted in non-profit applications. In such

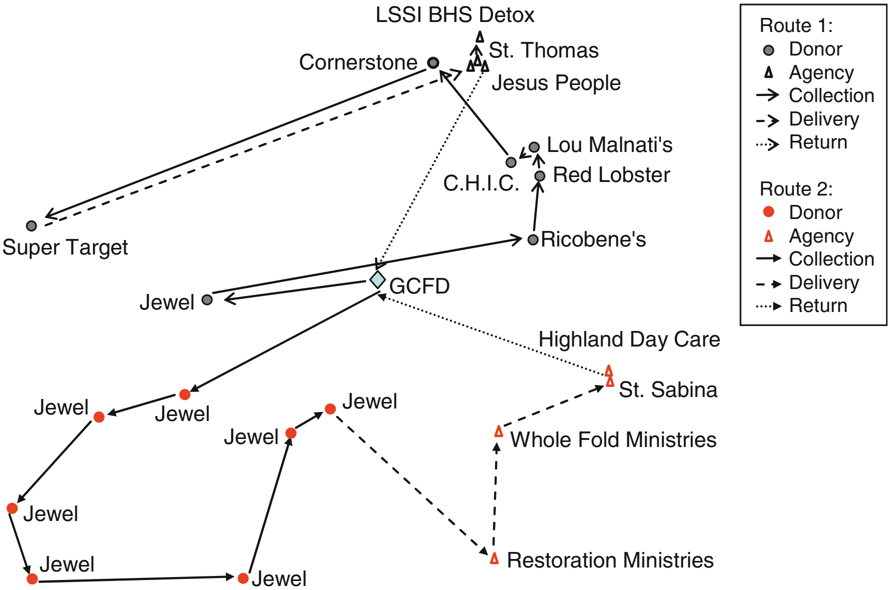

Fig. 2.1 Food Rescue Program Sample Routes

settings, the objectives are often more difficult to quantify since issues such as equity and sustainability must be considered, yet efficient operations are still crucial.

The Greater Chicago Food Depository (GCFD) is an active ASH member. According to a recent study by the GCFD and ASH (2005), 500,000 people in the Chicago region are served by the GCFD each year. One program run by the GCFD is the Food Rescue Program (FRP), which distributes perishable food from donors (e.g. supermarkets and restaurants) to agencies (e.g. shelters and soup kitchens). Over 80 donors and 100 agencies participate in the FRP, which moves over 4 million pounds of food annually.

The FRP operates 5 truck routes, each visiting between 3 and 17 donors and between 2 and 11 agencies daily. Two sample routes are shown in Figure 2.1. Routes begin at the depot, collect food from the donors, and distribute donations to the agencies. The frequency of visits to a location over the course of a month depends on the supply of the donor and the need of the agency. Routes are scheduled weeks in advance and remain fairly regular to facilitate driver familiarity with the routes they perform. Donation amounts and food demand are unknown until observed upon the driver's arrival. The donation amounts depend on daily sales at the donor location; food demands depend on available storage and budget at the agencies. Drivers collect the full donation available at a donor. The allocation of food to agencies is left to the discretion of the driver who tries to satisfy an agency's demand while reserving supply for the remaining agencies on the route. Agencies are charged 4 cents per pound of food and view the FRP as a supplement to their main food acquisition operations.

Ongoing work (Lien, Iravani, and Smilowitz 2007) has focused on the design of inventory and routing policies for the FRP. The aim of this project is to develop mathematical models and solution methods for related vehicle routing problems (assigning donors and agencies to routes and sequencing stops within each route) and inventory allocation problems (determining the amount to distribute to each agency). In the private sector, related sequential inventory allocation decisions are often made to either maximize revenue or minimize costs. Although cost-efficient operations remain desirable in the non-profit sector, focusing purely on cost can lead to inequitable solutions. The GCFD seeks to provide all agencies with adequate resources in an equitable manner. The paper proposes an alternative service-based objective function (maximizing the minimum expected fill rate) that incorporates fairness and agency sustainability.

The use of an alternative objective function has important implications on the solution methods used to determine routing and inventory allocation policies. The authors find that the useful mathematical properties of commercial distribution problems with profit maximizing or cost minimizing objectives (e.g., as in the multi-period newsvendor problem) do not hold with the service-based objectives. As a result, new solution methods must be developed. The paper also proposes simple routing and inventory allocation policies that perform well relative to more computer-intensive methods.

3.2 Affordable/Subsidized Housing

As of 2000, about 10 percent of the poor population in the U.S. lives in high-poverty neighborhoods (Census tracts with poverty rates of 40% or greater). An overall decrease in concentrated poverty between 1990 and 2000 has been accompanied by stagnant or increasing levels of poverty concentration in the Northeast and West regions of the U.S., and increasing numbers of poor families living in communities far away from the centers of America's cities (Joint Center for Housing Studies of Harvard University 2006). Housing mobility, i.e. relocation of low-income families from distressed communities to more affluent, opportunity-rich communities, has been one goal of affordable and subsidized housing policy.

The Moving to Opportunity Program for Fair Housing (MTO), a national demonstration intended to evaluate outcomes of housing mobility program participants, offers the possibility of significant improvements in living conditions and life outcomes for very low-income families who relocate using subsidies from the Housing Choice Voucher Program (HCVP). Over 6,000 families have participated in the experiment to date. Such areas for improvements in life outcomes include: risk of criminal victimization, housing quality and mental health (U.S. Department of Housing and Urban Development 2003). MTO and HCVP is the inspiration for development of a prototype spatial decision support system (SDSS) for housing mobility counseling that might enable programs like MTO to be implemented on a large scale. This SDSS, called the Pittsburgh Housing

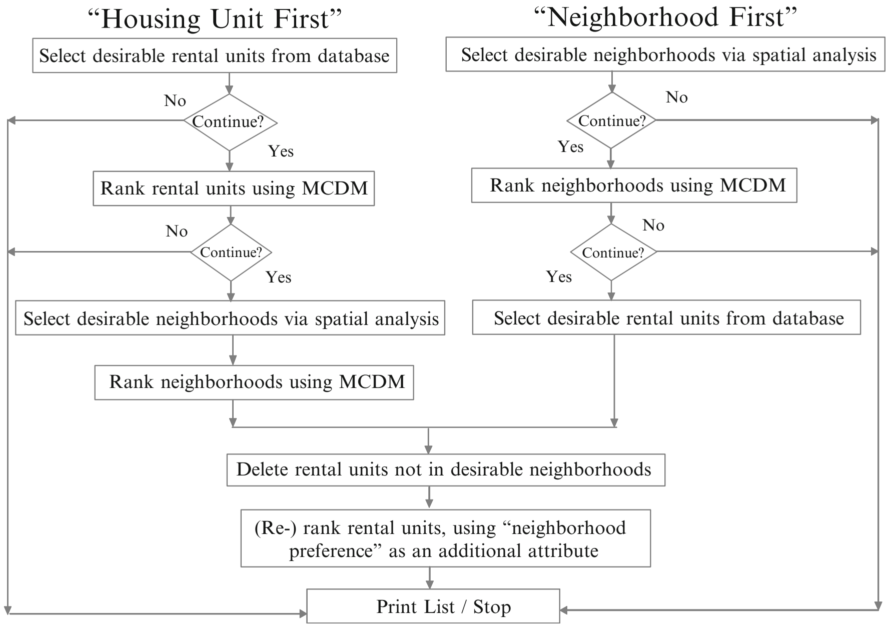

Fig. 2.2 Counseling Support System Destination Search Algorithm

eCounselor (www.housing-ecounselor.org) (Johnson 2005) is intended to assist housing counselors, clients and landlords in connecting low-income families to good-quality housing in opportunity-rich neighborhoods.

This research confronts a number of gaps in current knowledge. First, there is little research on the actual decision-making process by which housing mobility program participants (or HCVP clients) search for housing. Second, the extent to which PHAs and other housing service agencies can assist creative decision-making by clients who may face multiple life challenges is limited by a lack of technical knowledge on IT-assisted decisionmaking and the necessary IT infrastructure. Last, little is known about the ability of low-income families to frame and solve difficult problems using decision models and IT.

The Pittsburgh Housing eCounselor guides users through the process of identifying candidate housing units and neighborhoods, and ranking these candidate sites with two alternative multi-criteria decision models (MCDM). The eCounselor uses Keeney's (1992) value-focused thinking method to enable clients and counselors together to identify characteristics of housing units and neighborhoods that are important to the client and generate a subset of housing units and/or neighborhoods based on user-defined criteria. This process is represented by Figure 2.2, in which users start the search by identifying candidate neighborhoods or, alternatively, candidate housing units, through appropriate queries and rank candidate destinations using MCDM. Given these candidates for relocation, users choose acceptable housing units or, alternatively, neighborhoods,

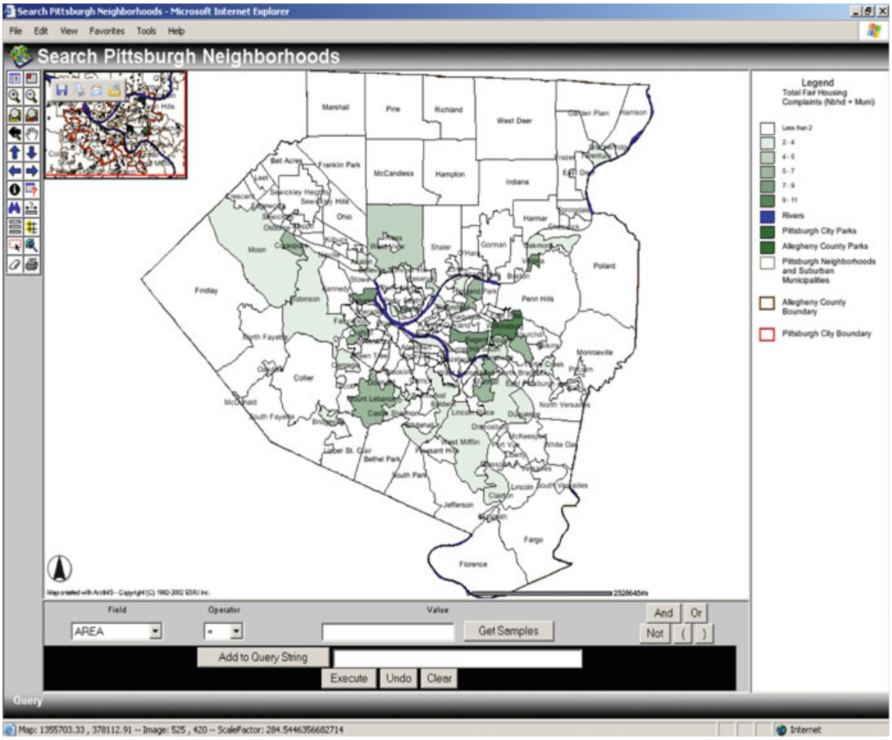

Fig. 2.3 Search Pittsburgh Neighborhoods - Fair Housing Complaints

thus creating a set of acceptable housing units in acceptable neighborhoods suitable for site visits.

Neighborhood characteristics are represented with spatial data describing demographic, employment and housing characteristics of Allegheny County, PA and displayed in a Web browser. Figure 2.3 shows an example of this spatial data display, for fair housing complaints in Allegheny County.

Housing unit characteristics are represented with tabular data describing actual housing units available for rent in the city of Pittsburgh and displayed in a Web browser similarly.

Neighborhoods or housing units can be ranked using one of two MCDMs: elimination by aspects (i.e. simple sort), in which users rank candidates in ascending order according to attribute values, or PROMETHEE (Brans and Vincke 1985), in which users specify the form of preference functions that measure the extent of a users' preference for one alternative over another with respect to the difference in performance of any pair of alternatives according to a single attribute. For example, a user could specify an increasing preference for one alternative over another as a linear function of the difference in crime rates of two neighborhoods.

The SDSS project has motivated subsequent field research to better understand the ability of typical clients to make use of various MCDMs (Johnson 2006b). A sample of eight housing voucher clients of a local public housing authority used a custom application to rank hypothetical neighborhoods using three MCDMs: simple additive weighting using rank sum weights (Malczewski 1999, p. 199), Analytic Hierarchy Process (AHP; Saaty 1990) and PROMETHEE. We found that representative assisted housing clients appear to appreciate the increased insight provided by more analytically-demanding MCDMs such as PROMETHEE, and that neighborhood rankings were largely dissimilar across the three MCDMs. Thus, this research is supportive of the notion of model-based decision methods as a tool for improving housing counseling, and provides suggestive evidence that a range of MCDMs may allow clients to choose the application that is best-suited to their skills and preferences.

3.3 Discussion

These case studies have demonstrated the potential of diverse methods in OR/MS to address important problems of a local nature whose solutions may provide direct benefits to traditionally underserved or underrepresented populations. Equity is addressed in the food distribution application through an objective function that accommodates the needs of as many food pantries as possible; the housing relocation SDSS incorporates equity by allowing clients themselves to define criteria and alternatives consistent with their own preferences, while enlarging their choice sets to the greatest extent possible. Though the two applications are inspired by region-specific policy problems, the solution methods may be applied to many other regions. Finally, both applications reflect a concern with the ability of local organizations to implement the models' recommendations: the food distribution model uses heuristic solution methods and the housing relocation DSS has a user interface that guides clients' interactions with decision models.

4 Conclusion

In this chapter we have described a subfield of public-sector OR called "community-based operations research" that addresses topics of interest to researchers and practitioners for over 30 years and known to different audiences in the US and UK under a variety of names. Common in our definition of community-based OR is a localized focus, a high degree of ambiguity, complexity and controversy, and an emphasis on stakeholder groups that are traditionally under-represented or under-served by social and political systems of interest to the modeler. Also, we emphasize the need for modelers to combine a focus on inclusion of individual actors and community-based organizations in defining and solving the problem (the traditional focus of UK-style "community OR") with an emphasis on quantitative models that generate actionable and policy-relevant recommendations. We have provided case studies in food security and affordable/subsidized housing that are consistent with the various components of the definition above.

Based on our review of the research literature and resources within higher education, we believe there is an opportunity to increase the influence of community-based OR upon education, scholarship and practice. Most importantly, we advocate an increase in the number of courses in undergraduate and graduate programs in business administration, industrial engineering/ operations research, and public affairs that address special characteristics of nonprofit and government organizations and the decision problems they face. These courses should not be limited to project or capstone courses that have nonprofit organizations as clients, but theory-based lecture courses as well. These courses should provide: greater emphasis on cross-disciplinary evidence to support OR/MS modeling, multidisciplinary solution approaches that emphasize less complex and/or qualitative solution methods, field research to generate realistic problem instances, and low-cost IT platforms for model and service delivery. Such courses could leverage the considerable teaching resources associated with spreadsheet-based management science rather than specialized mathematical modeling applications.

Also, we recommend that professional societies increase the returns to community-based OR research and practice. This could be done by encouraging workshops and conference sessions devoted to community-based OR, greater awareness within the profession of public policy/equity implications of models and applications, more support for cross-disciplinary research that provides an evidentiary basis for community-based OR models, and increased emphasis on international public-sector applications of community-based OR.

There are many potential application areas for community-based OR. These include: location of businesses and services in low-income, especially urban and predominately minority communities, such as financial services for the unbanked; decision support systems for system-level redesign for mass transit, public schools and senior services and community revitalization through re-use of vacant lots and abandoned buildings. Finally, given the ubiquity of the Internet, and recent decreases in the 'digital divide' across race, ethnic and income categories, there are opportunities for community-focused individual decision applications that use the Web as a facilitator. Examples of these applications include identifying health and financial impacts of alternative food purchase strategies, especially for low-income families, behavior change for energy reduction, and matching needs and locations of low- and moderate-income families seeking family support services with service providers.

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Chapter 3
Operations Management in Community-Based Nonprofit Organizations

Natalie A. Privett

1 Introduction

Nonprofit organizations are a vital and integral part of our society, affecting individual lives and serving as both a social and economic force in communities of every shape and size. Such institutions are so pervasive, in fact, that most people interact with at least one nonprofit organization on a daily basis. Whether national or local in their structure, addressing the needs of underrepresented, underserved, and vulnerable populations at a local level is the central goal of many charitable nonprofit organizations. As such, the intersection of operations research and nonprofit organizations is certainly relevant in the domain of community-based operations research (Johnson & Smilowitz, 2007). This chapter explores this intersection by dissecting a high-level nonprofit supply chain. As the supply-side (inputs), production, and demand-side (consumers, beneficiaries, etc.) are uncoupled, we review relevant operations research and nonprofit studies literature and identify potential future research in each area. The current state of operations research and management science scholarship in this intersection is still young. Thus, this chapter emphasizes and encourages academic inquiry in operations research in nonprofit organizations as key in furthering community-based operations research.

The Internal Revenue Service defines nonprofit organizations via exemptions to taxes on revenues on over 27 categories of trusts and corporations in Section 501 of the United States Internal Revenue Code. This code further specifies "charitable" organizations within section 501(c)(3). In order to qualify for 501(c)(3) status, an organization must have a "charitable" purpose, cannot be political, and cannot benefit private shareholders or individuals.

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Nonprofits provide social, leadership, and expressive opportunities, thereby influencing the depth and connectedness of communities (Frumkin, 2006). Their associational properties give even underrepresented community populations a voice and help individuals shape community policies and directions. Furthermore, these organizations provide services to underserved and vulnerable individuals who would otherwise not receive them, in many cases partnering with the government and/or corporations. Nonprofits also provide public goods for which no individual directly pays but from which all can reap benefits. All in all, a huge variety of nonprofits provide goods and services that benefit community members either directly or indirectly.

Beyond these contributions, the nonprofit sector's economic impact should not be underestimated, especially at local levels. In 2009, the IRS registered a growing number of 1.5 million nonprofits, which reported $1.4 billion in revenue and held $2.6 billion in assets. In 2008, the output of nonprofits serving households generated 5% of the 2008 United States gross domestic product, and, in terms of employment, it was estimated that 10% of the United States workforce is employed in the sector (Sherlock & Gravelle, 2009). Within bounded communities, these economic contributions are even more consequential. For example, Michigan cites the nonprofit sector as critical to the state's future, where 47,000 nonprofits generate $108 million of economic activity annually (Public Sector Consultants, 2009).

Managing and operating community-based nonprofits efficiently and effectively is necessary in addressing localized problems, especially those issues facing underrepresented, underserved, and vulnerable populations. As such, operations research in community-based nonprofit organizations is a natural extension of community-based operations research – one that offers a wealth of opportunity to researchers, practitioners, and the sector alike. Operations management has not traditionally been applied to the nonprofit sector, especially outside of the humanitarian/disaster relief area. However, this intersection creates valuable opportunities where similarities and differences between the for-profit and nonprofit sectors can be leveraged for both scientific and operational advances in both sectors. Similarities between community-based nonprofits and operations research traditional for-profit settings can be leveraged to create innovative models with new impact, even at the local level. Yet the notable differences indicate complexities far beyond simply adapting traditional for-profit solutions and, thus, result in provocative research questions. As such, the nonprofit sector presents operations research and management with an unfamiliar and fertile new frontier for research.

This chapter is organized from an operations supply chain perspective as illustrated in Fig. 3.1; that is, topics are organized according to supply, production, and consumers. First, the supply-side or inputs of community-based nonprofits will be examined; fundraising, earned income (profits), and foundations will be surveyed in Sect. 2. Next, nonprofit production and activity, specifically the topics of objectives, centralization and organizational form, and productivity, will be explored in Sect. 3. Finally, Sect. 4 addresses consumer-side outputs and outcomes through examination of competition, collaboration, and performance measurement and evaluation. Nonprofit organizations vary on many dimensions, such as mission,

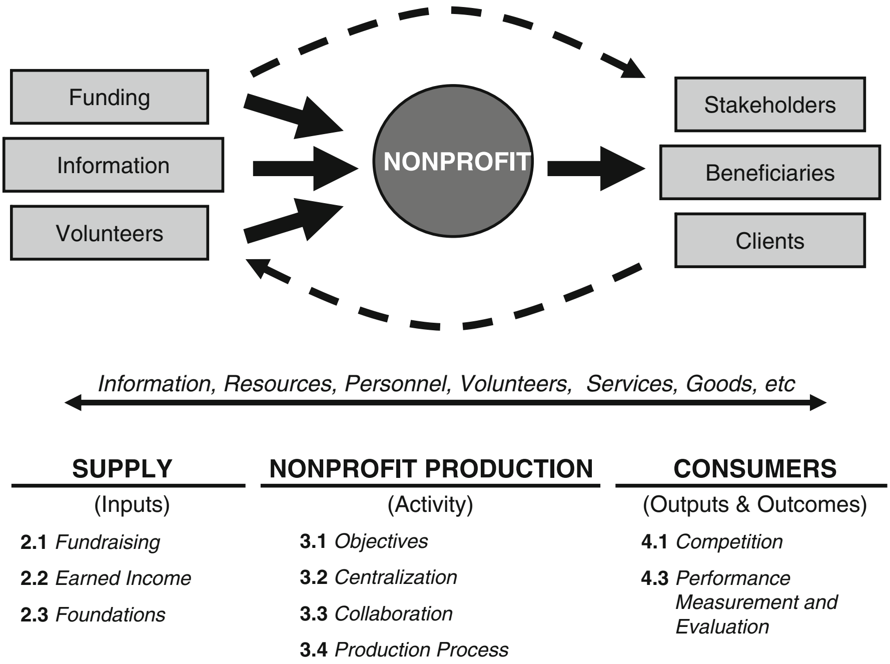

Fig. 3.1 Nonprofit operations and chapter organization

size, and revenue mix; hence, the relevance and challenges of operations research will vary across this diverse sector. Accordingly, this chapter will be more suitable for certain areas of the sector (e.g., service delivery and foundations), though the full range of nonprofit expression is certainly invaluable.

Fundraising Tiers

McCardle, Rajaram, and Tang use a utility-based donor model to analyze the behavior of nonprofit donations in the presence of publicized tiered fundraising structures (McCardle, Rajaram, & Tang, 2009), which they show can generate larger donations. Building upon their model, the authors develop an Excel-based decision analysis tool combining their theoretical findings with nonprofit experience, which empowers nonprofits to utilize scenario analysis to select their best fundraising tiers. The authors provide an illustrative example using publicly available data from St. Mark's High School in Wilmington, Delaware, a private Catholic school. In this example, the authors estimate model parameters and demonstrate how the model can be used to perform scenario analysis and evaluate different tier settings. The authors use their model to compare the nine tiers implemented by St. Mark's to the case of no tiers, and estimate the nine-tier structure increased donations

(continued)

(continued)

by $13,000. This work is an example of academic rigor and theoretic modeling blended with practice-based utility and function.

2 Supply-Side Challenges

Nonprofit supply is characterized by competition and uncertainty. As funding is often viewed as the most critical nonprofit input, this section discusses operations research in the context of nonprofit fundraising and earning income (profits). It also looks at the funding process from the perspective of funders and grantmakers by examining fundraising competition and foundations.

2.1 Fundraising

Availability of resources is one of the most critical issues in the nonprofit sector. Nonprofits cannot raise capital by issuing stock. Loans to nonprofit organizations are not backed by shareholder investments, leading to a high cost of debt for nonprofits (Hansmann, 1980). Yet, outside of these traditional for-profit capital raising methods, nonprofits can garner donations, win grants, employ volunteers, charge fees, utilize bonds, and accrue investment earnings (Steinberg, 2006).

2.1.1 Individual Donations

Data from 2009 indicate that 75% of donations are from individuals The center on Philanthropy at Indiana University (2010). According to Hansmann, nonprofit contributions are essentially a form of voluntary price discrimination (Hansmann, 1980). For example, consider a local museum that may charge for admission and solicit donations. Such donations are a form of voluntary self-price discrimination whereby museum supporters contribute the value they place on the museum beyond standard admission fees. In areas where fixed costs account for a large fraction of total costs, such as performing arts, museums, and libraries, price discrimination can be the key to organization survival.

Nonprofit organizations relying (in part or in whole) on donations can employ strategy for fundraising from individual. Some examples include capital campaigns and fundraising tiers. Capital campaigns involve raising funds for a specific goal, typically a capital need such as a new building. These campaigns are usually multiple years in duration. Many organizations of varied size and mission implement fundraising tiers where donors are assigned a level based upon the amount of their donation. In fact, McCardle, Rajaram, and Tang show that such tiers can generate larger donations by using a utility-based donor model to analyze the behavior of nonprofit donations in the presence of publicized tiered fundraising structures (McCardle et al., 2009). These authors investigate an application of their model in a local high school as detailed in the inset. Innovative strategies for fundraising and analysis of current strategies (e.g., fundraising tiers) create interesting research problems where economic models of individual behavior can be analyzed and incorporated from an operations perspective. Furthermore, nonprofits must strike balance in their portfolio of strategies by balancing trade-offs. Such portfolio balance is discussed further in the context of foundations in Sect. 2.3.

2.1.2 Government Funding

According to Foster, Kim, and Christiansen, many local nonprofits work with government to "provide essential services, such as housing, human services, and education, for which the government has previously defined and allocated funding" (Foster et al., 2009, p. 36). This is especially true for nonprofit agencies that provide local services to underrepresented, underserved, and vulnerable populations. In 1995, Salamon noted the steadfast, reliable importance of government funding and that government income sources outdistanced "private charity by roughly two to one" (Salamon, 1995, p. 99). The specific types of nonprofit assistance provided by government include service contracts, in-kind donations, grants, and fees. Salamon's remark continues to be true. In 2008, government grants and fees accounted for 27.4% of reporting public charity revenue as compared to 10.4% contributed to private contributions (Wing et al., 2010). Service contracts with government are further discussed from a collaboration perspective in Sect. 3.3. Grants are touched on below and further discussed in Sect. 2.3.

2.1.3 Grants

Both governmental agencies and non-governmental foundations award grants, which are another significant source of funding for many nonprofit organizations. Grantmaking is discussed further in Sect. 2.3 of this chapter.

2.1.4 Fundraising Competition

In nonprofit fundraising, whether grant funding or individual donations, operations researchers may recognize the dynamics of supply-side competition. These dynamics exacerbate contention over the necessary income and arguably excessive expense associated with fundraising. Cordes and Rooney wonder if greater competition for donations actually increases the donation pool or merely redistributes it, the latter inducing nonprofit fundraising expenditures that may be individually rational but collectively wasteful (Cordes & Rooney, 2004). Considering the significant portion of nonprofits' resources being dedicated to raising and competing for funds, the issue of exactly how much social benefit is being lost in this competition is certainly critical, especially in geographically restricted areas where the resource pool is inherently bounded.

Operations researchers bring the skills and expertise to analyze such supply-side competition where nonprofits compete for a fixed pool of resources within communities. The areas of for-profit supply and capacity competition and centralized versus decentralized supply chains may provide a good base of understanding. In the nonprofit context, organizations compete for limited financial resources and capacity within a bounded community. Several operations research and management science authors model game theoretic, competitive capacity allocation problems (Cachon & Lariviere, 1999a; 1999b; Dewan & Mendelson, 1990; Hartman & Dror, 2005; Lippman & McCardle, 1997; Mallik & Harker, 2000). For example, Cachon and Larivere look at for-profit supply-side competition where retailers compete for scarce supplier capacity but not for customers (Cachon & Lariviere, 1999a; 1999b). The basic framework of this inquiry can be recast for nonprofits in that they serve different missions yet still compete for donations and grants in a bounded community. Thus, nonprofits serve as "retailers," funding as "capacity," and grantmakers or individual donors as "suppliers". However, one cannot underestimate the care and prudence that must be exercised as nonprofit models require more complexity and nuance than a simple change of characters. For example, in using the Cachon and Larivere model as a base, distinctive and diverse objective functions must be formulated for all parties, potentially including reputation, risk, and numerous stakeholder perspectives. Furthermore, the geographic boundaries of community-based fundraising present specific challenges, such as the tragedy of the commons, which is discussed further in Sect. 3.2 as it also pertains to allocation of resources.

Future analysis of such competition may change how the funding process is viewed and operated by those in the field and may help avoid social losses resulting from supply-side competition. If the social consequences of competition is found to be substantial, an exploration into mechanisms that may be imposed to prevent this competitive waste would be valuable to the sector and most importantly to those that it serves.

2.2 Earned Income

In light of such resource scarcity, nonprofit leaders constantly seek financial sustainability. Since the late 1990s, this search has resulted in a surge of commercialized nonprofit strategies aimed at making profit. Such enterprising endeavors, whether nonprofit run concession stands or fees for service, each carry with them the danger of moving an organization away from its central social mission. In fact, only 32% of profit seeking nonprofits surveyed did so for predominately mission-related reasons (Foster & Bradach, 2005). Where Foster and Bradach are skeptical, Dees contends that success is possible, and cites particular potential in earning income from intended beneficiaries and third party payers with a vested interest (Dees, 1998). The disagreement between these authors signals that many questions still loom regarding profits in nonprofits. This section discusses such questions in the context of management and decision making; however, such earned income also introduce competition between nonprofits and for-profits, as is discussed further in Sect. 4.1.

Many nonprofits use a business model that blends commerce and philanthropy, subsidizing charity services with fee services, such as nonprofit hospitals that use fees from paying and insured customers to provide charity care to the uninsured and underinsured. In such cases of nonprofits engaged in for-profit ventures as a means to fund their mission, de Vericourt and Lobo investigate a revenue management problem, namely how to allocate funds among revenue and mission customers (de Vericourt & Lobo, 2009). The organization's objective is to maximize its social benefit as measured by the number of mission-related customers served. The authors find a threshold policy optimal: Resources are allocated to serving revenue customers up to the threshold amount; resources above this threshold are used to serve mission customers.

Nonprofits engaged with third party payers with a vested interest (as opposed to beneficiaries) will need to create and maintain contracts. Contracts involving such vested parties may be unusual, involving payment for services that impact the third party in ways that may or may not be easy to quantify. Foster and Bradach state that "third parties cannot calculate with any precision the financial benefit they would receive, so structuring a deal that's attractive to them would be difficult" (Foster & Bradach, 2005, p. 6). Structuring contracting mechanisms for such multiple stakeholder situations where different parties consume and pay for the services/goods will require innovation. This presents an interesting research area, and, although it may be challenging to create a general model, more work in this area would be notable progress. Quantifying indirect benefits that third parties receive from nonprofits may also be of interest.

While nonprofits continue to find for-profit ventures tempting, researchers can bring more understanding to the conditions that create successful ventures and expose the associated trade-offs. Quantifying these trade-offs, even through simple break-even analysis, can provide valuable decision-making capability, helping nonprofits avoid being part of what Foster and Bradach believe to be the majority of nonprofit business ventures that are "ultimately wasting precious resources and leaving important social needs unmet" (Foster & Bradach, 2005, p. 2). With such disagreement over whether business ventures are a healthy direction for the sector, operations research can provide a valuable lens for analysis.

2.3 Foundations

Philanthropic foundations, themselves nonprofit organizations, are positioned between resources and causes, typically focused on specific impact areas. For example, the Gates Foundation focuses on the areas of global health, poverty, and education, while the Robert Wood Johnson Foundation concentrates exclusively on American health and healthcare. Community foundations are a particular foundational form concentrating on a bounded geographic community, such as, Silicon Valley Community and Communities Foundation of Texas, Inc. Community foundations raise money through localized public support, which also distinguishes them from other types of foundations. It is important to recognize the variety and types of foundations; see Council of Foundations, (2010) for further information on the different types of foundations.

Following years of noteworthy grantmaking growth, the current economic downturn has had considerable effects on foundations. For more than 75,000 US foundations, assets dropped an estimated 22% in 2008 (Lawrence, 2009). This 2008 financial shock combined with previous grantmaking growth resulted in a cumulative 3.9% decline in grantmaking over 2007, 2008, and 2009 (Lawrence, 2010), though foundations still made up 13% of US donations in 2009 (The center on Philanthropy at Indiana University 2010). While grantmaking continued its decline in 2010 (− 8.9%) (The center on Philanthropy at Indiana University 2010), the Foundation Center predicts modest growth in 2011 (Lawrence, 2010). As more than three quarters of foundation leaders agreed, the silver lining of this resource constriction is that the nonprofit sector will emerge more strategic (Lawrence, 2009), which presents new opportunities for operations researchers.

Foundations should be thought of as more than funding intermediaries, especially by operations researchers and managers. Instead, foundations can be thought of as portfolio and supply chain managers, though such language may be foreign to nonprofit practitioners as well as some social scientists. As portfolio managers, foundations seek to generate social change by managing a portfolio of grants and other activities, which may include nonprofits, businesses, or governmental programs. Figure 3.2 illustrates the mission and areas of support for the W.K. Kellogg Foundation (www.wkkf.org). Furthermore, Fig. 3.2 reveals the embedded supply chain of producing social change. The figure expounds upon the "healthy kids" focus area, which looks at food, health, and wellbeing, and describes a small sample of the associated funded initiatives. It is clear that such broad social change goals require a portfolio-based approach, even for a limited geographic area.

Foundations must consider the myriad factors that complicate their portfolio, including time, difficulty of measurement, and risk. Foundations must make tradeoffs in their choices of response. They may invest in prevention, mitigation, or relief, or they may choose postponement; appropriate consideration must be given to the consequences. Furthermore, social change may require long-term investment, making it difficult to measure progress. Another consideration is the nature of a foundation's finances or endowment, that is, whether the foundation's resources can be assumed in perpetuity or must be spent-down within a specific time frame. Social change is also much less tangible and its inherent risk and likelihood must be considered.

Foundations are often viewed as the venture capitalists of the nonprofit world in their grants since they are largely independent and endowed. As Raymond states, "where private enterprise must minimize risk to ensure return, and where government must beware of risk in its role as the guardian of the taxpayers' purse, foundations can seize risk" (Raymond, 2004, p. 53). Though they are largely

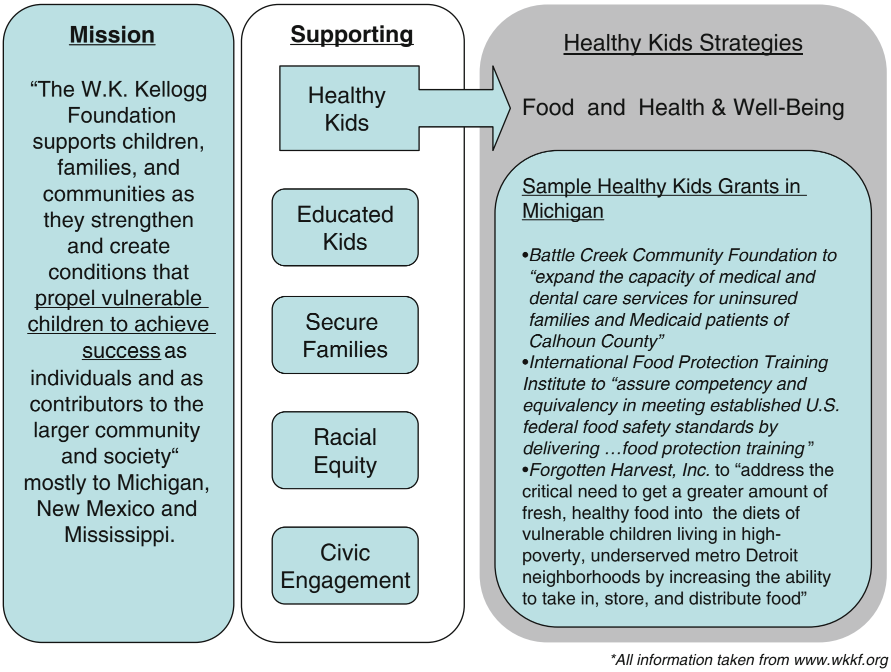

Fig. 3.2 Excerpt of W.K. Kellogg foundation strategy

considered risk averse in financial investment, foundations *can* be risk-takers in their grant portfolios. As such, they are likely to experience more failures – both social and financial – in their grant portfolio. Awareness of the possibility of failure in their investments will provide incentives for foundations to appropriately account for risk their funding portfolios.

Clearly, foundations' choices of investment are complex and multidimensional. Within portfolio management, financial institutions quantify risk and recognize its sources so that they can be managed and controlled. While prudence is appropriate in defining risk in such social change settings, risk modeling efforts can be worthwhile. This is because if the risk of a portfolio can be measured, then the main risk contributors can be identified, the portfolio can be reallocated accordingly, and, thus, potential loss can be minimized (Rachev et al., 2008). Fabozzi etal. outline the stages of a "robust quantitative investment framework," which are reframed for the foundation context below:

1. Robust Estimation: Reliable and robust estimations of parameters are necessary to minimize aggregated error in the final stage.
2. Robust Portfolio Allocation: Optimization frameworks and sensitivity analysis make this one of the most important parts of the process. How risk and return are defined must be carefully and thoughtfully considered, especially in regard to often intangible social returns.

3. Portfolio Rebalancing: While achieving socially effective asset allocation is critical, so is obtaining good and consistent performance. "Portfolio managers need to decide how to rebalance their portfolios efficiently to incorporate new views on expected returns and risk" as factors, such as policy or knowledge, change. It is this step that incorporates time dynamics, "successfully combining long-term and short-term views on the future direction and changes in the markets," even markets of social change (Fabozzi et al., 2007, p. 395).

While this framework may seem overly technical and idealized to nonprofit practitioners, portfolio management offers wide expertise on decision making under risk. However, its fundamental concepts must be challenged to incorporate the distinctions of social change (Fabozzi et al., 2007).

As foundation executives Brest and Harvey state, "Sometimes a philanthropist may have a project in mind that requires bringing together the capacities of several different actors. In these cases, you can think of the philanthropist as a combination of architect and general contractor, hiring disparate subcontractors... and coordinating their work to get the job done" (Brest & Harvey, 2008, p. 106). This metaphor of a nonprofit as a "seller" of services to a funder captures a lot about the funder-nonprofit relationship and lends naturally to viewing grant agreements as contracts (Brest & Harvey, 2008); funders have goals and contract with nonprofits to perform the activities necessary to, in part, achieve these goals. In a preliminary study, Privett & Erhun, (2010) model this contractual relationship, claiming that granting agencies such as foundations can more effectively allocate funds. These authors find that current grant methods are not efficient in themselves, but that auditing has the potential to increase grant allocation efficiency and utilities for both the funder and the non-profit population. The authors claim that auditing positions funders to initiate efficiency improvements for the sector overall. Further research in this vein could prove fruitful. For example, long-term or multiyear contracts are becoming increasingly common and the use of such contracts may provide incentives through future allocations. Issues such as commitment, renegotiation, and breach of contract will need to be considered when analyzing such contracts.

Viewing foundations as portfolio or supply chain managers lends naturally to exceptional applications of operations research. Whether foundations themselves are geographically-limited (e.g., community foundations) or not, foundations often include locally acting nonprofits in their portfolios. Foundation portfolio optimization and contracts are merely two examples of academically interesting and practically relevant problems drawing from for-profit theory with a social change perspective.

3 Production

Nonprofit organizations take supply inputs and transform them into a variety of goods, services, and expressions. Thus, production is still fundamental to nonprofit operations. This section discusses nonprofit objectives, centralization, collaboration, and production processes as they relate to the nonprofit production process.

Table 3.1 Example nonprofit objectives

Nonprofit objectives	Sample references
Quantity maximization	Privett and Erhun (2010), De Vericourt and Lobo (2009), Harrison and Lybecker (2005),Liu and Weinberg (2004)
Quality maximization	Harrison and Lybecker (2005)
Budget maximization	Steinberg (1986), Niskanen (1971),Tullock (1966)
Behavior change	Steinberg (2006)
Collective goods provision	Steinberg (2006)
Fundraising and donations	McCardle et al. (2009), Privett and Erhun (2010)
Effort minimization	Privett and Erhun (2010)
Social return maximization	Brest and Harvey (2008)
Failure risk minimization	Brest and Harvey (2008)

3.1 Objectives

At the most basic level, both for-profit and nonprofit organizations use inputs to produce goods and services; however, nonprofit objectives are much less straightforward as compared to a bottom-line profit. Unlike a for-profit corporation that distills the objectives of their shareholders, managers, employees, and clients into one quantifiable profit measure, nonprofit stakeholders and their interests vary considerably making organizational goals difficult to express and define clearly (Speckbacher, 2003). Hence, quantifying and modeling the objectives of a nonprofit organization can be ambiguous and contentious. Insights of theorists, modelers and practitioners must be incorporated into operations management models for the nonprofit sector. Example of nonprofit objective functions are listed in Table 3.1.

Organizations may have multiple, shared, or conflicting objectives (Steinberg, 1986; Weisbrod, 1998). Such multiplicity in objectives and stakeholders involves trade-offs. Accordingly, Speckbacher states, “The organization cannot realize all the desirable objectives of key stakeholders nor fulfill all of their implicit claims” (Speckbacher, 2003, p. 278). Instead, strategic philanthropy “calls for choosing whatever mix of approaches will best achieve your philanthropic objectives,” according to Brest and Harvey (2008, p. 11). However, Weisbrod (1998, p. 51) asserts that “there is no simple measure of the efficiency of the trade-offs being made among goals”.

Specifying such objective functions, especially within modeling contexts, may necessitate goal programing or multi objective optimization, both pertaining to the achievement of a collection of goals. (See Baum & Carlson, 1974; Ehrgott, 2005; Ignizio, 1978 for reviews.) Group ranking and multi-criteria decision modeling methods (e.g., Baucells & Sarin, 2003; Hochbaum & Levin, 2006; Klamroth & Miettinen, 2008) can also be leveraged to integrate and operationalize the numerous varied stakeholder objectives of nonprofit organizations. For instance, Tavana uses a multi-criteria decision model to evaluate and rank

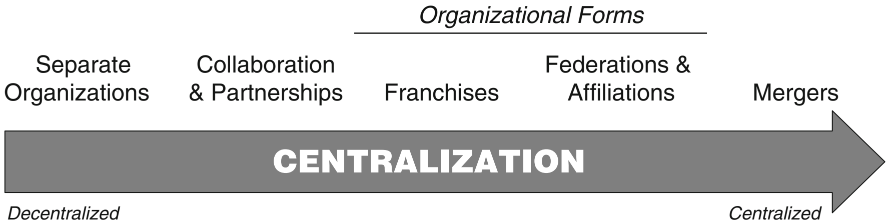

Fig. 3.3 Spectrum of centralization

projects at NASA and has implemented this model in the field (Tavana, 2003). Such undertakings in community-based nonprofits can even be less involved while still achieving similarly significant gains.

We have discussed a range of objectives for decision models that reflect concerns of nonprofit practitioners; additional research will certainly yield many others.

3.2 *Centralization*

Mergers, organizational structures, and collaboration are potential mechanisms for coordination and centralization in the nonprofit sector as illustrated in Fig. 3.3. Like the for-profit sector, the nonprofit sector struggles with coordination. In operations research, Li and Wang provide a comprehensive review of centralization and coordination literature (Li & Wang, 2007). The nonprofit sector presents a new sphere to study the value and limits of such principles.

3.2.1 Mergers

Mergers represent the most extreme form of centralization and coordination (Fig. 3.3) and offer significant potential benefits. Though mergers are still debated in the nonprofit sector, those organizations that do consider merging offer a variety of reasons, such as size, clout, influence, leadership, competitive advantage, and financial sustainability (Gammal, 2007; Gottfredson, Schaubert, & Babcock, 2008; Singer & Yankey, 1991). However, the strongest motivations remain financial, particularly financial sustainability (Singer & Yankey, 1991). In studying the frequency and outcomes of nonprofit mergers, Gammal concludes that anticipated cost savings or increased donations are often not borne out in practice (Gammal, 2007). This is reinforced by research that finds reduced individual donations post merger (e.g., Siino, 2003).

Instead, appropriate reasons for merging may be mission and/or geographic overlap of the organizations (Gammal, 2007; Nee, 2007), that is, when organizations serve the same population, same need, and/or same geographically bounded region. Though specific forms of market overlap may be motivations for mergers, the theories of centralization still dictate many benefits, such as visibility, economies of scale, power, and capacity (Gottfredson et al., 2008). Some organizations have already gained such benefits. For example, Crittenton Women's Union (CWU) is the result of a merger between Crittenton and the Women's Union, both well-established nonprofits each with a mission to serve Boston area low-income women. "Following the merger, CWU has raised its visibility in the community and among potential donors, and lowered its service delivery costs – turning an operating loss of more than $500,000 into an operating surplus of more than $200,000" (Gottfredson et al., 2008, p. 36).

Mergers and centralization also occur on the nonprofit supply-side when considering foundation mergers, which are typically motivated also by overlapping mission and/or geographic area. For instance, the Peninsula Community Foundation and Community Foundation of Silicon Valley merged "in an effort to better serve the [overlapping] local community and create positive social impact on a larger scale" (McGurk, 2006, p. 1). The decision to merge was proceeded by research indicating benefits of the merger, including increased efficiency, capacity, expertise, and investment options. Each of these are often hailed as benefits of centralization.

While maximum centralization has strong appeal to operations researchers, community-based nonprofits often dismiss mergers, unwilling to relinquish control and independence (Haider, 2007). In such cases, centralization may also be achieved using organizational form.

3.2.2 Organizational Forms

Organizational form is another, less extreme instrument for coordination in the nonprofit sector. While most nonprofit organizations incorporate, some nonprofit organizations, such as the Girl Scouts, utilize the franchise structure with local chapters. Others, such as United Way and Planned Parenthood, utilize a federated or affiliation structure where mission, brand, and program model are shared while local affiliates remain legally independent. Though headquartered nationally or in a central business district, franchised and federated nonprofit organizations may work in multiple geographic areas across a city, state, or nation. Both of these organizational forms offer some degree of centralization for such multisite organizations as seen in Fig. 3.3.

Oster studies the existence and justification of franchise relationships (Oster, 1996), while O'Flanagan and Taliento investigate the federated nonprofit organizational structure as a very formal collaborative structure that provides nonprofits with an equivalent to mergers and acquisitions (O'Flanagan & Taliento, 2004). Overall, the authors conclude federations can be a powerful means of uniting nonprofits, though not without struggle. In fact, Grossman and Rangan cite key sources of tension between headquarters and affiliates that are well known to operations researchers familiar with supply chain coordination issues: payment and value of headquarters, allocation of resources, and organizational governance (Grossman & Rangan, 2001). These issues are explored in detail below.

Payment and Value of Headquarters

When headquarters demonstrate value and support to their affiliates, payments to headquarters are not a significant issue. Yet as O'Flanagan and Taliento note, managing and providing value to local affiliates is not an easy task (O'Flanagan & Taliento, 2004). Grossman and Rangan mention several levers by which organization headquarters may create value, including brand name creation, expert assistance, economies of scale, program standardization, and fundraising centralization. For example, headquarters can leverage economies of scale to gain cost advantages for their networks. Such economies of scale can manifest as purchasing power, which is the case for Planned Parenthood National's quantity price discounts for contraceptives (Grossman & Rangan, 2001). Oster notes that "franchises are particularly prevalent in nonprofits with monitoring problems, strong use of volunteers and large capital needs," findings that may illustrate value that headquarters' can demonstrate at local levels and that operations researchers can effectively structure in studying centralization (Oster, 1996, p. 94).

Allocation of Resources

Tensions regarding the allocation of resources typically center around centralization of resources and ownership of donations. Most nonprofit work and service delivery occur at the local level, and most donation dollars are raised at the local level. In many federated structures, however, national offices manage the allocation of all donations across the system. This ability to centralize fundraising functions has powerful potential. At the local level, nonprofit fundraising is often thought to be a problem of the commons, where many local entities compete for limited funding in a restricted geographic area without any incentives or mechanisms in place to prevent overuse of the common potential funding pool. The associated tragedy is that the common pool will be overused and ultimately depleted due to individual incentives. Both inter- and intra-firm resource allocations have been topics of operations research where more recent literature has focused on information and incentive problems in capacity and resource allocation. Inter-firm capacity allocation among retailers with private demand information is studied by Cachon & Lariviere, (1999a, 1999b). In contrast, Karabuk and Wu (2005), Rajan and Reichelstein (2004), and Harris, Kriebel, and Raviv, (1982) explore intra-firm allocation problems. Centralization of fundraising can be studied through such resource allocation problems in the context of various nonprofit organizational structures, where findings can significantly reduce the problem of the commons while increasing brand power to affiliates.

System Governance

Whether a merged or federated organization, nonprofit structures must strike a delicate balance in system governance, namely the degree of decision making coordination. Centralized systems can offer standards and consistent quality across the organization. A strength of the nonprofit sector, however, is that it can "decentralize the production of public goods," resulting in "public goods that are more sensitive to local demand and delivered with greater efficiency than would [centralized] governmental institutions" (Reich, 2005, p. 26). While this is certainly familiar territory for operations researchers, the unique challenges of the nonprofit sector bring less explored tension between centralization and decentralization. In related for-profit research, Harrington and Chang look at innovation in multisite organization of heterogeneous retailers and find value of *de*centralization in the presence of sufficient market diversity (Chang & Harrington, 2000). These findings illustrate that the appropriate and best extent of centralization is still undecided for alternative and heterogeneous objectives. As discussed previously, nonprofits face just such heterogeneous and varied objectives compared to the more homogenous profit objective, objectives that can vary even between affiliates. Furthermore, since nonprofit work and services are delivered at the local level, decentralization offers flexibility close to the client in local delivery.

Where mergers offer the greatest extent and formality of centralization, organizational structures, such as federations and franchises, offer somewhat fewer features of centralization. However, collaboration in its many different forms can offer some benefits of centralization with significantly less formality, as seen in Fig. 3.3. Collaboration is further discussed in the next section.

3.3 Collaboration

Literature regarding collaboration is rich and multi-disciplinary, as one can find both research and practice literature related to a wide-range of potential collaborators from government to businesses to other nonprofit organizations, each with distinct dynamics. Increasingly, community-based nonprofits must see themselves embedded within communities of potential collaborators, creating a network of resources, information, and beneficiaries where collaboration decisions become strategic production and operations decisions.

3.3.1 Government

Today, public services, particularly human and social services, are delivered by community-based nonprofit organizations (Kendall, Knapp, & Forder, 2006; Smith & Gronbjerg, 2006). As Salamon noted, "For better or worse, cooperation between government and the voluntary sector is the approach this nation [United States] has chosen to deal with many of its human service problems . . .This pattern of cooperation has grown into a massive system of action that accounts for at least as large a share of government funded [nonprofit] human services as that delivered by government agencies themselves" (Salamon, 1995, p. 114). Thus, community-based nonprofit organizations serve as mediators between the government and citizens, especially through provision of critical local services to underrepresented, underserved, and vulnerable populations. For example, Privett examines collaboration between community-based nonprofits and local public health departments, which provide critical health services in localized jurisdictions. This research offers an example of nonprofits shaping their communities through the delivery of local health services (Privett, 2010). Another instance is interorganizational relationships in early child care and education where nonprofits increasingly provide these services to children yet public funding remains fragmented (e.g., Head Start, state initiatives, and subsidies). Seldon, Sowa, and Sandfort find that the value of these collaborations has impacts in management, processes, and outcomes of the organizations engaged (Selden, Sowa, & Sandfort, 2006).

A parallel can be drawn between business outsourcing and government contracting to community-based nonprofit organizations. Competitive processes award government contracts and/or grants for public supportive services to specific community-based nonprofits, "which in turn serve specific neighborhoods and individuals" (Marwell, 2004, p. 265). Necessarily, such contracting frameworks were initiated due to tension in the government-nonprofit relationship, with primary concerns of control and independence (lack of control). Yet, the absent *public* voice within this contracting framework is no less important with concerns of inflated costs and undermined public objectives (Salamon, 1995).

3.3.2 Business

The growth of government service outsourcing and subsequent nonprofit expansion has also brought businesses into these new areas. These circumstances give rise to both competition and collaboration between business and nonprofit organizations. Such competition is discussed in Sect. 4.1; such collaboration takes various forms and grows from an assortment of motivations.

Many forms of business-nonprofit collaboration warrant contracting of varying degrees, and thus present new ground to study the benefits and limits of collaboration and operational contracts. From a business perspective, the corporate social responsibility movement continues to gain momentum. Such programs typically involve nonprofit collaborations for purposes of marketing, human resources, and employee satisfaction. Additionally, some businesses find operational opportunities and efficiencies through collaboration with nonprofits. Resources remain the primary nonprofit collaboration driver, although exposure, communication, knowledge expansion, and influence are also driving factors (Vernis, Iglesias, Sanz, & Saz-Carranza, 2006). These partnerships pose several risks to nonprofits, such as reduced donations, loss of reputation, and/or reduced effectiveness (Andreasen, 1996).

These risks not only provide further avenues for investigation but also interesting extensions to the contracting framework. An example of such nonprofit-business interactions occurs in life sciences collaborations, which involve academic institutions, industry partners, research institutes, hospitals, and government laboratories. According to Powell and Own-Smith, such collaborations "offer ample opportunities for [nonprofit] universities to diversify their funding base and to contribute to both the advancement of life-sciences research and the development of powerful new medicines that will be of considerable benefit to society" (Powell & Owen-Smith, 1998, p. 191).

Chicago Public Schools
Collaborative Procurement and Internal Markets

Chapman and Hardt illustrate the latent opportunities for operations management in the nonprofit sector, finding that "bringing better discipline to purchasing and supply management can save school systems" 10%–35% – annual savings of $30–$40 million for large urban districts. Figure 3.4 displays categories of savings for the Chicago Public Schools. Analysis found both many different purchase prices and small quantity orders result in large procurement and administrative costs.Furthermore, "a surprising number of teachers have expressed interest in coordinating their purchases" through collaborative procurement or internal markets, which may indirectly benefit the district by enabling communication between teachers. This example, though applied here to a *public* school system, could just as easily apply to a nonprofit school system (e.g., charter). it is an excellent example of the potential impact relatively simple operations management methods and techniques can provide to improve the nonprofit sector (Chapman & Hardt, 2003).

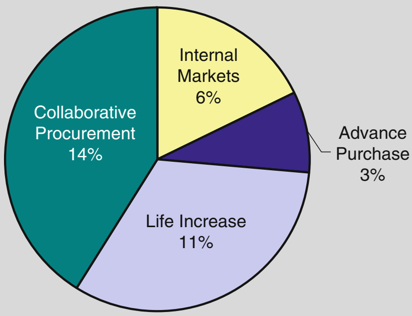

Fig. 3.4 Thirty-three percent textbook savings

3.3.3 Nonprofits

The benefits of collaboration within the nonprofit sector are considerable. Apart from collaboration as instrument for coordination, which is discussed further in Sect. 3.2, collaboration between nonprofit organizations can improve operational efficiency, allow more complex issues to be addressed, avoid duplication in effort and increase acquisition of important skills.

Overall, many community-based nonprofits are small and lack sufficient capacity and resources, yet collaborations enable synergies and coordination that can optimize their limited and scarce resources (Vernis et al., 2006). For example, collaborative procurement, which has been studied by Keskinocak and Savasaneril in the for-profit context (Keskinocak & Savasaneril, 2008), has the potential to benefit nonprofits through economies of scale by leveraging combined needs as opposed to individual needs. An example of this is the case of Chicago Public Schools (see inset). Thus, collaboration can be viewed by operations researchers as a type of strategic operations decision where the benefits of collaboration must exceed additional production and participation costs (Hill & Lynn, 2003). Such collaborative operations often pose collective action and contractual problems that can be explored analytically, and, as Vernis et al. implore, innovative collaboration mechanisms, specifically contracting mechanisms, must be devised for these cross-sector relationships (Vernis et al., 2006).

While scholars have offered general suggestions regarding government-nonprofit contracting and even novel ideas, such as challenge grants that reward volunteer use and private sector fund generation (Salamon, 1995), operations and efficiency focused contracting mechanisms are open applications for operations research. Likewise, each type of aforementioned business alliance warrants investigation from a contracting perspective, such as licensing contracts, which have been a topic of interest in operations research (e.g., Crama, De Reyck, & Degraeve, 2008; Kulatilaka & Lin, 2006; Lin & Kulatilaka, 2006). Erhun and Keskinocak both provide general reviews of collaboration from an operations management perspective, which can serve as a strong basis for research encompassing nonprofits (Erhun, 2009; Erhun & Keskinocak, 2007). These authors delineate both inter- and intra-firm collaboration and coordination, which are applicable to government, business, and nonprofit collaboration discussed above. Also, Cachon gives a review of methods and literature focused on for-profit contracting and coordinating mechanisms (Cachon, 2003). The nonprofit context offers novel opportunities to explore the dynamics of objective functions, power, nonprofit incentives, service contracting, and public social consequences.

3.4 Production Process

Every organization has processes by which inputs become outputs, even those in the nonprofit realm. Nonprofit organizations must still be concerned with using their “resources to achieve the greatest possible impact” (Brest & Harvey, 2008, p. 15).

However, the distinctions of the nonprofit sector create challenging opportunities for innovative research, especially distinctions inherent in nonprofit supply, demand, and structure.

3.4.1 Logic Models and Process Maps

In strategizing, nonprofits often use logic models that outline “a theory of change [that] is fundamentally an analysis of the causal chain that links your philanthropic interventions to the goals you want to achieve” (Brest & Harvey, 2008, p. 47). Thus, such logic models are production process maps, detailing the conversion of inputs to outputs/outcomes using specific processes. Although a basic logic model is a great first step, nonprofit operations planning often stops there. Enhancing such a model to incorporate risk, alternatives, probability, redundancy, and allocation can help to ensure the nonprofit’s goals. Such a production process map presents operations researchers with excellent opportunities.

3.4.2 Supply and Demand

Nonprofit operations face not just the traditional risk of stochastic demand but also that of stochastic supply (e.g., resources, funds, volunteers). While this naturally brings donations and funding to mind, even staffing, particularly volunteers, is uncertain, erratic, and, consequently, difficult to manage. For example, staffing creates compounded forecasting and scheduling problems, especially since nonprofits rely on a mix of paid staff and volunteers.

Further complications are the interdependencies among revenue sources, volunteer inputs, production costs, outputs and outcome measures which represent achievement of organizations missions. Nonprofit stakeholders frequently supply and consume the organizations output. As an example, foundations supply nonprofit funding but also serve as major stakeholders assessing nonprofit output. Additionally, limited inputs – constrained nonprofit resources and restricted access to capital – cause nonprofits to respond very slowly to demand changes.

The nonprofit sector is plagued by unusually high and interconnected risks in its production process, from supply to demand with staffing in between. Due to these coupled supply and demand risks, improved forecasting presents interesting problems for operations research both in theory and application as well as significant potential for progress in nonprofit operations. Also understanding how these issues affect supply is an interesting research problem that can contribute to literature on capacity and supply response.

3.4.3 Inefficiency

Lack of sufficient competition and earnings ownership is assumed to lead to inherent nonprofit production inefficiency. In practice, nonprofit organizations do lag in improvements relative to the for-profit sector. However, as nonprofits become mature, established, and accepted in their communities, there is an expectation that nonprofits will operate efficiently (Werther & Berman, 2001). In one of the first operations management models of nonprofit production, Privett and Erhun model production as a concave function of effort, resources, and "efficiency," that is, the ratio of funds going directly toward mission-related work. Their model illustrates direct and practical ways that nonprofits can increase production by increasing efficiency, reducing costs, and increasing resources and effort (Privett & Erhun, 2010). It can also be used as a basis for incorporating nonprofit production into future operations research.

Profit-seeking behavior and commercialization can be a positive force when considering production inefficiency. Nonprofits must deliver efficiently in mixed markets due to the forces of competition. This is likely to drive nonprofits toward professionalization and business-like techniques at least in their production and delivery of revenue generating services (Tuckman, 1998). Thus, when considering efficiency, nonprofit commercialization "should not just be dismissed as inefficient and counter productive. It offers real advantages; despite the problems it poses" (Weisbrod, 1998, p. 288). How and to what extent competition creates incentives and brings about production improvements is an open research area that can enhance our understanding of competition and its effects more in mixed market settings.

Hansmann states that nonprofits will generally produce any good or service at a higher cost than a for-profit firm (Hansmann, 1987), though cost reduction is an obvious way to increase efficiency. Purchasing practices, staffing decisions, inventory excess, indirect costs, and resource waste are just a few areas for improvement through mechanisms such as collaboration, coordination, and organizational form (see Sect. 3.2). Each of these involves some agreement and equilibrium, which has become a significant area of research in operations management. In fact, the recent trend in operations management literature of simple yet efficient contracts (Kayis, Erhun, & Plambeck, 2009; Lariviere & Porteus, 2001), such as price-only contracts, certainly complements the nonprofit sector, though these models cannot be directly applied.

The concept of increasing efficiency must be considered in trade-off with the nonprofit's mission. Mandell demonstrates multicriteria programing methods to facilitate decision making incorporating trade-offs between output (efficiency) and equity in allocating resources among delivery sites. Allocation of new books among public library branches is used as an illustrative example (Mandell, 1991). Even simple cost-benefit analyses can enrich decision making by quantifying and comparing alternatives, possibly exposing unnecessary actions and ineffective systems.

Even nonprofits must be concerned with production and production improvements, especially as they strive to achieve the greatest possible impact under notorious ambiguity. Evaluation and measurement are also a critical part of such improvements and are further discussed in Sect. 4.2.

4 Consumers and Markets

Nonprofit "consumers" or stakeholders are many and can include funders, donors, government, employees, board members, and the intended end-consumer beneficiaries. This section first discusses both consumer-side competition and collaboration, which especially relate to the assortment of local consumer markets that nonprofits find themselves, even within a single community. Nonprofits' heterogeneous consumer base is then considered in performance measurement and evaluation.

4.1 Market Competition

Profit ventures and service-related missions thrust nonprofits into for-profit and mixed markets, such as health care, social services, and education. Opposing viewpoints exist on whether nonprofits are at a competitive advantage or disadvantage. Those arguing in favor of competitive advantage mainly cite the tax benefits associated with nonprofit status. On the other hand, disadvantages may include lack of financial resource, lack of financial bottom line, and talent drain (Frumkin, 2002). Ritchie and Weinberg (2003) discuss nonprofit competition, collaboration, and combinations. Ritchie and Weinberg assert that literature on nonprofit competition does not appropriately consider the fundamental differences between for-profits and nonprofits, notably nonprofits' non-monetary goals that dominate financial considerations and the diversity of these goals resulting in very different objective functions motivating competitors.

However, the authors neither analytically model nor empirically examine their ideas, thus leaving for future research the task of exploring the consequences of varied nonprofit goals and nonprofit competitive settings. Harrison and Lybecker provide an example of such research as they examine the effects of the nonprofit motive in price competition between non-profit and for-profit hospitals. They model the nonprofit objective function as a weighted linear combination of profit and nonprofit motive, specifically quantity, charity, and quality, with the main result that nonprofit motive has great importance and impact in competition between nonprofit and for-profit hospitals (Harrison & Lybecker, 2005). In these heterogeneous markets where for-profits and nonprofits compete, contention can arise over supposed nonprofit regulatory and tax advantages. Liu and Weinberg use game theory to analyze these supposed advantages by modeling nonprofits as quantity maximizers and conclude that it is not these advantages, rather the difference in firm objective functions that causes the observed competitive behavior (Liu & Weinberg, 2004).

Nonprofit objectives are evidently crucial for insight into nonprofit competition, nevertheless foundational operations research competition models are most often based on for-profit firms' monetary motives. However, diverse and less traditionally explored competitive factors have been the subject of some recent for-profit operations literature. For instance, Tsay and Agrawal examine coupled service and price competition, specifically looking at strategy drivers and consequences in sales, market share, profit and coordination (Tsay & Agrawal 2000), while So investigates coupled price and time guarantees (So, 2000). A few additional examples of for-profit competition aspects from operations literature with appeal in nonprofit dynamics are customer service, customer loyalty, and quality competition (Boyaci & Gallego, 2009; Gans, 2002). Each of these objectives may be a point of competition in nonprofit and mixed markets. Accordingly, these models can offer researchers a base of understanding.

Bridging operations research work, such as that of Tsay and Agrawal and So, with nonprofit research like Ritchie and Weinberg can involve models of nonprofit competition with for-profits or nonprofits in homogeneous or mixed markets. Furthermore, such research can also inform nonprofit decision making. For example, operations research can equip nonprofits to best decide between engaging in competition, collaboration, both, or neither in their given market by considering strategic trade-offs (i.e., activities, programs, resource requirements, etc.). By better understanding nonprofits' dynamics of competition, such complicated trade-offs can be further elucidated.

Both competition and corresponding nonprofit strategy invite operations research and serve merely as examples of research possibilities in this area where the nontraditional nonprofit setting presents many unique challenges that have not been effectively analyzed nor thoroughly understood. For instance, due to the unique nature of nonprofit objectives, nonprofit competitive scenarios can consider the unusual option of subordinating to competition because of a common cause, which may in fact present the best social option. Hybrid organizations, which are blends of nonprofit organizations and for-profit firms, are one emerging and innovative option in the presence of such competitive forces. These organizations are creating a spectrum of organizations and firms that are blurring lines between nonprofit and for-profit models. Examples of these include the B corp (www.bcorporation.net) and triple bottom line firms (Elkington, 1998; Savitz, 2006), whose measures of success are broadened by social and environmental values. Thus, extending competition models to objectives beyond profit can also illuminate interactions among these types of firms and the changing nature of business and firm typology.

4.2 Performance Measurement and Evaluation

Nonprofit organizations continue to experience a growing demand for performance measurement and evaluation from government, foundations, and donors (Carman, 2009). As such, this is also an expanding area for nonprofit research

(Alexander, Brudney, & Yang, 2010). It is difficult to determine the performance of an organization or any of its particular activities given the diverse and complex nature of nonprofit objectives. Furthermore, ineffective nonprofits can affect many stakeholders, such as unserved clients, donors whose charity is thwarted, and tax payers who subsidize nonprofits (Frumkin, 2002). As modelers, operations researchers understand the importance of identifying performance measures for assessment, decision, improvement, and, ultimately, realization of goals and greatest impact.

In academia, there exists a large, multidisciplinary body of social science literature on nonprofit evaluation. For example, Stufflebeam identifies, describes, and assesses 22 different nonprofit evaluation approaches including many different ways of measuring program outputs and outcomes (Stufflebeam, 2001). More recently, an entire issue of the *Nonprofit and Voluntary Sector Quarterly* was devoted to performance measurement and evaluation (Alexander et al., 2010). By examining the body of academic research, Baruch and Ramalho provide a review and analysis of business, nonprofit, and mixed organization effectiveness and performance literature (Baruch & Ramalho, 2006). Through this analysis, the authors find common ground between business and nonprofit measures, which supports the idea that for-profit and nonprofit effectiveness and/or performance are not differentiated enough to be considered entirely distinct constructs.

Such similarity highlights opportunities for cross-sectoral learning where the nonprofit setting can benefit from the depth of for-profit experience in process improvement, while also bringing the challenge of multiple, often less tangible, objectives. Instead of focusing on a single output or outcome measure in the nonprofit sector, which would be a direct analog to a profit measure, evaluation measures with the goal of improving nonprofit operations can perhaps focus on all operations that improve any measure of value. Multi-goal and multi-objective approaches must be utilized to integrate performance measures and the numerous varied stakeholder objectives of nonprofit organizations. Once measures are established, operations management applications might include integrating operational measures into programs and establishing benchmarks that appropriately incorporate multidimensionality. For example, Athanassopoulos develops a target-based model combining performance measurement and resource allocation. Methodologically, he incorporates a principal-agent model with goal programing. The goal programing formulation, composed of operating productivity, individual performance contributions, and equity measures, is characterized by its interactive representation of the trade-offs between these three objectives (Athanassopoulos, 1998).

Another evaluation framework, social cost-benefit analysis, can be applied as a public sector decision making tool that, at its most basic level, values projects, programs, etc. as the net social benefit minus the net social cost (consequence) where all impacts must be monetized. Its purposes are to help social decision making, facilitate efficient resource allocation, and provide an efficiency measurement framework. Alternatively known also as cost-effectiveness, cost-utility, or cost-feasibility analysis. Prest and Turvey provide a foundational survey (Prest & Turvey, 1965).

