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COMMUNITY OPPOSITION TO PUBLIC FACILITY LOCATION

A METHODOLOGY FOR DETERMINING THE DIMENSIONS OF COMMUNITY OPPOSITION TO PUBLIC FACILITY LOCATION

by

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A Research Paper

Submitted to the Department of Geography

in Partial Fulfilment of the Requirements

for the Degree

Master of Arts

McMaster University

August 1975

MASTER OF ARTS (1975)
(Geography)

McMASTER UNIVERSITY
Hamilton, Ontario

TITLE: A Methodology for Determining the Dimensions of Community Opposition to Public Facility Location

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NUMBER OF PAGES: vii, 103

SCOPE AND CONTENTS:

This paper is concerned with developing a methodology for identifying and measuring the dimensions of community opposition to externality-generating public facilities. It critically reviews the traditional modelling approaches to public facility location. The methodology, by which the dimensions of facility impact might be established for incorporation into political decision-making models of facility location, is then proposed. The results of a pilot empirical test of this methodology, using techniques of non-metric Multidimensional Scaling for the analysis of individuals' perceptions, indicate the types of dimensions which might be derived from the application of the methodology to questions concerning public facility location.

ACKNOWLEDGEMENTS

The encouragement and guidance of my supervisor, Dr. Michael Dear, during the preparation of this paper, is gratefully acknowledged. Also helpful were the suggestions of Arden Brummell, Peter Hall and Valerie Preston.

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CHAPTER 1

INTRODUCTION

Recent studies have recognized that community opposition is often a significant factor in the location of public facilities. Opposition seems to be generated in response to perceptions, by residents of the host community, of the external effects which will arise from the siting of the facility, especially when these effects are perceived to be negative. This paper is concerned with developing a methodology for identifying and measuring the dimensions of community opposition to externality-generating facilities.

This concern is based firstly on the need to devise a method for evaluating the impacts of public facility location. We should be able to specify the impacts of such public programs in order to ensure that positive and negative outcomes of facility location are equitably distributed. This is not possible in current models of public facility location, which, whilst often specifying the maximization of social welfare as their objective, usually merely employ cost or distance minimization as surrogates for this. If we are to maximize social welfare in public facility location, it is necessary to look very closely at the implementation costs, represented by community opposition, which are incurred in facility location. These complaints surely represent community members' perceptions of the equity, or fairness, with which the costs and benefits they have incurred from the facility location have been distributed.

The first concern of this paper is, then, the necessity for a method of measuring public facility impact, so that the external effects generated by facility location may be equitably distributed. Its second concern is that decision-makers should have a knowledge of the components of community opposition. Only then will locational decisions be able to take these important factors into account.

Clearly, the nature and strength of opposition to public facility location will differ according to the type of facility being located. Community members will object more strongly to the siting of facilities they perceive to be more noxious, and will make different judgements about facilities which have such impacts. A methodology for the determination of the dimensions of community opposition to the location of public facilities is vitally necessary if decision-makers are to have a knowledge of the impact factors which they should be considering in making equitable locational decisions. With such knowledge, opposition attitudes could be taken into account in locating externality-generating facilities, rather than being treated as an implementation cost to be dealt with *after* the facility has been located. At the very least, the identified opposition dimensions would clarify the circumstances under which community opposition to certain types of facilities is likely to occur.

The methodology used to identify and measure community opposition dimensions must take into account the characteristics peculiar to this "public" facility location problem. We must be able to evaluate the facilities from a point of view other than that of how much people are willing to pay for the goods provided. The external effects to which community members object appear often to be intangible, and not measurable in dollar terms. We are dealing, then, with citizens' preferences about non-monetary matters. The methodology must describe these preferences, and permit their synthesis and aggregation for use in decision-making. It should also indicate ways in which basic differences of opinion within the set of preferences may be recognized.

For the proposal of a suitable methodology, it is necessary to undertake four tasks, which will be described in the following four chapters. Chapter 2 will review and criticize public facility location modelling to date. It will note the derivation of public from private facility location models, and will look at models proposed as alternatives to this traditional approach. From this review, it will become clear that no facility location model takes full account of the dimensions of community opposition to facility location.

Chapter 3 will propose the methodology whereby this state of ignorance about the dimensions of community opposition can be remedied. It will review the empirical evidence relating to such opposition, and will suggest a method for the determination of opposition dimensions. Considerations of research design, data, and techniques of analysis will be emphasized.

In Chapter 4, a pilot empirical test of the methodology will be presented. Its purposes will be to illustrate one application of the methodology, and to indicate the form and nature of data and results to be expected in such a study.

Finally, Chapter 5 will summarize the research findings of this paper, evaluate the significance of the proposed methodology, and describe the conceptual and analytical problems which remain.

CHAPTER 2

CRITICAL REVIEW OF MODELLING APPROACHES TO
PUBLIC FACILITY LOCATION

1. Definitions and Classifications of Public Goods and Facilities:

A useful definition and classification of public goods is given by Steiner (1970, p. 23), who loosely defines them as those goods and services vested with the public interest. Steiner distinguishes three types of public goods:

1. Those arising from intrinsic characteristics of specific goods, generating externalities which are non-marketable;

2. Those arising from imperfections in the market mechanisms, rather than from the goods themselves;

3. Those arising from aspects of the quality or nature of the environment, rather than from the goods themselves.

Steiner's definition and classification is in contrast to those traditionally given, which define public goods as perfect collective consumption goods, where all the output is individually unmarketable, and all the benefits external. Tiebout (1956, p. 416) and Margolis

(1968, p. 540) describe public goods in this traditional way, making much of the "non-excludability" characteristic, which defines the public good as one which, if available to anyone, is equally available to all others.

Traditionally defined, these public goods may be seen as an extreme case of externalities. As such, they may be classified in the first of Steiner's categories. According to Steiner (1970, p. 27), however, this commonly cited "non-excludability" description is somewhat unrealistic, since the list of such goods is really very short. Movies, concerts, hospitals and colleges, he states are all "public goods", but all use walls to exclude those who will not meet requirements placed upon their use. Furthermore, the use of the traditional definition does not allow the useful distinctions made by Steiner, between the three types of goods.

In categorizing public *facilities*, we are combining classes of the public *goods* which they provide with characteristics relating to the facilities themselves. Public facilities, distinct from public goods, may be classified as "service" or "dispatch", where "service" means the type of facility to which people come for assistance, and "dispatch" is the facility from which the public good is delivered to clients. Facilities may be "large-scale" or "small-scale", and they may be "noxious" or non-noxious", though the latter is a characteristic applicable to public goods, public facilities, or to a consideration of them jointly.

Teitz (1968, p. 39) further classifies public facilities by focussing on the geometric properties of facility *systems*. Facility systems are seen to take two common forms, point patterns and networks. While point patterns characterize distributive services in which the final phase of distribution is flexible and intermittent, networks characterize those services, generally utilities, which call for "continuous connections" in space.

This paper is concerned to identify and measure, through studies of community opposition to public facility location, the impacts of externality-generating public facilities. Steiner's (1970) definition and classification of public goods, and thus of the facilities providing them, is chosen as most useful for this purpose. It permits a distinction to be drawn between public goods and facilities whose external effects have significant impacts on host communities, and those goods and services which do not generate such outcomes. Traditional definitions have not permitted this distinction.

At the stage of methodology proposal represented by this paper, it is not necessary to define the public facilities being considered more specifically than to say they are "externality-generating", and fit within Steiner's first category. In empirical studies based on this methodology, however, where impacts relating to particular facility types are being sought, it would be necessary to classify facilities in more detail, according to the facility categories mentioned above.

2. <u>The Traditional Approach to Facility Location:</u>

The traditional approach to general facility location relies upon the use of optimization models (Dear, 1974b; Lea, 1973; Scott, 1970).

Location-allocation models, which consider simultaneously the location of facilities and the assignment of flows, subject to certain cost or distance constraints, have been used in the solution of private sector problems, and have recently been applied to questions of public facility location. Dear (1974b, p. 21) describes a typical private sector location-allocation model. In the private sector plant or warehouse problem, he notes, a trade-off typically exists between facility costs and transportation costs. The greater the number of facilities, the lower will be the cost of distribution. The optimal balance between facility and transport costs is achieved when the cost of adding an extra facility just equals the saving in distribution costs due to that facility.

The location-allocation model has recently been applied to questions of *public* sector facility location. The resulting public sector model takes the same form as the private sector one, but its inputs differ: it designates m out of a possible n service locations so as to minimize the aggregate distance travelled by clients to obtain service. The distance minimization criterion of the public sector model may be formally expressed as follows:

$$\text{Minimize} \quad Z = \sum_{i}^{n} \sum_{j}^{n} a_i \, d_{ij} \, X_{ij} \tag{2.1}$$

subject to

$$\sum_{j}^{n} X_{ij} = 1 \qquad i = 1, \ldots, n \qquad (2.2)$$

$$X_{jj} \geq X_{ij} \qquad i, j = 1, \ldots, n; \; i \neq j \qquad (2.3)$$

$$\sum_{j}^{n} X_{jj} = m \qquad (2.4)$$

$$X_{ij} \geq 0 \qquad i, j = 1, \ldots, n \qquad (2.5)$$

where a_i = demand at node i

d_{ij} = shortest distance from node i to node j

X_{ij} = 0 if node does not assign to a facility at j
1 if node does assign to a facility at j

n = # of nodes in network

m = # of facilities in the system.

(Dear, 1974b)

Note that constraint (2.2) ensures that the demand is fully assigned; (2.3) restricts assignment of clients to those nodes where facilities are located; and (2.4) fixes the number of facilities in the system. Assignment is automatically made to the nearest facility.

The link between the commonly used private and public facility location models is clear. Many variations upon this basic public sector model have been proposed. Rojeski and ReVelle (1970) locate an unknown number of central facilities, minimizing total population travel distance or travel time subject to a budget constraint. In a discussion of five uses of the public sector model, ReVelle, Marks and Liebman (1970) explore social welfare surrogates for the objective function, using distance and time variables, with constraints on number of facilities and investment in facilities.

3. Criticisms of the Traditional Approach for Public Sector Problems:

The application of the traditional location-allocation model to problems of public facility location may be criticized on five major grounds. These important criticisms are discussed in the following subsections.

a. Differences Between the Public and Private Facility Location Problems

The use of location-allocation models for public facility location misses much of the uniqueness of the public sector problem. It assumes that the character and location of public facilities simply reflect the private decisions on residential, commercial and industrial location. Furthermore, these models assume that the market-based competitive behaviour relevant to the location of private facilities is applicable also to public services, an assumption which cannot validly be made. As Teitz (1968, p. 37) points out, public decisions, unlike private, are made with regard to some welfare criterion in a mixed market-non-market setting. Following from this, considerations of equity should be included with those of efficiency as the main objectives of public location tasks.

The designation of public facilities so as to minimize aggregate distance travelled by clients to the facilities, which is the basic public sector use of the location-allocation approach, focusses on considerations of efficiency. Important variables relating to questions of equity, which are relevant to public but not to private sector problems, are omitted. Basic differences in the public and private facility location tasks relate to the need for variables measuring equity to be included with efficiency variables in the public sector problem. Since the traditional location-allocation model cannot cope with this necessary addition, it is at present an unsuitable approach to the location of public facilities.

b. Implementation Costs and Externalities

What is it that makes a consideration of equity necessary in the location of *public* facilities? It is basically the fact that the siting of certain types of public facilities causes external effects, which may be positive or negative, to be felt by members of the host communities. Community members, then, may incur serious impact costs, because of the implementation of the facility. This externality-generating characteristic is not relevant to the location of private facilities. But *public* facility locating models should make efforts to distribute externality costs and benefits equitably among members of impacted communities. Evidence that such external effects, especially when they are negative, are objected to strongly, comes from the fact that community opposition to public facility location often arises when a facility is located with respect to efficiency criteria alone.

The use of the market-based location-allocation model for public sector problems, then, may be further criticized. It does not take into account the distribution of external effects generated by many public facilities.

c. Public Government Organization

The nature of government organization necessary to cope with the location of public facilities and the provision of public goods, indicates further differences between the public and private facility location problems. Public good provision must be made with some concern for the external effects to be generated by the good, and by the facilities providing it. This involves the notion of government jurisdictional boundaries. A public good may be successfully "packaged" or "internalized" within the jurisdictional boundaries of the government supplying it. It often happens, however, that spillover effects are incurred by communities outside the government boundaries, as a result of the provision of the good to people within the boundaries. Ostrom, Tiebout and Warren (1961) provide an interesting discussion of the appropriate sized regions for municipal government jurisdiction, to best cope with the problem of externalities, or spillovers resulting from the provision of public goods.

No such government organization is necessary for the provision of private goods, and the location of facilities supplying them. A private good, by definition, must be "packageable", that is, able to be differentiated as a commodity before it can be purchased and sold on a private market (Ostrom, Tiebout and Warren, 1961, p. 544).

The traditional location-allocation approach, then, when used for public facility location, is inadequate for the reason that it cannot consider the external effects generated by public facility location and by the provision of public goods. It cannot, furthermore, take into account political factors relating to the size of areas of government jurisdiction, which must be considered, together with facility impacts, in locating public facilities and providing public goods.

d. Demand

The concept of demand upon which the location-allocation model is based is applicable to private good provision and private facility location, but not to problems of the public sector. This concept is of "effective demand"; demand is "effective" when people are prepared to back it by pecuniary allocation, and "ineffective" or non-existent when they are not (Bradshaw, 1972, p. 71). Such a measure of demand is clearly inappropriate for the provision of public goods and the location of facilities supplying them, where there is rarely a link between service and payment.

"Need", to date, has been the focus of planning for demand for public goods, though the identification of need is a political judgement, and it may be measured in a variety of different ways. Bradshaw (1972) gives four definitions of need which are used by administrators. "Normative need" is that defined as need in a given situation; a desirable standard is laid down, and compared with the existing situation. "Felt need" is equated with want; the needy are asked whether they feel they want something. "Expressed need" is need turned into action by people demanding a service. "Comparative need" is a measure obtained by studying the characteristics of those already receiving a service; if there are people with similar characteristics not being provided with that service, then they are in need.

Harvey (1973, p. 101), discussing the formulation of principles of territorial distributive justice, emphasizes the complexity of the problem of identifying and measuring the need for public services. We must determine what each of three criteria, need, contribution to common good, and merit, means in the context of particular regions, and in the context of tasks such as public good provision and location of public facilities.

The concept of effective demand upon which the location-allocation model is based, then, is completely inappropriate in the context of public sector problems. No matter which definitions of need are considered in the location of public facilities, it is impossible to quantify them in a manner suitable for use in a market-based model.

e. Social Welfare Functions and Surrogates

The distance, time and cost minimization factors considered in location-allocation models are fundamental to the location of private sector services. However, in locating public facilities and supplying public goods, we should be maximizing some social welfare function for which these variables alone are insufficient. It is very difficult to consider social welfare using the traditional location-allocation approach, and though attempts have been made to use surrogates for social welfare, none of these has been suitable. They usually continue to define social welfare with respect to efficiency criteria alone. Wagner and Falkson (1975), for example, state that the proper efficiency criterion for social welfare should measure the net gains to the beneficiaries of a public system minus the cost of supplying the service. They present some models, which claim to maximize social welfare, in which both producers' and consumers' surplus are maximized.

It seems doubtful that social welfare can ever be satisfactorily specified in a location-allocation optimization model, since there are unquantifiable political variables, relating to questions of equity and need, which are equally as important as distance, cost and time considerations in the provision of public services. The task of incorporating such necessary variables, relating, for example, to the distribution of public facility impacts, into the location-allocation format would be difficult. Furthermore, it seems unlikely that the optimization model can cope adequately with the multiple objectives which must be satisfied in most public sector location problems.

The case of the location of *emergency* public facilities, however, seems more appropriately modelled by location-allocation, optimization techniques. Only one variable is of over-riding concern here: the time taken for travel between facility and user, or the distance between them. Several papers validly consider the location of emergency public facilities in this manner (Toregas, Swain, ReVelle and Bergman, 1971; Toregas and ReVelle, 1972). In these, the total number of facilities is minimized, to meet response times or distance standards for users.

Traditional location-allocation models, then, fail to consider adequately the unquantifiable social welfare variables which must be considered in the location of all public services, except those specifically providing emergency services.

4. Alternative Modelling Approaches to Public Facility Location:

In recognition of the inadequacies of the location-allocation model for public sector problems, several alternative modelling approaches have been suggested. These models may be grouped into three categories: those concerned to improve the use of the optimization framework by deriving objective functions better related to social welfare considerations; those which reject the traditional optimization framework, in favour of a political decision-making approach to public facility location; and those models which fit into neither of these two categories, so are simply termed "others".

a. Use of Better Surrogates for Social Welfare Within the Optimization Framework

Staying within the location-allocation framework, Alperovich (1972) has developed a model using welfare criteria, where any solution reached using efficiency criteria in the objective function cannot be said to be optimal unless it is contained within the "welfare criteria" of the impacted population. The task is stated as a series of linear programming problems, where, given a public service and a fixed budget, the sizes, number and locations of a set of facilities are calculated, to maximize the total value of realized service without incurring community opposition. This model, though simply imposing extra constraints relating to equity on the usual efficiency criteria, at least recognizes that facilities do impact communities with their external effects and that the resulting community opposition should be taken into account in facility location.

