A spatial decision support system for the planning of retail and service facilities

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55

A spatial decision support system for the planning of retail and service facilities

Theo Arentze

BOUWSTENEN

A SPATIAL DECISION SUPPORT SYSTEM FOR THE PLANNING OF RETAIL AND SERVICE FACILITIES

PROEFSCHRIFT

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aan de Technische Universiteit Eindhoven,
op gezag van de Rector Magnificus, prof. dr. M. Rem,
voor een commissie aangewezen door het
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door

Theo A. Arentze

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Eindhoven, 18th of June 1999

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CHAPTER 1

INTRODUCTION

1.1 Background

Physical planning in the context of local/regional governments aims at formulating plans for spatial policies in the areas of housing, industry, recreation, retailing and services. Retail and service planning is a part of physical planning from which a distinct body of methodologies and expertise has emerged over the years. This area has common problem characteristics that follow from the different roles of users and providers of the facilities. Irrespective the specific type of facilities such as stores, schools, banks etc., users are able to choose which outlet to patronise and to travel to the places where the outlets are located (in contrast to service delivering systems), whereas companies or local/regional governments are charged with the costs of establishing and maintaining the facilities. Leonardi (1981) introduces the term user-attracting facilities to refer to facilities that meet these characteristics.

The planning of user-attracting systems requires decisions how to design a facility network for a local population. Making such decisions is an inherently complex cognitive task. Objectives of the various parties involved, i.e. consumers, producers and the community in general, are often conflicting. At the same time, there are typically uncertainties about what the outcomes of decision options will be, how to trade-off advantages and disadvantages of specific decision options and even what the possible courses of actions are. Local and regional government in the Netherlands and abroad generally have acknowledged the need for adequate information. This is reflected by the fact that applied research has always been considered necessary for plan formulation (Van der Heijden 1986; Borgers and Timmermans 1991; Oppewal 1995). Clearly, government does not have the means or intention to control physical developments in sectors such as retailing where facilities are commercially exploited. In these sectors, the realisation of plans eventually depends on initiatives of companies. Available policy instruments, however, provide government with the means to create the conditions and facilitate desired developments. Moreover, a dialogue between government and the commercial sector is the dominant framework in which contemporary planning takes place.

In retailing and other commercial sectors, location decisions are made by companies in the context of formulating a market strategy to establish, maintain or improve the position of a chain in a given market area. Location is the element of the retail mix, besides price, promotion and other instruments, that is generally considered crucial for the success of a market strategy. The distance of a store to places where consumers live or work determines to an important extent the attractiveness of the store compared to competitors. Moreover, location decisions have a long-term impact and investment costs for new outlets are high compared to other marketing instruments. In recent years, the competition in many retail markets has intensified as a consequence of a consistent trend of saturation of markets. Due to intensified competition it is generally difficult to find good locations for new outlets. At the same time, market research has become more important as preferences and choices of consumers have become more diverse and harder to predict. Many retail companies nowadays acknowledge the need for adequate information to base their decisions on (Breheney 1988; Beaumont 1991; Longley and Clarke 1995a). At least the larger companies have established internal research units to carry out market research and strategic planning on a continuous basis or rely on consultants to carry out this research for them.

Market and location research for planning requires geographic and attribute data about demand, supply and transportation networks in the study area. In the last decade, one can see a rapidly growing availability of geographic, spatial economic and demographic data bases in digital form on national levels and sometimes even an European level (see Waters 1995). Moreover, geographic information systems for handling the geographic and spatial data are increasingly implemented in governmental and commercial organisations that are dealing with spatial planning. GIS provides facilities for managing the data, areal analysis and producing maps for presentation (Nijkamp and Scholten 1990; Scholten and Stillwell 1990; Ottens 1990; Grothe *et al.* 1994; Maguire 1995). We may expect that in the near future, the software will be as common as other general-purpose packages such as spread-sheets, statistical packages, presentation software and so on (Waters 1995).

1.2 Purpose of the study

The availability of data and data handling software raises a need for methodologies to extract information from the data for strategic decision making. Potentially, methodologies developed in the spatial sciences, decision analysis, operations research and Artificial Intelligence (AI) are relevant for this purpose. These include techniques for modelling spatial behaviour, optimising the spatial configuration of facility networks, multicriteria evaluation and so on. Decision Support Systems (DSS) provide a framework for facilitating the integration of such methodologies in the planning process. The design of these systems is adapted to characteristics of the decision making process and the preferences and constraints imposed by users of the system. DSS for spatial planning (in short, spatial DSS) can benefit from current advances in GIS technology and Artificial Intelligence for developing a graphic and easy-to-use environment for problem solving. DSS not only benefits from advancements in methodological research, but can also contribute to such developments. DSS research includes an analysis of the information needs in a given problem area. This may guide basic research towards problem relevant issues. Thus, in a longer time perspective DSS has the potential to improve the match between fundamental and applied research.