Considering such complexities of nonprofits such as multiple stakeholders, lack of profit motive, and social importance of goods and services provided, it is not surprising that studying nonprofit performance, evaluation, and effectiveness might be considered more difficult than analogous research in the business sector (Baruch & Ramalho, 2006). Such complexities present operations researchers with uncommon challenges where rigorous research can result in significant impacts. Operations research prospects in this area, such as measurement design and system development, can have considerable effects at the community level by extending expertise and capability. This is important because evaluation training is unusual among community-based program administrators (Carman, 2009). Such research can also broaden knowledge of performance, evaluation, and operations in for-profit situations of multiple bottom lines, environmental responsibility, and corporate social responsibility, where measurement of *nonmonetary* performance remains an important challenge.

5 Conclusion

From serving the underrepresented to delivering to the underserved and supporting the vulnerable, a remarkable portion of localized problems are addressed by community-based nonprofit organizations. As this chapter has demonstrated, there exist both similarities and differences between the traditional for-profit settings of operations research and those in the nonprofit sector. These similarities yield a potential for relevance and value of operations research techniques applied in the nonprofit sector, while the differences expose a fertile frontier for future research where traditional operations research solutions are no longer directly applicable.

In exploring operations research in community-based nonprofits, we examined a supply chain structure of nonprofit supply, production, and consumers (i.e., demand for services). We examined important supply-side issues such as fundraising, earned income, and foundations that yield novel research opportunities related to fundraising competition, revenue strategies, and portfolio management. In nonprofit production, we discussed multiple objective functions. Mergers, organizational forms, and collaboration were developed on a spectrum on centralization. Lastly, in considering nonprofit outputs and outcomes (consumers), market competition and performance measurement and evaluation were reviewed. In each area, relevant operations research and nonprofit studies literature was reviewed and potential future research identified.

Insights gained from exploration of these new nonprofit lines of research can further inform traditional research lines as well. For example, advances in understanding supply-side risk have value in venture funded firms; investigation of the interplay between supply and demand broadens understanding of how products and services can shape firm inputs. Adapting foundational research to include multiple objectives can produce robust models for corporations operating on multiple bottom lines. Recognition of the more elaborate nonprofit concept of consumers can result in new avenues of research regarding technology-based companies. For example, nonprofit volunteers both produce and consume nonprofit output; similarly, Apple consumers create "apps" (products) that affect the value of the iPhone.

The current state of operations research and management science scholarship in community-based nonprofit operations research is still young. Accordingly, a strong research base is necessary before providing specific prescriptions in the field. This chapter has emphasized and encouraged academic inquiry in operations research in nonprofit organizations as key in furthering community-based operations research. As the traditional solutions of operations research are not merely exportable to the nonprofit sector, expanding research to the nonprofit setting will surely provide a source of innovation and pertinent research. The nonprofit sector is ripe with opportunity for operations research and application, where advances will ultimately lead to a better economy, increased social welfare, and, most importantly, changed lives.

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Chapter 4
Modeling Equity for Allocating Public Resources

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1 Introduction

Equity is a concern of many disciplines, including operations research (Sarin, 1985), philosophy (Rawls, 1999), political science (Stone, 2002), economics (Bowles, 2004; Camerer, 2003), and anthropology (Ferraro, 1998, pp. 261–282). There are both descriptive and normative issues with respect to making equitable decisions, including how to describe a stakeholder's preferences toward equity and how to model equity as a quantity of social value. In operations research models for allocating public resources, both of these issues are relevant. If a public resource is to be allocated, equity in the distribution of that resource is a significant concern, and how equity is defined within the model may generally depend on how equity is perceived by stakeholders.

Equity is a critical and controversial factor when deciding how to allocate public resources (Stone, 2002). Despite the important role which modeling equity naturally occupies in the allocation of public resources, little consensus exists concerning which equity measures researchers should use (Marsh & Schilling, 1994). Consequently, operations research models do not always reflect a systematic analysis of the alternative functions that might be chosen to represent equity, and hence, operations research models frequently choose equity functions in a relatively ad hoc fashion. However, a significant multidisciplinary literature has developed, which can aid operations researchers in navigating the complexities of equity.

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Equity is one of many criteria for allocating public resources. Including equity, Savas (1969, 1978) identifies three primary criteria by which allocations should be evaluated: effectiveness, efficiency, and equity. *Effectiveness* is the degree to which a resource allocation causes needs to be met, and is also intended to reflect the extent to which unintended negative impacts of an allocation are avoided. In an Emergency Medical Services (EMS) setting in which ambulances respond to emergency medical 911 calls, the proportion of all emergency calls that are responded to within a pre-specified time threshold is a natural measure of effectiveness. *Efficiency* represents the ratio of outputs to inputs given a particular resource allocation, and thus, in part, reflects costs. With respect to EMS systems, a measure of efficiency might be the number of all emergency calls that are responded to within a pre-specified time threshold divided by the number of ambulances owned or paramedics used. *Equity*, of course, is the focus for the remainder of this chapter. Equity may be taken as synonymous with fairness, but it is desirable to elaborate on this definition so that different models of equity may be carefully compared, contrasted, and analyzed. In this chapter, we systematically analyze how different models of equity may be produced by making modeling decisions along two major dimensions: (1) substantive definition and (2) choice of algebraic form. Throughout, we discuss the advantages and disadvantages of each modeling decisions made with respect to each dimension. The literature suggests that there is no single, best way to model equity. However, operations research models for allocating public services often explicitly or implicitly reflect differing models of equity. This chapter explores how operations research models can be systematically designed to accommodate the need to achieve equity in the context of public services allocation problems.

This chapter synthesizes the multidisciplinary literature to provide a systematic guide to modeling equity in public service models by critically examining different perspectives on equity. The goal of this chapter is to review, synthesize, and critically evaluate key contributions to modeling equity for allocating resources in public service systems. This chapter explores the concept of equity through public services resource allocation problems. Public services are ideal for exploring equity for two reasons. First, equity is often an important political concern when changing aspects of a public process. Second, resource allocation issues provide particular challenges for identifying equitable solutions. Therefore, the issues explored here have the potential to provide important insights into challenging problems where fairness is expected. This chapter is similar in spirit to Marsh and Schilling (1994); however, Marsh and Schilling focus on assessing the properties of various algebraic models which have been used in practice, whereas this chapter focuses on the component decisions which must be addressed in determining which of all possible equity models should be used and explicitly reflects equity models from a broad, multidisciplinary perspective. This chapter also differs from Sarin (1985) and Keeney and Winkler (1985) in which it aims to synthesize their contributions into a larger body of work, and consider how the ideas they discuss relate to the modeling of equity in its broadest sense.

Throughout this chapter, important equity modeling obstacles and decisions are illustrated through resource allocation problems faced in EMS. EMS resource allocation problems include a family of well-studied public sector problems (Larson & Odoni, 1981), especially facility location models (Current, Daskin, & Schilling, 2002; Marianov & Serra, 2002; Rajagopalan, Saydam, Setzler, & Sharer, 2011). This research literature provides many examples of key issues in equity modeling. Moreover, many equity modeling issues that arise in the EMS literature are pertinent to equity modeling across a wide array of public services problems, and hence, they provide a lens through which to explore equity modeling across many public services. Examining equity modeling issues in this way highlights numerous ways in which equity may be effectively modeled in public service resource allocation problems, and it helps to identify several key areas in which our knowledge of how to model equity should be improved.

This chapter proceeds as follows. First, definitional issues of equity are discussed to capture a spectrum of how equity is conceptualized that draws on the multidisciplinary literature. Second, various functions and measures for equity are discussed to illustrate how different models of equity can lead to drastically different resource allocation decisions. Third, efficiency-equity-effectiveness tradeoffs are considered. Lastly, recommendations are made to improve equity models and to more effectively include equity in operations research models.

2 Definitional Issues

Defining equity is critical for identifying a model of equity that satisfies a particular decision maker's needs. All definitions of equity have at least one commonality, namely, that for equity to be achieved, the distribution of some resource should be equalized across a set of people or between groups of people. Nevertheless, this commonality leaves much to be decided concerning how to define equity in a specific decision-making context. Stone (2002) suggests that stakeholders can evaluate equity using one of a group of distinct principles, and that no single performance measure for equity satisfies all such principles. Perhaps, the most obvious allocation principle is that equity is achieved when every individual considered receives an equal proportion of the resource being allocated. However, Stone proposes eight alternative allocation principles: stakeholders may receive *equally deserved amounts* of a resource, where equality is determined according to (1) *group membership*, (2) *community membership*, or (3) *rank*. Alternatively, stakeholders might receive (4) *resource allocations of equal value or utility* or (5) *equal total resource allocations*, inclusive of the potentially uneven distributions of other resources. Stakeholders might also be provided with (6) *equal votes concerning how to distribute resources*, (7) *equal statistical expectations of resource amounts to be received*, or (8) *equal opportunities to compete* for access to a resource.

Stone classifies principles (1)–(3) as *Recipient-related principles,* because they ground equity in individual differences between stakeholders, and specifically in individual differences which are regarded as determining the amount of a resource merited or deserved. Stone classifies (4)–(5) as *Items-related principles*, or principles that may redefine equity by altering the boundaries in space or time of the resource being allocated. Principles (6)–(8) are classified by Stone as *Process-related principles*, which define equity as a feature of the process used to determine resource allocations, rather than as a feature of the final resource allocations themselves. Drawing on Stone's work, we discuss the definition of equity as involving three elements: determining *what resource* to divide between recipients, determining between *which sets* of recipients or groups to divide that resource, and determining *across what time period* the resource should be divided. These three dimensions correspond to Stone's two dimensions of Recipients and Items, where Items has been subdivided into allocation time horizons (what time period) and resource definition (what resource). The analysis is therefore primarily framed in terms of Stone's Recipients-related and Items-related dimensions, because these dimensions are very immediately relevant to understanding how equity has most often been modeled in the operations research literature. However, we discuss issues relevant to Stone's Process-related dimension as well.

Consider the following example in the EMS domain. The most widely used method for evaluating EMS performance prescribes that ambulances should respond to 90% of Priority 1 (life-threatening) calls in less than 9 min (a 9-min response time standard) (Fitch, 2005). Here, what is being distributed is the expectation of a particular degree of timeliness for EMS service, while the timeframes and groups of people across which EMS service is distributed vary with the policies of particular regions. Despite its appeal, numerous objections exist to defining equity as equality of patients' expected wait times. As McLay and Mayorga (2010) and McLay (2011) observe, ambulance response time is a proxy measure for the true goal of EMS systems, which is patient survivability. Significant evidence of a link between response time and patient survivability exists, particularly for emergency calls involving cardiac arrest (Larsen, Eisenberg, Cummins, & Hallstrom, 1993; Stiell, Wells, & Field, 1999; Waaelwijn, de Vos, Tijssen, & Koster, 2001). For other types of emergency calls the magnitude of covariation between response time and patient survivability is less clear (Fitch, 2005).

The 9-min response time standard in EMS systems bears immediately on equity, because it requires equal allocation of the quality of EMS services, where quality is understood as a minimal timeliness of arrival. However, this timeliness is only required for a subset of all calls (Priority 1 calls); the standard for service does not require that responses to non-life-threatening calls occur within the same 9-min timeframe. This standard therefore implies an implicit ranking of the population, whereby individuals more frequently prone to life-threatening problems are allocated a greater proportion of EMS resources than individuals less frequently prone to life-threatening problems. Certainly, such an equity principle seems quite reasonable in many cases; however, stakeholders who are regarded as relatively cautious may argue that they are deserving of faster EMS service than are riskier stakeholders. Or, rather than equalize wait time before access, equity might be defined with respect to the amount spent per call (e.g., dollars in a US setting), so that achieving equity means investing equal dollars per capita, or perhaps per life saved. Such a decision would have the effect of allocating resources relatively heavily toward urban, population-dense areas, and away from relatively rural areas, where low population densities create longer travel times, leading to longer response times.

Similarly, it might be disputed what individuals or groups should be considered in the equitable allocation of resources. The timeliness of EMS responses might be equalized across all members of a county or a state, between urban and rural areas, within different areas of a particular city (e.g., districts), or between different socioeconomic classes. In such a scenario, the stakeholders must be defined to identify who has a legitimate claim to the resource being allocated. This suggests that *to whom* a resource should be allocated is closely related to determining *what resource* is allocated. If what is being allocated is redefined such that individuals or groups are allocated equally deserved portions of a resource, where some individuals or groups are evaluated as deserving no portions at all, then the equity definition which results is equivalent to the definition that results from determining that certain groups are to be included and others excluded from a model of equity. Thus, identifying whom to allocate equal levels of resources may be viewed as a special case of identifying the deserved level of a resource for different individuals.

Note that in many public service applications, not including various individuals or groups as stakeholders in an equity model does not imply that they will not receive any portion of a resource, but rather that they will not necessarily receive an equalized portion of a resource. For example, consider a 9-min response time standard in EMS systems in which responding to 90% of patients within 9-min is only required for some – but not all – groups. Since EMS systems typically dispatch an ambulance to every call, then a feasible and equitable solution would dispatch ambulances to calls from included and non-included groups in such a way that (a) responds to 90% of calls from the included groups within 9 min and (b) responds to any given percentage of calls from the non-included groups within 9 min. Hence, members of non-included groups would still receive EMS service, but the percentage of calls responded to within 9 min for these individuals could range from 0% to 100%.

The stakeholder (individuals or groups) that should be included in an equitable allocation of a resource can be defined rather broadly and do not need to be limited to customers (i.e., those who use public services). This concept has not been directly considered in operations research models for allocating public resources, but it has been considered in other contexts. For example, Tseytlin (2007), Armony and Ward (2010), and Atar, Shaki, and Shwartz (2009) consider equity from the perspective of employees working in hospital treatment and call centers. Tseytlin observes that policies intended to minimize patient wait times in hospitals may imply extremely high utilization of the most efficient employees, an outcome which is efficient from the perspective of the patients but is highly inequitable from the perspective of the employees. Tseytlin also observes that such a policy might create unwise incentive structures for employees, in which relatively efficient employees are "punished" with increased workloads for being unusually efficient. Thus, equity may be worth including in an objective function not only for its terminal value but also to improve employee incentives via equity.

In the context of EMS, patients might be regarded as customers, and equity might be defined with respect to service providers, such as emergency medical technicians (EMTs) and paramedics. Equity from the employee point of view has many consequences in the EMS domain. For example, EMS service providers could consist of volunteers and paid staff. All types of EMS service providers – and volunteers in particular – have lower levels of job satisfaction if they treat fewer Priority 1 patients and mainly transport patients to the hospital rather than provide treatment (Studnek & Fernandez, 2007). This is particularly important when considering volunteer service providers, since volunteers may be less likely to volunteer in the future if their skills are not used (Sampson, 2006), negatively impacting service quality and patient health outcomes in the future. Thus, equity from the service provider perspective can be linked with equity and efficiency from the patient perspective.

Returning again to Stone's (2002) principles, the *scope of equalization* must be defined to determine over what time period equalization is to be performed or equity is to be achieved. In general, defining equity over different time periods may result in very different resource allocations. Problems of scope become especially important in situations where past allocations have been inequitable and permanent; if equity is to be attained on the average over some time period that includes these past allocations, then past inequities must be compensated for with increased allocations to previously disadvantaged groups. To see this, consider the following example. Consider that a long history of ambulance location policies in one particular region has led to artificially low allocations of EMS resources to certain neighborhoods. Members of these neighborhoods might, then, argue that the scope of equalization should be defined over a sufficiently long period that these past inequities will be redressed. These groups might argue that rather than equalize EMS resource allocations in the present or near-future (e.g., over the next month), EMS resource allocations should be markedly unequal in the present with a bias favoring the underserved neighborhoods, so that resource allocations may be called equitable over a long time horizon that includes the past inequities. Such a bias is analogous to affirmative action as a means to remedying historic disparities in allocations for disadvantaged groups (Barnett, 1996; Caulkins, 1996).

Another example involves the 9-min response time standard in EMS systems, which does not define a scope of equalization if no guidance is given as to how to interpret this standard based on time of day, which is typically the case (Erkut, Ingolfsson, & Erdogan, 2008; Henderson & Mason, 2004). For example, a 9-min EMS standard does not indicate if it is acceptable to respond to, say, 80% of Priority 1 calls in less than 9 min during the day and, say, 95% of Priority 1 calls in less than 9 min overnight, averaging to 90% of Priority 1 calls across all times. In addition, the 9-min response time standard sets a target for the 90th percentile but not to the entire cumulative distribution of response times that are observed. Different response time distributions all with 90th percentiles equal to 9 min may lead to vastly different patient survival rates.

It is important to note that the time-scope of equalization may be important depending on the area of application. For example, in long-distance transportation of hazardous materials (Gopalan, Kolluri, Batta, & Karwan, 1990), where completion of a specific project may require significant amounts of time, the time horizon across which equity is to be achieved may be unclear, allowing a great deal of freedom in how to select the time horizon over which to optimize equity. This point is all the more important for issues like facility location (Marsh & Schilling, 1994), where site location decisions will have consequences for many years following the time of a decision. By contrast, in arenas like queuing (Larson, 1987), the time horizon over which equity is to be achieved is likely to be very small, since customers will not generally remain in a queue for longer than 1 day (although certainly counterexamples to this general trend could be imagined). Selecting a time horizon over which to equalize is significant, because the time horizon bears importantly on the nature of a model created as well as on the solutions prescribed on the basis of that model. Specifically, choices of the time horizon over which to equalize that are too narrow may not capture the long-term effects of the decisions made, while choices of the time horizon that are too long can needlessly slow the solution time of a model. Moreover, time horizons that are too long may lead to solutions in which equity is achieved at acceptable levels in the aggregate, but for which, across smaller time intervals, unacceptably inequitable solutions are found.

Note that various stakeholders may simultaneously select different definitions of equity, all of which cannot be simultaneously used to equalize a resource. From an operations research point of view, this means that simultaneously considering multiple definitions of equity typically leads to an infeasible solution, with the resulting policy definition not to distribute any resources whatsoever. In addition, focusing solely on equity could lead to worse solutions for all and to undesirable outcomes. To give a simple example, giving no one a piece of a pie is more equitable that giving one person 90% and the other 10%, but it is not very efficient. Therefore, to identify feasible resource allocation decisions in an operations research model, tradeoffs across equity and efficiency must be considered to simultaneously address multiple definitions of equity.

Sarin (1985) and Keeney and Winkler (1985) contribute a different set of principles for defining equity. They argue that resource allocations may differ with respect to equity in two distinct senses: ex ante (before the case, equity of process) and ex post (after the fact, equity of outcomes). Ex ante and ex post equity are not as comprehensive nor are they perfectly aligned with Stone's (2002) eight equity principles, but they are useful for exploring additional notions of equity from an operations research point of view where outcomes are uncertain or probabilistic. Sarin, and Keeney and Winkler explore ex ante and ex post equity from the perspective of individuals surviving or dying as a result of resource allocations. If under a given resource allocation, the a priori probability of all individuals surviving is equivalent, then such an allocation is ex ante equitable. Thus, ex ante equity is akin to Stone's equity principle of equal expectations over outcomes, and reflects, in part, Stone's third major dimension of equity, which is the equity of an allocation process. Consider the following example with two individuals.

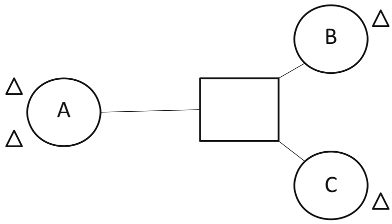

Fig. 4.1 Ambulance routing example, where the ambulance is located in the *square*, demand nodes *A*, *B*, and *C* are denoted by *circles*, and each of the patients is denoted by a *triangle*

The first resource allocation results in an a priori probability of either individual surviving with a probability of 0.5 (ex ante equity). Assume that this resource allocation implies a lottery with two outcomes that each occur with a probability of 0.5, leading to (1) the first individual surviving and the second dying or (2) the second individual surviving and the first dying. In this case, both individuals have the same a priori expected probability of survival of 0.5, but the realized outcomes lead to one individual surviving at the expense of the other. Both individuals experience the same exposure to a public risk, but they experience that risk in disparate ways. Consider a second resource allocation that implies a lottery with two outcomes that each occur with a probability of 0.5, leading to (1) both individuals surviving or (2) both individuals dying. This lottery has no chance for either individual of dying alone. This latter allocation Sarin (1985) and Keeney and Winkler (1985) regard as ex post equitable, since possible outcomes are symmetric in the sense that all realized outcomes are themselves equitable, in addition to each person's a priori expected outcome being equivalent. Thus, while the expected outcomes of a process might be equitable, the actual outcomes allowable by that process may not be equitable; it is readily seen that ex post equity implies ex ante equity, but ex ante equity does not imply ex post equity. Note that Sarin, and Keeney and Winkler explore these notions of equity from the perspective of the individual rather than from the perspective of the group. However, the intuition behind the distinction between ex ante and ex post equity may be applied when equity is defined with respect to groups as well, by simply defining the allocation magnitudes in terms of the groups rather than the individuals.

The distinction between ex ante and ex post equity is relevant in EMS systems, since the link between time of EMS care and patient survival is probabilistic (Fitch, 2005; Stiell et al., 1999). Suppose that one ambulance is available to service EMS calls, and that four calls have been received at the same time from three distinct demand nodes. This example is depicted in Fig. 4.1 where the ambulance is located in the square, demand nodes *A*, *B*, and *C* are denoted by circles, and each of the patients is denoted by a triangle. The single node from which two calls have emanated, *A*, is further from the ambulance's original position and from the other two nodes (*B* and *C*) than either nodes *B* or *C* are from the ambulance's original position or from one another. Moreover, owing to stochastic variations in traffic patterns and weather conditions, there is uncertainty about how quickly the ambulance can travel to *A*, *B*, and *C*. It is known that, if the ambulance travels to *A*, then it

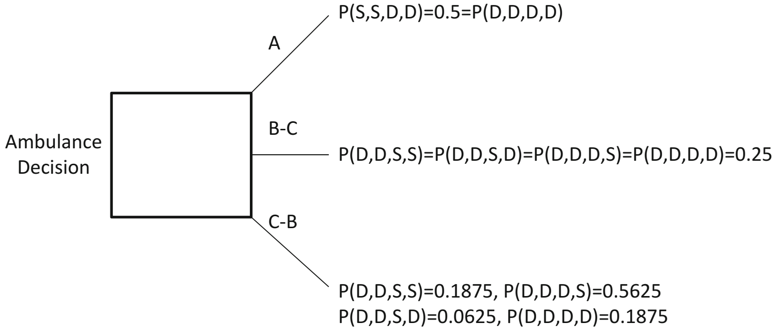

Fig. 4.2 Decision tree for the ambulance routing example

is not available to travel to *B* or *C*. If the ambulance is routed to node *A* (routing option *A*), then the probability of arriving at node *A* in time to save both of the patients at *A* is 0.5; otherwise, both patients die. If the ambulance is routed to node *B* and then to node *C* (routing option *B–C*), the probability of arriving at *B* quickly enough to save its patient's life is 0.5, and, given that node *B* has been visited (successfully or not), the probability of then arriving at *C* quickly enough to save its patient's life is also 0.5, independently of the outcome at *B*. If the ambulance is routed to node *C* and then to node B (routing option *C–B*), then the probability of arriving at *C* and then *B* quickly enough to save these patient lives are 0.75 and 0.5, respectively. For concreteness, we might regard the patient at *B* as experiencing a more urgent emergency than the patients at *A* or *C*, which we could regard as experiencing about equally urgent emergencies.

First, note that there is one expected survival for each of these routing options, and so criteria of effectiveness (i.e., survival) cannot distinguish between the three routing options. However, ex ante and ex post equity may both be used to rank these options. Denoting by (X,X,X,X) the conditional probabilities that individuals *A1*, *A2*, *B1*, and *C1* survive, respectively, under different routing options, we have (0.5,0.5,0,0) for routing option *A*, (0,0,0.5,0.5) for routing option *B–C*, and (0,0,0.75,0.25) for routing option *C–B*. Based on these conditional probabilities, routing option *C–B* is less ex ante equitable than routing options *B–C* or *A*, since the conditional probabilities of survival implied by routing options *B–C* and *A* could be created from the conditional probabilities of survival implied by routing option *C–B* by transferring the probability of death from the relatively well-off individual *B1* to any of the other less well-off individuals. The marginal distributions do not distinguish between routing options *B–C* and *A*, which are equally equitable ex ante. Let $P_R(O_1, O_2, O_3, O_4)$ denote the conditional probability of outcome (O_1, O_2, O_3, O_4) for routing option $R \in \{\underline{A, B\text{–}C, C\text{–}B}\}$, where $O_i \in \{\underline{D,S}\}$ indicates survival (S) or death (D) for the corresponding individual. In this notation, we have $P_{B\text{–}C}(D,D,S,S) = 0.25$, $P_{B\text{–}C}(D,D,S,D) = 0.25$, $P_{B\text{–}C}(D,D,D,S) = 0.25$, $P_{B\text{–}C}(D,D,D,D) = 0.25$, $P_A(S,S,D,D) = 0.5$, and $P_A(D,D,D,D) = 0.5$. Routing option *A* yields the most ex post equitable outcomes, since it reassigns probability from highly inequitable outcomes like *(D,D,S,D)* to more equitable outcomes like *(S,S,D,D)*. The decision facing the dispatcher and the resulting outcomes are illustrated by the decision tree in Fig. 4.2. One can estimate $P_R(O_1, O_2, O_3, O_4)$ by examining historical data collected from hospitals or using ambulance travel times as a proxy for patient outcomes using computer-aided dispatch data (McLay & Mayorga, 2010). This example demonstrates how ex ante and ex post equity may represent useful principles in addition to those set forth by Stone (2002) and discussed earlier.

Several authors note that modeling ex ante equity implies several interesting properties for social utility functions. Specifically, Keeney (1980) shows that adopting an intuitive definition of equity requires risk proneness, while Diamond (1967) demonstrates that ex ante equity is inconsistent with expected utility maximization, and hence, with representing equity as a von Neumann-Morgenstern utility function. Broome (1982) and Sarin (1985) also demonstrate ex ante equity's inconsistency with the von Neumann-Morgenstern axioms, with Sarin explicitly introducing the label ex ante. Specifically, the von Neumann-Morgenstern axioms imply that a decision maker should be indifferent between a fair coin toss over the deaths of two individuals, and a "sure-thing" that one of the two individuals will die (the first, say). Valuing ex ante equity, however, requires that the coin toss be preferred to the certainty of the first individual dying.

Similar to the distinction between ex ante and ex post equity is a distinction between *procedural* and *distributive* fairness. As Joshi (1990) discusses in a management information systems (MIS) application, procedural fairness refers to the equity of a process used for allocating resources. Stone (2002) also makes a similar distinction, arguing that a major dimension along which equity might be evaluated concerns the equity of the process used to perform allocations. Joshi found that users in an MIS context ranked issues of procedural equity as generally of greater importance than those of distributive equity, which is the equity of the resource allocation ultimately selected. Note that much of the equity modeling literature, including that synthesized above, focuses on distributive equity, as distributive equity is implicitly acknowledged in defining equity in terms of the final resource allocations between individuals or groups. Distinguishing between ex ante and ex post equity provides one way to begin to address issues of procedural equity in public services allocation problems. These two concepts do not fully address the problems of procedural equity: for example, although ex post equity implies ex ante equity, it is not generally true that distributional equity implies procedural equity. However, in the specific sense that ex ante equity captures equitable properties of an allocation process, as distinguished from the equitable properties of a final allocation, the distinction between ex ante and ex post equity provides the beginnings of an approach to modeling issues of procedural equity.

Definitional issues such as those discussed at length in Stone (2002) and Sarin (1985) are the first step in creating a model of equity. Resolving these definitional issues is foundational for a public services resource allocation application that seeks to optimize or improve equity. Selecting principles along which to substantively define an equity measure is only a first step, however, since a fully specified function for the selected measure of equity is ultimately needed in any operations research model.

3 Functional Form

Choice of a functional form is crucial for fully specifying a measure of equity. Defining what is to be equitably distributed, to whom, and over what time horizon identifies the most equitable resource allocation which can be achieved for a given problem, but it does not establish how less than fully equitable allocations are to be ordered with respect to one another, nor precisely how inequitable these allocations may be. Since the most equitable resource allocation may be unattainable in a given public services allocation problem, or may be undesirable if it only allows for low levels of efficiency or effectiveness to be achieved, constructing and solving an operations research model require choosing a particular functional form with which to represent levels of equity. This situation arises, since selecting substantive principles along which a measure of equity is to be defined only determines a single functional point: it identifies as maximally equitable that point where all individuals or groups have precisely equal shares of the resource being divided. Even the properties of that particular point are only partially determined, since identifying a point as maximally equitable does not establish what numeric value (for equity) should be associated with that point, but only that its value should be higher than the equity values attained at all alternative points. Thus, modeling equity requires that a particular definition of equity be supplemented by the choice of a particular function.

To motivate the importance of functions for equity, consider, for example, the problem of equitably distributing EMS resources. Suppose "disparity in survival rates for patients in rural and urban areas" has been selected as the measure of equity. This selection uniquely identifies how equity may be maximized: equity is maximized if and only if there exist *no* survival rate disparities between rural and urban regions. However, it is unclear *how much* inequity should be attributed to distributions of EMS resources for which non-maximal equity is achieved, and hence, it is unclear which of the two distinct distributions of EMS resources, both creating some inequity, should be preferred. Choosing a function that associates a number with each resource distribution indicating the amount of equity or inequity implied by the solution provides a means for determining a preference ordering across such EMS resource distributions. In examining the range of choices that might be made when selecting a particular equity function, this section draws heavily on the excellent survey by Marsh and Schilling (1994), who explore equity function issues in great detail. We do not repeat all of the functions considered by Marsh and Schilling, but rather, a sampling of forms have been selected from their list to provide a clear view of the range of options available. When presenting each of the selected forms, we also discuss some computational tractability issues raised by each form.

First, we illustrate how different functions for the same definition of equity lead to different implications when implemented in mathematical programming models. One way to evaluate inequity (I) is as a function of the deviations of some measure, say survival rate, between each group and the mean survival rate. For example, one could measure the maximum of absolute deviations, as in (4.1) or the sum-of-squared deviations, as in (4.2) below. Where n is the number of groups considered, let S denote the mean survival rate over all groups, S_i denote the survival rate for group i, $i = 1,2,\ldots,n$. Then, equity is maximized when I is minimized, where the functions for inequity are:

$$I = \max_{i=1,2,\ldots,n} |S_i - S|. \tag{4.1}$$

$$I = \sum_{i=1}^{n} (S_i - S)^2. \tag{4.2}$$

Notice that (4.2) minimizes the variance of survival rates. Equations (4.1) and (4.2) differ computationally in which (4.2) is comparably simpler to implement. To implement (4.1) exactly within a mixed integer program, additional variables and constraints must be added, reflecting that each term $|S_i - S|$ is to be assigned a weight of 1.0 if it is greater than all other terms, and zero otherwise. Note that implementing a constraint of form (4.1) may be significantly simpler than doing so as part of an objective function, because requiring that the maximum absolute deviation be within a predetermined range can be written by simply requiring that every pair-wise difference be weakly less than some parameter value. Gopalan et al. (1990) implement (4.1) as a constraint in this fashion. By contrast, (4.2) may be directly incorporated as the objective function of a quadratic programming problem.

Instead of comparing each group's survival rate to the mean survival rate, one could compare the survival rates between groups. This concept is sometimes called envy, since it relates to dissatisfaction of one group in relation to another group. The simplest envy objective looks at the sum of the absolute deviations between groups, as given by (4.3).

$$I = \sum_{j=1}^{n} \sum_{i=1}^{n} |S_i - S_j|. \tag{4.3}$$

Computationally implementing (4.3), as in (4.1), requires the use of additional constraints to reflect the use of the non-smooth absolute value function. Assuming that inequity appears as an additive term in the objective function, one such implementation is:

$$\begin{gathered} I = \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} e_{ij} + s_{ij} \\ (S_i - S_j) - e_{ij} + s_{ij} = 0, i = 1,2,\ldots,n-1, j = i+1, i+2,\ldots,n \\ e_{ij}, s_{ij} \geq 0, i = 1,2,\ldots,n-1, j = i+1, i+2,\ldots,n, \end{gathered} \tag{4.4}$$

where the new variables e_{ij} are excess variables indicating the magnitude of the difference between S_i and S_j if S_i is greater than S_j, and the new variables s_{ij} are slack variables indicating the magnitude of the difference between S_i and S_j if S_j is greater than S_i; if S_i is greater than S_j, then e_{ij} is zero, while if S_j is greater than S_i, s_{ij} is forced to zero, so that the sum of e_{ij} and s_{ij} represents the absolute value of the difference between S_i and S_j. The second and third sets of constraints together impose these relationships between the variables S_i, e_{ij}, and s_{ij}. The idea reflected in the first line is that inequity is equivalent to the sum of the absolute differences between allocations to each pair of individuals or groups, *i* and *j*. This implementation requires $O(n^2)$ additional continuous variables and $O(n^2)$ additional constraints. However, it maintains the linear nature of mathematical programming formulations minimizing (4.3), allowing such models to be solved with well-established mixed-integer linear programming techniques, such as branch-and-bound.

Noted by Marsh and Schilling as "the most widely recognized in the economic and social welfare literature," and building on the concept of envy, the Gini coefficient, as shown in (4.5) provides another way to evaluate equity:

$$I = \frac{\sum_{j=1}^{n}\sum_{i=1}^{n}|S_i - S_j|}{2n^2 S}. \tag{4.5}$$

Implementing (4.5) in a linear mathematical programming model requires the use, as in (4.1) and (4.3), of a set of new either continuous or integer variables and constraints to represent the absolute-value function. In addition, however, (4.5) is nonlinear in which both its numerator and denominator contain decision variables. Upon representing the numerator in (4.5) linearly and continuously, as in our model for (4.3) above, mathematical programming techniques like fractional programming (Bazaraa, Sherali, & Shetty, 1993, p. 524) might be used to optimize a mathematical programming involving (4.5). Mandell (1991) applies the constraint approach to multiobjective programming to solve a bi-criteria mathematical programming model featuring an objective in the form of (4.5).

Notice that the Gini coefficient can be thought of as a weighted measure of envy. Other formulations that consider different forms of envy are provide by Espejo, Marin, Puerto, and Rodriguez-Chia (2009) and applied to a location model. Notice that functions (4.1)–(4.5) are qualitatively similar in which they all define inequity as some form of each group's deviation from some standard (the average survival rate, or the survival rate of others). In these four functions, inequity is guaranteed to be zero when the all of the groups' survival rates are identical. Nevertheless, these equations differ dramatically when examined in detail, and they have very different implications for the optimal solutions identified by and the implementations for particular mathematical programming models. For example, note that (4.1) is not continuous, while (4.2)–(4.5) are continuous. Discontinuities in (4.1) cause it to violate what Marsh and Schilling (1994) refer to as the *Principle of Transfers*, which states that any measure of equity should increase if reward or wealth is transferred from a more highly to a less highly rewarded individual, all else equal. In addition, on a typical dataset, (4.2) and (4.3) produce much larger values in an absolute sense than (4.1) or (4.5). This leads to challenges when considering the tradeoffs between equity and effectiveness or efficiency, since their values may be of vastly different magnitudes. This suggests that inequity functions (4.1)–(4.5) should be rescaled if they are to be combined in a weighed objective function with other criteria of interest. All four functions are nonlinear, but in quite different fashions (via absolute values or via squaring of values), and these nonlinearities bear importantly on what form of mathematical programming algorithms, if any, can be used to solve models incorporating (4.1), (4.2), (4.3), or (4.5). Moreover, the rates of change of each equity function with respect to changes in the underlying variables differ, implying different relative valuations of the various combinations of values for the survival rate variables.

The functions (4.1)–(4.5) are just 5 examples of the 20 functions that Marsh and Schilling (1994) systematically analyzed. We do not summarize all of these 20 functions, but instead focus on a set of organizing principles identified by Marsh and Schilling. By focusing on these principles, it is our intent to convey a systematic framework through which an equity function might be selected, and to identify the kinds of questions that are of interest in choosing such a function. First, Marsh and Schilling observe that all of the equity functions they consider attempt to evaluate equity (or inequity) with respect to some ideally equitable reference distribution of resources, but that the functions differ in which reference distribution is identified. Consider when inequity is represented as the sum of the magnitudes of the pair-wise differences between individuals' resource allocations, which might be written as in (4.3). In (4.3), the ideally equitable reference distribution of resources is defined with reference to each individual's peers. By contrast, (4.1) defines equity with respect to the mean survival rate ($\bar{S}$). In still other functions, some set of resource allocations or outcome magnitudes thought to be appropriate for each individual or group of individuals is chosen to replace $\bar{S}$ in (4.1), and hence, inequity increases with distance from these ideal variable values. In an EMS setting, a target survival rate for each group in consideration might correspond to such a selection of ideal outcome magnitudes.

Second, Marsh and Schilling (1994) observe that equity functions differ significantly in their scaling properties. The Gini coefficient (4.5) lies between 0 and 1, for example, whereas defining inequity as a sum-of-squares as in (4.2) results in an inequity measure that is only required to be greater than or equal to zero. Hence, the Gini coefficient uses 0–1 scaling, while (4.2) and (4.3) do not use scaling. Infinitely many variations on these two scaling schemes are also possible, of course, and they are significant in the selection of an equity measure, since they alter its interpretation. It is simple to communicate whether a Gini coefficient is relatively high or relatively low, for example, but interpretation of functions using less standard scaling procedures or no scaling at all requires contextual knowledge (about the units used) to assess whether a particular magnitude of inequity is large. This is important in public services, where the realized value of equity may need to be communicated to stakeholders, and functions such as the Gini coefficient offer naturally clear and intuitive explanations of equity. This is particularly important in EMS systems, where resources are dynamically allocated to incoming calls. Equity functions that are intuitive and unambiguous are ideal for EMS service providers making optimal decisions in real-time (McLay & Mayorga, 2010).

The 20 functions surveyed by Marsh and Schilling (1994) also vary dramatically in the complexity of their algebraic form. It is precisely this issue of algebraic form that causes (4.1) to defy the *Principle of Transfers*, and it is, moreover, choices of algebraic form that largely govern appropriate solution techniques. For example, with the introduction of appropriate dummy variables, (4.1) could be solved by a routine application of any linear programming algorithm, such as the Simplex algorithm. Solving (4.2) requires evaluating a quadratic expression, which could be optimized using the methods of quadratic programming (Winston & Venkataramanan, 2003, pp. 723–730). As Mandell (1991) demonstrates, (4.3) may be incorporated into a bi-criteria math programming problem, and – assuming a convex feasible region – the resulting mathematical programming model may be solved by separable programming. Inequity functions may also be defined as arithmetic expressions, involve logarithms, maximization/minimization statements (aside from those appearing around the objective function), or absolute values. Therefore, the algebraic form used to measure equity has significant bearing on the algorithms that are appropriate for optimizing the resulting mathematical programming problem. Certain algebraic forms may even produce equity functions that do not have convex feasible regions, a prospect that would motivate a simpler definition of equity, the use of heuristics, or the use of nonlinear programming techniques. For example, Chanta, Mayorga, & McLay (2010a) develop a Tabu-search to solve a minimum p-envy model for locating emergency vehicles, in which an equity measure that considers the weighted envy of demand zones with p open stations (which allows for the consideration of back-up coverage) is developed. This meta-heuristic approach solves the problem in seconds, which cannot be done with traditional approaches due to its nonlinear structure.

Lastly, we should be concerned with how the algebraic form of the *objective function* addresses the relationship between effectiveness, efficiency, and equity (assuming that effectiveness or efficiency are to be included in the objective function alongside equity, as is frequently desirable). Perhaps, the simplest approach to combining these three attributes in an objective function is to additively combine separate expressions for each. This assigns possibly different, constant weights to each of the equity and efficiency expressions. The weights may also serve to scale the effectiveness, efficiency, and equity attributes, since it is clear that scaling issues are of critical concern when combining these various attributes. Still more complicated objective functions could easily be considered that combine, for example, efficiency and equity in a nonlinear fashion. Consider a function in which the contributions of equity and effectiveness to an objective function depend on one another, in the sense that as levels of either attribute are increased, increments in the other attribute become increasingly attractive. One such function is:

$$I = \frac{\sum_{i=1}^{n} S_i}{\sum_{i=1}^{n} (S_i - S)^2}, \tag{4.6}$$

in which the numerator captures effectiveness (summed over all groups) and the denominator captures equity. Similarly, low levels of equity or effectiveness in (4.6) constrain the possible values of the objective function, with, for example, a zero value on effectiveness implying a zero overall value, regardless of equity's value. Of course, (4.6) presents novel optimization-theoretic and computational obstacles: linear fractional programming algorithms (Bazaraa et al., 1993, p. 524), for example, cannot be used to solve it, because the denominator is nonlinear. Problem-specific optimization algorithms and heuristics may need to be developed if problems with objective functions similar to (4.6) are to be successfully solved.

Instead of assigning weights to each criterion, another option is to solve multicriteria models using the epsilon constraint method. Using this method one objective is minimized, while all others are bounded at acceptable levels; see Chankong and Haimes (1983) for an extensive discussion on this approach. This provides the decision maker with a set of solutions, which show the tradeoff between objectives. Chanta, Mayorga, & McLay (2010b) applied this method to solve three different bi-objective covering location models where inequities are minimized while coverage is maximized.

Felder and Brinkmann (2002) provide an interesting illustration of how equity and efficiency can be rendered comparable in an EMS setting. Using this method, one objective is to determine in a retrospective analysis whether the German EMS data were more consistent with EMS allocation policies seeking a fair distribution of resources (equity) between urban and rural areas or with policies minimizing the loss of life (effectiveness). After analyzing their data set, Felder and Brinkmann observed that, in the German region of Brandenberg, "lives saved in non-urban areas of Brandenburg are valued up to 2.6 times higher than in densely populated areas." That is, in Brandenberg, the amount of money invested per life saved was 2.6 times higher in non-urban areas than in urban areas. Significantly greater amounts of investment are required in rural areas than in urban areas to attain equivalent survival rates, since rural populations tend to be sparsely distributed, which increases mean travel times for EMS vehicles relative to their travel times in urban settings. Often, more ambulances are allocated in non-urban areas per capita than in urban areas. Hence, Brandenberg appears to have pursued a policy emphasizing urban–rural equity rather than a policy solely minimizing total loss of life.

Thus far, we have only considered models that explicitly address equity. The analysis of Felder and Brinkmann (2002) suggests that models that do not explicitly address equity often indirectly address equity. Furthermore, equity can be indirectly evaluated by the choice of a mathematical programming model. For example, consider the decision context of locating ambulances to maximize a measure of effectiveness using facility location models. Typically, effectiveness can be maximized on an aggregate level, where the level of effectiveness may vary across the groups considered. A second way to model effectiveness would be to add chance or reliability constraints that enforce minimum levels of effectiveness for each group (Ball & Lin, 1993; ReVelle & Hogan, 1989). The latter model of effectiveness would implicitly enforce a particular notion of equity, since the chance or reliability constraints would ensure a minimum level of effectiveness thought to be appropriate for each group considered (Erkut, Ingolfsson, Sim, & Erdoğan, 2009).

This discussion of functions for both equity in isolation and equity as modeled in concert with other criteria of interest (e.g., effectiveness, efficiency) highlights three issues that should be considered in selecting an equity function in operations research models: (1) choice of reference distribution, (2) choice of scaling properties, and (3) choice of algebraic form (Marsh & Schilling, 1994). After a definition of equity has been selected, addressing these issues is a further, natural step in selecting a model of equity appropriate for a particular decision maker's needs.

4 Gaps, Goals, and Recommendations

Several critical issues in the modeling of equity have been addressed in the course of this chapter, largely through systematically synthesizing the existing multidisciplinary literature both within and outside of the operations research domain. This has helped to identify areas where knowledge regarding the modeling of equity is inadequate at present, and where past insights may be fruitfully extended to further improve our understanding of how to model equity. We argue that operations research models for equity should be extended in four directions. First, there is a need for careful analysis of the algebraic forms most appropriate for modeling the relationship between effectiveness, efficiency, and equity. Second, the possibility that equity might be modeled as a constraint rather than as a part of the objective function should be explored in a rigorous manner, with particular care taken in evaluating how the largely nonlinear functions available to measure equity bear on the convexity of a model's feasible region. Third, significant research effort should be directed to developing models that may be used to assess the presence and absence of procedural (Joshi, 1990) or process (Stone, 2002) equity, as opposed to defining equity primarily as a characteristic of final resource allocations. Fourth, it would be useful to identify a small set of equity functions, including some identified by Marsh and Schilling (1994), to develop a canonical "toolbox" of equity functions that might be applied separately in operations research models to assess the sensitivity of analytic results to changes in the function chosen to represent equity.

The first proposal, that the algebraic forms of objective functions combining effectiveness, efficiency, and equity be systematically surveyed and analyzed, could be approached as a natural extension of the work of Marsh and Schilling (1994). Where Marsh and Schilling systematically surveyed and categorized the functions that have been used in the isolation for measuring equity in location problems, a similar review could be carried out for objective functions incorporating effectiveness, efficiency, and equity in concert for a broader set of optimization problems beyond location analysis. Similar to the work of Marsh and Schilling, such a review would benefit greatly from a conceptual consideration of ethical principles that may be reasonably expected to hold for the relationship between effectiveness, efficiency, and equity (as, e.g., the *Principle of Transfers* was used in Marsh and

Schilling's analysis). A review that focuses on the mathematical programming formulations (and corresponding solution algorithms) would be useful for understanding how such models could be efficiently solved. Therefore, a discussion of how the algebraic form of the objective function bears on considerations of computational complexity, convexity, and concavity would be critical in such a review.

There is a dearth of papers that address this first proposal. Kozanidis (2009) addresses this issue in the context of a bi-objective linear multiple choice knapsack problem. The two objectives considered by Kozanidis are effectiveness (profit) and equity. Kozanidis considers only one formulation for equity that reduces the maximum disparity between the resources allocated to any two sets of activities. The resulting problem is formulated as a bi-objective linear programming model. An algorithm is provided which yields the entire efficient frontier. Mandell (1991) explores the tradeoff between effectiveness and equity in optimization models for allocating public resources. Mandell considers the Gini coefficient for evaluating equity and constructs a bi-criteria mathematical programming model. Mandell uses the model to determine how to allocate new book acquisitions in a library system with multiple branches. Both Kozanidis and Mandell provide excellent analyses of the theoretical issues in modeling equity as a second objective in optimization models. The many other definitional issues for equity considered in Sect. 2 would benefit from similar analysis.

The second proposal – to explore the use of equity as a constraint – is interrelated with the first proposal. It may be natural in many situations to model equity directly as part of the objective function, but in other situations – those where some threshold level of equity is required, in particular – equity might most naturally be incorporated in the constraints of a mathematical programming model. Gopalan et al. (1990), for example, modeled equity as a constraint to study the tradeoffs between equity and efficiency in the transportation risks associated with hazardous materials. When equity is not viewed as a hard constraint, equity constraints could alternatively be modeled as chance constraints (Charnes & Cooper, 1962). This kind of investigation should naturally motivate efforts to linearize the equity constraints and to ensure a convex feasible region, since such structural properties of the model bear importantly on the techniques suitable for solving operations research problems in which equity is a concern.

The third proposal effectively recommends that equity considerations in operations research models be addressed in a rigorous way that reflects the important role of process equity (Joshi, 1990; Stone, 2002) in the broad literature on equity. In part, the concepts of ex ante and ex post equity (Keeney & Winkler, 1985; Sarin, 1985) capture what is meant by process equity, and these ideas could be applied outside of decision analysis and could be included in optimization models, for example. The hypothetical EMS example in this chapter demonstrates how these two ideas may be significant – and significantly different from one another – in an EMS setting, and hence, they should be considered as meaningful additions to the substantive principles that Stone identifies. Additional work in this spirit is needed.

The fourth proposal is largely distinct from the first three. It urges the identification of a canonical "toolbox" of functions for representing equity. This issue is important, since equity is addressed in an ad hoc manner in many operations research models. Such a toolbox could standardize the modeling of equity, better align equity functions with theory, and streamline the process of building models that are intended to incorporate equity concerns as a critical part of their design. Of course, identifying such a generally acceptable set of equity functions presents major difficulties. In particular, it is not clear how the definitional issues – those included in Sect. 2 – might be resolved. However, it may be significantly easier to identify a set of suitable functions as standard. That is, given a certain universe of possible functions or types of functions, such as those surveyed in Marsh and Schilling (1994), operations researchers could select a small array of distinct equity functions, where differences between the functions could be evaluated by examining the varying mathematical properties of the functions, such as asymptotic form, tractability, and continuity. Such a small, finite subset of all possible equity functions could help to serve as a standard suite of functions for evaluating the robustness of a particular model's results to choice of equity function. If results are relatively similar across all the functions in the suite, this result might be taken as inductive evidence in favor of the robustness of the model's implications with respect to the choice of function.

Lastly, the reader is reminded that although EMS problems have been used as examples throughout this chapter, the issues considered and recommendations produced are pertinent to public services domains generally. Indeed, many of the papers drawn on in the foregoing discussion illustrate the importance of equity in non-EMS contexts, including: Gopalan et al. (1990) in the transportation of hazardous materials, Joshi (1990) in the allocation of MIS resources, Mandell (1991) in the administration of a public library system, Sampson (2006) in volunteer assignment, Tseytlin (2007) in hospital employee assignments, and Marsh and Schilling (1994) in public-sector facility-location in general. Some further illustrations consider the importance of equity in certain very general classes of models: Larson (1987), for example, discusses the importance of preserving equity in evaluating queue performance, while Kozanidis (2009) present an algorithm for assessing the tradeoffs between optimizing profit and equity in a bi-criteria knapsack model. Equity also often emerges as a significant issue in the discussions of public sector projects even when it was not intentionally selected as an object of study. For example, Green and Kolesar (2004) discussed the successful applications of management science/operations research to improving the provision of police and firefighting resources. During this discussion, they noted that the ability to easily consider efficiency-equity tradeoffs in firefighting company assignments was a significant advantage to firefighting departments of certain management science/operations research models and solution techniques.

Of course, the most appropriate uses of equity may vary with the domain of application. The impacts of equity in employee assignments are likely more important in areas where volunteer labor is critical (Sampson, 2006), for example, than in areas where most employees are paid for their services. Hence, the uses of equity across different public services sectors may require that certain of the elements discussed above be varied systematically, as appropriate for the arena of application. Nevertheless, it is expected that the foregoing discussion should be of broad usefulness for practitioners and analysts interested in assessing issues of equity in the public services realm very generally.

5 Conclusions

Although the considerations discussed throughout this chapter have been viewed primarily through the lens of EMS resource allocation problems, the concerns are quite general, and of special importance to problems of public interest. In modeling equity, decision makers, stakeholders, and researchers benefit from considering for what resource an allocation should be equalized, for what time period that equalization should achieved, and for which groups of people or individuals the equalization is relevant. Having addressed these questions, a natural next step for determining how to model equity is to select a reference distribution, scaling properties, and algebraic form for the measure to be used. The literature provides significant guidance in determining both how to define equity and how to represent it in a particular function. However, there is a dearth of research in the operations research domain that systematically analyzes the functions through which equity may be combined with other attributes in an objective function, or that addresses how to incorporate equity into the constraints of a mathematical programming model from a methodological point of view. Future work should consider each of these problems and, moreover, attempt to identify a diverse "toolbox" or test suite of functions for measuring equity, which researchers could apply as tests of their results' robustness with respect to the form in which equity is measured.

By providing guidance for how to construct measures for equity that draw upon the multidisciplinary literature, it is hoped that this chapter can provide a useful basis for operations researchers concerned with equity in public resource allocation problems. By providing explicit recommendations for further research, it is also hoped that the foregoing analysis may motivate novel research regarding the modeling of equity, and that such research can contribute to improving the sensitivity of operations research to issues of equity.

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Part II
Facility Location and Spatial Analysis

Chapter 5
Spatial Optimization and Geographic Uncertainty: Implications for Sex Offender Management Strategies*

Alan T. Murray and Tony H. Grubesic

1 Introduction

As of October 2010, there were 716,750 registered sex offenders in the USA and its territories (National Center for Missing & Exploited Children [NCMEC], 2010). In addition to federal legislation, such as the Adam Walsh Child Protection and Safety Act requiring that convicted offenders register with law enforcement agencies on a regular basis (Freeman & Sandler, 2010; Harris & Lobanov-Rostovsky, 2010), many states and thousands of municipalities have passed laws restricting residence options for convicted offenders (Grubesic, 2010). In general, residence restrictions mandate that offenders cannot live within a specified distance (e.g., 1,000 ft) from "sensitive" facilities, such as locations where children congregate. Although the definition of sensitive facilities can vary, they often include some combination of schools, parks, bus stops, and swimming pools (Meloy, Miller, & Curtis, 2008).

While much of the recent debate concerning the efficacy of sex offender laws focuses on the effects of residence restrictions on offender housing availability, rehabilitation, and other collateral consequences (Mulford, Wilson, & Parmley, 2009), very little attention has been paid to the practical aspects of measurement and accuracy in spatial data and sex offender residency information. The use of

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geographic information systems (GIS) for delineating boundaries and developing spatial databases of offender locations improves both efficiency and analysis capabilities, but there are limitations associated with data accuracy, precision, and reliability in geographic base files (or data layers) and offender registries. Further, although these uncertainties may not have a significant impact on the analysis of one or two offenders, the propagation of error and inaccuracy in an analysis involving several thousand offenders (or more) may be significant. The same can be said for the analysis of sensitive areas. If these types of errors are not understood and accounted for, analysis suffers and the ability to evaluate the contingencies of sex offender management strategies is jeopardized – potentially giving misleading or erroneous outcomes relative to danger, risk, and public policy.

The purpose of this chapter is to discuss a range of issues associated with sex offender data and its analysis, with particular attention paid to the effects of geographic uncertainty on spatial modeling. This type of analysis is important for several reasons. First, as mentioned previously, the presence of data uncertainty will surely influence the quality of analyses conducted and the legitimacy of public policies based on them. Second, while many practitioners might be relatively comfortable with basic GIS analysis techniques, such as proximity analysis, buffering, and aggregation, their familiarity with projection systems, spatial data quality, and geographic representation may be limited. In addition to addressing these issues in detail, approaches that help better understand data uncertainty used in spatial analysis are greatly needed because of a growing interest in both developing and applying spatial approaches for evaluating contingencies associated with sex offender management strategies throughout the USA (Grubesic & Murray, 2009; Mulford et al., 2009).

The remainder of this chapter is organized as follows. The next section provides a brief review of several elements related to data uncertainty and geographic representation for sex offender analysis. This is followed by a review of spatial analysis approaches for sex offender management. Approaches accounting for data uncertainty in spatial models are then presented. The chapter ends with a discussion of results and concluding thoughts.

2 Data Uncertainty, Geographic Representation and Sex Offender Analysis

Many aspects of spatial data uncertainty have been recognized in geography, epidemiology, and other disciplines. Uncertainty stems from imperfections in spatial data and the need to generalize complex phenomena as simpler abstractions. This is frequently accomplished through an *object* perspective or a *field* perspective in geographic analysis and GIS. As noted by Longley, Goodchild, Maguire, and Rhind (2005), object-based perspectives attempt to represent geographic space as a region populated with discrete entities, each with a unique identity and suite of attributes. For example, buildings, highways, and lakes are three classes of phenomena that can be modeled using an object-based framework. Typically, these types of phenomena are represented as points, lines, or polygons (Miller & Wentz, 2003). The field-based model is a slightly different approach, where each location in space is represented by a value selected from an attribute domain. For example, continuous spatial variables such as elevation and snowfall/precipitation are typically captured using a field-based approach (Longley et al., 2005), operationalized using a raster system or vector-based contours. The major problem inherent to both field and object perspectives is the process of abstracting real, three-dimensional phenomena occurring on the earth's surface into a simplified digital representation. One common problem in the object-based framework, for example, is omitted features. Reasons for omission are myriad, from incompatible spatial scales to the improper understanding of the problem at hand. For instance, the evaluation of sex offenders and community risk often includes spatial restriction zones (SRZs) around schools and parks, but can mistakenly omit features or locales where sex offenders congregate, such as rehabilitation facilities or drug/alcohol treatment centers. Obviously, these types of omissions can negatively influence the quality of methods-based analysis geared toward better understanding the movements of convicted offenders. In turn, these errors can lead to poorly informed public policies.

Regardless of the framework under consideration, imperfections in spatial information are multidimensional in nature. Goodchild and Gopal (1989) provide a review of these imperfections with particular emphasis on how they manifest in a GIS environment, outlining seven major themes. Several facets of imperfect spatial information can be extracted from their themes relevant for sex offender analysis, including *accuracy*, *precision*, *spatial scale*, and *geographic abstraction*. In addition to these facets, we present several other dimensions of imperfection directly relevant to sex offender analysis, including *distance measurement*, *data redundancy* and *completeness*, *map projection*, and the *co-mingling of imperfection*. Each are now discussed in turn.

2.1 Accuracy

A primary concern of any GIS-based analysis concerns the accuracy of spatial data and the inherent limitations associated with accurately capturing geographic phenomena in a digital environment (Leung, Ma, & Goodchild, 2004a). Accuracy generally reflects how closely a measurement or observation reflects the actual quantity measured. Problems with accuracy often arise in both temporal and spatial domains (Verigin, 1999). In the context of sex offender analysis, for example, the accuracy of positional data related to both offender residency and sensitive facility locations is extremely important for evaluating residence restrictions. Consider the ramifications associated with a failure to accurately identify the location of a school for determining residence restrictions in a community. From a policy and analysis perspective, there would simply be an incorrect characterization of offenders violating residency restrictions, either no one in violation, when there are in fact violations, or vice versa. However, the failure to accurately locate the residence of a convicted offender may endanger vulnerable members of a neighborhood or limit the overall effectiveness of legislative efforts intended to protect a community.

2.2 Precision

A second uncertainty issue is precision. In GIS, precision typically refers to numeric storage (e.g., 8 decimal places) and is related to the overall exactness of a description in a database (Verigin, 1999). At issue is the fact that no existing GIS has the capacity to warn users when geographic base files (or spatial data layers) at varying or incompatible scales are combined. This is a major concern because of the positional accuracy that exists for any spatial scale. For example, data associated with a 1:1250 scale provides positional accuracy to within 0.652 m or so, data derived at 1:24,000 scale has positional accuracy to within 12 m, and data at a 1:250,000 scale has positional accuracy only to within 125 m (Longley et al., 2005). Not only would the spatial precision associated with features in these layers be different, but there is nothing to stop analysts from performing operations such as buffering, overlay, or proximity analysis using objects/elements from such geographic layers. As noted by Abler (1987) and Goodchild and Gopal (1989), when subjected to ground truthing, analyses based on mismatched scales and spurious precision are often inconsistent with geographical truths. This is particularly problematic for sex offender analysis where data generated by and collected from a diverse range of public and private agencies (e.g., state departments of education, law enforcement agencies, second party data vendors, county auditors, etc.) are rarely in congruence. In part, this lack of consistency can be attributed to data generation procedures and incompatible scales. Data are typically generated for a particular use or application and are not easily transferable or modifiable for other purposes.

In terms of significance at the neighborhood level, the imprecise placement of school bus stops, playgrounds, or parks can have implications on the spatial morphology of offender restriction zones, particularly when one is considering distances on the order of 350 m. If a bus stop is located 50 m south of its actual location (combined with a restriction distance of 350 m), then the spatial extent of a restriction zone based on the inaccurately located bus stop fails to delineate some 10% of the actual area in this case. The use of federally generated data for delineating municipal boundaries, such as cartographic boundary files for Census Designated Places (CDPs), can also influence precision in this way. For example, CDP boundaries are designed for use at geographic scales ranging from 1:500,000 to 1:5,000,000 (United States Census Bureau [Census], 2001), which translates to, at best, 250 m positional accuracy of features. Considering that many sex offender analyses are conducted at more refined scales (e.g., 1:24,000), the potential to imprecisely characterize municipal boundaries and restriction zones is significant.

2.3 Reliability and Completeness

In many instances, the process of collecting data can be problematic. While reliability often refers to the level of consistency and stability in the measurement of phenomena, completeness is primarily concerned with the inclusion of enough data for generating accurate distributional predictions, taxonomies, or trends (Peterson & Cohoon, 1999). In a typical analytical framework, complete data that lacks reliability or reliable data that lacks completeness can significantly skew results. Thus, both facets are important when considering information quality and/or uncertainty. This is particularly salient for sex offender analysis because of the problems associated with data collection efforts across numerous communities, political jurisdictions, and law enforcement agencies. First, registries can become outdated and inaccurate. As noted by Bedarf (1995) and Matson (1999), in many jurisdictions there are simply not enough paid staff members to maintain a high-quality sex offender registry. Second, while states are mandated to develop sex offender registries in correspondence to the newly developed national sex offender registry, there are no specifically designated federal funds for this purpose. As a result, many states and local law enforcement agencies are forced to compete for federal monies through domestic violence grants or other record-upgrade grants (Chaiken, 1998). Third, it is not uncommon for sex offenders to change residences, either within a single jurisdiction/region or to proximal ones (Mustaine, Tewksbury, & Stengel, 2006). With each movement, registries must be updated to reflect the new residence, and potentially employment information. Fourth, there is a need to *deregister* offenders, particularly if a move is made out-of-state or if the registration requirements expire.[1]

Finally, there are many instances where offenders simply fail to register. According to the National Center for Missing and Exploited Children [NCMEC] (2010), there are over 100,000 convicted sex offenders who are noncompliant with current registration requirements in the USA. In fact, recent research in the state of California also reveals that authorities lost track of approximately 33,000 sex offenders, representing 44% of the 76,350 offenders who had registered with the state at least once in 2002 (Curtis, 2003). When confronted with this information, the Attorney General of California acknowledged that a lack of human resources and funding for maintaining the state sex offender registry plays a major role in the accumulation of so many “lost” offenders (Curtis, 2003).

[1] The Walsh Act requires that states monitor the whereabouts of convicted offenders for at least 15 years, and up to a lifetime, after release from prison. Convicted offenders are also required to report to local law enforcement agencies, in person, for address verification every 3–12 months, depending on their offense classification.

2.4 Distance

A fourth facet of uncertainty is the distance between two locations in space. In GIS there are a number of ways to compute and/or evaluate distances, all conceptually reflecting possible paths of travel through space (Leung, Ma, & Goodchild, 2004c). One possible path is travel along roads in the transportation network. GIS can readily derive the shortest path in a network between two locations. Whether this accurately reflects the distance separating two locations is another matter. For example, it may be possible to walk through a park or other green spaces; so travel would depend on whether it was by foot or in a vehicle. A generalized path of travel associated with the distance between two locations x_i and x_j is the l_p metric:

$$d_p(\mathbf{x_i}, \mathbf{x_j}) = \left[\sum_{k=1}^{n} \left|x_i^k - x_j^k\right|^{\rho}\right]^{\frac{1}{\rho}}, \rho \geq 1, \tag{5.1}$$

where $\mathbf{x_i}$ is a n-dimensional vector of location coordinates and ρ is a real number corresponding to the length parameter. When $\rho = 2$, the length (and path) measurement corresponds to the standard Euclidean (straight line) distance, and when $\rho = 1$ it corresponds to Manhattan distance (movement north-south or east-west). As noted by Love, Morris, and Wesolowsky (1988), actual travel distances in urban areas are usually best represented by $1 \leq \rho \leq 2$ because of the availability of walking paths, shortcuts, and streets/sidewalks. Whether network distance or an l_p metric is used, there remains uncertainty in such measures depending on the intended purpose of analysis. Given the nature of most sex offender laws in the USA, particularly residence restrictions, the accurate and precise measurement of distance is one of the most important aspects of public policy evaluation. Failure to accurately portray travel routes and associated distances in any analysis creates a number of problems. One is that correlation to other activities or spatial attributes may be missed, particularly with respect to routine activity spaces of sex offenders and potential victims. Another is that analysis is open to litigation if distance measurement is not accurate (see American Civil Liberties Union [ACLU], 2009).

2.5 Geographic Abstraction

Another relevant representational issue arising from the use of GIS has to do with object-based frameworks where points, lines, and areas are used for representing locational information. As noted previously, while this type of abstraction is necessary, it is hoped that the digital representation is not overly simplistic (Murray & O'Kelly, 2002). That said, there are several different potential representations for regions in geographic space. Consider, for example, 30 contiguous Census blocks that represent a neighborhood within a community. In a GIS, it is possible to dissolve the boundaries of each census block to create a single polygon that delineates the spatial extent of the neighborhood. As an alternative, the initial unaltered block boundaries can also delineate a neighborhood and its 30 Census-defined partitions as a composite. One could also represent each block as a point by generating their associated centroids. It is also possible to construct a regularized grid approximation of the neighborhood (Murray & O'Kelly, 2002).

Given these variations in abstraction methods within an object-based framework, uncertainty for sex offender analysis may arise in several ways. For example, the combination of points, lines, and areas for representing schools, restriction zones, and offender locations demands consistency. While schools can be represented by latitude and longitude coordinates (as a point) in a geographic base file, they are in fact areas, consisting of buildings, parking lots, athletic fields, etc. Their representation as a point is problematic because it likely leads to an underestimation of the actual area occupied and lacks shape characteristics of the represented feature. Additional problems can be introduced when representational elements are mixed. For example, while schools might be represented as points, parks are represented as areas. Again, this unevenness can jeopardize comparative and quantitative consistency relative to restriction zones, thereby negatively impacting policy evaluation.

Of much importance in sex offender analysis is the abstraction of streets, highways, and freeways as centerlines because they add uncertainty to the actual location of the road. Widely used for characterizing local street networks, centerlines can be misleading because street widths in most urban areas vary significantly. For example, consider the difference between a centerline representation of an alley and a two-lane urban arterial. Although the alley is 3 m wide and the major arterial is 8 m wide, both are represented with a single centerline that fails to accurately characterize differences in width. These types of representational issues are particularly relevant to sex offender analysis because of the use of geocoding routines to locate sensitive facilities and sex offender residences (Zandbergen & Hart, 2009). Specifically, addresses of convicted offenders are collected from a public registry system, assigned geographic coordinates (i.e., geocoded), mapped, and evaluated to determine whether they fall within an established restriction zone. As noted by Zandbergen and Hart (2009), this process is fraught with uncertainty, and the quality of these types of analysis is heavily contingent upon the type of geocoding process used. For example, it is not uncommon for analysts to use street centerlines as the basis for geocoding sex offender residences (Chajewski & Mercado, 2009; Zgoba, Levenson, & McKee, 2009), even though the problems with accurately locating residential structures through this type of approach are widely recognized (see Cayo & Talbot, 2003; Grubesic & Murray, 2004; Ratcliffe, 2001; Zandbergen, 2008; Zandbergen & Hart, 2009). Linear interpolation and irregularity in street width and house setbacks create considerable inaccuracy and affect the quality of any proximity analysis.