Dear (1974b) also considers the distributive equity issues which should be taken into account in models for locating public facilities. He formalizes the program design criterion as an equity measure, which may be constrained by "efficiency" criteria (the reverse, in fact, of what Alperovich (1972) has done). The objective function of Dear's optimizing model, then, minimizes the aggregate deviations of the actual program costs and benefits, from the cost and benefit equity norms. Though this model is not yet operational, it, again, is an attempt to incorporate impacts into planning stages.

Calvo and Marks (1973), having reviewed the usual objective function formulations, suggest the use of a quasi-additive "multidimensional utility function", where this function is comprised of utility functions specified for the user, operator, and community sectors. The objective function, then, maximizes utility for the entire region.

Analytical difficulties arise with this formulation of the locational problem, however, since the individual utility functions are difficult to specify, causing further problems in the assessment of the multi-dimensional function. For this reason and because of non-linearities in the constraint set, the writers have not considered a solution approach to their model.

A further new direction is taken by Hall (1973a, 1973b) who, having investigated several criteria for judging the location of public facilities, uses a mixed integer programming model, instead of the usual linear programming model, to locate facilities according to the selected criteria.

Perhaps the most innovative optimization approach to public facility location has been proposed by Mumphrey, Seley and Wolpert (1971), who advocate a method which develops "implementation solutions" to the location problem, combining with the cost of the main facility to be located a least-cost package of auxiliary facilities, plus a cost of community opposition to the organization. Austin, Smith and Wolpert (1970) have given formal mathematical expression to this suggestion.

Various attempts, then, have been made to extend the optimization approach to facility location, and to make it more relevant to problems of the public sector. Most of these models have been limited by the optimization format, rather than benefiting from it. Furthermore, in the attempts to incorporate unquantifiable variables relating to equity into the location-allocation framework, the one advantage of the traditional model, the fact that it does yield a solution, has been lost.

No direct effort has been made to incorporate different measures of equity, as social welfare functions, into the optimization approach. Levy, *et al.* (1974, pp. 240-41) use three possible standards of equity: under "market equity", an agency distributes resources to citizens in proportion to the tax revenues they pay; with "equal opportunity", the agency distributes an equal dollar amount of resources to each citizen, regardless of tax payment; for the standard known as "equal results", when the agency distributes its resources, *outcomes* are equal for each citizen. A problem, of course, in using one of the definitions of equity, is to decide which one is most appropriate. It is suggested that the third, "equal results", is best for questions of public facility location, though it is obviously the most difficult of the three given concepts of equity to measure and administer. If incorporated as a social welfare function into optimization models, however, this measure of equity would cope well with the distribution of external costs and benefits generated by the location of public facilities.

b. Political Decision-Making Models

In some recent models, the traditional location-allocation, optimization approach to public facility location has been rejected altogether, in favour of political decision-making models. These models seek to account for characteristics unique to the *public* facility location task. Rather than calculating optimal locations for facilities, the models' purpose is to describe realistically the processes resulting in and from public facility location. Because of the complexity of this task, most of these models have not been made operational.

Hinman (1970) has used a game theoretic approach in formulating a model to explain the emergence of opposition coalitions, the distribution of political power and side payments, and the political process by which decisions are made. Seley and Wolpert (1974), also, have used game theory to show the implications of decision-makers' using a strategy of ambiguity in interacting with citizens' interest groups before making a locational decision. In their paper, a series of two-person zero sum encounters is modelled, where adversaries become convinced of their respective abilities to anticipate each other's response, before one player lapses into randomized plays so as to avoid being predictable. Mixed-motive settings (prisoner's dilemma) and Monte Carlo simulation trials are also modelled.

Two simulation approaches to the public facility location problem are presented by Mumphrey and Seley (1973). Here, an attempt is made to make the locational conflict process explicit, on the basis of the knowledge that policy-makers are aware of the types of facilities which will be objected to as noxious, and their skills will often include strategies to deal with any opposition which may arise. Mumphrey and Wolpert (1973) have used a referendum model, abstracted from a case study of the controversial locating of a bridge in New Orleans, to observe the consequences of majority group benefit and minority group losses. Discussed are the questions of government compensation to the losers in this locational decision, and of allocative efficiency and equity with respect to the different bridge sites.

The work of Mumphrey (1975), concerning group losses resulting from the implementation of public facilities, may soon be incorporated into models of this type. Mumphrey (1975) has determined a method, related to Multidimensional Scaling, for measuring demoralization costs. His paper is an extension of the work of Williamson (1970), who advocates that the concept of externalities be expanded to include costs which take the form of secondary adaptive responses. Such "demoralization costs" may be incurred by a group if it suffers losses after the implementation of a public facility decision, and is not adequately compensated for this loss.

In an attempt to indicate the complex nature of decision-making with respect to the location of public facilities, Dear (1975a) has listed the following elements as basic to the making of such decisions by a political group:

1. The power in the potential host community;
2. The power in all other communities;
3. The limits of power of the political group making the decision;
4. The "facility package" characteristics (see Austin, Smith and Wolpert, 1970);
5. The client need in the potential host community.

It is suggested that these "political" and "impact" elements are important to the making of public sector locational decisions, and should be incorporated into any model which aims realistically to describe that process.

The political decision-making models, which have recently been proposed as alternatives to the traditional location-allocation models, have not yet been made operational. This is understandable, since the problems of variable specification in such models are great. Despite the fact that they do not yield an "optimal" facility location solution, the political decision-making models do permit the consideration of facility impacts *within* the making of the locational decision. The traditional location-allocation model, based as it is on criteria of efficiency, and even the optimization models adapted to relate better to questions of social welfare, allow the consideration of the distribution of external effects to take place only *after* the facility has been "optimally" located.

c. Other Models

Several models for public facility location have been proposed, which fit into neither of the two categories described above.

Schneider and Symons (1971) have developed an interesting evaluation model, to look at the impacts of different facility location proposals from the viewpoints of efficiency, equity and welfare. The task of the model is to find a solution that will *satisfy* a given set of objectives, rather than one which is optimal with respect to a given objective function. The paper is based on the concept of "access opportunity" (fitting in well to Williams'(1971) discussion of social access), and the model is aimed to improve users' access to public (here, health care) facilities in a large metropolitan area. It proposes an Access Opportunity Index, against which plans for facility location and impacts may be measured in terms of actual measures of efficiency, equity and welfare. If used by decision-makers in locating public facilities, in conjunction with normative facility locating models, the Schneider and Symons (1971) model might prove to be a very valuable evaluative tool.

A further useful evaluative model is proposed by Hodge (1974), who attempts to make explicit the effect of the location of public goods on the distribution of real income in society. The study reviews the spatial and demographic distributional characteristics of the provision of public goods, and shows how conventional evaluation models (particularly benefit-cost analysis) must be changed to account for these distributional considerations. An Equity Evaluation Model is developed, which measures the distribution of impacts and the equity of that distribution.

Tiebout (1956) sets up a model purporting to yield a solution with respect to the level of expenditures for local public goods, which reflects the preferences of the population more adequately than they can be reflected at the national level. If it were workable, this model would be a useful facility-locating tool. The model is based on the assumption that consumer-voters are fully mobile, and will move to that community where their preference patterns are best satisfied. Here, then, moving or failing to move replaces the usual market test of willingness to buy a good, thus revealing the consumer-voter's demand for public goods (Tiebout, 1956, p. 420). This model is unsatisfactory for several reasons. First, the assumption that people will move to satisfy their preferences is unrealistic. Many people cannot afford to move, even if their preferences indicate they should. There are more ways of expressing preferences than just moving house; none of these is considered by the model. And perhaps most importantly, when considering Tiebout's model as a potential facility locating tool, the model gives no indication of the dimensions of people's preferences with respect to the area they vacated. No information is gained from the model about the particular aspects of the vacated area's public services which were *not* preferred, or those characteristics of the new area which *are* preferred. The model, therefore, can be of no use as a predictive tool for helping to locate public facilities, for it merely monitors movements, rather than giving some explanation of the reasons for which the movements were made. Barr (1973) has extended Tiebout's concept, but still fails to make empirically valid assumptions.

5. Summary:

The discussion in this chapter clearly indicates that the traditional location-allocation model is inappropriate for the location of public facilities. It fails to take into account many characteristics particular to the supply of *public* goods, especially the generation of external effects by facilities providing these goods. It does not consider questions of government jurisdiction, which must be combined with questions of the distribution of external effects in any public facility location decision. Furthermore, the concept of effective demand upon which the model is based is relevant only to the supply of *private* goods. A social welfare function, or suitable surrogates for this, is generally not incorporated into traditional optimization models.

This paper is written in the context of the political decision-making models described above. In Chapter 3, it proposes a methodology for establishing the dimensions of community opposition to externality-generating public facilities. The identification and measurement of these dimensions would be helpful to decision-makers in locating facilities, so that facility-generated external effects might be equitably distributed. Furthermore, the clarification of community opposition dimensions, and thus of perceived facility impacts, will help in a more complete and accurate specification of the political decision-making models themselves.

CHAPTER 3

A METHODOLOGY FOR ESTABLISHING COMMUNITY OPPOSITION DIMENSIONS

This chapter proposes a methodology for establishing the dimensions of community opposition to public facility location. First, however, some indication should be given of the nature of the opposition *dimensions* the methodology is expected to expose. Complaints about facility location may be based on tangible or intangible fears. The dimensions being sought by applications of the methodology, then, will be clear statements of these tangible and intangible reasons. Tangible dimensions will relate to quantifiable losses suffered or anticipated by community residents as a result of facility location, such as decline in property values, or increase in neighbourhood traffic levels. Intangible dimensions may include unquantifiable fears of the incurrence of neighbourhood stigma as a result of facility location. Commonly, as locational conflict matures, it appears that intangible opposition fears are translated into tangible, seemingly more credible complaints.

1. Empirical Evidence Relating to the Nature of Dimensions:

One of the most frequent rationalizations used by opponents of mental health facility locations is that their property values will decline if a facility is opened in their neighbourhood. Dear (1974a, 1975b) in a study of reactions to the location of small-scale mental health facilities, examines several hypotheses relating to this problem:

1. The introduction of a mental health facility in a neighbourhood will have a detrimental impact upon property transactions in that neighbourhood;

    a. The number of transactions will increase;

    b. The value of the transactions will decrease;

2. Any impact, if it can be attributed to the facility, will decline with increased distance from that facility (i.e., as the external effect dissipates).

From his empirical analysis of the effect upon property values of 12 mental health centres in Philadelphia, Dear (1975b) concludes that no consistent downgrading or upgrading could be seen. In fact, the siting of small-scale mental health facilities, here, had an indeterminate effect upon property values. Though some evidence suggests that property values rose as distance from the facility increased, it is not at all clear whether this was attributable to the presence of the facility, or to wider market conditions. Clearly, this example is not comparable to situations involving public facilities of other types. However, it does indicate that for some locational conflict situations, where a small-scale externality-generating public facility is involved, the decline in property values argument may be neither valid nor reasonable. This reason for opposing facility location, then, may be consistently brought up because people are not aware that property values will not be greatly affected, or because they wish to hide their less tangible fears about the effects of the facility's location under this seemingly more "sensible" economic reasoning.

In a further study of the siting of small-scale mental health facilities (Crawford and Wolpert, 1974), the preliminary observation is made that community objections to drug and alcohol treatment and residential centres seem to be focussed on the issues of danger of physical harm, neighbourhood stigma, property value decline, generalized fear of the mentally disabled and the possible traffic congestion effects of facilities on the surrounding neighbourhood. A large number of case studies is described in that paper, and huge amounts of data amassed. Various hypotheses are drawn from the data about the conditions under which proposals for such facilities are likely to be accepted, and the conditions under which community opposition is likely to arise and be successful in blocking the building of the facility. From the data is drawn the following frequency distribution (Figure 1), showing, for the 15 cases considered, the number of times certain specific community objections were raised, and whether they were raised tacitly or explicitly.

Despite the fact that no rigorous analysis of data is undertaken, the Crawford and Wolpert (1974) paper does provide a very useful list of some of the factors likely to be present in community opposition to facilities of this type.

A further unpublished paper (Gingell, *et al.*, 1975) investigates the perceptions of residents in two different neighbourhoods of the location of 15 types of public facility in their neighbourhoods. This study

FIGURE 1

FREQUENCY DISTRIBUTION: COMMUNITY OBJECTIONS

Case Number

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	Tally	N*
36	E	T			E				T				T	T	T	2E,5T	7
37	E	E			E	E			E			E	T	E		7E,1T	8
38		T			E	E			E			E	E	E		6E,1T	7
39	E								E			E	E	E	T	5E,1T	6
40	T	E			T	E			E			T		T		3E,4T	7
41		E				E			E		E	T	E	T		5E,2T	7
42		E							E			T			E	3E,1T	4
43	T	E							E			E	E	T	T	4E,3T	7
44	E	E					E					E	E		E	6E,0T	6
45									E		E		E			3E,0T	3
46					E	E										2E,0T	2
Q*	4	6	0	0	4	5	1	0	8	0	2	5	6	3	2		

SOURCE: Crawford and Wolpert (1974), p. 17A

T = tacit

E = explicit

N = number of times objection raised across cases

Q = number of explicit objections raised per case

Objections:
36. Fear of property value decline
37. Fear of corporal danger
38. Fear of property crime
39. Loitering
40. Stigma
41. Ideological/Racist
42. Increased Traffic
43. Fear of general neighbourhood downgrading
44. Proximity to schools, playgrounds, etc.
45. Community power
46. Other arguments (specify)

does not bear directly on the concerns of this paper, since it deals with residents' *perceptions* rather than their *opposition* to facilities, and it considers *many* types of public facilities rather than focussing on one. It is mentioned, however, as one of the few empirical studies on residents' attitudes towards public facility location.

Personal constructs used by individuals to differentiate and evaluate the locational impact of the facilities are determined in the Gingell, *et al.*, (1975) study. Individuals are then asked to rate the desirability of the location of each facility at varying distances from their homes, to rate each facility on the previously elicited constructs, and to rate, according to a given scale of possible reactions, their response to the proposed location of each of the facilities. The impact of a given facility upon property values proves to be the first consideration expressed by individuals tested in the study, followed by a noise construct and a clean/dirty construct. To identify the cognitive dimensions people use in their evaluation of the locational impact of the public facilities, the data are analyzed using techniques of dimensional analysis (Multidimensional Scaling and Principal Components Analysis). It is found that the most important dimension used is "degree of noxiousness", and that the most intense reactions to the location of a facility are those of residents whose homes are in close proximity to the proposed location. (This latter result indicates the existence of a distance decay effect.)

There is a small amount of empirical evidence, then, on the perceptions and objections of community residents concerning the location near them of public facilities. In the papers by Dear (1975b) and Crawford and Wolpert (1974), the distinction between tangible and intangible objections to facility location stands out clearly. But the evidence does not make clear whether or not tangible complaints, such as decline in property values, are the real basis of non-user community opposition.

The rest of this chapter proposes a methodology by which the "real" dimensions of community objections to the location of specified types of public facility might be empirically determined.

2. Potential Research Designs:

In attempting to identify the dimensions of community opposition, it is possible to take two research strategies:

1. The specific dimensions of opposition may be hypothesized, and analysis may be performed to obtain support for, or refutation of the hypothesis.

2. Survey data may be analyzed, with very general hypotheses in mind, and the results used to generate specific hypotheses about the nature of opposition dimensions. The suggestion could then be made that the dimensions hypothesized be empirically validated at some later date.

Furthermore, one could take two different approaches to the problem, depending on the generality of the dimensions one wishes to identify:

1. Objections of a group to the same "type" of facility, such as small-scale, service-oriented, externality-generating facilities, might be analyzed, to obtain an indication of the types of factors used by the group in evaluating the locational impact of that type of facility. What characteristics of these facilities are most important to sample members? Do considerations of the "goodness-of-fit" of the facilities into the proposed neighbourhood locations affect residents' perceptions of the desirability of having these facilities sited nearby? And which particular externality effects generated by the facility being considered, do non-users find most objectionable? This approach to the problem, where one type of facility is used to generate subjects' judgements, would yield some evidence of the externality effects particular to that type of facility, to which residents object. Such information would be useful in locating facilities of this type.