Several authors (Densham and Rushton 1988; Densham 1991; Beaumont 1991) have advocated the development of DSS for retail and service planning already in the late eighties and early nineties. Van der Heijden (1986) comprehensively assesses the potential of a retail planning DSS for local/regional government and concludes that the DSS-concept matches the nature of the decision problems. Examples of spatial DSS described in the literature (e.g., Reitsma 1990; Borgers and Timmermans 1991; Armstrong et al. 1991; Kohsaka 1993; Birkin et al. 1994; Grothe and Scholten 1993; Clarke and Clarke 1995) provide further evidence for the potential of this approach. However, current operational systems are typically constructed on the basis of a single analytical technique, such as consumer choice modelling, mathematical programming or multicriteria evaluation, or with a certain user and sometimes even a certain study area in mind. None of the existing operational systems fully utilise the potential of available methodologies or are sufficiently generic to be able to support the wide range of problems that exists in retail/service planning. Densham and Rushton (1988) stress the potential of a spatial DSS that is adaptable to a wider variety of contexts, information needs and preferences.

The purpose of the present study is to develop such a *generic* DSS for retail and service planning. The system should be useful for planning in the context of local/regional government (public sector) as well as in the context of retail/service companies (private sector). The aim of the system is to improve the effectiveness of decision making by making advanced methodologies available to end-users. This aim reflects the assumptions: (i) information provision is critical for the effectiveness of plan decision making; (ii) it is possible to develop a single DSS that is adaptable to problems in both public and private sector contexts and (iii) a DSS is the most appropriate system concept for decision support in this domain. We do not make an a-priori choice between available methodologies, but rather consider a wide range of fields relevant for possible contributions to DSS development including GIS, AI and spatial and decision modelling.

The goal of this study is threefold: (i) specify an appropriate system concept for the spatial DSS; (ii) integrate and develop suitable methodologies for the model base of the DSS and (iii) develop and implement a system design. Some emphasis is put on the second objective. Making contributions to the state-of-the-art in spatial and decision modelling in the context of a DSS is an explicit goal of this study besides developing a system for integrating the models.

1.3 Outline

To this effect, this study is organised into three parts which relate to the three main objectives. The first part is concerned with developing an appropriate system concept for the retail/service domain. This part consists of two chapters. First, Chapter 2 develops a research framework for developing the DSS. Work on DSS started off in the late seventies and has resulted in an articulated body of concepts and system development methodologies. For this field, the basic concepts are reviewed, the issues that need to be addressed are identified and the proposed approach for developing the DSS is outlined. GIS and expert systems are considered as related fields of research that may provide tools for developing the spatial DSS. Then, Chapter 3 describes the field of retail planning in terms of the issues, problems, approaches and the role of applied research in both public and private sector contexts. The concept of a DSS that best matches the domain characteristics and that provides a direction for developing the system is proposed and motivated.

The second part develops and integrates the methodological knowledge to be incorporated in the model base of the proposed DSS. The fields of research that may supply relevant methodologies are diverse. Therefore, Chapter 4 proposes a conceptual framework for identifying and structuring knowledge in spatial planning. Following well-known KADS methodology in knowledge-based-system development, a layered organisation of knowledge is proposed and specified for the spatial domain. The remaining chapters in this part deal with the particular components of the framework in turn. In main lines these chapters are structured as follows. First, an overview of the state-of-the-art in the concerned research field is given and shortcomings of existing approaches in the context of the DSS are identified. Then, extensions or alternative approaches to overcome the shortcomings are proposed and empirically demonstrated. First, Chapter 5 considers causal/associative forms of knowledge that serve to predict and explain spatial behaviour in retail/service systems. Chapter 6 is concerned with conceptual knowledge required to analyse retail/service systems in terms of the objectives in spatial planning. These two components – causal/associative and conceptual – are descriptive in nature and constitute the inference layer of the model base. Finally, Chapter 7 considers knowledge in the next task layer, which describes how particular problem solving goals can be achieved (in terms of inference processes). A knowledge-based system is developed to specify the task layer of the model base.

The third and final part discusses the design, implementation and application of a DSS that integrates the methodological knowledge developed in the foregoing part. This part is organised into two chapters. First, Chapter 8 reviews existing spatial DSS approaches and describes the proposed DSS in terms of the structure of the system and user interfaces. The system is implemented in a windows application called *Location Planner*. Second, Chapter 9 discusses two empirical applications of Location Planner. The applications are illustrative for retail-impact problems (typical public sector) and retail-network-optimisation problems (typical private sector).

Finally, the last Chapter concludes with a summary of major conclusions and a discussion of the potentials of the system and possible ways of future research.