2.6 Map Projections

Another element of uncertainty in sex offender analysis is the use of a two-dimensional surface representing the three-dimensional earth. A standard feature of any GIS is the ability to project three-dimensional geographic data to a two-dimensional coordinate system. Working with a two-dimensional representation is convenient but also practical in many ways. While it is beyond the scope of this chapter to provide a complete review of the strengths and limitations associated with different projection systems, the important point is that the projection process necessarily introduces uncertainty in the form of error. Some projections preserve shape (e.g., conformal projections) while others preserve direction (e.g., azimuthal) or area (e.g., equal area). The exact type of error and its magnitude depends on the location of an area on the surface of the earth and its size, as well as the projection used. Because many geographic studies are interested in evaluating the consequences of sex offender residence restrictions (e.g., 1,000 ft from sensitive facilities), it is important that analysts select a projection that minimizes the distortion of distance. In such cases, the universal transverse Mercator (UTM) projection is often a good choice for several reasons. In the UTM grid system, areas between 84° north and 80° south latitude are divided into a series of columns, quadrilaterals, and 100,000 m zones that enable a user to specify both an easting and northing up to five digits. In theory, this makes UTM coordinate systems accurate to 1 m. Because of the precision to which distances can be calculated using UTM systems, virtually all US military maps make use of it.[2]

While there is no need to belabor the importance of projections for proximity analysis, many of the published studies relating to sex offender residence restrictions fail to identify which coordinate system was used. Further, in a recent academic exchange, Zandbergen (2008) notes that Duwe, Donnay, and Tewksbury (2008) use the Google Earth ruler tool for calculating the distance between offender addresses and the locations where their victims were contacted. Zandbergen correctly noted that the default projection in Google Earth is either simple cylindrical or Plate Carree – both of which are less than ideal for fine scale distance measurement. That said, very little information is known regarding how other GIS packages (e.g., ArcGIS) compute straight line distances. Evidence suggests that ArcGIS uses the Pythagorean formula for calculating distances between two points (Environmental Systems Research Institute [ESRI], 2010). Because this fails to account for the curvature of the earth's surface, like a great-circle distance calculation would, it is clear that the coordinate system chosen for representing spatial data is extremely critical in a GIS. Analysts with limited training in both the spatial sciences and cartography are likely unaware of the problems in using alternative projection systems. These problems are also compounded by popular

[2] In order to cover polar areas with similar accuracy, the universal polar stereographic (UPS) grid system is used (Robinson, Morrison, Muehrcke, Kimerling, & Guptill, 1995).

commercial GIS packages, where the default coordinate system is the unprojected geographic coordinate system, which uses raw latitude and longitude coordinates for representing a location on the earth's surface.[3] It is also important to note that many local agencies (cities, counties, states, etc.) use the State Plane Coordinate System for their area. Many of these systems are based on a Conformal projection – which preserves shape rather than distance.

2.7 Co-Mingling of Imperfection

Given the various facets of imperfection and data uncertainty outlined above, it is evident that they do not occur in isolation. Often, elements of uncertainty co-mingle, serving to amplify their associated effects. For example, consider the analytical ramifications of conducting a proximity analysis of sex offender residency restrictions using the following protocol:

1. Offender and sensitive facility locations are determined by street centerline geocoding.
2. Distance measurements and spatial buffers are derived using an equirectangular projection (e.g., Plate Carree).

This is not particularly far-fetched, as these protocols are easily accessed in most desktop GIS packages. In addition to the lack of locational accuracy associated with geocoded points generated using a street centerline, measurement errors stemming from the use of a projection that is neither equal area nor conformal will also skew the location of objects in unintended ways that cannot be explained or quantified.

From a more pragmatic perspective, the consequences associated with disallowing an offender from living in locations that were identified with poorly implemented proximity measures can be significant. For example, the American Civil Liberties Union (ACLU) has an established track record of litigation seeking to protect convicted offender rights. From Iowa (ACLU, 2005) to Miami (ACLU, 2009), the apparent willingness of the ACLU to challenge state and local offender housing ordinances means that poorly implemented offender management strategies may prove to be both time consuming and costly to local governments, particularly if they are found liable for damages incurred by offenders.

In sum, each element of uncertainty outlined above can influence the quality of sex offender residency analysis and the resulting efforts to craft effective and fair public policies for managing this population. Perhaps most relevant to this chapter is the fact that abstracted geographic features (e.g., schools, streets, and residences)

[3] The geographic coordinate system is problematic for measuring distances because the only location where one line of longitude is equal in distance to one line of latitude is at the equator. As one proceeds either north or south to the poles, the distance between the lines of longitude becomes increasingly small.

in a geographic information system are often subjected to further abstraction (e.g., areas to points and streets to centerlines) when conducting analysis. Thus, it is important to better understand the types of impacts these abstractions might have on an analysis. In the next section, we review several spatial modeling approaches developed for managing sex offender populations within a community, and then discuss how they can be viewed in terms of data uncertainty.

3 Models for Examining Sex Offender Residency Issues

Sex offender residency and associated policy and planning frameworks are of growing importance at the federal state and local levels given the significant consequences that sexual abuse crimes have on society (Robinson, 2003; Thomas, 2005). Given the popularity and wide-ranging nature of management strategies to deal with sex offenders in the USA and abroad (Cohen & Jeglic, 2007; Grubesic, 2010; Sample & Kadleck, 2008), there is a clear need to support this type of legislation with sound quantitative analysis before implementation. A failure to evaluate the contingencies associated with proposed offender management strategies can lead to poorly designed policies and weakened efficacy. As a result, spatial models have been developed to aid in evaluation and planning processes for law enforcement agencies and state and local governments. These models make use of spatial information in various ways, but as noted above, all spatial information has various aspects of uncertainty. As a result, to develop the most effective planning and support models possible, these elements of uncertainty must be better understood in the analysis context.

Saturation statutes and dispersion ordinances for controlling the spatial distribution of offenders (Boyd, 2008; Eakins, 2008; Mazza, 2008) have necessitated the use of two specific spatial optimization approaches. One approach, introduced in Grubesic and Murray (2008), structures sex offender residency as a dispersion process.[4] Specifically, the geographic requirements stipulating areas where residency is not permitted as well as minimal separation between offenders are considered. Thus, a model is produced to ensure that no violations of the separation requirements occur, providing important information to corrections officials and policy makers for benchmarking the number of offenders that could potentially reside in a region, under the proposed restrictions. This model is structured as follows:

k = index of potential residences for convicted sex offenders.
Γ = minimum geographic separation between offender residences.
Φ_k = potential residences within stipulated separation Γ of residence k.

[4] For a thorough review of dispersion models, see Curtin and Church (2006).

$$Z_k = \begin{cases} 1 \text{ if a convicted sex offender resides at } k \\ 0 \text{ otherwise} \end{cases}.$$

Maximize

$$\sum_k Z_k. \tag{5.2}$$

Subject to

$$Z_k + Z_l \leq 1 \qquad \forall k, l \in \Phi_k, \tag{5.3}$$

$$Z_k = \{0, 1\} \qquad \forall k. \tag{5.4}$$

As noted previously, this model can be used to benchmark the number of convicted offenders that could potentially reside in a region, as well as where, while simultaneously ensuring that separation restrictions are maintained. The objective, (5.2), maximizes the number of offenders residing in a region. Constraints (5.3) ensure that no two selected residences are within the separation requirement. This is based on Γ that defines the set Φ_k, and is established by a community or local law enforcement agency. Integer restrictions are imposed in Constraints (5.4).

Another modeling approach is detailed in Grubesic and Murray (2009). Rather than focus on an explicit notion of dispersion reflective of Γ, an alternative approach provides the capacity to examine and plan for equitable spatial distributions of convicted sex offender residences across a region. In contrast to benchmarking how many could reside in an area based on separation between offenders, this alternative approach focuses on a spread of offenders relative to a base population or distribution. The model is as follows:

i = index of spatial units (total Ψ).
β_i = number of people at risk in unit i.
ρ = number of sex offenders residing in region.
Ω_i = units neighboring unit i.
X_i = number of offenders allowed to reside in area i (0, 1, 2, 3, ..., ρ).
Y_i^+ = deviation above regional average for the number of offenders around unit i.
Y_i^- = deviation below regional average for the number of offenders around unit i.

Minimize

$$\sum_i \left(Y_i^+ + Y_i^-\right). \tag{5.5}$$

Minimize

$$\sum_i \beta_i \left(X_i + \sum_{j \in \Omega_i} X_j \right). \tag{5.6}$$

Subject to

$$X_i + \sum_{j \in \Omega_i} X_j + Y_i^+ - Y_i^- = \frac{(\rho(|\Omega_i| + 1))}{\Psi} \qquad \forall i, \tag{5.7}$$

$$\sum_i X_i = \rho, \tag{5.8}$$

$$X_i = 0, 1, 2, 3, \ldots \qquad \forall i, \tag{5.9}$$

$$Y_i^+, Y_i^- \geq 0 \qquad \forall i. \tag{5.10}$$

The first objective, (5.5), minimizes the relative proportion of offenders in local areas. The second objective, (5.6), minimizes the residential risk of exposure by offenders. Constraints (5.7) establish a regional proportion around each area. Constraint (5.8) specifies the number of sex offenders in the region. Integer and nonnegativity conditions are imposed in Constraints (5.9) and (5.10) accordingly.

The two reviewed modeling approaches enable sex offender residency issues to be examined in complementary ways. A prevailing question in many communities is what are, or would be, the impacts of sex offender residency restrictions. To answer such a question, the first model interprets the restriction requirement as limiting any two offenders from residing within the separation distance of each other. What is found using the model is the maximum number of offenders who would be allowed to reside in an area, if residency restriction were imposed. Further, it enables exploration of alternative separation standards. The second model approaches the situation differently, seeking to find how many offenders should reside in neighborhoods relative to some distributional baseline. This assumes that some given number of offenders will reside in an area. At issue, then, is the distribution of the offenders and questions of equity within a community.

4 Addressing Uncertainty

Given the previous discussion of spatial data uncertainty, the issue arising in the application of either of the two detailed models concerns the implications of data uncertainty, spatial or otherwise. Further, if data uncertainties exist, how would one go about assessing their effects within the context of a discrete optimization model?

There has been some related work on addressing data uncertainty issues. In a very general sense, any introductory course in optimization discusses data uncertainty through the process of sensitivity analysis (e.g., Winston, 2004), where effectively any model parameter can be systematically evaluated. While sensitivity analysis is valuable and helpful, much of the inherent issues of uncertainty in spatial analysis are often outside of the parameter coefficients in models. Instead, they are associated with the spatial structure embedded in the mathematical model.

In spatial analysis, there has been work that examines aspects of uncertainty. Prominent examples are Goodchild (1972), Larson and Stevenson (1972), and Asami and Isard (1989) where various aspects of data uncertainty were considered. Additionally, a significant literature exists in the area of location modeling, a review of which can be found in Murray (2003). Finally, work focused on the so-called modifiable areal unit problem (Openshaw & Taylor, 1981) is loosely related to the issue of data uncertainty, recognizing that scale variability and unit definition can lead to uncertainty in the interpretation and significance of statistical tests.

Unfortunately, none of the above work explicitly examines the sort of issue posed here, nor gives definitive guidelines for understanding the effects of observed data uncertainty. In order to develop any kind of understanding of possible biases or impacts of data uncertainty in sex offender residency modeling, it is first necessary to highlight the model components subject to uncertainty. In the Grubesic and Murray (2008) model, dispersion is reflected using a node packing framework. Spatial issues associated with applying the model have to do with the location of potential residences, the location of sensitive facilities, the measurement of distance, and the interpretation of proximity. The residential and sensitive facilities boundaries represent where offenders can and cannot live.

Consider, for example, the residential parcels and school parcel shown in Fig. 5.1. Are the boundaries accurate, and what is their associated precision? The uncertainty that arises in this case is depicted in Fig. 5.2, where a boundary (or point) may actually lie within the ε_b shaded area. The precision of the data therefore would dictate what the associated ε_b value would be, as discussed previously. The measurement of distance is also a source of uncertainty in this case. As noted previously, there are numerous possible interpretations of distance, and three variants are illustrated in Fig. 5.3 (Euclidean, rectilinear, and network). When considered in the context of exclusion areas and the minimum geographic separation distance, Γ, this means that the actual distance could be closer *or* further away. For example, in Fig. 5.3, point A is within Γ of point B if Euclidean distance is considered, but point B is beyond Γ according to the other two measures of distance. The significance is that there exists another form of uncertainty around exclusions areas, or when examining

Fig. 5.1 School and residential parcels and streets

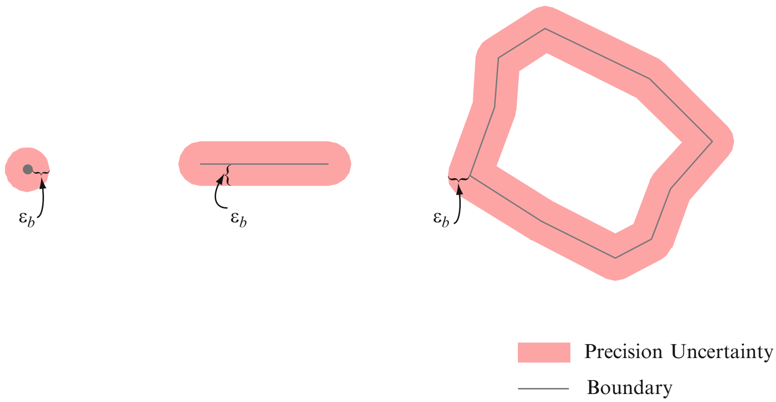

Fig. 5.2 Potential error due to positional uncertainty

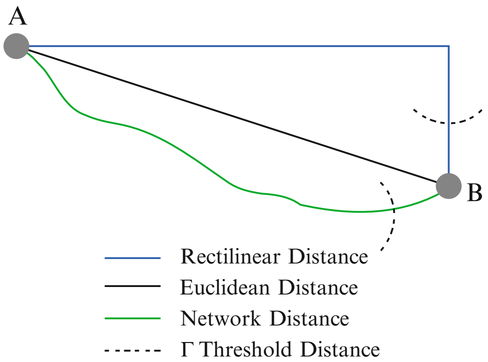

Fig. 5.3 Distance measure uncertainty for points

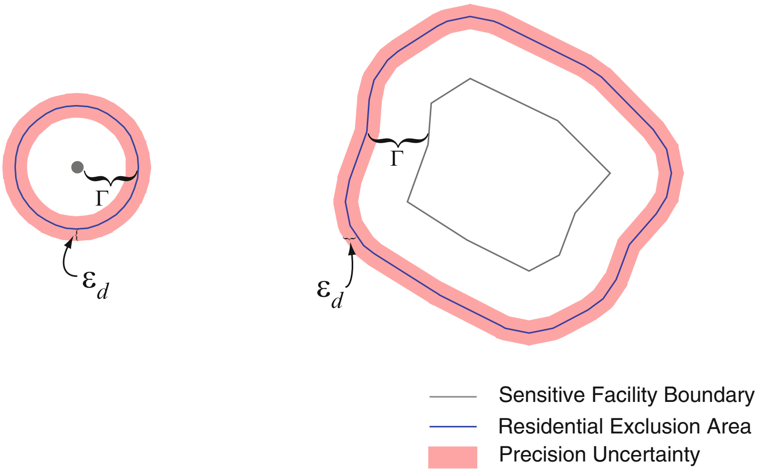

Fig. 5.4 Potential error due to Γ distance uncertainty

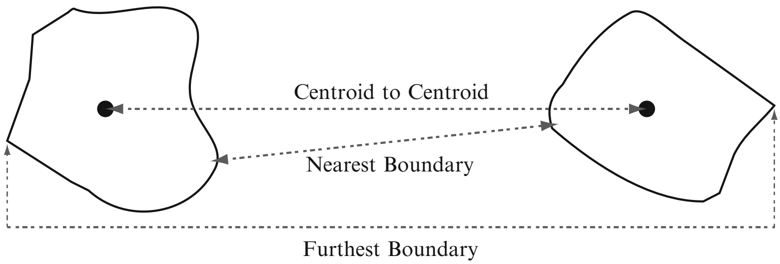

Fig. 5.5 Proximity interpretation uncertainty for polygons

Fig. 5.6 Co-mingling of spatial uncertainty

separation between residences, as shown in Fig. 5.4, and can be interpreted spatially as ε_d. This has implications for what are deemed to be potential residential locations as well as effecting the composition of the set Φ_k around a residence k. A third source of uncertainty in applying the Grubesic and Murray (2008) model is associated with GIS-oriented details related to the interpretation of proximity in the case of polygon units (Leung, Ma, & Goodchild, 2004b). Shown in Fig. 5.5 is that it is possible to consider centroid to centroid distance, nearest edge/boundary, and furthest edge/boundary. It is therefore conceivable that this introduces spatial uncertainty that can be represented by ε_p, not unlike the boundary issue depicted in Figs. 5.2 and 5.4. Finally, as noted in Sect. 2, it should be clear that these various sources of uncertainty do not act independently. Rather, uncertainties associated with distance, proximity, boundaries,

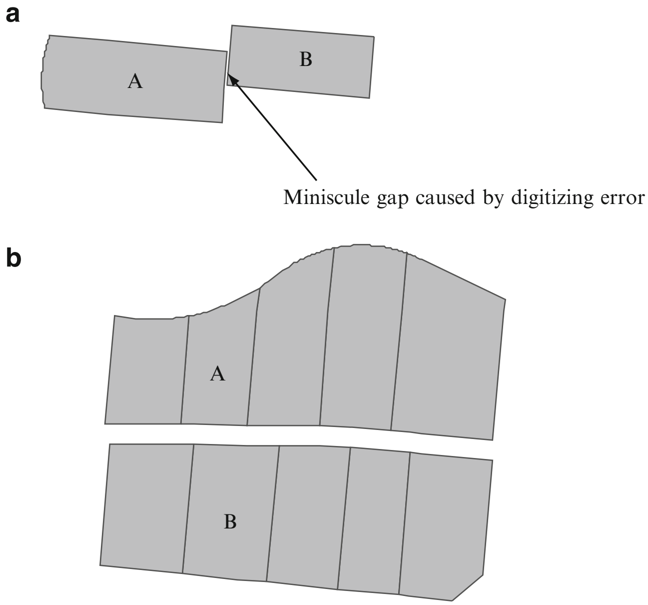

Fig. 5.7 (**a**) Uncertainty associated with the misspecification of spatial adjacency sets: lack of planar enforcement. (**b**) Uncertainty associated with the misspecification of spatial adjacency sets: adjacency interpretation

and adjacency interact with each other, creating a co-mingled landscape of potential errors in the mathematical modeling of sex offender management strategies. For example, consider the neighborhood depicted in Fig. 5.6. In this instance, a sensitive facility (a school parcel) has a 1,000 ft SRZ around it. This restriction zone, for better or worse, has associated with it a composite level of uncertainty, ε, which is a function of the various uncertainty components: distance (ε_d), boundary delineation (ε_b), and proximity interpretation (ε_p). Specifically, $\varepsilon = f(\varepsilon_d, \varepsilon_b, \varepsilon_p)$. A case in point concerns the two residential parcels highlighted along the SRZ in Fig. 5.6. In both instances, portions of these parcels intersect with the SRZ, but their inclusion or exclusion as a restricted set of residences remains uncertain. While the southernmost parcel is more likely to be included in a restricted set if membership is defined by the intersection of the restriction zone with parcel centroids, both parcels would be included if the restricted set was defined by the nearest boundary edge but neither if further boundary edge is considered.

The second model detailed, that of Grubesic and Murray (2009), has elements that are uncertain as well, but in different ways. First, objective (5.5) makes use of an estimate, β_i, that represents the number of people at risk. There is nothing inherently spatial about this coefficient/parameter other than it is associated with a particular place. Thus, it would be possible to examine uncertainty in traditional ways, such as using sensitivity analysis. Another item of uncertainty is the set of neighbors to a unit i, Ω_i, and it is spatially defined. If neighbors are a function of distance, then uncertainty in the form of ε_d and ε_p is possible. Alternatively, if neighbors are defined in terms of adjacency, where a common edge or point is shared, then uncertainty could arise if the polygon geometry is incorrect or inappropriate for the intended use. Consider for example the polygons shown in Fig. 5.7a. The common boundary for polygons A and B do not touch, but in this case they should. The error is due to how the polygons were created, possibly in the digitizing process. Specifically, this can occur if created data is not cleaned or if no planar enforcement is imposed. The implications are that the set Ω_i will be misspecified. Alternatively, it is possible that the polygon geometry is correct, but the interpretation should be different. As an example, the polygons shown in Fig. 5.7b are separated by a street. Technically, the parcels along the street are not adjacent to those parcels directly across the street, as the polygons do not share a common edge or point. However, commonsense tells us that they are in fact neighboring, or adjacent, parcels. Both cases, Fig. 5.7a, b, create potential for misspecification, and subsequent uncertainty. These types of errors are not uncommon, as official cadastral property definitions are taken from actual ground surveys, using highly precise geometry. When these geometric coordinates are then converted into a GIS, the procedures used can introduce a wide variety of errors (Dangermond, 1988; Jones, 1997).

5 Discussion and Conclusion

The identification of potential sources of uncertainty in the application of optimization models to address sex offender residency planning and policy highlights that there is much potential for bias and spurious findings. We now attempt to outline options available for addressing potential uncertainty in the context of applying these two models. Four categories of options follow:

1. Object geometry
   (a) Assume object geometry is correct, and proceed with analysis.
   (b) Clean object geometry. Impose planar enforcement in the case of polygon units, if applicable, or account for an accurate interpretation of adjacency.
2. Data precision
   (a) Assume spatial precision of geographic data is adequate ($\varepsilon_b \approx 0$ and $\varepsilon_f \approx 0$), and proceed with analysis.
   (b) Work to improve data quality to ensure an acceptable level of spatial precision. That is, $\varepsilon_b \rightarrow 0$ and $\varepsilon_f \rightarrow 0$, then proceed with analysis.
3. Distance measurement
   (a) Assume a particular distance measure/metric is sufficient ($\varepsilon_d \approx 0$), and proceed with analysis.
   (b) Evaluate the range of travel distances possible for the study, and develop new method or model to account for this.

4. Proximity interpretation
   (a) Assume one proximity interpretation method (e.g., centroid–centroid, nearest boundary, furthest boundary) is satisfactory ($\varepsilon_p \approx 0$), and proceed with analysis.
   (b) Evaluate the range of proximity interpretation approaches, and develop a new method or model to account for this.

Based on the above points, the options are to focus on improving data, validating proximity measurement, or enhancing specification of relevant model components to account for potential uncertainty. When co-mingling of uncertainty is considered, the process by which data are improved or measurements are enhanced is codependent. It is possible that if one improves precision, but fails to mitigate problems associated with proximity interpretation, there may be no appreciable improvement in the modeled results. As a result, it is obvious that model extensions are necessary to more accurately account for potential sources of uncertainty – only then will the potential consequences and significance of sex offender management strategies be clearly understood.

It is also important to emphasize that some of the problems associated with data uncertainty, spatial modeling, and policy development could be mitigated by infusing additional clarity to the enacted ordinances and statutes for managing convicted offenders. For example, rather than simply stating that convicted offenders are prohibited from establishing a residence within 1,000 ft of a school, policies need to be more explicit by also incorporating language that outlines how these distance restrictions will be measured (e.g., from nearest parcel edge to nearest parcel edge using Euclidean distance). Further, this information must be made easily available to offenders to ensure that they are aware of the restrictions and how they manifest in a local community. In this context, transparency is critical to the development and enforcement of residence restrictions – making both offenders and local communities accountable for the outcomes.

Not discussed here is that the application of optimization models to support public policy may well encounter solution features that could obscure findings. Although not a "geographic uncertainty" per se, there may be spatial implications. One facet of this could be attributed to the heuristic rather than exact solutions. A second facet of this issue could be the existence of alternative optima, or even near optima. Given that spatial patterns and relationships underlie sex offender residency questions, patterns identified using optimization models could vary in significant ways, and understanding the landscape of optimal and near optimal solutions might be important.

In conclusion, this chapter explored a range of issues associated with sex offender data and analysis. Issues of spatial uncertainty were highlighted and their potential effects on mathematical models that support sex offender policy development and management were detailed. It was shown that data uncertainty can influence the results of sex offender residency analysis. Specifically,uncertainty manifests in many ways in mathematical models, including distance measurement, boundary delineation, interpretation of proximity, and defining spatial adjacency. Perhaps most important was the recognition that these elements of uncertainty do not exist in isolation. Instead, it was shown that they can co-mingle, further complicating analytical efforts. Finally, a framework was provided for analysts engaged in sex offender residency issues that outlined a series of basic steps for either accepting or effecting change in dealing with data and model uncertainties.

Given the increasing interest in better understanding the implications of sex offender management strategies at the federal, state, and local levels, the use of geographic data analysis and GIS is growing (Mulford et al., 2009). While the results of this chapter certainly do not address the full spectrum of issues and limitations associated with using spatial data for sex offender analysis, many of the issues outlined for dealing with uncertainties in the mathematical modeling of offender residency strategies are widely applicable in GIS, location modeling, and spatial statistics. It is hoped that this chapter will serve both as a foundation for additional work in the area of data uncertainty for sex offender analysis and as a resource for law enforcement agencies and local communities considering the geographic implications of sex offender policies.

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Chapter 6
Locating Neighborhood Parks with a Lexicographic Multiobjective Optimization Method

Jorge A. Sefair, Adriana Molano, Andrés L. Medaglia, and Olga L. Sarmiento

1 Introduction

In rapidly urbanized and dense cities public parks, open green spaces, and recreational infrastructure have been associated with physical and mental health, quality of life (Sarmiento et al., 2010), promotion of healthy life style, and social, economic, and environmental benefits (Li, Wang, Paulussen, & Liu, 2005; Coley, Kuo, & Sullivan, 1997). Urban parks promote healthy lifestyles including physical activity (Gómez et al. 2010a, 2010b; Humpel, Owen, & Leslie, 2002; Bedimo-Rung, Mowen, & Cohen, 2005), contributing to the prevention of chronic diseases (Andersen, Schnohr, Schroll, & Hein, 2000; Cohen et al., 2007; Yancey et al., 2007; Floyd, Spengler, Maddock, Gobster, & Suau, 2008). In addition, urban parks also offer communities a space to socialize (Gobster, 1998; Seeland, Dübendorfer, & Hansmann, 2009), experience nature, relax, and even contribute to climate stabilization (Chiesura, 2004; Nilsson et al., 2007; del Saz & García, 2007).

The city of Bogotá (Colombia) is one of the largest cities in Latin America, with an estimated population of about eight million inhabitants in 2007 and likely to reach ten million by 2025 (Departamento Administrativo Nacional de Estadística de Colombia (DANE), 2007; United Nations, 2007). The city has implemented a number of urban changes that have included recovery of public spaces and the improvement of public parks (Parra et al., 2007). In Bogotá, parks are classified as one of four types by the Instituto Distrital de Recreación y Deporte – IDRD

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(Recreation and Sports Institute of Bogotá): pocket, neighborhood, zonal, and metropolitan. Park type is based on size and the types of activities facilitated within the park. Pocket parks are green areas of less than 1,000 m^2 dedicated to passive recreation while neighborhood parks are devoted to active recreation and community integration. Both pocket and neighborhood parks typically serve only one neighborhood. In contrast, zonal parks provide both active and passive recreation for several neighborhoods. Metropolitan parks, with an area of more than 100,000 m^2, provide not only active and passive recreation for the whole city, but also landscape and environmental benefits.

Both the limited park area of the city and the benefits provided by urban parks motivated the mayor and city council to support the sports and recreation master plan for Bogotá in 2006 (City Decree 308). The plan states that by 2019 the city must reach a minimum level of neighborhood park area of 2.71 m^2 per inhabitant. The IDRD is the metropolitan office in charge of executing the master plan. For this reason, the IDRD has invested resources to determine the parcels that should be converted into new parks. However, aside from being expensive, locating green areas is also a complex process because it is necessary to balance the compromise among geographic, social, and economic criteria.

Although there exist many decision making techniques that can be used, the IDRD problem contains some elements that make it suitable to be handled by a multiobjective optimization approach. Given that IDRD planners have to select from a substantially large number of candidate parcels, the decision implies a virtually infinite number of possibilities (every subset is a possible solution). The underlying combinatorial structure of the problem makes neither the pairwise comparison methods (e.g., Analytic Hierarchy Process (AHP) (Saaty, 1980), ELECTRE (Roy, 1996), PROMETHEE (Brans, Vincke, & Mareschal, 1986), nor the utility (or value measurement) approaches (e.g., multi-attribute utility theory (MAUT) (Keeney & Raiffa, 1993)), suitable to handle the problem faced by IDRD planners. In addition, both the presence of constraints (e.g., minimum required area per inhabitant) and multiple criteria, find in multiobjective optimization a good fit for the problem at hand.

The problem faced by the IDRD planners motivates a novel application of (multiobjective) facility location that brings new tools and methodologies to urban (and park) planners concerned with the problem of locating multiple neighborhood parks from a set of available parcels. This work proposes a multiobjective facility location model linked to a Geographic Information System (GIS) that interacts with decision makers to determine which parcels should be transformed into new neighborhood parks. The proposed location model considers a variety of criteria including the number of beneficiaries; geographic coverage; sidewalk and road accessibility; connectivity with other facilities; the (positive and negative) externalities provided by nearby facilities; and the construction and parcel acquisition cost. The proposed solution method follows an ε-constraints approach (Chankong & Haimes, 1983; Goicoechea, Hansen, & Duckstein, 1982; Villegas, Palacios, & Medaglia, 2007) using an a-priori lexicographical ordering of the criteria (Steuer, 1989). The methodology is illustrated in a zone with the largest park deficit in Bogotá.

This chapter is organized as follows. Section 2 reviews the literature related to park quality measures and the existing approximations to the park location problem. Section 3 describes the data preparation for the evaluation criteria of the candidate parcels, while Sect. 4 shows the proposed optimization model. Section 5 presents the case study in Bogotá and discusses the results from our experience with a series of model runs for the IDRD. Finally, Sect. 6 concludes the chapter and outlines future work.

2 Literature Review

The problem faced by the IDRD relates not only to the selection of parcels that should be transformed into new neighborhood parks, but also to the selection and calculation of the evaluation criteria. In both aspects, other researchers have tackled problems that share common elements with the problem faced by the IDRD planners.

2.1 Criteria for Evaluating the Quality of a Park

To select specific evaluation criteria for locating parcels it is necessary to know what people value most when making a decision to visit a park. In this context, a widespread result is that people value accessibility, usually measured as the distance from their home to the park (Majid, Sinden, & Randall, 1983; del Saz & García, 2007). A person is defined to have access to a park if he or she lives within the park's service area, that is, within a maximum distance from the park's centroid or boundary (Nicholls & Shafer, 2001; Oh & Jeong, 2007). Indeed, it has been well documented that distance is the main reason for not visiting the nearest park and conversely, that people living close to a park tend to visit it more often (Erkip, 1997; Cohen et al., 2007; Mowen, Orsega-Smith, Payne, Ainsworth, & Godbey, 2007; Kaczynski & Henderson, 2007). Although the service area seems to be a valid measure of accessibility, it ignores how individuals reach the park. Therefore, some authors have considered the number of sidewalks (or roads) as a complementary measure of park's accessibility (Majid et al., 1983; Oh & Jeong, 2007).

The number of potential users, measured in neighborhood parks as the number of inhabitants living in the park's area of influence, has also been used as a measure of the park's quality. Oh and Jeong (2007) proposed an index of park service based on the fraction of people within the area of analysis that is affected by parks. They found an association between the service area and the park's size, that is, as the park size increases more people are willing to visit it. Indeed, Erkip (1997) found that larger parks attract visitors beyond the park's vicinity who choose to drive or use public transportation.

Other measures of the quality of a park focus on the available infrastructure such as sport facilities, paved trails, and lakes (Erkip, 1997; Kaczynski & Henderson, 2007; Kaczynski, Potwarka, & Saelens, 2008); landscape and ecological features like natural assets (Zucca, Sharifi, & Fabbri, 2008); and non-aesthetic attributes such as perception of safety (Cohen et al., 2007).

In addition, in the city of Bogotá, the IDRD planners identified quality measures of their own, such as the connectivity with existing facilities in the city (e.g., bus rapid transit – BRT stations) and positive and negative externalities provided by nearby facilities (e.g., schools). These measures were also included in the neighborhood park location methodology developed for IDRD.

2.2 Location of New Parks

The problem faced by the IDRD falls into the field of discrete facility location problems since it is required to choose among some candidate facilities (parcels) a subset from which an organization (IDRD) will serve its customers (inhabitants) (ReVelle, Eiselt, & Daskin, 2008). The literature on locating (public) facilities is rich and their related methodologies have been successfully applied in locating disaster recovery centers (Dekle, Lavieri, Martin, Emir-Farinas, & Francis, 2005), urban rail terminals (Horner & Grubesic, 2001), fire stations (Badri, Mortagy, & Alsayed, 1998), park-and-ride facilities (Faghri, Lang, Hamad, & Henck, 2002; Farhan & Murray, 2008), depots in the coffee supply chain (Villegas et al., 2007), hospital waste management (obnoxious) facilities (Medaglia, Villegas, & Rodríguez-Coca, 2009), and healthcare facilities (Galvão, Acosta-Espejo, & Boffey, 2002; Boffey, Yates, & Galvão, 2003; Kim & Kim, 2010), among others. For an overview and introduction of facility location, the reader is referred to the surveys by Owen and Daskin (1998), Daskin (2008), ReVelle and Eiselt (2005), and ReVelle, Eiselt, & Daskin (2008); for a survey on multiobjective facility location, the reader is referred to Farahani et al. (2010).

Despite the large existing body of literature on facility location, few researchers have dealt with locating new parks. Zucca et al. (2008) proposed a multicriteria analysis considering economic, social, and environmental criteria, to select the best park out of four alternatives. Although their approach considers multiple criteria, it is suitable for the location of metropolitan parks (the smaller area they considered is 8.59 km^2), but not easily applicable to locate a large number of neighborhood parks. Tajibaeva et al. (2008) used a discrete-space urban model to determine the optimal size and location of open green areas, but they discretized the city in equally-sized areas rather than considering the available parcels as potential locations. Similarly, Neema and Ohgai (2010) proposed a model to determine the best location of urban parks in a continuous region. Here, the decisions relate to the optimal coordinates (x, y) for each park, ignoring whether the correspondent parcel is available or not.

Despite the number of criteria used to measure a single park's potential, there is no work in the literature that combines and analyzes the compromise among geographic, economic, and social criteria while simultaneously considering multiple locations for neighborhood parks.

3 Evaluation of Candidate Parcels

The candidate parcels are evaluated through indices comprising information along five axis: geographical coverage, number of beneficiaries, sidewalk (and road) accessibility, nearby facilities, and cost. These indices were agreed upon by consent on meetings with urban planners not only from IDRD but also from other metropolitan offices involved with park location decisions such as Secretaría Distrital de Planeación – SDP (Metropolitan Planning Office) and Taller del Espacio Público (Public Space Committee), following the guidelines of Bogotá's strategic master plan for parks.

All indices, except cost, are calculated based on the service area of the candidate parcel (potential park). The service area is calculated using the centroid radii or buffer method (Mladenka & Hill, 1977) as a circular area of radius r from the parcel's centroid. Notice that the service area can also be constructed by considering any other reference point than the centroid such as the park's boundaries or its entrance. The radius of influence (r) can be either a fixed distance or a function of the parcel's area (Oh & Jeong, 2007). The following sections present a brief description of each index.

3.1 Geographical Coverage

Geographical coverage is calculated as the number of blocks in the parcel's service area and it is used as a proxy of the potential access to the park system. A large index translates into a service area covering a large number of blocks. Although this index ignores the density of people living in the service area, it mitigates the uncertainty related to population growth or changes in urbanization patterns. The analysis based solely on the number of beneficiaries will suggest the construction of parks in dense areas, ignoring those areas under development or likely to experience fast population growth. On the contrary, by covering as many blocks as possible, planners guarantee access not only to current but future beneficiaries. Moreover, the count of residential blocks is preferred over covered area because it avoids affecting the index by the effect of open spaces with no direct beneficiaries such as large industrial facilities and roads. An example of the geographical coverage index is shown in Fig. 6.1.

Fig. 6.1 Geographical coverage index

3.2 Number of Beneficiaries

The number of beneficiaries index quantifies the potential number of park users. Unlike the geographical coverage index, this measure includes the population in the service area to promote parcels that benefit a large number of people. For instance, in case of having two candidate parcels covering the same number of blocks, the one with the largest population is preferred. An example of the number of beneficiaries is shown in Fig. 6.2, where solely based on this index, parcel 1 is preferred over parcel 2 given that it potentially benefits more than 800 people compared to the 500 beneficiaries of parcel 2.

The problem faced by the IDRD relates to an economically depressed region of the city of Bogotá with a homogeneous low-income distribution. The city of Bogotá classifies its households (neighborhoods) based on socioeconomic variables into one of six strata, one being the poorest and six the richest. According to the Secretaría Distrital de Hacienda de Bogotá (Bogota's Secretary of Finance), the region of Bosa-Central, selected by IDRD for the current study, has 97% of its population classified in households of strata 1 and 2 (Secretaria Distrital de Hacienda de Bogotá – Bogotá's Secretary of Finance, 2010). Thus, the use of the number of beneficiaries as evaluation criteria for a candidate parcel was enough to

Fig. 6.2 Number of beneficiaries

capture the social impact of a new park. Moreover, by focusing on improving the park area in Bosa-Central, the IDRD provides an example of social equity at the city level. Through the use of indices such as the geographical coverage and the number of beneficiaries, IDRD planners are seeking a fair spatial distribution of parks where the largest possible number of inhabitants in Bosa-Central has access to parks. However, some studies have suggested the use of socioeconomic or demographic characteristics of the served population as a direct measure of social equity to motivate the location of facilities in poor and densely populated areas (Nicholls & Shafer, 2001; Macintyre, Macdonald, & Ellaway 2008). For instance, Medaglia et al. (2008) used a social index based on the number of people below the poverty line (BPL) to evaluate infrastructure projects. Even though this index can be extended to the park location problem by considering the people BPL in the park's area of influence, it will be better suited in more heterogeneous populations or regions. In a wider (public) facility location context, Marsh and Schilling (1994) reported a comprehensive set of equity measures and discussed how can they be effectively included in facility siting decisions.

Fig. 6.3 Accessibility index

3.3 Accessibility

This index is based on the density of sidewalks (and roads) that make the park accessible. Given a park's service area, the accessibility index is calculated as the total length of sidewalks (and roads) per square meter. For the sake of clarity, we normalize the accessibility index of a given park by dividing it over the accessibility index of the whole area of analysis; thus, an index greater than one represents that the park is relatively more accessible than the rest. An illustration of the accessibility index is shown in Fig. 6.3. While Bosa-Central UPZ has a global accessibility index of 0.028/m, parcel 1 has a service area of 17,671 m^2 and a total sidewalk length of 433 m. Thus, parcel 1 has a normalized accessibility index of 0.85, meaning that it is 15% less accessible than the whole area of study. On the other hand, parcel 3 has an accessibility index of 1.07, thus it is a relatively more accessible park.

3.4 Connectivity

This index is a measure of the connectedness between the candidate parcel and the existing nearby urban facilities. The existing facilities are classified into one of two groups. The first group contains infrastructure that could potentially harm the perceived benefits of the park or, in other words, those facilities that provide a negative externality to the park benefits (e.g., jails and morgues). The second group contains the infrastructure that could potentially increase the benefits of the park or, in other words, those facilities that provide a positive externality (e.g., schools and BRT stations). The connectivity index is calculated by subtracting the number of facilities with a negative externality from the number of facilities with a positive externality within the park's service area. Thus, a connectivity index greater than

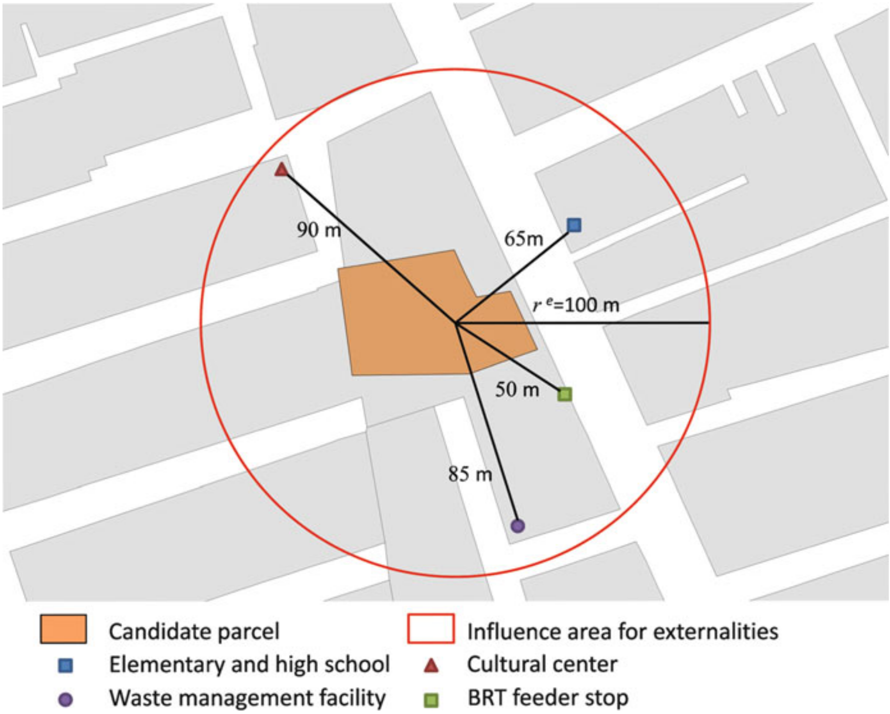

Fig. 6.4 Connectivity and externality proximity indices

zero means that the park is expected to capture some extra benefits (beyond the pure attraction of the population in the service area), given its connection to other urban infrastructure. Notice that the connectivity index is a pure count since there is no primary information available to state the relative importance of the externalities provided by each facility. If such information exists, the connectivity index can be calculated by including a weight that reflects the relative importance of each positive or negative externality into a (weighted) aggregated index. An illustration of the connectivity index is shown in Fig. 6.4, where the candidate parcel has a connectivity index equal to 2 (=3 − 1) given that there are three facilities with positive externalities (cultural center, school, and BRT feeder station) and one with a negative externality (waste management facility).

3.5 Weighted Proximity to Externalities

The externality proximity index considers the nearby facilities (and their externalities) weighted by their proximity. This index assumes that the effect of the externalities reduces as the distance from the candidate parcel increases. Let r^e ($\leq r$) be the maximum radius of influence for the externalities and let d be the radial distance of the facility to the candidate parcel. The effect of a facility located at a radial distance greater than r^e is neglected, whereas the effect (weight) of a facility located within a radial distance of less than r^e is given by $1 - d/r^e$. Similarly to the connectivity index, the weighted proximity to externalities is calculated by subtracting the effect of the facilities with negative externalities from the effects of the facilities with positive externalities within the park's service area. The externality proximity index can also include a weight reflecting the relative importance of each positive or negative externality into the aggregated index. This index is illustrated in Fig. 6.4, where four facilities are located within a radial distance $r^e = 100$ m. In this example, the weighted proximity to externalities is equal to 0.8, given by the sum of the effect of the cultural center ($1 - 90/100$), the BRT feeder stop ($1 - 50/100$), and the school ($1 - 65/100$); and subtracting the effect of the waste management facility ($1 - 85/100$).

3.6 Cost

The (total) cost is calculated as the parcel acquisition cost plus the construction costs of the park. The first component is estimated according to real estate appraisals, while the second component includes construction materials, amenities (e.g., swings and slides), design, operations, and administrative obligations.

4 Optimization Model and Solution Strategy

4.1 Model

The model formulation includes a set of candidate parcels ($\mathcal{I}$) partitioned into two sets: set $\mathcal{I}_F$ which contains those parcels with an area less than or equal to 10,000 m^2; and set $\mathcal{I}_V$ which contains larger parcels. As compared to parcels in $\mathcal{I}_F$, which are also called *fixed-size* parcels, parcels in $\mathcal{I}_V$ are called *variable-size* parcels because the effective park area is yet to be determined (by the model). The model formulation also considers a set of existing urban facilities $\mathcal{E}$ ($\mathcal{E} = \mathcal{E}_P \cup \mathcal{E}_N, \mathcal{E}_P \cap \mathcal{E}_N = \emptyset$), where $\mathcal{E}_P$ and $\mathcal{E}_N$ represent the set of facilities with positive and negative externalities, respectively.

The (circular) service area of parcel i is defined by its radius r_i measured from its centroid. Consequently, let $\mathcal{J}$ be the set of all blocks serviced by at least one candidate parcel, that is, set $\mathcal{J}$ contains all blocks that could potentially benefit from the construction of new parks. The set of all candidate parcels servicing block

$j \in \mathcal{J}$ is defined by $\mathcal{W}_j$. Conversely, candidate parcel i belongs to set $\mathcal{W}_j$ if block j is within r_i from the parcel's centroid.

The model also includes parameters p_i, v_i, and e_i, representing the number of beneficiaries, accessibility index, and connectivity index of candidate parcel i, respectively. Parameters c_i^l and c_i^b represent the parcel (lot) acquisition cost and the construction (building) cost for candidate parcel i, respectively. To calculate the proximity externality index, let d_{ik} be the distance between candidate parcel i and facility k ($k \in \mathcal{E}$) and recall that r^e is the maximum radius of influence of the externalities of a given facility.

The area (in square meters) of candidate parcel i is denoted by a_i. The minimum area of parks required to accomplish Bogotá's master plan is denoted by $\underline{a}$; while $\bar{a}$ denotes the maximum area of parks that could be handled by IDRD and it is a proxy of their management and financial capacity during the planning horizon. In case of selecting a variable-size parcel, parameters $\underline{s}_i$ and $\bar{s}_i$ ($i \in \mathcal{I}_V$) represent the minimum and maximum construction areas for the new park i.

The model identifies those candidate parcels that should be transformed into parks. Consequently, the binary decision variable y_i takes the value of 1 if candidate parcel i is to be transformed into a park; it takes the value of 0, otherwise. For the variable-size areas, variable x_i represents the area of the candidate parcel i that is to be transformed into a park. The binary variable z_j takes the value of 1 if block $j \in \mathcal{J}$ is covered by at least one park; it takes the value of 0, otherwise. The proposed multiobjective mixed-integer program follows:

$$\max f_1 = \sum_{j \in \mathcal{J}} z_j \tag{6.1}$$

$$\max f_2 = \sum_{i \in \mathcal{I}} \left(\sum_{\{k \in \mathcal{E}_P : d_{ik} \le r^e\}} \left(1 - \frac{d_{ik}}{r^e}\right) y_i - \sum_{\{k \in \mathcal{E}_N : d_{ik} \le r^e\}} \left(1 - \frac{d_{ik}}{r^e}\right) y_i \right) \tag{6.2}$$

$$\max f_3 = \sum_{i \in \mathcal{I}} p_i y_i \tag{6.3}$$

$$\max f_4 = \sum_{i \in \mathcal{I}} v_i y_i \tag{6.4}$$

$$\max f_5 = \sum_{i \in \mathcal{I}} e_i y_i \tag{6.5}$$

$$\min f_6 = \sum_{i \in \mathcal{I}} \left(c_i^l + c_i^b\right) y_i \tag{6.6}$$

subject to,

$$z_j \leq \sum_{i \in \mathcal{W}_j} y_i, \; j \in \mathcal{J} \tag{6.7}$$

$$|\mathcal{W}_j| z_j \geq \sum_{i \in \mathcal{W}_j} y_i, \; j \in \mathcal{J} \tag{6.8}$$

$$\sum_{i \in \mathcal{I}_F} a_i y_i + \sum_{i \in \mathcal{I}_V} x_i \geq \underline{a} \tag{6.9}$$

$$\sum_{i \in \mathcal{I}_F} a_i y_i + \sum_{i \in \mathcal{I}_V} x_i \leq \bar{a} \tag{6.10}$$

$$\underline{s}_i y_i \leq x_i \leq \bar{s}_i y_i, \; i \in \mathcal{I}_V \tag{6.11}$$

$$y_i \in \{0, 1\}, \; i \in \mathcal{I} \tag{6.12}$$

$$z_j \in \{0, 1\}, \; j \in \mathcal{J} \tag{6.13}$$

$$x_i \geq 0, \; i \in \mathcal{I}_V \tag{6.14}$$

Our model jointly optimizes six objectives: (6.1) maximizes the geographical coverage, (6.2) maximizes the externality proximity index, (6.3) maximizes the number of beneficiaries, (6.4) maximizes the accessibility index, (6.5) maximizes the connectivity index, and (6.6) minimizes the total cost. Note that the total cost is considered an objective function rather than in a more classic budget constraint since the IDRD lacks of a specific budget allocated to the location of new parks. Thus, by treating the cost as an objective, the model becomes a tool to negotiate such a budget.

The set of constraints (6.7) guarantees that if block j is covered, then at least one candidate parcel covering the block must be selected. On the other hand, the set of constraints (6.8) guarantees that if block j is not covered, none of the candidate parcels close to block j should be selected. The bound constraints in (6.9) and (6.10) guarantee that the total area of parks should fall between the allowable limits. Similarly, the set of constraints in (6.11) enforce size limits on parks in variable-size parcels. Note that constraints (6.11) also link decision variables x and y, so that if a candidate parcel is not selected, then the park area must be nil. Variable-type constraints (6.12), (6.13) and (6.14) define variables y and z as binary, while variables x are defined as non-negative. Note that the objective function shown in

(6.1) and the set of constraints (6.7) closely resemble a maximal covering model (Owen & Daskin, 1998), where the blocks are the customers and the new parks the facilities. Loosely speaking, in our model, constraints (6.9)–(6.10) impose a limit on the number of facilities.

4.2 Solution Strategy

Our solution strategy follows an ε-constraints approach (Chankong & Haimes, 1983; Goicoechea et al., 1982) combined with an a-priori lexicographic ordering of the decision criteria (Steuer, 1989). The proposed solution scheme allows decision makers to interactively incorporate their preferences as long as the decision criteria are optimized under the lexicographic order. Through this process, planners may reveal acceptable tradeoffs between objectives to produce a good compromise solution. Unlike methods designed to reveal the whole set of non-dominated solutions, the proposed interactive solution narrows the set of possible solutions to only those with a good compromise of objectives, facilitating the final choice to the decision maker (Alves & Clímaco, 2007).

The methodology is divided into two stages. In the first stage, each of the objectives (6.1)–(6.6) is optimized in isolation, subject to constraints (6.7)–(6.14), henceforth referred as Ω. The optimal value of each objective function in the first stage is denoted by $f_k{}^*$ $(k = 1, 2, \ldots, 6)$.

In the second stage, we incorporate a lexicographic ordering of the objectives. This order was established jointly with the IDRD planners based on their experience and aligned with the sports and recreation master plan for the city. In this particular case, the planners stated the order of the objectives as they are shown in (6.1)–(6.6). We define a compromise threshold for each objective denoted by $(1 - \alpha_k)$, where the value α_k represents the maximum acceptable deterioration of objective $k = 1, 2, \ldots, 5$. No compromise threshold was assigned to the last objective in the lexicographic order, since it corresponds to the last optimization model to be solved. Note that the cost was defined as the last objective in the lexicographic order since it was implicitly included in constraints (6.9) and (6.10).

The second stage proceeds as follows. We solved a model to optimize the objective function shown in (6.2) subject to the set of constraints Ω. To consider the compromise threshold of $100(1 - \alpha_1)\%$ for $f_1{}^*$ we must also add the following constraint:

$$\sum_{j \in \mathcal{J}} z_j \geq (1 - \alpha_1) f_1^* \tag{6.15}$$

The constraint shown in (6.15) guarantees that the new solution covers at least $100(1 - \alpha_1)\%$ of the maximum number of covered blocks given by f_1^*. Next, we solved a model to optimize the objective in (6.3), considering the set of constraints Ω, constraint (6.15), and the following constraint:

$$\sum_{i \in \mathcal{I}} \left(\sum_{\{k \in \mathcal{E}_P : d_{ik} \le r^e\}} \left(1 - \frac{d_{ik}}{r^e}\right) y_i - \sum_{\{k \in \mathcal{E}_N : d_{ik} \le r^e\}} \left(1 - \frac{d_{ik}}{r^e}\right) y_i \right) \ge (1 - \alpha_2) f_2^* \quad (6.16)$$

The constraint shown in (6.16) guarantees that the new solution reaches at least $100(1 - \alpha_2)\%$ of the maximum externality proximity index (f_2^*). Note that this solution also guarantees a minimum level of geographical coverage (f_1^*) through the set of constraints (6.15). Then, the objective function shown in (6.4) is optimized subject to the constraints Ω, constraints (6.15)–(6.16) and the following constraint:

$$\sum_{i \in \mathcal{I}} p_i y_i \ge (1 - \alpha_3) f_3^* \quad (6.17)$$

The constraint shown in (6.17) limits the deterioration of the objective regarding the number of beneficiaries (f_3^*) beyond $\alpha_3\%$. Then, the objective shown in (6.5) is optimized subject to constraints Ω, constraints (6.15)–(6.17) and the following constraint:

$$\sum_{i \in \mathcal{I}} v_i y_i \ge (1 - \alpha_4) f_4^* \quad (6.18)$$

The constraint shown in (6.18) avoids the deterioration of the accessibility index (f_4^*) beyond its maximum accepted compromise of $\alpha_4\%$. Finally, the objective shown in (6.6) is optimized subject to constraints Ω, constraints (6.15)–(6.18), and the following constraint:

$$\sum_{i \in \mathcal{I}} e_i y_i \ge (1 - \alpha_5) f_5^* \quad (6.19)$$

The constraint shown in (6.19) guarantees a solution with at least $100(1 - \alpha_5)\%$ of the maximum connectivity index (f_5^*).

At this point we emphasize that, depending on the quality of the intermediate solution, the planners can change the compromise thresholds for the already optimized objectives. For instance, if the objective shown in (6.6) is optimized and the quality of the solution is not deemed satisfactory, the planners can update the values of α_1 through α_5 to try to improve the quality of the current objective compromising the most important ones. Otherwise, the planners may choose to make the compromise thresholds tighter to improve the solution under the light of the most important objectives, thus sacrificing the quality of the current (less important) objective.

To illustrate how the solution strategy works, let us consider a set of four candidate parcels as shown in Fig. 6.5. Without loss of generality, assume that according to constraint (6.10), only two candidate parcels can be converted into parks; and that planners consider as the evaluation criteria just the geographical

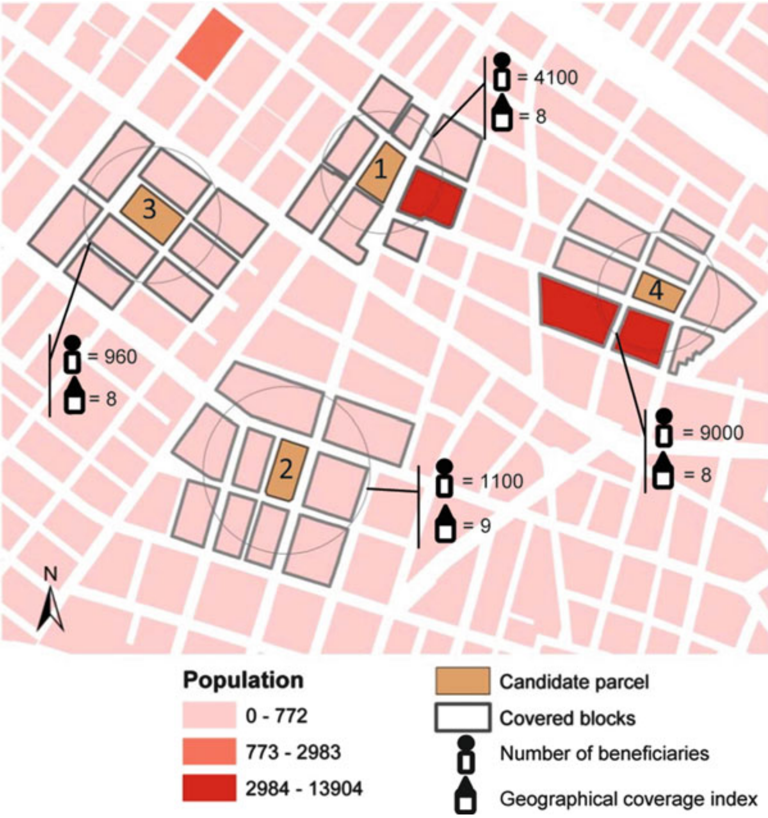

Fig. 6.5 Illustration of the solution strategy in a four-parcel example

coverage index and the number of beneficiaries. Thus, when the geographical coverage index (6.1) is maximized subject to constraints (6.7)–(6.14), the optimal solution is the selection of candidate parcels 2 and 3. This solution accounts for a total geographical coverage of 17 blocks (nine covered by parcel 2 and eight by parcel 3). For the second stage, assume that planners determine a value of α_1 equal to 0, meaning that no deterioration in the geographical coverage index is allowed. Hence, the right hand side of constraint (6.15) is equal to 17. When the number of beneficiaries (6.3) is maximized subject to constraints (6.7)–(6.15), then the selected parcels become 2 and 4. This configuration accounts for a geographical coverage of 17 blocks and a total number of beneficiaries of 10,100; this is in contrast to the merely 2,060 beneficiaries covered by parcels 2 and 3. Note that this solution maximizes the number of beneficiaries, while keeping the optimal geographical coverage index obtained in the first stage. At this point, planners can update the value of α_1 if the solution of the second stage is deemed not satisfactory. To illustrate the effect of this change, assume that planners must develop a solution that has more beneficiaries. Thus, planners allow a deterioration of up to 10% of the geographical coverage index. Accordingly, the right hand side of constraint (6.15) is set to 17 $\times 90\% = 15.3$. After solving the model with this change, the selected parcels are now 1 and 4, accounting for a total number of beneficiaries of 13,100 and a geographical coverage of 16 blocks. Compared to the original solution with $\alpha_1 = 0$, the new solution (i.e., $\alpha_1 = 10\%$) increases the number of beneficiaries by 30%, just by merely sacrificing one covered block in the geographical coverage index.

Compared to other well-known multiobjective optimization techniques, the proposed solution strategy presents some advantages for the IDRD problem. For instance, in contrast to goal programming (Schniederjans, 1995), the proposed strategy does not require a priori target values for each objective. On the contrary, the strategy uses the best achievable value for each objective (obtained in the first stage), allowing planners to move to better solutions by tuning the values of the α's in the second stage. Moreover, the proposed solution strategy avoids the compensatory effect when the criteria are aggregated into a single function (Triantaphyllou, 2000). For instance, when a weighted sum approach is used, the poor performance of a solution according to one criterion can be compensated by a good performance in other criteria, ignoring the preemptive importance of the criteria established by the planner, as is the case in the IDRD problem.

5 Case Study: Locating New Neighborhood Parks in Bogotá

The city of Bogotá is divided into 117 regions called Unidades de Planeamiento Zonal – UPZ (Zonal Planning Units). The rationale behind this division is to group together homogeneous neighborhoods based on their socioeconomic characteristics, allowing city planners to conduct the urban developing strategies more accurately. The IDRD planners selected one of the most depressed UPZs of the city, the one named Bosa-Central, to apply the proposed model.

The Bosa-Central UPZ exhibits one of the worst indices of park area per inhabitant, barely reaching 2 m^2 per person. Currently, the Bosa-Central UPZ has approximately 275,000 residents and its population is likely to exceed 360,000 by 2019 (Administrativo Nacional de Estadística de Colombia (DANE), 2010). With the expected population growth, by that time the park area will not be enough to satisfy the demand for green space nor to accomplish minimum park area per inhabitant required by the 2006 sports and recreation master plan for Bogotá. Moreover, aside from the park deficit, the construction of parks in Bosa-Central is a priority from an income redistribution perspective, given that its population is among the poorest of the city (Secretaria Distrital de Hacienda de Bogotá – Bogotá's Secretary of Finance, 2009). The geographical location of Bosa-Central and its population distribution in 2007 are shown in Figs. 6.6 and 6.7, respectively.

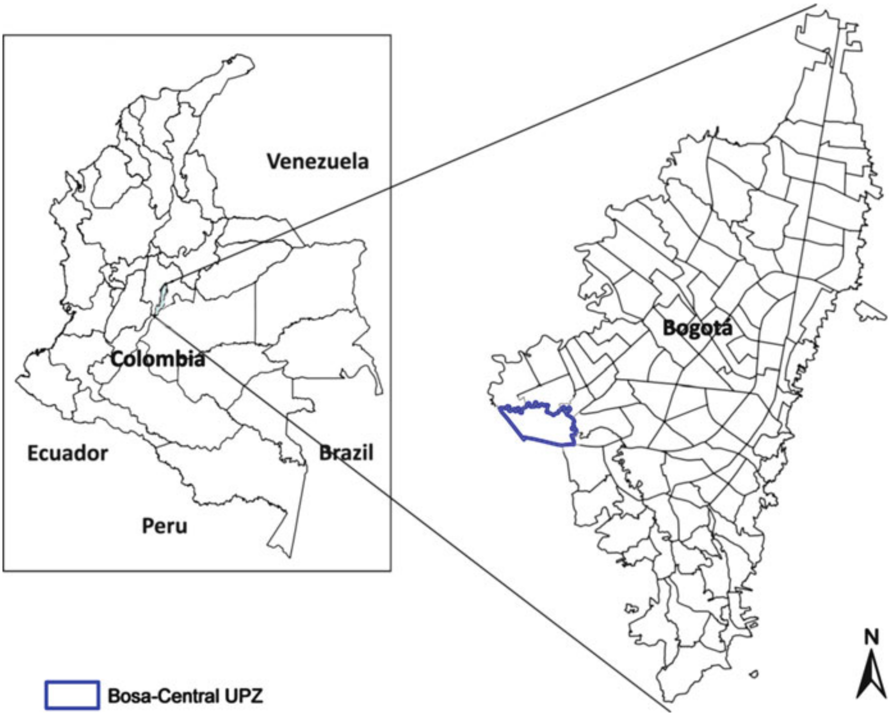

Fig. 6.6 Geographical location of Bosa-Central UPZ

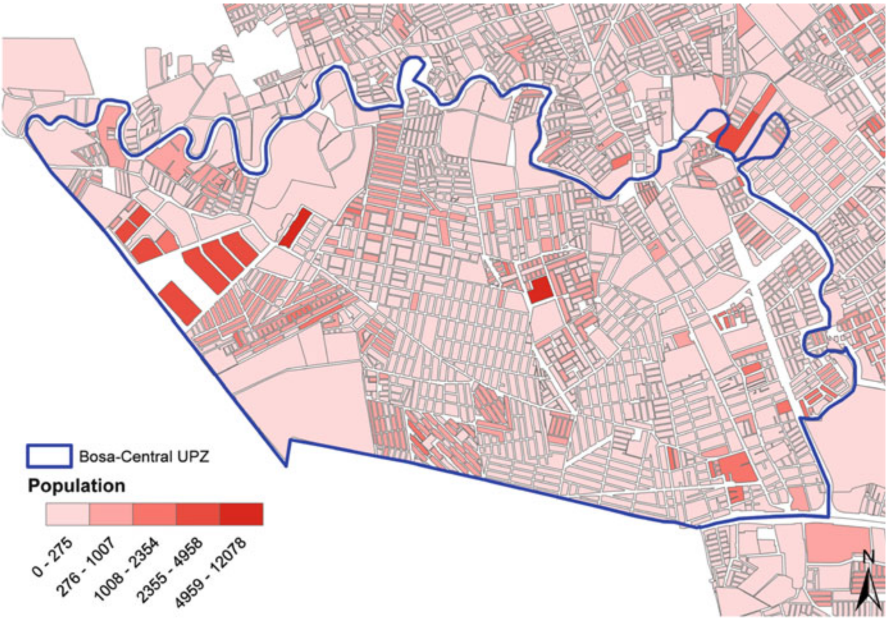

Fig. 6.7 Population distribution in Bosa-Central UPZ

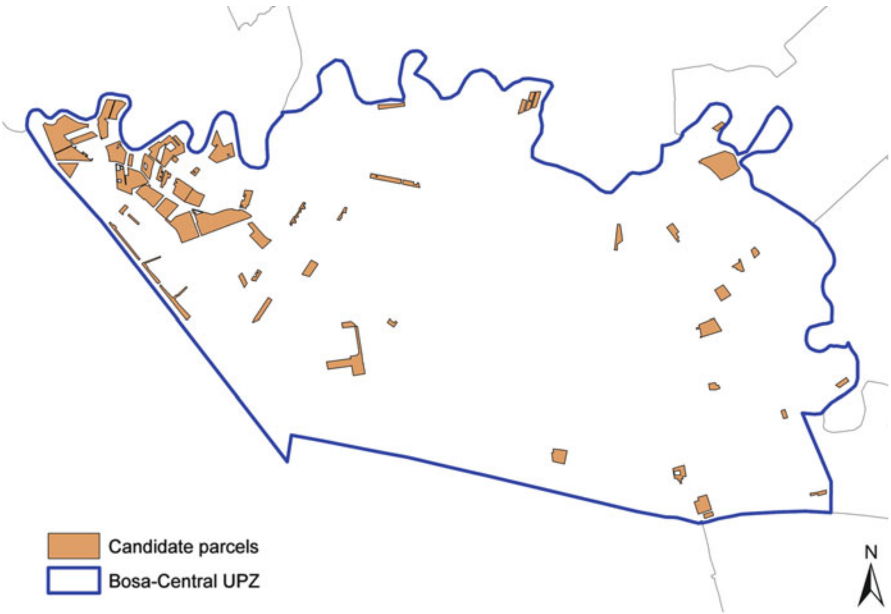

Fig. 6.8 Identified candidate parcels in Bosa-Central UPZ

5.1 Data Collection and Parameter Estimation

The IDRD planners identified a set of 58 parcels, shown in Fig. 6.8, from both non-urbanized and private non-developed parcels as candidate parks. These candidate parcels were selected from areas with none or very few existing parks nearby. Each individual parcel ranges from 1,000 to 25,000 m^2 and the overall area accounts for over 320,000 m^2. Although this area is not even enough to meet the goal of 2.71 m^2 per inhabitant, it is the available area for park construction in the short term. To increase the number of candidate parcels, the IDRD is currently working on long term strategies to find new parcels to build parks (e.g., urban renovation). However, the process is expensive and requires the coordination of many metropolitan offices. We implemented the proposed methodology to recommend IDRD planners which of the 58 currently-designated parcels in Bosa-Central were the best candidates to be transformed into parks. Nevertheless, the methodology is easily replicable to other UPZs.

For the case study, we set the minimum and maximum total park area to range between $\underline{a} = 50{,}000$ and $\bar{a} = 100{,}000$ m^2. Similarly, for the variable-size parcels, IDRD planners established that the construction area should range between $\underline{s}_i = 2{,}000$ and $\bar{s}_i = 50{,}000$ $(i \in \mathcal{I}_V)$. We estimated the park construction cost from historical information of IDRD's previously conducted projects. Using the Colombian Construction Price Index, the historical costs per square meter were converted to present value. Then, using experts' knowledge, the cost per square meter was forecasted as a function of the built area considering economies of scale, that is, the bigger the built area, the lower the cost per square meter. Using this forecast and using the parcel's size, we calculated the construction cost for all the candidate parcels in the analysis. In addition, the parcel (lot) acquisition cost was estimated according to the real estate appraisals available for candidate parcels.

The indices for each candidate parcel were calculated using ESRI's ArcGIS as the GIS engine (Environmental Sciences Research Institute (ESRI), 2004). The service area radius (r_i) was defined by $r_i = \min\{417, f(a_i)\}$, as a function of both the parcel's area and the maximum distance that a person is willing to walk to the park; where $f(a_i)$ is a function that returns the influence radius of candidate parcel i as a function of its area (a_i). A maximum walking distance of 417 meters is considered given that, according to IDRD planners, there is no evidence that pocket and neighborhood parks may attract people from a larger distance who access the park by car or public transportation; consequently, the service area radius function limits its influence to a maximum of 417 meters. In fact, Oh and Jeong (2007) report a catchment distance of no more than 500 meters for parks with an area of less than 10,000 m^2. On the contrary, metropolitan parks, those with an area of over 30,000 m^2, may attract people from a distance longer than 1,000 meters.