2. An alternate approach is to analyze perceptions over a wide range of public facility types, as was done in the Gingell, *et al.* (1975) study. Individuals' groupings of these facilities might indicate how well the classification of public facilities chosen by the researcher fits in with the mental groupings of the subjects. Investigations could be made as to whether objections to facilities are location specific. Would residents of the neighbourhood condone the location of a facility at some distance from their home, or from what they perceive to be their neighbourhood? If so, what is an acceptable distance, and does it vary with different types of facilities? It is anticipated that the results gained from such a study would be very general statements about the nature of perceptions of public facility location, such as those of the Gingell, *et al.* (1975) study. Such results are of limited use, because of their very general nature, in the location of facilities of any particular type.

The research design chosen is obviously specific to the purpose of the research, and relates to the researcher's state of knowledge about the selected problem. If an exploratory study is proposed, where specific hypotheses cannot be made through lack of knowledge of the possible results of analysis, then a strategy must be selected which will generate these hypotheses, later to be tested. A further fundamental in designing the directions to be taken by the research is a knowledge of the relevant analytical techniques. Whilst the techniques available should not dictate the manner in which the study is undertaken, it is important to be aware that certain techniques of analysis do limit the types of data one can use, and thus the types of question one can consider. Data, then, should not be collected, and research questions should not be chosen, without some knowledge of the techniques available for meaningful analysis.

The size and method of selection of the sample, and the characteristics of the population from which it is drawn, will depend on the purpose of the research question selected, but are also important aspects of research design. Whatever the nature of the question under study, it should be made quite clear which group of opinions the sample is representing.

If the study is to relate to the objections of people to the impact of a facility which is *already built*, then the sample members should consist of those residents in a community who are actually impacted by a facility, or who perceive themselves to be impacted. The analysis should distinguish between the perceptions of impacted non-users, and impacted users of the facility. The population and sample should also include users of the facility who are not areally impacted, otherwise, by its presence. If the study is to consider the perceptions of community members about a public facility which is *to be placed* in their neighbourhood, then the sample should be selected from communities who perceive that they *will be* impacted non-users, from people who anticipate being impacted, and non-impacted users. It seems pointless to consider the judgements of individuals who are not anticipating, or directly experiencing, the impact of a public facility in their neighbourhood. Presumably, the views of residents unlikely ever to be living near a public facility will be somewhat different to those of residents anticipating or experiencing negative externality effects.

Common to all such studies are the following technical and analytical problems:

1. It is difficult to find some suitable control against which to measure impact changes.

2. It is almost impossible to exactly delimit the area which is impacted by the presence (or anticipated presence) of a public facility. Furthermore, in trying to delimit this area, we must consider if it is more appropriate to consider that area within which people *perceive* themselves to be impacted, or that area delimited by some exogenously determined measure of facility impact.

3. There is no way to hold all exogenous variables constant, to allow for an evaluation of the importance of selected impact variables or community objections.

3. Techniques Available for Use in the Analysis of Perceptions of Public Facilities:

Before suggesting which techniques seem most appropriate in an analysis of public facilities perceptions, a brief and general review of the statistical techniques which may be of use is warranted. Regression analysis and the techniques of dimensional analysis: Factor Analysis, and Multidimensional Scaling, might be used.

Dear (1975b) uses regression models to test for the existence of a distance-decay effect in the impact of mental health facilities upon property values. The models used here assume a linear relationship to exist between decline in property values, and increased distance from the facility. Dear (1974a, Ch. 5) also explores the consequences of other assumptions about the form of distance-decay (e.g., exponential and polynomial). It is difficult, however, to use regression models for hypothesis-generating, exploratory research designs. Independent and dependent variables used in regression need to be well defined if a result of any significance is to be obtained. Furthermore, data for input to regression models should be at least interval scale; the number of ordinal scale dummy variables which may be used in a regression model is limited.

Regression models, then, are restricted to the measurement of interdependencies between well-specified, measurable variables. Since the opposition dimensions being sought have neither of these characteristics, regression models are of little use in this exploratory stage of analysis.

Techniques of dimensional analysis might be used in studying the questions of public facility perception raised in this paper. Factor Analysis, a vector model, and Multidimensional Scaling, a distance model, are applicable. Factor Analysis (FA) differs from Multidimensional Scaling (MDS) in several ways, so the situations in which each technique is appropriate for use correspondingly differ.

Let us take a study in which FA has been used, to indicate the differences between situations appropriate for the use of FA and MDS, and to make clear the reasons for the choice of MDS as the more appropriate method of analysis for problems of public facility perception. FA is used by Berry and Tennant (1965) to identify the principal social area dimensions by which community populations within the Chicago metropolitan region vary. The technique is used to analyze census tract data relating to such population characteristics as age, racial or ethnic status, religious affiliation, income, occupation and education. It is found that five factors relating to minority group and ethnic characteristics identify spatial segregation.

In FA, then, as is clear in the Berry and Tennant (1965) study, the attributes of objects are usually defined and measured before the analysis takes place. In that study, ratings of objects (the community populations) on the attributes (the census tract variables) were obtained, and the relationships between attributes explored to determine the factors underlying them. Interpretation in FA, therefore, is concerned to identify factors underlying previously determined stimulus attributes.

In MDS, however, the attributes of objects are not usually predefined. It is the task of the interpreter of the solution to identify the nature of the attributes, or dimensions, against which the objects are scaled. It follows from this difference that FA might be used in preference to MDS in some situations where the research design involves testing specifically defined hypotheses (providing, of course, that its other assumptions are met). MDS may prove more useful as an exploratory, hypothesis-forming technique, or perhaps as a form of analysis which will evaluate very much more general hypotheses about cognitive dimensions. Since the significant attributes of perceptions of public facility location have yet to be identified, and since any empirical study whose purpose is to identify these dimensions must be largely exploratory, MDS is preferable to FA for the purposes of this methodology.

The use of FA requires that data be measured at least at interval scale. In the Berry and Tennant (1965) discussion, the data are quantifiable census tract numbers. With most forms of MDS, however, the level of data measurement need simply be ordinal, though this does not preclude the use of interval scale data. Despite the fact that MDS input data need only be ordinal, the output from an MDS algorithm will have metric properties, that is, it will be interval scale. The ability of MDS to extract quantitative metric information from qualitative non-metric data is its major advantage over the more traditional FA methods. This characteristic is clearly an advantage for the analysis of data collected from human subjects, who can reliably only give ordinal judgements about stimuli, for example, that one subjective magnitude exceeds or falls short of another, without being able to specify by how much

(Shepard, 1972b, p. 6). For the types of data to be analyzed in problems of public facility location perception, which are human judgements measured at ordinal scale, MDS is a far more appropriate method of analysis than FA.

An important emphasis of MDS is that the structure in the data be revealed in a space of the minimum possible dimensions. This aids greatly in the interpretation of the final configuration dimensions. With FA, however, the reduction of the solution to a minimum number of factors is not emphasized, although FA interprets the power of factors to a far greater extent than do the few MDS models which deal with this question. For studies where it is necessary to determine the importance attached by groups of subjects to the identified dimensions or factors, it may be preferable to use FA, always providing the data is in at least interval form.

To summarize, then, regression models are rejected as inappropriate for the analysis of public facility perception proposed in this study, because they are restricted to the analysis of well-specified, quantifiable variables. Techniques of dimensional analysis, FA and MDS, are both more useful. MDS models are selected as more appropriate than FA, however, because of their two major advantages over factor analytic techniques. First, most MDS models are non-metric in nature, that is, they analyze data which are ordinal in scale. For this reason, they are more applicable to the analysis of the psychological data necessary in studies of public facility perception. Secondly, the attributes of objects analyzed by MDS models need not be pre-specified as they must be with FA. This means that MDS models are more appropriate than FA for studies establishing the nature of community opposition dimensions, for the attributes significant to perceptions of public facility location cannot yet be specified.

4. Multidimensional Scaling Models:

MDS models are a recent development in that branch of statistical theory which represents data by placing a set of points in a geometric space, and defines some function between them to reflect relations existing in the data (Coxen, 1973, p. 1). Using MDS models, and computer algorithms of these, n objects (for this purpose, public facilities) are represented as points in an "r" dimensional space, and given quantitative scale values. The purpose of scaling in this way is to uncover the structure of relationships in a matrix of raw data, not apparent when it is in an unscaled form. Used in the context of this paper, it is suggested that MDS be employed in the analysis of individuals' judgements about public facility locations, in an attempt to clarify the components or dimensions of their opposition to the location of facilities nearby. In thus scaling the public facility stimuli, we are assuming that the dimensions of the output configuration represent the attributes of the facilities, with reference to which individuals discriminate between the facilities they are asked to judge. Since we are specifically studying attitudes of *opposition* to public facility location, then the dimensions of the configuration space will indicate those attributes of the facilities to which the individuals concerned are *opposed*, and also, those particular negative facility characteristics which individuals use in discriminating between the stimuli.

MDS techniques take individuals' judgements of objects, and output an "averaged" or group impression of the objects in the space. The objects are scaled so that distances between them may provide significant information about the unknown dimensions, or attributes. As a result of scaling the data, then, we will have derived scale values for each object on each dimension, by simply locating the objects in the space. Furthermore, we will have recovered the number of dimensions in which these points exist, and therefore the number of relevant attributes distinguishing the objects (Brummell and Harman, 1974, p. 18). In order to interpret the MDS solution in this manner, various assumptions must be made about relationships between stimuli, the space in which they are represented, and the manner in which individuals perceive the stimuli. These assumptions are given by Brummell and Harman (1974, p. 18 ff.).

Various different MDS models and computer algorithms are available. Generally these are categorized according to the forms of data they analyze. The following discussion will look first at the types of data which may be analyzed using MDS models, then at the specific models to be used with these types of data.

5. <u>Types of Data Suitable for Analysis by Multidimensional Scaling:</u>

Suitable data for analysis by MDS are any measures of proximity between pairs of objects i and j in a set of k objects, where the smaller the "distance" between points i and j, the greater their similarity or proximity. These data, using Shepard's (1972a) taxonomy, are "proximity data". (Other taxonomies are given by Coombs (1964), Coombs, Dawes and Tversky (1970).)

In a matrix of proximity (or "similarities") data, each element is a measure of similarity between the row and column objects. Normally, the matrix used is intact and symmetric. In a study of perceptions of public facilities, then, we might ask each individual to indicate, on a scale of 1 to 7, where 1 means least and 7 most similar, how alike they perceive each pair of facilities to be. It has been pointed out (Brummell and Harman, 1974, p. 16) that intact conditional (as opposed to intact symmetric) matrices of this type of data are often more realistic, as individuals may perceive the distance between objects i and j differently to the distance between objects j and i.

Proximity data may also be presented in a rectangular matrix, where each cell contains some measure of proximity between one object in a set of n objects, and another object in a set of m objects. Here, there are no measures of proximity between any two objects in the same set. An example of such data, in the context of this paper, might be the 1 to 7 ratings of m individuals on the desirabilitty of living close to n different public facilities, or of having the same public facility in n different locations.

The second category of Shepard's taxonomy is dominance data, often collected by the method of paired comparisons. Dominance data may be given in a square matrix, where each cell contains a measure of the extent to which the row object is preferred to, or dominates, the column object. The cells of the matrix might contain, for example, a measure of the frequency with which a population of respondents state that they would rather live near public facility i than public facility j.

A set of m square matrices, whose rows and columns correspond to the same n objects, may also be used in the presentation of dominance data. The matrices will be of the same form as that described above, but each will have been obtained under different conditions, e.g., from different individuals.

Shepard goes on to complete his four-part taxonomy with a discussion of profile data, and conjoint measurement data. However, these two types of data are not used as frequently as proximity and dominance data.

Profile data is presented in the conventional form: a rectangular matrix whose rows correspond to n objects, and columns to m variables (or vice versa). Each cell contains the measured value of one object with respect to one variable, so that the row for any object is considered to be a "profile" characterizing that object. An example of this sort of data might be an individual's or group's rating of n public facilities with respect to m pre-determined attributes. Since these data are usually reduced to proximity data for analysis, by collapsing all the attribute measures to a single measure of proximity between each of the objects, models for the analysis of profile data will not be discussed in the following section.

The final category is that of conjoint measurement data, which is presented in a rectangular matrix, whose rows correspond to n levels of one variable and columns to m levels of another variable. Each cell entry, then, shows the magnitude of an effect which arises when the two contributing variables take on the levels corresponding to the row and column of that entry (Shepard, 1972a, p. 28). We might, for example, present individuals with variable combinations relating to public facility size and nearness of the facility to their homes. The individuals might be asked to rank these combinations on a 1 to 100 scale, where 1 represents the least desirable and 100 the most desirable imaginable.

Shepard's classification ends with these four data types. He does not specifically include preference rankings, though his dominance data category does take into account preference orderings of two objects. He notes, however (1972a, p. 29) that an important generalization of the dominance model has been provided by Coombs' unfolding model which, instead of giving the geometrical interpretation "i dominates j", which can take into account only two objects, gives the interpretation "i falls closer than j to a particular ideal point". This allows us to extend the dominance category to include preference orderings of more than two objects. By doing this, we are implicitly assuming that individuals ranking more than two stimuli are making paired comparison judgements between each of the stimuli, and that transitivity assumptions hold, i.e., that an individual who ranks 5 stimuli ABCDE, also means A > B, A > C, A > D, A > E, B < A, B > C, etc.

The data types with which we are dealing, then, are proximity, dominance, profile and conjoint measurement. Each of these data types might be analyzed in studies relating to community opposition to public facility location.

6. MDS Models and Algorithms Used in the Analysis of the Data Types:

In discussing the different MDS models which may be used in the analysis of the above data types, it is important to draw a distinction between two different processes, which lead to an individual's judgements about stimuli. In using data which represent the similarity or proximity of pairs of objects, we are assuming that differential *cognition* of the stimuli is being represented. Each judgement is being made according to which attributes of the stimuli are perceived, the amount of each attribute, and how the attributes are mentally combined to produce the comparative judgement (Brummell and Harman, 1974, p. 7). In analyzing proximity data, then, we are trying to discover the dimensions of individuals' *cognition* about the objects (in this case public facilities) in question. A different judgement is made in the individual's mind when he/she *evaluates* each stimulus he/she is aware of, and weights the cognized attributes of the objects in a *preference* judgement (Brummell and Harman, 1974, p. 8). In analyzing dominance data, then, we are considering the mental process of evaluation, which is based on cognition but which differs from it, and we are trying to discover the attributes of objects which are used in the making of evaluative judgements.

The transformation function(s) which relate the cognition of stimuli to their evaluation, termed the subjective preference function(s), is unknown. It is felt, however, that conjoint analysis (using conjoint measurement data) has great potential for the accomplishment of the synthesis of cognitive and evaluative judgements (Brummell and Harman, 1974, p. 12).

a. Models Used in the Analysis of Proximity Data

The non-metric MDS model developed by Shepard (1962a, 1962b) and Kruskal (1964a) is generally used in the analysis of proximity data to find n points whose interpoint distances match the measures of proximity (usually similarities or dissimilarities) of the n points. Input data need only be ordinal, and are presented in a single "group" matrix, where the individuals' proximity matrices have been collapsed into a single "group" table. The fundamental hypothesis of this model is that dissimilarities and distances are *monotonically* related, i.e., the *order* of the proximity measures corresponds to the *order* of the distances. The model then proceeds by iteration to find a configuration which optimizes the goodness-of-fit measure, by which the points in the space will best represent the original data.

Coxen (1973, p. 7) discusses the basic steps of the iteration procedure used in this model as follows:

1. An initial configuration (X, Y) is produced, in a space whose number of dimensions is determined by the user.

2. The configuration is normalized.

3. Pairwise distances (d_{ij}) are calculated in this space.

4. *Monotone regression.* The (d_{ij}) are fitted by the best-fitting monotone function values $(\hat{d}_{ij})$.

5. From the (d_{ij}) and the $(\hat{d}_{ij})$ the *stress* (goodness-of-fit) of the current configuration is calculated. Stress is a residual sum of squares measure; it is usually normalized in non-metric MDS algorithms, and then is expressed in the following way:

$$S = \left[\frac{\sum_{i>j} (d_{ij} - \hat{d}_{ij})^2}{\sum_{i>j} d_{ij}^{\ 2}} \right]^{1/2} \qquad (3.1)$$

where S = stress

d_{ij} = pairwise distances

$\hat{d}_{ij}$ = monotone function values fitted to the d_{ij}.