PART I

SPECIFICATION OF A DSS CONCEPT

CHAPTER 2

A RESEARCH FRAMEWORK FOR DSS DEVELOPMENT

2.1 Introduction

Over the last decade there has been a vast growing interest in GIS from the side of the academic world, software industry and more recently also from practitioners. The strong academic interest in GIS is reflected by the numerous conferences, journals and other outlets of GIS-related research that exist nowadays. There is, however, a growing awareness that the concept of GIS falls short in providing effective support to strategic (and tactic) decision making. Recently, DSS has been introduced to shift the focus from information to decision making and to improve the interactive properties of the systems and their ability to adapt to the decision making process (Densham 1991, Armstrong and Densham 1990, Clarke and Clarke 1995).

DSS was first introduced in business management. Similarly, the aim was to improve the decision support capabilities of the management information systems that were used at the time. The first DSS-applications began to appear in the early 1970s. Since the early 1980s DSS-efforts gained in strength under influence of the PC revolution, the increasing performance-price ratio of hardware and software and the increasing availability of public databases and other sources of external data (Sprague 1989). Although there is not a generally agreed upon definition, the term DSS commonly refers to "computer-based systems, which help decision makers utilise data and models to solve unstructured problems" (Sprague 1989). Spatial DSS is generally defined as a DSS which combines geographic information with appropriate algorithms, to support locational decision making (Crossland *et al.* 1995, Keenan 1998, Maniezzo *et al.,* 1998). As implied by this definition, SDSS uses a combination of GIS and DSS methodology.

Another research field related to DSS concerns Expert Systems (ES) or more broadly knowledge-based systems. Recently, the complementarity between DSS and ES has been recognised. A new field of research has emerged where ES techniques are used to improve the intelligence of DSS. The hybrid systems are commonly referred to as Knowledge-Based DSS or, in short, KBDSS (Zopounidis *et al.* 1997).

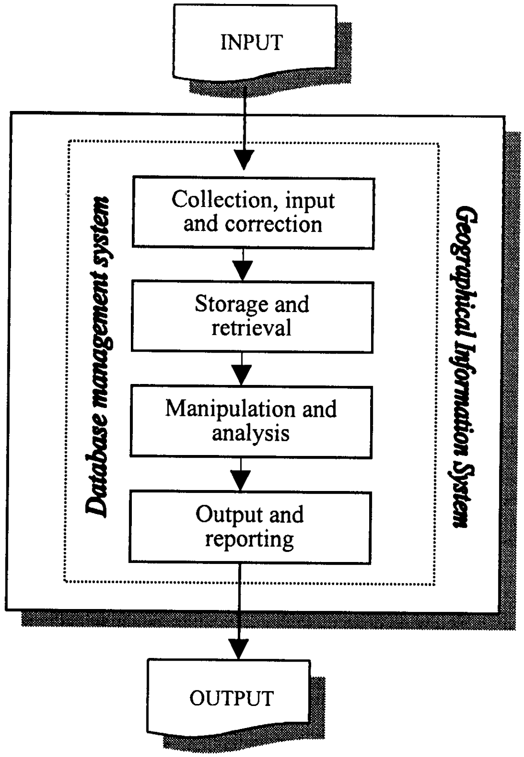

Figure 2.1. The structure of a GIS (source: Longley and Clarke 1995).

The purpose of this chapter is to identify the issues and outline a research framework for development of the spatial DSS. First, to position DSS relative to related systems, sections 2.2 and 2.3 consider basic concepts and applications in the fields of geographic information systems (GIS) and expert systems (ES). The discussion highlights the relationships with DSS. Second, to outline a research framework, section 2.4 discusses basic concepts and development issues in DSS.

2.2 Related fields of research: Geographic Information Systems

The earliest work on GIS in academic geography goes back to the 1960s. However, only since the early 1980s GIS is a vast growing area of research benefiting strongly from the vast improvements in hardware and software that have occurred in the past three decades (Goodchild 1991). Since the late 1980s we have seen an increasing use of

GIS for socio-economic applications (see Martin 1991). Despite a late start, many private and public planning agencies are now considering the implementation of GIS in their organisations or have done so in the recent past (as noted earlier). For a review of GIS development in terms of principles and applications see Maguire et al. (1991), Martin (1991), Goodchild (1991), Fotheringham and Rogerson (1994) and Longley and Clarke (1995b).

Essentially, GIS establishes a coupling between spatially referenced data (e.g., population) and a geographic database (e.g., postcode areas). As Longley and Clarke (1995a) put it, one can think of a GIS as a database management system with an additional, geographical shell that accounts for the special properties of spatial data in storing retrieving, manipulating and reporting data (Figure 2.1). This shell offers systematical solutions to data handling problems often encountered in studies in retail and service planning, such as: integration of datasets which are based on different geographies (e.g., postcode-based population data and point-based customer data); modifying the areal unit (e.g., between postcode areas and reporting zones), spatial aggregation (e.g., point data to areal units) and spatial interpolation (e.g., defining surface models). Apart from data handling facilities, GIS provides powerful tools for spatial analysis (such as polygon overlay, buffer analysis, network analysis). These tools allow one to compute relationships between spatial objects (e.g., interactions), generate attribute data of spatial objects (e.g., proximity data), compute new spatial objects (e.g., the delineation of catchment areas) and define spatial selections and spatial clusters of objects (Goodchild 1991). The graphic representation of data on a map facilitates insight in spatial patterns of the phenomena and probably explains a great deal of the popular appeal of the systems.