The expression of $f(a_i)$ for the service area radius function was estimated using linear regression, with the radius of influence of existing parks as the dependent variable and the park area as the independent variable. To estimate the radius of influence for existing parks, we assumed that current parks meet a level of 2.24 m^2 of park per inhabitant, which, according to IDRD planners, is an acceptable measure of park access. Thus, the radius of influence is such that the park service area covers approximately $a_i/2.24$ inhabitants. For instance, if the park area is 1,000 m^2, then the radius of its service area should be large enough to assure that approximately 370 people are covered. We repeat this calculation over all existing parks to form the data set with pairs (a_i, r_i), input for the linear regression. The estimated linear function $\hat{f}(a_i) = 58.55 + 0.163a_i$ has an acceptable fit with an $R^2 = 0.69$; moreover, the estimated coefficients are significant at the 95% confidence level.

5.2 Results

To facilitate the analysis and foster discussion among IDRD planners, the solutions of the optimization models were displayed using GIS. This visual aid proved to be intuitive to explore the effect of multiple objectives on the selection of new parks. For instance, Fig. 6.9 shows the new parks that maximize geographical coverage, while Fig. 6.10 shows those that maximize the number of beneficiaries. As expected, the set of new parks in Fig. 6.9 tends to cover as many blocks as possible, avoiding the overlap among service areas. On the other hand, the new parks in

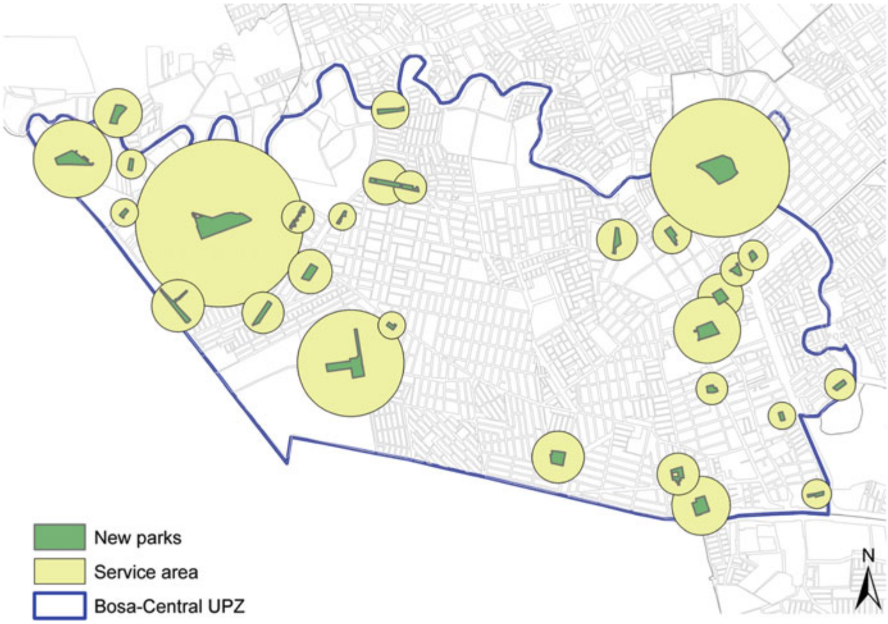

Fig. 6.9 New park locations after maximizing geographical coverage

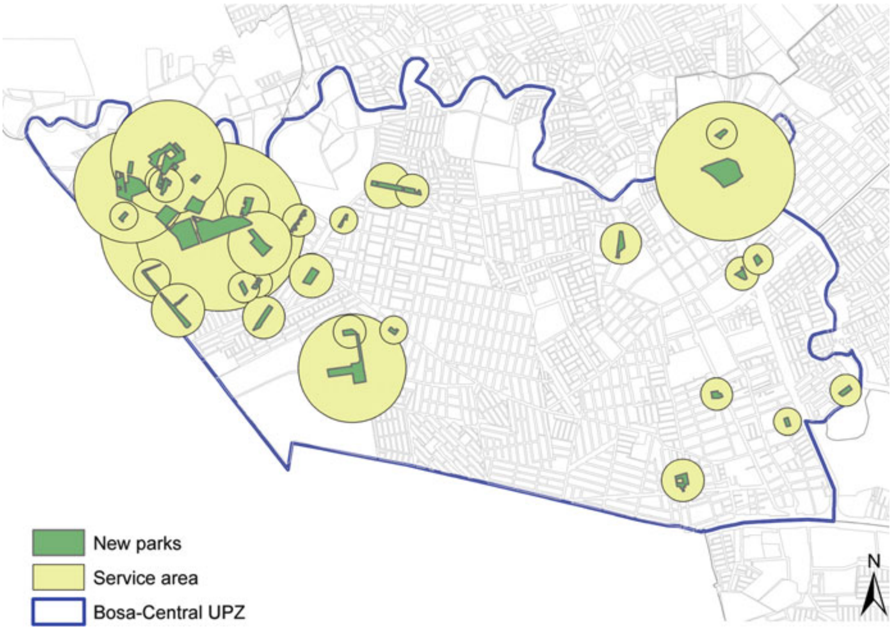

Fig. 6.10 New park locations after maximizing number of beneficiaries

Fig. 6.10 cover as many beneficiaries as possible; being the northwest the most populated area of Bosa-Central (see Fig. 6.7).

Table 6.1 compares the optimal values of the six objective functions (6.1)–(6.6) at the end of the first stage. For sake of clarity and to highlight the compromise among objectives, the achieved index is shown as a percentage relative to its best possible value, that is, while optimizing the index in isolation (first stage). For instance, the second column of Table 6.1 shows that when the geographical coverage is maximal, the number of beneficiaries reaches only 61.7% of the population that is affected when maximizing the number of beneficiaries. The second column also shows that the maximal coverage solution implies a threefold increase over the minimum cost solution. Note that the achieved indices in the diagonal are always 100% because they match the index that is being optimized.

Table 6.1 also illustrates the existing tradeoff among indices, that is, while optimizing a single objective (index), there is no solution that satisfies all the indices at the same time. For instance, maximizing the proximity to externalities (third column in Table 6.1), makes the geographical coverage drop to 64.4% of the maximal coverage solution. Also, choosing park locations that maximize the proximity to existing infrastructure results in halving the number of beneficiaries and the accesibility index. This existing tradeoff motivates the second stage, where planners are able to control the maximum deterioration of each index through the parameters via an interactive approach.

The results of the second stage are shown in Table 6.2. Similar to Table 6.1, the results are presented relative to the best achievable value for each index (stage 1). The upper part above the diagonal of Table 6.2 shows the achieved index after allowing a maximum compromise threshold (shown in parenthesis as $1 - \alpha_k$) for objectives with a higher priority. For instance, when maximizing the number of beneficiaries (fourth column of Table 6.2), the planners required maximal coverage, but were willing to accept an 18% degradation of the externality proximity index. As compared to Table 6.1, note that because of the compromise thresholds, the diagonal of Table 6.2 is not always equal to 100%.

After a set of meetings with the IDRD team to design the quality measures for candidate areas and the lexicographic order of the objectives, we proposed a first set of α's to ensure the minimum deterioration of the objectives. After analyzing the results, this first set of α's was updated according to the tolerable tradeoff among objectives reached by consensus after a couple of meetings. In each meeting we discussed the results with the IDRD planners by showing them the numerical value of each index and the visual display of the location of the parks in maps obtained with the GIS engine. The interactive process with the IDRD planners led to the results shown in the last column of Table 6.2. This compromise solution, shown in Fig. 6.11, involves the construction of 35 new parks (out of 58 candidate parcels) with a total area of 99,334 m^2.

Figure 6.12 graphically compares the compromise solution at the end of the second stage with those of the first stage where each criterion is optimized in isolation. Each radial axis represents a single criterion and each point reflects the percentage of the best possible value achieved at each stage. Because each criterion

Table 6.1 First-stage results

Index	Objective function					
	Maximizing geographical coverage (%)	Maximizing proximity to externalities (%)	Maximizing number of beneficiaries (%)	Maximizing accessibility (%)	Maximizing connectivity (%)	Minimizing total cost (%)
Coverage	**100**	64.40	81.40	73.20	76.80	7.20
Externalities	54.40	**100**	59.50	75.10	92.40	0
Beneficiaries	61.70	47.50	**100**	68.80	74.40	1.79
Accessibility	70.80	55.50	89.00	**100**	54.00	0.78
Connectivity	61.50	63.40	69.20	46.10	**100**	0
Cost	316.40	243.30	337.00	352.40	278.50	**100**
Number of new parks	29	21	34	37	22	1
Total park area (m^2)	99,257	79,096	100,000	100,000	97,200	50,000

Table 6.2 Second-stage results

Index	Objective function					
	Maximizing geographical coverage (%)	Maximizing proximity to externalities (%)	Maximizing number of beneficiaries (%)	Maximizing accessibility (%)	Maximizing connectivity (%)	Minimizing total cost (%)
Coverage	**100**	100 (100)	100 (100)	93.42 (93)	93.42 (93)	91.38 (91)
Externalities	54.47	**82.85**	82.85 (82)	84.54 (84)	84.54 (84)	84.55 (84)
Beneficiaries	61.70	68.55	**74**	92.97 (83)	92.97 (83)	92.90 (83)
Accessibility	70.86	76.55	81.57	**90.93**	90.93 (90)	93.91 (93)
Connectivity	61.54	71.15	71.15	71.15	**71.15**	80.77 (80)
Cost	316.47	307.33	324.08	337.37	337.37	**328.65**
Number of new parks	29	30	32	35	35	35
Total park area (m^2)	99,257	96,745	100,000	100,000	100,000	99,334

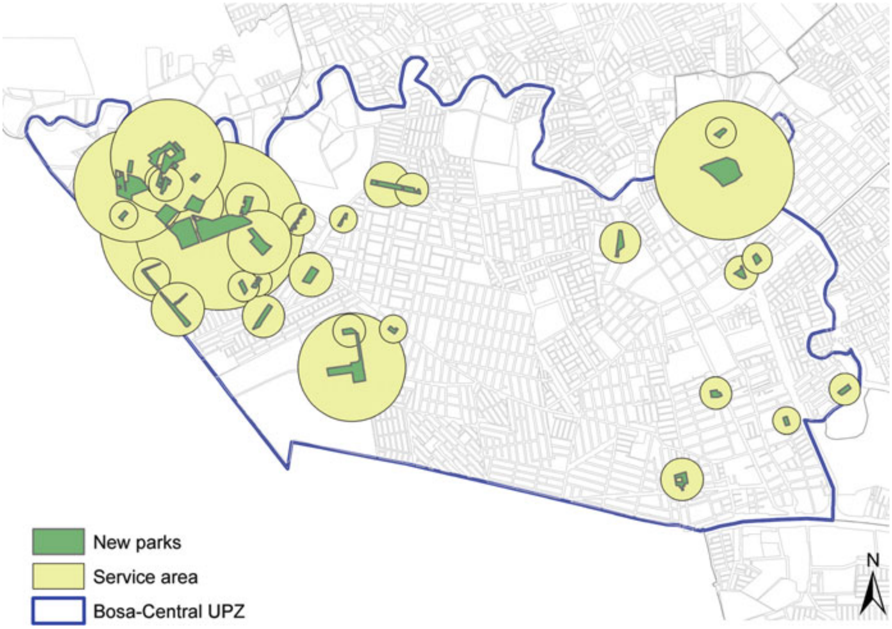

Fig. 6.11 Location of the new parks under the compromise solution at the end of second stage

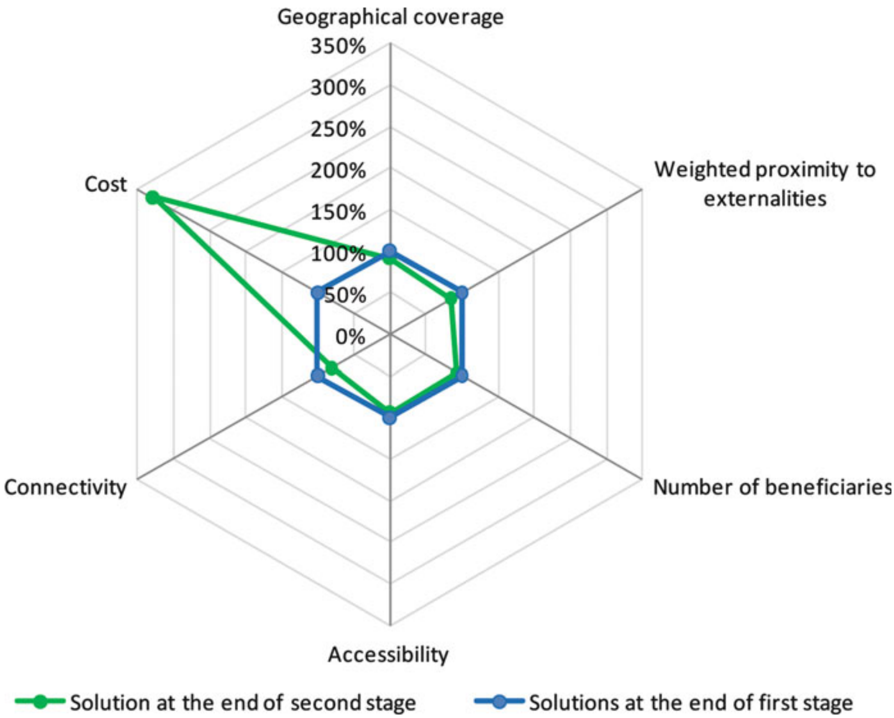

Fig. 6.12 Comparison of the compromise solution at the end of second stage versus the first-stage solutions

is optimized in isolation in the first stage, the percentage is always 100% for the first stage. The figure shows that for all criteria but cost, the compromise solution obtained in the second stage is close to 100%. Note the close distance between the two series, except for the cost criterion. For instance, the number of beneficiaries at the end of the second stage is about 93% of the best attainable value (first stage).

Figure 6.12 also shows that even though the solution at the end of the second stage clearly compromises cost (least important criteria) with a threefold increase over the minimum cost solution, this investment is overcompensated by achieving high levels on the remaining five criteria –ranging from 80.77% to 93.91% of their best value–, ultimately increasing social welfare.

6 Concluding Remarks

In this chapter we have proposed a multiobjective optimization model to help city planners to locate new urban parks in Bogotá. It was shown that a location analysis of this kind may include several criteria in the selection of the best candidate parcels such as geographic coverage; sidewalk and road accessibility; connectivity with other facilities; the externalities provided by nearby facilities; and the construction and parcel acquisition cost. In this sense, the proposed method not only helped IDRD planners to identify the best candidate parcels to be transformed into parks, but also to define evaluation indices for each candidate parcel, some of them absent from the literature.

The proposed solution method included a lexicographic order of the evaluation criteria (indices) and a maximum deterioration (compromise) of the objectives with higher priority. Through this solution approach, the planners were able not only to include their preferences towards the importance of the indices, but also to interactively adjust the compromise of each index to improve the overall quality of the solution. The model gave planners the possibility of running several scenarios, varying the lexicographic order of objectives and exploring the compromise among them. The results were displayed using GIS, helping the multidisciplinary IDRD staff (architects, engineers, economists, and geographers) to explore the solution through a visual language.

The proposed methodology contributed to the planning process of the IDRD and provided the city of Bogotá with a quantitative tool to meet the goal of achieving 2.71 m^2 of park area per inhabitant by 2019. Particularly, the proposed model provides IDRD planners with a tool to efficiently allocate resources for new parks in areas inhabited by vulnerable populations, thus ultimately, providing an example of social equity. Moreover, the methodology helped IDRD planners to quantify the budget required to implement the plan, given that before the application of the proposed methodology, there was no precise estimate of the cost of satisfying the required park area by 2019. In this way, the model is also providing IDRD's planners with valuable information to negotiate budget additions and new resources to fund the construction of new parks. From a public management perspective, the proposed model serves IDRD's decision makers with a tool that identifies the most convenient solutions for the city, mitigating the subjectivity or external pressure involved in public sector decisions; a factor that often undermines the efficacy of public investment in developing countries. A critical issue that guaranteed the success of this project was the active interaction between IDRD experts and researchers. First of all, we learned that by assembling a multidisciplinary team involving architects, engineers, public health experts, geographers, economists, and operations researchers, we enriched the discussion by allowing multiple points of view, ultimately helping the group to identify the most relevant questions to be answered. Nevertheless, several meetings were required to break down barriers regarding different domain languages (i.e., terminology). Even though IDRD planners were not familiar with operations research, they brought into the model constructive contributions, criticisms, and knowledge of their problem. Most importantly, IDRD experts were key gathering information and pointing us to sources required to feed the model with data spread over several offices and government agencies. From our end, we faced the challenge of explaining how operations research models work on city planning problems by carefully choosing examples and reports that were appealing across disciplines.

Finally, although the motivation and the case study came from the city of Bogotá and the IDRD, the proposed model and solution method can be easily extended to other cities with other evaluation criteria. Our experience shows that the conformation of multidisciplinary teams including operations research experts, economist, geographers, and architects, among other, will enrich the decision making process by gathering multiple perspectives to solve the problem. Also, the collaboration scheme that we were able to set between academia and public sector helped us to combine theory and real-world applications, ultimately improving the way the decisions are made and accordingly generating high impact on the society.

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Chapter 7
Using GIS-Based Models to Protect Children from Lead Exposure

Douglas Hastings and Marie Lynn Miranda

1 Introduction

Throughout the USA, children's blood lead levels have declined dramatically over the past 30 years, primarily due to the elimination of leaded gasoline and the banning of lead-based paint. Nevertheless, childhood lead exposure remains a critical environmental health concern even at low levels. Mounting research demonstrates that lead causes irreversible, asymptomatic effects at levels far below those previously considered safe. The Centers for Disease Control and Prevention (CDC) has responded by lowering its blood lead action level from 60 to 10 μg/dL from 1960 to 1991 (CDC, 2006). Recent research, however, suggests that significant adverse health effects including learning and behavioral disorders occur at blood lead levels below the current CDC threshold (Canfield et al., 2003; Chiodo, Jacobson, & Jacobson, 2004; Lanphear Dietrich, Auinger, & Cox, 2000; Schnaas et al., 2006). Furthermore, research indicates that there is no safe level for blood lead in children, and thus any amount of lead can have detrimental effects on development (Gatsonis & Needleman, 1992; Lanphear, Hornung, Khoury et al., 2005; Schwartz, 1994).

The 2007–2008 National Health and Nutrition Examination Survey (NHANES) survey data reveal blood lead levels at or above the CDC blood lead action level of 10 μg/dL in about 1.1% of 1- to 5-year olds in the USA (National Center for Health Statistics, 2010). According to the 2008 American Community Survey (ACS) data, 1.1% of 1- to 5-year olds corresponds to about 270,000 children (U.S. Census Bureau, 2010). A much larger group, however, are exposed to lower levels of lead. The NHANES data estimate that 3.7% of children in the USA, or about 920,000 children, have blood lead levels above 5 μg/dL. Unfortunately, even the most capable doctors cannot easily diagnose low-level lead exposure, so testing children

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for blood lead is essential to combating lead poisoning. From a public health perspective, it is critical to get children who are at risk screened for lead in a timely manner to intervene and reduce lead hazards.

Analysis by the Children's Environmental Health Initiative (CEHI) has confirmed studies suggesting that lead exposure can affect educational performance by examining the relationship between blood lead surveillance data and end-of-grade test scores. CEHI found that blood lead levels as low as 2 μg/dL can have a discernible impact on end-of-grade test performance (Miranda et al., 2006). These findings highlight an important environmental justice issue, as blood lead levels are consistently higher in low-income and minority children than in children in more-advantaged environments. Lead exposure may therefore contribute to the achievement gap between socioeconomically advantaged and disadvantaged children in the US educational system (Miranda et al., 2009).

Public health agencies can best combat lead poisoning through minimizing the exposure of children to lead-based paint. Despite the fact that it was banned in the USA in 1978, lead-based paint remains the leading cause of childhood lead poisoning today (Centers for Disease Control and Prevention, 1991). Approximately 50 million US homes still contain lead-based paint (Shannon, 1996). Young children and often ingest chips of lead-based paint because of their sweet taste. Children can also be exposed to lead through household dust containing lead particles, which are easily absorbed by both the gastrointestinal and pulmonary tracts. Lead-based paint found in older, poorly maintained housing runs the greatest risk of deteriorating into chips or dust. Old or low-income housing is therefore an important risk factor for lead exposure.

In response to research highlighting the dangers of even low blood levels of lead, CEHI has developed a GIS-based model to identify individual households in which children face an elevated risk of lead exposure. CEHI's model estimates lead exposure risk in North Carolina and replication sites through the USA by identifying homes that are likely to contain biologically available lead from deteriorating lead-based paint. Government agencies and other organizations can use the model to plan lead poisoning prevention programs and select the homes or neighborhoods where projects can have the greatest impact. CEHI's model can also be helpful to organizations that are choosing between a variety of strategies for lead poisoning prevention which can differ greatly in results and costs. While these organizations do not currently use quantitative decision models when planning interventions, there is potential to extend CEHI's research through operational modeling and develop low-cost interventions that achieve significant reductions in childhood lead poisoning.

This chapter will discuss the development of CEHI's lead exposure risk model, the current usage of the model by public health organizations, and potential decision modeling applications. Section 2 describes the goals and applications of CEHI's lead exposure risk model. Section 3 explains how the model was developed and presents summary statistics and regression results for key model variables.

Section 4 briefly describes how the model was disseminated to organizations that use it to plan interventions. Section 5 highlights the current usage of CEHI's model in the field. Finally, Sect. 6 assesses the effectiveness of the model and proposes future extensions and decision modeling applications.

2 Goals of CEHI's Lead Exposure Risk Model

A significant body of recent research has focused on methods for conducting various health interventions more efficiently by identifying people at the highest risk for particular conditions. For example, recent studies have analyzed different screening methods for colorectal cancer to determine the most cost-effective means of detecting the disease (Telford, Levy, Sambrook, Zou, & Enns, 2010; Lansdorp-Vogelaar et al., 2010). Other studies have considered such optimization issues as the costs and benefits of using specialists to pre-read mammograms (Van den Biggelaar, Kessels, van Engelshoven, & Flobbe, 2009) and the performance of various cervical cancer screening techniques (Yabroff et al., 2009). A number of analyses have sought to reduce the costs and improve the detection rate of blood lead screening (Binns, LeBailly, Fingar, & Saunders, 1999; Lanphear, Hornung, & Ho, 2005; Vaidyanathan et al., 2009). These analyses have attempted to target blood lead screening efforts by identifying the children or groups of children who are at the highest risk of lead exposure.

CEHI's lead exposure risk model attempts to identify children who are at highest risk of being exposed to biologically available lead. CEHI's model has two unique goals that make it a particularly powerful tool for preventing lead poisoning. First, it seeks to determine the risk of lead exposure based on housing and demographic factors at a very highly resolved spatial scale. Predicting lead exposure risk at the household level enables organizations to finely tune their intervention strategies to meet the needs of specific communities. Second, CEHI works with health organizations and others to target not only blood lead screening, but also a variety of lead poisoning prevention strategies. Using CEHI's model, organizations can determine the most effective strategies for lead interventions based on their resources and abilities, and how best to implement these strategies in different geographic areas. The lead model can thus help organizations with limited budgets to have a greater impact in lead poisoning prevention. Decision modeling applications have the potential to help allocate funding even more efficiently across lead poisoning prevention strategies.

Whatever implementation strategy a particular organization chooses, CEHI's lead model can help them to shift from a mitigative approach to lead poisoning to a preventive one. By identifying the highest risk households, CEHI hopes to enable public health and housing organizations to remove or reduce lead hazards before children are exposed.

3 Developing the Lead Model

CEHI developed its lead exposure risk model through regular consultation with potential end users. CEHI wanted to create a model for predicting lead risk that could be easily understood and used by a diverse group of organizations and individuals. To this end, CEHI generated a series of GIS maps that displayed lead exposure risk in such a way as to allow users to easily identify important trends and information. When the GIS models were complete, organizations such as county health departments, the North Carolina Department of Environmental and Natural Resources (NCDENR), and community groups were quick to put them to use. These groups had been involved in the development process and had already considered applications of the lead model.

CEHI began to work on its first lead exposure risk models in 2000. CEHI initially constructed models for six North Carolina counties in which GIS data layers were readily available, as the lead model requires data from a variety of different sources to predict the risk of lead exposure. One of the most important sources of data for CEHI's model is tax parcel data, which CEHI obtained from county tax assessors' offices. Tax parcels in residential areas typically represent an individual household or apartment complex. Using tax parcels as a primary data layer therefore allowed CEHI to generate predictions for lead exposure risk at individual homes. CEHI used land use codes included in tax parcel data to focus on residential properties.

In order to predict lead exposure risk, CEHI obtained data on variables that had been identified in the published literature as risk factors for lead exposure. These variables included age of housing, median household income, percentage renter occupied, percentage of persons in poverty, percentage of children in poverty, percentage of one-parent households, percentage Hispanic, and percentage African-American. Age of housing information was available from tax parcel data, but the rest of the variables were taken from US census data. Census data are published at the scale of blocks, block groups, and tracts, all of which are larger than tax parcels. Through GIS analysis with ArcGIS 9.x software, however, CEHI was able to spatially join variables at the Census block and Census block group level to tax parcel data. CEHI was thus able to obtain a value for each of the lead exposure risk variables at residential tax parcels in the six study counties.

To determine the relative importance of each of the lead exposure risk variables in predicting actual elevated blood lead levels in children, CEHI used blood lead surveillance data. The Children's Environmental Health Branch of the North Carolina Department of Environment and Natural Resources maintains a database of blood lead surveillance data for all children tested for lead in North Carolina. Each blood lead screening record in the database includes the address where the child who was tested resided. CEHI generated spatial coordinates for the addresses in this database in a process referred to as geocoding. Geocoding these addresses allowed CEHI to connect blood lead surveillance data to Census and tax parcel data. Table 7.1 contains descriptive statistics for the lead exposure risk variables and the North Carolina blood lead surveillance data.

Table 7.1 Descriptive statistics for primary variables in CEHI's lead exposure risk model, summarized at the census block group level

Variable	Observations	Mean	Standard deviation
Lead	280,318	4.01	3.25
Year built	280,318	1968	24.34
Median Income	280,318	40169	17864.28
Percent Black	280,318	34.2	34.54
Percent Hispanic	280,318	6.7	12.99
Percent receiving public assistance	280,318	3.7	4.61

Source: CEHI lead exposure risk model

Note: Seasonality variables and county dummy variables not shown

Table 7.2 Regression results for primary variables in CEHI's lead exposure risk model

Sample size = 280,318; $r^2 = 0.088$; $F(50, 3553) = 167.22$

Variable	Coefficient	Standard error	T	P
Year built	−0.0036	0.00008	−43.53	<0.0001
Median income	−0.000002	0.0000002	−12.43	<0.0001
Percent Black	0.0025	0.00007	35.46	<0.0001
Percent Hispanic	0.0016	0.00016	9.93	<0.0001
Percent receiving public assistance	0.0035	0.00071	4.95	<0.0001

Source: Miranda, Dolinoy, and Overstreet (2002), Kim, Overstreet Galeano, Hull, and Miranda (2008)

CEHI then conducted a multivariable analysis that regressed blood lead levels on the lead exposure risk variables, clustered at the Census block group. The regression generated coefficients for each of the lead exposure risk variables, which indicated the effect that the variables had in modeling blood lead levels in children. CEHI also included a dummy variable for each of the six counties in the regression to capture unexplained county-level differences in blood lead levels. The coefficients obtained from this regression could then be applied to every residential parcel in the area under study and thus used to develop a lead exposure risk model display. Table 7.2 contains results of the regression for the primary lead exposure risk variables.

After creating the lead exposure risk model for the initial six counties, CEHI evaluated the performance of the model in several ways. First, CEHI assessed how well the model predicted where elevated blood lead levels would occur in new blood lead screening data. CEHI found that a majority of blood lead levels above the CDC's action level of 10 μg/dL occurred in tax parcels that CEHI had designated in the top 25% in terms of lead exposure risk.

Second, CEHI used X-ray fluorescence (XRF) technology to test homes in four of the six counties. CEHI attempted to test a representative sample of the counties by examining homes in one eastern coastal county, two counties in the central Piedmont region of North Carolina, and one county in the western mountain region. Homes in each of the four counties were divided into deciles according to their lead risk index, and sampling occurred evenly across the deciles. Preliminary results

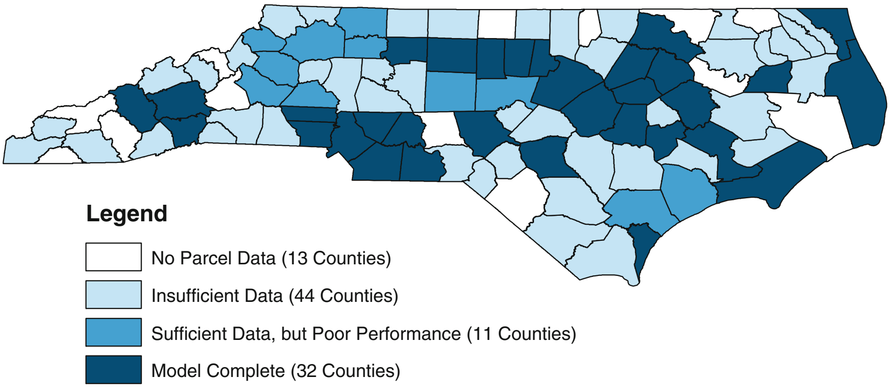

Fig. 7.1 Status of CEHI's lead model in North Carolina counties as of May 2010. *Source*: CEHI lead exposure risk model

from the XRF analysis indicated that the primary lead model variables were significantly correlated with lead concentrations in household dust at the 5% level. Finally, the effectiveness of CEHI's lead model was indirectly validated by the results of the organizations that used it.

CEHI later replicated the lead model in additional North Carolina counties. To support this effort, CEHI constructed a database to track the availability of the GIS layers necessary to construct the model for each of the 100 counties in North Carolina. In an ongoing process, CEHI was able to communicate with county tax assessor's offices and obtain GIS layers for 87 counties. Of these 87 counties, 43 had tax parcel data tables that included age of housing, a key variable in model construction. CEHI attempted to create a model for all 43 counties with tax parcel and age of housing data, but in some counties the model did not perform to CEHI's standards for predicting elevated blood lead levels because less than 50% of blood lead levels above 10 μg/dL occurred in parcels ranked in the top quartile of lead exposure risk. In some poor-performing counties, CEHI was able to improve the model by incorporating more complete tax parcel data that was compiled by county tax assessors after the initial models were created. In 11 counties, however, the model continued to perform poorly, likely due to the low blood lead screening rates or neighborhoods with no age of housing data. Thus, as of 2010, CEHI has been able to create an accurate lead exposure risk model in 32 North Carolina counties. Figure 7.1 shows the status of CEHI's lead model in North Carolina.

CEHI is continually working with lead exposure risk model users, tax assessors, and county GIS officials to replicate the lead exposure risk model in new locations. In addition to expanding the model to new counties in North Carolina, CEHI has created lead models at several replication sites throughout the USA. CEHI has created such models by establishing contacts with local or state health officials who are interested in using a lead model and can help CEHI locate the necessary GIS layers. For example, CEHI has generated lead models for Detroit, Michigan and Kenosha, Wisconsin by working with health department staff.

CEHI is also working to update and improve existing lead models. One major improvement has been updating the 1990 Census data used in the first generation of models to 2000 Census data. Incorporating 2000 Census data made the demographic variables in the model more current and allowed CEHI to incorporate a new variable: percent of population that is Hispanic. Research has indicated that Hispanics have a higher incidence of lead exposure, and the 2000 Census enabled CEHI to use percent Hispanic in lead models by reporting the variable more accurately than in 1990. The model results presented in this chapter, as well as the county lead models that have been disseminated to public health organizations, were calculated using Census 2000 data.

CEHI will incorporate 2010 census data when it becomes available and is currently working to include new blood lead screening data and age of housing data. CEHI also maintains relationships with lead model users and solicits ideas for new ways to improve the model or disseminate it to interested organizations or individuals.

4 Lead Model Dissemination

To facilitate the use of the lead exposure risk model, CEHI creates user-friendly maps that display the model in an intuitive and helpful format. Based on the input of end users of the model, CEHI decided to categorize lead exposure risk into four color-coded groups on these maps. In these four categories, “priority 1” represents the top 10% of all tax parcels in terms of lead exposure risk, “priority 2” represents the next 10%, “priority 3” represents the next 40%, and “priority 4” represents the lowest 40%. This categorization can help organizations choose interventions such as targeted blood lead screening or home lead investigations, based on our lead risk priorities. Figure 7.2 shows the lead exposure risk categories for parcels in Central Durham. Patterns become easily recognizable when users view the lead model outputs in this format. For example, in Central Durham, viewers can see a “horseshoe” shape of high lead risk homes in central and eastern Durham, surrounded by lower lead risk homes.

CEHI can disseminate lead exposure risk models in a variety of different formats to suit the needs of particular groups. For example, some groups who are actively removing lead hazards from homes want to identify the worst houses in a particular county in terms of lead exposure risk. CEHI has provided these organizations with maps that show only the parcels that are in the top 5% in terms of lead risk.

Different users of the model also have widely varying capacities for using GIS; so CEHI creates copies of lead models in both GIS and non-GIS formats. Most county health departments have dedicated GIS personnel, so CEHI provides these organizations with complete ArcGIS shapefiles that the health departments can manipulate and analyze. For organizations that have computer ability but do not have ArcGIS software, CEHI provides GIS maps that are viewable with free software and can still be manipulated to some degree. Many community organizations want to use the lead model without any GIS software, and CEHI provides these groups with printed or PDF maps. Finally, some groups are

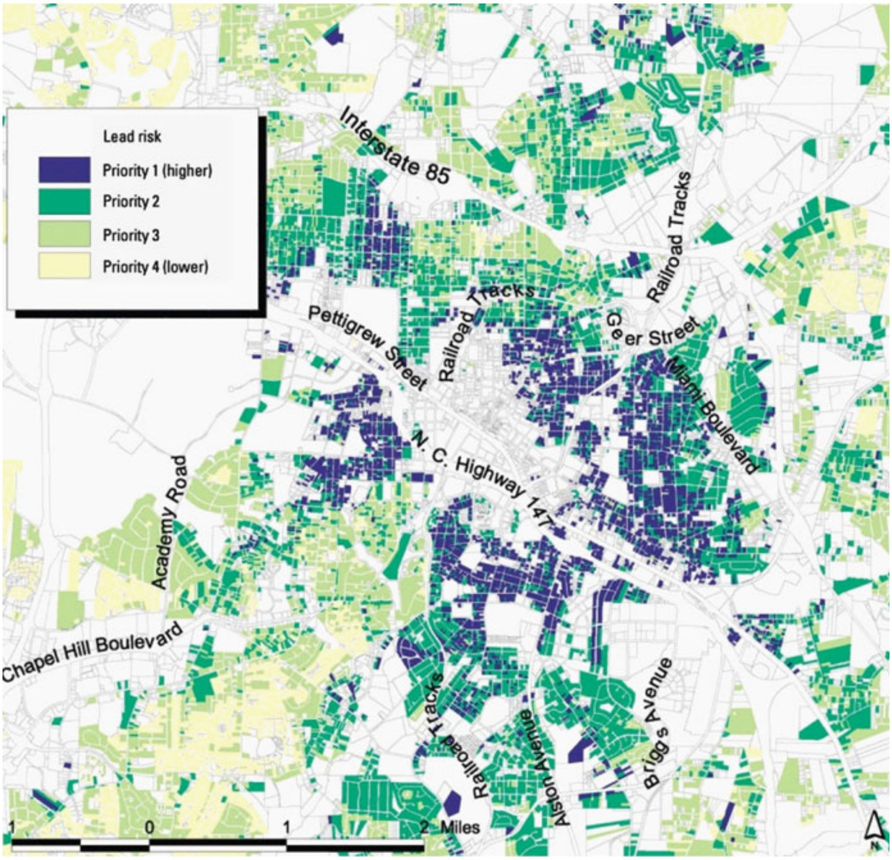

Fig. 7.2 Lead exposure risk priorities for the city of Durham, NC. *Source*: Miranda, Dolinoy, and Overstreet (2003)

interested in lead model products other than maps, such as statistics or databases. CEHI works with these groups to create lead model outputs that are the most helpful to their specific goals.

5 Applications of the Model

CEHI's lead model has been used by a variety of organizations to plan the most effective lead poisoning prevention strategies based on their unique local context and resources. These organizations include county health departments, city housing authorities, nonprofit organizations, state agencies in North Carolina, and groups in other states. CEHI meets with all of these groups and provides suggestions for ways that the model is typically used, as well as discussing new ways to apply the model for particular projects. Through collaboration with CEHI, these various organizations have developed innovative applications for the lead model.

The lead model can serve several different roles in planning lead intervention projects. For example, the lead model can help groups target their projects toward high-risk households and can facilitate the distribution of materials or personnel to areas with a large number of high-risk homes. The lead model can also help groups to select which strategy out of a set of options would be the best fit for a particular situation. In some cases, the model has even enabled organizations to take novel approaches to reducing lead poisoning. Later we discuss possible decision modeling applications for the lead model, though no organization has yet used the model in this way.

5.1 Targeted Blood Lead Screening and Home Lead Investigations

One of the first ways that CEHI's lead exposure risk model was put to use was for targeting blood lead screening in Durham. At the time that CEHI created its first lead models, many residents in Durham were concerned about high rates of lead poisoning in the city. Community organizations were calling for the Durham County Health Department to institute universal screening, but the health department had a limited budget and felt that, given their housing situation, some children were not at risk for lead exposure. Rather than attempting to screen every child in Durham, the health department used CEHI's lead model to offer blood lead screens to the children that were at the greatest risk of lead exposure. The health department sent nurses to a variety of locations, such as clinics, churches and day care centers, in neighborhoods with a high proportion of houses that CEHI had designated as priority 1 and offered free blood lead screening.

CEHI provided the health department with a GIS layer containing the locations of these community resources so that the health department could determine the best locations for providing screens. Using these techniques, the Durham County Health Department increased its detection of elevated blood lead levels by 600% with approximately the same amount of funding.

Community groups in Durham continued to be active in combating lead poisoning even after the Durham County Health Department dramatically improved its blood lead screening. One of these groups, the Durham Affordable Housing Coalition (DAHC), acquired an XRF machine and used it to offer free testing for lead in homes by door-to-door canvassing. CEHI provided a series of maps to DAHC that showed the lead risk priorities in the neighborhoods where they worked. These maps helped DAHC to select neighborhoods with a large quantity of high-risk housing and to prioritize those homes at the greatest risk. Since DAHC wanted to use maps in the field, CEHI was able to generate printed maps containing street names and landmarks that volunteers could easily use as they moved through neighborhoods.

5.2 Lead Paint Abatement

Several county health departments and city housing authorities in North Carolina have received funding from the Department of Housing and Urban Development (HUD) to abate lead-based paint in homes. In home lead abatements, lead paint is either removed completely or covered with a sealant that will prevent its deterioration. Both of these processes are expensive and time consuming; so organizations that conduct lead paint abatements typically work only on homes in which the presence of high amounts of lead has been confirmed with an XRF machine. Most county health departments only investigate homes with an XRF machine when a child has been tested with a blood lead level at or above 10 μg/dL. Some groups, however, have used CEHI's lead model to anticipate potential incidences of lead poisoning by testing for lead in high-risk homes even if a child has not yet had an elevated blood lead level. Other groups have contacted the parents of children living in priority 1 housing and encouraged the parents to seek testing and subsequently conducted a lead paint abatement if high blood lead levels were found. Many of the organizations in North Carolina that receive HUD funding for lead paint abatements have also used CEHI's lead model when applying for their grants. Through CEHI's model, these organizations were able to demonstrate to HUD that a particular area had a large percentage of housing that would likely require lead abatement.

5.3 Educational Programs and Community Outreach

Many organizations in North Carolina, particularly local nonprofit groups and health departments in rural areas, have limited funding but are nonetheless motivated to combat lead poisoning. One important way that these organizations can help reduce lead exposure is through educational outreach and the dissemination of information. CEHI's lead model can help these organizations plan educational initiatives that are helpful and are of low cost. Many of these organizations plan educational programs about lead at local centers such as schools, daycares, or religious institutions. CEHI has assisted these organizations by mapping the locations of community resources along with the lead exposure risk model to facilitate the planning of educational programs in high-risk neighborhoods. Figure 7.3 shows the locations of daycares, religious institutions, physicians, and schools for a neighborhood in Durham superimposed over the lead model. One group that has had a great deal of success disseminating educational information about lead is Forsyth CHANGE, a faith-based organization that educates Forsyth County residents about lead through a network of churches. In addition to providing Forsyth CHANGE with lead model maps, CEHI has given its organizers detailed demographic maps to help them plan locations for offering Spanish-language lead education to Forsyth's Latino community.

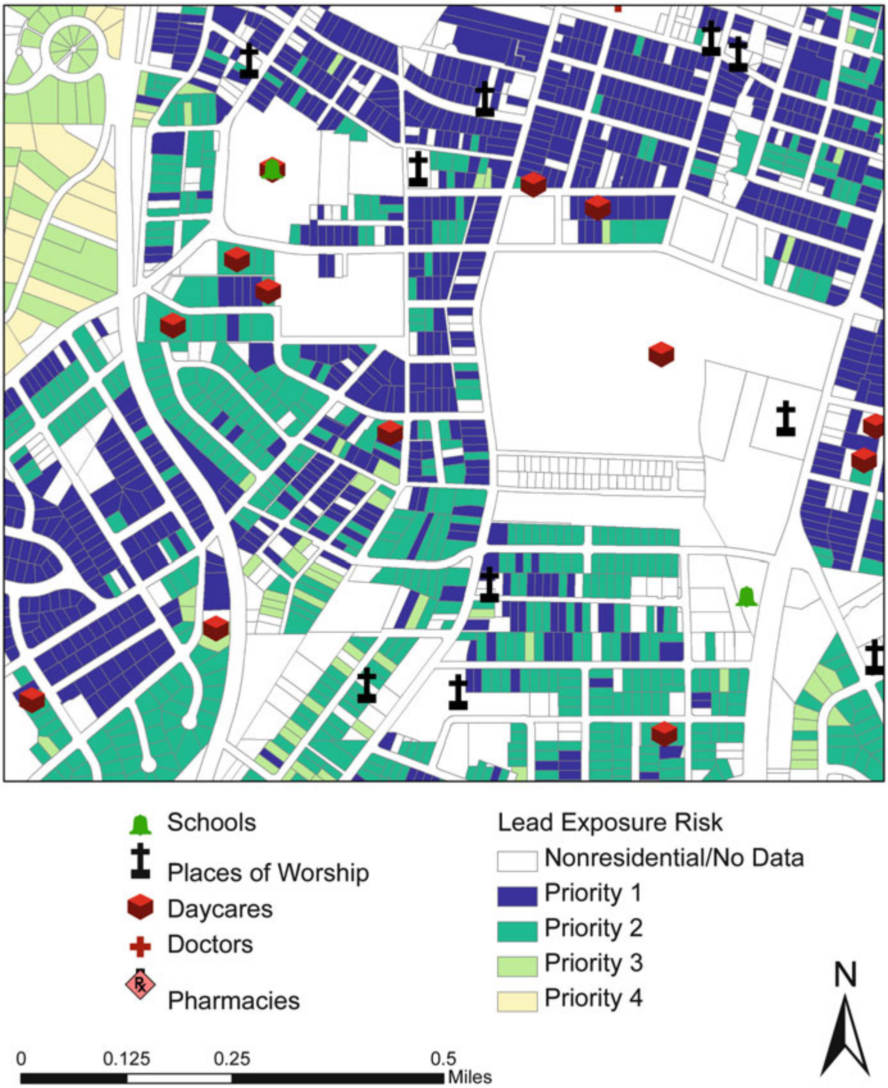

Fig. 7.3 Community resources mapped in conjunction with CEHI's lead exposure risk model. *Source*: CEHI lead exposure risk model

Some groups in North Carolina have focused on disseminating information about lead exposure through mailings rather than in-person programs. Many of these groups have used CEHI's lead model to selectively send informational pamphlets about lead poisoning to homes where children are at high risk of lead exposure. One county health department plans to use the lead model to send free home lead dust testing kits to high-risk homes along with lead poisoning information. These home lead testing kits are inexpensive and will hopefully motivate residents to have their children screened for blood lead if there are high concentrations of lead in their household dust. In addition, larger agencies have developed such mailings to complement other initiatives. For example, the Guilford and Forsyth County health departments have combined CEHI's lead model with birth record data to send lead poisoning information to high-risk households where young children live. The health departments send information in the form of birthday cards when the children in these homes turn age 1 and age 2. The cards inform parents about home cleaning methods that can reduce lead and remind them about the availability of blood lead screening.

5.4 Lowering Lead Action Levels

The CDC's action level for childhood blood lead requires that public health agencies offer to investigate any home in which a child has a confirmed blood lead level of 10 μg/dL or greater. The CDC further requires public health agencies to investigate any homes in which a child has a confirmed blood lead level at or above 20 μg/dL, regardless of the wishes of parents or guardians. In recognition of the fact that harmful health effects can occur below the CDC's action level, two county health departments in North Carolina have chosen to lower the action level in their counties. These health departments, Forsyth and Guilford, lowered the level at which they offer an investigation to 5 and 8 μg/dL, respectively. Forsyth also lowered the blood lead level at which an investigation is mandatory to 8 μg/dL, and Guilford established mandatory investigations at 10 μg/dL. Officials from these two county health departments used CEHI's lead model to help argue their case for lower action levels to their boards of public health. They used the lead models for Forsyth and Guilford to show areas of high lead risk housing that would be investigated far more frequently with lower action levels.

Forsyth County also used age of housing data provided by CEHI to demonstrate that Forsyth had a high prevalence of pre-1978 houses compared to other counties in North Carolina. Lowering the blood lead thresholds at which interventions are warranted allowed the Forsyth and Guilford county health departments to develop more effective programs to reduce lead exposure. Other health departments in North Carolina, including the Chatham County Health Department, have sought to follow the example of Guilford and Forsyth. Members of the Chatham County Health Department and a nonprofit group called the North Carolina Rural Communities Assistance Project are currently using CEHI's lead model to discuss lowering action levels with the Chatham County Board of Health.

5.5 State-Level and National Applications

While CEHI's original lead exposure risk models were created for counties in North Carolina, CEHI has expanded the scale and location of lead models for several different projects. One of CEHI's most important partners in combating lead poisoning has been the Children's Environmental Health Branch of NCDENR. In addition to receiving blood lead data from NCDENR, CEHI has also collaborated with the department in several efforts. One of these projects was an analysis of the lead exposure risk for zip codes throughout the entire state of North Carolina. CEHI created a model to assess the lead exposure risk of zip codes with variables similar to those that were used to predict the lead risk of tax parcels. The goal of this analysis was to determine whether physicians should screen all children for blood lead at checkups or use a questionnaire to selectively screen only children who live in high-risk housing.

Based on CEHI's analysis, NCDENR provided recommendations to doctors in each zip code to either test children for blood lead universally or screen children in a targeted manner with a questionnaire. NCDENR has also used CEHI's lead models based on tax parcels to help enforce the federal lead disclosure rule, which requires the disclosure of information about lead-based paint when any homes built before 1978 are sold or leased. Finally, NCDENR has used lead models to recruit landlords into North Carolina's Preventive Maintenance Program, which provides training and assistance to help landlords reduce lead hazards in their rental properties.

CEHI has also extended the lead exposure risk model to areas outside the State of North Carolina. The lead model can be replicated for any location in the USA that has a tax parcel GIS layer, age of housing data, and blood lead screens. CEHI was contacted by health officials from Kenosha County, Wisconsin and the City of Detroit, Michigan who were interested in using a lead exposure risk model in their lead exposure reduction efforts. These officials were able to provide CEHI with the necessary data layers. The model for Detroit did not perform as well as the models in many North Carolina counties, as less than 50% of blood lead levels above 10 μg/dL occurred in parcels in the top 25 percentile of lead risk. The model likely performed poorly in Detroit because almost all of the houses in the city were built before 1978, and thus most of the city is at high risk for lead poisoning. Nevertheless, CEHI's lead model is still helpful in identifying houses that are particularly likely to have deteriorating lead-based paint in Detroit. Members of the Detroit Health Department and researchers at nearby Wayne State University hope to use the Detroit lead risk model to identify neighborhoods that are in particular need of lead education or blood lead screening.

6 Discussion and Conclusions

CEHI's lead exposure risk model is a flexible GIS-based model that can be expanded, improved, updated, and disseminated in new formats. CEHI has now developed a model for 32 counties in North Carolina and several replication sites throughout the country and disseminated copies of relevant models to a variety of health departments, community groups, and state agencies. These groups have used the lead model to achieve significant improvements in lead poisoning prevention, such as the Durham Health Department's 600% increase in the detection of elevated blood lead levels in Durham children.

The lead model can be applied to a wide variety of projects designed to reduce the incidence of childhood lead exposure. CEHI maintains working relationships with health organizations using the lead model throughout North Carolina and elsewhere to maintain relevant data and apply the model. These relationships help address shortcomings of CEHI's model such as a lack of data in certain counties and poor performance of the model in other counties. CEHI has constructed models in additional counties by acquiring new tax parcel data and improved the performance of existing models by obtaining more up-to-date or accurate datasets. CEHI is also working with public health organizations to develop the lead model further and extend it in innovative ways.

One exciting potential application of the lead model is the development of least-cost interventions through decision modeling. Currently, government agencies and other users of the model weigh CEHI's estimates of lead exposure risk along with other factors including geography, resources, and the costs and benefits of particular intervention strategies when planning lead poisoning prevention programs. Decision modeling would allow these organizations to quantitatively determine optimal courses of action. For example, an organization could apply a multi-objective linear program to select specific households for home lead dust testing based on estimated lead exposure risk, available budget, the costs of a test, the distribution of lead exposure risk in the surrounding neighborhood, and the potential health impact as a result of testing.

CEHI is continually working to improve the lead model and its implementation in several ways. First, CEHI plans to update current lead exposure risk models with new blood lead screening results and 2010 Census data when they become available. Second, CEHI hopes to expand the model to new counties in North Carolina as they shift to providing publicly available GIS data, and to replicate the model outside of North Carolina through collaboration with interested organizations. Third, CEHI strongly believes in the power of GIS for analyzing public health issues, and therefore provides GIS training to health officials in North Carolina and nationally. These health officials will be able to investigate a variety of public health issues, including potential optimization applications of CEHI's lead model.

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Part III
Minorities and Disadvantaged Groups

Chapter 8
A Model for Hair Care Flow in Salons in the Black Community

Farmer L. Lee Stenson

1 Introduction

Hair care, a source of pride, beauty, and confidence for all women, has special customs and implications for African-American[1] women. First, there are only certain places women of color can go to get their hair styled as many mainstream stylists lack the experience in cutting, straightening, and conditioning African-American hair styles. Additionally, most mainstream salons do not have the knowledge of the various products that are most effective in maintaining the health of black female hair. The lack of knowledge by majority-culture hair salons of black female hair originates in part from the diversity of hair textures of women of African ancestry, whose hair represents a range of curl patterns generally distinct from those of Caucasians. The majority of women of color use a local community salon and most of these salons are located in predominantly minority neighborhoods (Taylor, 2005). As noted by Prof. Tiffany Gill, these community-based salons are a social, political, and financial bedrock of the communities they serve (Gill, 2010). Salons that service women of color usually use a technique known as "stacking" to increase their profit margin. Stacking allows a stylist to schedule multiple clients within the same appointment time. This process is similar to other industries such as airlines that overbook customers. As one might expect with stylists who have many customers who must be washed, dried, and styled, service times and waits can be quite long. Many of the most popular styles requested by African-American females require from 2 to 10 h to complete service. The final and probably largest differentiator of African-American

[1] In this paper we explore the hair care needs of American women of African descent, which may include diverse national and ethnic origins. We alternate use of the terms "African American", "black" and "women of color".

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stylists and mainstream stylists is the diversity in styles that a salon and individual stylist must manage. Top African-American hair care magazines such as *Sophisticate's Black Hair* list over 500 styles spanning the spectrum of relaxed, natural, and braided hair. Some of these styles, such as micro-braids, sister-locks, and natural hair weaves, are not present in the curricula of typical beauty schools and comprise a skill-set that is unique to those who style African-American hair (Fanter, 2010).

This analysis looks at the processing time and profit expectations for African-American serving salons and develops some recommendations to minimize the processing time while balancing the need for community-based salons to continue to make a strong profit.

1.1 African-American Stylists vs. Mainstream Stylists

In order to compare salons that primarily serve African-American patrons to other general public serving salons it is important to understand the differences between them. Salons that service African-American women are distinguished from those that service the general population by greater expertise in styles available to women of color as well as larger service and wait times. Salons that serve women of color are well known for having what many would consider being exceptionally long waits. Journalist T. Shaun Taylor notes that "even small storefront shops are known for having long waits to get to the shampoo bowl" (Taylor, 2005). The primary contributor to the long wait at African-American serving salons is the aforementioned stacking process. The long waits are produced by the combination of the stacking process and the fact that the service times for many of the more complex styles requested by black women require in some cases as much as 10 h to complete (Locked Online, 2008).

Many African-American salons do not accept walk-ins, given that the waits could be extraordinary when multiple clients with long service times are already waiting. In comparison to mainstream salons, where clients can walk in, often without an appointment, and be serviced in 2 h or less, one can see the tremendous loss of time women of color are facing. From a customer's time and productivity standpoint, the loss is quite extensive. The other differentiator is the fact that for African-American salons, the social atmosphere plays a large role in why a particular salon is patronized. Many clients of African-American stylists consider their stylist as a friend and confidant and much of the pain that is associated with long waits is offset by a sense of family and community connection that fellow patrons share.

1.2 Cost and Time Considerations

Depending on her hair style and texture, most American women have their hair cut or styled every 2–6 weeks. Some African-American hair styles allow up to 12 weeks between visits, but these styles also require the longest time to restyle. Depending on where a patron goes, what services she has performed, and the particular stylist, a client may pay as little as $25 or as much as $200 at a mainstream salon.

Table 8.1 Time and costs for mainstream services

Hair style	Processing time (min)	Cost	Typically lasts
Perm and shampoo	25–45	\$50–\$60	4–6 weeks
Hair coloring/ highlights	25–45	\$65–\$150	4–6 weeks
Styled cut	20–40	\$12–\$30	4–6 weeks

Table 8.2 Time and costs for popular black hair styles

Hair style	Processing time (min)	Cost	Typically lasts
Perm/press	90–120	\$65–\$120	2 weeks
Sister locks	420–600	\$300–\$500	4–5 weeks
Micro-braids	120–360	\$130–\$200	12 weeks
Synthetic/natural hair weave	120–180	\$150–\$2,500	6–8 weeks
Short texturized natural	45–90	\$65–\$90	2 weeks

Research indicates that most of the Caucasian women visit their hair stylist on an average of every 6 weeks and most black women go every 2.5 weeks (Wellington, 2010). These services range from a simple cut to coloring and a perm. Completion of the process typically takes from 20 min to 1 h. A survey conducted for this chapter gathered cost and processing time data for one mainstream salon (see Table 8.1) and 30 African-American serving salons (see Table 8.2) throughout the US. Survey questions and summary responses are contained in Appendix A.

For African-American stylists, clients pay \$65 to \$2,500 depending on what they have done (Table 8.2). The lower end of the price spectrum encompasses services such as cutting, coloring, and bumping and the higher end covers more complex services such as micro-braids, sister locks, French braids, and hair weaves. Natural hair weaves are the most expensive service offered to black clients. A less expensive alternative to the natural hair weave is synthetic hair weaves. Data from the national survey indicate that braids, locks, hair extensions, and hair weaves remain some of the most popular styles. Total out-of-pocket costs in time and money for hair styling can be quite large. Table 8.3 shows the impact of visit cost and frequency on total cost, and the impact of visit frequency on total time.

Table 8.3 indicates that a women who might receive basic services at a mainstream salon (visit every 6 weeks, spending \$50–\$60 per visit for a perm and shampoo) spends an estimated \$433 as compared to a woman who receives basic services at an African-American salon (visit every 2 weeks, spending \$65 per visit for a perm and press) and spends an estimated \$1,690. Black women outspend other women by a factor of two to six for hair care (Treasured Locks, 2006). Despite long wait times for their clients, African-American hair care can be lucrative; stylists of such salons may serve 30–60 customers per week and generate up to \$500,000 in revenues per year (Taylor, 2005).

Table 8.3 Hair cost per year vs. visits per year

	Salon visit interval (weeks)				
Visit characteristics	2	4	6	8	12
Approximate number of visits/year	26.0	13.0	8.7	6.5	4.3
Yearly cost @ $25/visit	$650	$325	$217	$163	$108
Yearly cost @ $50/visit	$1,300	$650	$433	$325	$217
Yearly cost @ $65/visit	$1,690	$845	$563	$423	$282
Yearly cost @$80/visit	$2,080	$1,040	$693	$520	$347
Yearly cost@ $120/visit	$3,120	$1,560	$1,040	$780	$520
Yearly cost @$200/visit	$5,200	$2,600	$1,733	$1,300	$867
Yearly cost @$300/visit	$7,800	$3,900	$2,600	$1,950	$1,300
Yearly cost @$500/visit	$13,000	$6,500	$4,333	$3,250	$2,167
Yearly cost @ $1,100/visit	$28,600	$14,300	$9,533	$7,150	$4,767
Yearly cost @ $2,500/visit	$65,000	$32,500	$21,667	$16,250	$10,833
Time/year at 2 h (service)	52.0	26.0	17.3	13.0	8.7
Time/year at 4 h (service)	104.0	52.0	34.7	26.0	17.3
Time/year at 6 h (service)	156.0	78.0	52.0	39.0	26.0
Time/year at 8 h (service)	208.0	104.0	69.3	52.0	34.7

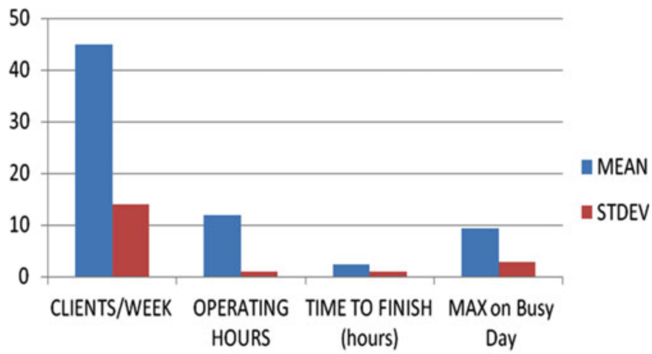

Fig. 8.1 Descriptive statistics for hair stylists survey

Figure 8.1 lists some statistical results from surveyed stylists who serve African-American patrons throughout the USA. The survey instrument is presented in Appendix A.

1.3 Importance of Styled Hair for African-American Females

In order to understand the relevance of stylists to the African-American community, it is imperative to understand the connection of black stylists to their clientele. The issue of hair care for African-American women and girls is deeply personal and is closely aligned with issues of self-esteem, pride, and cultural identity, as illustrated by the recent documentary *Good Hair* (Stilson, Rock, George, Donnell, & Hunter, 2009). The close relationship between a nice hairstyle and feelings of self-worth translates into African-American women accounting for 30% of all hair maintenance business in the USA despite African-Americans comprising only 13% of the US population (Richardson, 2007). Like all women, African-American women associate well-styled hair with beauty, confidence, and self-esteem. However, these feelings are uniquely magnified for African-American women because of a history of cultural messages disparaging "natural" black hair and conveying an expectation that straightened black hair is necessary for acceptance and advancement. As a result, African-American women perceive unique pressures to spend time and money on beauty products and treatments, not limited to hair care beyond those of other American women (Gill, 2010). When a woman or girl of color is unable to get her hair done due to time, finances, or unavailability of styling personnel, it can often time lead to feelings of inadequacy and lower self-esteem (Villarosa, 1994). This stems in part from many years of negative portrayals of black women in popular culture. In addition to the time and cost disparity between African-American and mainstream stylists, the issue of hair care is further differentiated by years of women of color being made to feel (by mainstream media, social circles, and many work environments) that natural African-American hair styles (Afros, corn rows, and such) are not attractive. Lester (2000, p. 206) summarizes these cultural issues as follows:

> Competing mythologies around something as deceptively insignificant as hair still haunt and complicate African Americans' self-identities and their ideals of beauty, thus revealing broad and complex social, historical, and political realities. The implications and consequences of the seemingly radical split between European standards of beauty and black people's hair become ways of building or crushing a black person's self-esteem, all based on the straightness or nappiness of an individual's hair. Within African-American culture, head hair is a big deal – so many choices in hairstyles: dreadlocked, "natural," curled, faded, braided, twisted, straightened, permed, crimped, corn rowed, and even bald.

Traditional hair care practices for African-American women have changed in recent years. African-American women increasingly wear natural hair styles, and mainstream salons feature African-American stylists. However, continuing ethnic stereotypes related to hair styles of African-American women are likely to result in significant expenses borne by black women for specialized services of hair salons and hair products for some time to come. As a result, operations models that provide evidence of efficiencies in salon services associated with changes in salon practices may provide substantial social benefits.

1.4 African-American Female Members of the Armed Services

African-American female members of the armed services have unique needs that make hair care more complex, given the requirements of their world of work to include exceptional time constraints, restrictions on how hair may be worn, and challenging operational environments. Any solution that minimizes the service and wait time for women of color in uniform will certainly work for other women who generally do not have the same time, availability, and operational restrictions. For women in uniform, the waits associated with many traditional African-American stylists are usually unacceptable and, given service-specific uniform regulations, usually opt for styles that allow for lower levels of maintenance and longer periods before having to be redone. An example of this can be seen in an African-American female military officer who described her haircare experienced during her first 2 years at the U.S. Coast Guard Academy. She went completely “natural” since work activities resulted in most of her processed hair breaking off. By her junior year, she found an off-base stylist to tend to her natural braid style. She and other female service members assert that maintaining styled hair is very difficult while on deployment due to a lack of facilities and skilled stylists. The chapter concludes that increased cultural sensitivity and awareness can increase personal comfort by minority women in the armed forces.

2 Computer Simulation and Queuing Models for Salon Operations

2.1 Assumptions, Surveyed Processing Times, and Model Development

Stylists specializing in African-American female hair were surveyed to establish benchmarks for service types, durations, and prices. We received 30 completed surveys from 100 distributed. Survey respondents estimated times to complete tasks typically associated with hair care, grouped into three categories: “wash,” “style,” and “dry.” Survey results indicate that salons are open between 8 and 13 h each day. After compiling the data from stylist surveys and observing specific salon operating processes, it became clear that for most salons the whole process could be improved if most stylists hired a person to only wash hair and a person to only dry hair. Setting up a multistage process frees the stylists to concentrate on one primary task, styling hair.

This analysis assumes that stylists’ goals are to maximize the number of clients that can be served in a maximum work-day of 13 h, assuming 1 h for lunch, with each client receiving three discrete services: washing, styling, and drying. The process is illustrated in Fig. 8.2. Based on the survey results, washing hair requires between 20 and 45 min; drying hair requires between 20 and 30 min; styling times range widely, between 20 and 355 min, depending on the style requested. In addition, drying times tend to be fairly constant at 22 min; we will treat them as deterministic. It is also assumed that there is only one server at each station (washer, stylist, dryer-machine). In most salons, drying is automated requiring minimal human input.

This analysis will focus on examining two primary salon operating policies. The first policy is *stacking clients* (multiple clients scheduled at the same appointment

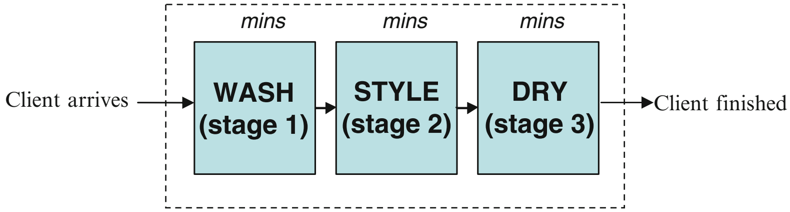

Fig. 8.2 A typical salon sequential serving process

time) and the second is *not stacking* (clients strictly arrive according to their separate appointments). Standard analytic queueing models require inter-arrival and service times to be exponentially distributed. However, results based on examination of actual salons, described below, indicate that service times for washing and styling hair are not exponentially distributed. Therefore, we use simulation to model alternative salon operating policies. Given that washing and styling are discrete processes, the washing and styling times are modeled as two servers with deterministic arrival times (scheduled appointment) and drying times. We represent this system as a $D/G/n$ queue (Winston, 2004), where D denotes a deterministic arrival or service time, G represents a generally distributed arrival or service time, and n represents the number of servers.

2.2 *Simulating a Salon Queue with a Discrete Event Simulation*

For the purposes of this analysis, we assume that appointments are scheduled in *blocks* of two or three clients every 60 min which was the strategy of some of the stylist surveyed. In reality, the scheme for stacking is purely at the discretion of an individual stylist and based on stylist capacity as clients could be stacked as many as 4 per hour. Queue discipline is first in first out (FIFO).

To simulate the $D/G/2$ queue, we compute the time to complete an appointment as a function of the component steps as:

$$\begin{aligned}[\text{Finish\_Time}]_{\text{N}} &= ([\text{Arrival\_Time}]_{\text{N}} + ([\text{Wash\_Time}]_{\text{N}} + 1 \\ &\quad + [\text{Style\_Time}]_{\text{N}} + 1 + [\text{Dry\_Time}] + [\text{Style\_Time}]_{\text{N}-1}) \bmod 780 \qquad (8.1)\end{aligned}$$

where:

$[\text{Finish\_Time}]_{\text{N}}$ = completion time of customer N.
$[\text{Style\_Time}]_{\text{N}}$ = time required to style customer N.
780 = minutes associated with 12 h for operations plus 1 h for lunch.

Suppose a client arrives 105 min after the previous client, whose styling was completed 480 min after the start of business, and requires 25 min to wash, 45 min to style, and 22 min to dry, with a 1-min transition time between steps. Then this client would be finished 678 min after the salon opening time; the maximum time the salon is open has not been exceeded.

In contrast, suppose another client arrives 135 min after the previous client, whose styling was completed 500 min after the start of business, and requires 35 min to wash, 90 min to style, and 22 min to dry, with a 1-min transition time between steps. Then (8.1) yields a value of 3, i.e., the maximum time the salon is open has been exceeded by 3 min. This customer would then be the last customer to receive services for the day.

Our simulation records waiting and processing times for all steps in the hair styling process. These times are computed using (8.2)–(8.4). A delay factor accommodates work breaks.

Styling wait time:

$$\mathrm{Style\_Wait}_n = \begin{cases} \mathrm{Style\_Finish}_{n-1} - \mathrm{Wash\_Finish}_n, & \text{if } \mathrm{Style\_Finish}_{n-1} > \mathrm{Wash\_Finish}_n \\ 0, & \text{if } \mathrm{Style\_Finish}_{n-1} < \mathrm{Wash\_Finish}_n \end{cases} \tag{8.2}$$

Washing time completion:

$$\mathrm{Wash\_Finish}_{n+1} = \begin{cases} \mathrm{Arrival}_{n+1} + \mathrm{Wash}_n + \mathrm{Wash\_Time}_{n+1} + \mathrm{delay}, & \text{if } \mathrm{Wash\_Finish}_n > \mathrm{Arrival}_{n+1} \\ \mathrm{Arrival}_{n+1} + \mathrm{Wash\_Time}_{n+1} + \mathrm{delay}, & \text{if } \mathrm{Wash\_Finish}_n < \mathrm{Arrival}_{n+1} \end{cases} \tag{8.3}$$

Styling time completion:

$$\mathrm{Style\_Finish}_{n+1} = \begin{cases} \mathrm{Style\_Finish}_n + \mathrm{Style\_Time}_{n+1} + \mathrm{delay}, & \text{if } \mathrm{Style\_Finish}_n > \mathrm{Wash\_Finish}_{n+1} \\ \mathrm{Wash\_Finish}_{n+1} + \mathrm{Style\_Time}_{n+1} + \mathrm{delay}, & \text{if } \mathrm{Style\_Finish}_n < \mathrm{Wash\_Finish}_{n+1} \end{cases} \tag{8.4}$$

The *delay* factor adds additional time to finish time for washing and styling if activated. For a typical salon day the delay factor is activated for 60 min each day for lunch and randomly between 2 and 5 min each day for restroom breaks for salon personnel.