(Kruskal, 1964a, p. 5)

6. If stress is sufficiently low, the final configuration and summary data are output. Alternatively:

7. A correction factor to move the configuration in the direction of lower stress is calculated. This is an iterative procedure based on the vector of first partial derivatives, i.e., the gradient vector. The gradient consists of the set of derivatives of S (stress) with respect to the configuration X. Each element is defined as:

$$g_{ia} = \frac{\partial S}{\partial X_{ia}} = \frac{1}{NS} \sum_j \left(1 - \frac{\hat{d}_{ij}}{d_{ij}} - S^2\right) (X_{ia} - X_{ja}) \tag{3.2}$$

where N = the norming factor $d_{ij}^{\ 2}$

X_{ia} = the co-ordinate value of stimulus i on dimension a

X_{ja} = the co-ordinate value of stimulus j on dimension a

g_{ia} = an element of the gradient vector; a value of stimulus i on dimension a

$\frac{\partial S}{\partial X_{ia}}$ = partial derivative of stress with respect to the a th dimension of point i.

$$G = (g_{11}, \ldots, g_{1r}, \ldots, g_{n1}, \ldots, g_{nr})$$

$$g_{ia} = \frac{\partial S}{\partial X_{ia}}$$

<u>NOTE:</u> G indicates the direction the configuration should be moved to decrease stress.

As a solution to the problem of how far to move the configuration in the direction of "steepest descent", i.e., to lower stress, Kruskal (1964b) has developed several rules for calculation of a best step-size, based on the angle between successive gradients.

8. The configuration is then moved to one of lower stress, and again is normalized.

For a further discussion of the Shepard-Kruskal iteration procedure and its technical problems, see Brummell and Harman (1974, pp. 28-34).

The algorithms using the non-metric MDS model for the analysis of proximity data are basically three: those developed by Young and Torgerson, named TORSCA (Young, 1968); the Smallest Space Analysis series developed by Guttman and Lingoes (Lingoes, 1972); and the algorithms named MDSCAL, developed at the Bell Laboratories (Kruskal, 1964a). Recent programs have made technical improvements in the performance of non-metric MDS, but the basic framework of all the algorithms remains that set up by Shepard and Kruskal.

Plotted output from non-metric MDS algorithms is a geometric configuration of dimensionality specified by the user, in which the stimulus points are located. This is a group space, and, having been derived from a group matrix, it need represent the perceptions of no one individual in particular. The smaller the distance between each pair of points, the greater the similarity perceived between them. Interpretation of the dimensions of the configuration, or the significant attributes of the objects, is made by the user according to the positions of the configuration points relative to each other, and his/her prior knowledge of the situation to which the data relate.

Metric MDS procedures were developed before the non-metric model described above. The metric model, whilst it produces output of at least interval scale in the same way as does the more recent non-metric model, requires that input data as well be at least interval scale (see Torgerson (1958), Coombs (1964)). Furthermore, the metric approach assumes a linear relationship to exist between data and distances in the configuration space. In this model, proximity data are related to distances among points in a configuration space to be recovered, in a way which depends upon an exogenously specified function. The model has two basic steps:

> 1. The specified function is used to compute distance estimates from the proximity data.
>
> 2. Characteristic roots and vectors of a scalar-product matrix derived from the distance estimates are computed to determine dimensionality and co-ordinates for the points in the space (Shepard, 1972a, p. 34).

With the development of the non-metric MDS model, the metric approach is very rarely taken, because of its restrictive assumptions and stringent data requirements.

A recent technique, developed by Carroll and Chang (1970), uses multidimensional scaling of proximity data in a different way. Instead of assuming, as the Kruskal-Shepard model does, that individuals can validly be represented as a group, that they have homogeneity of cognition, agree on what attributes are relevant and on how much of each attribute an object possesses, the Carroll and Chang model allows for individual differences (Brummell and Harman, 1974, p. 34). The model still requires that individuals use the same dimensions in judging objects, but the importance placed on dimensions by individuals is permitted to vary. The algorithm generally used for Individual Differences scaling is INDSCAL. It is not strictly non-metric in the sense of the non-metric algorithms mentioned above, for input data should be at least of interval scale, and subjects' sets of dissimilarities are assumed to be linear functions of the distances. A non-metric version of the model has been developed (NINDSCAL) where input data can have merely ordinal scale properties, and where subjects' proximity measures are assumed to be simply a monotonic function of the distances (Coxen, 1972, p. 7). As yet, however, INDSCAL enjoys greater popularity and circulation than NINDSCAL.

Typical input to the INDSCAL program are matrices of proximity measures between pairs of stimuli, one matrix for each individual. The model follows the following steps (Coxen, 1972, pp. 7-8):

1. Assume that the data are a square symmetric matrix of dissimilarities obtained from each individual. The dissimilarities are assumed to be a modified, weighted function of distances $d(i)_{jk}$ in a common cognitive space.

$$\delta(i)_{jk} = F_i \; (d(i)_{jk}) \tag{3.3}$$

where $d(i)_{jk} = \left(\sum_{a=1}^{r} w_{ia} \; (x_{ja} - x_{ka})^2 \right)^{1/2}$

$\delta(i)_{jk}$ = the proximity measure obtained from individual i with respect to stimuli j and k

r = number of dimensions of the space in which the stimuli are represented

w_{ia} = the weight (or "salience") placed on dimension a by individual i

x_{ja} = co-ordinate value of stimulus j on dimension a

x_{ka} = co-ordinate value of stimulus k on dimension a.

2. To obtain the group space co-ordinates and subject weights, a simplified MDS procedure is used to convert input dissimilarities into estimates of Euclidean distances, d_{ij}, and these are converted to scalar products $b(i)_{jk}$ between "individualized" vectors $y(i)_{ja}$.

$$b(i)_{jk} = \sum_a y(i)_{ja} \, y(i)_{ka} \tag{3.4}$$

since

$$y(i)_{ja} = w_{ia}^{\;1/2} \; x_{ja} \tag{3.5}$$

and

$$y(i)_{ka} = w_{ia}^{1/2} \; x_{ka} \qquad (3.6)$$

then

$$b(i)_{jk} = \sum_{a} w_{ia} \; (x_{ja} \; x_{ka}) \qquad (3.7)$$

where $b(i)_{jk}$ = the scalar product of stimuli j and k for individual i

$y(i)_{ja}$ = vector of values of j on dimension a for individual i

$y(i)_{ka}$ = vector of values of k on dimension a for individual i

w_{ia} = weight placed on dimension a by individual i

x_{ka} = co-ordinate value of stimulus k on dimension a

x_{ja} = co-ordinate value of stimulus j on dimension a

This gives the scalar products specification of INDSCAL.

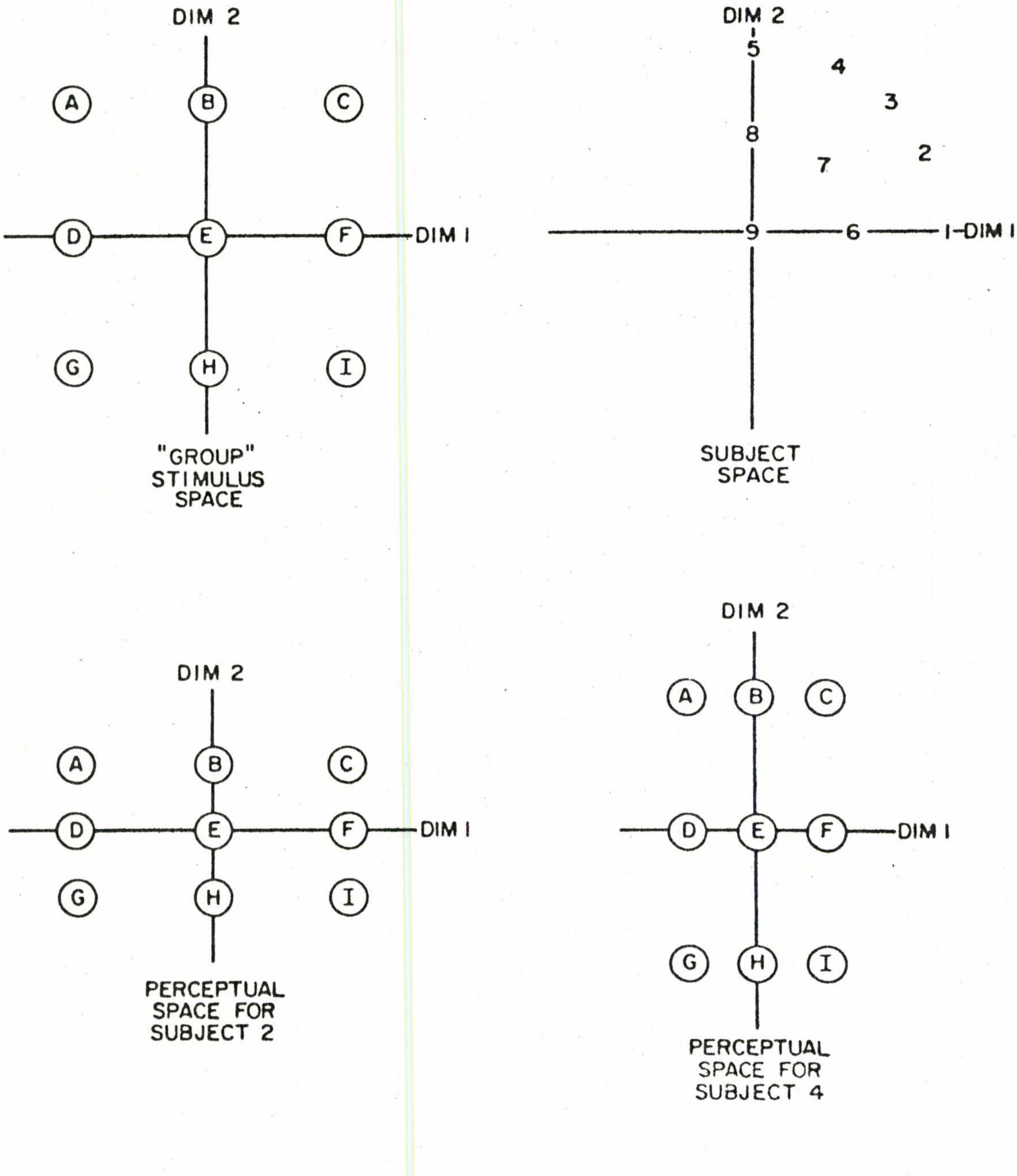
3. A non-linear iterative least squares procedure is used to estimate the configuration values x_{ja} and subject weights w_{ia} by means of a Canonical Decomposition procedure described by Carroll (1972, pp. 109-110).

The main output of an INDSCAL analysis is a "group space", in which the stimuli (objects) are located as points. This is an "average" space, and represents no one of the individuals from whose judgements it was derived. Output also is a "subject space". It has the same dimensions as the group space, but in it the individuals, not the stimuli, are represented as points. The co-ordinates of each point in the subject space indicate the numerical weight, or salience, attributed by the individual to each dimension. Information given in the output on individuals' saliences with respect to the dimensions makes it possible to construct a "private" stimulus space for each individual.

Coxen (1972, p. 4) notes that two things are particularly important in interpreting the subject space information. The distance of subject points from the origin of the space is significant. When the points are located close to the origin, relatively little variance in those subjects' data is being explained by the dimensions in the space. Following from this, the further a point from the origin, the more of that subject's judgements are being accounted for. This fact enables the analyst to pick out groups of subjects for whom the space fits well, or poorly. The extent to which the points form distinct clusters in the subject space is also felt to be important. Clusters of points may be interpreted as distinct "points of view", and indicate that the individuals place similar importance on the dimensions, when judging the stimuli.

Besides the nature of its output, INDSCAL has two characteristics which further differentiate it from the Shepard-Kruskal model. First is the fact that it produces a *unique* orientation of the axes of

FIGURE 2: OUTPUT FROM INDSCAL



SOURCE: Carroll (1972), p. 108.

the group space, so that it is not permissable to rotate axes to facilitate interpretation. Furthermore, there is nothing in the model which constrains the axes to be orthogonal (since their correlations are zero) (Coxen, 1972, p. 6). The second characteristic is that the square of the distance from the origin of the subject space to the subject point is approximately interpretable as the proportion of variance in that individual's data which is explained by the solution. Hence, individuals may be differentiated by the clusters in the space, and also by the extent to which the solution fits their data.

Individual differences scaling has potential for very valuable applications in work on perceptions of public facility location. Though it is limited to dealing with a small number of individuals, and thus is not really oriented to analyzing survey data, it is possible to input, instead of matrices from single subjects, averaged group matrices representing different viewpoints. For example, if various different groups held opinions about the location of a public facility in a neighbourhood, their judgements could be scaled using INDSCAL or NINDSCAL, to produce a group or averaged view of the situation, together with information on the extent of difference felt between the various opinions. With a knowledge of the dimensions along which people basically disagree, the decision on a locational solution may be facilitated.

b. Models Used in the Analysis of Dominance Data

Thurstone's Law of Comparative Judgement is generally used in the analysis of dominance data collected by the method of paired comparisons.

Thurstone assumes a relationship to exist between the degree of consistency of judgement and the subjective difference between two stimuli. The model converts the proportion of times one object is judged to dominate another into a measure of the subjective difference between them (Coombs, Dawes, Tversky, 1970, p. 42). The model takes the form of a set of equations relating the proportion of times any given stimulus k is judged greater on a given attribute than any other stimulus j, to the scale values and discriminal dispersions of the two stimuli on the psychological continuum (Torgerson, 1958, p. 159). Assumptions of the model are:

1. Each stimulus, when presented to an observer, causes a discriminal process which has some value on the psychological continuum of interest.

2. The values of discriminal processes are such that the frequency distribution of discriminal processes associated with a stimulus is normal on the psychological continuum.

3. The mean and standard deviation of the distribution associated with a stimulus are taken as its scale value and discriminal dispersion respectively (Torgerson, 1958, pp. 159-160).

The complete form of the Law of Comparative Judgement is the following equation:

$$S_k - S_j = x_{jk} [\Theta_j^2 + \Theta_k^2 - 2r_{jk} \Theta_j \Theta_k]^{1/2} \qquad (3.8)$$

where S_j, S_k = the scale values of stimuli j and k

Θ_j, Θ_k = their discriminal dispersions

r_{jk} = the correlation between the pairs of discriminal processes d_j and d_k

x_{jk} = the normal deviate corresponding to the theoretical proportion of times stimulus k is judged greater than stimulus j

(Torgerson, 1958, p. 162).

Because the "law" is not always solvable in its complete form, there always being more unknowns than observation equations, Thurstone makes various simplifying assumptions in order to make the law workable. Accordingly, he presents five cases of the Law of Comparative Judgement. Case 5 is the simplest and most commonly used for psychological scaling, so it alone will be discussed here. (See Torgerson, 1958, Ch. 9, for a full discussion of the other four cases.)

In Case 5, the expression inside the brackets in equation (3.8) is assumed to be constant for all pairs (j, k) and for convenience is arbitrarily set equal to one. The equation then becomes

$$\bar{S}_k - \bar{S}_j = x_{jk} \qquad (3.9)$$

Then, for each pair of stimuli there is an observational equation (as above) with the unknowns on the left and the numerical value on the right. The total number of equations, if the data are complete, will be greater than the unknowns. Because the solution is over-determined, and the equations, being based on empirical data, will certainly be inconsistent, an averaging process is used in the model to find a best estimate of the parameters (Coombs, Dawes, Tversky, 1970, p. 45). Torgerson (1958, p. 170 ff.) has shown this process to be a least squares solution. The assumption of the constancy of the unit of measurement in Case 5 is equivalent to requiring that the discriminal dispersions of all stimuli to be the same, and that the correlational term be the same for all pairs (Coombs, Dawes, Tversky, 1970, p. 45).

An algorithm called CASE5 is available for Thurstone Case 5 scaling of paired comparisons dominance data. Raw input is a square intact matrix showing the number of times each row stimulus is judged greater than (dominates, or is preferred to) each column stimulus. Symmetric cells sum to the total number of judgements of the pair made.

The output of the CASE5 algorithm is a Z matrix, yielding a unidimensional scale which indicates the deviation of each stimulus from the mean of all the scale values. For a lengthy discussion of the method of paired comparisons, the derivation of unidimensional scales, Thurstone's Law, and significance tests for paired comparison judgements, consult Edwards (1957, Chs. 2 and 3).

Models for the analysis of preference orderings will be included in this discussion of scaling of dominance data, since Shepard's dominance data category may be extended to include preference rankings of more than two objects.

The model widely used in the scaling of preferential choice data is that developed by Coombs (1950), termed "unfolding". The basic assumptions of the unfolding technique in its simplest form (unidimensional) are the following (Coombs, 1964, p. 80):

1. Each individual and each stimulus may be represented by a point on a common dimension, called a J-scale.

2. Each individual's preference ordering of the stimuli from most to least preferred corresponds to the rank order of the absolute distances of the stimulus points from the individual's ideal point, the nearest being the most preferred.

3. The individual's preference ordering is called an I-scale, and may be thought of as the J-scale folded at the ideal point, with only the rank order of the stimuli given in order of increasing distance from the ideal point. (For a diagrammatic description of this, see Coombs (1964), p. 80).

4. The data consist of a set of I-scales from a number of individuals, and the problem is to unfold these I-scales to recover the common J-scale.