The early use of GIS in retail and service planning was often restricted to the visualisation of problems (e.g., drawing maps). The first applications that made more sophisticated use of GIS concerned market analysis and more specifically geodemographic analysis (Cresswell 1995). By visualising spatial patterns of (potential) customers and competitors inside GIS one obtains insight in the market potential of areas. However, for supporting decision making (at a tactic and strategic level) the systems should go beyond describing "what-is" patterns and be capable of addressing "what-if" type of questions. The application of GIS for decision support is a relatively recent area of research. The general finding is that the analytic possibilities of GIS falls short of offering effective decision support. In most packages even basic forms of analysis (e.g., network analysis) are absent. Other packages only offer the most simple forms of models (e.g., gravity models) typically based on outdated 1960s technology. In short, the modelling capabilities of the systems are far behind the state of the art in spatial analysis and modelling (Arentze, Borgers and Timmermans 1996; Openshaw 1995; Clarke 1990, Timmermans 1997). The answer from the GIS-tradition is to add analytic models (e.g., spatial interaction, multicriteria evaluation etc.) to the toolkit of

GIS or to establish linkages between spatial analysis software and GIS (Maguire 1995). Typical examples of the first strategy involve the integration of multicriteria evaluation (e.g., Fedra and Reitsma 1990, Carver 1991, Pereira and Duckstein 1993, Jankowski 1995, Lin *et al.* 1997, Malczweski 1996, Jankowski and Ewart 1996, Crossland *et al.* 1995), location selection models (e.g., De Jong et al. 1991) and routing models (e.g., Keenan 1998) in GIS. Vendors of GIS-software are (slowly) following the results of this research, as new releases tend to offer more analytic capabilities (Maguire 1995).

A related approach to improving the decision support capabilities of GIS involves the development of GIS applications customised to specific problems or problem areas. In contrast to general-purpose GIS, customised or dedicated GIS are tailored to the information needs of a specific user or a problem area in terms of the database or spatial models (see Cresswell 1995; Ottens 1990; Clarke 1990). They are either developed from scratch or by using elements of general-purpose GIS as building blocks. In fact, the distinction between general-purpose and customised GIS is not a dichotomy but rather a continuum. Of interest here are GIS systems for geomarketing (e.g., Tactician), which form a recent branch of proprietary GIS to be located somewhere halfway this continuum. These generic systems offer tools tailored to micro-marketing, market analysis, catchment area analysis and other kinds of analysis useful for geomarketing (see Cresswell 1995; Grimshaw 1994 p.105). The so called "digital shopping map" (Brayé and Wapenaar 1995) is an example of such a system in the Dutch context. Based on nation wide population, shopping centre and interaction data (expenditure flows) the system allows one to delineate and analyse catchment areas for location studies in retailing. The term spatial DSS has been used to label customised systems that result from integrating spatial models in a GIS framework (see Clarke and Clarke 1995; Clarke 1990; Birkin et al. 1996, Densham and Rushton 1996). Chapter 8 will review the state of the art in this line of research, being one of the approaches in spatial decision support.

Parallel to improving GIS for decision support a research tradition has been established which applies the DSS concept originally developed in business management to the spatial domain. Exponents of this "DSS-tradition" argue that expanding the analytic capabilities of GIS is not enough to accomplish an effective decision support tool. The assumption underlying this view is that effective decision support requires another system design that is adapted to the decision making process. Where GIS provides (a highly advanced) technical toolbox designed to work for multiple applications, SDSS targets a specific problem area and an end-user rather than analysist (Crossland *et al.* 1995). This study is based on the same assumption and considers the well-established literature on DSS in non-spatial domains as useful for developing spatial DSS. Nevertheless, given the common characteristics of spatial problems, it is useful to consider spatial DSS as a distinct field of research. To deal with the special requirements spatial data impose on system solutions, GIS-research is highly relevant to this field.

In sum, we can distinguish two research traditions in the field of spatial decision support. The objective of the GIS-tradition is to improve the decision support capabilities of current GIS primarily by enhancing the analytic capabilities of these systems. The objective of the DSS-tradition, on the other hand, is to develop spatial DSS by applying the DSS-concept to the spatial domain, whereby GIS-technology is used to improve the spatial capabilities of the systems. Although the traditions are distinguishable they are not isolated research areas. There is a lot of cross-referencing between studies and common platforms are used for presenting and publishing research output. Moreover, where GIS becomes customised to specific problem areas, the distinction between system-concepts become vague. It has also been argued that spatial DSS is best viewed as a next stage in the evolution of GIS towards more sophisticated analysis and modelling capabilities (Maguire 1995 p. 177; Grimshaw 1994 p.100). Here, DSS is viewed as a system specifically designed to support decision making in a certain problem area.