2.3 Clients Stacked with Styling and Washing Times Allowed to Vary, vs. Clients Not Stacked

In order to analyze and develop a realistic model of stylist operations, sample data were collected from an African-American female serving salon with multiple stylists whose patrons received the full spectrum of services ranging from perms and micro-braids to hair weaves. Processing times were recorded for the washing, styling, and drying of each of the 99 patrons sampled. Figure 8.3

Fig. 8.3 Histogram of sampled salon wash times

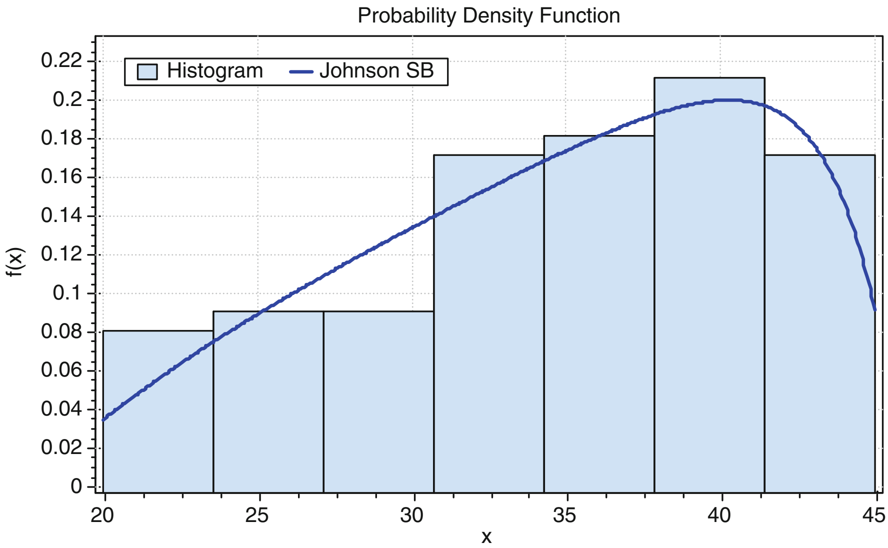

Fig. 8.4 Sampled histogram wash data fitted to a probability distribution

is a histogram of the results of the wash times and Fig. 8.4 is a histogram of the styling times. The recorded drying times had only small variations (between 20 and 26 min). By fitting the recorded data for both styling and washing to respective probability density functions (pdf) using *Easyfit* (Version 5.3) (Software) (2010), it is clear that the wash times and style times are not exponentially distributed. Therefore, the processing/service time is best simulated using a general distribution. The washing and styling of individuals are modeled as servers with queues developing at the washing and styling stations. Analysis of wash times (Figs. 8.3 and 8.4) indicates that the distribution of service times for this step is best described by the Johnson probability distribution function. A similar analysis of style times (Figs. 8.5 and 8.6) indicates that the distribution of service times for this

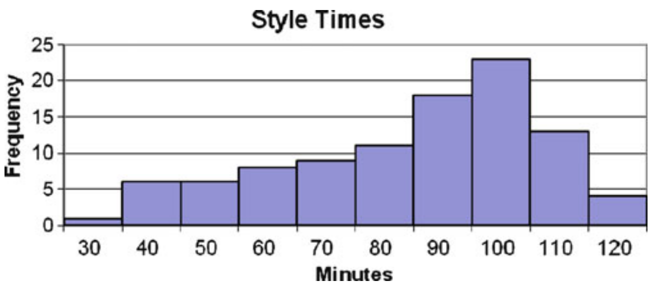

Fig. 8.5 Histogram of sampled styling times

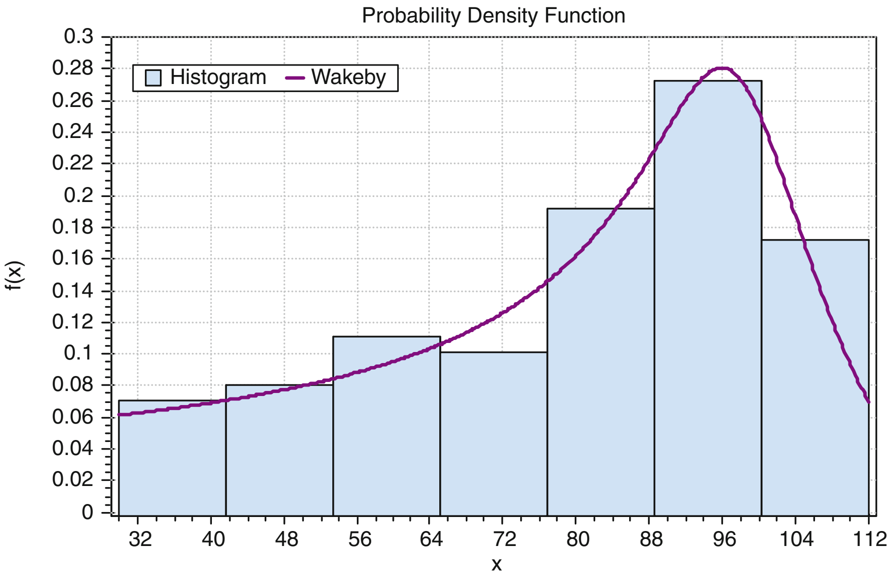

Fig. 8.6 Wakeby probability density function of sampled data

step is best described by the Wakeby probability distribution function. Chi-square goodness-of-fit tests (details provided in Appendix B) indicate strong support for these approximations.

The *Johnson SB* [13] Probability Density Function is defined by:

$$f(x) = \frac{\delta}{\lambda\sqrt{2\pi}z(1-Z)}\exp\left(-\frac{1}{2}\left(\gamma+\delta\ln\left(\frac{z}{1-z}\right)\right)^2\right) \tag{8.5}$$

where the following parameters apply:

$$z \equiv \frac{x - \xi}{\lambda}$$

γ – shape parameter
δ – shape parameter ($\delta > 0$)
λ – scale parameter ($\lambda > 0$)
ξ – location parameter

2.4 Domain

$$\xi \leq x \leq \xi + \lambda$$

For this distribution: $\gamma = -0.493$, $\delta = 0.860$, $\lambda = 29.97$, $\xi = 16.298$.

The Wakeby distribution defined by the *quantile function* is as follows:

$$x(F) = \xi + \frac{\alpha}{\beta}\left(1 - (1 - F)^{\beta}\right) - \frac{\gamma}{\delta}\left(1 - (1 - F)^{-\delta}\right) \tag{8.6}$$

where (8.6) is the *quantile function* definition of the Wakeby distribution.

A *quantile function* is defined by $F^{-1}(p) = \min\{x \in \mathbb{R} : F(x) \geq p\}, p \in (0, 1)$.

Wakeby parameters: $\alpha = 183.59$, $\beta = 3.310$, $\gamma = 13.011$, $\delta = -0.291$, $\xi = 27.485$.

(All distribution parameters are derived from the Easyfit software tool)

2.5 Simulation Results

Table 8.4 is one iteration of a simulated day of salon operations for one stylist and assistant, where clients are stacked according to the scheme of three customers per hour. Clients arrive according to appointment and are serviced in a FIFO queuing discipline. Client services are completed once the drying stage is complete. Customer 7 completes the services 675 min after opening of the salon. This simulation is run for 1,000 iterations corresponding to 1,000 days (approximately 2.7 years). Tables 8.5 and 8.6 are the corresponding service times, wait times, and description of services received for each of the customers during the simulated day. Total processing time is the time for completion of stages 1 and 3 and does not include the time waiting to begin any of the three stages.

Table 8.4 Example D/G/2 stylist simulation run (stacking three clients every hour)

Client	Arrival (min)	Finish wash (min)	Finish style (min)	Dry (min)
1	0	42	100	122
2	0	76	204	226
3	0	114	243	265
4	60	211	333	355
5	60	364	472	494
6	60	468	558	580
7	120	620	653	675
8	120	779	874	896

Table 8.5 The corresponding styling and wash times for the above simulation run

Client	Wash time (min)	Style time (min)
1	42	56
2	34	104
3	38	39
4	37	90
5	33	108
6	44	86
7	32	33
8	39	95

Table 8.6 Processing and wait times

Total processing (min)	Wash wait (min)	Style wait (min)	Service provided
120			Braids
160	42	24	Braids
99	76	90	Perm/press
149	54	32	Perm/press
163	151	0	Hair heave
152	304	4	Hair weave
87	348	0	Short texturized

2.6 Processing and Clients Served

After 1,000 *Monte Carlo* simulations with service times allowed to vary according to the two probability distributions for styling and washing, it was determined that the maximum number of clients that can be processed is 9, given that clients are stacked at 3 clients every 70 min and 12 if they are stacked and the maximum allowable processing time is 90 min for each client with the salon open for 13 h (Tables 8.7 and 8.8).

Table 8.7 Stacking results for simulation

Stacking scheme	Max clients processed	Max processing time/customer (min)	Average wait/ customer (min)
2 customers/70 min	7	70	116
2 customers/90 min	6	90	82
2 customers/120 min	5	120	33
2 customers/180 min	5	180	35
2 customers/240 min	4	240	45
3 customers/70 min	9	70	151
3 customers/90 min	8	90	150
3 customers/120 min	7	120	133
3 customers/180 min	7	180	120
3 customers/240 min	5	240	80
3 customers/20 min	12	90	208

Table 8.8 Results for not stacking

No stacking	Max clients processed	Max processing time/customer (min)	Average wait/ customer (min)
1 customer/35 min	7	70	80
1 customer/45 min	6	90	41
1 customer/60 min	5	120	5
1 customer/90 min	5	180	6
1 customers/120 min	4	240	27

2.7 *Stylist Revenue Model*

We have previously focused on process efficiency as the primary measure of salon success. However, since salons are for-profit enterprises, it is reasonable to assume that profits are at least as important to owners as throughput. Therefore, in this section we examine the impacts of our simulation analysis on stylist revenue. We assume in the analysis which follows that a salon is open 5 days per week, or 260 days per year (Table 8.9).

2.7.1 Net Revenues, Accounting for Assistants

The revenues listed in Tables 8.9 and 8.10 must be reduced to account for having one or two assistants available who would work for \$10 to \$12/h for 12 operating hours.

Assistants would cost around \$34,320 per year each at \$11 per hour. Results of the national survey indicate that the normal practice is to have one assistant per stylist (Table 8.11). Although not presented in this analysis, similar results can be examined for two assistants.

Table 8.9 Revenue range without stacking

Max clients/day	Max processing time/customer (min)	Clients/year	Low revenue/year	High revenue/year
7	70	1,820	$118,300	$163,800
6	90	1,560	$140,400	$187,200
5	120	1,300	$169,000	$273,000
5	180	1,300	$169,000	$585,000[a]
4	240	1,040	$156,000	$312,000

[a]Revenue for higher cost services scaled to percentage of customers requesting services at the highest cost spectrum based on surveyed data (e.g., according to surveyed data 25–30% of all customers who request hair extensions request natural hair weaves costing from $700 to $1,500)

Table 8.10 Revenue range when stacking is used

Stacking scheme	Max clients/day	Max processing time/customer (min)	Clients/year	Low revenue/year	High revenue/year
2 customers/70 min	7	70	1,820	$118,300	$163,800
2 customers/90 min	6	90	1,560	$140,400	$187,200
2 customers/120 min	5	120	1,300	$169,000	$273,000
2 customers/180 min	5	180	1,300	$169,000	$585,000[a]
2 customers/240 min	4	240	1,040	$156,000	$312,000
3 customers/70 min	9	70	2,340	$152,100	$210,600
3 customers/90 min	8	90	2,080	$187,200	$249,600
3 customers/120 min	7	120	1,820	$236,600	$382,200
3 customers/180 min	7	180	1,820	$236,600	$682,500[a]
3 customers/240 min	5	240	1,300	$195,000	$390,000
3 customers/20 min	12	90	3,120	$280,800	$374,400

[a]Revenue for higher cost services scaled to percentage of customers requesting services at the highest cost spectrum based on surveyed data (e.g., according to surveyed data 25–30% of all customers who request hair extensions request natural hair weaves costing from $700 to $1,500)

Table 8.11 Stacked revenues/year minus cost of an assistant

Service cost range (processing time)	Low-assistant	High-assistant
$65–$90 (70 min)	$83,980	$129,480
$90–$120 (90 min)	$106,080	$152,880
$130–$210 (120 min)	$134,680	$238,680
$130–$1,500 (180 min)[a]	$134,680	$550,680
$150–$300 (240 min)	$121,680	$277,680
$65–$90 (70 min)	$117,780	$176,280
$90–$120 (90 min)	$152,880	$215,280
$130–$210 (120 min)	$202,280	$347,880
$130–$1,500 (180 min)[a]	$202,280	$648,180
$150–$300 (240 min)	$160,680	$355,680
$90–$120 (90 min)	$246,480	$340,080

[a]Revenue for higher cost services scaled to percentage of customers requesting services at the highest cost spectrum (e.g., natural hair weaves)

2.8 Discussion

It has been shown that stylists can continue high profit margins without stacking and subsequently reduce client wait time. In fact, analysis indicates that when the stacking scheme is two customers per appointment, there is no difference in potential revenue between stacking and strictly scheduling one client per appointment period (no stacking). Analysis also makes clear that when stacking is removed and service to customers is partitioned according to processing time, long waits are essentially removed and greater revenue can be achieved. The $D/G/2$ simulation results for stacking customers at three customers per appointment in Sect. 2.3 is consistent with many of the surveyed salons in terms of the average wait times exceeding 2 h and potential revenues for a stylist exceeding \$100,000 per year. Simulation throughput data of nine clients for the three customer per appointment period is consistent with the surveyed average number of clients per day for a given stylist at 9.4. The potential revenue associated with the three customer per appointment stacking scheme clearly showcases why this method is so attractive to many stylists and salons. As the analysis indicates, the problem with stacking three or more customers per appointment is the exceptional processing and wait times for customers.

Analysis and observation of specific salon service times allowed for the determination that washing and styling times have different probability distributions. Much of the differences have to do with client preference for many of the more time intensive hair styles. From the observed salon-sampled styling times, the highest frequency of styling times is between 80 and 110 min, which correspond to styles such as micro-braids, hair weaves, and some of the more elaborate perms. Although both discrete processes have different distributions, there is a common characteristic of the data being skewed to the right which indicates that despite the Wakeby and Johnson distributions being the respective best fits, other right skewed curves may also well approximate the data.

The model presented in this analysis is an initial effort to model a complex operational process that will require more robust analytical methods. In particular, we have not attempted a more realistic representation of salon operations using multiple servers. Nevertheless, the results in this chapter demonstrate how operations methods can be used to improve stylist strategies for efficiencies and revenue maximization.

A recommended strategy to minimize customer waits times would be for stylists to schedule the longer services (180 min or more of expected processing time) only 1 or 2 days per week. By partitioning services, foregoing stacking and setting up a maximum processing time for the days that the longer services are not scheduled, a higher volume of these customers can be served thereby increasing potential revenue. Services such as micro-braids, natural hair weaves, and sisterlocks are promising candidates for these operations processes. During high volume periods, salons should consider making sure they have a sufficient number of designated assistants on staff to keep the process moving quickly. These individuals could be cosmetology students or salon apprentices or college students working for $10 to $12 per hour.

Clients may also consider the time value of selecting styles that require far less processing time and maintenance. Styles such as short texturized naturals require 45–90 min and have costs that are a fraction of those of other natural styles such as micro-braids, natural hair weaves, or sisterlocks. Use of these styles could result in significant savings of time and money for salon clients. If clients decided to request these styles in large numbers, it would virtually reduce the waits at salons by magnitudes and save women millions in precious resources and allow women to regain precious time for work, family, and recreational activities. Given that none of the military service academies, officer candidate schools, or basic training facilities throughout the USA currently have stylists who are African-American hair care specialists, the opportunity to be the first stylist to establish a business on the facility presents a unique business opportunity. These businesses could potentially be mobile, meaning that a stylist could have a designated "service" day that they travel to the military facility and provide services to clients and follow an operations model similar to the non-stacking case presented in Sect. 2.3 to allow for efficient processing of clients. Additionally, each service component should research the best techniques for handling processed and natural African-American hair styles and develop instructions for new recruits that cover how to protect hair against water damage while maintaining a sharp military appearance. Whether a recent high school graduate attending basic training or reporting to one of the service academies, a college student in an R.O.T.C program, or a college graduate about to attend Officer Candidate School, these instructions should discuss options for hair maintenance that conform to service regulations. Issues associated with African-American females in uniform problem can also be aided by sending government employed civilian barbers and mainstream stylists to receive specialized training in the particulars of African-American hair care.

3 Conclusions and Next Steps

This analysis has bounded the range of expected processing times for a variety of services offered to African-American salon clients, established a baseline for stochastically modeling styling services in salons that service black clients, looked at strategies to maximize throughput, and presented an analysis of potential revenues for stylists. Additionally, recommendations are given to improve salon operations as well as strategies for black females to regain valuable time and resources by selecting styles that do not require the lengthy processing times. A potential business model is recommended that would allow for stylists to help provide salon services for black female military personnel.

A primary conclusion from this analysis is that stylists can maintain high revenues streams while eliminating long client waits by not stacking, deciding on each given operating day the maximum amount of time they are willing to spend on one client, restricting the longer processing time services (180 min or more) to 1 or 2 days each week and employing the services of an assistant. Another key discovery is that the distribution of styling times for the majority of the most popular African-American female hair styles can be modeled by the Wakeby probability distribution. Surveyed salon data also back the conclusion that given the extreme variability in processing time between services requested, the maximum number of clients that can be processed in a day seems to be restricted to be between 6 and 13, which is consistent with the surveyed average number of clients per day of 9.4 which includes all stacking schemes and busy periods.

Additional future research could expand upon the analysis presented in this model and produce an explicit algebraic relationship between processing time, waiting times, and number of customers that can be processed during business hours. It would also be useful to explore differences in salons throughout the country in terms of processing time differences based on specific services offered to customers. As an example, are salons that do not offer sisterlocks, natural hair weaves, or micro-braids more efficient in terms of processing time for clients and do stylists of such salons have the same potential for revenues? Are there new probability distributions that could be developed that are specific to processing times associated with specific hair styles? Another point of research would be to develop analytical queueing results for the salon in this analysis to help guide the development of general policies and guidelines that could be applied to a variety of salons. Future work should also consider building an operational model of salon services offered to African-American military personnel on bases and on deployment.

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Appendix A

Stylist Survey Instrument and Response Data

Survey question	Response summary
How many clients do you serve per week?	35–68 (5 days/week)
Do clients balk (refuse to wait) or renege (stop waiting for service)?	28 No, 2 Yes
How many stylists are in your salon?	1 (10) ,2 (8), 4 (1), 3 (1), 5 (10)
How long is your lunch break?	30 min (10), 60 min (20)
How long is your salon open?	8–12 h/day
What are the most requested styles?	Braids (12), weaves (6), extensions (2), locks (10)
What times are your busiest times?	Weekends, holidays, spring (weddings, dances, graduations)
Do you stack clients?	27 Yes, 3 No
Do you serve a large number of female military clientele?	10 Yes, 20 No
If yes, what styles are requested most by female military clientele?	Locks and braids due to low maintenance
What is your average wait time?	20–180 min
Is your salon located in a predominately minority neighborhood?	26 Yes, 4 No
Do you have any procedures/SOP unique to your salon?	(4) salons only do weaves, braids, or locks 1 day/week
Do you accept walk-ins?	25 No, 5 Yes
What is your annual income range?	$50 K to $160 K (average is $64 K)
Do you use an assistant?	12 Yes, 18 No
How many clients do you serve in 1 day during busy season?	17 (1),14 (2),13 (1),12 (3) ,11 (3),10 (2), 9 (5), 8 (4),7 (4),6 (2),5 (3)

Returned survey no.	Clients/week	Operating hours	Avg. time to finish clients (min)
1	35	8	90
2	50	12	120
3	68	12	120
4	25	12	90
5	45	12	180
6	61	12	180
7	28	12	180
8	40	12	180
9	55	12	240
10	31	12	240
11	43	12	180
12	64	13	240
13	27	12	240
14	34	12	180
15	57	13	180
16	62	12	60
17	29	12	60
18	45	12	65
19	57	12	90
20	65	13	60
21	23	13	75
22	60	12	180
23	33	10	180
24	41	12	180
25	65	12	90
26	46	12	90
27	39	12	120
28	28	13	45
29	52	12	120
30	38	12	45

Appendix B

Statistical References and Methods

Distribution Goodness-of-Fit Tests

The chi-square test was used to evaluate the goodness of fit for the distributions used.

The chi-square test is defined for the hypothesis:

H_o: The wash data follow the *Johnson SB* distribution

H_a: The sampled wash data do not follow the *Johnson SB* distribution

Test statistic: $\chi^2 = \sum_{n=1}^{N} \frac{[O_n - E(O_n)]^2}{E(O_n)} = 4.19$

where

$E(O_n) = \text{SAMPLE\_SIZE} \times (\text{F(U)} - \text{F(L)})$

F(U) = Cumulative Distribution Function evaluated at upper limit U

F(L) = Cumulative Distribution Function evaluated at lower limit L

O_n = observed frequency (from histogram)

$E(O_n)$ = expected frequency

N = number of frequency bins in histogram

Results: assuming 6 degrees of freedom.

α	0.2	0.1	0.05	0.02	0.01
χ_α^2 (critical value)	8.5581	10.645	12.592	15.033	16.812
If $\chi_\alpha^2 < \chi^2$ Reject H_o	No	No	No	No	No

Thus we accept the null hypothesis (H_o).

For the Wakeby distribution, the test results yielded the following for

$$\chi^2 = \sum_{n=1}^{N} \frac{[O_n - E(O_n)]^2}{E(O_n)} = 2.23$$

α	0.2	0.1	0.05	0.02	0.01
χ_α^2 (critical value)	8.5581	10.645	12.592	15.033	16.812
If $\chi_\alpha^2 < \chi^2$ Reject H_o	No	No	No	No	No

Thus we accept the null hypothesis (H_o).

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Chapter 9
Street Gangs: A Modeling Approach to Evaluating "At-Risk" Youth and Communities*

B. Jacob Loeffelholz, Richard F. Deckro, and Shane A. Knighton

1 Introduction

Curbing street gangs is an important issue due to the influence they have on the overall crime rate. Street gang influence has expanded from a major city problem to contaminate surrounding areas as well as the rural communities (National Alliance of Gangs Investigators Associations, 2005, p. 14). The crimes committed by these groups can range from drug trafficking, money laundering, and violent crimes, to fraud and intimidation. Factors enabling street gang recruitment are present in many communities (Cairns & Cairns, 1991; Craig, Vitaro, Gagnon, & Tremblay, 2002; Fagan, 1989; Hagedorn, 2005; Klein, 2005; Sanchez-Jankowski, 2003).

This study examines the underlying factors associated with youth gang membership. We do not advocate the use of unethical and invasive measures to collect individual information to apply the methods described in this study. Rather, this chapter is intended to provide multiple discussion points on different focus areas when considering at-risk children and street gangs. Furthermore, much of the required information can be gathered from open census data or public knowledge on individuals. Any personal data required by appropriate users of the proposed modeling approach must, of course, confirm to local, state, and national standards and regulations. While any analytic tool might be abused, our goal in this study is to encourage the use of quantitative techniques to assist community decision making regarding at-risk children and street gangs.

Two different yet similar approaches are used to assess potential at-risk youth. Each approach is an established technique to study decision science problems but

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have not generally been applied to aid decision making concerning street gangs and at-risk youth. The first method, known as the Ishikawa diagram, uses an established quality framework to help identify and group common factors associated with at-risk youth. These factors are determined through scholarly research on youth and street gangs. The second approach, value focused thinking (VFT), uses a subject matter expert (SME) in the field of street gangs and the literature to identify factors leading to potentially at-risk children. These two approaches contribute to community modeling and decision making by providing insight into pinpointing areas or youths for possible additional attention. Through the use of a systematic process, a degree of quantification can be provided to aid in establishing gang prevention programs or policy changes, which are crucial to curbing the initiation of youth in street gangs.

For the purpose of this study, a street gang is defined as "individual members, gang cliques, or entire gang organizations that traffic drugs; commit shootings, assaults, robbery, extortion, and other felonies; and terrorize neighborhoods" (Johnson, Webster, & Connors, 1995, p. 2).

A two-staged methodological approach was used in this study. To begin the study, a total quality control tool known as the Ishikawa (fishbone) diagram was used. The Ishikawa diagram is a tool to review factors that might affect some problem area (Herrmann, 2001). This diagram was constructed through an extensive literature review. As a pictorial summary of key elements affecting recruitment, it serves as a necessary summary and beneficial tool when examining street gangs and at-risk children. The Ishikawa diagram captures the factors or indicators that the literature suggests might contribute to youth gang membership. This diagram was reviewed with a detective currently investigating street gangs and is used to identify and organize inputs into a model developed by using VFT. The Ishikawa diagram aids the analyst in providing a visual summary of factors and provides a common point of discussion to aid in facilitating discussions with the SMEs and community stakeholders in developing of further analyses.

The Ishikawa diagram provides a good summary of contributing factors to examining at-risk youth. Since policy change or program development may require quantitative, prescriptive methods, Ishikawa diagrams provide a starting point for VFT. The Ishikawa diagram establishes a well-organized and researched foundation for discussion with a SME on the true factors leading to at-risk youth joining street gangs. In addition, it provides a visual summary of key factors for those new to the issue or in community discourse.

VFT (Keeney, 1996; Kirkwood, 1997) was used to develop a decision analysis model. Specifically, the concept of the value hierarchy from VFT is used in this study. The decision maker (DM) for this study is a current detective responsible for investigating street gangs in an Ohio county and will serve as a SME due to his knowledge and expertise in the area of street gangs and at-risk children. Different values were solicited from the DM to develop a complete hierarchy capable of identifying potentially at-risk children likely to join a street gang. A similar hierarchy was also developed to identify potentially at-risk communities within the same Ohio county. The first hierarchy is intended to assist child counseling professionals such as psychologists, school officials, and parents, whereas the second hierarchy may support policy analysis and program design.

The use of VFT as one approach to identifying at-risk children or communities may support current or proposed gang prevention efforts. While the research into street gangs often has focused on where crimes will occur, which groups commit the crimes, and trouble areas for gang related violence, this study focuses on aiding a community on where resources might be focused to inhibit recruitment into a gang. Curbing the influence of street gangs is a large problem; the use of VFT and Ishikawa diagrams in this chapter address only a small portion of this problem. Understanding the factors related to youth being at risk allows adults, such as parents, teachers, and administrators, to help identify a potentially at-risk child and take necessary steps to reduce possible gang influence in their lives. This chapter does not suggest policy to target specific youth, nor to take unethical means of identifying children, but rather to provide insight into the problem of at-risk children and to aid in its quantification. Knowledge about which children or communities are at risk also allows a tighter focus of gang prevention efforts and possibly greater reductions in the number of children joining street gangs and/or the impact street gangs have on the county. The hierarchy is tractable, traceable, and easy to implement as a useful tool in the public sector areas. In addition, if a decision model does not contain alternatives that adequately reflect the values of the decision maker, VFT can help develop better alternatives.

The remainder of the chapter is organized as follows. Section 2 provides some background on street gangs, Ishikawa diagrams, and VFT. Section 3 describes development of the Ishikawa diagram. It also describes the hierarchy created and discusses the values, evaluation measures, value functions, weights, and scoring of different alternatives (children or communities). Section 4 explains the results of scoring each child/communities and gives an example of its uses. Section 5 concludes with recommendations and suggestions for future studies involved in similar areas.

2 Supporting Literature Review

2.1 Street Gangs

Gangs have been prevalent across many societies and time periods: they "no longer start and stop with local conditions but must also be rooted in the global context" (Hagedorn, 2005, p. 153). Types of gangs vary widely throughout the USA, as well as the world. Gangs can form based on location, religious views, blood "type," race, presence in an institution, and an array of other factors. This study focuses solely on the formation of street gangs. Many definitions for a street gang exist; the one used in this study is "individual members, gang cliques, or entire gang organizations that traffic drugs; commit shootings, assaults, robbery, extortion, and other felonies; and terrorize neighborhoods" (Johnson et al., 1995, p. 2).

Gangs are a social problem; research supports the finding that gang members commit more crimes than nonmembers (Gordon et al., 2004; Thornberry, Krohn, Lizotte, Smith, & Tobin, 2003; Tita & Ridgeway, 2007). This propensity for violence causes serious problems for not only the members involved but also the surrounding communities. These studies also indicate that if a child is more likely to commit crimes, they are more likely to join a gang.

A longitudinal study was conducted to determine why individuals joined a gang (Thornberry et al., 2003). This study examined pre-gang characteristics and behaviors to individuals who either joined a gang or did not join a gang between the ages 13 and 22. An extensive background of characteristics is examined in the study by Thornberry et al. This chapter takes a similar approach of examining potential at-risk youth without the use of a longitudinal study; rather it uses the expertise of gang experts and previous research.

Many studies suggest behavior plays a large role in why youth join different gangs (Gordon et al., 2004; Thornberry, Huizinga, & Loeber, 2004). Decker and Van Winkle (1996) research finds that economic and demographic variables were the most important factors when discussing youth and gang membership. Therefore, a number of descriptive, family, and economic/social factors play a role in an individual's desire or reasoning to join a street gang. While individuals often have specific personal reasons for joining a gang, overall, as a group, similar traits exist. The Ishikawa diagram developed in the next section organizes scholarly research regarding gang membership across diverse individuals.

2.2 *Ishikawa Diagrams*

The Ishikawa diagram, also known as a "fishbone diagram," "cause-and-effect diagram," or a "characteristic diagram," was developed in 1943 by Professor Kaoru Ishikawa (Herrmann, 2001; Ryan, 2000). Ishikawa diagrams have their origins in problems of quality control but have been used in many other areas, such as business, healthcare, psychology, and criminal profiling (Barry, Murcko, & Brubaker, 2002; Kleen, 2001; Phipps, 1999). Since Ishikawa diagrams appropriately review all factors that might affect a problem (Herrmann, 2001), many problem areas can be approached using an Ishikawa diagram (Brussee, 2004).

Ishikawa diagrams provide a number of beneficial insights to a problem analysis. It is a tool that encourages a great deal of brainstorming to be done on one particular problem, allowing every person involved in the process to voice their opinion on what cause might exist in the system (Herrmann, 2001; Streibel, 2003). The bones (or branches) can be added onto later allowing clearer conclusions to be drawn as the process evolves (Ryan, 2000). The Ishikawa diagram allows all the relevant information to be gathered and organized in a particular fashion that is easy to understand and implement (Barry et al., 2002).

It is important to note that Ishikawa diagrams remain useful even if data are lacking. However, given appropriate data, statistical and graphical techniques such as histograms, Pareto charts, scatter plots, and control charts may supplement Ishikawa diagrams (Hubbard, 1999; Ryan, 2000). Ishikawa diagrams can provide deeper understanding of the causes of various factors, or the impact these factors may have on an entire problem. In addition, Ishikawa diagrams can serve as a guide in determining data requirements of the problem and how that data might be used for future research (Herrmann, 2001).

In this application of identifying potentially at-risk youth, the Ishikawa diagram provides a basis to organize key factors in a visual display and to facilitate discussion in the development of the VFT model by providing a common, mutually agreed upon frame of reference. In addition, in its own right, the Ishikawa diagram visually summarizes key attributes for individuals new to the area or in discussing issues with community members and leaders. Ishikawa diagrams are also flexible; new factors sub-factors can be added at any time.

2.3 Value Focused Thinking

Ralph Keeney, the developer of value-focused thinking (VFT), has stated that VFT "is a way to channel a critical resource- hard thinking- to lead to better decisions" (Keeney, 1996, pp. 537–538). Some decisions can be simple to make, but the more complex a decision context becomes, the more difficult the decisions may be to make. VFT allows the decision maker (DM) to focus on the values of the decision rather than the different alternatives presented to the DM. VFT also provides a framework or knowledge base to develop or design new alternatives (Kirkwood, 1997).

Value hierarchies should be complete, non-redundant, independent, operational, and small in size. (Kirkwood, 1997, pp. 16–19). To assure that all critical values and sub-values are included (complete), but not repeated so no double counting occurs (non-redundant) and concepts are independent, care must be taken in developing the value hierarchy. Particular attention must be paid to the specific specifications of the single-dimension value functions to assure these characteristics. In addition, while complete, the hierarchy should only include necessary values and measures, maintaining a concise model that can be used operationally. Care must be taken in model development to assure these factors. VFT can look deceptively easy, but a trained analyst and facilitator are required in developing the model to assure that the decision maker's values are correctly modeled.

VFT is typically presented in contrast to alternative focused thinking, a method by which a DM makes a decision by choosing a most-preferred alternative without necessarily considering the values involved with the decision (Keeney, 1996, p. 537). The values involved in decisions are what should be important. These values consist of what is important, of concern, or what is to be achieved through the decision (Leon, 1999, p. 214). Advantages are gained when thinking about the different values that go into a decision that could be missed when performing only alternative focused thinking (Keeney, 1996).

The concept of value hierarchies from VFT is used in this study. Value hierarchies provide many different uses in decision making. They guide the DM in the process of what information to collect. It aids in avoiding the trap of collecting too much information or information that is not important to the current decision. This also helps facilitate communication among the decision makers involved in a decision. Good alternatives can be designed using values (Kirkwood, 1997, p. 23). Sometimes alternatives are not explicitly identified, but collecting information on a value hierarchy helps identify "value gaps" aiding in the design of new alternatives. Finally, value hierarchies are suitable for evaluating alternatives (Kirkwood, 1997, p. 23). Value hierarchies can distinguish desirable alternatives from the undesirable alternatives simply by inspection. Quantitative methods are also useful in determining the best alternative for the decision (Kirkwood, 1997). VFT is especially unique in that it is typically used to make a decision among alternatives. However, in this application, potentially at-risk children are identified as the "decisions" through the established mathematical techniques. The VFT approach naturally applies to this research because it provides a value score by which individuals or regions can be distinguished and classified. This value score provides mathematical justification in ranking these "decision alternatives," which is important in this chapter.

VFT and Ishikawa diagrams can provide value to policy analysis in the area of street gangs. Ishikawa diagrams demonstrate the overview of extensive vetted research in the area of at-risk youth and street gangs, while VFT provides a mathematical approach guided by the expertise of a SME in the area of street gangs. Separately, each approach provides a specific contribution to the area of street gangs using knowledge on established operations research techniques in an attempt to determine methods of diminishing the effect of street gangs and their recruitment.

3 Method

3.1 Ishikawa Diagram

Based on the literature review and discussions with SMEs, the principle underlying causes for an increased propensity of an individual youth to join a street gang in this study are grouped as Descriptive traits, Family life, Social influence, Economic influence, and Protection and Security.

Descriptive traits include the age of an individual. Ages at which gang affiliation occurs may vary widely (Sanchez-Jankowski, 1991), but a common at-risk range from the literature is between 5 and 18 with a primary age group of 10–14 showing the greatest propensity for joining a street gang (Craig et al., 2002). Members of street gangs are predominantly male; estimates of female membership range between 10% and 38%, although female membership appears to be increasing (Fagan, 1990; Klein, 1971; Maxson & Whitlock, 2002; Miller, 2001; Moore, 1991). Yet another descriptive trait examines the ethnic background of the individual. Trends exist where specific ethnic groups may join specific gangs. For example, Hispanic individuals account for a greater percentage of gang membership within America, compared to other ethnic backgrounds (Delaney, 2006). Of course, being a member of a specific ethnic group does not mean an individual will join a gang. Family life consists of the family structure in which the child is currently involved. No current research has found a direct correlation with experiencing a positive upbringing due to being in a nuclear family; however, much of the research agrees that a broken home is a warning indicator for joining a street gang (Delaney, 2006). A change in a family structure, such as death, divorce, incarceration, or abandonment, can all have negative effects on a child's upbringing, cause stress, and cause the child to seek a new "family" within a street gang (Delaney, 2006; Trojanowicz, Merry, & Schram, 2001; Yoder, Whitbeck, & Hoyt, 2003). Drug use within the household has been associated with increased violence and aggression within the child (Curran & Renzetti, 1994) as well as a parent's inability to raise the child in a healthy environment (Dishion, Nelson, & Yasui, 2005). Abuse (physical, mental, or sexual) can push children away from the households to seek protection and acceptance in a perceived protective environment within the protection of a street gang (Delaney, 2006; Yoder et al., 2003). Finally, another family-related factor is the influence that current or past gang-affiliated members have on a child's decision to join the same gang to seek acceptance (Zimmerman et al., 2004).

Social influence addresses the desire to have access to drugs (Sanchez-Jankowski, 2003), and the decision whether to use or sell drugs (Fagan, 1989; Trojanowicz et al., 2001). Individuals who find they commit either crimes against people or crimes against property (Criminal Justice Research Center, 2001) tend to find their ways into street gangs as well (Nafekh, 2002). Social influence also ties back to the hierarchy of Maslow (1951), and his explanation that feelings of acceptance are important to every human being, among others. Peer pressure causes children to follow aggressive friends and join street gangs (Cairns & Cairns, 1991; Craig et al., 2002; Galinsky & Salmond, 2002; Moore & Hagedorn, 2001; Zimmerman et al., 2004).

Economic influence addresses the personal income status of the individual. Fast and easy money, far beyond what an individual might reasonably expect to make in traditional jobs, can be an extraordinary incentive to gang membership for individuals working minimum-wage jobs (Portes & Rumbaut, 2001). The income of the household also has an effect on the individual's need for easy money (Sanchez-Jankowski, 2003). Finally, an individual's perceived economic opportunity has a great effect if an individual feels achievement beyond their parents is unattainable, causing the individual to seek street gangs to earn more than a subsistence living (Sanchez-Jankowski, 2003).

Protection and security denotes another collection of risk factors for gang membership. Protection can be necessary in an array of different environments such as a school, in a neighborhood, or during incarceration. The large presence of street gangs in an area can have a tremendous pull on individuals to join a street gang (Delaney, 2006; Hughes & Short, 2006; Johnstone, 1983).

We have assembled the five main classes of indicators described above into an Ishikawa diagram (Fig. 9.1). This structure gives a quick summary of the indicators

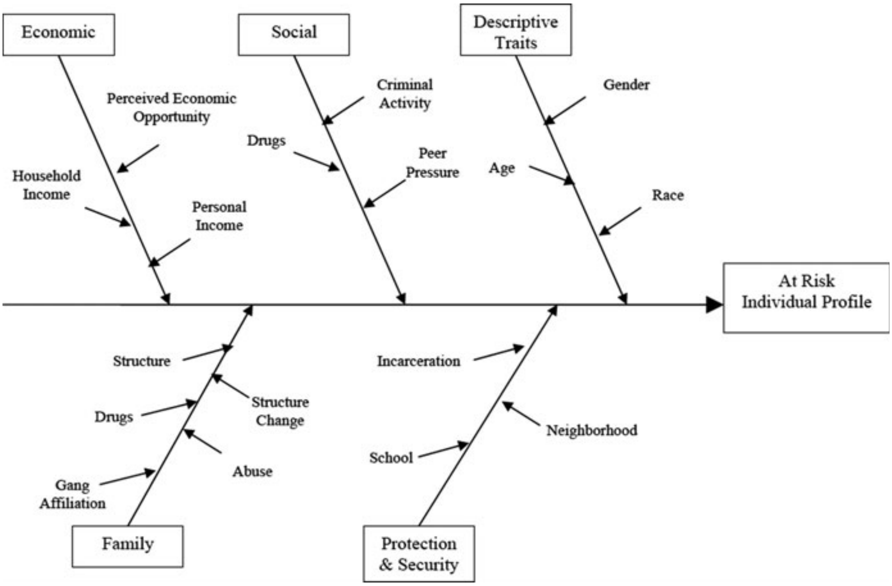


Fig. 9.1 At-risk individual profile

that contribute to a person's potential risk proneness to gang membership. This profile can be used as a visual aid for further research in the areas of at-risk youth and street gangs. Specifically, in this study it was used in association with VFT to assist in the decision modeling. Developing the Ishikawa diagram before performing VFT helps to ensure that all factors of at-risk youth are considered. It also provides a useable framework to introduce new counselors, teachers, officers, analysts, or parents to the effectors of youth at risk of joining a street gang. The Ishikawa diagram also provides a visual overview of key factors influencing at-risk youth to aid in analysis and discussion within a community. Finally, it helps to organize the principal concepts to assist in building a VFT hierarchy.

3.2 *Individual VFT Hierarchy*

To create a VFT-based hierarchy to identify a potentially at-risk child likely to join a street gang, we chose as a decision maker (DM) a detective working for an Ohio county who also served as a SME. Another detective working on street gangs in Florida was chosen as an additional SME. The DM is an expert in the field of street gangs and was very knowledgeable on why children join gangs and why new street gangs form. All VFT solicitation was done before displaying the Ishikawa diagram to the DM. After completing the process, the DM was shown the Ishikawa diagram to allow for adjustments to the value hierarchy; however, no changes were required post-discussion. While the development of the Ishikawa diagram provided a framework for the analyst to organize key points regarding at-risk youth and facilitated discussion, ultimately, the values in a value model should be those of the DM, not the analysts. In addition, it is recommended that one uses the DM's terms and phrasing where possible to aid their "buy in" of the model. Values, goals, objectives, and means need to be carefully distinguished in the value model development (Kirkwood, 1997, pp. 11–12). Tenets of VFT were followed to assure the model's development.

The DM proposed four main areas as important to identifying a potentially at-risk child likely to join a street gang. The main areas expressed by the DM were similar to those outlined in the Ishikawa diagram, thus providing support as to the accuracy of the Ishikawa diagram. These areas are family stability, survival/security, acceptance, and lifestyle. These four top tier values are then extended into sub-tiers to conform to the completeness property of value hierarchies (Kirkwood, 1997, p. 16).

Family stability is subdivided into abuse and family structure. Abuse deals with the presence of any type of abuse (verbal, physical, mental, or sexual) that might be in the child's history and committed by a member of the household. Family structure is further divided into current structure and change in structure. Current structure examines the family type in which the child is currently living. Change in structure observes any loss of parents or guardians within the previous year.

Survival/security has only one subgroup, gang violence. Gang violence examines the number of gangs that are present in the child's neighborhood and the magnitude of their presence in terms of crime rates.

Acceptance is subdivided into family gang history and peer pressure. Family gang history deals with any past or present affiliation a current family member (first cousin or closer) might have with a street gang. Peer pressure is further subdivided into current friends involved and need for friends. Current friends involved considers if the child has any friends currently involved with a street gang. Need for friends investigates whether the child has feelings of being an outcast or outsider in his or her social surrounding.

Lifestyle is subdivided into financial stability, addiction, and criminal activity. Financial stability examines the current income level of the household. Addiction looks at any type of drug or alcohol addiction that the child may have (either as a user or seller). Criminal activity represents an individual's violent criminal offending, such as assaults, burglary, murder, grand theft, and other offenses.

These four values and their subgroups make up the value hierarchy for the gang model. The five desired properties of a value hierarchy, as discussed in Kirkwood (1997, pp. 16–17), are also achieved by this hierarchy. Of course, different communities might yield different value hierarchies. Figure 9.2 displays the value hierarchy for the gang model in its entirety.

Following the construction of the hierarchy, each value was decomposed to the lowest level fundamental objective that could be quantified by a single-dimensional evaluation measure. The values are broken down until such a measure can be defined. Working with the DM, an appropriate evaluation measure for each lowest tier value was developed. To be operational in aiding a potentially at-risk youth, these evaluation measures were developed to be items in which detectives or school

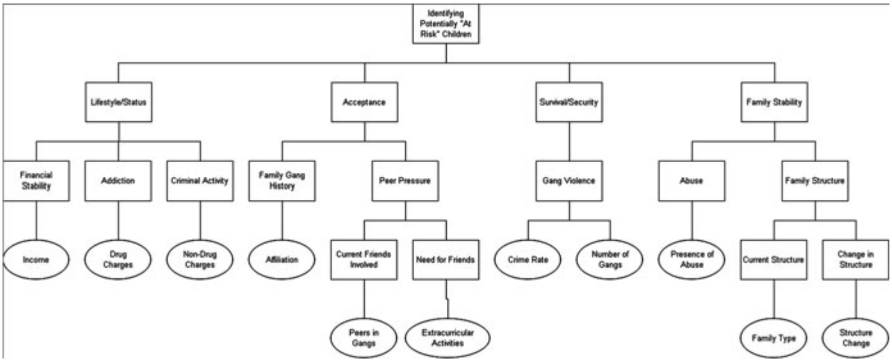


Fig. 9.2 Value hierarchy for identifying potentially at-risk children

officials would know, be able to obtain, or estimate for each child and their family. Once the measure was defined, ranges of least preferred ( ) and most preferred ( ) were placed on each measure to determine the bounds. Table 9.1 displays a summary of all the evaluation measures for each lowest tier value.

Single-dimensional value functions (SDVFs) allow the analyst and DM to translate scores to normalized values between 0 and 1. Specific details on the procedure to construct SDVFs can be found in Kirkwood (1997, pp. 61–65). The use of properly constructed SDVFs and ensuring no values overlap within the same tier provide the necessary property of mutual exclusivity. Each measure was developed based on the literature review and discussions with the SMEs. Each evaluation measure was also reviewed and approved by the DM and SMEs. SDVFs were then created and approved for each evaluation measure. Table 9.2 provides a summary of a select group of SDVFs (expanded in Appendix A).

To complete the value hierarchy process, the hierarchy needed to be weighted. Weighting the hierarchy allows the user to determine how much effect each value has on the overall decision. To determine the weights for the different values, "swing" weighting is used (Kirkwood, 1997, pp. 68–70). While performing swing weighting, the DM is asked to compare the "swing" from worst to best for one value against a similar swing of the other values on the same tier and branch of the hierarchy. This is known as "local weighting"; this process enables global weights to be computed. Since the hierarchy was determined to be mutually exclusive, the weights can be linearly added to provide an overall score for each individual or community.

The global weights for the lowest tier values are given in Table 9.3. The weights in Table 9.3 reflect the preferences of the decision maker in this study. A different community, with different problems and needs, might develop different weights appropriate to their own community. However, the fundamental hierarchy would remain.

Construction of the individual hierarchy at this point is complete and analysis can be conducted on children in the target Ohio county. Unlike traditional VFT

Table 9.1 Summary of evaluation measures for at-risk youths

Value	Evaluation measure	SDVF	Low risk	High risk
Financial stability	Income of surrounding neighborhood	Decreasing exponential	150,000+	0
Addiction	Number of drug charges in household	Categorical	0	3 or more
Criminal activity	Number of violent crime charges of child	Categorical	0	2 or more
Family gang history	Gang affiliation of family member	Categorical	No	Yes
Current friends involved	Number of peers in a gang	Categorical	0	3 or more
Need for friends	Number of extracurricular activities involved in	Categorical	5 or more	0
Gang violence	Number of gangs in city (or community)	Categorical	0	10 or more
Gang violence	Estimated crime rate responsible by gangs (percentage)	Increasing exponential	0	100
Abuse	Report or suspicion of abuse in household	Categorical	None	Reported
Current structure	Child's family type	Categorical	Mother/father	Foster
Change in structure	Number of parents or guardians lost in last year	Categorical	0	2

models, this hierarchy is not used to identify new alternatives or to support choice of a most-preferred alternative. Instead, the VFT approach is intended to generate scores for each young person; multiple applications of VFT allow ranking of individual youth at varying levels of derived risk for gang membership. Each child's inputs are implemented into the model, and a score between 0 and 1 is produced by assessing all low level value scores generated by each child and adding across the top tier of the hierarchy. A score close to 1 indicates the child is highly at risk to join a street gang, while a score of 0 indicates the opposite. It should again be noted that while a high score is a warning, it does not mean any individual will join a gang. It is an indication, however, that the individual may be in a potential crisis period and community resources and attention should be focused to assist the potentially at-risk youth. Community-based thresholds can be determined, such as 0.500, a child scoring higher than the given threshold for that community suggests the child as potentially being at risk compared to a child scoring below the threshold. Such potentially at-risk children may then be given additional attention. Of course, the scoring does not replace the critical attention and insight of parents or guardians, councilors, teachers, administrators, law enforcement, or community leaders, but may assist them in identifying individuals who may be in need of additional attention.

Table 9.2 Summary of individual SDVFs

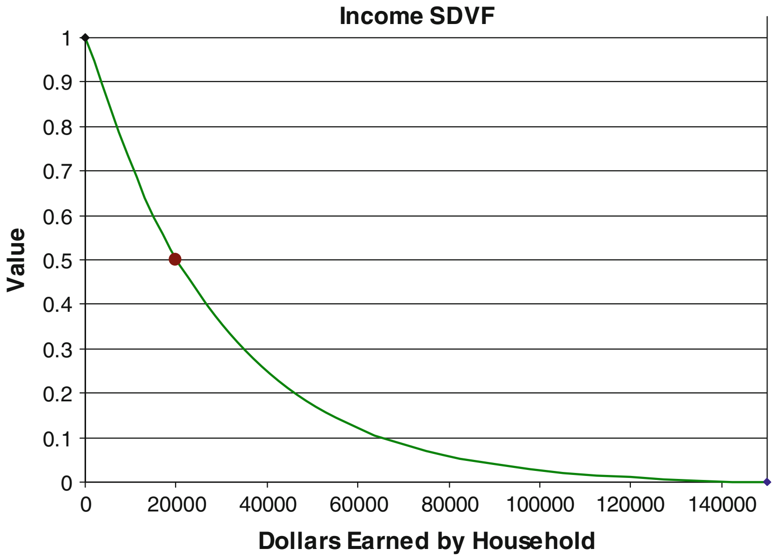
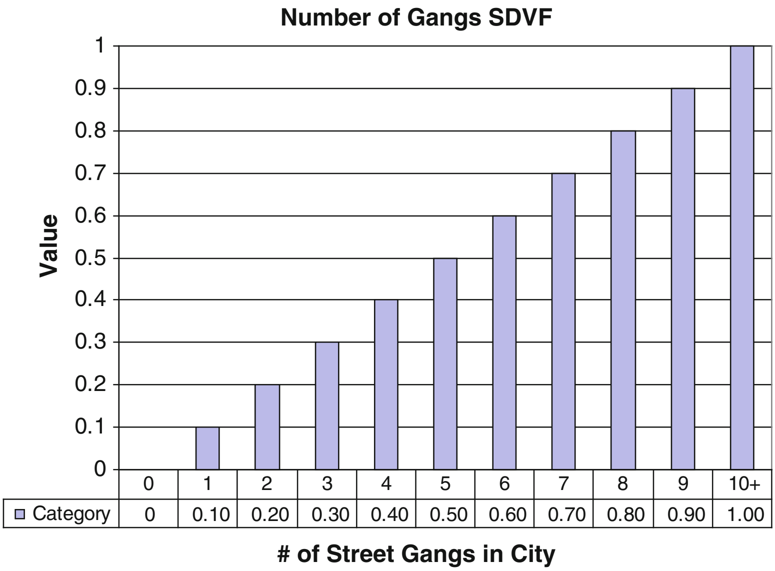
<table>
<tr><th>Evaluation measure</th><th>SDVF</th></tr>
<tr><td>Family income</td><td>
</td></tr>
<tr><td>Number of gangs</td><td>
</td></tr>
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Table 9.2 has been expanded in Appendix A at the end of this study to facilitate viewing

Table 9.3 Global weights

Value	Global weight
Financial stability	0.168
Addiction	0.024
Criminal activity	0.120
Family gang affiliation	0.268
Current friends involved	0.036
Need for friends	0.009
Number of gangs	0.031
Crime rate	0.031
Abuse	0.045
Current structure	0.039
Change in structure	0.229

Knowledge on which children are potentially at risk can help guide psychologists, school officials, or parents in their allocation of time and resources in helping these children and preventing them from possibly joining a street gang. Preventing new recruits from joining street gangs can have a long-term effect in reducing the number and magnitude of street gangs around the country.

3.3 Community VFT Model

Knowledge about individual children being at risk is helpful for school psychologists, councilors, teachers, and parents allocating the appropriate time and resources, but knowledge on communities that are at risk is also important to public policy decision makers. A "community" can be any appropriate political or cultural subdivision. The individual value model can be extended to consider which communities in a county are possibly at risk of producing more street gang recruits.

Based on the expertise of the DM and SME, the community model is similar to the individual model, incorporating nearly all the same values, but scored at the community level rather than the individual level. The only value not included in the community hierarchy is the change in structure at the lowest level; this single-family value does not apply to a community composed of many families. Although the values remain the same in the community hierarchy, their definitions, evaluation measures, and associated SDVFs were changed, based on the opinion of the DM, to measure the groups or cities correctly.

Financial stability addresses the likelihood that lower income status households produce more at-risk communities. Addiction examines the community's likelihood to have a large drug market and numerous users or sellers of drugs. Criminal activity determines the amount of violent crimes that are attributed to children in each community.

Family gang history looks at the number of families or households that have a member associated with a street gang in hopes to determine how much children are being influence by their own families to join street gangs. Current friends involved

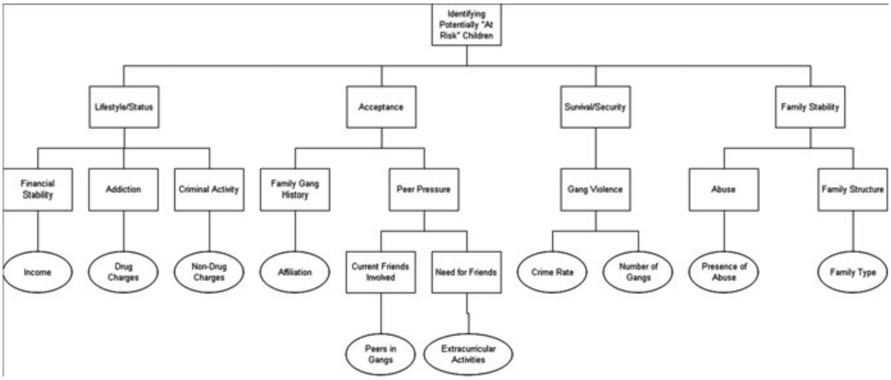


Fig. 9.3 Value hierarchy for identifying potentially at-risk communities

Table 9.4 Summary of community evaluation measures

Value	Evaluation measure	SDVF	Low risk	High risk
Financial stability	Average income of community	Decreasing exponential	150,000 +	0
Addiction	Percentage of households with drug charges	Increasing exponential	0	50
Criminal activity	Percentage of children with nondrug charges	Increasing exponential	0	50
Family gang history	Percentage of households with a street gang affiliated member	Increasing exponential	0	40
Current friends involved	Percentage of school children known to be in a street gang	Increasing exponential	0	40
Need for friends	Number of youth programs per 1,000 children	Categorical	5 or more	0
Gang violence	Number of gangs in community	Categorical	0	10 or more
Gang violence	Estimated crime rate responsible by gangs (percentage)	Increasing exponential	0	30
Abuse	Number of abuse reports per 1,000 children	Categorical	0	10 or more
Current structure	Percentage of households that are single parent or "less"	Increasing exponential	0	65

is similar to family gang history, but rather looks at peers than family members. Need for friends examines the community's ability to provide supportive opportunity for children to be involved with activities outside of the school.

Gang violence is measured the same as in the individual hierarchy. It is divided into crime rate that street gangs are responsible for and the number of street gangs in each community.

Abuse addresses whether the community possesses abusive families, abuse being any type of abuse. Last, family structure determines what percentage of

Table 9.5 Summary of community SDVFs

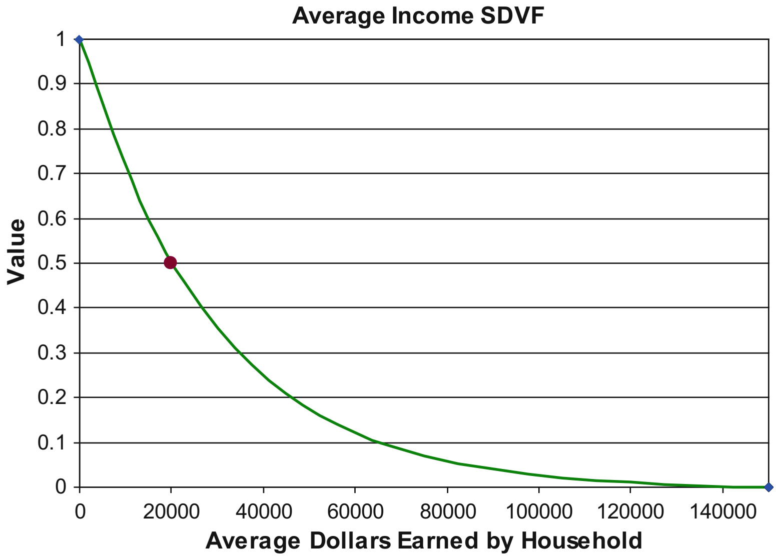
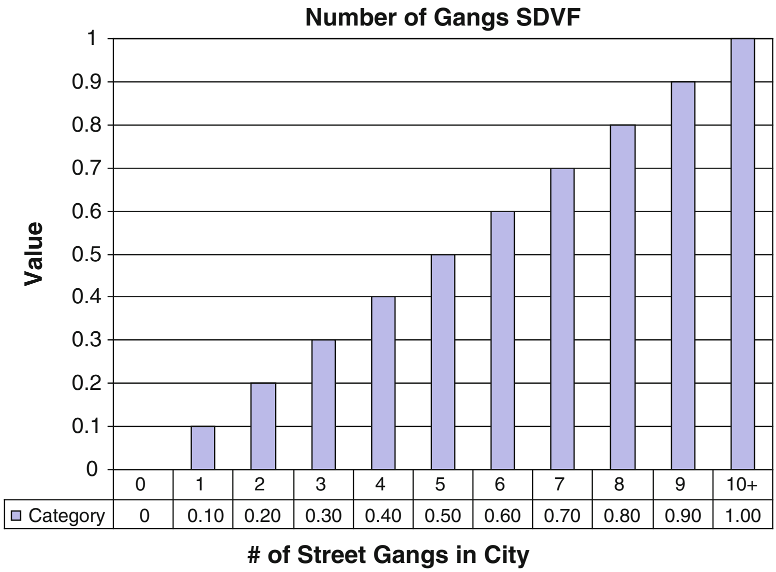
<table>
<tr><th>Evaluation measure</th><th>SDVF</th></tr>
<tr><td>Average income</td><td>
</td></tr>
<tr><td>Number of gangs</td><td>
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Table 9.5 has been expanded in Appendix B at the end of this study to facilitate viewing

Table 9.6 Global weights for community hierarchy

Value	Global weight
Financial stability	0.135
Addiction	0.019
Criminal activity	0.096
Family gang affiliation	0.214
Current friends involved	0.029
Need for friends	0.007
Number of gangs	0.125
Crime rate	0.125
Abuse	0.036
Family structure	0.214

households in each community involves only one blood parent or no blood parents (either foster or other third-party guardians). Figure 9.3 displays the group hierarchy for identifying potentially at-risk areas or communities in the county.

Following the construction of the group hierarchy, evaluation measures and their associated SDVFs were developed for each lowest-tier value. Table 9.4 provides a description of each evaluation measure and its ranges, while Table 9.5 illustrates select SDVFs for the various evaluation measures.

The final step in constructing the community hierarchy is assessing the correct weights, which were provided by the DM for this study. The main difference between the individual and community hierarchy weights, based on the study's DM preferences, is that the survival/security has an equal weight to the other top-tier weights. Another difference is in the fact that the group hierarchy only has two values under family stability rather than the three seen in the individual hierarchy since change in structure is difficult to measure on a group scale. The global weights are given in Table 9.6.

The review of the community hierarchy is complete at this point. The decision analysis hierarchy properties are satisfied and further analysis can be conducted. The communities of this Ohio county can be examined and scored on the hierarchy to determine which communities are at risk for children being likely to join a street gang. This can assist policy makers in the allocation of different gang prevention programs among the communities.

4 Results

4.1 Gang Prevention Programs

Rather than simply identifying potentially at-risk children likely to join a street gang, steps can be taken by parents or guardians, teachers, administrators, or other adults in a child's life to encourage a child to get involved with certain programs.

To assist in choosing the right program, different hypothetical gang prevention programs were developed to demonstrate what to do with the results of the value hierarchies. Each hypothetical program can target one or two different values in hopes to reduce the at-risk score of a child or community. For this demonstration, six hypothetical gang prevention programs, each having a specific mission, were developed. The hypothetical programs developed represent currently established programs but are not considered to be the same programs in this research.

Recommending different hypothetical programs to a child or community is simply a demonstration of how to use the results of the different value hierarchies. Matching different programs with different at-risk children or communities is in itself a decision problem. In terms of a community model, a knapsack problem could be performed to determine the optimal placement of programs based on funding, need, and benefit of the different programs. Other operations research tools could be used if the policy change for gang prevention programs were required. These are clearly areas for future potential research.

The first hypothetical program developed is Drug Resistance Education and Training (DRET). This hypothetical program involves police officers and teachers providing knowledge and skills to children on how to avoid drugs and gangs. Officers Against Gangs (OAG) is a hypothetical program constructed to provide a school-based curriculum in which officers attend classrooms to teach children the dangers of joining street gangs. The third hypothetical program, Sports with Police (SWP) is a program that extends youth the opportunity to be involved in sports and other extracurricular activities within a safe environment.

Police Force (PF) is another hypothetical prevention program in which a community adds detectives experienced in the area of gangs, increases time spent on street gangs, and/or devotes more resources to gang research. A fifth hypothetical program, Child Outreach Services (COS), is designed to have professionals on hand to assist youth in areas of abuse, peer pressure, loneliness, family situations, and many other common symptoms associated with troubled children. The fifth program is intended to represent those that are available to psychologists already working in the school system. The last hypothetical program developed is the After School Outreach Program (ASOP). This program provides latchkey children or children who need a safe environment with a place to go after school. This hypothetical program, if properly administered, offers children opportunity to avoid being alone and avoid turning to the streets for companionship.

4.2 Individual Hierarchy Results

For this study, we created a comprehensive, simulated list of children that are assumed to live in the Ohio county under consideration. Due to confidentiality issues, the actual list of juveniles could not be used in this study. However, data were collected from national surveys, local surveys, and other census collections. A synthetic environment of 83,004 children was created to mimic the county while allocating the appropriate number of children to each community.

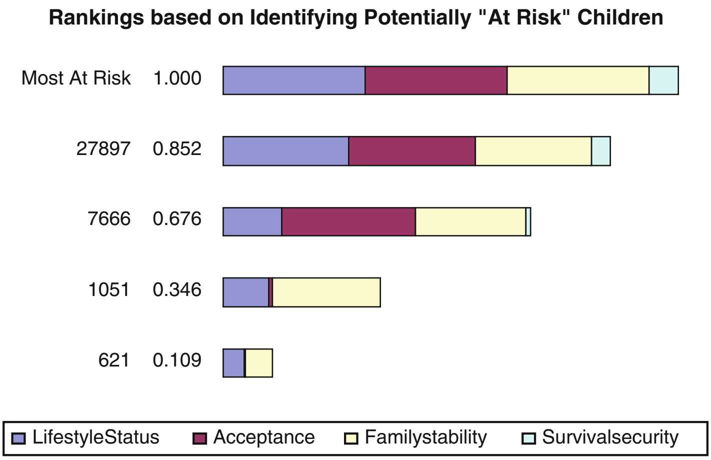

Fig. 9.4 Overall scores for example 4 children

Each child was generated a set of raw attributes, based on the surveys, for each of the evaluation measures developed in Sect. 3. These were checked to assure consistency. These raw attributes were implemented into the additive value function developed from the value hierarchy, and each child was given the appropriate score. The overall scores for the entire data set ranged from 0 to 0.864. It is important to note that the higher the score, the more potentially at risk the child is to join a street gang. Where resources are limited, thresholds can be set by the school psychologists or other officials as to which children should be addressed sooner than other children. This threshold can vary among communities and can be based on the expertise of the official working in the community or county being examined.

We discuss model results for four children from our hypothetical group to demonstrate the steps that could be taken to reduce the likelihood of gang membership. Figure 9.4 represents total scores for each child and the contribution to each score represented by lower-tier value categories. The "Most At Risk" bar provides a reference point, showing the worst possible scenario. Table 9.7 provides numerical global weights for each lowest-tier value which were aggregated by lower-tier value category component scores. We observe that the three factors with the greatest influence on children's scores are family gang affiliation, change in structure, and financial stability.

In our example, Child 1051 and Child 621 would generally be considered at lowest risk to join a street gang. In contrast, Child 27897 exhibits conditions that might make him or her one of the most at-risk children studied. A school psychologist or counselor may consider encouraging this child to enroll in the OAG and COS programs. These programs may provide the necessary information and assistance the child may need in his or her life. Learning the dangers of street gang life can

Table 9.7 Global weights for four selected children

Value	Child 27897	Child 7666	Child 1051	Child 621
Financial stability	0.1559	0.1289	0.0994	0.0471
Addiction	0.0000	0.0000	0.0000	0.0000
Criminal activity	0.1202	0.0000	0.0000	0.0000
Family gang affiliation	0.2679	0.2679	0.0000	0.0000
Current friends involved	0.0000	0.0238	0.0000	0.0000
Need for friends	0.0089	0.0015	0.0089	0.0000
Number of gangs	0.0313	0.0063	0.0000	0.0000
Crime rate	0.0235	0.0076	0.0000	0.0000
Abuse	0.0000	0.0000	0.0000	0.0000
Current structure	0.0272	0.0111	0.0080	0.0027
Change in structure	0.2296	0.2296	0.2296	0.0574

hopefully downplay the effects of a current family member having gang ties. In addition, the child has lost two parents/guardians within the previous year; therapy or simply conversations with the child could prove to be beneficial. Assistance is not limited to simply these two programs, but it could provide a large influence in deterring the child from gang membership.

Child 7666 does not score quite as high on risk factors as Child 27897, but shows similar trends. The same advice can be given to a school official in lowering this child's risk of joining a street gang. In fact, of all the children scored in the synthetic data set, the children scoring higher than 0.500 typically scored high in the three outlined areas.

If Child 1051 was determined to be within the threshold of being at risk in the particular community, addressing change in structure would provide an excellent benefit in reducing the child's propensity for gang membership. Although the value score for change in structure may not be changed, the assistance in this area would drop the likelihood of a child joining a street gang.

These results and recommendations are entirely hypothetical and are not the only ways in which a child's risk for gang membership might be reduced. However, our model provides a mechanism to quantify the notion of "at risk." Other individual assessments may be necessary before recommending each child to a specific program or course of action. This preliminary screening mechanism can help to focus a counselor's efforts.