Unfolding is based, then, as is the proximity model, on the idea of interpreting the distances between points. The difference is that where the proximity model takes the distance between the two points in each pair, the unfolding (dominance) model considers the relative distances of two points in a pair to some other "ideal" point.

Coombs (1964, Ch. 5) develops a method which derives metric information on the inter-point distances, based solely on mid-point information contained in the I-scales. So, given preferences about one attribute, where individuals' judgements are transitive, unfolding yields a unidimensional metric J-scale from the non-metric I-scale data.

Many preference rankings are based on more than one attribute, and may contain intransitive judgements. For this situation, a unique J-scale cannot be obtained, and multidimensional unfolding models have been developed. In multidimensional unfolding theory, then, the assumption is made that stimuli have a fixed configuration in a space of r dimensions, and that each subject's preference ordering reflects the order of increasing distance of the stimulus points from his ideal point (Coombs, 1964, p. 141). For a clear statement of the general unfolding theorem, see Coombs (1964, pp. 160-2). Bennett and Hayes (1960) initially extended Coombs' unfolding model to the multidimensional case, their method being to derive a rank ordering of ideal points on each dimension. (See description in Coombs, 1964, Ch. 7.) Since then, multidimensional unfolding algorithms have been developed, extending the algorithms of Shepard(1962a, 1962b), Kruskal (1964a, 1964b) and Young and Torgerson (Young, 1968) to scale preference data in a joint space. Here, the individuals and the stimuli are mapped as points in a common space.

The program MDA-RC in the Guttman-Lingoes nonmetric program series will perform Coombs' multidimensional unfolding analysis, if the rows of the data matrix are individuals and the columns stimuli (Lingoes, 1972,

p. 58). Brummell and Harman (1974, p. 43 ff.) provide a clear discussion of three other models concerned with individuals' preferences: Tucker and Messick's "point of view" or "vector" model, Carroll and Chang's "general unfolding" model and Carroll and Chang's "weighted unfolding" model. They point out that the latter two models are included in Carroll and Chang's four phase computer program PREFMAP. For a discussion of the different assumptions made in these models, and the various purposes for which the available computer algorithms may be used, consult Brummell and Harman (1974, pp. 43-49).

c. Models Used in the Analysis of Conjoint Measurement Data

Conjoint measurement procedures are considered to be among the most promising in scaling. To date, however, they have been used far less than have proximity and dominance models. Young (1972, p. 69) justifies conjoint measurement models in the following way:

> "... When the factors can be measured independently, one desires to account for their joint effects by the appropriate combination rule. It is often the case, however, that the factors cannot be measured independently, and that only the order of their joint effects is known. In this case it is desirable to be able simultaneously to reduce the complex phenomena to its basic factors and to obtain a measurement of these basic factors such that the combination of the factors accounts for the order of the observations. This is the conjoint measurement problem, and the combination rule is known as the conjoint measurement model."

These models give measures of the relative values of certain stimuli attributes (independent variables) from data on combinations of these attributes (the dependent variable) (Brummell and Harman, 1974,

p. 49). If the combination of stimuli attributes with which we are dealing, then, is public facility size and nearness of a facility to an individual's home, the task of the model is to provide measures for the various levels of these known attributes, such that when the values of each attribute are combined according to some function, they account for the order of observed preferences (the dependent variable).

The combination rule, which is generally additive, defines the conjoint measurement model. Shepard (1972a, p. 39) states that, in most cases, the method of the model is iterative adjustment of a value for each of the rows and a value for each of the columns, to minimize some measure of overall departure from the specified rule of combination. The model may be nonmetric, in that the data is required to be related to the values generated by the specified combination rule, by a function which is merely monotonic. The *order* of the derived values of the dependent variable, then, must match the observed *order* of preferences.

Young (1972) has generalized the conjoint measurement model, by using a combination rule called a polynomial function, which may be additive, subtractive or multiplicative. His hypothesis is that the approach for constructing nonmetric MDS models may also be used in the construction of algorithms for polynomial conjoint analysis. Young (1972) develops a model for building such algorithms, gives examples of different cases of this model, and gives the necessary definitions and operations for writing polynomial conjoint analysis computer programs. He has constructed an algorithm related to the concepts in this paper, named POLYCON, which is now available.

Further conjoint analysis algorithms are available from the Guttman-Lingoes nonmetric program series. There are at least three such programs available in this series to date, CM-l, CM-ll, and CM-lll, which have applications to analysis of variance, regression analysis, and factor or correlational analysis (Lingoes, 1972, pp. 63-64). For a description of the specific aims and advantages of these algorithms, see Lingoes (1972).

Brummell and Harman (1974, p. 51) note a number of conceptual problems in this approach. The attributes relevant to the stimuli are assumed to be already known; only their values are not specified. The model assumes, furthermore, that the attributes are independent. Providing these restrictions are met, however, the interpretation of the results of conjoint measurement analysis gives fewer problems than does the interpretation of point configurations in nonmetric MDS. Output is a set of numerical values, readily matched with the known attributes.

7. <u>Summary</u>:

The preceding discussion of the available MDS models and algorithms indicates that MDS is a useful technique for decision-making which considers community preferences. Most MDS algorithms will aggregate a set of community judgements into a "group space", and some will indicate the deviation of individual responses from those represented in the group space. From a MDS analysis of public facility perceptions data, then, we may derive information about the attributes, or dimensions, of people's opposition to public facility location. Not only will we find those dimensions which individuals agree upon, but also those dimensions about which people have differences of opinion.

The usefulness of the models discussed must be seen in terms of the types of data they analyze. Many questions about community opposition to public facility location may be studied using the four forms of data described earlier in this chapter, in conjunction with the MDS models designed to analyze them. The various models, however, are appropriate to specific types of resarch design. The non-metric MDS model, which is the most widely used and readily available of the models presented here, is flexible. It may be used for generating specific hypotheses about the nature of community opposition dimensions, as an exploratory tool, or it may be used to confirm hypotheses already made about the perceived attributes of facility location. Individual Differences Scaling is equally adaptable, and provides additional information about the perceived significance of the dimensions.

Models for the analysis of dominance data are less widely used, probably because very complete data sets are required to produce a meaningful result. These models, like the nonmetric MDS models, may be used with both types of research design mentioned above.

Conjoint measurement models have been used very little to date, though they are considered to be promising. These models, which analyze perceptions of different combinations of attributes, are applicable to research designs where specific hypotheses are to be tested, rather than generated, since significant attributes must be specified, with this model, before data are collected.

For the initial work of establishing the dimensions of community opposition to the location of certain types of public facilities, an exploratory research design should be used. The non-metric MDS models, and models for the analysis of dominance data, are most appropriate for such research designs. For this reason, and for reasons of availability, the algorithms TORSCA-9 and INDSCAL are selected for use in the pilot empirical study presented in Chapter 4.

CHAPTER 4

AN EMPIRICAL TEST OF THE METHODOLOGY

This chapter describes an empirical pilot study which was undertaken as an illustration of the use of the proposed methodology. Data available from a previous study were used. The sample members were four graduate students and one faculty member, who were non-users of the facilities being considered, and who did not live in areas negatively impacted by the facilities. The public facilities which sample members were asked to consider are all mental health centres in Philadelphia, providing out-patient services for mental health clients, drug and alcohol addicts. Each of the centres is small scale, being about the size of a local branch library.

Because of the use of these data, the analysis results give only the *perceptions* (as opposed to distinct feelings of *opposition*) of non-impacted non-users of the facilities. It is not reasonable to expect the judgements of the sample members to be the same as those of residents of a neighbourhood who definitely oppose the presence of a facility in their midst, and who feel themselves to be negatively impacted. Thus, little can be concluded about the nature of community opposition to public facility location from the actual results of this study, because the sample members constitute neither "community" nor explicit "opposition".

1. Research Design:

It was generally hypothesized that the individuals would perceive the public facilities themselves in terms of four factors: design, visibility, activity and impact. "Design" relates to the quality of the building itself; "visibility" is defined with respect to how noticeable the facility is, and whether the building seems attractive; "activity" concerns the number of people using the facility; and "impact" relates to the "goodness-of-fit" of the facility into the surrounding neighbourhood.

Furthermore, it was hypothesized that the sample members would perceive the *neighbourhoods* in which the facilities are located in terms of the same four variables, concentrating on how well each facility fits its particular neighbourhood in terms of these variables. With respect to the neighbourhoods, the four variables are defined slightly differently; "design" concerns the appearance of buildings in the neighbourhood; "visibility" relates to the attractiveness of that neighbourhood for facility clients; "activity" refers to the numbers of people circulating within the facility's neighbourhood, and "impact", again, to the "goodness-of-fit" of the facility into the neighbourhood.

The particular research questions addressed in the study, then, relate to the *perceptions* individuals have of public facilities of the same type. Two analyses were undertaken: the first was to establish if and how the sample members discriminated between facilities of the same type. The second analysis was required to indicate how the individuals judged the neighbourhoods in which the facilities are located, and how well these particular public facilities fitted them.

2. Description of Data Preparation:

The data used are semantic differential rankings, where individuals were asked to consider pairs of bi-polar adjectives (such as clean-dirty) with respect to each of 10 particular mental health centres, and to 10 neighbourhoods where these facilities are located. The sample members were asked to rank each facility and each neighbourhood on each of the adjective pairs, using a scale where 1 could represent a very negative characteristic, say, very dirty, and 5 its opposite, say, very clean. Initially, 30 adjective pairs relating to the facilities, and 20 to the neighbourhoods were presented to the subjects. A subset of these data was chosen for analysis here, however: 11 facility adjective pairs and 7 neighbourhood adjective pairs were chosen. The subset is given below:

FACILITIES	NEIGHBOURHOODS
Dirty-clean	Dull-interesting
Ugly-beautiful	Ugly-beautiful
Deteriorated-well kept	Deteriorated-well kept
Inhuman-human	Dirty-clean
Dull-interesting	Unpleasant-pleasant
Insignificant-relevant	Untidy-neat
Repellent-attractive	Dangerous-safe
Unfriendly-sociable	
Negative-positive	
Tense-relaxed	
Depressing-happy	

The set of neighbourhoods data, and the set of facilities data, were analyzed separately. There were two forms in which each set of data could be analyzed by the chosen non-metric MDS model. Matrices of data could be compiled, one to represent each individual's rankings; or one matrix could be compiled, to represent the rankings of the group as a whole. It was decided to analyze both sets of data both ways, using the non-metric MDS model in the forms of the algorithms TORSCA-9 and INDSCAL.

a. Preparation of Raw Data for Input to TORSCA-9

Four steps were involved in transforming the individuals' raw data into a group matrix of proximity data suitable for input to TORSCA-9. The steps are outlined below:

STEP 1: Individuals' Raw Data Matrices. Each individual submitted two matrices of data - one rating facilities, the other, neighbourhoods.

	10 NEIGHBOURHOODS									
	1	2	3	4	5	6	7	8	9	10
Dull-interesting	4	5	4	4	4	5	4	2	5	4
Ugly-beautiful	4	4	1	2	4	2	4	1	1	1
Deteriorated-well kept	5	4	2	2	5	5	4	1	4	2
Dirty-clean	5	4	2	2	5	5	3	2	2	2
Unpleasant-pleasant	4	4	2	2	4	4	4	1	1	1
Untidy-neat	5	4	1	2	5	4	4	1	2	2
Dangerous-safe	5	3	2	1	5	5	3	2	5	2

FIGURE 3a: Individual Raw Data Matrix

STEP 2: Generation of a Group Matrix for Facilities Rankings, and for Neighbourhoods Rankings. The rankings of each individual for each facility or neighbourhood on each adjective pair was arrayed, and the median of these rank values was taken. The median values were entered into the cells of a "group matrix", to indicate an "averaged" ranking for each facility or neighbourhood on each adjective pair.

	10 NEIGHBOURHOODS									
	1	2	3	4	5	6	7	8	9	10
Dull-interesting	4	2	4	4	4	4	3	4	4	2
Ugly-beautiful	4	3	2	2	3	2	2	1	2	1
Deteriorated-well kept	4	4	2	2	5	3	3	1	3	1
Dirty-clean	4	4	2	2	5	2	3	2	2	1
Unpleasant-pleasant	4	2	2	2	4	2	2	1	2	1
Untidy-neat	3	4	1	2	5	2	3	1	2	1
Dangerous-safe	4	3	2	2	5	3	3	2	3	2

FIGURE 3b: Group Matrix

STEP 3. For input to TORSCA-9, this group matrix had to be converted to a matrix of proximity data. It was therefore necessary to derive a square symmetric matrix, with the 10 facilities (or neighbourhoods) represented on both rows and columns. The adjective-pair (hereafter *attribute*) rankings had to be collapsed into a single measure of similarity (or dissimilarity) between the 10 facilities.

To accomplish this, the raw data group matrix was input to a non-parametric correlation program, NONPAR CORR, from the SPSS package (Nie, Bent and Hull, 1970, p. 153 ff.), and Kendall's tau correlation coefficients were computed for the facilities and for the neighbourhoods. A non-parametric correlation procedure was chosen because it requires only that the input data be ordinal in scale; it does not assume the data to be normally distributed or to have interval scale properties. It was decided that Kendall's tau coefficients, rather than Spearman's r coefficients, should be compiled, since the Kendall's tau are thought to be more meaningful when the data contain a large number of tied ranks (Nie, Bent and Hull, 1970, p. 153).

Two data matrices of Kendall's tau coefficients, showing the results of correlating every facility with every other facility, and each neighbourhood with each other neighbourhood, resulted. These coefficients were interpreted as measures of proximity between each pair of objects (facilities or neighbourhoods). The larger the positive correlation between the objects, the greater the perceived similarity between them; the larger the negative correlation between the two objects, the smaller the similarity perceived between them. If the coefficients approached zero, then no relationship was perceived to exist between the two objects; they were neither very similar nor very dissimilar.

<u>STEP 4</u>. Because the TORSCA-9 routine interprets all negative and zero values to be missing data, the proximity data obtained from the Kendall's tau computations had to be made positive and non-zero. To

do this, each coefficient was enlarged by +1.000. It is possible that this addition distorted the magnitudes of the original Kendall's tau coefficients. There was insufficient time, however, to investigate this possibility.

A qualifying point is usefully mentioned here: there is more than one method of collapsing semantic-differential data to proximity data. As an alternative procedure to that used in Steps 3 and 4 of this study, Betak, Brummell and Swingle (1974, p. 7) use the following formula:

$$d_{ij} = \sum_{a=1}^{n} | x_{ia} - x_{ja} | \tag{4.1}$$

where

n = # semantic differential adjective pairs (attributes)

d_{ij} = the "absolute distance" (or perceived proximity) between a pair of objects, i and j, for a single individual

x_{ia} = the semantic score on attribute "a" for object i

x_{ja} = the semantic score on attribute "a" for object j.

For each individual who responds to a pair of objects, then, d_{ij} is a measure of perceived proximity between the two objects. To obtain a group matrix, showing a representative value over the group of individuals, Betak, Brummell and Swingle (1974, p. 7) take median values. These median values are the cell values in the matrix of proximity data which they input to the TORSCA-9 routine.

b. Preparation of Raw Data for Input to INDSCAL

Similar steps were involved in the preparation of raw data for input to INDSCAL. The initial individual raw data matrices, with which the data preparation for TORSCA-9 was begun, were converted to matrices of proximity data, one for each individual rather than one to represent the whole group. This was accomplished by submitting each individual's data matrix to the SPSS NONPAR CORR routine, generating a matrix of Kendall's tau correlation coefficients, to be interpreted as proximity data, for each individual. Again, the value of +1.000 was added to each coefficient to meet the requirement that the matrix cell entries be non-zero and positive.

3. Results of Data Analysis and Interpretation of Results

a. The Analysis (Using TORSCA-9) of Neighbourhoods Rankings

The group matrix, containing proximity measures on the 10 neighbourhoods which individuals were asked to rank, was analyzed by the TORSCA-9 routine. Three, two and one-dimensional solutions were obtained. The three-dimensional solution was preferred for interpretation since its dimensions were plausibly interpretable, and because its stress (.024), after the maximum number of iterations, was considerably lower than that of the two-dimensional solution (.073).