2.3 Related fields of research: expert systems

Expert Systems (ES) are computer programs that perform tasks usually performed by human experts based on knowledge of narrow and clearly defined problem domains (e.g., Parsay and Chignell 1988 p.1). The development of ES involves the acquisition of knowledge from some source and next the representation of the knowledge in some formal system. Most often knowledge is acquired from one or more experts and complementary sources (e.g., literature or documents). An expert system incorporates a control mechanism (the inference engine) that is able to use the knowledge stored in a knowledge base for recommending solutions to problems in the domain (Figure 2.2). Because of the typical heuristic character of the knowledge, the system may not find the best solutions but often finds useful solutions quickly.

Following several successful examples of ES during the mid 1970s, some commercial application programs began to appear in the mid 1980s. Since the late 1980s ES-projects have been set up by many organisations in a variety of application domains (El-Najdawi and Stylianou 1993). Expert systems are particularly becoming prevalent in financial and business applications. The most common application types are fault finding and diagnosis and providing advice or assessment, whereas expert systems for managerial decision support (planning) are relatively rare (Moutinho et al. 1994 p.9). Also, the application of ES in marketing and urban planning has received considerable attention in the academic literature. Moutinho et al. (1994; p. 35) provide a comprehensive review of the literature on ES in marketing. A number of ES

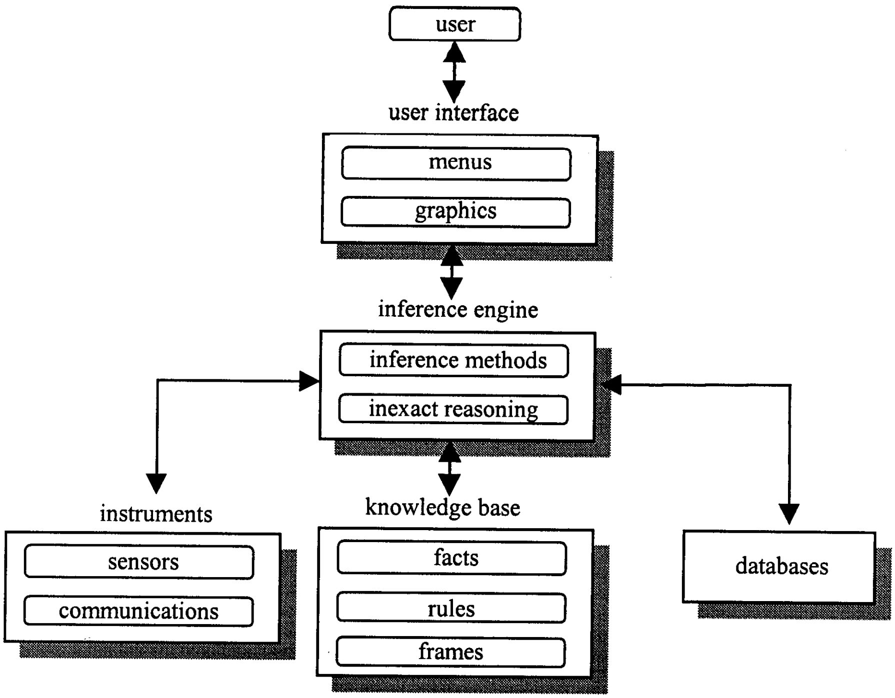

Figure 2.2. *The structure of an expert system (source: Parsay and Chignell 1988).*

applications has been described for subfields such as market research, forecasting, advertising, sales promotion and others. A relatively large number of systems exists, but only few are fully developed or operational. ES research in urban planning has a similar status, as argued by Ortolano and Perman (1990) and Battey and Yeh (1991) in the early nineties. An ES approach has been proposed to model various subfields such as analysing land use laws, judging proposed land uses and site selection. However, it is safe to say that in urban planning as in marketing many of the systems reported in the literature are in a research or prototype stage and that few, if any, are used routinely in field settings. The general conclusion that holds for both marketing and urban planning is that ES has potential for modelling subfields but cannot provide a solution for the entire problem domain. In both areas the nature of the knowledge is likely to be the limiting factor. Moutinho et al. (p. 38, 42) argue that in marketing a generally agreed upon body of formal expertise is lacking and that marketing professionals tend to use intuition and experience that are hard to formalise. Han and Kim (1990a), Densham and Rushton (1988) and Masri and Moore (1993) argue that the multidimensional nature of knowledge in urban and spatial planning prohibits an ES solution. Professional planners must deal with social, economic, legal, constitutional and political aspects that are hard to articulate. In sum, both domains are not sufficiently well-defined and self-contained to permit an overall ES solution. Consequently, studies on spatial ES are necessarily limited to *sub*areas of spatial planning. One such subarea for which ES has proven to be useful is the selection of sites for locating facilities (e.g., Findikaki 1990; Suh et al. 1990; Han and Kim 1990a; Rouhani and Kangari 1990; Moutinho et al. 1994 p. 93, Witlox 1998).