4.3 Community Hierarchy Results

The first step involved with the community hierarchy was to obtain the raw attributes to be implemented in the additive value function. These numbers were drawn from the national and local surveys conducted on the county studied. This

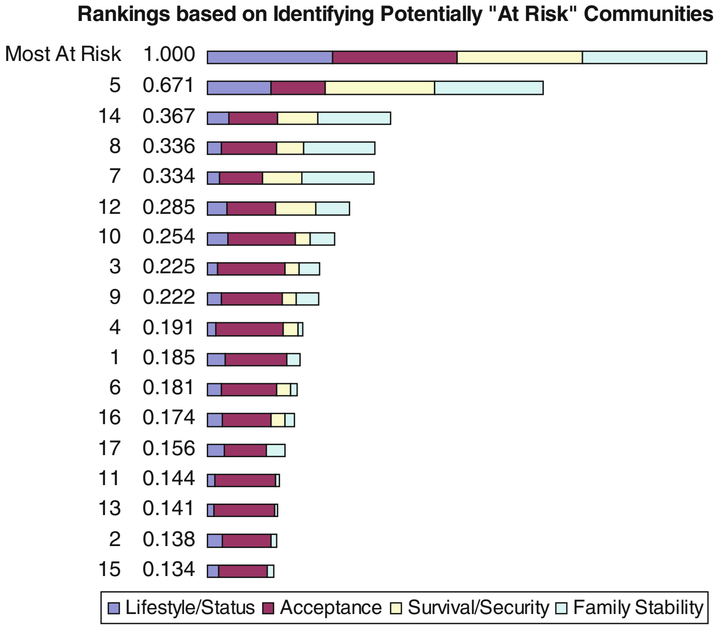

Fig. 9.5 Overall scores for 17 communities

data may not reflect current conditions if they have materially changed since being reported, so they should be treated as hypothetical data. While drawn from open sources for demonstration purposes, a specific community would have access to governmental records. Once the raw attributes were implemented in the community hierarchy, overall scores were obtained for each of the 17 communities in the county studied. Figure 9.5 displays a bar chart determining each community's individual score and how much effect each top tier value had on the overall score.

Community 5 appears to be at the highest risk for increased incidence of gang membership. Indeed, the DM agrees that the real-world community associated with Community 5 is at great risk for increased youth gang membership. Once again, a threshold could be set by an expert in the area to determine which communities are most at need for gang prevention programs.

Figure 9.5 indicates that most communities' scores are driven by the value of acceptance, though the proportion of the total score represented by acceptance appears to decline as the aggregate at-risk membership increases. To combat this area, the implementation of SWP and ASOP could prove to be most beneficial in terms of reducing the community's likelihood of being "at risk." These two programs focus on giving children an opportunity to be involved with sports and other activities in a safe environment and encourage meeting new people who are not involved with gangs.

The higher scoring communities also score high in family stability and survival/ security. In terms of survival/security, the PF program would provide more security and hopefully a safer environment for the respective communities. To assist in the area of family stability, OAG and COS would be important considerations in establishing gang prevention programs. OAG would provide education on the negativity of joining street gangs, and COS would personally help children who are having trouble at home or living in an unsafe or negative environment.

The information obtained from the community value hierarchy provides public policy decision makers a quantifiable guidance as to which community gang prevention efforts should be focused. In addition, this information could be used with other operations research tools, such as knapsack analysis, to determine the optimal allocation of resources among the county in an effort to reduce street gangs and at-risk children likely to join street gangs.

5 Conclusions

An Ishikawa diagram was constructed to facilitate discussion in creating a value model in determining potentially at-risk children likely to join street gangs. It allows the analyst to organize the key factors related to at-risk children and provides a basis for discussion in the facilitation of the DM's values. The models developed captures the decision-maker's preferences and necessary values, measures, and weights. After creating the models, a hypothetical dataset representative of the county and its respective communities was also created. The children each possessed raw attributes and were scored according to the individual value model. The scores provide a method to screen and highlight trouble areas or the individuals that posed the highest "risk" for joining a street gang. This can help to guide counselors in their selection of options. The community scores provided information on the communities that posed the highest "risk" in which the children of that community would be likely to join a street gang. This information can be used by public officials alone or in conjunction with other analysis techniques to assist in decision making.

The Ishikawa diagram and value models developed in this study can assist the ongoing process of reducing the number of children joining street gangs. The model provides tools to educate communities on the sources of at-risk youths. In addition, the value model provides a mechanism to screen and rank the severity of at-risk youths for further attention. This can help in focusing efforts and resources. Caution should be taken, however, to remind all stakeholders at each step of the process that simply possessing a high at-risk score does not mean the individual will join a gang. In addition, quantification cannot and should not replace informed decision making. The proposed models should aid in focusing community efforts and resources, but do not supplant community leadership. In addition, there is always a danger that people will begin to assume a level of precision from any quantitative model that is not justified. This is particularly problematic in behavioral modeling. Finally, as with any model, there is always the possibility that it could be abused and used in a method for which it was not intended or developed.

The VFT hierarchy aids in identifying factors key to the community dealing with at “risk children.” At the individual level, it helps to understand the varying contributions to aggregate measures of propensity for gang membership across diverse individuals. At the community level, it can aid decision makers in allocating limited resources or provide inputs to allocation model. In addition, it can identify potential shortfalls in proposed courses of action if values exist that are not adequately addressed by the available options.

The proposed models can be adjusted to represent other counties or communities around the country. The models were developed in a traceable and transparent format for easy adjustments. The Ishikawa diagram can be expanded if new research or knowledge proves important.

Extensions to at-risk children and other criminal associations could be performed using a similar model and approach. Researching the similarities of those children likely to join street gangs and terrorist groups, for example, could provide necessary knowledge in reducing the number of terrorists in the world (Bott et al., 2009). Individuals become members of organizations because they seek to have specific needs met; individuals remain members of organizations because their needs are being met [Turner, Hogg, Oakes, Reicher, & Wetherell, 1987, pp. 24–25]. Other extensions into other problem areas can be made using a similar model and approach.

This study has examined the use of VFT and Ishikawa diagrams in a social sciences setting rather than the usual business or total quality control types of setting typically used. The use of decision analysis tools within a social sciences area prove to be useful in assisting in obtaining quantifiable justification in possible public policy decision making.

Acknowledgments The authors wish to thank the decision maker and subject matter experts for the time and effort they expended on this study. It would not have been possible without their assistance. We also wish to thank the editor and reviewers for their insightful comments.

Appendix A: Individual Single Dimension Value Functions

This appendix includes the plots of the single-dimension value functions (SDVFs) developed in this study for the individual at-risk child. An SDVF is a monotonically increasing or decreasing function for each measure used to convert a measure’s score on the x-axis to a value on the y-axis, denoted by $v(x)$. The purpose of the SDVF is to provide a value of a measure, typically between 1.0 and 0.0, based on the score given by the decision maker (Kirkwood, 1997, p. 68). These value functions may be discrete, including categorical functions, piecewise linear, or continuous. Each measure was developed based on the literature review and

Fig. A1 Value hierarchy for identifying potentially at-risk children

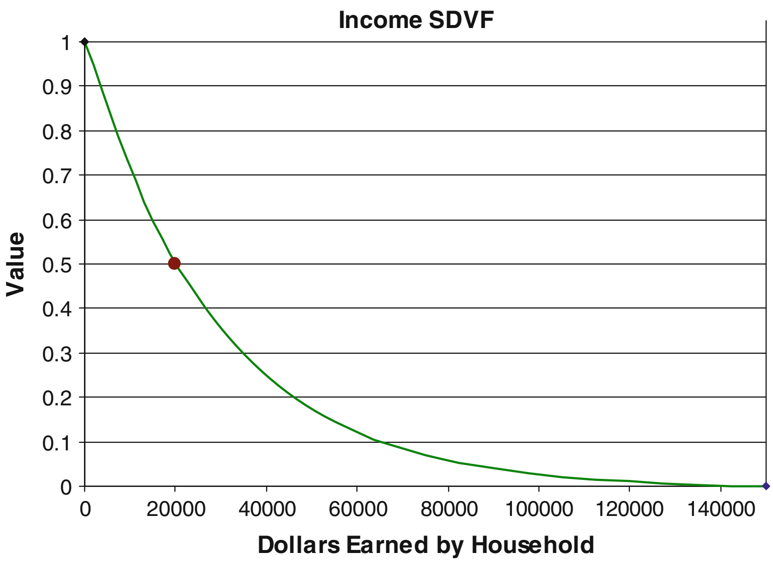

Fig. A2 Income SDVF – individual

discussions with the subject matter experts (SME). Each evaluation measure was also reviewed and approved by the decision maker (DM) and SMEs; SDVFs were then created and approved for each evaluation measure. A higher value score implies a higher risk for the individual. While these SDVFs are robust and should be extendable to other communities, they do represent the opinions of the SMEs and community used in the study. Before they are applied in a different setting, the measures and the weighting should be reviewed for their appropriateness in the community in question (Figs. A1–A12).

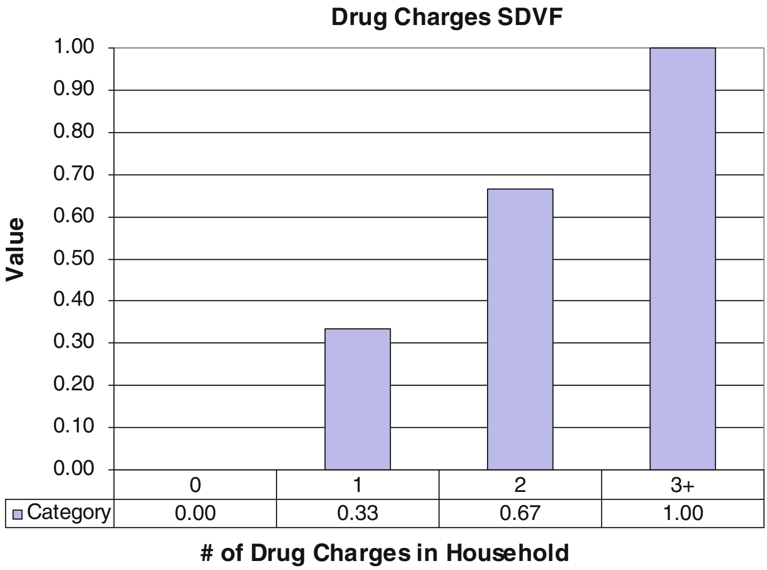

Fig. A3 Drug charges SDVF – individual

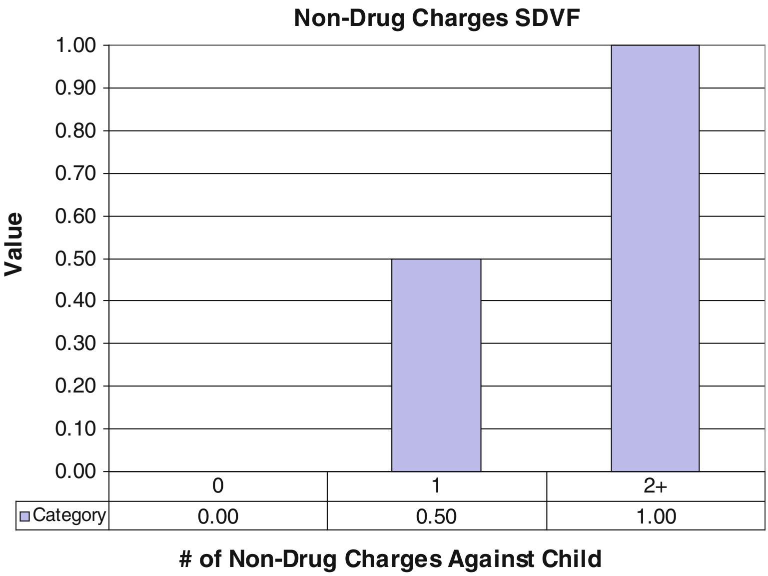

Fig. A4 Nondrug charges SDVF – individual

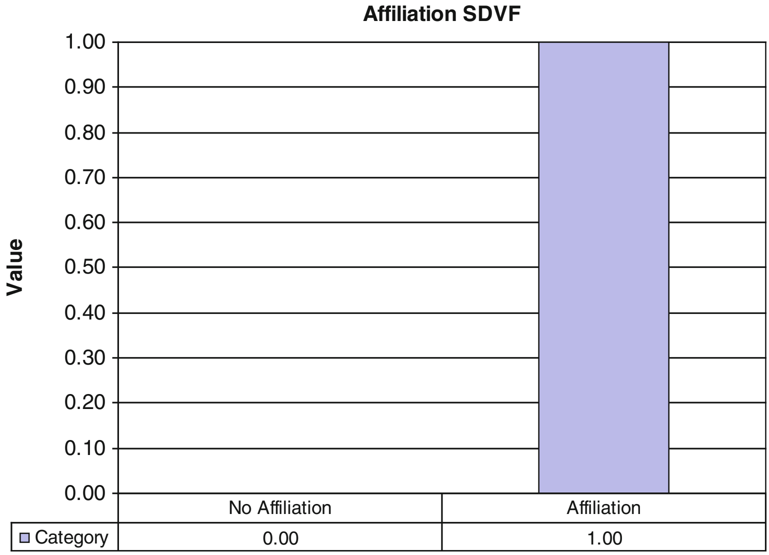

Fig. A5 Affiliation SDVF – individual

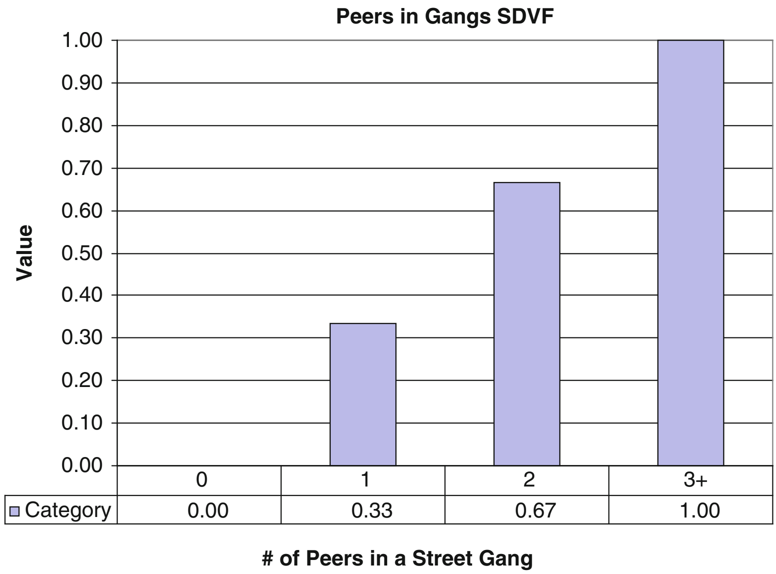

Fig. A6 Peers in gangs SDVF – individual

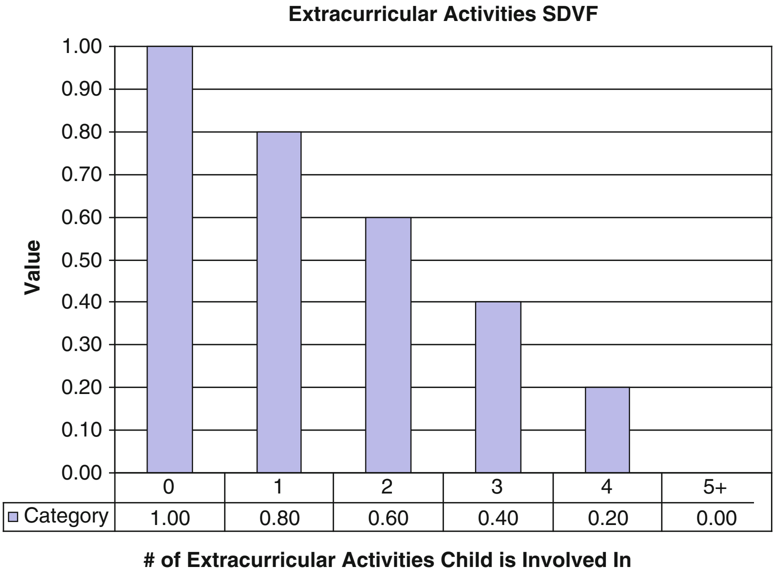

Fig. A7 Extracurricular activities SDVF – individual

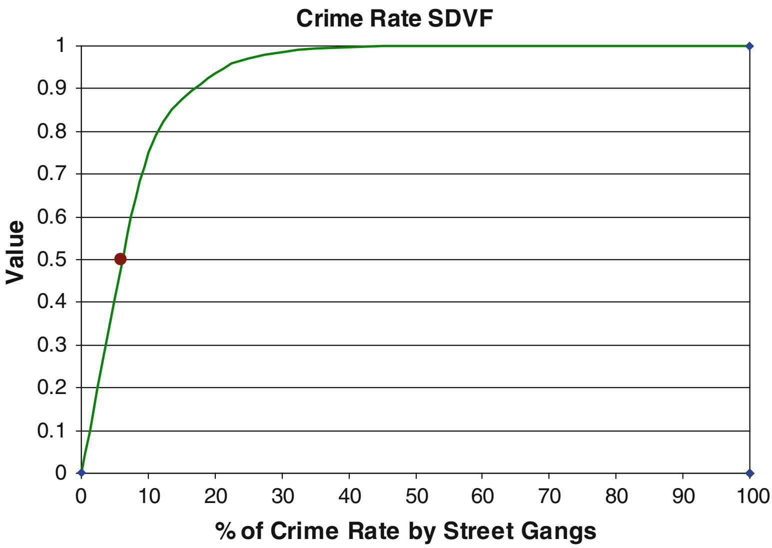

Fig. A8 Crime rate SDVF – individual

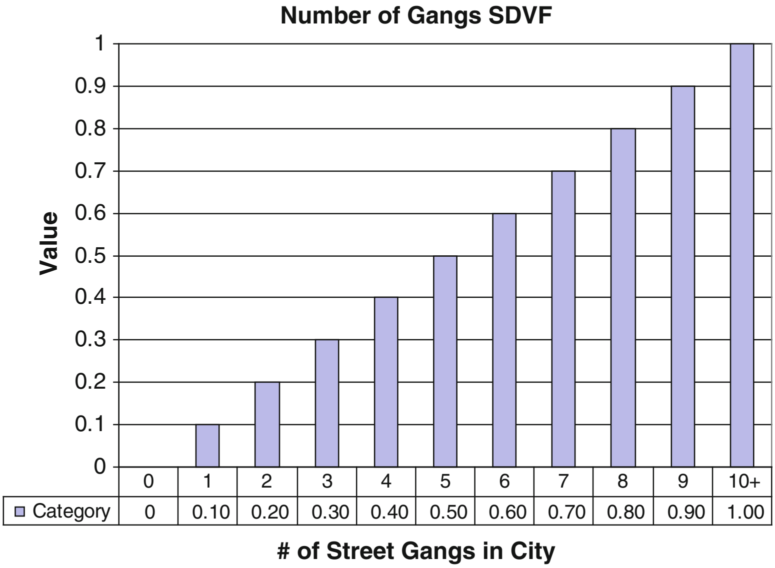

Fig. A9 Number of gangs SDVF – individual

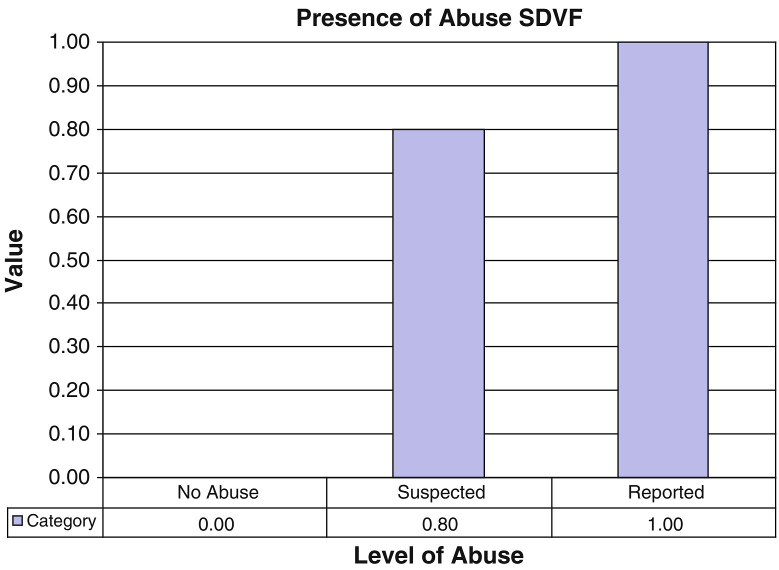

Fig. A10 Presence of abuse SDVF – individual

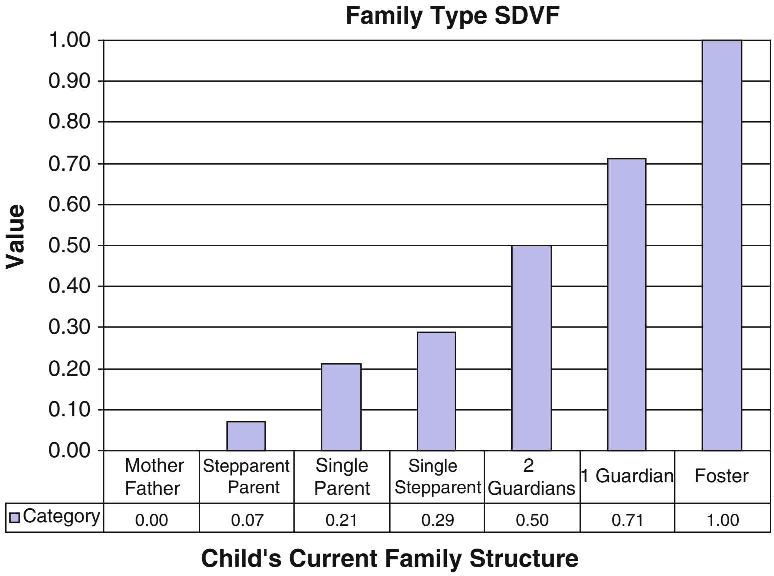

Fig. A11 Family type SDVF – individual

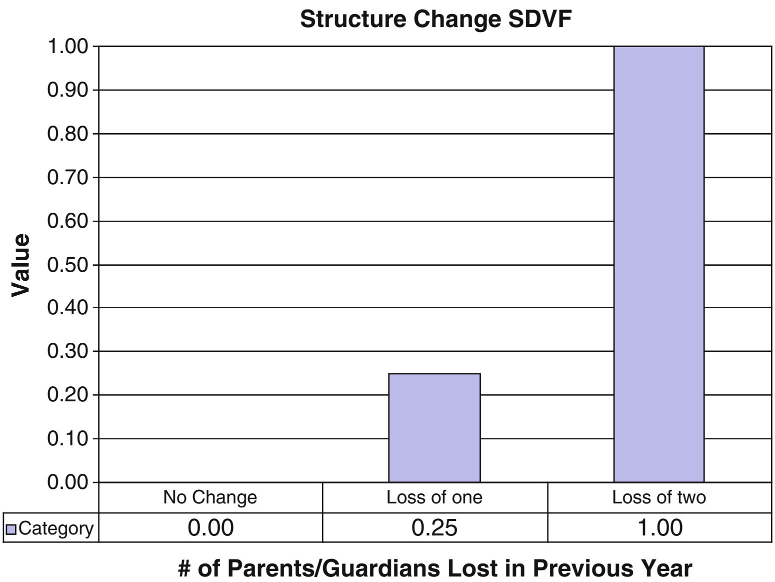

Fig. A12 Structure change SDVF – individual

Appendix B: Summary of Community Single-Dimension Value Functions (Table 9.5)

This appendix includes the plots of the single-dimension value functions developed in this study for the communities at risk. Each measure was developed based on the literature review and discussions with the subject matter experts (SMEs). Each evaluation measure was also reviewed and approved by the decision maker (DM) and SMEs; SDVFs were then created and approved for each evaluation measure. A higher value score implies a higher risk for the community. While these SDVFs are robust and should be extendable to other communities, they do represent the opinions of the SMEs and community used in the study. Before they are applied in a different setting, the measures and the weighting should be reviewed for their appropriateness in the community in question (Figs. B1–B11).

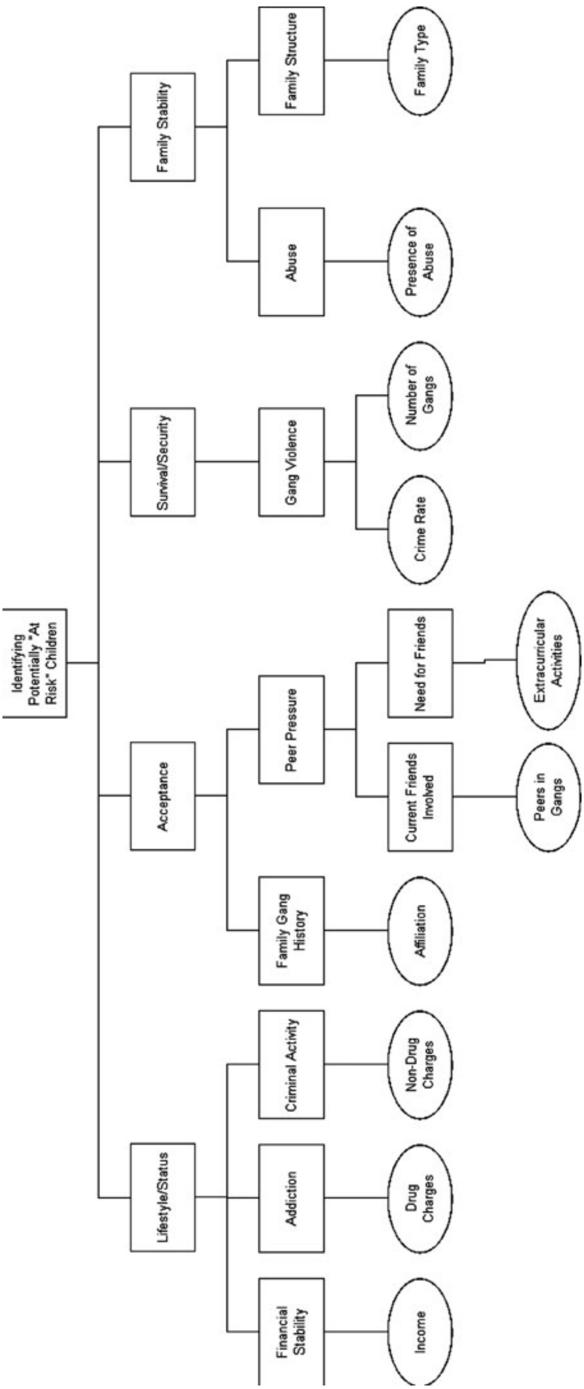

Fig. B1 Value hierarchy for identifying potentially at-risk communities

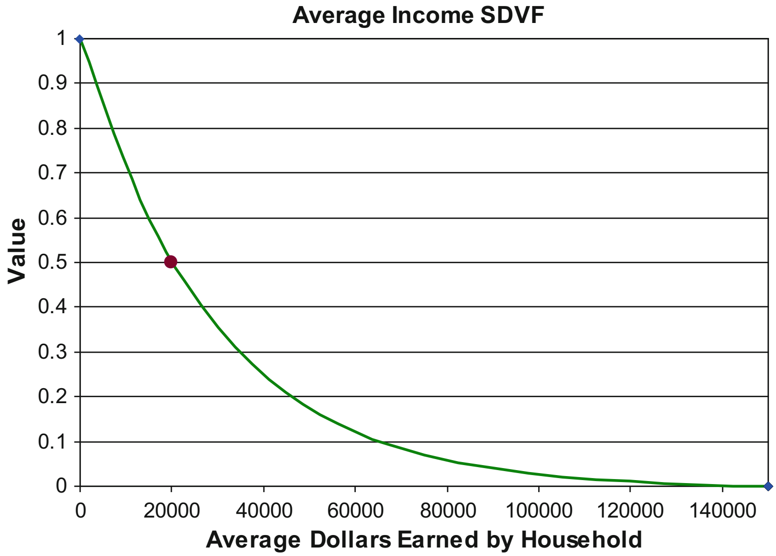

Fig. B2 Community average income SDVF – community

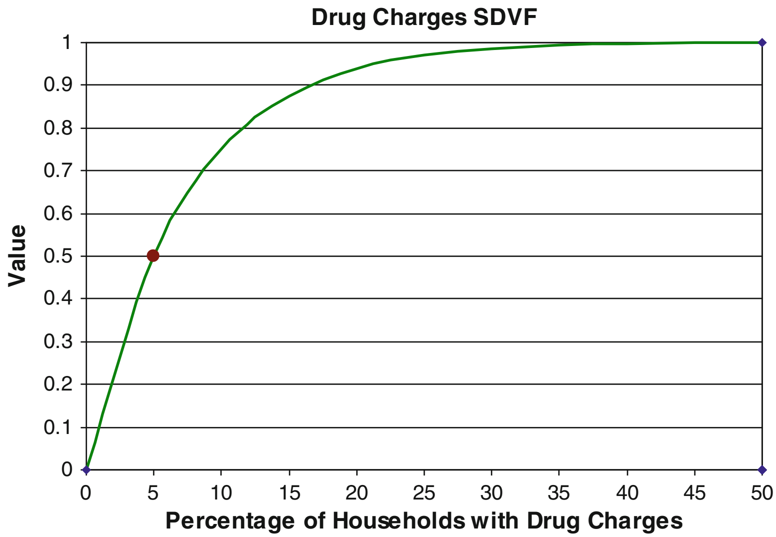

Fig. B3 Percent household in community with drug charges

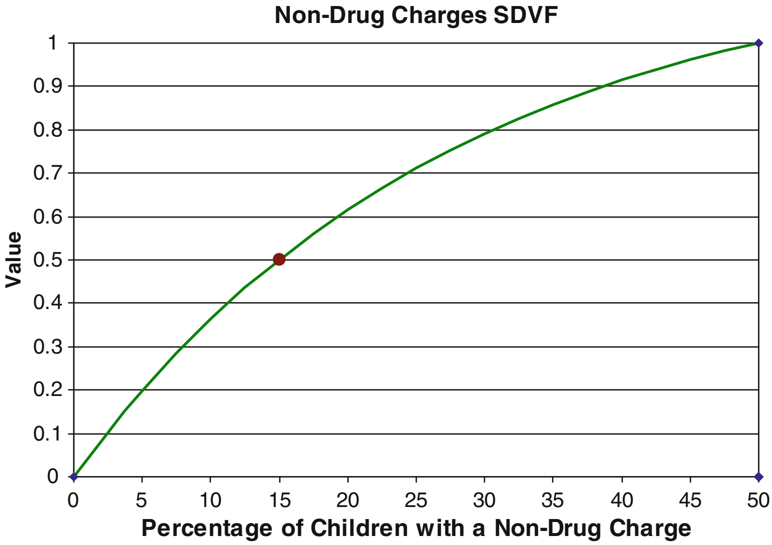

Fig. B4 Percent of children in the community with a nondrug charge

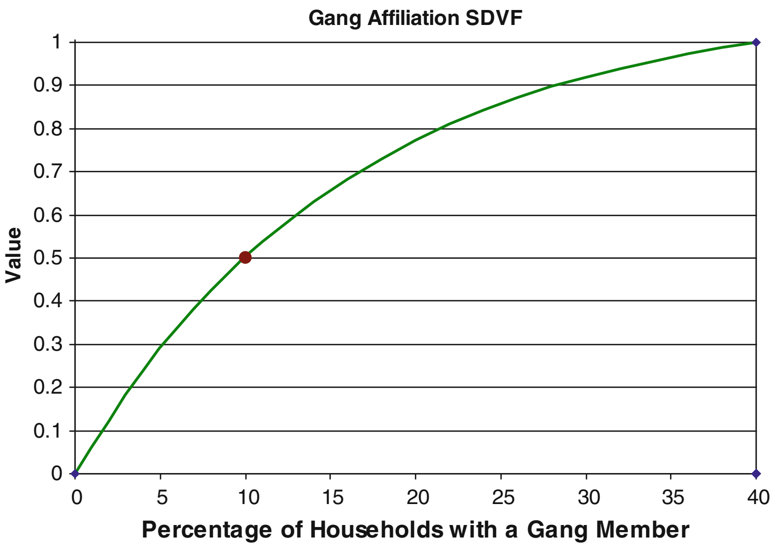

Fig. B5 Percent household in community with at least one gang member

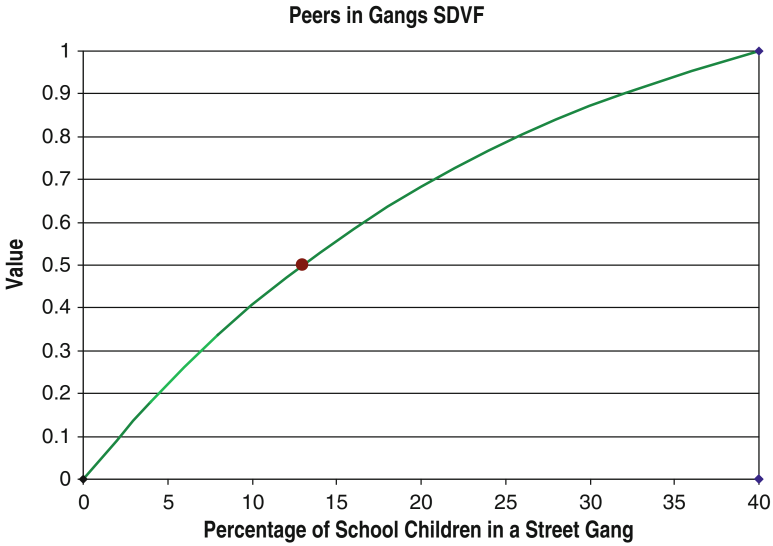

Fig. B6 Percent of school children in community in a street gang

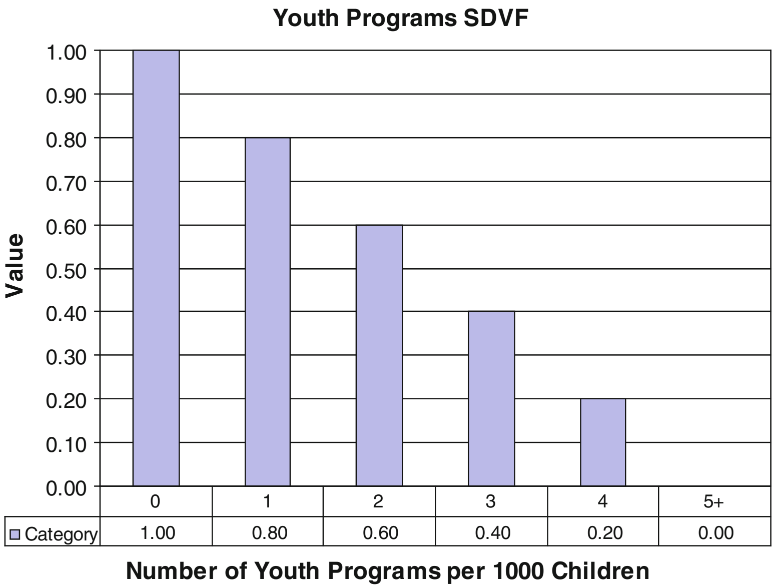

Fig. B7 Number of youth programs per 1,000 children in community

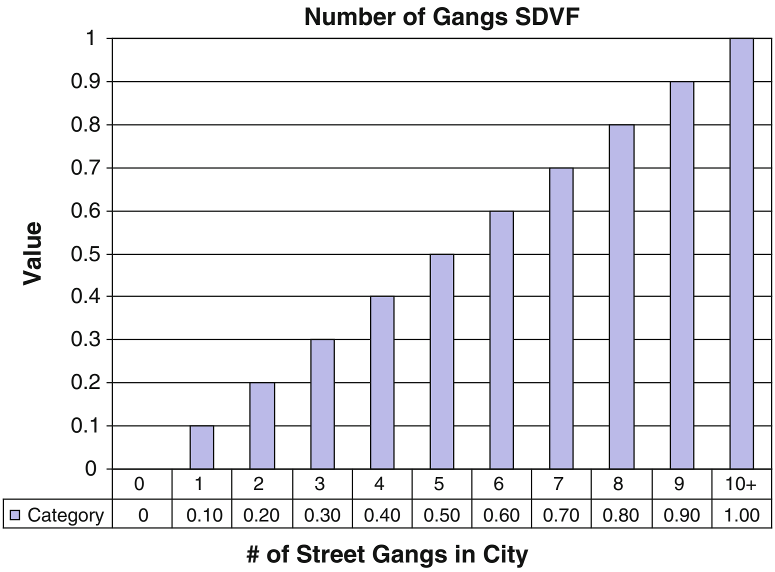

Fig. B8 Number of street gangs in community

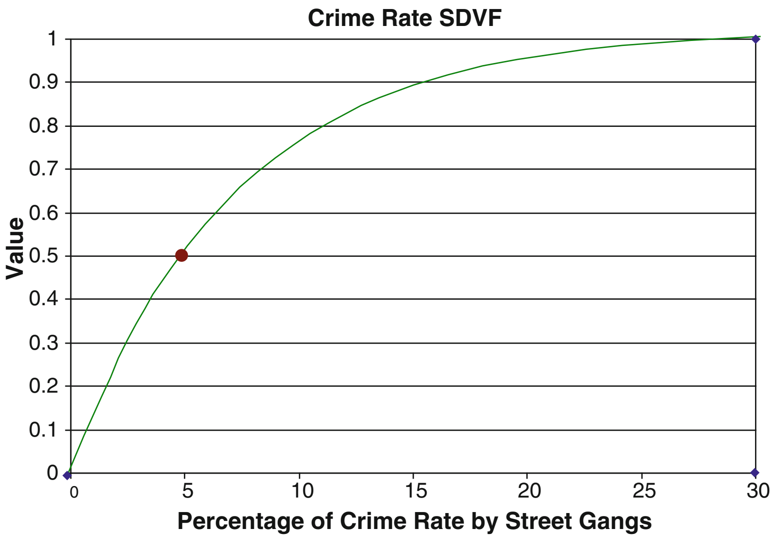

Fig. B9 Percent of crime rate in community by street gangs

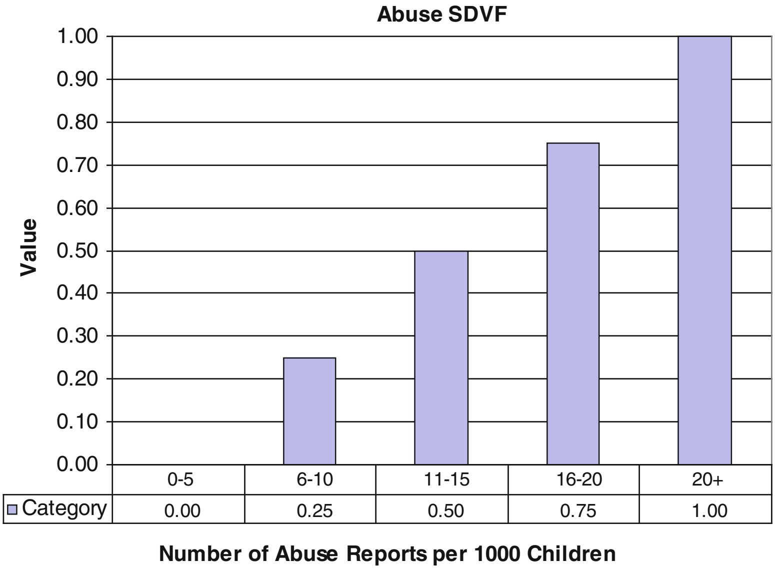

Fig. B10 Number of abuse reports per 1,000 children in community

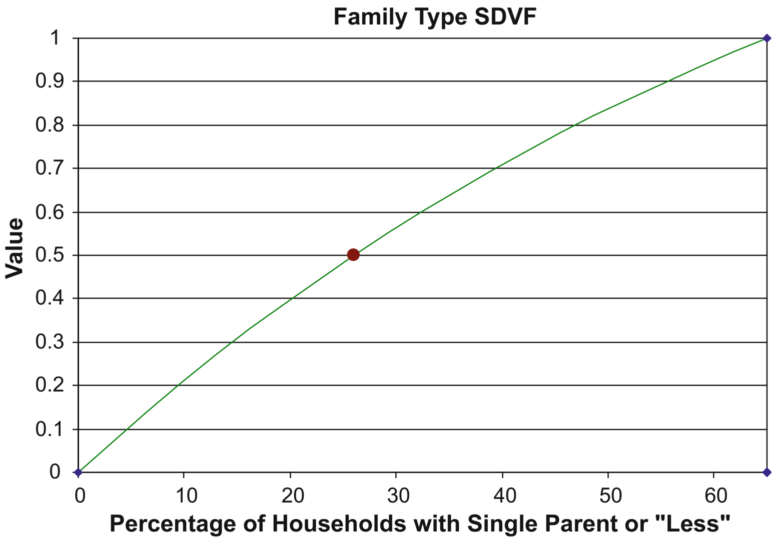

Fig. B11 Percent of households in community with single parent or less

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Chapter 10
Fair Fare Policies: Pricing Policies that Benefit Transit-Dependent Riders

Kendra C. Taylor and Erick C. Jones

1 Introduction

One primary benefit of mass transit is its ability to provide mobility for all by offering transportation that is economically and physically accessible to everyone. Buses and trains can serve as a redistributive tool to reduce inequalities in our society (Jones, 1985). They allow transit-dependent individuals (i.e., those with lower economic means, mental or physical disabilities, or those who are too young to drive) access to resources, jobs, stores, and schools.

Recent changes in the economic landscape have resulted in increased passenger fares for mass transit. According to a 2009 survey conducted by the American Public Transportation Association (APTA), 74% of the 98 agencies that responded (representing transit service to more than half of the nation's riders) reported that they raised fares in the past year. At the time of the report, half of the agencies indicated that they were considering another fare increase (APTA, 2009).

Fare increases by transit agencies are not new, but a new technology is available to agencies to mitigate the impact of increased fares on the transit-dependent. In the late 1990s, various community groups across the country began to file lawsuits and expressed concern over fare increases that negatively affected riders who depend on transit and use it differently than riders who have non-transit options. In each of the five lawsuits filed, court rulings upheld the fare increase (Fleishman et al., 2003). Nevertheless, more transit agencies have attempted to make more equitable those policies that provided discounts for riders who could afford to pay for multiple trips in advance. More equitable strategies include offering transit passes covering

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smaller time increments (e.g., week passes and month passes) and providing multi-ride discounts.

Motivated by the attempts of transit agencies to deliver equitable fare policies to their communities, this chapter proposes a strategy that can benefit both transit agencies and transit-dependent passengers. We introduce the concept of a "Best Fare" in a Fair Fare Policy (FFP) model and examine the benefit to both agencies and lower-income passengers of implementing a "Best Fare" policy alongside a transit agency's next fare increase. This strategy is made possible by advances in fare collection technology and the adoption of smart cards by several transit agencies.

Smart card technology for automated fare collection (AFC) allows an opportunity for transit agencies to provide the same discounts that passes provide for frequent travel without requiring transit-dependent passengers to prepay for multiple trips. A true "smart" card has the ability to provide volume discounts without the requirement that those passengers prepay for multiple trips to receive the benefit (Andrews, 2006).

US public transportation agencies will spend more than $500 million between 2010 and 2014 to build and maintain AFC systems for bus, subway, and light-rail systems (Spivey, 2010). As shown in Table 10.1, this trend has been building momentum in 15 cities over the last decade and over $1 billion has been invested. Through smart card technology, transit agencies can develop fare policies that charge passengers equally as they use the system and not according to their ability to prepay for multiple trips.

All of the top 20 US transit agencies, representing 83% of all transit rides (APTA, 2010), either have smart cards or are planning to implement smart cards for fare collection.[1] Despite the complex fare structures available for use with smart cards, no agency in the USA has implemented a fare policy that provides passengers a guaranteed lowest fare regardless of their ability to prepay for multiple trips.

Outside of the USA, smart card AFC systems are widely implemented. In Canada, the card is implemented in transit systems in the Gatineau region of the province of Québec, and in Montreal, Kingston, and Brantford, with planning ongoing in other jurisdictions. The concept is well advanced in Europe, especially in France, the UK, and Italy, and in Asia. The smart card is also increasingly used in Santiago, Chile, and elsewhere in South America (Jara-Diaz & Gschwender 2005 and Munizaga, Palma, & Mora, 2010).

Despite the worldwide use of smart cards, few transit Jara-Diaz and Gschwender, 2005 and agencies have implemented pricing policies that guarantee the lowest fare (Pelletier et al. 2011). This policy, called a "Fair Fare" or "Best Fare" policy, benefits the transit-dependent by converting rides that would otherwise have been paid from a cash balance on the card to free rides once the aggregated cost of trips reaches the cost of a pass within a certain period of time (Andrews, 2006).

[1] Top 20 transit agencies are ranked based on number of unlinked passenger trips as reported by transit agencies reporting to Federal Transit Administration FY 2008 National Transit Database.

Table 10.1 Spending for automated fare collection systems

City	Year installed	Total AFC spend to date	Anticipated AFC future spending
San Francisco (Bay Area)	2006	$368 million	About $300 million over 20 years
New York	2014	$0	MTA has a budget of $200 million to implement AFC
Washington, DC	1999	$135 million	At least $20 million for fare gates, vending machines, etc.
Los Angeles (metro area)	2007	$153.9 million	About $2 million annually for routine maintenance
Chicago	1997	$106 million	Routine maintenance. No major projects planned
Miami	2009	$79 million	$15 million to integrate with South Florida Regional Transportation Authority
Boston	2006	$75 million	Routine maintenance. No major projects planned
Philadelphia	Unknown	$0	Portion of $300 million capital budget expected to implement AFC
Seattle	2009	$43 million	Purchase validators for streetcar service, add two transit agencies
San Diego (metro area)	2004	$40 million	Working through software glitches. No major projects planned
Phoenix	2007	$20.4 million	Routine maintenance. No major projects planned
Atlanta	2006	$72.5 million	Routine maintenance. No major projects planned
Pittsburgh	2010	$33 million	Ancillary costs associated with system launch, maintenance
Minneapolis/ St. Paul	2003	$15.2 million	Integration with $675 million light-rail line under construction
Houston	2003	$30 million	$3 million annually for maintenance. 60–70 vending machines and 150 validators to support light-rail expansion

Source: Spivey (2010)

The version of this policy used by the city of London, called a “Pay-As-You-Go fare,” has a daily cap on total fare amounts equal to the 1-day pass on their Oyster smart card (Zureiqat, 2006). The public transport system of Melbourne, Australia, instituted a Best Fare with the introduction of their Myki smart card in 2010[2] (State Government of Victoria, 2010). In the USA, the Washington Metropolitan Area

[2] More information available at http://www.myki.com.au/Fares/Fares/default.aspx.

Transit Agency and the Maryland Transit Administration considered this option in the late 1990s (Booz Allen Hamilton 2004), but did not adopt it.

One primary obstacle to agencies implementing an FFP is the expected revenue loss from passengers who would otherwise pay for rides that this fare policy provides for free (Lindquist et al. 2009). The passengers whose fares would be lost would be those who used the system enough to qualify for a pass (e.g., a day, week, or month pass), but who either did not anticipate their transit usage or who did not have the ability to prepay for multiple trips. We show how transit agencies can actually enjoy increased revenues when Fair Fare policies are introduced along with a fare increase. Recent fare increases provide cross-elasticity data on passenger response to a fare increase.

This chapter uses a case study based on data from one US transit agency, TexasRail,[3] to show how revenue captured from a fare increase that includes a Best Fare option for passengers is greater than that of a proportional fare increase without this option. Doing so provides benefits to both the transit agency and the transit-dependent rider in addition to other riders in general. In response to a fare increase, we observe that TexasRail passengers purchased fare products that require a lower initial outlay. This behavior is consistent with loss aversion. This behavior resembles that of transit-dependent passengers who tend to buy a one- or two-trip ticket instead of prepaying multiple trips at a discount when choosing among established fares. The potential benefit to TexasRail is an additional 5–6% in revenue and reduction in ridership loss by up to 9%.

This chapter contributes to research on passenger responses to fare changes and the impact of these fare changes on total revenue. This chapter also provides decision makers at transit agencies adopting smart card technology with evidence on implementing Best Fare options. In addition, this chapter adds to the limited research on cross-elasticity of fare products resulting from a fare increase.

The chapter is divided into five sections. Section 2 provides policy and practice background to mass transit fare design. Section 3 develops theory and a decision model for designing equitable fare policies. Section 4 provides relevant limitations of the model and Sect. 5 summarizes conclusions.

2 Policy and Practice Preliminaries: Mass Transit, Low-Income Riders, and Fare Design

2.1 Pricing Options for Low-Income Riders

Minorities and low-income households account for 63% of transit riders in the USA (Pucher & Renee, 2003). Research on the transit-dependent population, for which

[3] A pseudonym.

minorities and low-income households are disproportionately represented, indicate that they tend to travel during off-peak hours, travel more frequently, use bus more often than rail, and make more transfers between modes (Beirão & Cabral, 2007; Graham, 2010; Hine & Scott, 2000; Lovely & Brand, 1982; Nuworsoo, Golub, & Deakin, 2009; Pucher, 1983; Wardman & Hine, 2000; White, 2009). This travel behavior suggests that unlimited ride passes may meet the needs of the transit-dependent, but that high initial outlays may be a deterrent to purchasing these products.

As transit agencies have increased fares, some have also evaluated options to reduce the impact of fare increases on transit-dependent riders. Five pricing options have been identified and evaluated as holding promise for aiding low-income riders when agencies increase fares. These pricing options were described in an article by Lovely and Brand (1982), which focused on policy changes at the Metropolitan Atlanta Rapid Transit Authority (MARTA) and were also noted by Pucher (1983) in research on six metropolitan areas.

The pricing options were: *Direct user subsidies*, which give transit subsidies directly to low-income riders through organizations such as county welfare departments; *Quality-based fares*, which relate fares to quality of service provided such as charging more for rail than bus because transit-dependent riders tend to use bus more than rail; *Reduced fares on designated routes*, which offer lower fares on bus stops or routes serving low-income residential areas; *Peak/off-peak fare differentials*, in which higher fares are charged during peak periods of time associated with the beginning and end of the work day while providing off-peak riders lower fares for non-work travel; and *Distance-based fares*, in which fares increase in distance traveled, under the assumption that transit-dependent riders travel shorter, in-town distances.

Each pricing option in the MARTA study was evaluated based on five criteria:

Target efficiency, or the degree to which the fare relief reaches the target population; *Coverage* or the percent of all aid-eligible riders who would receive the relief; *Administrative Cost* or the relative difficulty of administering the relief; and *Total Cost/Financial Responsibility* or the total agency revenue loss to be covered by other means.

Lovely and Brand (1982) found that direct user subsidies, such as providing discounted passes through a county welfare department, provided the highest degree of relief to low income riders with the least revenue loss. Furthermore, the study acknowledged that after a given trip frequency, a low income rider would be better off purchasing a weekly or monthly pass than paying even a subsidized cash fare, regardless of which of the five pricing options were used. This acknowledgement provides evidence in support of a Best Fare option that allows a low-income rider access to discounted fares without requiring prepayment of multiple trips.

Separate research on MARTA published in the same year by Parody (1982) noted that one challenge to low income riders purchasing weekly or monthly passes was the initial purchase cost. Low income bus passengers cited a high initial cost as a reason for not purchasing a monthly pass. As the income of respondents increased, the prevalence of this response decreased. The researchers observed that some passes were even purchased well into the middle of the month for which they were valid. They reasoned that this may have occurred because these customers could only afford to purchase the pass by that point, though still managing to save money under this scenario (Parody, 1982).

These observations are not unique to MARTA. A study of the Los Angeles County Metropolitan Transit Authority found that ethnicity, income, and age were primary factors in whether a passenger paid with cash or used a discounted pass (Luhrsen & Taylor, 1997). In general, despite the benefit of discounted travel for frequent riders, low income populations are less likely to purchase more expensive and larger volume-discounted fare products, like the monthly pass. This is because the cost is substantially more than the base fare (Pucher,1982 and Fleishman et al., 2003).

This preference of low-income individuals to purchase one or two trips at a time over discounted monthly passes is in keeping with behavioral economic theory that these passengers have a stronger aversion to loss than to acquiring savings (Kahneman & Tversky, 2003). This preference is also demonstrated when riders switch their fare product purchase (i.e., from a pass to a one or two trip ticket) when agencies increase fares. The switching behavior of passengers is measured by the cross-elasticities witnessed by agencies as demand for fare products shifts.

Although low-income passengers may prefer to purchase one or two trips at a time, agencies prefer to have as many transit passes in circulation as possible. Fare prepayment has been shown to significantly increase the number of off-peak transit trips taken by riders who previously paid for individual trips (Lago & Mayworm, 1982). In addition to the increased ridership, agencies are able to earn interest on prepaid revenues. Other benefits include fewer lines to purchase tickets and fewer resources expended on associated costs of managing lines and maintaining equipment (Weinstein, Lockhart, & Rolandson, 1999).

2.2 Best Fares with Smart Cards

The recognition of the transit preferences of low-income individuals and the benefit to agencies of transit passes, coupled with the capabilities of smart card technologies, has led fare policy analysts to develop special logic for smart cards that provides discount benefits to frequent travelers without requiring prepayment for multiple trips (Andrews, 2006).

The goal of the real-time fare management system developed by Andrews (2006) for use with smart card systems is to allow the agency to automatically determine and apply the lowest possible transit fare called the Best Fare to a patron's account. This releases the patron from deciding which of the available fare products would be most cost-effective for his or her travel pattern. In addition, the patron does not need to know his or her travel pattern in advance to secure the lowest cost travel.

To illustrate the application of a Best Fare, consider two scenarios. In the first scenario, multiple fare purchases, made in an ad hoc manner, result in dollar losses to customers. In the second scenario, a Best Fare reduces customer outlay even if customers do not know in advance how many trips they will make. Suppose an agency charges $2.00 for a one-way ticket, $3.50 for a round-trip ticket, and $5.00 for a 1-day pass, which allows unlimited trips until the end of the day of first use. Now, suppose a passenger needs to make four trips in a single day, but she does not know of all of these necessary trips at the start of the day. Without the Best Fare option, she might pay up to $8.00 for four one-way tickets, $7.50 for two one-way tickets and one round-trip ticket, or $7.00 for the initial one-way ticket and a 1-day pass. In any case, having realized the true amount of travel necessary, the passenger might regret not having purchased the 1-day pass initially or, having already purchased one one-way ticket, wish to receive a $2.00 credit toward the cost of the 1-day pass. The Best Fare option allows such a customer to pay no more than the cost of the most economical option for meeting daily transit needs.

In the second scenario, the passenger will never have to pay more than $5.00 for a full day of travel. The passenger who purchased a $2.00 one-way ticket and later realized the need for an additional trip would be charged $1.50 for the second trip (the difference between a $3.50 round-trip ticket and the money already paid for the one-way ticket that day). The passenger would be charged $1.50 for the third trip as well, which is the difference between the cost of the 1-day pass and the money already paid that day. Since the passenger has now paid $5.00 in transit that day, there will be no charge for the fourth trip taken that day.

This fare policy therefore rewards passengers who accrue trips within each timeframe (e.g., day, week, or month). Although the two scenarios cover a 1-day pass, the logic holds for week and monthly passes as well. The aggregated cost of trips is capped at the cost of the pass and subsequent trips during that time period are free. Without the requirement that they prepay for multiple trips, transit-dependent riders are able to receive the same discounts as “choice” riders, which are those riders who also own a vehicle but choose to use transit. Choice riders have the same incentive to use transit for non-work trips as they do with a pass and have the option to prepay for multiple trips or pay as they go from a cash balance they may store on the card at levels they determine.

If an agency chooses to implement an FFP by including a Best Fare option, they risk losing the expected revenue from passengers who would otherwise pay for rides (e.g., losing the $2.00 to $3.00 above the cost of the 1-day pass from our first scenario). We argue, in contrast, that it is possible for a fare policy that includes a Best Fare option to increase revenue when used in conjunction with a fare increase.

Instituting a Best Fare along with a fare increase may increase the portion of revenue captured from a fare increase by reducing the number of passengers who discontinue transit usage when faced with a fare increase. Discounting multi-trip and pass products has been shown to reduce ridership loss from a fare increase (McCollum & Pratt, 2004). Introducing a Best Fare option makes those discounted pass products accessible to all passengers and also has the effect of reducing “sticker shock.” In addition, passengers who would have switched from a monthly or weekly pass to a one-way or round-trip ticket to forgo the initial outlay of money when an agency instituted a fare increase could instead use a Best Fare knowing that their total savings would be equivalent to the savings from a pass.

However, there is limited research on the economics and behavior of transit customers, e.g., the cross-elasticity of fare products, or how passengers shift between passes and tickets in reaction to a fare increase. Much of the research on cross-elasticities in transit centers on shifts in mode (Litman, 2010; Tsekeris and Stefan, 2010). There is also limited evidence on the impact of these new fares on total revenue. This chapter contributes to the research body of knowledge in this area.

2.2.1 Compliance with Title VI

An FFP also supports an agency's compliance with Title VI requirements for fare changes. Transit agencies that receive federal funds are required to demonstrate compliance with Title VI of the Civil Rights Act of 1964. This statute prohibits discrimination on the basis of race, color, and national origin in programs and activities receiving federal financial assistance. Moreover, if a recipient of Federal assistance is found to have discriminated and voluntary compliance cannot be achieved, the federal agency providing the assistance should either initiate fund termination proceedings or refer the matter to the Department of Justice for appropriate legal action (United States Department of Justice (USDOJ), 1964).

Several community-based organizations who filed suit in the 1990s against the fare policies of transit agencies cited violations of Title VI (Fleishman et al., 2003). According to Title VI requirements of the Federal Transit Administration (FTA) of the US Department of Transportation, any change in fare cannot be borne predominately by a minority population and/or a low-income population. FTA guidelines recommend two options that recipients may use to evaluate the impacts of their service and/or fare changes. They may either conduct ridership surveys or develop their own method to determine whether minority and low-income riders are more likely to use the mode of service, payment type, or payment media that would be subject to the fare change. Some agencies implement a fare increase across all fare products by a fixed percent to avoid predominantly impacting one rider population (McCollom & Pratt, 2004). Research indicates that Best Fares may be well received by minority or low-income riders (Fleishman et al., 2003; Luhrsen & Taylor, 1997; Parody, 1982). However, ridership surveys could provide a current and more accurate assessment of local preferences (Suwardo and Kamaruddin 2010).

Title VI also requires that the adverse effect of a fare change should not be more severe or greater in magnitude for the minority population and/or low-income population than the adverse effect that will be suffered by the non-minority population and/or non-low-income population (United States Department of Transportation (USDOT), 2007). The use of Best Fares mitigates the severity of a fare increase on the transit-dependent. If the adverse effects of fare increases nationally are being absorbed by the transit dependent, then the benefits of a Best Fare perhaps should be as well.

3 Analysis of Best Fare Policies: A Case Study

3.1 Approach

The goal of the case study is to compare the revenue impacts of a fare change with and without the Best Fare option. We expect the portion of revenue captured to increase and the ridership loss to decrease as passengers take advantage of the option to pay incrementally for discounted passes. The portion of revenue captured and reduction in ridership loss from this approach represent an upper bound on values that would occur in practice. The value of the approach is to demonstrate that the upper bound is positive.

We use data from a transit agency that did not use the Best Fare option and changed fares to estimate changes in passenger behavior had the Best Fare option been implemented optimally. The first step in this approach is to use year-over-year ridership comparisons to estimate elasticity and cross-elasticities by fare product. The second step is to then use these elasticities to determine the portion of riders who would have taken advantage of the Best Fare given their response to the fare increase. The third step is to allocate that demand to the Best Fare option to determine the agency's revenue had the Best Fares option been available.

The first major contribution to elasticity analysis was the Simpson–Curtin formula. It was used to approximate the overall ridership impacts of fare changes. The developers of the formula studied over 70 fare changes across two decades beginning in 1947 and performed regression analysis to develop a relationship between fare changes and ridership changes. The formula approximates that for every 10% increase in fare, the agency will experience a 3% decrease in ridership. This translates to a direct elasticity of −0.3 (Curtin, 1968). Subsequent studies have shown significant differences in elasticities across regions of the USA (Balcombe et al., 2004; Pham & Linsalata, 1991).

One of the first economic studies to recognize the need for transit operators to have price elasticity *and* cross-elasticity data to optimize revenue from fares and to evaluate the addition or deletion of fare products was Hensher (1998). Previous economic studies considered only direct elasticities in using average fares across all fare products (Goodwin, 1992; Luk & Hepburn, 1993; Mayworm, Lago, & McEnroe, 1980; Oum, Waters, & Yong, 1992). Hensher (1998)departed from reliance on average fares and derived full matrices of direct- and cross-elasticities to predict rider response to fare changes. He noted that these elasticities can then be incorporated into a decision support system (DSS) that allows a transit agency to evaluate the implications of various fare policies on revenue.

In research sponsored by the Federal Transit Administration in cooperation with the Transit Development Corporation that produced a comprehensive summary of passenger responses to fare changes, McCollum & Pratt, (2004) note that the more robust analytical techniques for estimating elasticities use some form of "before-and after" approach, as contrasted to cross-sectional analysis. At a minimum, "before-and-after" analyses require data on the fare levels before and after a transit pricing and fare change, the number of existing riders subjected to the change ("before" ridership), and the response of riders to the change ("after" ridership). Much of the complete data on rider response to transit pricing and fare changes is not current, and applies primarily to general fare level changes. Many recent studies have focused on results without collecting or presenting the "before" data needed to develop elasticity estimates.

Most fare elasticities in the literature are short-run elasticities, addressing effects within 1 or 2 years following a change. Some recent investigations, primarily at the University College London, have estimated long-run in addition to short-run elasticities (McCollum & Pratt, 2004). Findings include 1975–1995 mean transit fare elasticities of −0.51 to −0.54 short-run and −0.69 to −0.75 long-run in the UK and −0.30 to −0.32 short-run and −0.59 to −0.61 long-run in France, international bus fare elasticities of −0.28 short-run and −0.55 long-run, and UK bus fare elasticities of −0.2 to −0.3 short-run and −0.4 to −0.6 long-run (Litman, 2004).

Transit agencies tend to develop their own elasticity models based on historic data because elasticities differ across agencies and because they possess their own "before" and "after" data. In addition, general predictive models were found to be less relevant to quick response needs of transit decision makers in the face of shocks such as the sharp increase in gasoline prices in 2008 (Gallucci & Allen, 2009). Agency elasticity models work well for fare changes that are broadly in line with inflation but are less accurate in predicting the impact of large changes in fares or the introduction of fares on new transit systems (Buchanan, 2006). This observation is included as a constraint in our model.

MARTA developed a fare elasticity model to forecast ridership and revenue impacts from a fare change. The model specifically takes into account shifts in different fare media (e.g., tokens, magnetic stripe cards). The approach they used was to apply fare elasticities to predict post-fare-change ridership levels and then apply those levels to forecast revenue (Harris, Thomas, & Boyle, 1999).

The Metropolitan Transportation Authority's New York City Transit subsidiary (NYCT) also developed its own model when it raised its subway and bus fares for the first time since introducing electronic fare cards. Partly on the basis of work done by other transit agencies, NYCT developed a spreadsheet model that used direct fare elasticities to estimate ridership loss and used trip diversion rates (similar to cross-elasticities) to estimate the likelihood that passengers would shift from a fare instrument with a larger percentage increase to one with a smaller increase (Hickey, 2005).

In keeping with the practice of transit agencies, our approach is to develop a mathematical model that determines the impact on revenue of using the Best Fare. We use cross-elasticities to estimate the portion of riders who would likely use a Best Fare option instead of switching to another fare product after the fare change and translate it to a spreadsheet model. We use sales data before and after a recent fare increase by one agency as a case study to determine the direct and cross-elasticities for fare products and the subsequent revenue impact.

The model is used to calculate revenue under the implemented fare increase and to compare it to the scenario of including the Best Fare option. We maximize revenue with respect to the fare increase. The revenue is constrained by the initial ridership who could switch fare products. There is also an upper limit on the fare increase (50%) after which elasticity models have been shown to have less accurate outcomes. Nonlinear programming is appropriate for our model because the revenue formulation includes the decision variable in both the price and quantity which are multiplied to calculate the revenue. A Generalized Reduced Gradient (GRG) algorithm was used to reach an optimal fare increase under the constraints.

3.2 Model Development

We developed a Fair Fare Policy model that determines the revenue from a fare increase that has been coupled with a Best Fare option thereby creating an FFP. The revenue is dependent on the fare structure, number of rides needed to reach each pass level at the agency, and the portion of riders who choose to use the Best Fare option instead of purchasing passes.

3.2.1 Assumptions

We assume that riders only purchase one fare product at a time. For example, riders do not purchase both a round-trip or 12-trip ticket and a monthly pass. In addition, riders who select the Best Fare option will not purchase a pass.

We only look at the full fare adult rider class because full fare riders cannot switch to discount rider classes (e.g., seniors or disabled). In addition, discounted rider classes have no incentive to purchase rides at full fare.

We also assume that all fare products increase by the same percentage. In addition, passengers select each fare product solely based on its price and their income. We assume that the maximum demand for the Best Fare option is equal to the passengers who would switch from a 12-trip or monthly pass to a one-way or round-trip ticket or vice versa. In reality, the demand for the Best Fare may be greater, but the intent is to show the impact on revenue from the introduction of the Best Fare option.

3.2.2 Step 1: Determine Passenger Demand Elasticities

Price elasticity of demand is used in transportation planning models to provide predictions of how passenger ridership behavior changes in response to changes in fare prices. Three methods for computing the price elasticity of demand are log-arc elasticity, midpoint elasticity, and the shrinkage ratio.

In the transit fare literature, the log-arc elasticity is the most frequently used form, and it describes the ratio of the rate of changes in demand given changes in price (Pratt, 2003). The midpoint arc elasticity closely approximates the log-arc elasticity and describes the demand response for both an increase and a decrease in fare using a consistent measure. When elasticities involve free fares, midpoint arc elasticity formulation is used out of mathematical necessity.

The shrinkage ratio describes the ratio of percentage changes in demand, given changes in price. It has historically been used to report passenger response to transit fare changes, primarily fare increases, but the industry has begun to move away from its use due to a conceptual difficulty: the formulation is based on the percent change from a starting value and therefore, in an experiment, does not produce the same elasticity in the case that an implemented price or service change returns back to the initial levels. The log-arc formulation does produce the same value in this case. For this reason, log-arc elasticities are preferred in the literature and historical findings have been updated with shrinkage elasticities converted to log-arc elasticities when data are available (Pratt, 2003).

We provide formulas for these elasticity measures. Let $E_{\text{log-arc}}$ be the log-arc elasticity; let E_{arc} be the arc elasticity; and let E_{shr} be the shrinkage ratio.

Define Q_1 and Q_2 as quantity demanded before and after a market stimulus is applied; define P_1 and P_2 as actual price before and after a market stimulus is applied. Then we have:

$$E_{\log-\text{arc}} = \frac{\log Q_2 - \log Q_1}{\log P_2 - \log P_1}, \tag{10.1}$$

$$E_{\text{arc}} = \frac{(Q_2 - Q_1)/(Q_1 + Q_2)}{(P_2 - P_1)/(P_1 + P_2)}, \tag{10.2}$$

$$E_{\text{shr}} = \frac{(Q_2 - Q_1)/Q_1}{(P_2 - P_1)/P_1}. \tag{10.3}$$

In order to estimate the impact of a change in price of one fare product upon the demand for another fare product, we compute cross-price elasticities. Products that are substitutes for each other will have a positive cross-elasticity, while products that complement each other will have a negative cross-elasticity.

After determining the direct elasticity, we can use the Cournot aggregation condition to determine the cross-elasticity. For each pair of fare products, we assume an ordinary downward-sloping demand function where the quantity of the commodity (e.g., transit trip) demanded is a function of the price of each fare product, and the budget that all passengers collectively spend for the two fare products before the fare increase. With the Cournot aggregation condition, the cross-elasticity between the two fare products includes that budget along with the elasticity for each fare product.