The three-dimensional solution configuration is given in Figures 4a, 4b and 4c. In each plot, the 10 points located in the space represent the 10 Philadelphia neighbourhoods judged by the individuals. The

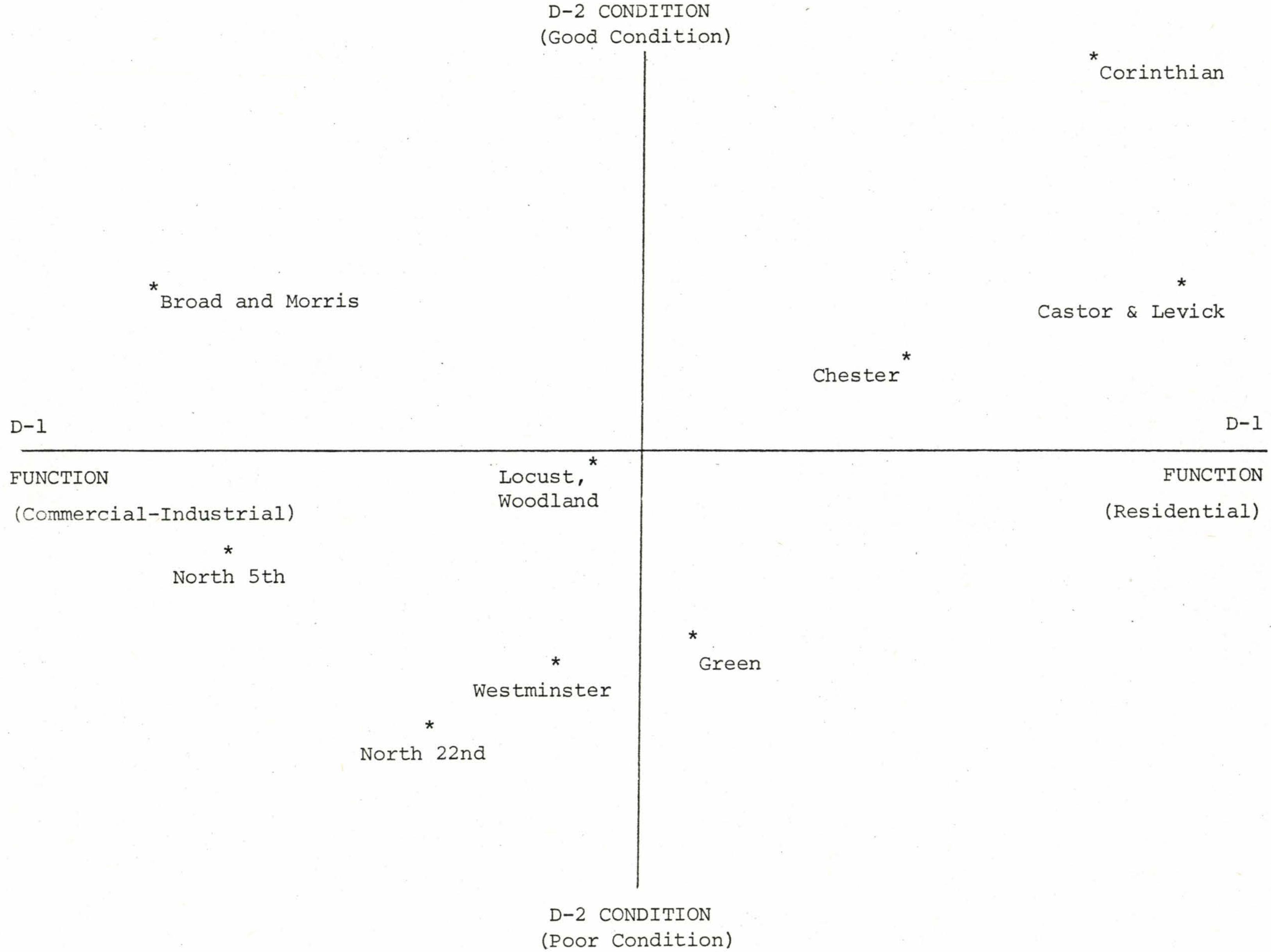


FIGURE 4a: 3-DIMENSIONAL TORSCA-9 NEIGHBOURHOODS SOLUTION: DIMENSIONS 1 AND 2

FIGURE 4b: 3-DIMENSIONAL TORSCA-9 NEIGHBOURHOODS SOLUTION:
DIMENSIONS 1 and 3

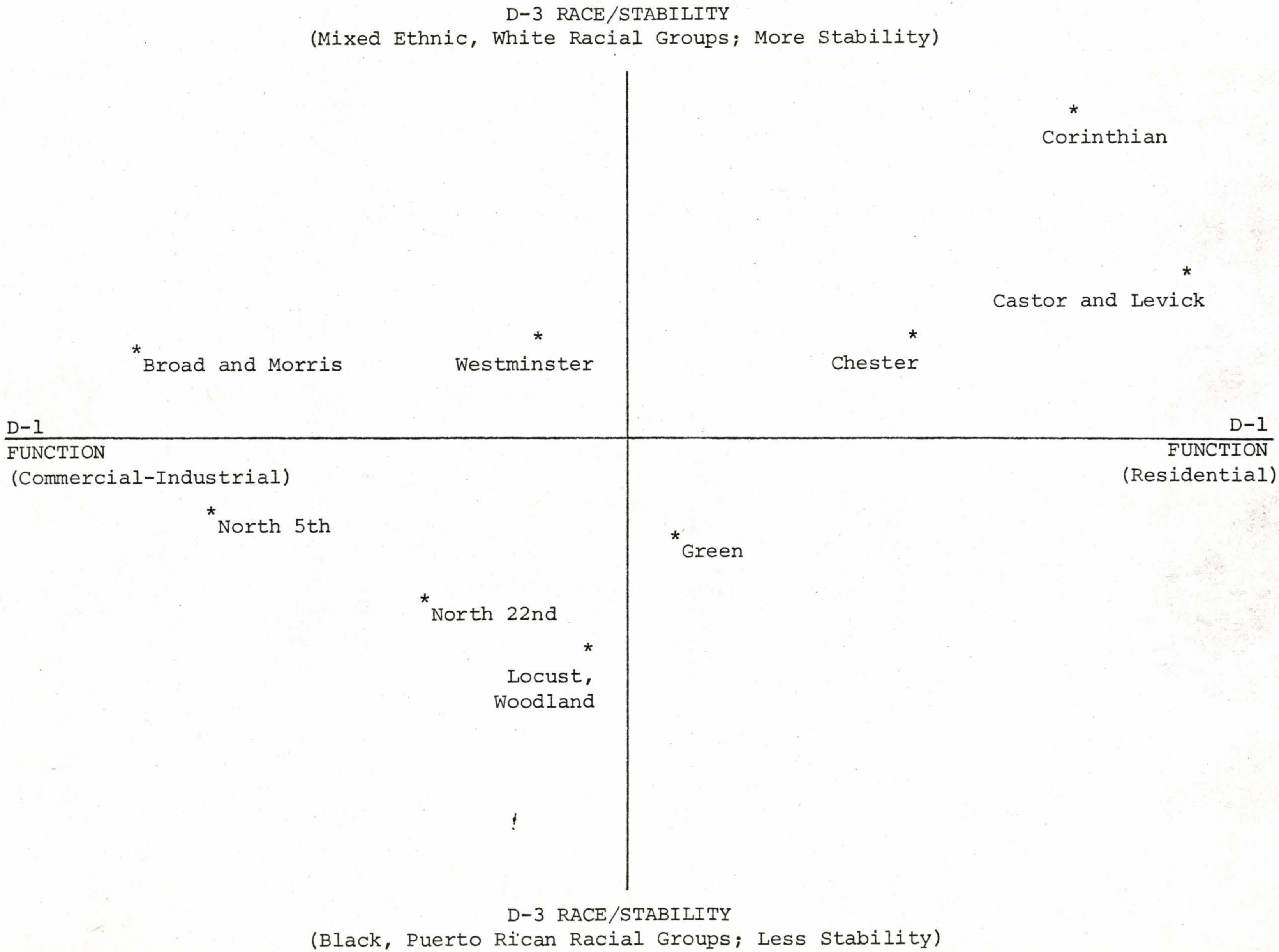
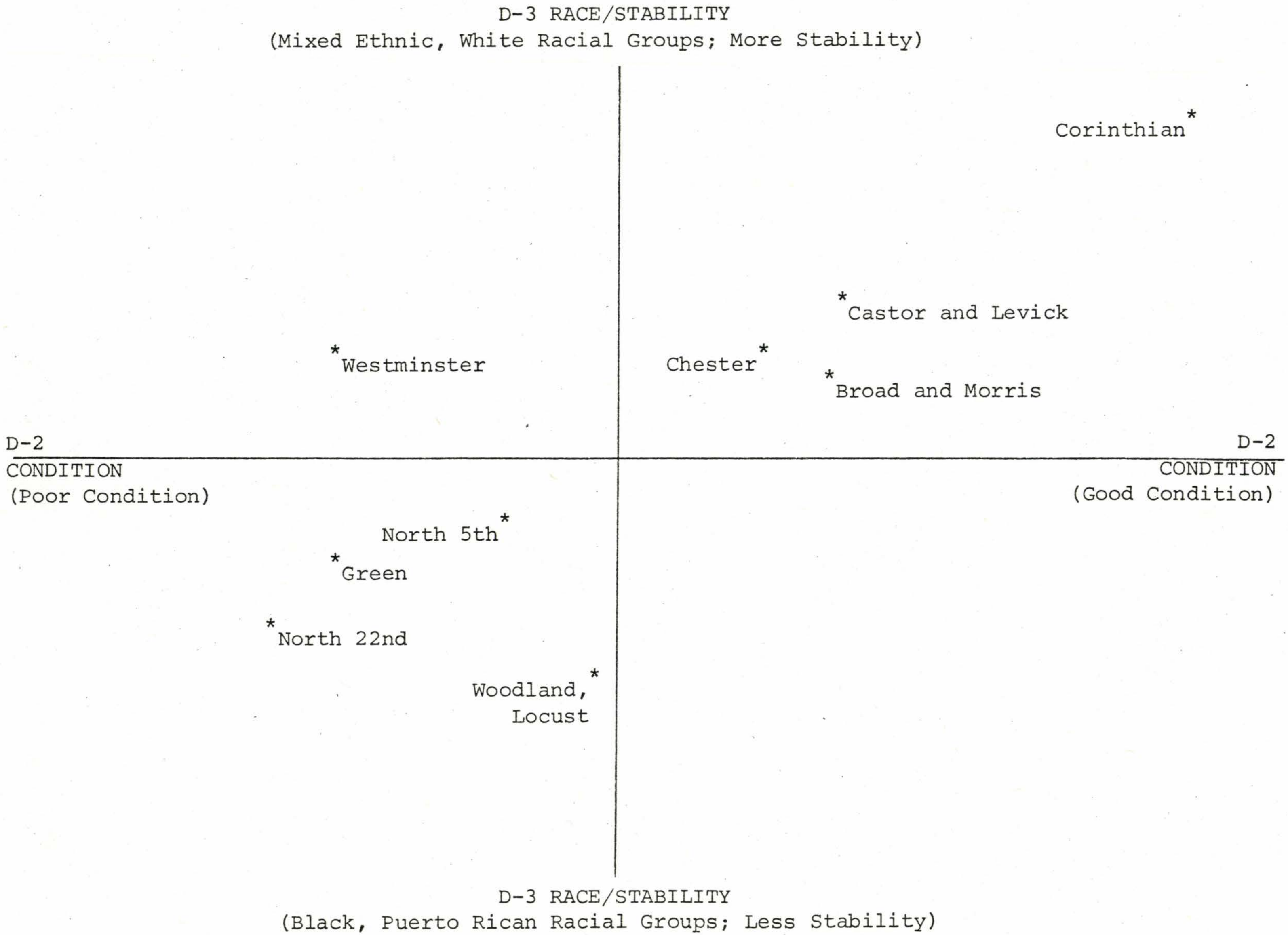


FIGURE 4c: 3-DIMENSIONAL TORSCA-9 NEIGHBOURHOODS SOLUTION: DIMENSIONS 2 AND 3



neighbourhood locations are written beside the points. This is a group space, representing no *one* of the individuals from whose data it was derived. The dimensions of the space, representing the significant attributes by which the group discriminated between the neighbourhoods, have been interpreted as those of *Function* (D-1), *Condition* (D-2) and *Race/Stability* (D-3). It was decided not to rotate the axes of the space, since the placement of dimensions, as they are, yields a plausible interpretation.

As can be seen from the configuration labelling, the Function dimension ranges from commercial/industrial (or non-residential) to residential. From this continuum, it is clear that most of the neighbourhoods are perceived to be semi-residential -- only the Broad and Morris and North 5th Street facilities stand out as being clearly non-residential. The second dimension is that of neighbourhood condition. The labels indicate that the dimension ranges from well-cared for, to poorly-kept, neighbourhood conditions. The third dimension was not as readily identifiable as were the other two. Dimension three seems to combine the characteristics of race, and neighbourhood stability. The location of points at one end of the dimension suggests black and Puerto Rican racial groups, and some feelings of neighbourhood instability. Point placement at the other end of the dimension suggests that mixed ethnic/white racial groups are characterizing those neighbourhoods, as is a sense of greater stability.

What the analysis suggests, therefore, is that from this "averaged" space, it appears that the survey respondents (as a group) judge the 10 neighbourhoods in terms of three main attributes -- Function, Condition and Race/Stability. The weight or importance placed on each of these dimensions, however, is not revealed in this method of analysis.

The identification of dimensions has been made on the basis of point placement in the solution configuration, and a knowledge of the characteristics of these neighbourhoods, largely based on the data. It is clear that the technique being used will not give a unique description of the sample group's perceptions. However, if the analyst has a knowledge of the data, then the configuration clusters will usually provide some plausible meaning. It is purely the responsibility of the analyst, however, to decide which of the solution plots output by the algorithm gives the most meaningful result.

Initial hypotheses which may be drawn from these results suggest that individuals will perceive city neighbourhoods (where small-scale mental health facilities have been located) in terms of the three identified dimensions. How do these dimensions relate to the general hypotheses made about perception of the neighbourhoods? Recall that it was hypothesized that judgements would be made in terms of visibility, activity, design and impact. These four terms do not seem to be represented directly in the identified dimensions. The Function dimension may contain considerations of activity, as may the Race/Stability continuum. The Condition dimension perhaps hides notions of visibility and design. But none of this is at all obvious. There appears to be no consideration in the three identified dimensions of the extent of "goodness-of-fit" of the facility to the neighbourhood, or of its impact. In order to measure the judgement of such a question, it would probably be necessary to actually ask respondents to consider the goodness-of-fit of the facility, rather than just ask their judgements of the neighbourhood itself, as was done in the collection of these data.

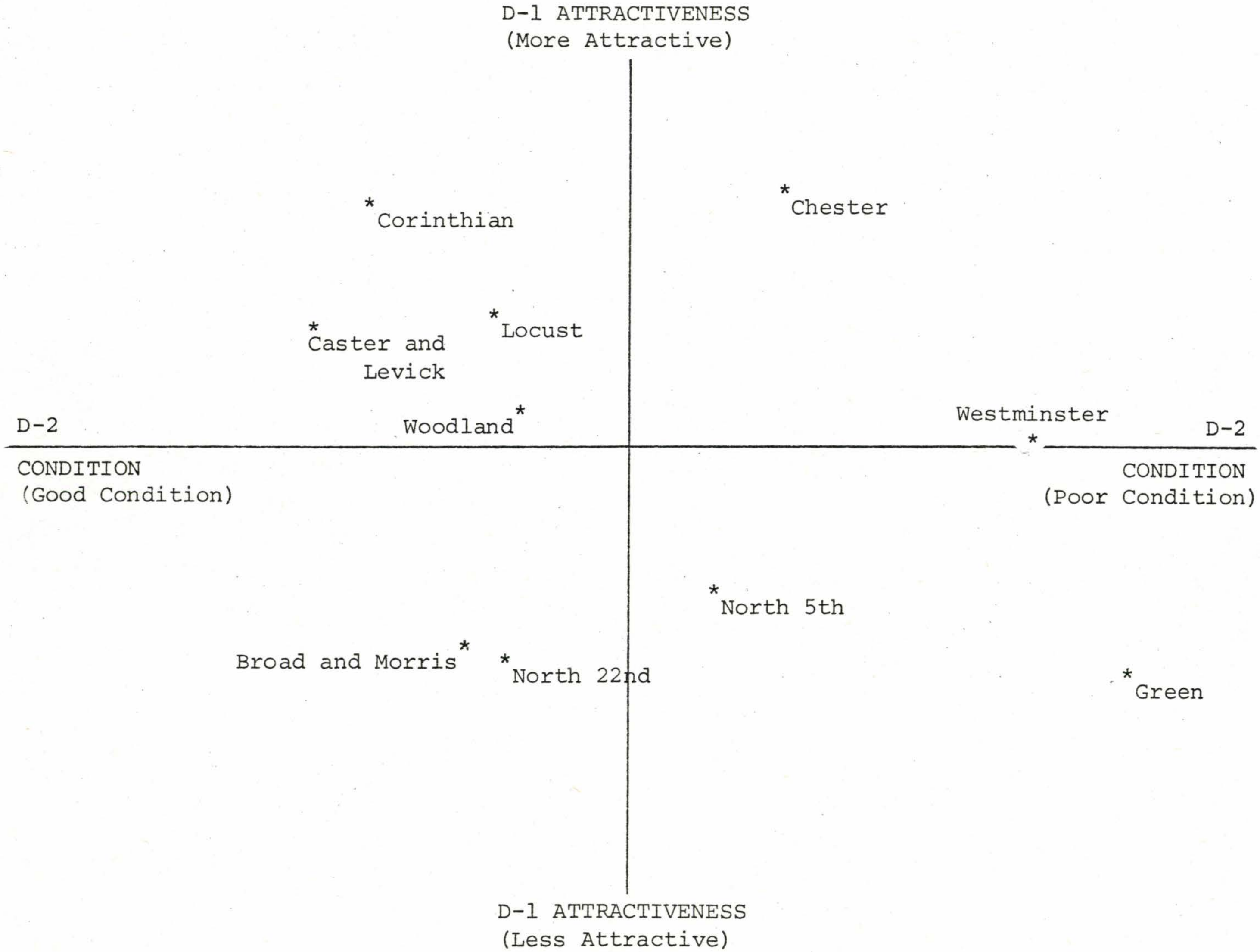
b. <u>The Analysis (Using INDSCAL) of Facilities Rankings</u>

The *individuals'* proximity matrices from the facilities rankings were analyzed using the INDSCAL program. As was described in Chapter 3, the output of this algorithm is a group space (locating objects), and a space in which the individuals themselves are located (subject space). The three-dimensional solution was again selected as most plausible, since the correlation between the group space scores and each of the individual's raw data scores was much higher than that for the one and two-dimensional solutions. The three-dimensional group space better represents each one of the individuals' rankings than do the other solutions. The error term in the three-dimensional solution (2.11) also, was less than that of the two-dimensional solution (3.09), though both these error terms are quite large. INDSCAL does not have a direct measure of "stress", as TORSCA-9 does.