Another approach, which currently receives much attention, involves the use of ES within a DSS framework. This line of research has been followed in operation research, business management and spatial planning, and has led to a new generation of systems referred to by different authors as intelligent DSS (IDSS), intelligent support systems, expert DSS (EDSS), expert support systems (ESS) and knowledge-based DSS (KBDSS) (El-Najdawi and Stylianou 1993, Han and Kim 1990b, Luconi et al. 1986, Lolonis 1994, Zopounidis *et al.* 1997). There are several forms of integration that have been discussed in the literature. ES has been used for enhancing the modelling capabilities of the systems (by modelling elements of planning problems, such as site suitability analysis) and for improving the intelligence of the system in various components including data management, model management and user interface. In Chapter 8 this line of research will be reviewed being one of the approaches in spatial DSS.

2.4 A framework for system development

The development of information systems involves many interdependent choices regarding the definition of the system concept (role and use of the system), functional specification (contents of the system), and design and construction (architecture) of the system. At a general level the choices are given by the choice of the type of system used - in this case a DSS. The literature on DSS in business management and spatial science formulates the essential features (concept) of DSS and provides guidelines for the development of systems that meet these features. This section is based on this literature and aims to articulate a framework for developing the spatial DSS (in the chapters that follow). The first sections (2.4.1 and 2.4.2) derive a goal-oriented definition of DSS and Group DSS in terms of a set of system performance objectives. The sections that follow (2.4.3 - 2.4.5) discuss for the major steps in DSS development the research issues. The steps considered include the definition of the system concept, the functional specification and the design and construction of the DSS. The discussion will provide an introduction to DSS theory and concepts. However, as an introduction it has a limited focus, because it considers only the aspects that are relevant for the present study. Readers are referred to the general literature for a broader overview. Next,

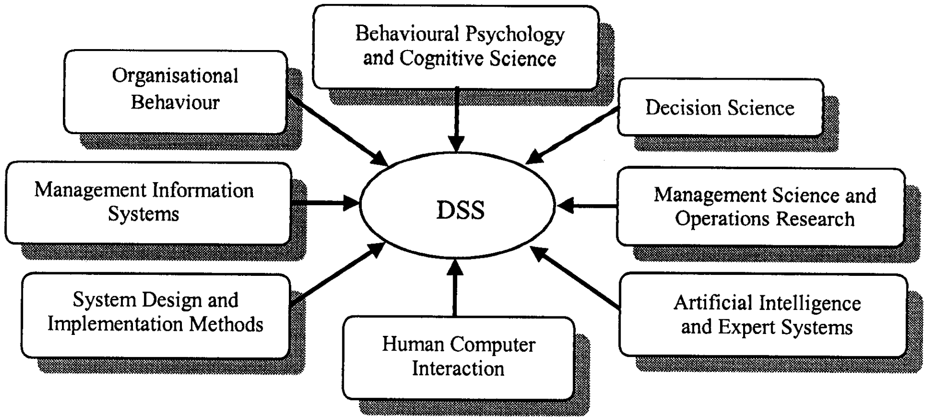

Figure 2.3. The disciplines in DSS research (source: Angern and Jelassi 1994).

section 2.4.6 considers the proposed specification of research steps for the present study. Finally, the last section considers the user involvement and proposed development process.

2.4.1 DSS objectives

Many DSS concepts and definitions are based on the classification of decision problems originally proposed by Corry and Morton in the early seventies. They defined semi-structured decision problems at an operational or strategic management level as the unique domain of DSS. In this domain, the goal of DSS is to improve the effectiveness (and secondary the efficiency) of decision making by supporting rather than replacing the judgement of decision makers (Keen and Scott Morton 1978 p.1). Before formulating the objectives, the domain of DSS as implied by this definition should be clarified. The various disciplines involved in DSS research are shown in Figure 2.3.