The corresponding utility function is $U = q_1 q_2$, and, using prices and quantities before the fare change, it gives a budget constraint for the two fare products of $y^0 - p_1 q_1 - p_2 q_2 = 0$. The Cournot aggregation condition provides the proportion of total expenditures for the two fare products as

$$\alpha_1 \varepsilon_{11} + \alpha_1 \varepsilon_{21} = -\alpha_1, \tag{10.4}$$

where $\alpha_1 = p_1 q_1 / y^0$ and $\alpha_2 = p_2 q_2 / y^0$. Given that we have the direct elasticities, ε_{11}, for each fare product, we may determine cross-elasticities, ε_{21} as well (Henderson & Quandt, 1980).

3.2.3 Step 2: Estimate Best Fare Usage

Given the cross-elasticities between fare products, we can apply certain cross-elasticities toward demand for the Best Fare option. Without the Best Fare option, passengers may fall into two categories. They may switch from prepaid to day-of-travel fares or vice versa. In the first category, there are a portion of passengers who purchased the multi-trip and pass products before the fare increase, but would prefer to purchase a one-way or round-trip ticket after the fare increase. In the second category, there are passengers who purchased multiple one-way or round-trip tickets before the fare increase who would prefer to purchase a multi-trip or pass product to make use of the volume discount savings after the fare increase.

These two categories of passengers are candidates for the Best Fare option. Their cross-elasticity values are applied to the demand for the Best Fare. For example, a positive cross elasticity from the 12-trip ticket to the one-way ticket indicates that a 1% increase in the cost of the 12-trip ticket corresponds to an increase in the purchase of one-way tickets, which can be seen as a substitute.

3.2.4 Step 3: Determine Fare Revenue

With a set of elasticities and cross-elasticities for each fare product, the transit agency is in a position to estimate the revenue impact of a fare increase under scenarios with and without a Best Fare option. The model is formulated as follows:

Index sets	
F	Set of all fare products (e.g., one-way, round-trip, 12-trip, monthly pass)
F'	Subset of pass fare products in the set F(e.g., 12-trip and monthly pass)
Parameters	
ε_f	Price elasticity for fare product f
$c\varepsilon_{f,-f}$	Cross-elasticity of the demand response of another fare product to a fare increase for fare product f
$P_{f,0}$	Initial price of fare product f
$Q_{f,0}$	Initial ticket quantity demanded for fare product f
n_f	Number of trips associated with the typical use of pass fare product f
Decision variable	
x	Percent increase in price for all fare products

Estimating revenue impact of fare increases requires that we compute prices of fare products and ticket quantities demanded for each fare product after the fare change. Important quantities for our model are price of the fare product f after the fare change, which we denote as $P_{f,1}(x)$, and the ticket quantity demanded for fare product f after the fare change, which we denote as $Q_{f,1}(x)$. In addition, the ticket quantity demand for the Best Fare after the fare change is denoted as $Q_{\text{Best},1}(x)$. This quantity includes the ticket quantity demand for the Best Fare from passengers who would prefer a Best fare to each pass fare product f (e.g., a 12-trip or monthly pass), which we denote as $Q_{f,1}^{\text{Best}}(x)$. The associated price for the Best Fare, which we denote as $P_{f,1}^{\text{Best}}(x)$, is the unit price for the pass fare product in the subset F' (e.g., 12-trip and monthly pass) that the passenger would replace with the Best Fare. We represent these values as a function of the decision variable in (10.5)–(10.9) as follows:

$$P_{f,1}(x) = (1+x)^* P_{f,0}, \forall f \in F \tag{10.5}$$

$$Q_{f,1}(x) = (1+x)^* Q_{f,0}, \forall f \in F \tag{10.6}$$

$$Q_{f,1}^{\text{Best}}(x) = x^* |c\varepsilon_{f,-f}|^* Q_{f,0}, \forall f \in F' \tag{10.7}$$

$$Q_{\text{Best},1}(x) = \sum_{f \in F'} Q_{f,1}^{\text{Best}}(x) \tag{10.8}$$

$$P_{f,1}^{\text{Best}}(x) = \frac{(1+x)^* P_{f,0}}{n_f}, \forall f \in F' \tag{10.9}$$

Definitions (10.5) and (10.6) provide the new price and quantity demand, respectively, for fare product f after the fare increase is applied. Definition (10.7) gives the quantity of fare product sales that would switch to a Best Fare in the event of a fare increase. It provides the quantity, specifically when f is a pass product (e.g., a 12-trip or monthly pass) and $-f$ is non-pass product (e.g., a one-way or round-trip) and vice versa. For every percent increase in fare, x, the absolute value of the cross-elasticity parameter, $c\varepsilon_{f,-f}$, is applied to the demand before the fare increase, $Q_{f,0}$. We take the absolute value of the cross-elasticity parameter because the cross-elasticity may be negative, and we are only interested in the quantity that would switch and not in the direction of the switch. The total demand for the Best Fare is the sum across the quantity of fare product sales that would switch to a Best Fare by pass product f as provided in definition (10.8). Definition (10.9) provides the unit price for the fare product sales that would switch to a Best Fare in the event of a fare increase. It is based on the fare for pass product f and on the typical number of trips taken using that pass product.

3.2.5 NLP Formulation

Max

$$\sum_{f \in F} [P_{f,1}(x)^* Q_{f,1}(x)] + \sum_{f \in F'} [P_{f,1}^{\text{Best}}(x)^* Q_{f,1}^{\text{Best}}(x)] \tag{10.10}$$

Subject to

$$\left[P_{f,1}^{\text{Best}}(x) - (1+x)^* P_{f,0}\right] \leq 0, \forall f \in F \tag{10.11}$$

$$Q_{\text{Best},1}(x) - \sum_{f \in F} x^* |\varepsilon_f|^* Q_{f,0} \leq 0 \tag{10.12}$$

$$0 \leq x \leq 0.5 \tag{10.13}$$

The objective of this NLP formulation is to maximize revenue resulting from a fare increase. This revenue is based on the amount of the fare increase and the demand elasticities and cross-elasticities. The objective function (10.10) is a function of the fare increase and the elasticity impact of the fare increase.

Constraint (10.11) prevents the price paid for incremental Best Fare travel from being greater than any new fare. Constraint (12) is included for the scenario when the Best Fare option is made available in addition to the fare increase. The total demand for the Best Fare after the fare increase, $Q_{\text{Best},1}(x)$, as defined above must be less than the total demand lost for each fare product, f, under the base scenario. For every percent increase in fare, x, the absolute value of the price elasticity, ε_f, is applied to the demand before the fare increase, $Q_{f,0}$. The absolute value is used to capture the sales quantity that would switch between fare products, regardless of the direction of the switch. Given the finding by Buchanan (2006) that fare elasticity models are less accurate for fare changes above 50%, constraint (13) limits fare increases to 50% and sets the fare change to a nonnegative number given that agencies have been increasing fares to cover costs instead of decreasing them.

3.3 Case Study

TexasRail, a commuter rail line serving three counties in Texas, provided over 4 million rides in 2009. In June 2009, TexasRail increased all fares by 25%. As a commuter rail line, the proportion of low income passengers serviced is lower than other modes of public transit with 10% for TexasRail compared to 35% for all public transit (Neff & Pham, 2007). TexasRail was selected for a case study because of readily available sales data both before and after a recent fare change that revealed a switch in fare product purchases from higher-cost prepaid pass products to day-of-travel fare products despite their higher incomes. The evidence of a switch between fare products indicated that passengers might have been open to using a Best Fare. Figure 10.1 displays the increased demand for one-way and round-trip purchases and the decreased demand for 12-trip tickets and monthly passes, which increased from \$80 to \$100 and from \$46 to \$57.50, respectively, after the June 2009 fare increase. The TexasRail passenger response to a fare

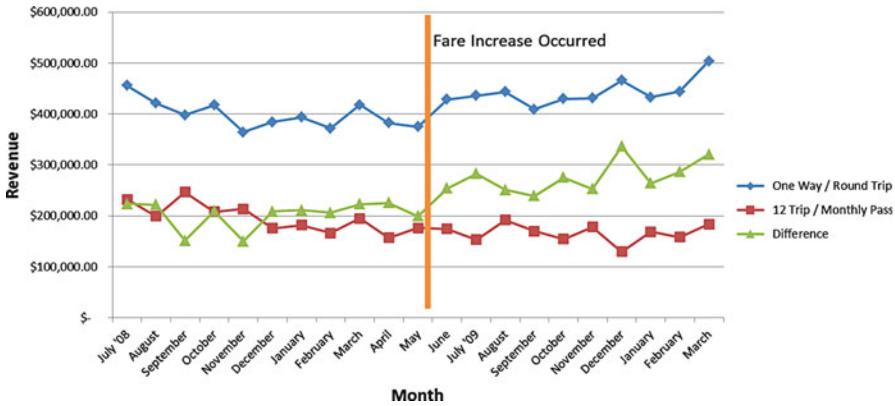

Fig. 10.1 Difference in pass product purchases pre/post uniform fare increase

Table 10.2 Initial fare price and ticket/pass sales

Fare products	Initial fare ($)	Initial sales	Number of trips taken
One-way trip ticket	5.50	60,279	1
Round trip ticket	9.25	25,024	2
12-trip ticket	46.00	1,105	12
Monthly pass	80.00	683	20

increase resembles the stronger aversion to loss than to acquiring savings exhibited by transit-dependent passengers choosing among established fares.

TexasRail has a zone-based fare structure with a different fare charged for each zone but with monthly pass holders receiving full access to all zones for one price. Given data limitations, to equate the value of trips to a monthly pass, each ticket sold both before and after the fare increase is assigned the value of a ticket for all zones. The initial fare, fare product sales, and the typical number of trips passengers use with each fare product are provided in Table 10.2.

For the case study, the optimization formulation was transferred to a spreadsheet and price and ridership data from TexasRail was included to solve using the Microsoft© Excel Solver and to draw conclusions. Additional details on the spreadsheet implementation are available from the authors. We validated the model (10.10)–(10.13) by computing demand and revenue using the log-arc elasticities derived from TexasRail's current data and comparing these computed demand and revenue values to actual values after the fare increase had been applied. The run-times of the model were nominal.

When comparing the actual demand to the demand derived using log-arc elasticities and assuming no Best Fare, the derived demand was equal to the actual demand for one-way tickets and less than the actual demand for round trip tickets by 4% for round trip tickets. The derived demand was less than the actual demand by 12% and 14% for monthly passes and 12-trip tickets, respectively. When we used the shrinkage ratio as shown in Table 10.3 to derive the demand, we found that

Table 10.3 Estimated demand elasticities

	Estimated demand elasticities		
Fare product	Log-arc elasticity	Midpoint arc elasticity	Shrinkage ratio
One-way trip ticket	(0.23)	(0.23)	(0.25)
Round trip ticket	(0.77)	(0.77)	(0.70)
12-trip ticket	(1.51)	(1.50)	(1.21)
Monthly pass	(1.41)	(1.40)	(1.20)
Overall	(0.40)	(0.40)	(0.40)

The values in parentheses are negative while those without parentheses are positive.

Table 10.4 Estimated demand cross-elasticities

	Estimated demand cross-elasticities			
Cross-elasticities	One-way trip	Round trip	12-trip ticket	Monthly pass
One-way trip ticket	(0.23)	(1.24)	(6.68)	(6.08)
Round-trip ticket	(0.14)	(0.77)	(1.24)	(1.13)
12-trip ticket	0.06	0.10	(1.51)	0.46
Monthly pass	0.05	0.08	0.45	(1.41)

The values in parentheses are negative while those without parentheses are positive.

the derived demand was less than the actual demand by 5% and 3% for monthly passes and 12-trip tickets, respectively. The shrinkage ratio, therefore, provides a reasonable lower bound; however, given the conceptual difficulty with the shrinkage ratio noted in Sect. 3.2, we used the log-arc elasticity for our model. We also note that the revenue calculated using elasticity data was 3% higher than the observed revenue for the base case. For Step 1, we estimated the demand elasticities – see Table 10.3 (Negative values are in parentheses).

We note that the log-arc elasticity is consistent with the elasticities calculated by other methods and select these values for our case study. As expected, the direct elasticities are negative corresponding to the downward-sloping demand curve. The overall elasticity is consistent with the Simpson and Curtin formula introduced in Sect. 3.1, which predicts a range of (−0.41, −0.39) when converted to a midpoint arc elasticity. It is slightly higher than the four other studies of commuter rail elasticity which have a range of (−0.22, -0.09) (McCollum & Pratt, 2004). We also estimated demand cross-elasticities as described in Table 10.4.

From Table 10.4, we see that an increase in the fare for the 12-trip ticket and monthly pass corresponded to an increase in the demand for one-way and round-trip tickets. For example, each 1% increase in the 12-trip ticket price corresponds to a 0.06% increase in demand for the one-way ticket. This indicates that the one-way and round-trip tickets serve as substitutes for the 12-trip ticket and monthly pass for some passengers. Positive cross-elasticity values for monthly pass and 12-trip ticket indicate that passengers saw these products as substitutes and switched between the two products.

There were some passengers whose travel patterns made the purchase of a monthly pass a preferred option when the price of the 12-trip increased. They had a positive cross-elasticity of 0.46. These passengers may expect to justify the increased cost with the unlimited number of rides available with the monthly pass. A separate

Table 10.5 FFP model output of actual and optimal fare increase

Percent increase	Revenue without best fare ($)	Revenue increase (%)	Revenue with best fare ($)	Percent increase	Revenue captured with best fare (%)	Reduced ridership loss (%)
25	708K	6	738K	11	5	7
32*	710K	6	751K	12	6	9

Note: *represents the optimal value

group of passengers with a similar cross-elasticity of 0.45 preferred a 12-trip ticket when the cost of a monthly pass increased. These passengers may have decided to reduce their use of transit and opt for another mode of travel instead.

We also observe that the demand for the 12-trip ticket and monthly pass are highly responsive to fare increases for the one-way and round trip ticket. These high cross-elasticities reflect the multiple individual tickets purchased instead of the multi-trip ticket or pass. In addition, choice riders tend to have a more elastic response to fare increases (McCollum & Pratt, 2004). Commuter rail lines such as TexasRail tend to carry a higher proportion of choice riders; we infer that a large fraction of TexasRail's riders are choice riders since about 95% of TexasRail riders own one or more cars according to a 2008 on-board survey.

Our spreadsheet optimization computes revenue with and without the Best Fare option both for the fare increase that was instituted and for the fare increase that optimizes revenue – see Table 10.5. We find that the additional revenue captured by including the Best Fare option ranged between 5% and 6%. This is due to the Best Fare option being used by passengers who would otherwise discontinue using transit when the fare increased.

The use of Best Fare with a 25% increase in fares contributed to a 3% ridership loss, as compared to a 10% ridership loss with the conventional fare structure. When Best Fare was used in conjunction with a 32% fare increase, the loss in ridership was 4% as compared to 13% with the conventional fare structure. These results indicate that Best Fares may moderate ridership losses that occur with fare increases.

The graph in Fig. 10.2 plots the revenue for each percent increase in fare from 25% to 50%. It shows the optimal fare increase without the Best Fare and the relationship between the revenue received with and without the Best Fare option. The vertical line on Fig. 10.2 indicates the optimal solution of 32% without the Best Fare and the revenue benefit of Best Fare at the corresponding fare increase.

4 Limitations

The FFP model uses the assumption that many of the riders who would discontinue using transit when the fare increased will continue to use it under the FFP which includes a Best Fare option. Evidence from non-US implementations for the Best Fare will provide insight into the strength of this assumption.

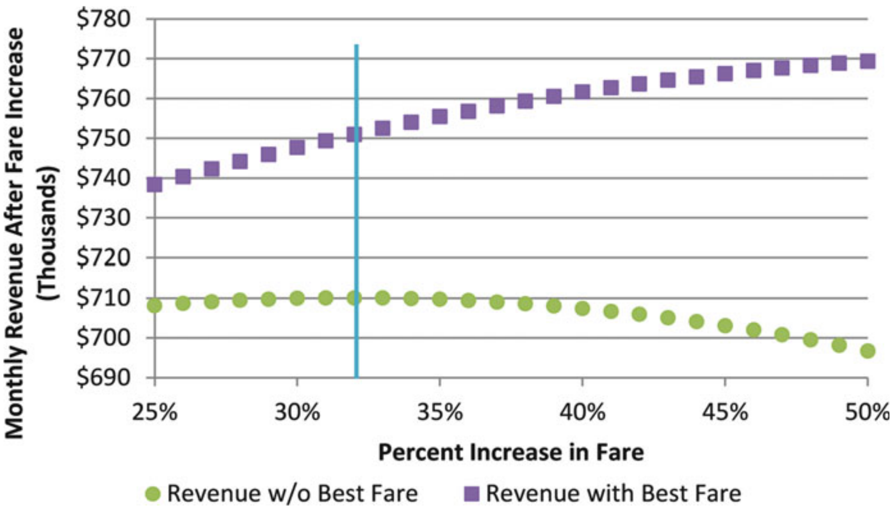

Fig. 10.2 Revenue with and without best fare option

Our analysis is based on the concept of price elasticity. It is important to note that elasticity is a relative measure best used for current services and systems. Also, the magnitude of the fare change impacts the usefulness of historical elasticities to predict rider response. Previous fare changes may influence expected elasticities and short-term elasticity can be quite different from long-term elasticity.

5 Conclusions

In the past, transit agencies did not institute complex fare policies primarily because of the administrative challenges of doing so with tokens, a paper ticket or a magnetic stripe card (Cervero, 1981 and Fleishman et al., 2003). The smart card technology provides a mechanism to easily deliver complex fare policies to the public. Transit agencies with smart card fare collection systems were concerned about the loss of revenue associated with implementing a Best Fare. We have demonstrated that, when coupled with a fare increase, a Best Fare can benefit both the transit agency and the low income passengers who depend on transit.

Agencies have introduced deeply discounted passes to reward passengers who switch fare products after a fare increase. This type of behavior does not yield significant revenue increases. Transit agencies who instituted a 25% or 33% increase in cash fares and an accompanying deep discount of 20–30% on passes saw a revenue increase of only 4–7% (McCollom 2004). With our case study, we saw an increase of 11–12% with half of the increase attributed to the use of a Best Fare. In addition, ridership loss was reduced to a loss of 4% compared to 13% without the Best Fare option.

As demonstrated by our case study, demand for particular fare products may be quite responsive to changes in prices (e.g., the price elasticity of demand for the monthly pass is −1.4), though ridership overall tends to be quite inelastic (−0.4). This is expected as a range of fare products for different rider frequencies would demonstrate a range of elasticities. This difference also highlights the importance of more elasticity studies using cross-elasticities and disaggregated direct elasticities.

The FFP model uses elasticities by fare product instead of an aggregate elasticity to represent all passengers. Transit agency decision makers can use it to estimate the revenue impacts of a contemplated fare increase that includes a Best Fare option in consideration of the income restrictions of the transit-dependent. Using a Best Fare can also provide evidence of compliance with Title VI requirements in that all passengers have access to each discounted fare product regardless of their ability to prepay for it. Therefore, a fare increase will not disproportionately impact low income and/or minority riders.

Smart cards provide more accurate usage data that can lead to more accurate elasticity data as input for the model. Given that an FFP charges passengers equally for usage and can be used with other fare pricing options that benefit the transit-dependent (e.g., peak/off-peak fares), smart card data on system usage can provide a clearer picture of the system usage before and after a fare increase. As the data input into the model improves, the model output becomes more beneficial. Over time, patterns may emerge that provide guidance for strategic long-term fare policies specific to each agency.

The model can be used in concert with other methods as part of a DSS for fare policy analysis. Ridership surveys can provide insight behind the demand elasticities of the riders. Agencies can better understand how their price increases impact riders and work collaboratively with riders to set and increase fares. As agencies track the demand elasticity for their specific ridership, they can make more informed decisions about fare increases.

Disclaimer The opinions and conclusions expressed in the chapter are those of the authors and do not necessarily reflect the views or policy of C2HM Hill or Booz Allen Hamilton or the University of Texas, Arlington.

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Part IV
Service Delivery

Chapter 11
Decision Making for Emergency Medical Services

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1 Introduction

In the USA, local governments have a mandate to provide emergency medical services (EMS) to their constituents. EMS administrators have the responsibility of staffing and deploying rapid response vehicles to provide a certain level of service, accounting for limited resources. Bailey and Sweeney (2003) state that the public expects an ambulance to arrive within a reasonable time when a perceived medical emergency occurs and an ambulance is requested. Furthermore, Williams and Ragone suggest that public expects a quick response and problem resolution (Williams & Ragone, 2010). Hence, a critical operational measure of service is response time (RT) to an emergency call, from the patient's perspective (Fitch, 2005; Williams & Ragone, 2010).

Although there is no universally accepted RT standard, nor federal or state laws regulating response times, most cities, fire departments, and private EMS providers use the National Fire Protection Association (NFPA) 1720 standard (NFPA, 1720). For medical emergencies, the NFPA 1720 travel time objective is to have an ambulance arrive within 8 min, 90% of the time. Since NFPA 1720 stipulates a maximum of 60 s of call handling time, in the USA the most widely used EMS (ambulance) total RT standard is 8 min 59 s. However, a 2009 survey of 200 cities found that only 27.7% of those cities using the NFPA 1720 standard were in compliance (Williams & Ragone, 2010). Surprisingly, very few countries have RT standards. Canada does not have a

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single standard; however, similar to the USA, most urban areas use 8 min 59 s for 90% of the life-threatening calls. England assigns emergency calls to one of three categories: life threatening, serious but not life threatening, and not serious. England requires that 75% of life-threatening calls must be reached within 8 min. Australia has a 10 min RT standard with rather low compliance statistics (50–60%) (Fitch, 2005). In Hong Kong, the RT standard is 12 min with 92% reliability (Graham, Cheung, & Rainer, 2009). The RT standards in Germany vary across the country, requiring that 95% of the calls be reached within response times that range from 10 to 15 min (Erkut, Ingolfsson, & Erdogan, 2008).

There is an extensive academic literature on decision models for ambulance deployment to minimize response times. Brotcorne, Laporte, and Semet (2003) describe the numerous deployment and redeployment models from the early 1970s through 2003. Recent research has focused on the tactical operations of EMS administrators to better match supply to demand. Demand for ambulances (i.e., calls) varies temporally and spatially based on the day of the week, as well as time of day (Rajagopalan, Saydam, & Xiao, 2008; Setzler, Saydam, & Park, 2009). Fitch argues that the most effective way to improve response times is to predict *accurately* where and when demand will occur, adjust resource levels, and develop redeployment strategies to improve coverage without increasing the load on staff (Fitch, 2005).

In order for these optimization models to be effective, the emergency call forecasts must be accurate with respect to both time and location. Past research in forecasting demand has focused on determining accurate forecasts of EMS call volumes for an entire region, for an entire year (Setzler et al., 2009). However, using aggregated forecasts for an entire region is not sufficient to effectively deploy often limited, resources to minimize response time (Goldberg, 2004). The tactical day-to-day decisions that EMS administrators face require forecasts for smaller spatial units, as well as smaller temporal units.

Once the forecast is completed, administrators face the complicated process of determining how many ambulances are needed and the deployment locations for each ambulance. There is also the problem of redeploying ambulances over a geographical area as demand varies over time (Rajagopalan et al., 2008). For example, in many communities, such as Charlotte, NC, the focus of this chapter's analysis, ambulances are not kept at fixed stations but are dispersed across the city. In this case, an ambulance might be positioned in a parking lot or on the side of an interstate. Once a call arrives, the ambulance is dispatched from wherever it has been stationed to the call location.

There are many different types of emergency calls and the survival probability depends on the type of emergency. Out-of-hospital cardiac arrest calls are of the highest priority and response time is crucial. The sooner the ambulance arrives at the call location, the higher the probability that the patient will survive (Erkut et al., 2008; Stoeckl et al., 2010). This compels EMS administrators to carefully consider the locations for ambulances so that they can be positioned closer to probable call locations.

This chapter focuses on the need and use of analytical models to provide timely emergency medical care in local communities. The work of hourly planning and decision making performed by EMS administrators requires accurate call forecasts coupled with realistic analytical models to help determine the optimal location and relocation of ambulances. To illustrate these decisions, we selected two recent papers from a rather rich and diverse literature on EMS station and ambulance positioning and one paper from a relatively less investigated area of EMS call volume forecasting. We used data from Mecklenburg County, in which the city of Charlotte is located, to demonstrate the models' efficacy. Section 2 contains a brief literature review. The forecasting and location models are reviewed in Sect. 3. Section 4 presents the application of the models which is followed by the conclusions and implications for communities in Sect. 5.

2 Literature Review

2.1 Forecasting

Traditionally, the forecasting procedure has been based on a review of historical demand data for different areas (zones, precincts, etc.) within a region. Future demand is assumed to follow past demand (Goldberg, 2004). Examples of papers that use these assumptions are Savas (1969), Aldrich, Hisserich, and Lave (1971), Baker and Fitzpatrick (1986), and Ingolfsson, Erkut, and Budge (2003) discussing New York, NY, Los Angeles CA, South Carolina, and Edmonton Alberta, Canada, respectively. All these models, as well as Siler (1975), Kvalseth and Deems (1979), Kamenetzky, Shuman, and Wolfe (1982), and Cadigan and Bugarin (1989), used various regression techniques in an attempt to accurately forecast total demand in a city. Trudeau, Rousseau, Ferland, and Choquette (1989) recognized that EMS call volumes vary spatially and temporally. They used the Autoregressive Integrated Moving Average (ARIMA) model to generate daily forecasts which were further disaggregated into 3-h time blocks using the logit market share model. However, they did not account for the spatial variability of calls. Channouf, L'Ecuyer, Ingolfsson, and Avramidis (2007) used autoregressive models to generate hourly forecasts, but they too did not consider the spatial variability of calls. Brown, Lerner, Baxter, LeGassick, and Taigman (2007) conducted a large-scale comparative study of accuracy of call volume predictions generated from demand pattern analysis and concluded that while it was a reasonable predictor for overall demand, the lack of spatial variation was a drawback. Section 3.1 of this chapter describes the study by Setzler et al. (2009), who uses an artificial neural network (ANN) to forecast demand that is changing both spatially and temporally.

2.2 Coverage

Once EMS administrators have generated a demand forecast, they need to determine where to locate their ambulances to best cover the projected demand for services. Coverage models are used to handle this part of the decision-making process. The earliest models where deterministic, assuming that an ambulance is always available (Church & ReVelle, 1974; Toregas, Swain, ReVelle, & Bergman, 1971). By ignoring the probability that an ambulance would be busy and thus not available, these models tended to overestimate coverage or underestimate the number of ambulances needed (Rajagopalan, 2006).

Probabilistic models, on the other hand, acknowledge the possibility that a given ambulance may not be available when called. Daskin's maximum expected coverage location problem (MEXCLP) (Daskin, 1983) and ReVelle and Hogan's maximum availability location problem (MALP) (ReVelle & Hogan, 1989) address this issue by assuming that (1) ambulances are busy with the same busy probability, and (2) ambulances operate independently of one another. These assumptions enable ambulance availability to be computed beforehand, thus allowing the MEXCLP and MALP models to prescribe ambulance locations using integer programming. The assumption of these models that the busy probability of ambulances be defined as inputs, however, does not reflect real-world concerns accurately. When ambulances cooperate through centralized dispatching, busy probabilities vary across ambulances whose usage level is a function of location and demands. How busy an ambulance is depends on its location with respect to demand. These early models require the busy probability of the ambulances as input data to find the optimal locations to deploy the ambulances.

True probabilistic models are based on either spatially distributed queuing theory (Larson, 1974) or simulation (Henderson & Mason, 2004; Zaki, Cheng, & Parker, 1997). Define a dropped (lost) call as a call that could not be reached within a specified time threshold. Then, given the locations of ambulances, these models evaluate performance metrics such as individual ambulance busy probabilities and the number of dropped calls. This structure and its various extensions have beenuseful in evaluating the performance of EMS systems (Batta, Dolan, and Krishnamurthy, 1989; Burwell, Jarvis, & McKnew, 1993; Chan, 2001; Daskin, 1995; Goldberg, 2004; Jarvis, 1985; Larson, 1974, 1975, 1979, 1981; ReVelle, 1989; Saydam, Repede, & Burwell, 1994; Takeda, Widmer, & Morabito, 2007). Galvao, Chiyoshi, and Morabito (2005) relax the simplifying assumptions that busy probabilities are uniform across ambulances and that ambulances operate independently. They present a unified view of the MEXCLP and MALP by embedding Larson's hypercube model (Larson, 1975) into a heuristic algorithm to calculate each individual ambulance's busy probability at run time. They show that removing these simplifying assumptions reduces the overestimation of coverage.

None of the models discussed so far account for the changing nature of demand and the need for EMS administrators to redeploy their ambulances during different times of the day (e.g., morning and evening rush hours). Repede and Bernardo (1994) extend MEXCLP, calling their model TIMEXCLP, for multiple time intervals, to capture the temporal variations in demand. Gendreau, Laporte, and Semet (2001) develop a dynamic double standard model (DDSM) to maximize backup coverage while minimizing redeployment costs. Schmid and Doerner (2010) allow coverage to vary across time periods, enabling vehicles to be repositioned to maintain a coverage standard. Rajagopalan et al. (2008) extended earlier works by developing the dynamic available coverage location (DACL) model which computes location-specific ambulance busy probabilities to determine the minimum fleet size and the corresponding redeployment strategy to meet the stated coverage objectives. DACL is discussed in further detail in Sects 3.3 and 4.2 of this chapter.

2.3 Patient Survivability

The coverage models discussed above use a travel distance or time standard for service delivery (i.e., coverage). All demand points that are within the threshold are considered covered. The major limitation of this approach is that it does not distinguish one location as better than another as long as both locations are within the given threshold limit, even if one location would result in faster response times. However, distinguishing between two points on the basis of actual response times might improve the survival probability of the patient (Pell, Sirel, Marsden, & Cobbe, 2001; Pons et al., 2005; Valenzuela et al., 2000). McLay and Mayorga (2010) show that while 7 and 8 min response time thresholds maximize patient survival, at least in the case of Hanover County, Virginia, 9 and 10 min thresholds reduce disparity between the lives saved in urban and rural areas. Erkut et al. (2008) incorporate a survival function into the existing coverage models. The survival function is modeled as a monotonically decreasing function that returns the probability of survival for the patient based on the response time of an EMS vehicle. In a similar approach, Rajagopalan and Saydam (2009) develop the minimum expected response location problem (MERLP) which extends coverage models to incorporate expected response times. MERLP, which will be discussed in further detail in the next section, uses the Jarvis (1985) approximation of the hypercube model to not only calculate the coverage, but also to minimize the total expected response time. We discuss comparisons between MERLP and DACL (Rajagopalan et al., 2008) in Sect. 4.

2.4 Equity

An important omission in the EMS modeling literature is research to address specifically the needs of underrepresented, underserved, or vulnerable populations. It can be argued that models focusing on covering demand (hence population regardless of economic or other demographic profile) evenly do provide services to all without discrimination or prejudice. However, as Leclerc, McLay, and Mayorga (2011) clearly illustrate in the Modeling Equity for Allocating Public Resources chapter in this volume, equity functions need to be explicitly developed and incorporated in the respective OR models. We refer the reader to this chapter for an elaborate discussion and four specific recommendations on how to define and model equity in public service allocation problems.

3 Data and Methods

This chapter discusses EMS scheduling applications using data from Mecklenburg County, North Carolina (Fig. 11.1). All data were obtained from MEDIC, the Charlotte–Mecklenburg EMS agency for the time period 1997–2004. Starting in the late 1990s, substantial population growth in the Charlotte area was accompanied by significant urban sprawl. Places that had once been sparsely populated (i.e., comprising a small number of EMS calls per year) became communities with 10,000–15,000 residents generating several hundred calls per year. Given such significant changes in population levels, as well as a shifting population since 1997, our experiments confirmed that older data would not improve the predictive power of the forecasting models. Therefore, the MEDIC data for 2002 and 2003 were used for training and testing, while the MEDIC data from 2004 were used for model validation.

Each EMS call that came into the MEDIC dispatch via 9-1-1 was recorded and included a time stamp, the longitude and latitude of the call, a call priority level, street address, and the medical situation. We deleted from our dataset those elements that might compromise anonymity of callers requesting EMS. The final data fields included the time stamp, longitude and latitude, and priority level for each data record (i.e., call). In order to conduct comparative experiments, the data were reformatted and coded as follows: MEDIC indicated that only priority levels 1 and 2 were considered emergency calls, only these calls were retained. We removed duplicate instances of calls from the database. Based on each time stamp, calls were then recoded to indicate hour of the day represented by (0–23); 3-h time blocks

Fig. 11.1 Map of Mecklenburg County (Greater Charlotte, NC)

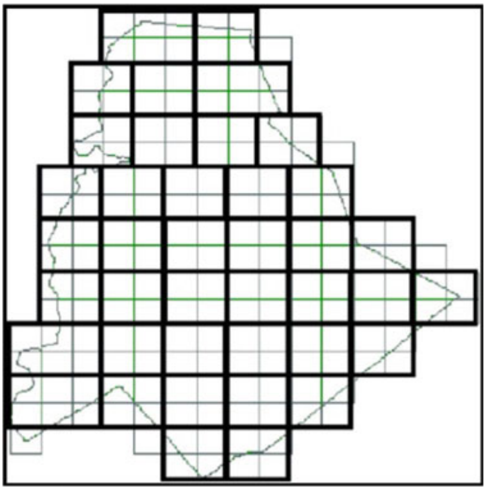

Fig. 11.2 The 2 × 2 and 4 × 4-mile grid configurations overlaying Mecklenburg County, NC map

Table 11.1 Demand distribution per daily time block, Mecklenburg County, NC, for 2004

Time block	Sun.	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.
12 a.m. to 2 a.m.	743	428	446	427	442	459	643
2 a.m. to 4 a.m.	684	380	338	356	386	352	565
4 a.m. to 6 a.m.	382	297	265	302	304	313	361
6 a.m. to 8 a.m.	399	587	524	577	553	544	420
8 a.m. to 10 a.m.	622	850	816	850	854	797	660
10 a.m. to 12 p.m.	780	1015	959	942	1033	951	822
12 p.m. to 2 p.m.	863	994	941	1044	1041	1049	934
2 p.m. to 4 p.m.	870	1026	992	993	1014	1091	927
4 p.m. to 6 p.m.	821	1029	1067	1033	1063	1108	949
6 p.m. to 8 p.m.	866	883	916	884	911	888	970
8 p.m. to 10 p.m.	847	728	757	760	764	876	875
10 p.m. to 12 a.m.	648	591	648	612	673	812	906
Total	8,525	8,808	8,669	8,780	9,038	9,240	9,032

represented by (1–8); day of the week represented by (1–7); month of the year represented by (1–12); and season of the year represented by (1–4). The data were then aggregated spatially. Two different spatial grids were placed over the map of Mecklenburg County, NC. The first grid configuration consisted of 168, 2-mile × 2-mile, squares, while the second grid configuration had 40, 4-mile × 4-mile, squares, as shown in Fig. 11.2. The squares within each grid configuration were labeled, and the program ArcMap™ (ArcMap, 2007) was used to assign each call, or record, based on the calls latitude and longitude, to its appropriate geographic node (i.e., square) number on each of the grid configurations.

For the year 2004, data (see Table 11.1 and Fig. 11.3) show that the county's call demand distribution fluctuates significantly depending on the day of the week and time of day. For the purpose of deployment/redeployment of ambulances, Rajagopalan et al.

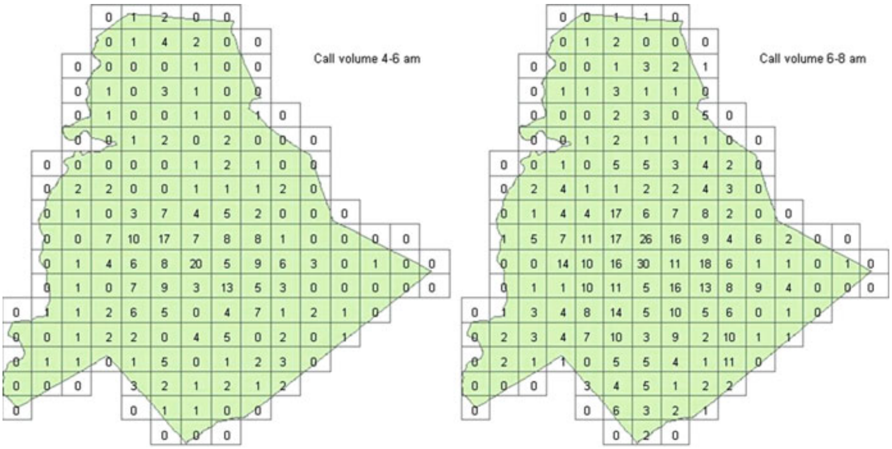

Fig. 11.3 Spatial distributions of calls for Mondays in 2004 for 4–6 a.m. and 6–8 a.m.

(Rajagopalan et al., 2008; Rajagopalan & Saydam, 2009) disaggregate the daily demand into twelve 2-h time blocks. This creates 84 different scenarios (12 time blocks per day × 7 days per week) with varying demand volumes and different spatial demand distributions. Table 11.1 displays the aggregate demand for each of the 2-h time blocks for 2004, while Fig. 11.3 shows the aggregate spatial demand distribution for Mondays in 2004 for the following time periods: 4–6 a.m., and 6–8 a.m. Figure 11.3 illustrates how the call distribution over the entire county before (4–6 a.m.) and during the rush hours (6–8 a.m.) changes. We can easily observe the increase in the call volume specifically in city center and the surrounding access roads. Table 11.1 shows that the volume of calls begins to increase around 8 a.m. and peaks between 4 and 6 p.m., before slowly declining.

3.1 Forecasting Using ANNs

Demand pattern (Brown et al., 2007; Fitch, 2005), especially moving averages, are the most common forecasting methods used in practice. They produce accurate forecasts of EMS call volumes across entire service regions, allowing managers to make more effective resource allocation decisions. Such forecasts have helped EMS managers make more effective resource allocation decisions. However, using such aggregated forecasts over an entire region is not sufficient to effectively deploy often limited resources to minimize response time to an emergency call. These kinds of forecasting models show overall demand for large geographic areas over a long period of time, which is helpful for strategic and tactical capacity planning (long- or intermediate-range planning), but does not help with hourly operational deployment plans (short-range planning). Therefore, these models are difficult to integrate into deployment/redeployment models because the resulting forecasts lack sufficient detail (Channouf et al., 2007).

ANNs are an increasingly popular forecasting method. They represent a viable alternative to traditional causal forecasting techniques because they do not require detailed assumptions about data or error terms: they are not affected by multicollinearity and are adaptable to complex data patterns (DeTienne, DeTienne, & Joshi, 2003). Smith and Gupta (2000) survey applications of ANNs for a variety of business problems. Denton (1995), Cao, Leggio, and Schniederjans (2005), and Chiang, Zhang, and Zhou (2006) demonstrate the advantageous performance of ANNs for causal forecasting as compared to regression models.

ANNs can be applied to EMS call demand forecasting (Setzler et al., 2009). They represent an improvement over conventional methods because of their ability to self-learn, to generalize, and to model nonlinear relationships (Smith & Gupta, 2000). This may make them more valuable than linear models for EMS call demand forecasting since the goal is to generate accurate forecasts for space and time combination for which collecting data on explanatory variables to be used in regression class models is rather problematic. That is, although we know that population and calls for 9-1-1 are highly correlated, we have no means of finding out resident or transient population at a specific time and zone. Therefore, we have excluded explanatory approaches in favor of a neural network approach which does not explain the underlying causal mechanism but can help capture complicated associations leading to accurate predictions (Shmueli, 2010).

The neural network used in Setzler et al. (2009) is a forward feeding multilayer perceptron (Zhang, Patuwo, & Hu, 1998). This approach was motivated by the fact that approximately 95% of ANN business applications use a multilayer feed-forward neural network (MFNN) with back propagation learning (Wong, Bodnovich, & Selvi, 1997). MFNNs are found to be very good at learning relationships between inputs and known outputs (Smith & Gupta, 2000). The input nodes focus mainly on temporal factors (time of day, day of the week, etc.). ANNs provide connections between inputs and a hidden layer, and between the hidden layer and an output layer. If there is a linear relationship between inputs and outputs, however, the connection can skip the hidden, learning, layer and go directly from input to output (Zhang et al., 1998). Figure 11.2 illustrates the ANN's physical framework for forecasting EMS call demand during time blocks for geographic nodes, where each type of input and output node has a unique number of n nodes.

H_n= time blocks (0–23 or 1–8); where $n = 24$, or 8, total input nodes;
S_n= season of the year (1–4); where $n = 4$ total input nodes;
D_n= day of the week (1–7); where $n = 7$ total input nodes;
M_n= month of the year (1–12); where $n = 12$ total input nodes.

There are a total of 47, or 31, input nodes depending on whether 1- or 3-h time blocks are used. Each node is assigned a binary value of 0 or 1. For each of the four input variables, only one input node out of n nodes has a value of 1, and all others have a value of 0. The number of output nodes depends on the grid size, resulting in

V_n= volume of calls for each geographic node; where $n = 168$, or 40.

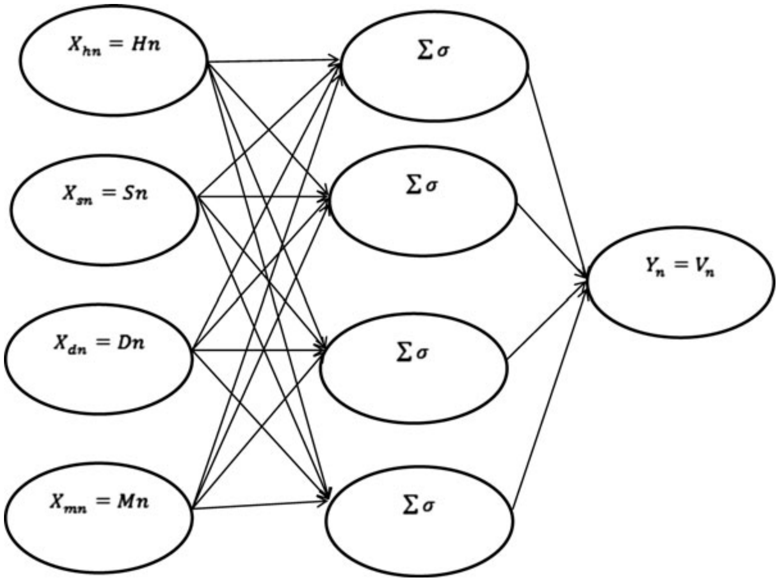

Fig. 11.4 Physical network for the ANN

The ANN in Fig. 11.4 contains three layers (input, hidden, output). The hidden layer allows ANN to accommodate the nonlinearity in the data (Ling, Leung, Lam, & Peter, 2003; Trudeau et al., 1989) and allows the ANN to be adaptive. This study uses one hidden layer to reduce the complexity of the network, as well as reduce the time for training. Each input node is fully interconnected to all the nodes in the next layer. According to Zhang et al. (1998), there are no definite rules for determining the number of nodes in the hidden layer. There are many heuristics, ranging from $H = I, H = I + 1, H = I - 1, H = 2I$, where "$H$" represents the number of hidden nodes and "I" is the number of input nodes. Under these conditions, this model could have anywhere from 30 to 94 hidden nodes. However, when using categorical variables in ANNs, each variable can be considered to be one input variable when determining the number of hidden nodes to use (Golden, 1996). Since this model has four categorical input variables, then only four input nodes will have nonzero values; therefore, four hidden nodes were initially introduced into the model. Several activation functions, including the two most widely used: sigmoid and hyperbolic tangent were tried within this model. The most common activation function for causal forecasting is the former, whereas the latter is also sometimes used for forecasting problems (Zhang et al., 1998). In this work, there was little difference in forecasting performance between the two. The training algorithm used here is back propagation because it was shown to perform well in predictive models. SAS® software package was used to model the ANN in this study.

3.2 Optimization Methods

As noted earlier, recent models have used spatially distributed queues (Jarvis, 1985; Larson, 1974; Larson, 1975) to determine ambulance locations and individual busy probabilities, but these models use heuristic algorithms (Michalewicz & Fogel, 2000) which can recalculate the individual ambulance busy probabilities at run time. Rajagopalan, Vergara, Saydam, and Xiao (2007) used a statistical experimental design to analyze the effectiveness of four different meta-heuristic search methodologies (genetic algorithms, tabu search, simulated annealing, and hill climbing) for the MEXCLP model and compared the results to the optimum solution produced by linear programming. This study showed that all four meta-heuristic methods produced close to optimal solutions and thus could be used as a solution methodology when solving problems which are mathematically intractable and which preclude the use of integer linear programming or other mathematical programming techniques.

3.3 DACL Model

Once the forecast for demand is complete, the DACL (Rajagopalan et al., 2008) can be used to help EMS administrators determine the minimum number of ambulances required and the deployment locations for each ambulance during each time block while meeting the coverage requirements with a predetermined reliability (i.e., coverage). Reliability is defined as the probability that a demand node will be covered. DACL uses the Jarvis hypercube approximation (Jarvis, 1985) to ensure that ambulance cooperation is taken into consideration. Larson's hypercube approximation (Larson, 1975) assumes service times to be exponentially distributed, Jarvis extension (Jarvis, 1985) relaxes that assumption and uses general distributions for service times.

Let t be the index of time blocks from 1 to T, m_t be the number of ambulances at time period t, $h_{j,t}$ be the fraction of demand at node j (e.g., grid) at time block t, k be the nodes in which ambulances are located, n be the number of nodes in the system, and c_t be the minimum expected coverage requirement at time block t, and α_t be the reliability of the system at time block t. Let $\rho_{i,t}$ be the busy probability of a ambulance i at time block t, ρ_t be the average system busy probability at time block t, P_0 be the probability of having all ambulances free in an $M/M/m/m$ system, P_m be the probability of having all ambulances busy in an $M/M/m/m$ system, and $Q(m, \rho_t, j)$ be the correction factor (Q factor) for Jarvis' algorithm which adjusts the probabilities for ambulance cooperation in the models. We represent the correction factor as follows:

$$Q(m, \rho_t, j) = \frac{\sum_{k=j}^{m-1} (m-j-1)!(m-k)(m^k)(\rho_t^{k-j})P_0}{(k-j)!(1-P_m)^j m!(1-\rho_t(1-P_m))} \forall j = 0, 1, ..., m-1. \quad (11.1)$$

We define the following decision variables:

$$x_{ikt} = \begin{cases} 1 \text{ if server } i \text{ is located at node } k \text{ at time } t \\ 0 \text{ if not} \end{cases},$$

$$y_{jt} = \begin{cases} 1 \text{ if node } j \text{ is covered by atleast one server with } \alpha \text{ reliability} \\ 0 \text{ if not} \end{cases},$$

Finally, we define:

$$a_{ijt} = \begin{cases} 1 \text{ if node } j \text{ is within the distance threshold of server } i \text{ at time interval } t \\ 0 \text{ if not} \end{cases},$$

Then our optimization model is:
Minimize

$$\sum_{t=1}^{T} \sum_{k=1}^{n} \sum_{i \in k} x_{ik,t} \tag{11.2}$$

Subject to

$$\left[\left\{1 - \prod_{i=1}^{m_t} p_{i,t}^{\sum_{k=1}^{n} a_{ij} x_{ik,t}} Q\left(m_t, \rho_t, \sum_{j=1}^{n} \sum_{i=1}^{m_t} a_{jk,t} x_{ij,t} - 1\right)\right\} - \alpha_t\right] y_{j,t} \geq 0 \quad \forall j, t \tag{11.3}$$

$$\sum_{j=1}^{n} h_{j,t} y_{j,t} \geq c_t \quad \forall t. \tag{11.4}$$

$$y_{j,t}, x_{ik,t} \in \{0, 1\} \; \forall i, j, k, t. \tag{11.5}$$

The objective function (11.2) minimizes the number of ambulances across nodes and time blocks. Constraints (11.3) stipulate that only the demand nodes that are covered with alpha reliability will be included in the system-wide expected coverage statistic. Constraints (11.4) ensure that the total system-wide coverage will be greater than c_t, the minimum expected coverage requirement for each time block. All decision variables are defined as binary through (11.5).

The DACL model (11.2)–(11.5) requires that individual ambulance busy probabilities be known at run time. Since this is difficult to do with conventional optimization-based methods, we developed a search heuristic to solve DACL. We start by defining an initial number of ambulances for the first time period. The main algorithm uses reactive tabu search (Battiti & Tecchiolli, 1994; Glover & Laguna,

1997) to select the best deployment locations for the ambulances. Next, Jarvis' hypercube approximation algorithm computes the individual ambulance busy probabilities and the resulting system-wide coverage. If the coverage does not meet minimum requirements, we run the reactive tabu search algorithm and the hypercube approximation again. This process continues until the resulting system-wide coverage is within the required response time threshold.

If the system-wide coverage exceeds minimum requirements, an ambulance is removed and the reactive tabu search algorithm along with the Jarvis hypercube approximation is run again to find a new set of locations, and this process continues until the coverage is just under the required threshold. Once the ambulance deployment locations for the first time period are generated, the algorithm uses these locations in the second time period as the initial solution. If the coverage requirements are met, then the algorithm goes to the next time period. Otherwise, the algorithm redeploys ambulances to meet the coverage requirements. If, post-deployment, ambulances do not meet coverage requirements, we add another ambulance and the algorithm continues redeploying until the coverage threshold is met. The details of the algorithm can be found in Rajagopalan et al. (2008).

3.4 MERLP Model

While useful, coverage models have an inherent limitation: coverage is treated as a binary variable and a demand node is treated as covered when an ambulance is available within a predetermined distance (or equivalently response time) threshold. As a result, coverage models do not favor solutions where ambulances are located closer to demand and thereby result in decreased response time over those solutions where the incident would still be covered but response time would be greater. MERLP begins by using the locations identified from DACL; the DACL solution is then improved upon by taking into consideration response travel distances.

Let n be the number of nodes in the system, m the total number of ambulances available for deployment/redeployment, d_{jk} be the distance or time from node j to k^{th} preferred (closest) ambulance capable of serving node j, where set N_j contains all ambulances that can cover node j. Also, let ρ be the average busy probability of all ambulances, ρ_k be the busy probability of the k^{th} preferred ambulance for a given demand node, and h_j be the fraction of total demand originating from node j. To be able to compute individual ambulance busy probabilities, it is necessary to identify (track) exactly which ambulances are located at a given node. Hence, we define the main decision variable as follows:

$$x_{jk} = \begin{cases} 1 \text{ if server } k \text{ is located at node } j \\ 0 \text{ otherwise} \end{cases}.$$

Conversely, we track those ambulances that cover node j with the following decision variable:

$$y_j = \begin{cases} 1 \text{ if node } j \text{ is covered with } \alpha \text{ reliability} \\ 0 \text{ otherwise} \end{cases}.$$

In developing expressions for the objective function and the expected coverage requirement constraint, it is first necessary to compute the location-specific ambulance busy probabilities, ρ_k, using Jarvis' hypercube approximation algorithm and the correction factor (Q factor). The Q factor adjusts the joint probabilities for ambulance cooperation. Thus, the system-wide expected response distance objective can be written as: $\sum_{j=1}^{n}\sum_{k=1}^{m} Q(m,p,k-1)d_{jk}h_j y_{jk}(1-p_k)\prod_{l=1}^{k-1} p_l$.

Then the model MERLP is written as follows:

Minimize

$$\sum_{j=1}^{n}\sum_{k=1}^{m} Q(m,p,k-1)d_{jk}h_j y_{jk}(1-p_k)\prod_{l=1}^{k-1} p_l. \tag{11.6}$$

Subject to

$$\left[\left\{1-\prod_{k=1}^{m} p_k^{x_{jk}\in N_j} Q\left(m,\rho,\sum_{k=1}^{m} x_{jk\in N_j}-1\right)\right\}-\alpha\right] y_j \geq 0 \quad \forall j, \tag{11.7}$$

$$\sum_{j=1}^{n} h_j y_j \geq c, \tag{11.8}$$

$$\sum_{j=1}^{n}\sum_{i=1}^{m} x_{ij} = m, \tag{11.9}$$

$$y_j, x_{ij} \in \{0,1\}. \tag{11.10}$$

The objective function (11.6) represents the expected sum of distance traveled in response to demand from each node for demand nodes covered with α reliability. Constraints (11.7) compute the difference between the actual probability of covering node j and α. If this difference is positive, y_j is set to 1, indicating that node j is covered with the required reliability α. System-wide target coverage requirements are implemented via the second constraint (11.8), where, as with expression (11.6), those demand nodes covered with α reliability are subsequently accounted for in the system-wide tally of expected coverage with target (c), for example, $c = 95\%$. The remaining nodes are either not adequately covered, or uncovered. The third constraint (11.9) specifies the number of ambulances in the system while the last constraint (11.10) includes integrality restrictions.

In order to solve model (11.6)–(11.10), we must first compute values for parameters ρ_k and $Q(m, \rho, k-1)$. Their values are dependent on the decision variable $x_{j,k}$. Therefore, this model cannot be solved using conventional ILP optimization software. Instead, we apply heuristic solution methods. As stated earlier, the solution algorithm that Rajagopalan and Saydam (2009) chose for this model uses as its initial input the solution obtained from DACL (Rajagopalan et al., 2008) and then improves upon that solution. The improvement algorithm is a greedy search algorithm with a large neighborhood size. While greedy search algorithms tend to get stuck in local optima, using a large neighborhood size improves the quality of the locally optimal solution, thereby increasing the accuracy of the final solution. Also, the starting solutions used in the MERLP algorithm are not randomly generated; the algorithm uses an initial high-quality solution. Details of this algorithm can be found in Rajagopalan and Saydam (2009).

4 Results

4.1 Forecasting Using an ANN

We initially used several variables to predict demand for the Charlotte MEDIC dataset. These variables included time of day, day of the week, month of year, and season of the year. During testing of the ANN, it was found that the inclusion of the season of the year variable generally improved the model's performance.

The best performing ANN had the following structure: The ANN was an MFNN using back propagation as the training method, with one input layer using binary data and one hidden layer using four (one for each category) hidden nodes. The sigmoid activation function was applied and the performance (error) measure used during the training was the mean squared error (Zhang et al., 1998). The data for 2002 and 2003 were divided, with 75% of the data used for training and 25% of the data used for validation. These data were used to forecast demand for the first weeks of June and November for 2004.

We conducted a descriptive statistical analysis of forecast errors for 4×4 square mile grids and 1-h time period to determine the quality of ANN forecasts. The forecast bias (error) is simply the difference between the forecast and the actual value during a specific time bucket in a specific geographic grid. During a randomly selected 1-week time period, using 1-h time blocks, 39 geographic nodes, and 6,552 observations, 6,552 forecasts can be made. Therefore, for the 2 weeks shown in Table 11.2 using ANN, we generated a total of 13,104 forecasts and analyzed the resulting errors.

On average, ANN showed a slight negative bias; -0.025. Since averages may hide significant deviations that could lessen the practical value of forecasts that

Table 11.2 Bias summary statistics for 2 weeks of forecasts for 4 × 4 1-h granularity

Bias	±0.25	±0.50	Min	Max
ANN	75%	88%	−6.17	1.00

MEDIC requires, a detailed investigation of forecast errors for each time block-grid combination was conducted for 4 × 4, 1-h blocks for 2 weeks. However, there is currently no established benchmark for forecast accuracy in the EMS literature. A notable exception is a recent study by Brown et al. (2007) in which they arbitrarily defined forecasts as accurate if they were within ±1 call. According to Gorr, Olligschlaeger, and Thompson (2003), forecast accuracy somewhat depends on the average call volumes. The study by Brown et al. (2007) looked at hourly call volumes for entire counties (regions) with hourly call volumes ranging from 0 to 31. Therefore, we concur that their definition of accuracy is reasonable. In 2004, the average and the range of hourly call volumes for 4 × 4 square mile regions were 0.18, [0, 8]; and for 3-h increments they were 0.54, [0, 15]. Hence, in our study we considered forecasts accurate if they are within ±0.25 of actual calls for hourly forecasts. Table 11.2 shows the frequency of forecasts having a bias less than 0.25 and less than 0.5, as well as the maximum and minimum biases.

The *range* of bias could be of concern to practitioners they use forecasts as an input to the complex decision of relocating ambulances at various locations throughout the day. In this regard, the minimum bias associated with extreme underestimation may also be of importance, given that a practitioner may seek in excess of 90% coverage throughout the county with a minimum of 85% coverage in each zone. The maximum (largest over-forecast) and the minimum biases (largest under-forecast) from all 13,104 observations were 1.00 and −6.17 for the ANN. Given that approximately 75% of the forecasts are within ±0.25 calls, these forecasts can be used in conjunction with a relocation model such as DACL.

4.2 DACL Model and MERLP Model

DACL minimizes the number of ambulances needed to cover a region during each time block, whereas MERLP locates ambulances to meet coverage requirements while minimizing expected system-wide response distances. Rajagopalan et al. (2008) used 3-h time blocks to calculate the number of ambulances needed and the redeployment plans. However, to compare the results from DACL and the MERLP, in this chapter we opted to use 2-h time blocks. First, we ran the DACL to obtain the minimum number of ambulances required to cover the Charlotte–-Mecklenburg area for the forecasted demand for 2004 in 2-h time blocks which are shown in Table 11.3.

Table 11.4 shows the number of redeployments needed after period 1 to maintain coverage. Redeployments vary from a maximum of 10 ambulances to 0. DACL tries to minimize the number of ambulances needed to maintain coverage, but it

Table 11.3 Minimum number of ambulances to cover Charlotte–Mecklenburg in 2004

Time block	Sun.	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.
1	18	13	14	15	14	16	17
2	17	14	15	15	14	15	17
3	15	13	13	13	13	14	14
4	14	17	16	17	16	15	14
5	16	19	18	19	19	19	16
6	18	20	20	20	20	19	18
7	20	20	19	21	20	21	20
8	19	20	19	22	18	22	19
9	18	19	20	20	18	21	19
10	18	19	18	18	18	18	19
11	18	18	18	17	17	19	18
12	17	16	17	17	16	18	18

Table 11.4 The number redeployments required to meet required coverage for DACL

Time block	Sun.	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.
1	–	–	–	–	–	–	–
2	1	1	4	0	1	0	0
3	0	0	1	1	0	0	4
4	5	3	3	4	2	10	5
5	1	1	2	9	4	2	2
6	6	4	1	10	9	1	2
7	0	2	0	4	1	4	4
8	0	0	0	0	0	7	0
9	0	0	7	2	0	0	1
10	6	1	1	0	0	0	0
11	0	1	0	2	2	0	0
12	0	0	0	2	0	0	0

does not try to minimize the number of redeployments which is another important parameter for EMS administrators to consider. Because of this limitation, DACL can recommend a large number of redeployments.

By definition, MERLP and DACL both must meet or exceed coverage requirements for each time block; however, MERLP reduces the total redeployment distances traveled. In order to measure the benefits derived from using MERLP, the total response distances from both models was calculated, as well as the totals from DACL for each of the twelve 2-h time blocks. Response travel distances saved by using MERLP over DACL for each time period for the 84 problems are displayed in Table 11.5.

Consider the problem instance depicted in Fig. 11.5, which displays deployment for DACL and MERLP for a sample 1-h time block in the Charlotte–Mecklenburg region. We observe that MERLP tends to move ambulances to areas that have higher demand to reduce overall response travel time. In this example, the MERLP solution saves approximately 146 miles in response travel distance by moving ambulances closer to the center of the city where demand is higher.

Table 11.5 Savings in distance traveled (miles) for MERLP over DACL

Time block	Sun.	Mon.	Tue.	Wed.	Thu.	Fri.	Sat.
1	75.58	30.38	26.12	51.68	111.40	97.39	146.35
2	414.35	56.54	54.24	84.49	78.89	106.79	74.92
3	194.34	99.54	19.65	160.62	115.01	77.40	80.42
4	48.08	170.60	210.14	199.96	38.27	98.27	12.44
5	35.27	56.10	268.78	98.80	29.56	143.05	218.99
6	95.38	203.45	215.42	96.15	34.90	57.92	56.19
7	142.31	125.38	247.75	123.10	113.01	295.75	87.93
8	162.02	167.20	217.08	108.06	52.95	164.87	39.95
9	113.80	170.78	73.14	116.57	122.59	181.39	106.24
10	21.34	80.40	0.00	101.52	33.90	4.01	25.99
11	31.90	7.38	245.11	9.57	168.22	466.01	14.74
12	17.63	149.74	168.65	58.32	54.17	215.35	69.58

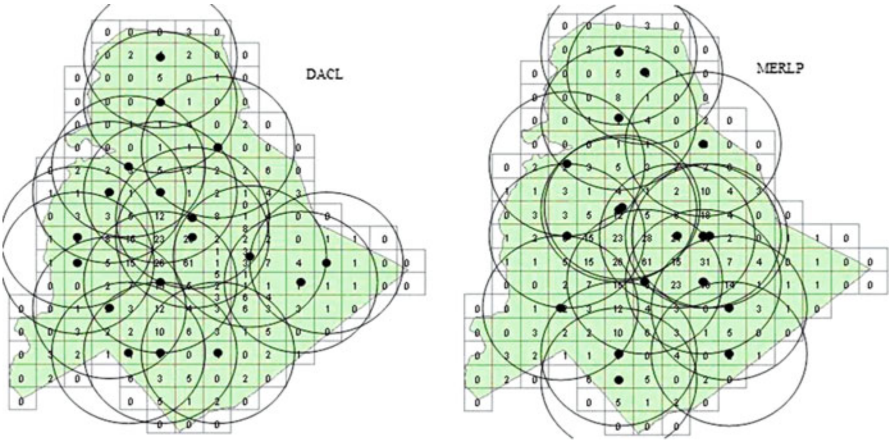

Fig. 11.5 Placement of ambulances for DACL and MERLP

While the savings can be marginal for a specific time block, the cumulative savings can be significant. For example, using Charlotte–Mecklenburg data we show that when MERLP is used in conjunction with DACL the total response distances saved would have been in excess of 9,419 miles in 2004.

5 Conclusions and Implications to the Community

This chapter has introduced research to assist EMS practitioners to make routine daily decisions regarding ambulance location across an urban area using specialized forecasting models and optimization models. We surveyed three recent papers in this area to illustrate these concepts. An ANN was used to forecast demand, and two deployment/redeployment models were presented for determining where ambulances should be located. Both of these deployment/redeployment models use meta-heuristics. The first model, DACL, determines the minimum number of servers (ambulances) that are needed to cover demand given a time standard threshold. The second model, MERLP, improves upon the DACL results by minimizing the total overall travel distance for a fleet of ambulances.

Using an integrated forecasting and ambulance deployment strategy could save more lives and lessen suffering, while, at the same time, making more efficient use of community resources. For example, an ANN-based forecasting system can be implemented which would be running in parallel to a deployment model decision support system where recent data are complied and the ANN is periodically retrained and deployment plans updated based on changing forecasts.

The findings from our research and other published articles are available for practitioners and software developers. The models in this chapter have not yet been implemented in practice; however, these and other findings from the academic literature are available for practitioners and software developers to adapt for operational use. Indeed, versions of the dynamic redeployment model have been incorporated into information technology applications. For example, MARVLIS Deployment Planner™ (Bradshaw Consulting Services, 2008) is one of the products used by MEDIC of Charlotte to determine where and when to post their ambulances.

One of the shortcomings of the models in this chapter is the explicit modeling of equitable allocation of the EMS services to all communities. Further, to the best of our knowledge, there is no published research specifically addressing the EMS needs of underrepresented, underserved, or vulnerable populations, at least not in the modeling literature. Suggestions for future research include an exploratory investigation of call handling (triage) and dispatching of ambulances from the perspective of these special communities. This might necessitate the ability to deploy and dispatch heterogeneous services based on the severity of the incident. Therefore, some areas that could be investigated include: EMS modeling studying emergency and nonemergency calls using multiple types of response vehicles, crew profiles, target response times for various categories, community education, etc. These efforts will undoubtedly require defining equity for each of the goals and developing corresponding models. For an in depth discussion on this topic, we refer the reader to the Modeling Equity for Allocating Public Resources chapter (Leclerc et al., 2011).

Another future research direction in modeling might include randomness (i.e., variations in travel times) in response times, using the concept of fuzzy coverage and an analysis of the impact of redeployment on EMS personnel. Finally, given how critically important it is to have accurate predictions of calls per space and time and very little work done in this area, future research might include a comparative study examining the accuracy of ANNs and other forecasting methods.

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Chapter 12
Capacity Planning for Publicly Funded Community Based Long-Term Care Services

Feng Lin, Nan Kong, and Mark Lawley

1 Introduction

Long-term care (LTC) provides medical and non-medical care to individuals who have limitations in activities of daily living (ADLs) due to chronic disease or disability. More than 10 million people in the U.S. need LTC; two-thirds of these people are 65 years and older (Health Policy Institute, Georgetown University, 2007; Stevenson, 2008). In 2005, the national spending on LTC was $207 billion, almost 60% of which was spent on the elderly (Health Policy Institute, Georgetown University; Stevenson). Public programs are the major financing source for LTC. In 2005, Medicaid covered 43% of the national LTC services (Kaiser, 2009a; Wiener et al., 2004), whereas Medicare covered 20%[1] (Health Policy Institute, Georgetown University). Along with the aging population (Humes, 2005), spending on LTC for older adults is projected to increase to more than $340 billion by 2040 (Burwell, Sredl, & Eiken, 2008; Harrington, Carrillo, Wellin, Miller, & LeBlanc, 2000; Stevenson 2008). To curb the escalating expenditure, federal and state policy makers seek more affordable LTC delivery methods.

LTC involves a variety of medical, personal, and supportive services, classified into two categories of assistance: ADLs, such as bathing, dressing, toileting, and walking, and instrumental activities of daily living (IADLs), such as housekeeping,

[1] Medicare is an insurance program administered by the United States government, providing health insurance coverage to people who are aged 65 and over, or who meet other special criteria (Centers for Medicare and Medicaid, 2011). Medicaid is the United States health program for low-income, financially needy people, which is jointly funded by the state and federal governments, and is managed differently in each state (Centers for Medicare and Medicaid, 2011). Generally, Medicare only pays for medically necessary skilled nursing facility or home health care (Centers for Medicare and Medicaid, 2011).

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shopping, preparing meals, and managing money (Smith et al., 2000). The traditional means of delivering LTC, that is, nursing home care, provides skilled nursing care in designated inpatient environment, such as nursing homes. This form of LTC is expensive and oftentimes may exceed the needs of many care recipients (Kaiser, 2009a, 2009b). Community-based services, on the other hand, provide personal care in the recipients' home rather than in an institutional setting. They are significantly less expensive and are preferable for those patients who do not need intensive nursing care (Kaiser, 2009a, 2009b).

Community-based LTC, which is paid by federal and state governments, is also known as home and community-based services (HCBS). HCBS program allows states to provide a wide-array of health and personal services to people who in their home or community would otherwise be cared for in nursing homes. Under various HCBS, states may provide LTC via various forms. Examples of HCBS include adult day care, respite, personal care, chore services, personal emergency response system, environmental adaptations, home delivery meals, nursing care, transportation, and medical equipment (Fox & Kim, 2004; Smith et al., 2000; Stone, 2000). People who meet nursing home admission criteria, or level-of-care criteria, may apply for a HCBS program (Smith et al. 2000). However, an applicant can receive HCBS only if the services are available in the nearby area and the array of services is appropriate for the applicants medical and personal needs. As a more flexible care option compared to nursing home care, community-based services can better personalize the LTC provided to each individual by determining appropriate level and amount of services according to his/her physical and mental status, his/her medical expenditures, and the availability of informal caregivers (e.g., family members).