Group space plots of the three-dimensional solution from the INDSCAL analysis of facilities data are given below in Figures 5a, 5b and 5c. The points located in the space are the facilities judged by the respondents.

The three dimensions used by the group in judging the facilities were identified as *Attractiveness* (D-1), meant in the sense of being

FIGURE 5a: 3-DIMENSIONAL INDSCAL FACILITIES SOLUTION: DIMENSIONS 1 AND 2 (GROUP SPACE)



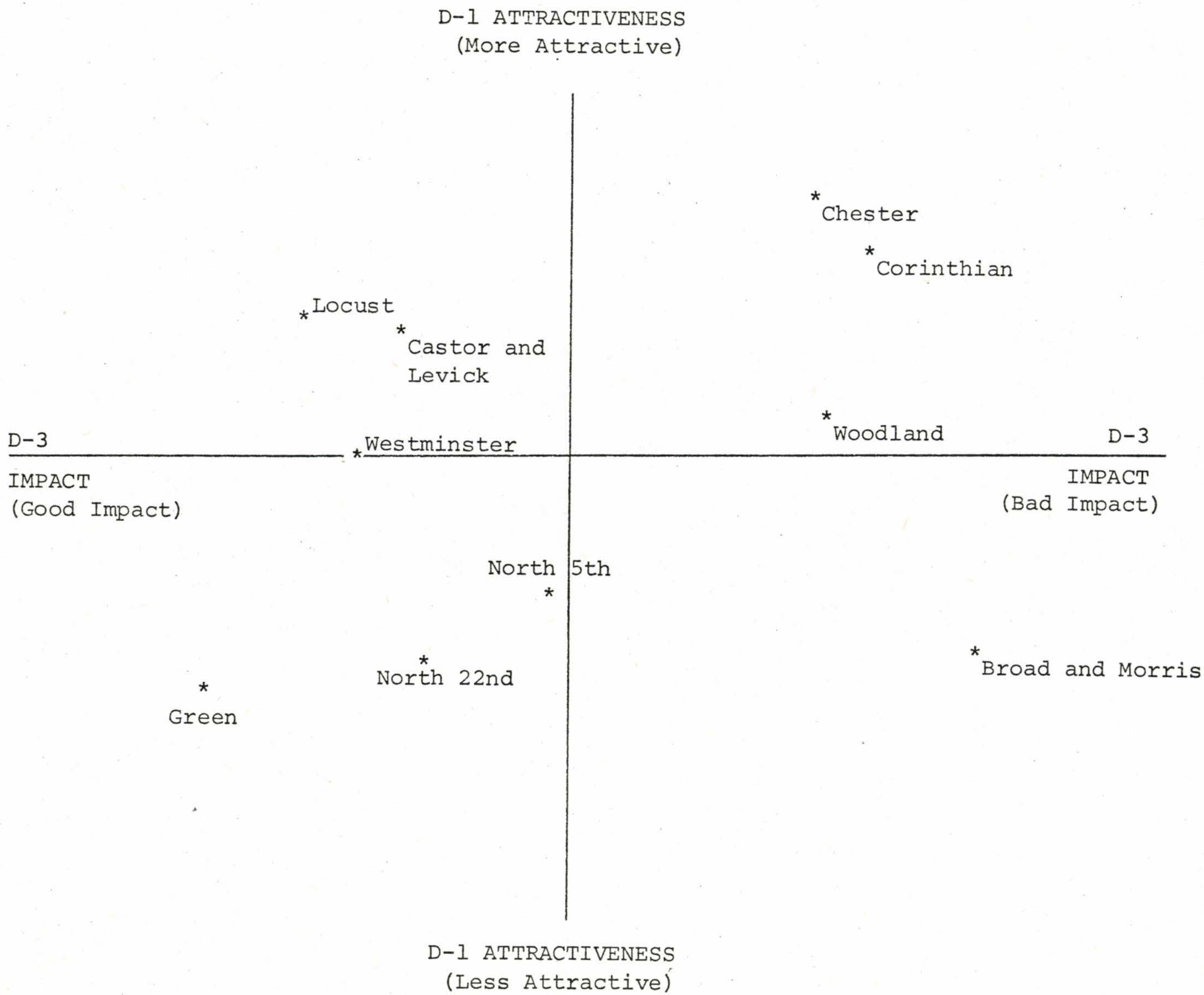


FIGURE 5b: 3-DIMENSIONAL INDSCAL FACILITIES SOLUTION: DIMENSIONS 1 AND 3 (GROUP SPACE)

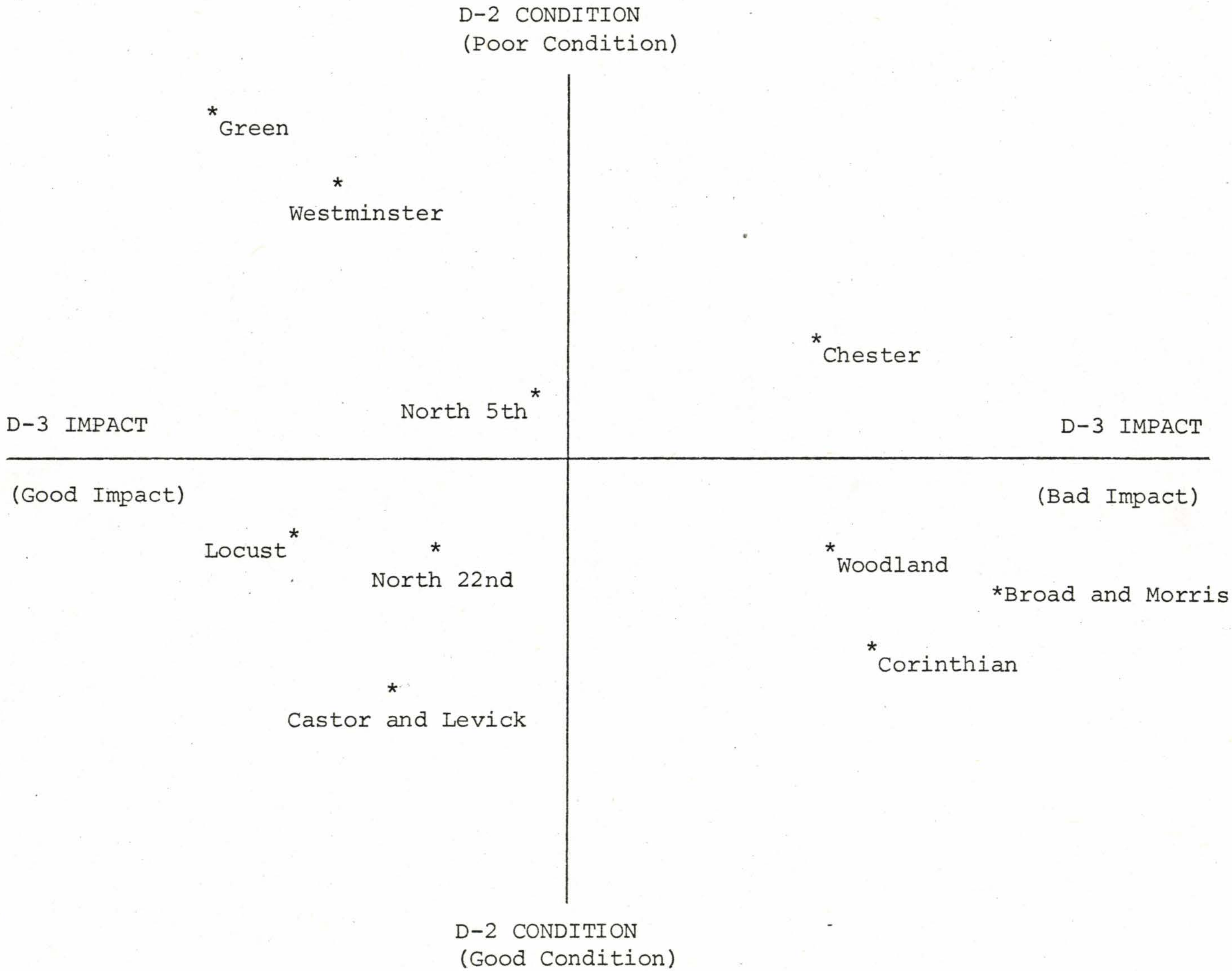


FIGURE 5c: 3-DIMENSIONAL INDSCAL FACILITIES SOLUTION: DIMENSIONS 2 AND 3 (GROUP SPACE)

welcoming, accessible and sympathetic to potential users, *Condition* (D-2), and *Impact* (D-3), meant in the sense of goodness-of-fit of the facility into the surrounding area. (Note that it is not possible to rotate the axes of an INDSCAL space; the program yields a unique solution configuration.) The groupings of points in the configuration indicate the means by which this interpretation was given; the dimension labels show the "negative" and "positive" ends of the continuums.

Thus, individuals will judge small-scale mental health facilities in terms of their attractiveness, condition and neighbourhood impact. Further understanding of these dimensions might be derived by using the INDSCAL program to yield an indication of how much weight is placed by each individual on each of the identified dimensions. This information is given in the subject space plots (see Figures 6a, 6b and 6c). The points represent the individuals whose judgements were used to derive the group space, and the dimensions of the subject space are the same as those of the group space.

Remember that if the point is located near to the origin of the space, relatively little variance in that individuals' cognition is being explained by the dimensions of the group space. In this solution then, the dimensions one and two explain very little of individual C's perceptions. This individual clearly places much more importance on dimension three in discriminating between the facilities. Individuals A, B, E and D, being far away from the origin with respect to dimensions one and two, have their judgements explained quite well by the group space. Individual A, however, considers dimension one to be more impor-

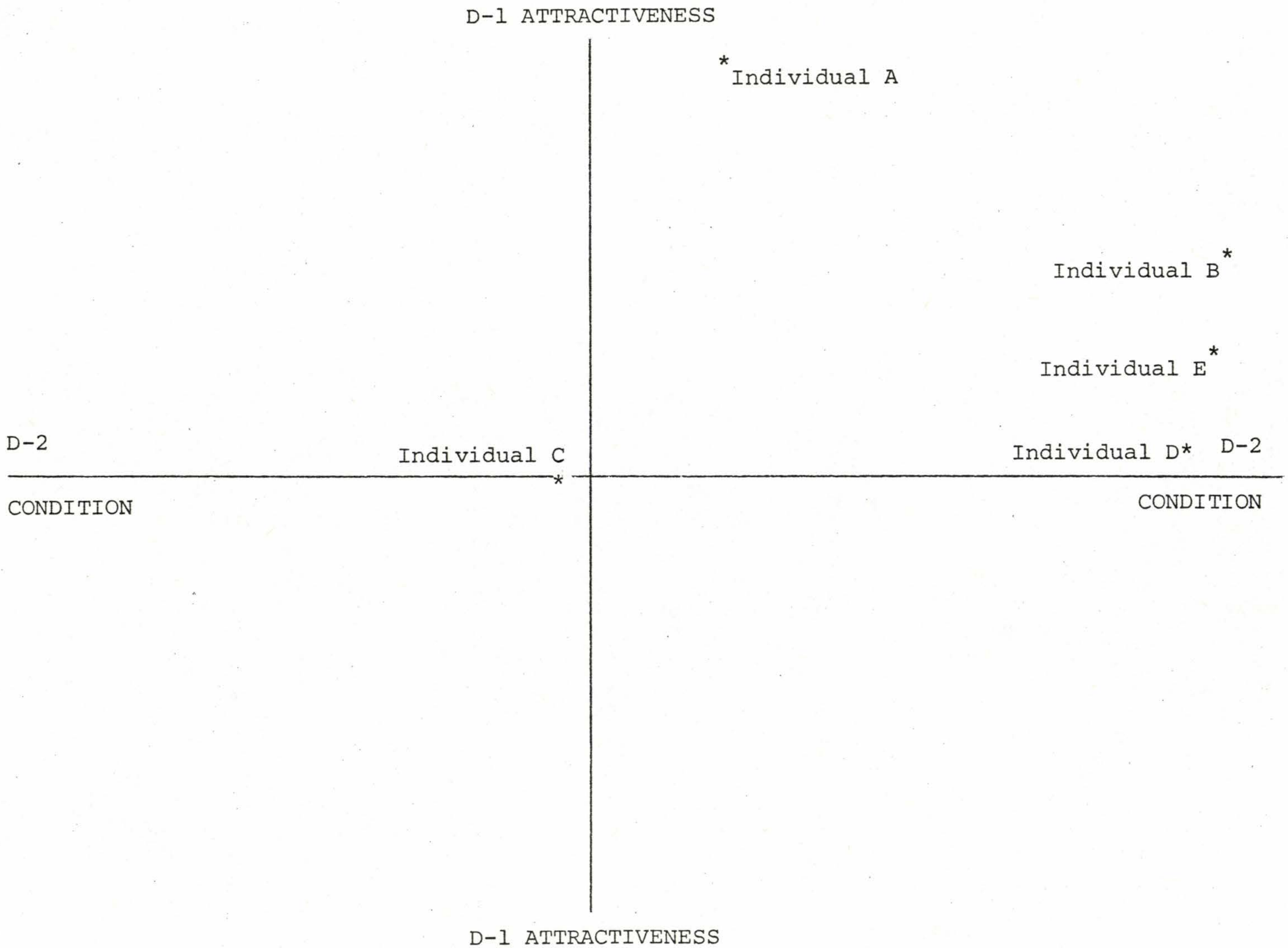


FIGURE 6a: 3-DIMENSIONAL INDSCAL FACILITIES SOLUTION: DIMENSIONS 1 AND 2 (SUBJECT SPACE)