Decision making takes place in the context of some problem, that is an observed difference between the present and the goal state of the system being monitored. A decision is defined as a choice among possible courses of actions aimed at reducing the observed difference. At least one of the possible courses of actions has consequences which cannot be determined for certain. The element of uncertainty is a distinguishing feature of decisions. If the consequences of possible actions and the preferences of outcomes were known, the decision problem would reduce to a choice problem (Rhodes 1993 p. 3). By explicitly focusing on semi-structured problems, DSS distinguishes itself from OR/MIS and GIS which assume problems that are well-defined and well-understood. A problem is considered semi-structured if there are uncertainties regarding the objectives of the decision maker and/or the cause and effect relationships in the problem (Stabell 1979; Bosman 1989 p.18). On the other hand, semi-structuredness implies that there are parts of the problem that are well-understood and can be approached by computable algorithms. Spatial planning problems provide a good example. In spatial planning there are often multiple, sometimes conflicting objectives so that the desired state of the system being planned can not be specified unambiguously. Furthermore, consequences of both possible actions and possible developments that are beyond the control of the planner are typically uncertain. On the other hand, there are parts of the problem which are well-understood and can be approached by models possibly developed in spatial science, decision analysis, operation research or artificial intelligence. By focusing on supporting rather than replacing decision maker's judgements DSS distinguishes itself from expert systems. Essentially, where expert systems derive conclusions about courses of actions to be undertaken, DSS provides information to support such decisions.

Having defined the goal and focus of DSS, the system performance objectives can be derived. Obviously, the derivation of objectives will depend on characteristics of the problem domain, the organisation and the decision maker under concern. However, it is helpful and possible to specify performance criteria that are considered essential. Many authors have provided lists summarising essential features of DSS. However, many of the features listed concern functional or structural characteristics of DSS. In the goal oriented-approach adopted here these features are not primary given but belong to the domain of solutions. Sprague (1989) provides a list of capabilities a DSS should have from the manager/user point of view. Since DSS is ultimately user-oriented this list corresponds most closely to the set of criteria that belongs to the domain of objectives. Modified for the present purpose Sprague (1989) lists the following objectives. An DSS should:

1. support decision making with emphasis on semi-structured decisions;
2. support all phases of the decision making process;
3. support a variety of decision making processes, but not be dependent on any one;
4. support an active participation of the user in the decision making process;
5. be easy to use.

The *first* objective essentially implies that DSS should assist in the reduction of the uncertainties inherent in decision making. For this, the system should support (tentative) search processes aimed at the formulation of objectives, investigation of possible actions and the assessment of the sensitiveness of possible outcomes. To stress this point, some authors prefer to use the term decision search rather than decision making (Densham 1991).

The *second* objective clearly differentiates DSS and MIS/GIS. The (potential) support of GIS is limited to the earlier stages of decision making. GIS is a powerful tool for the identification of patterns in spatial data and the search for locations that meet conditions defined by the planner. These operations are useful for the identification of the problem and search for possible solutions, which are a concern in the early stages in decision making. However, the analysis and selection of decision alternatives in subsequent stages have little or no support from GIS (and MIS) (Arentze, Borgers and Timmermans 1996, Timmermans 1997). In contrast, DSS should support both the earlier and later stages of the decision making process.

The *third* objective refers to the capability of the system to account for the large variance in structuring the decision making process which is typically present in a semi-structured decision task. There is no single structure of the decision making process that suits all decision situations (in a problem domain). Semi-structured problems leave room for many potentially relevant variables, types of decisions and preferences of decision-makers. To accommodate this variety a DSS should permit many alternative solution paths that cover a wide range of possible styles of problem solving. As Sprague (1989) puts it "a very important characteristic of a DSS is that it provides the decision maker with a set of capabilities to apply in a sequence and form that fits each individual cognitive style. In short, a DSS should be process independent, and user driven or controlled". Sprague and Carlson (1982 p. 132) refer to this form of flexibility as first level flexibility. In addition they distinguish a second level of flexibility which they define as the ability to modify the configuration of the DSS so that it can handle a different set of problems. Second level flexibility is an essential feature of a generic DSS, which must be adaptable to characteristics of each context (organisation) in which it is used and each set of problems for which it is used (problem domain). Or to put it another way, second level flexibility is a necessary and sufficient condition for a generic DSS. In the following, the term adaptability will be used to refer to this second level form of flexibility.

The *fourth* objective refers to a cluster of system capabilities that relates to the interactive use of the system. A system should allow users to vary conditions and parameters in a problem formulation and to obtain information on consequences. It is argued here that there are two components of interactiveness: (i) the openness of the system measured in terms of the degree to which it permits the manipulation of conditions/parameters that are relevant for decision search (investigating the problem); (ii) the length of the "feed-back loop" measured in terms of the time and effort involved in changing relevant conditions and obtaining feed-back information. Both openness and the length of the feed-back loop are crucial for the ability of the system to reduce uncertainty. The openness determines the richness of the information users can obtain. The length of the feed-back loop affects the height of the threshold to explore alternatives and the transparency of dependency relationships between problem elements. Interactiveness has been taken together with flexibility (the third objective) as the system's ability to respond to user's actions. This ability has been called responsiveness (Alter 1977).