Research on characteristics and health outcomes of people who receive publicly funded LTC has yielded a variety of results, including patient satisfaction, service level, and quality measurement. For example, people who use community-based services typically report higher level of satisfaction than those in nursing homes (Weissert & Hedrick, 1994; Weissert & Musliner, 1997; Weissert, Cready, & Pawelak, 2005). Studies on dementia patients conclude that a few hours of home care may be adequate for the majority of the patients; hence nursing homes may provide a level of care greater than what is needed (Fox, Maslow, & Zhang, 1999; Mechanic & McAlpine, 2000; Miller et al., 2004; Tonner & Harrington, 2003). Recent analyses of Indiana HCBS Aged and Disabled waiver patients suggest that the volume of HCBS received is low, but even a few hours of such services per month can reduce the risk of hospitalization as compared to people receiving no services at all (Xu et al., 2009). On the other hand, HCBS recipients are found to have higher rates of hospitalization after 12 months than nursing home residents (Sands et al., 2008). Some researchers investigate the development of standards for HCBS quality measurement (Caro, Gottlieb, & Safran-Norton, 2000; Morrow-Howell, Proctor, & Dore 1998; Wiener & Tilly, 2003). Proposed standards include presence or absence of specific conditions, overall health status, and assessment of need and assistance received in ADLs and IADLs.

Research on LTC has also addressed expenditures and correlates of these expenditures. HCBS is found to reduce the average per-capita cost as compared to nursing homes (Mitchell, Salmon, Polivk, & Soberon-Ferrer, 2006; Muramatsuand & Campbell, 2002; Schwab, Leung, Gelb, Meng, & Cohn, 2003, Weissert & Hedrick, 1994; Weissert et al., 2005; Wiener & Tilly, 2003). Identified factors associated with Medicaid LTC expenditures include demographics (socioeconomic and care needs), availability of informal caregiving, and other Medicaid expenditures (Andersen & Newman, 2005; Howell-White, Gaboda, Rosato, & Lucas, 2006; LeBlanc, Tonner, & Harrington, 2001; Muramatsuand & Campbell, 2002). The number of HCBS recipients has steadily increased since 2000 (Feder, Komisar, & Niefeld, 2000; Welch, Wennberg, & Welch, 1996). However, in many states, almost all LTC funding supports institutional rather than community-based care, especially for the elderly (Binstock & Spector, 1997; Feder, Komisar, & Niefeld, 2000; Kane, Kane, & Veazie, 1998). As a result, community-based LTC has very limited accessibility, even though most people prefer to stay at home (Kitchener, Ng, & Harrington, 2003). Thus, policy makers are interested in creating a balanced LTC delivery system that more effectively uses limited resources.

There are very few quantitative studies focusing on decision modeling for LTC. We are unaware of any quantitative studies that provide guidelines for informing resource allocation or care assignment of community-based LTC program in the context of a balanced LTC delivery system. The decision to expand community-based care, or HCBS, as an alternative to nursing homes is complex. This decision requires analysis of the publicly funded LTC system and many factors, such as the demand for LTC, costs of providing LTC in the communities and nursing homes, and the numbers of people currently receiving community based or nursing home care.

How should the publicly funded LTC be delivered? What are the cost and effectiveness of various strategies of LTC budget/service allocation? How many people should receive nursing home care and how many should receive community-based care? How should the policy makers assign constrained resources to meet various needs in a community? What are the most cost-effective means to coordinate and manage community-based LTC? All these issues are important yet do not have simple answers. Operations research and management science (OR/MS) has been advocated for use to improve health care delivery (Committee on Engineering and the Health Care System and Institute of Medicine and National Academy of Engineering, 2005), which is achieved through the application of mathematical modeling and analysis. Over the past 30 years, the application of engineering methods has been successfully applied in the manufacturing, logistics, distribution, and transportation (Kossiakoff & Sweet, 2003; Committee on Engineering and the Health Care System and Institute of Medicine and National Academy of Engineering, 2005). These OR/MS approaches, properly modified and applied, can provide similar impacts on the LTC delivery system.

In this chapter, we present an application of OR/MS to improve decision making regarding LTC. We apply optimal control theory to determine the optimal level of the infrastructure capacity for a publicly funded HCBS program. To the best of our knowledge, our work is the first that addresses the issue of balancing various LTC options with a systematic analysis. We develop a compartmental model to simulate the population flows through the publicly funded LTC system with a systematic analysis. The objective of the optimal control problem is to minimize the total spending on LTC and potential acute care for LTC patients over an extended period. In this optimization problem, the only decision variable is the conceptualized capacity level of HCBS program. A case study is presented using published LTC data.

This chapter is organized as follows. In Section 12.2, we describe policy and practice aspects of health care capacity planning. Section 12.3 presents the optimal control model for LTC with a case study. Section 12.4 discusses the opportunities and challenges for future research. Section 12.5 provides conclusion of this chapter.

2 Capacity Planning in Healthcare

There are very few quantitative studies on planning or decision making for the LTC system, especially for community-based services. Applications of decision analysis and operations research to LTC planning include (Hare, Alimadad, Dodd, Ferguson, & Rutherford, 2009; Pelletier, Chaussalet, & Xie, 2005; Xie, Chaussalet, & Millard, 2005; 2006a; Xie, Chaussalet, Thompson, & Millard, 2007; Xie, Chaussalet, Toffa, & Crowther, 2006b). Hare et al. developed a deterministic Markov model to predict the future demands for community-based LTC programs in Canada (Hare et al., 2009). Xie et al. developed a forecast model to predict the cost for various types of LTC (Xie et al., 2006b). They also used logistic regression model to support placement decisions for admissions to LTC in London, UK (Xie et al., 2002; Xie, Chaussalet, Thompson, & Millard, 2007). Xie and Pelletier et al. developed a continuous Markov model to study the transition and length of stay within and between residential home care and nursing home care in UK (Pelletier et al., 2005; Xie et al., 2005, 2006a). These studies used descriptive models to predict outcomes under predefined scenarios. They did not provide any strategy or policy for achieving certain goals for future development of LTC system.

Capacity planning problems in health care services have been studies by many operations researchers since the 1980s. Simulation has been used to evaluate operations of a health care facility under predefined capacity level of resources, such as inpatient bed, ICU bed, diagnostic equipment, nurses, and physicians (Harper & Shahani, 2002; Parry & Petroda, 1992; Vassilacopoulos, 1985a). Optimization models have been applied to identify optimal capacity level or resource allocation strategies for health care services (Bretthauer & Cote, 1998; 2005; Green, Savin, & Wang, 2006; Jaumard, Semet, & Vovor, 1998; Kwak & Lee, 1997; Patrick & Puterman, 2007; Smith-Daniels, Schweikhart, & Smith-Daniels, 1988; Vassilacopoulos, 1985a). Bretthauer et al. used mixed integer programing to determine the bed and staffing capacity (Bretthauer, & Cote, 1998). Green et al. modeled the operations of a medical diagnostic facility using a dynamic programing to derive real-time capacity allocation policy (Green et al., 2006). Patrick et al.

formulated an optimization model to derive scheduling policies to maximize the capacity utilization in a CT department (Patrick, & Puterman,2007). Kwark and Jaumard developed linear programing models to allocate limited human resources in a health care organization (Jaumard et al. 1998; Kwak, & Lee, 1997). Vassilacopoulis developed dynamic programing models to determine weekly shift of doctors in the emergency department (Vassilacopoulis, 1985a). Summaries of health care capacity planning are provided in (Green, 2005; Smith-Daniels et al. 1988) with discussion on the potential of operations research applications for addressing these problems.

Researchers have also used decision models to plan for senior service centers (Gorr, Johnson, & Roehrig, 2001; Johnson, Gorr, & Roehrig, 2002; Johnson, Gorr, & Roehrig, 2005). Gorr et al. developed demand forecasting models for home-delivered meals to identify specific demand points and levels of demands (Gorr et al. 2001). Johnson et al. formulated an optimization model to compare procedures of location routing of senior centers (Johnson et al., 2002). Later they used integer programing with domain-specific demand forecasts to optimally locate senior centers (Johnson et al., 2005).

3 Application of Operations Research in LTC Planning

In this section, we illustrate an example of applying operations research techniques to facilitate decision making in LTC planning, with emphasis of capacity planning of community-based LTC. The method we used is optimal control, which has been widely applied in policy analysis (Benchekrouna and van Long, 1998; Caulkins et al., 2005; Sethi, 2005). Ordinarily, the capacity of nursing homes should be another component of this decision model. However, taxpayers and patients alike have expressed preferences for HCBS to nursing homes, the former because of decreased fiscal impacts of HCBS and the latter because of desire for home-based services (AARP, 2010). Therefore, it is reasonable to assume that inpatient facilities and skilled nursing resources are abundant when investigating the impact of HCBS on the overall LTC delivery system.

3.1 Optimal Control Model

Our optimal control model for LTC provision is based on four population groups ("compartments") affected by LTC. All individuals in each compartment are identical with respect to some characteristics. Transition rates define the speed at which persons in one compartment are transformed into another compartment (Godfrey, 1983). Figure 12.1 shows the four compartments for the LTC model: the population receiving HCBS (compartment H); the population receiving institutional care (Compartment N); the population applying for LTC but not being

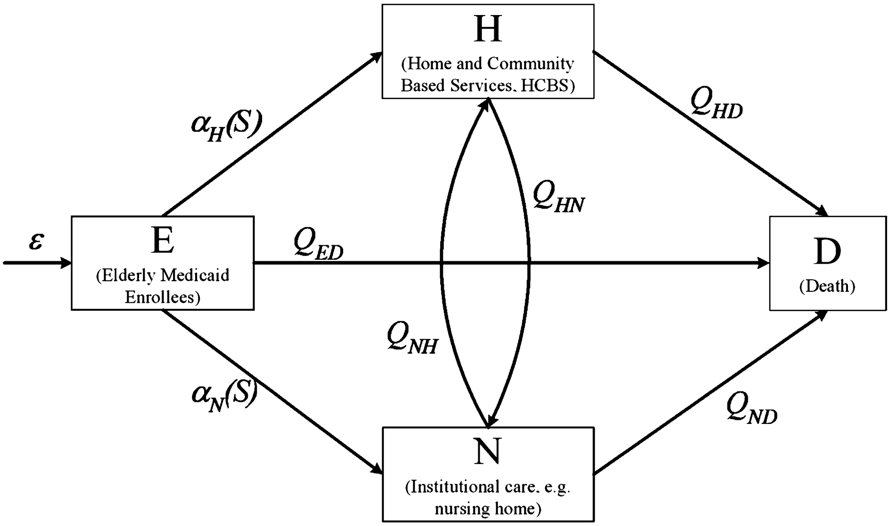

Fig. 12.1 The compartmental model for HCBS capacity planning. Boxes represent compartments and arrows represent flow between compartments. H – HCBS; N – institutional care; E – without LTC; D – death

admitted to either one (Compartment E), and the population who have died (Compartment D).

Let I be the set of symbols indicating the compartments, that is, $I = \{H, N, E, D\}$. We assume that the population in each compartment is homogeneous, that is, individuals in each compartment receive identical LTC services. This implies that for all individuals in a compartment $i \in I$, the transition rate to another compartment $j \in I$ is identical. Let T be the length of the planning period. At time $t \in [0, T]$, let $x_H(t)$, $x_N(t)$, $x_E(t)$, and $x_D(t)$ be the numbers of people in compartments H, N, E, and D, respectively. Let $x(t) = (x_H(t), x_N(t), x_E(t), x_D(t))$ for any $t \in [0, T]$.

We let ε be the rate of LTC enrollment. At any time $t \geq 0$, there are $x_H(t) + x_N(t) + x_E(t)$ publicly funded LTC enrollees and $x_D(t)$ deceased individuals. Among these enrollees, $x_H(t)$ individuals are on the HCBS, $x_N(t)$ individuals are in nursing homes, and $x_E(t)$ enrollees do not receive paid LTC services. Note that the people who currently do not receive paid LTC (people in compartment E) may use LTC services in the future, that is, an individual may transfer from compartment E to N or H. We summarize the model notation in Table 12.1.

The population in each compartment is homogeneous, that is, individuals in each compartment are identical. The rate of transition from compartment i to k, Q_{ik}, $i, k \in I$ is constant for all individuals in compartment i. Meanwhile, the per-capita cost of service j for people in compartment i, that is, C_i^j, is constant for all people in compartment i receiving service j.

Table 12.1 Model notation

Notation	Definition
I	Set of compartments $I = \{H, N, E, D\}$: H – HCBS, N – nursing home care, E – without LTC, and D – death
J	Set of acute care service types $J = \{IP, ER\}$: IP – in-patient acute care and ER – ambulatory care
S	Capacity of HCBS infrastructure
$\alpha_i(S, x(t))$	Approval rate for population in compartment E to receiving publicly funded LTC in compartment $i \in \{H, N\}$
ε	Incremental rate of people who are enrolled in the system from compartment E
Q_{ik}	Other constant feasible transition rate from compartment i to k, $i, k \in I$
d_i^j	Rate of using acute care of service type $j \in J$ for people in compartment i, $i \in I$
C^S	Expenditure of establishing one more unit of infrastructure
C^H	Unit-time per-capita expenditure of providing HCBS services
C^N	Unit-time per-capita expenditure of providing institutional care
C_i^j	Unit-time per-capita expenditure of providing acute care of service type $j \in J$ for people in compartment i, $i \in I$
β	Proportion of the population in compartment E whom the publicly funded program intends to admit to receive LTC
$x_i(t)$	Number of people in compartment i at t, $i \in I$
$x_i(0)$	Initial number of people in compartment i, $i \in I$
T	Studied duration
$V(S, x(0), T)$	Overall expenditure at time T for the studied population with initial condition $x(0)$

At any time $t \in [0, T]$, each individual in compartment E has equal probability that his/her LTC application is approved (admitted to receiving LTC via either care option). Furthermore, this probability is equal to a pre-determined constant over the studied duration. We call the two admission probabilities $P_H(S, x(t))$ and $P_N(S, x(t))$. On the basis of this assumption, the sum of probabilities $P_H(S, x(t))$ and $P_N(S, x(t))$ is constant, that is, $P_H(S, x(t)) + P_N(S, x(t)) = \beta$. The constant β can be interpreted as the probability that each individual in compartment E is admitted to any LTC option at any time. Hence, $x_E(t)\beta$ represents the number of people who are admitted to LTC options at time $t \in [0, T]$.

No one may receive HCBS if the capacity level is reached, that is, no LTC application can be approved. Thus, $P_H(S, x(t)) = 0$ if $x_H(t) = S$ for any time $t \in [0, T]$. This is a switching mechanism that controls the population flows from compartment E to H and N due to the infrastructure capacity.

At any time $t \in [0, T]$, if an individual in compartment E receives LTC, the publicly funded LTC program would always prefer admitting this person to HCBS than nursing home. This is so because federal regulations require that each state to ensure that the average per-capita spending on providing LTC via HCBS is no greater than that via nursing homes (Smith et al., 2000). This assumption is a manifestation of these regulations. When the remaining HCBS capacity at time $t \in [0, T]$ is greater than the actual number of people who are admitted to LTC at t, that is, $S - x_H(t) \geq x_E(t)\beta$, all the people who are admitted to LTC should be assigned to the HCBS option, that is, $P_H(S, x(t)) = \beta$.

At any time $t \in [0, T]$, if $0 < S - x_H(t) < x_E(t)\beta$, each individual in compartment E has equal probability to be allocated with one unit of HCBS resources. Note that the first inequality may be effective only when $x(0) > S$. This ensures fair allocation of HCBS resources among individuals who are admitted to LTC. We have

$$P_H(S, x(t)) = \frac{S - x_H(t)}{x_E(t)}, \quad \text{if } 0 \leq \frac{S - x_H(t)}{x_E(t)} \leq \beta. \tag{12.1}$$

That is, $P_H(S, x(t))$ is the real-time ratio of remaining HCBS capacity to the number of people in compartment E. The probability is dependent upon the HCBS capacity S, the HCBS utilization at time t, $x_H(t)$, and the number of people in compartment E, $x_E(t)$. To summarize, we have

$$P_H(S, x(t)) = \begin{cases} \dfrac{S - x_H(t)}{x_E(t)} & \text{if } 0 \leq \dfrac{S - x_H(t)}{x_E(t)} \leq \beta \\ \beta & \text{if } \dfrac{S - x_H(t)}{x_E(t)} > \beta \\ 0 & \text{if } \dfrac{S - x_H(t)}{x_E(t)} < 0 \end{cases}, \tag{12.2}$$

for any $S > 0$ and $t \in [0, T]$.

The admission rates to HCBS and nursing home, $\alpha_H(S, x(t))$ and $\alpha_N(S, x(t))$, are defined as the transition rates from compartment E to compartments H and N. As mentioned before, we assume the nursing home has infinite capacity and consider the HCBS capacity, S, as the only decision variable.

To model the admission rates, we consider the probabilities that an individual in compartment E will start receiving LTC via HCBS and nursing home care during each time unit. We assume that each individual in E does not have preference between the two LTC options (HCBS vs. nursing home) and thus always accepts the services made available to him/her by the public funded LTC program. We also assume that there is no time delay from the time an individual's LTC application is approved to the time he/she starts receiving LTC. The admission process of individuals receiving LTC via either care option is assumed to follow a stationary Poisson process. Thus, $\alpha_H(S, x(t))$ or $\alpha_N(S, x(t))$ can be interpreted as the expected numbers of admissions per unit time for receiving LTC via HCBS and nursing home care, respectively. Hence, the two stationary Poisson processes are parametrized by $\alpha_H(S, x(t))$ and $\alpha_N(S, x(t))$. Furthermore, with the definition of the admission probabilities, the two admission rates can be expressed as (Hoel, Port, & Stone, 1987):

$$\alpha_H(S, x(t)) = -\frac{\ln(1 - P_H(S, x(t))}{T} \tag{12.3}$$

and

$$\alpha_N(S, x(t)) = -\frac{\ln(1 - P_N(S, x(t))}{T}. \tag{12.4}$$

We assume that all other transition rates are constant over time and independent of the capacity. Hence, let Q_{ik} be the transition rate from compartment i to k for any pair $i, k \in I$ with patient flow. In addition, we denote ε to be the incremental rate that people enter the system (i.e., enroll in the publicly funded LTC system) from compartment E. We assume that there is no population inflow from any other compartments. Note that the individuals in compartment E are eligible for publicly funded LTC and have applied for the services, but have not yet been admitted to receiving LTC via either care option.

We consider the overall care expenditure incurred by both LTC and potential acute care services. For LTC services, we let C^H and C^N be the per-capita unit-time spending on receiving LTC in compartments H and N, respectively. In addition, we consider two types of acute care services, in-patient hospitalization care and ambulatory care, for the people in compartments $i \in \{H, N, E\}$. Although the major needs of people with chronic conditions or disabilities could be satisfied by LTC, these patients may still have severe conditions episodically, such as stroke and heart attack, which could only be treated by acute care. We denote inpatient hospitalization care and ambulatory care (or emergency visit) by IP and ER. Let $J = \{IP, ER\}$ be the set that contains the symbols indicating the two types of acute services. We let d_i^j be the rate of the population in $i \in I$ that need acute care service of type $j \in J$ and C_i^j be the unit-time spending of each individual receiving such type of acute care. We assume that informal care is not available to the studied population. Hence the LTC expenditure needed for the entire population must be covered by a publicly funded program. In some sense, this is the worst case scenario the public program may face.

We consider two types of LTC expenditures: fixed spending on HCBS and variable spending. The fixed spending on HCBS is modeled as $C^S S$, which is independent of the actual number of HCBS recipients and their service duration. Typically this spending relates to the fixed costs on setting up the infrastructure of HCBS, such as building adult day care centers and assisted living facilities, which is incurred at the beginning of the studied duration. Further, we assume this cost to be linearly proportional to the infrastructure capacity of HCBS. Note that our work does not deal with the capacity issue of nursing home care. In some sense, the needed nursing home facilities are already established. Also, some policy makers currently prefer HCBS to nursing homes; most patients prefer HCBS. Hence, we do not consider the fixed spending on nursing homes.

Variable expenditures occur over the course of the planning horizon, and can be divided into spending associated with each LTC option. The variable spending is modeled with the remainder in Equation (12.5). For each option, the variable spending consists of the spending paid for receiving LTC and anticipated acute care during the studied duration. For example, the term $C^H x_H(t)$ represents the spending on HCBS; the term $C^N x_N(t)$ represents the expense on nursing home care; and the term $C_i^j d_i^j x_i(t)$ represents the spending on acute care j for people in compartment i. Furthermore, for each option, the variable spending paid for receiving LTC is dependent upon the actual number of recipients via the option and the service duration for each recipient.

Given the initial studied population $x(0)$ and the studied duration T, we present the optimal HCBS infrastructure capacity planning model as:

$$\min_{S\in[0,\infty)} V(S,x(0),T) = C^S S + \int_0^T \left(C^H x_H(t) + C^N x_N(t) + \sum_{j\in J}\sum_{i\in I} \left(C_i^j d_i^j x_i(t) \right) \right) dt, \tag{12.5}$$

s.t.

$$\dot{x}_H(t) = -(Q_{HN} + Q_{HD})x_H(t) + \alpha_H(S,x(t))x_E(t), \tag{12.6}$$

$$\dot{x}_N(t) = Q_{HN}x_H(t) - Q_{ND}x_N(t) + \alpha_N(S,x(t))x_E(t), \tag{12.7}$$

$$\dot{x}_E(t) = (\epsilon - \alpha_H(S,x(t)) - \alpha_N(S,x(t)) - Q_{ED})x_E(t), \tag{12.8}$$

$$\dot{x}_D(t) = Q_{HD}x_H(t) + Q_{ND}x_N(t) + Q_{ED}x_E(t), \tag{12.9}$$

where $x(0) = (x_H(0), x_N(0), x_E(0), x_D(0))$.

Equations (12.6)–(12.9) describe the rates of population change in each compartment at time $t > 0$. For example, (12.6) means that the rate of population change in compartment H at time t is equal to the flow into H, $\alpha_H(S,x(t))x_E(t)$ minus the flow out from H, $(Q_{HN} + Q_{HD})x_H(t)$.

Given $x(0)$ and T, we let $S^*(x(0),T)$ be an optimal capacity level that minimizes the overall expenditure. That is,

$$S^*(x(0),T) = \arg\min_{S\in[0,\infty)} V(S,x(0),T) \tag{12.10}$$

3.2 Numerical Example: Application to Population with Dementia

We test the capacity planning approach based on the best available published data of Indiana Medicaid recipients with dementia who were enrolled in LTC between July 2001 to December 2004. Table 12.2 summarizes the input parameters used for the computation.

Table 12.2 Input parameters

Parameter	Value	Source
Infrastructure cost C^S ($ per person per day)	$\$5,000$	
Costs ($ per person per day)		
LTC (C^H, C^N)	$(\$22, \$82)$	AARP, (2006)
Hospitalization $(C_H^{\text{Hosp}}, C_N^{\text{Hosp}})$	$(\$22, \$24)$	AARP, (2006); Sands et al., (2008)
Emergency visits $(C_H^{\text{ER}}, C_N^{\text{ER}})$	$(\$1, \$1.12)$	AARP, (2006); Ackermann, Kemle, Vogel, & Griffin, (1998); Sands et al., (2008)
Enrollment rate ε (% per day)	$1.3e-4$	CDC, (2009)
Transition rate Q_{HN} (% per day)	$9.2e-3$	Temple, Andel, & Dobbs, (2009)
Death rates (% per day)		
Q_{HD}	$4.7e-4$	Slack, Salmon, Mitchell, & Hinton, (2006)
Q_{ND}	$9.8e-4$	Cohen-Mansfield, Marx, Lipson, & Werner, (1999)
Q_{ED}	$2.2e-5$	Arias, (2006)
Hospitalization rates $(d_H^{\text{Hosp}}, d_N^{\text{Hosp}})$ (% per day)	$(5.2e-3, 2.1e-3)$	Sands et al., (2008)
Emergency visit rates $(d_H^{\text{ER}}, d_N^{\text{ER}})$ (% per day)	$(9.1e-3, 4.8e-3)$	Sands et al., (2008)
Initial state $x(0)$ (persons)	$(174, 1534, 5294, 0)$	Sands et al., (2008)
LTC coverage threshold β (%)	25%	Estimate from $x(0)$
Studied duration T	1 year	

Given a capacity scale, we simulate the system evolution, described in Equations (12.6)–(12.9). With the simulation, we then calculate the overall Medicaid expenditures, $V(x(0), S, T)$, via (12.5). Comparing the values of $V(x(0), S, T)$ with respect to various values of S, we can find a value, the optimal capacity S^*, which minimizes the annual aggregate Medicaid expenditures. Figure 12.2 shows the relationship between the HCBS capacity S and the annual spending starting at $x(0)$.

Figure 12.2 shows that at the base case, HCBS capacity $S = 174$, the expenditures of HCBS is $\$2.09$ million, nursing home care consumes $\$43.06$ million, and acute health care costs $92,000. Our capacity planning model attains the minimum annual expenditure at $S^* = 1,334$. Under this HCBS capacity, the total LTC expenditures are $42.25 million, a reduction of $3.42 million from the base case. These expenses are comprised of $13.04 million on HCBS services, an increase of $10.95 million (524%) over the base case, and $28.67 million in nursing care expenses, a decrease of $14.39 million (33%) from the base case. The total spending on acute care, including hospitalization and emergency visits, has a small increase of $11,000, which is not significant as compared to the two LTC options. Saving from nursing home care offsets the expense increase in HCBS and acute care services.

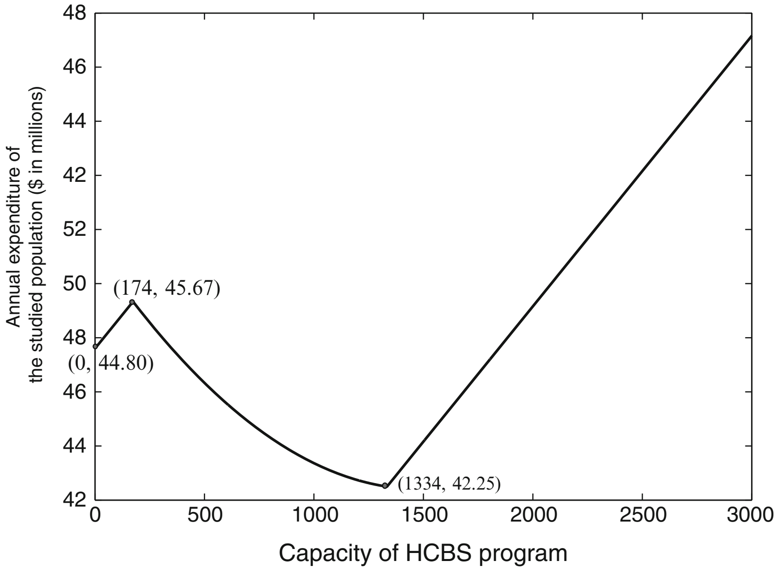

Fig. 12.2 Annual spending on the studied population vs. capacity of HCBS program using dynamic admission rates $\alpha_H(S, x(t))$ and $\alpha_N(S, x(t))$

Table 12.3 Summary of number of people in compartments E, H, N, and D at the end of one year ($x(T)$) and the annual expenditures under base case, $S = 174$, and optimal HCBS capacity, $S^* = 1,334$

HCBS capacity	Number of people (persons)				Annual expenditure (million)		
	$x_E(T)$	$x_H(T)$	$x_N(T)$	$x_D(T)$	Total	HCBS	Nursing home
Current level $S = 174$	4,135	131	1,319	1,645	$\$45.67$	$\$2.09$	$\$43.06$
Optimal level $S^* = 1,334$	4,177	1,113	665	1,276	$\$42.25$	$\$13.04$	$\$28.67$

Table 12.3 summarizes the number of people in each compartment at the end of one year and the expenditures under the current and optimal HCBS capacities. At the optimal HCBS capacity ($S = 1,334$), the number of HCBS recipients is $1,113$, a value more than seven times the base case value, whereas the number of nursing home residents is 665, a reduction of 56.6%. This decline is because the inflow into compartment N decreases as more people are sent to HCBS. The level of $x_E(T)$ is about the same under both HCBS capacity levels due to the assumption that eligibility requirement is not changed. The annual cumulative death under current HCBS capacity is $1,645$, whereas the cumulative death under the optimal capacity is $1,276$. The cumulative death at the optimal capacity is 369 less, mainly because there are fewer people staying in nursing homes in which the death rate is higher. The numbers of HCBS recipients $x_H(T)$ are less than the HCBS capacity, because we assume no more people will be sent to HCBS once its capacity is reached. In

Table 12.4 Design of experiment for sensitivity analysis

Factor	Levels
C^S	2,500 5,000 7,500 10,000 12,500
C^H	20 25 30 35 40 45 50 55 60 65
C^N	80 85 90 95 100 105 110 115 120 125
β	20% 30% 40%

Table 12.5 Partial rank correlation coefficients (PRCCs) for the optimal HCBS capacity and the corresponding total expenditure over 1,500 experiments

Input parameter	Optimal capacity, S^*		Minimum total expenditure, V^*	
	PRCC	p-value	PRCC	p-value
C^S	-0.609	<0.001	-0.218	<0.001
C^H	-0.459	<0.001	0.608	<0.001
C^N	0.531	<0.001	0.938	<0.001
β	0.455	<0.001	0.908	<0.001

both cases, HCBS capacity is reached before T, so the remaining LTC demand will be all sent to N and the mortality rate of HCBS recipients remains the same after that time point. A dynamic admission process would be more realistic, but more research is required to develop such a dynamic admission rate.

Our finding supports the idea of expanding the HCBS program. Expansion of the HCBS program not only reduces the total expenditure of publicly funded program but also enables states to reduce the number of nursing home residents. This finding is sensible as per-capita cost of receiving LTC in compartment H is $27 per unit-time, about one third of the per-capita cost of receiving LTC in compartment N. Although the HCBS recipients might have slightly higher use of acute care, possibly because many conditions that require acute care for community living older adults can be treated at nursing homes, the spending on acute care is small compared with the saving of LTC provision. Furthermore, because the HCBS is less expensive, it allows the public funded program to cover LTC for more people such that the substantial unmet needs can be satisfied. From a cost-saving standpoint, using a less costly LTC delivery system is desirable. Although our results in Fig. 12.2 indicate that the HCBS program can be increased without limit, such a policy change, allowed by the assumption of no capacity limits for the HCBS program, would also result in program expenditures increasing without limit, clearly an undesirable policy outcome.

A multivariate sensitivity analysis is performed to study the effects of five inputs (C^S, C^H, C^N, β) on S^* and V^*. A full factorial design with 1,500 experiments for the factors was performed. Table 12.4 summarizes the sample values of the inputs.

Table 12.5 summarizes the results of sensitivity analysis of four input parameters (C^S, C^H, C^N, β). We calculate the partial rank correlation coefficients (PRCCs) (Hollander & Wolfe, 1999) to evaluate the impact of each input on the optimal capacity and corresponding total expenditure. The PRCCs for S^* are all statistically significant, p-value < 0.05. The most influential parameters in determining S^* are the infrastructure cost and nursing home service cost ($PRCC > 0.5$). The PRCCs for V^* shows that all four tested inputs are statistically significant (p-value < 0.05). Among these parameters, C^N, β, and C^H, are the most influential to V^* ($PRCC > 0.5$).

The optimal S^* is negatively associated with C^S and C^H, whereas it is positively associated with C^N and β. This indicates that controlling both infrastructure and service costs of HCBS is critical for HCBS to remain a beneficial option from a cost-saving standpoint. If HCBS were as costly as nursing home care, a key rationale for HCBS would be violated. The cost of nursing home care, C^N, was the most influential to the minimum total expenditure, V^*. This is because a significant proportion of older adults have already been placed in nursing homes. Also, the total expenditure V^* would increase if the public program supported an increase in LTC, that is, when β was large.

3.3 Discussion

We developed a capacity planning model to determine the infrastructure capacity for a publicly funded HCBS program and thus to develop a balanced LTC delivery system. Our findings indicate that expanding the HCBS program to an appropriate level not only reduces the total expenditure of publicly funded program but also enables states to control spending on expensive institutional care. This capacity planning model is limited in several ways. First, the only direct control in this model is the capacity of HCBS program, S, which affects the admission rates into HCBS and nursing homes indirectly. We are unable to estimate the relationship between S and admission rates into H and N, α_H and α_N, due to data availability. Second, the homogeneity assumption simplifies the real LTC system, in which heterogeneous individuals need diverse types of LTC service. In addition, this model does not capture the cost and effort required to transition people between institutional setting and the HCBS programs. The change of LTC delivery system from institutionally-dominated to community-centered is complicated and not without cost. As individuals who need LTC have widely varying needs, the successful expansion of community-based LTC requires providing necessary infrastructure and other logistic supplies to support community living. Finally, we evaluate the various HCBS scales only from the cost-saving standpoint. Thus, we cannot say with certainty that the HCBS program is effective in terms of other measures, such as quality of life or burden of informal caregivers. In reality, the decision on the expansion of HCBS program should involve evaluation of various factors.

Despite these limitations, this capacity planning model provides a systematic framework to evaluate outcomes under different HCBS capacity scales, and provides working estimates for HCBS expansion. This decision-support approach showcases the potential of applying operations research techniques in planning for a more balanced and efficient LTC delivery system.

4 Future Research Opportunities and Challenges

Attention to the community-based LTC is increasing, as policy makers become increasingly concerned with allocating scarce resources effectively and efficiently. Yet, few conclusions or guidelines are available to justify or improve various policy interests. Policy makers need better decision support.

As this chapter has demonstrated, OR/MS provides valuable managerial insights to improve the LTC delivery system. Yet, modeling LTC delivery must deal with complexities such as tradeoffs between cost and effectiveness, personalized and localized demands, features of competing care options, and the often different perspectives of government, care providers, and patients. All of these place significant challenges in decision making for resource allocation and care coordination. OR/MS can be applied to evaluate various strategies and to identify which strategies are more attractive under certain conditions.

The capacity planning model presented in Section 12.3.1 deals with homogeneous population and static admission rates. A natural extension is to incorporate population heterogeneity, such as health conditions, demographic characteristics, and geographic locations. The admission rates to HCBS and nursing homes are approximated by Poisson processes, which might not reflect actual system. Further investigation is required to validate or better refine such functional relationships. The current framework builds a solid foundation for using objectives other than the total expenditure, such as quality of life, adverse consequence, and burden of informal caregivers. The new models, together with the current model, will provide the policy makers with a thorough picture of the performance of the LTC delivery system.

Another interesting research topic is to develop a decision support framework for assigning HCBS resources to individuals based on their demographic characteristics, health care needs, and geographic locations. One way to study this problem can be via developing an assignment model with an objective to minimize the adverse consequence, especially hospitalization. The elderly population is described by their demographic characteristics, health care needs, and geographic residency. Their health care needs could be measured by ADLs and IADLs. The output of such framework could inform the policy makers the appropriate type and amount of services for each individual and how to assign caregivers accordingly. Under the constraints of budget and available resources, the assignment model determines the optimal amount of HCBS allocated to different population categories. The implication of this model will provide insights of HCBS care planning and service provision at an operational level.

5 Conclusions

The LTC system in the U.S. is facing substantial unmet needs due to the aging population. The expenditure on LTC accounts for a large portion of total health expenses and this number is projected to escalate in the coming decades. Therefore, the government and state policy makers are seeking more affordable LTC delivery methods to curb the ever-increasing financial pressure. Community-based LTC, such as HCBS, can provide better personalized care by determining the appropriate level and amount of services as compared to nursing home care. It is also less expensive than nursing home care, which spends a significant amount of money on providing housing for patients. Further, most patients prefer to live in their own homes rather than in nursing facilities. In many states, the requests for community-based LTC still far exceed the care provision capacity and most funding is still used to finance nursing home care rather than community-based LTC. Thus, there is a need to expand community-based care. It is crucial to establish a more balanced LTC delivery system, including HCBS and nursing homes, to utilize the limited resource more efficiently.

Our study provides an example of applying OR/MS to provide guidelines for future development of the HCBS program and thus to develop a balanced LTC delivery system. This method can be easily generalized demographically and geographically. Although mathematical modeling and analysis are powerful tools, a major obstacle to applying these methods is the difficulty to obtain relevant data. If relevant data become available, the LTC delivery system will provide a rich area within which to apply OR/MS methods to improve quality of care and reduce costs.

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Chapter 13
A DEA Application Measuring Educational Costs and Efficiency of Illinois Elementary Schools

Jaye Samantha Flavin, Ryan Murphy, and John Ruggiero

1 Introduction

Education is perhaps one of the most important issues in America and around the world, and as such has been studied extensively within the realm of social sciences. Specifically, the concept of efficiency is often brought up during the discussion of public schools due to high levels of financial investment and public policy interest associated with the public school system. The public concern focuses on the efficiency and effectiveness of school funding and policy (Hanushek, 1986). Effectiveness measures the ability of schools to meet specific outcome goals while efficiency measures the degree to which expenditures on observed outcomes reflect minimum costs. A school district could be effective in providing outcomes but inefficient by spending above the minimum cost of providing those outcomes. Likewise, a school could be ineffective by not achieving desired outcome levels but efficient; in this case, the school would require additional resources (funding) to become effective.

There are many variables that have been analyzed in determining the efficiency of the public school system. Funding, students, teachers, and neighborhoods are often blamed for the poor performance of the students, though some have suggested that the lack of parental involvement in the educational process is really the culprit (Harris & Goodall, 2008). In addition to funding, urban school performance is hampered by a lack of qualified teachers, larger class sizes, as well as inadequate technology and infrastructure (Hochschild, 2003). Rural schools often have similar problems of funding due to sparse populations, especially since the passage of the

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No Child Left Behind Act of 2001.[1] The passage of the act, due to increased federal mandates without accompanying funding, has put increased pressure on rural schools. Many smaller schools have been forced either to close or to consolidate (Jackson & Gaudet, 2010).

The basis for the measurement of efficiency is the seminal work of Farrell (1957) which showed how efficiency can be measured as the maximum radial reduction in observed inputs, holding observed output constant. Farrell's measure was extended in the economics literature by Boles (1966, 1971) who showed that an estimate of efficiency could be achieved by linear programming. Afriat (1972) provided a variable returns to scale formulation to estimate the nonparametric frontier. Charnes, Cooper, and Rhodes (1978) introduced the nonparametric linear programming formulation assuming constant returns to scale to the operations research literature. Charnes, Cooper, and Rhodes dubbed their technique data envelopment analysis (DEA). Färe, Grosskopf, and Logan (1983) and Banker, Charnes, and Cooper (1984) extended efficiency measurement to variable returns to scale. The method estimates a production frontier using observed data under the assumption of monotonicity, free disposability, convexity, and minimum extrapolation.[2]

DEA has been applied extensively to measure performance in primary and secondary education. DEA was used to analyze productivity in the Houston Independent School District (Bessent, Bessent, Kennington, & Reagan, 1982). Jesson, Mayston, and Smith (1987) analyzed 96 English local education authorities using DEA. Ruggiero (2004) used DEA to analyze the efficiency of Ohio school districts and uses this information to identify districts where reallocated funds would allow for the greatest improvements. Primont and Domazlicky (2006) studied Missouri school districts to determine the efficiency of each and then try to measure the impact the No Child Left Behind Act would have on the inefficient schools. Mancebón and Muñiz (2008) analyzed the efficiency of Spanish public versus private schools and determined that ultimately the quality of students is the source of the largest disparity in efficient measures across these schools.

An important issue that arises in the analysis of schools using DEA is the influence of environmental variables, such as the background of the parents and other socioeconomic variables (Hanushek, 1979, 1986). These variables fall outside the bounds of the production process and thus are not fully accounted for in the original DEA model. Banker and Morey (1986) presented a modified DEA model that allows for exogenous inputs; however, as shown by Ruggiero (1996) the model imposes convexity with respect to the exogenous variables. As a result, the Banker and Morey model overestimates efficiency by allowing inappropriate benchmarks.

Ray (1991) provided a two-stage model to control for environmental variables. In the first stage, DEA is performed using only discretionary variables. The first-stage index captures not only inefficiency, but also the influence of the environment.

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[1] See http://www2.ed.gov/policy/elsec/leg/esea02/index.html.

[2] Färe, Grosskopf, and Lovell (1994) is an excellent source for production theory and various DEA models.

A second-stage regression is used to factor out the environment; the resulting residual is Ray's measure of inefficiency. Because the measure is a residual, it is mean zero. Ruggiero (1998) proposed a three-stage model that uses Ray's approach for the first two stages. Instead of using the residual to measure efficiency, the regression is used to construct an index of environmental influence. In the third stage, this index is incorporated into the Ruggiero (1996) model. The resulting efficiency index maintains the properties of the traditional DEA measures. In this chapter, we apply this three-stage model to the cost side to analyze costs and school cost efficiency.[3]

The rest of the chapter is organized as follows. In the next section, we describe the technology to serve as the basis for efficiency measurement. Our measure of cost efficiency is defined in Sect. 3. In this section, we present the DEA model that will be used in this chapter. Section 4 presents the empirical analysis of Illinois schools. In addition to measuring efficiency, we provide cost estimates necessary to overcome environmental impact on outcomes. The final section concludes.

2 Description of the Technology

We assume that each school uses a vector of m discretionary inputs $X = (x_1, \ldots, x_m)$ to produce a vector of s outputs $Y = (y_1, \ldots, y_s)$ while facing a vector of r nondiscretionary inputs $Z = (z_1, \ldots, z_r)$. Here, the discretionary inputs represent the traditional economic physical inputs such as labor (teachers, administrators, etc.) and capital (computers, books, etc.). The outputs are typically defined as desirable outcomes (performance on standardized tests, drop-out rates, etc.). The nondiscretionary variables represent environmental variables that affect the transformation of discretionary inputs into outputs. Typical measures include parental education or involvement, poverty, income, and minority status. For convenience, we define Z such that increases in any component z_1 $(l = 1, \ldots, r)$ implies a more favorable environment.

We represent the individual inputs and outputs with netput (Y_j, X_j, Z_j) for school j $(j = 1, \ldots, n)$ as x_{ij} $(i = 1, \ldots, m)$, y_{kj} $(k = 1, \ldots, s)$, and z_{lj} $(l = 1, \ldots, r)$, respectively. Given resource prices p_{ij} for input x_{ij} $(i = 1, ..., m)$, we obtain school j's observed expenditures per pupil $E_j = \sum_{i=1}^{m} p_{ij}x_{ij}/S_j,$ where S_j is the number of students in school j.

[3] This extends Ruggiero (1999). As correctly pointed out by an anonymous referee, the two-stage model has been criticized by Simar and Wilson (2007). However, Banker and Natarajan (2008) provide a statistical foundation and derive the conditions under which parameter estimates are consistent. McDonald (2009) proves that OLS is a consistent estimator while tobit is inappropriate. See Johnson and Kuosmanen (2009) for an alternative one-stage approach.

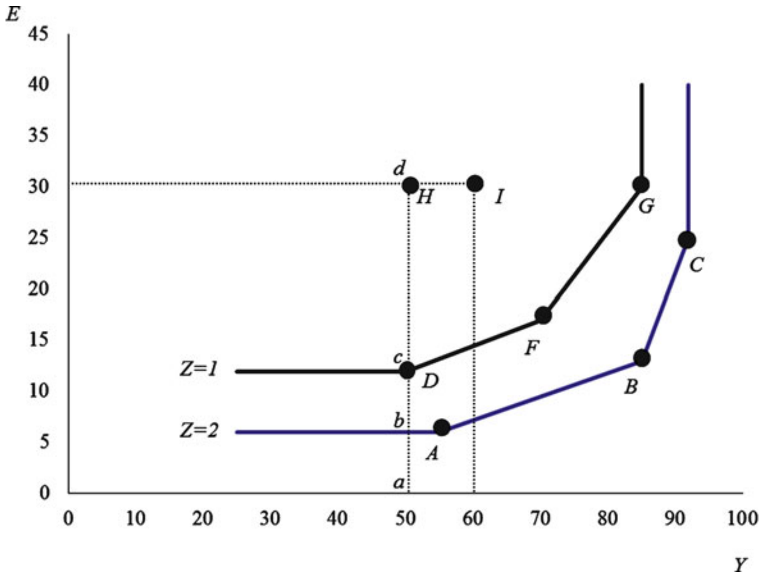

Fig. 13.1 Cost frontiers and efficiency with environmental influence

Following Ruggiero (1998), the production technology can be represented by the input set

$$L(Y,Z) = \{X : (Y,X,Z) \text{ is feasible}\} \ . \tag{13.1}$$

For each output vector Y, we define the isoquant for input set $L(Y, Z)$ as

$$\text{Isoq}\ L(Y,Z) = \{X : X \in L(Y,Z), \lambda X \notin L(Y,Z), \lambda \in [0,1)\} \ . \tag{13.2}$$

The isoquant represents the boundary such that observed production of Y cannot be achieved with any equiproportional reduction in the discretionary inputs, holding the nondiscretionary inputs constant. The effect of nondiscretionary inputs is to create nested isoquants; if a school has a more favorable environment, it should be able to efficiently produce more output for a given level of inputs. This is achieved with the following assumption:

$$\text{If } Z_1 \geq Z_0,\ L(Y,Z_1) \subseteq L(Y,Z_0). \tag{13.3}$$

We illustrate our representation of the cost environment in Fig. 13.1.[4] Data for the example are presented in Table 13.1. For simplicity, we assume one output Y is produced from spending E per pupil. In addition, we recognize the influence of the environment with two levels of Z.

[4] Figure 13.1 is based on Fig. 1 in Ruggiero (1999).

Table 13.1 Example data

School	Y	E (000$)	Z
A	55	6	2
B	85	13	2
C	92	25	2
D	50	12	1
F	70	17	1
G	85	30	1
H	50	30	1
I	60	30	2

Data illustrated in Fig. 13.1

We observe eight schools, A–D and F–I, producing one outcome Y by spending E (measure in $000/pupil) given one nondiscretionary input Z. Schools A–C have a favorable environment ($Z = 2$) and hence are able to efficiently produce on the lower cost frontier.

Schools D–H have a harsher environment ($Z = 1$) and hence must spend more to provide a given level of output. We also illustrate two schools, H (harsh environment) and I (favorable environment) that are operating inefficiently. Holding Z constant, we see that it is not possible for efficient schools to increase output without spending more.

3 Measuring Cost Efficiency

School expenditure is the dollar outlay on the discretionary inputs. In most education data sets, outcomes and expenditures are reported; data on the actual physical inputs are typically not reported. Ruggiero (1999) provided a method to measure efficiency with these data by focusing on cost efficiency.

Definition: A school is *cost efficient* if the observed level of expenditures is equal to the minimum cost of providing the desirable outcomes, holding resource prices and nondiscretionary inputs constant.

The primary resource price that differs among schools is the price of teachers, with variations due to the amount of education, amount of experience, and cost of living provisions. In our modeling, we construct a teacher price index and treat it as one of the nondiscretionary inputs. Efficiency of a given school is then measured using a three-stage model.

We measure an index $\left(0<\theta_o^C \le 1\right)$ using the first-stage DEA model of Ruggiero (1998) which is composed of inefficiency and environmental effects for school "o"[5]:

$$\theta_o^C = \min\ \theta, \tag{13.4}$$

[5] We use superscript C to indicate that the measured index is composed.

subject to

$$\sum_{j=1}^{n} \lambda_j y_{kj} \geq y_{ko}, \quad k = 1, \ldots, s, \tag{13.5}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta E_o, \tag{13.6}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{13.7}$$

$$\lambda_j \geq 0, \quad j = 1, \ldots, n. \tag{13.8}$$

This model seeks the maximum reduction in observed expenditures consistent with observed production allowing variable returns to scale. Variable returns to scale is achieved with the inclusion of constraint (13.7), which together with the nonnegativity constraints (13.8) insures that comparisons are to convex combinations. The left-hand side of the output constraints (13.5) and the cost constraint (13.6) identifies a frontier comparison defined as a convex combination of observed outputs and expenditures. We see that this frontier unit must achieve outputs that are at least as high as those achieved by unit "o" under analysis with lower expenditures. We note that minimizing the objective function (13.4) leads to the maximum reduction in expenditures consistent with the observed outcome levels.

We note that model (13.4)–(13.8) projects a school to the best practice isoquant, which is infeasible for many of the schools with a relatively harsh environment. In this case, schools with a relatively more favorable environment will have a higher value of θ^C holding efficiency constant because they can produce outcome levels with less discretionary inputs (and hence, a lower cost). Therefore, the index θ^C created by linear program (13.4)–(13.8) is best thought of as consisting of two components: cost efficiency and environmental costs. We note that this linear program is solved once for each school j ($j = 1, \ldots, n$) in the sample.

In the second stage, we specify the following regression model due to Ray (1991):

$$\theta_j^C = \alpha + \sum_{l=1}^{r} \beta_l z_{lj} + \varepsilon_j. \tag{13.9}$$

The dependent variable in (13.9) is the first-stage index obtained from the solution of (13.4)–(13.8). The independent variables are the r nondiscretionary variables ($z_1, \ldots, z_r$) defined above. Essentially, this regression model due to Ray (1991) provides a decomposition of the composed index θ^C into the effects of the nondiscretionary variables have on production $\left(\sum_{l=1}^{r} \beta_l z_{lj}\right)$ and efficiency (ε_j). As discussed in Ruggiero (1998), the resulting efficiency is the standard regression residual that has mean zero. Alternatively, Ruggiero (1998) defines an overall environmental cost index for school j,

$$z_j = \sum_{l=1}^{r} \beta_l z_{lj}, \tag{13.10}$$

where z_j is a predicted value from (13.9) that captures environmental influence on the cost of producing output. An overall environmental index is obtained by weighting the nondiscretionary variables with the parameter estimates obtained from regression (13.9). A higher value of z_j is indicative of a more favorable cost environment. We can now use this information to derive our efficiency estimate. For school "o," our measure of efficiency $(0 < \theta_o^E \leq 1)$ is given as the solution to the third-stage DEA linear program of Ruggiero (1998):

$$\theta_o^E = \min \ \theta, \tag{13.11}$$

subject to

$$\sum_{j=1}^{n} \lambda_j y_{kj} \geq y_{ko}, \quad k = 1, \ldots, s, \tag{13.12}$$

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta E_o, \tag{13.13}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{13.14}$$

$$\lambda_j = 0, \quad \text{if } z_j > z_o, \tag{13.15}$$

$$\lambda_j \geq 0, \quad j = 1, \ldots, n. \tag{13.16}$$

Model (13.11)–(13.16) is similar to model (13.4)–(13.8) but differs with the inclusion of weight restriction constraints (13.15). If any school j has a more favorable environment (i.e., if $z_j > z_0$) than does the school under analysis, it is removed as a possible benchmark. Ruggiero (1998) showed that the three-stage model is preferred to the one-stage model (Ruggiero, 1996) if there are multiple nondiscretionary variables; using simulated data, Ruggiero (1998) shows that the model properly decomposes efficiency from environmental influence.

Ruggiero (1999) developed an index of environmental costs for each school j, defined as:

$$\rho_j = \frac{\theta_0^E}{\theta_0^C} \geq 1. \tag{13.17}$$

Essentially, ρ_j measures the additional costs necessary to provide school j's observed outcomes relative to a school with the most favorable environment, holding efficiency constant. For example, if $\rho_j = 1.75$, school j has to pay an additional 75% more than schools with a favorable environment.

Returning to our example data illustrated in Fig. 13.1, solution of (13.11)–(13.16) reveals the cost efficiency. Schools *A*–*G* are cost efficient with $\theta^E = 1$. These schools are producing outcome Y at minimum cost. Schools and H and I are cost inefficient, producing observed outcomes above minimum cost. Consider first school H, observed spending \$30,000 per pupil while only producing an outcome of 50. Given the assumption that H faces the harsh environment, the appropriate comparison would be to school D, observed producing the same outcome with the same environment and lower spending (\$12,000). The cost efficiency of H would be $\theta_H^E = ac/ad = 12,000/30,000 = 0.4$. Hence, H is only 40% efficient.

Next, consider school I, observed spending \$30,000 and providing $Y = 60$. Since I faces a better environment than D, F, G, and H, the appropriate comparison would be a convex combination of A and B (with $\lambda_A = 0.833$ and$\lambda_B = 0.167$.) This convex combination produces the same output of $Y = 60$ by spending only \$7,166.67 per pupil. As a result, $\theta_I^E = 7,166.67/30,000 = 0.239,$, i.e., school I is only 23.9% efficient. This example shows that even though H and I spend the same amount per pupil and I produces a higher output level, I is more inefficient than H due to the differences in the environment.

In order to identify the cost differentials due to the environment, we first solve model (13.4)–(13.8) for the composed index θ^C. For schools *A*–*C*, the composed index is the same as the efficiency index, $\theta^C = \theta^E$, resulting in a cost index $\rho = 1$. This result indicates that these schools are operating in the best environment. For schools *D*–*G*, we find $\theta_D^C = 0.500$, $\theta_F^C = 0.559$ and $\theta_G^C = 0.433$. The cost index values $\rho_D = 2$, $\rho_F = 1.79$, and $\rho_G = 2.31$ reveal that D, G, and F have to spend 100%, 79% and 131%, respectively, more than schools with the more favorable environment.

For school I, $\theta_I^C = \theta_I^E = 0.239$, with $\rho = 1$. In this case, the deviation from the frontier is attributable to inefficiency and not cost differences. For school H, $\theta_H^C = ab/ad = 6,000/3,000 = 0.2$ and $\theta_H^E = ac/ad = 0.4$ indicating that school H is cost inefficient but face higher costs. The cost index of $\rho = ac/ab = 2$ suggests that, after removing inefficiency, school H (like school D) faces twice the cost as the most favorable environment.

4 Analysis of Illinois Schools

In this section, we analyze Illinois elementary school districts using 2008–2009 school year data.[6] Data were collected for 358 elementary school districts with complete data.[7] We restricted our sample to elementary school districts to ensure homogeneity with respect to educational function. We begin by defining the variables used in this analysis.

4.1 First-Stage Variables

In Illinois, standardized test are given to elementary school districts in third grade.[8] Students are classified based on test results into "below basic," "basic," "roficient," and "advanced." For this study, we consider two outcomes, the percentage of third grade students who met or exceeded the math (*Math*) and reading (*Read*) tests. Hanushek (1979) argues that the use of standardized tests is more appropriate for elementary schools because the tests are used to assess basic knowledge.

Descriptive statistics are reported in Table 13.2. The average district performance on *Math* was higher than expected; on average, district's had 89.47% of their students meet or exceed the state math standards. In reading, however, only 77.85% of the students met the minimum state standards. Expenditures per pupil (E) were measured using operating expenditures per pupil. The elementary school districts spent over $9,500 per pupil on average. Disparities in spending exist in expenditures. The range of our measure of expenditures per pupil varies from about $5,500 to over $22,750 per pupil.

We solved model (13.4)–(13.8) for each elementary school district using operating expenditures per pupil as the input measure and *Math* and *Read* as our two measures of output. The resulting index θ^C is a composed measure of environmental cost and cost inefficiency. The average value of $\theta^C = 0.62$ suggests that 38% of expenditures per pupil can be attributed to factors other than the provision of educational outcomes.

[6] Data are available online at http://www.isbe.state.il.us/research/htmls/report_card.htm.

[7] In 2009, there were 379 elementary districts.

[8] Because we focus on elementary school districts, we exclude Chicago School District 299, a district composed of 606 schools. Note that 40% of our sample is located in Cook and DuPage counties.

Table 13.2 Descriptive statistics ($N = 358$)

Variable	Mean	Standard deviation	Minimum	Maximum
Expenditures				
E ($ per pupil)	9,676	2,439	5,522	22,778
Outcomes				
Math	89.47	9.16	44.40	100.00
Read	77.85	12.61	40.00	100.00
Teacher				
Salary ($)	53,353	9,868	28,987	80,136
Experience (Exp)	12.86	2.72	6.00	22.40
At least Master's Degree (MA+)	47.63	20.45	0.00	89.60
Nondiscretionary inputs				
Minority (%)	31.79	29.43	0.00	100.00
Attendance (%)	95.37	0.92	91.80	98.70
Price index (P)	1.00	0.14	0.67	1.35
Cook county	0.32	0.47	0.00	1.00
DuPage county	0.08	0.27	0.00	1.00
Index (z)	0.62	0.09	0.46	0.82
DEA results				
First stage (θ^C)	0.62	0.14	0.24	1.00
Cost efficiency (θ^E)	0.78	0.14	0.36	1.00
Cost index (ρ)	1.30	0.30	1.00	2.88

All calculations are performed by authors. The price index P was obtained from (13.20) using regression (13.18); the results of the regression are reported in Table 13.3. Index z is the estimated value of (13.10); regression results are reported in Table 13.4

4.2 Second-Stage Variables

One of the largest drivers of expenditure differentials is variation in teacher salaries. On average, approximately 58% of operating expenditures are instructional. In order to derive a price index for the school districts, we first estimated the following wage equation:

$$\mathrm{Ln(Salary)} = \alpha + \beta_1 \mathrm{Exp} + \beta_2 \mathrm{Exp}^2 + \beta_3 \mathrm{MA}^+ + \varepsilon, \tag{13.18}$$

where *Salary* is the average district teacher salary, *Exp* is the average number of years of experience, and MA^+ is the percentage of the district's teachers with at least a Masters degree. Regression results are reported in Table 13.3.[9]

[9] As pointed out by an anonymous reviewer, a higher teacher price index could result from lower teacher turnover. However, a district with lower turnover faces higher costs, *ceteris paribus*; these costs should be controlled in the second-stage analysis. Also, a higher value of our teacher price index could be indicative of better quality teachers. As such, our index provides a control for teacher quality. The reviewer recommended an alternative fixed-effects model to control for teacher prices. We recognize the importance of this alternative specification; unfortunately, time constraints prevent us from performing this additional analysis.

Table 13.3 Teacher salary regression

Variable	Coefficient	Standard error
Intercept	10.209[a]	0.100
Exp	0.045[a]	0.015
Exp^2	−0.0015[a]	0.0001
MA^+	0.0069[a]	0.0003
R^2	0.615	

The dependent variable is the Ln (teacher salary)
[a]Significance at the 5% level

Table 13.4 Second-stage regression ($N = 358$)

Variable	Coefficient	Standard error
Intercept	0.607	0.679
Minority (%)	−0.0006[a]	0.0003
Attendance (%)	0.017[a]	0.007
Teacher salary index	−0.370[a]	0.048
Cook county	−0.072[a]	0.017
DuPage county	−0.092[a]	0.025
R^2	0.402	

The dependent variable is the first stage indeed θ^C obtained from (13.4)–(13.8)
[a]Significance at the 5% level

The coefficients have the expected sign; teacher's salaries increase with more experience, but at a decreasing rate. Further, teachers with an advanced degree earn more. We estimate teacher salary for district j as:

$$\text{Salary}_j^P = \mathrm{e}^{\alpha+\beta_1 \text{Exp}_j+\beta_2 \text{Exp}_j^2+\beta_3 \text{MA}_j^+}. \tag{13.19}$$

Our teacher price index for district j is then calculated by dividing predicted salary for district j by the average predicted salary in the sample:

$$P_j = \frac{n \text{ Salary}_j^P}{\sum_{j=1}^n \text{Salary}_j^P}. \tag{13.20}$$

The price index is calculated to be mean 1; districts with a higher price index face higher teacher costs due to more experience and/or more education.

The nondiscretionary variables considered for the second-stage regression are the percent minority, attendance percent, the price index (13.20) defined above, a dummy variable for Cook county, and a dummy variable for DuPage county. Ruggiero (1999) used the percentage of minority students and found it captured a significant amount of variation in the cost environment. The student attendance rate is used to control for the quality of the students; whether or not a student attends is beyond the control of the school. We would expect that higher attendance is associated with better performance. Cook county trails only Los Angeles county with respect to population. According to the census, nearly one fifth of the students live in poverty. DuPage is the second largest county in Illinois with approximately one million residents. DuPage is also the wealthiest county in the state. We include a dummy for DuPage to control not only for its size but also for its wealth.

The second-stage regression results are reported in Table 13.4. Approximately, 40% of the variation in the first-stage regression is captured by variations in our environmental variables. All parameters were statistically significant; the negative coefficient on percent minority, attendance, the teacher price index, and the dummy for Cook county all had the expected signs. As the percentage of minority students increase, the costs of providing a given level of education increases. Likewise, the teacher price index and the dummy for Cook had the expected negative sign.[10] And, as attendance increased, it became less costly to provide the given outcomes.

The coefficient on the DuPage county dummy was negative and statistically significant. There are two competing effects; while DuPage is relative large, it is also relatively wealthy. We would have expected that the second effect would have dominated, but the negative coefficient implies the opposite. We chose to include the dummy because it captures multiple effects and was significant. Other variables, including parental involvement, mobility rate, truancy rate, and the percent of the district that is low income, were considered but were not statistically significant.

Based on the regression results reported in Table 13.4, we derived our index z using (13.10). The average value of z was 0.62 with a range of 0.46–0.82. Importantly, z was used as a control variable to facilitate correct comparisons.[11] In the next section, we discuss the efficiency results.

4.3 Third-Stage Cost and Efficiency Results

As in Sect. 1.4.1, we applied DEA using operating expenditures per pupil as a discretionary input and *Math* and *Read* as our two measures of output. However, using our index z, we applied model (13.11)–(13.16); the average efficiency, reported in Table 13.4, is 0.78. Hence, inappropriate use of DEA would have overestimated the average efficiency by 0.16. The results indicate that districts could have spent 78% of current operating expenditures per pupil on average, holding output and environmental conditions constant.

Average results by various classifications are reported in Table 13.5. We report the average results for all districts as a benchmark. We first consider inefficient

[10] An anonymous reviewer suggests an alternative interpretation for the negative coefficient on the teacher price index: more experienced and/or better-educated teachers increase operating costs but not productivity.

[11] An anonymous reviewer requested an alternative second-stage regression using the percentage of households from low income instead of the percent minority. The correlation between the two environmental cost indices was 0.974, providing a measure of robustness.

Table 13.5 Average cost and efficiency results by classification

				$ per pupil			
Classification	Number of districts	Math	Read	*E*	Minimum cost	Environmental cost	Inefficiency
Cost inefficient districts							
Quartile 1 ($\theta^E \leq 0.683$)	80	88.35	75.55	11,828	7,019	1,370	4,810
Quartile 2 ($\theta^E \leq 0.765$)	80	89.45	77.20	9,584	6,910	1,223	2,674
Quartile 3 ($\theta^E \leq 0.842$)	80	88.46	76.18	8.857	7,103	1,464	1,754
Quartile 4 ($0.842 < \theta^E < 1$)	79	88.96	77.63	8,236	7,441	1,707	795
Efficient districts ($\theta^E = 1$)	39	92.60	84.20	7,178	7,178	4,013	0
County							
Cook county	115	87.16	75.22	11,013	8,567	2,888	2,445
DuPage county	29	90.52	81.05	11,297	9,506	3,818	1,791
All other counties	214	90.56	78.82	8,738	6,548	808	2,190
Environment							
Quartile 1 ($z \leq 0.537$)	90	87.28	76.50	11,529	9,241	3,563	2,289
Quartile 2 ($z \leq 0.631$)	89	89.33	77.63	10,367	7,923	2,207	2,444
Quartile 3 ($z \leq 0.697$)	89	90.89	79.52	8,566	6,637	936	1,930
Quartile 4 ($z \leq 0.697$)	90	90.38	77.74	8,236	5,941	173	2,295
Price index							
Quartile 1 ($P \leq 0.894$)	90	88.34	74.77	8,493	6,087	360	2,406
Quartile 2 ($P \leq 1.001$)	89	87.11	75.34	8,875	6,751	1,092	2,124
Quartile 3 ($P \leq 1.102$)	89	89.41	77.07	9,752	7,447	1,795	2,304
Quartile 4 ($P \leq 1.102$)	90	92.95	84.16	11,575	9,452	3,627	2,123
All districts	358	89.46	77.85	9,676	7,436	1,720	2,240

All calculations are performed by authors districts by quartile. The first quartile consists of 80 elementary school districts that are the least efficient. These districts have outcomes below the state average while spending over $2,000 per pupil more. The environmental costs are $350 below the state average; however, the inefficiency measured in dollars per pupil is more than double the state average. The second quartile produces outcomes similar to the state average, better than average socioeconomic environments, but spend over $400 per pupil above minimum cost. Relative to the first quartile, these districts produce better outcomes with slightly more favorable environments. The major difference between the quartiles is the amount of inefficiency; the second quartile is more efficient on average by about $2,200 per pupil.

Only 39 districts (10.89%) were identified as efficient. On average, these districts spent about $7,200 per pupil and produced higher outcomes than the inefficient quartiles. Interestingly, the minimum costs are about $250 per pupil less than the state average. These districts face the harshest environments, primarily due to high teacher prices. The average teacher price index (not reported) was 12% above the average districts. These results provide an important policy consideration: in tight fiscal times, it would be useful to identify inefficiency and provide incentives for more efficient behavior.

The next classification we considered were counties. On average, Cook county districts spent $11,000 per pupil, about $300 less than the 29 DuPage counties. DuPage districts produced higher outcomes and had higher environmental costs due to higher teacher salaries. DuPage districts had to pay an average 12% above the state average while Cook county districts 7% more. The results suggest that Cook county districts were the most inefficient, spending $2,445 in excess of minimum cost. Of note, Cook county districts had nearly 55% minority students. This compared to about 42% for DuPage districts and only 18% for all other counties.

Environmental costs were classified according to the second-stage index z; the quartile results show that on average, districts with the harshest environment had to pay over $3,500 to compensate for the relatively poor conditions. These districts had a 54% minority percentage with a price index 13% above the state average. The most favorable quartile faced a minority percentage of 9.4% and a price index of 17% below the state average. These results provide insight into how funding should be allocated; regardless of socioeconomic conditions, teacher salary prices are big determinants in school costs. Interestingly, average inefficiency is relatively consistent across the environmental quartiles.

The final classification is based on the price index P. Minimum costs for the quartile with the highest teacher prices are $2,000, $2,700, and $3,365 per pupil above quartiles 3, 2, and 1, respectively. Controlling for inefficiency, the primary driver of costs is teacher prices. Costs could be cut by focusing on teacher characteristics. Further, more flexibility in teacher staffing consistent with laws protecting teachers from discrimination based on age could be an important policy outcome from this study. Duncombe, Miner, and Ruggiero (1997) found statistical evidence that tenure leads to more inefficiency. Savings through reduced inefficiency could be compounded by lower average costs.

5 Conclusions

In this chapter, we explored the use of operations research methods and economic theory to estimate cost and inefficiency. We applied DEA to measure cost efficiency of educational service provision while controlling for environmental conditions for 358 elementary school districts in Illinois. A major concern of the public education system is that educational outcomes are relatively low in poorer districts. Indeed, measures of education outcomes typically indicate that urban schools serving minority populations are underachieving. The lower outcomes in these schools could result from inefficiency or because not enough resources are targeted to the poorer schools.

Our analysis of Illinois elementary schools suggests that there is substantial inefficiency; the average efficiency was 0.78, which is consistent with other efficiency studies (see Ruggiero, 2004).[12] We found that environmental costs are largely determined by teacher prices. As expected, districts that have to pay higher teacher salaries face much higher costs of educating the students. One policy recommendation is to find causes of inefficiency and find policies that provide incentives for better performance. In addition, socioeconomic conditions require additional money to compensate for the harsher environment. Funding should target the drivers of higher costs, which include student composition, teacher salaries, and socioeconomic conditions.

The study provided a useful first step. However, our study was based on a limited sample of Illinois elementary schools that provide the same desirable outcomes. The approach can be extended to analyze a larger sample of schools or districts if proper outcomes can be identified. Anonymous reviewers provided alternative methodological and econometric approaches for estimating teacher salaries and efficiency. A comparison of approaches would be a useful extension to test for robustness. While this is true for all empirical analyses, it is especially important for analyses of school costs and efficiency that have important policy implications.

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[12] As pointed out by an anonymous reviewer, it might be the case that wealthier districts offer other services and/or activities that may enhance education but not necessarily the outcomes chosen in our analysis.

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