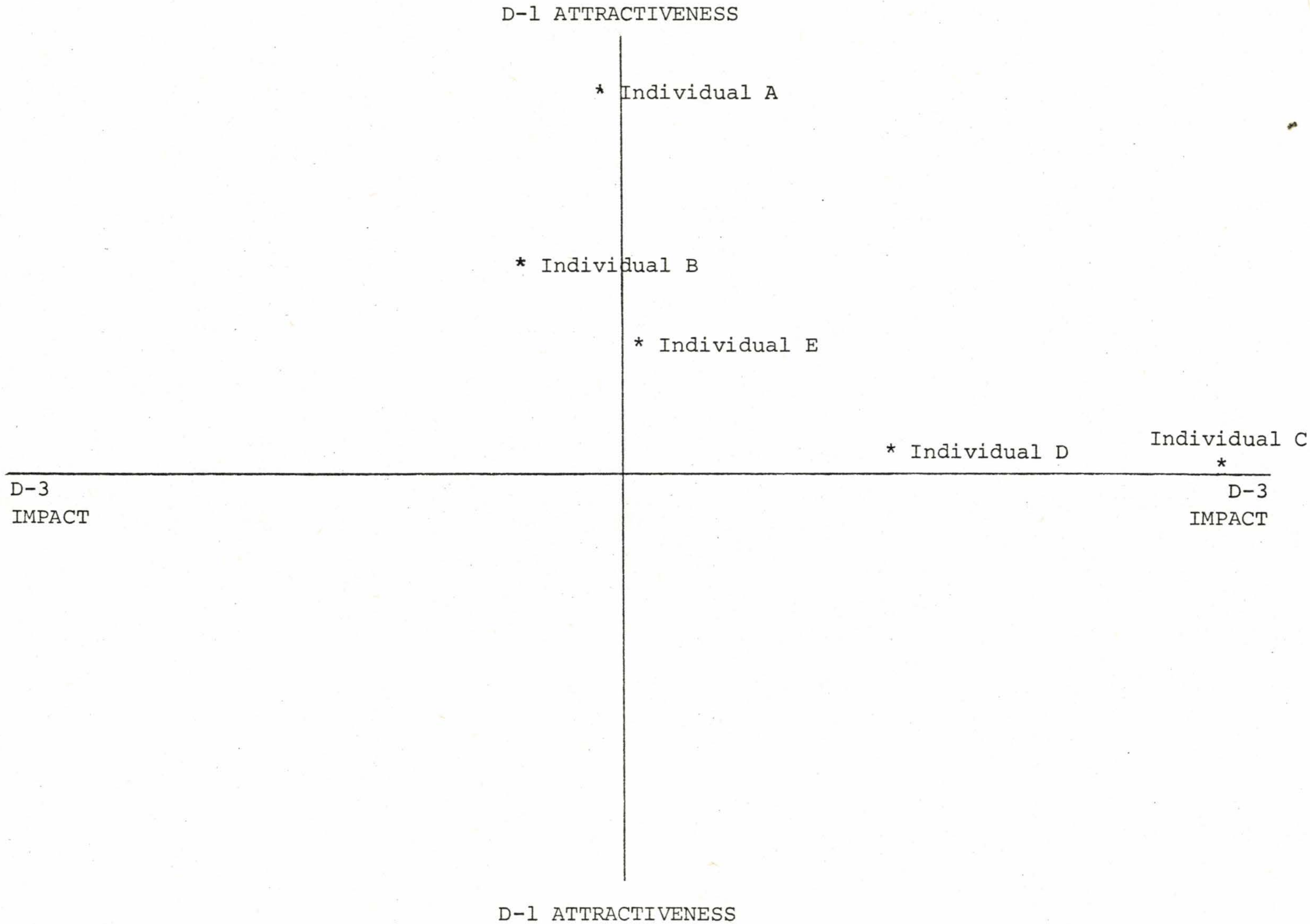
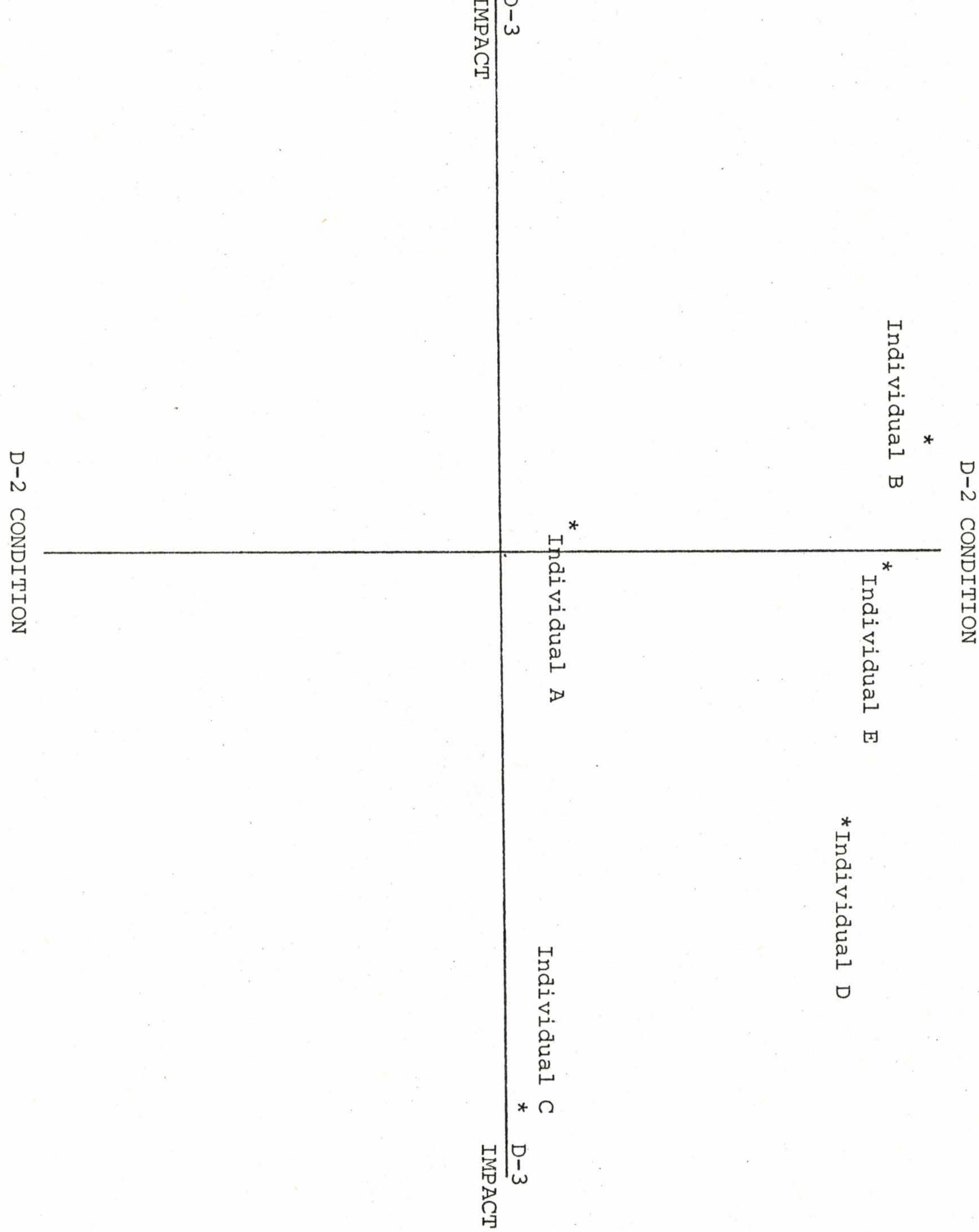


FIGURE 6b: 3-DIMENSIONAL INDSCAL FACILITIES SOLUTION: DIMENSIONS 1 AND 3 (SUBJECT SPACE)

FIGURE 6c: 3-DIMENSIONAL INDSCAL FACILITIES SOLUTION: DIMENSIONS 2 and 3 (SUBJECT SPACE)



tant than dimension two; B, E, and D weight dimension two more heavily than one. It is possible, from these two spaces (subject and group) to construct a "private" space for each of the individuals (see Carroll, 1972, p. 108, and Figure 2).

The nature of the dimensions revealed in the INDSCAL group space accords quite well with the notions suggested before the analysis on how the facilities would be perceived. Especially clear is the Impact dimension (D-3), which is one of the factors directly suggested in the initial ideas. The Attractiveness (D-1) dimension probably relates to the visibility factor originally suggested, and the Condition (D-2) dimension to the design criterion.

c. <u>The Analysis (Using TORSCA-9) of Facilities Rankings</u>

The group proximity measures from the facilities rankings were analyzed by TORSCA-9. Again, three, two and one-dimensional solutions were obtained and again the three-dimensional solution was chosen because its stress (.015), after the maximum number of iterations, was lower than that of the two-dimensional solution (.044). The final configuration plots take the same form as that shown in Figures 4a, 4b and 4c, so they will not be reproduced here. The points located in the configuration space represent the facilities. The dimensions of the three-dimensional group space were identified as Attractiveness, Condition and Impact. This interpretation is the same as that made of the results of the INDSCAL analysis of facilities rankings, but the dimensions in this TORSCA-9 result were not as readily identifiable as those of the INDSCAL solution.

The hypotheses which might be drawn from identification of these dimensions are discussed in Section 3b.

d. The Analysis (Using INDSCAL) of Neighbourhoods Rankings

INDSCAL was used to analyze the individual proximity matrices derived from the subjects' raw data on neighbourhoods. Three, two and one-dimensional solutions were obtained from this analysis. The two-dimensional solution was selected for interpretation, since its group space correlated nearly as well with the original subjects' data as did the more complex group space for the three-dimensional solution. After five iterations, the error for the three-dimensional solution was 2.95; that of the two-dimensional solution was 3.85. Furthermore, the axes of the two-dimensional space were more readily interpretable than those of the three-dimensional space.

The group space solution to the analysis of the neighbourhood rankings will not be reproduced here. It takes the same form as the configuration in Figures 5a, 5b and 5c, except that it has two instead of three dimensions, and the points located in its space are neighbourhoods rather than facilities. The subject space accompanying the group space will not be presented either: it indicates the weight placed on each of the two dimensions by the five subjects.

Dimension one of the INDSCAL neighbourhoods solution was identified as *Condition* (ranging from well-kept to poorly-kept), and dimension two as *Function* (ranging from residential to commercial). These dimensions are the same as two of those identified for the TORSCA-9 three-dimensional neighbourhoods solution.

Slight differences were evident in the group space plots of the same data, when the different algorithms TORSCA-9 and INDSCAL were used to analyze them. This is probably the result of two factors. First, group spaces may be derived from individuals' raw data matrices in many different ways, since a number of different "averaging" procedures may be used to obtain the group scores. The averaging procedure used to obtain the group matrix input to the TORSCA-9 routine was probably very different to that used within the INDSCAL program. Secondly, INDSCAL makes metric assumptions about the input data, and TORSCA-9 does not. The assumption that the data were at least interval scale was not justified in this study, but since the non-metric NINDSCAL routine was not available for use, INDSCAL was used regardless. The exact effect of making metric assumptions about the data is not known; no doubt it affects the validity of the solution somewhat. These two factors, then, probably account for a large part of the variation in the results of the two programs' analysis of the same data.

4. Summary:

Questions of research design, data and analytical techniques have been emphasized in this pilot test of the methodology. In a full empirical study, of course, more attention would be paid to the appropriateness of the sample used and the data collected. This test, however, has given a clear indication of the type of data and the form of results one might expect to deal with in using this methodology. The analysis results have permitted the identification of several dimensions relevant to the perception of public facilities. Though the nature of these identified dimensions may not be empirically valid, the process of their identification does indicate the problems of solution interpretation which may be encountered in the use of MDS models.

In analyzing the neighbourhoods and facilities rankings with the MDS algorithms TORSCA-9 and INDSCAL, it was hoped to gain an indication of how the sample members perceived the fit of the facilities into the neighbourhoods. It was hoped that the impact of the facilities, and the externality effects they generate, would emerge as clearly identifiable dimensions. This has not happened in the analysis, probably as a result of the division of the data collection into two distinct categories, where individuals were asked to record their perceptions first of facilities, then of neighbourhoods, but not to consider the two together. As was pointed out in Section 3a of this Chapter, in order to measure the judgement of the "goodness-of-fit" of facilities into neighbourhoods, it is probably necessary to ask respondents to consider first this question, rather than asking for a separate consideration of facilities and neighbourhoods.

The analysis of facilities rankings undertaken in this study is of use, in that some consideration of facility impact is prompted from respondents. It appears to have been useless, however, to analyze the neighbourhoods rankings by themselves, as respondents, when judging the neighbourhoods appear to have taken no account of the public facilities or their impact.

It may be possible, of course, to look separately at the neighbourhoods and facilities data, and to come to some general conclusions about how they *both* are perceived. The seven semantic-differential adjective pairs used in the data collection of the neighbourhoods rankings, were also used in the collection of facilities rankings. If both neighbourhoods and facilities rankings on these seven same attributes were analyzed in separate MDS runs, it would be possible to compare the solution configurations in a Configuration Comparison routine. The COMPARE algorithm is available (based on Shepard-Kruskal type MDS models), as well as the Schoenemann-Carroll-Lingoes-Fit algorithm in the Guttman-Lingoes Smallest Space Analysis series. These configuration comparison algorithms indicate where the differences and similarities lie in the two solutions being compared. For the purposes of this study, this would provide an indication of where perceptions of facilities and neighbourhoods overlap.

Alternatively, it would be possible, taking a group matrix of facilities rankings and a group matrix of neighbourhoods rankings, to analyze the divergence of perceptions in these data using INDSCAL. Individual Differences Analysis would also produce a group space, averaging and combining the two data sets.

With both the configuration comparison, and individual differences approaches to the problem of analyzing the goodness-of-fit of facilities into neighbourhoods, there may be severe difficulties in interpretation. It would be difficult to know whether similarities in configuration structures for the two data sets result from identical perceptions of the two phenomena, or from coincidence. Furthermore, the divergence of stimuli positions in the two solution spaces being compared may be the result of perceived differences in the phenomena being judged, or of idiosyncratic differences in ratings, despite the fact that perceptions of the neighbourhoods and facilities are basically the same.

The configuration comparison approach (where neighbourhoods and facilities solutions are compared in order to generate general conclusions or hypotheses about perceptions of the impact of facilities on neighbourhoods) seems interesting and worthwhile. To ensure that this goodness-of-fit is actually what is being measured, however, it is probably more valid simply to ask respondents, when the data are being collected, to record their perceptions of facility impact.

CHAPTER 5

SUMMARY AND CONCLUSIONS

This paper has proposed a methodology for establishing the dimensions of community opposition to the location of certain types of public facilities. It has been presented in three main sections. Chapter 2 exposed a "gap" in the literature on public facility location to date. Facility-locating models have not considered the nature of community opposition to the siting of public facilities. By this omission, the models have neglected political variables crucial to considerations of an equitable distribution of facility-generated externality costs and benefits.

Chapter 3, after reviewing the empirical evidence of community opposition to public facility location, described the methodology whereby the dimensions of such opposition might be empirically determined. In it, questions of research design, data types, and appropriate analytical techniques were emphasized. It was suggested that techniques of multidimensional scaling are most appropriate, since they cope best with the analysis of psychological data necessary for a study of public facility perception.

A pilot empirical test of the proposed methodology was presented in Chapter 4, in order to illustrate one application of the methodology to questions posed earlier in the paper. It should be noted that the methodology presented and tested in this study is not confined to negative externality costs and to perceptions of non-users. Opposition complaints may include reference to externality benefits, even if these are outweighed by negative externality costs. The results of the analysis in Chapter 4, then, are merely indicative of the types of dimensions one might expect to be revealed from an application of the suggested methodology to appropriate research questions and data.

The significance of the work undertaken in this paper may be restated with reference to points made in Chapter 1. The content and context of public decision-making with respect to public goods and services is extremely complex. In the past, public facility location models, whilst aiming to maximize social welfare, have disregarded the nature of community opposition. It is important that such "implementation costs" be considered throughout the planning process, however. Optimal location configurations for public facility sets should be calculated with community opposition factors having been included in the model. If these implementation costs, with respect to one or various facilities within the set, are left until the end of the locational planning process, then the optimal configuration will have to be re-calculated, as alterations made to it as a result of tardily considered implementation costs will render it invalid.

With empirical identification of the nature and strength of community opposition attitudes to the location of public facilities, several advances could be made in public decision-making. From this information, sets of planning standards could be set up, relating to such intangibles as compensation for community residents who perceive themselves to be negatively impacted by the location in their neighbourhood of a certain public facility. In addition, levels of environmental quality perceived to be suitable by community members, whose neighbourhood is or will be the site of a public facility, could be established.

Various problems, both conceptual and analytical, remain to be resolved in the study of opposition to public facilities. Two important analytical considerations are the following. First, a full empirical testing of the proposed methodology must be undertaken, to establish its validity, and to raise further pertinent questions of research design. These questions include a host of minor technical problems, as, for example, the need to devise a method of deriving averaged "group" data matrices, for input to non-metric multidimensional scaling algorithms, from the individual data matrices collected with the questionnaire used in an empirical study (cf. Ch. 4).

The second analytical problem is perhaps the more difficult of the two. Once the opposition dimensions have been identified in nature and strength, there remains the task of developing a decision model into which these dimensions can be incorporated. At the very least, existing normative and descriptive models of public facility location should be modified to include these important new variables.

The conceptual difficulties remaining are somewhat less well-defined. A methodology for determining the impact of externality-generating public facilities has been proposed. If used in empirical studies relating to public facility perception, it will reveal the different tangible and intangible dimensions by which people characterize facility impact. But how may the use of the methodology yield a measure of *net* facility impact, and how might perceptions of net impact be represented in community opposition attitudes? A single measure of net impact, incorporating trade-offs made by community members with respect to the different dimensions of facility external effects, would be an extremely useful evaluative aid for decision-makers.

Questions of research design pose further conceptual difficulties. One is the issue of *whose* perceptions are to be defined as representing "community" opposition. We should determine whether it is more appropriate to consider the perceptions of those who feel themselves to be impacted, or of all individuals within an area defined as being impacted.

Ultimately, however, all these conceptual and analytical difficulties will only be resolved by repeated empirical use of the methodology, and by experimentation with different ways of using it. It is hoped that empirical studies will follow this proposal, in order that decision-makers might use the identified community opposition dimensions to distribute more equitably the external effects resulting from the location of public facilities.

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