Finally, the system must be easy to use (the *fifth* objective). The system capabilities should be accessible in the sense that their use does not require efforts and insights at a technical level. Most important in this respect is that system capabilities are presented to users in a problem rather than technique-oriented way. General purpose systems, such as proprietary GIS, are in variance with this objective, because they offer tools in a technique-oriented way (e.g., "tools for overlay analysis" rather than "tools for location selection"). In sum, DSS should provide an environment that is intuitive and convenient to users.

The objectives discussed above are considered by most authors as essential features of DSS. However, the weights of the objectives and the implications for system design varies across applications. Nevertheless, collectively the objectives are useful for deriving the functional design of DSS in a given application.

2.4.2 Group DSS objectives

The original DSS concept applies to a situation where decisions are made by a single person. This is the case in firms using a hierarchical model of organising activities of the organisation. In the last decade, however, many firms have shifted away from the hierarchical model to autonomous teams and other forms of self-managing group processes (Pervan 1998). A team may bring together a wider range of skills, perspectives and values and, thus, is potentially better able to deal with the complex environments in which firms are operating nowadays.

Group DSS belong to a class of computer-based systems called Group Support Systems (GSS). The different types of GSS apply to different group settings dependent on whether group members meet at the same time and same place (typically in a Decision Room), synchronous but in different places (e.g., tele-conferencing, video-conferencing), asynchronous but in the same place (a local decision network) or asynchronous and dispersed (remote decision making). Work in GSS started in the late eighties and expanded rapidly in the nineties. Pervan (1998) gives an overview of the field. Group DSS targets group decision making in the first type of group setting, i.e. face-to-face meetings of group members.

There are four basic activities involved in group decision making: retrieving information, sharing information among members, generating alternative plans/policies and using information to reach a decision (Desanctis and Gallupe 1989, Gray and Nunamaker 1993, MacDonald 1997). The use of traditional DSS in such group settings is possible, but requires a facilitator who collects the input of group members, carries out the required analyses and brings the results back to the group. GDSS makes an intermediate person between system and group redundant, as it allows group members to manipulate elements of the system directly (Armstrong 1993). Compared to unsupported decision making, GDSS intends to improve decision making by better directing and organising group processes. Potentially, GDSS can assist in keeping the group focused on the task, organising information and documenting the process. Moreover, special features such as for example anonymous voting can be incorporated to avoid undesirable group behaviours (e.g., 'dominance' and 'group-think') and promote advantages of group decision making (e.g., diversity and consensus building).

The focus of GDSS imposes extra requirements on capabilities of DSS. First, existing requirements related to flexibility of DSS become more important, as a group brings in a wider range of preferences and decision styles into the decision making process. On the other hand, extra facilities are required to facilitate group processes. Group decision support is relevant for many spatial decision problems and will be reviewed in that context in Chapter 8.

2.4.3 Definition of the system concept

The system concept specifies the role and use of the system in the wider context of the activities of the organisation(s). The definition of the system concept involves the following questions:

- who are the decision makers?
- who are the users of the system?
- for which task is the system going to be used and how does this task fit in the overall operation of the organisation?
- what are the requirements and wishes regarding the use of the system?
- what is the intended surplus value of the system?

Choices with regard to these questions should be made interdependent so that a coherent system concept results. The general DSS literature draws the attention to several issues.

User and decision-maker are different roles which are often but not necessarily combined by the same person. Alter (1980, p. 110) defines the user as "a person who communicates directly with the system in either on-line mode or off-line mode and receives and decodes its outputs" and the decision-maker as "a person who makes business decisions on the basis of the outputs of the system". Whether or not the roles of decision maker(s) and user(s) are combined by the same person(s) depends on the choice whether or not a person is enlisted as an intermediate between the system and the decision maker(s) commonly referred to as a facilitator. A facilitator has specialistic knowledge about the operation of the system and the analytic models used. Based on this knowledge he or she conceptualises the problem and performs the analysis and reports his or her findings. Densham and Rushton (1988) discuss this issue for the case of spatial planning. They argue that a competent analyst can facilitate communication between decision-makers and system and the participation of the group of decision-makers in this communication.

A second issue relating to the pattern of using the DSS concerns the mode of interaction between system and decision maker(s) (with or without a facilitator). A direct form of interaction refers to the situation where the system is consulted during the decision-making session in on-line mode. In the case of indirect interaction, on the other hand, obtaining feedback information from the DSS, the interpretation of this information and the determination of further information needs take place in different sessions. Van der Heijden (1986, p.81) discusses this issue in the field of spatial planning. Obviously, direct interaction puts higher claims on system design and system construction in terms of speed, flexibility and user interface. The requirement of high interactiveness may limit the types of analysis that the system can support. Time-consuming algorithms that would delay the decision-making process are not suitable in a direct interaction mode. Therefore, Van der Heijden concludes that the trade-off between an interactive mode and substantive analyses need to be carefully considered. In sum, the choice of usage pattern depends on questions who operates the system and which form of interaction is to be used. Obviously, the choice of a usage pattern should depend on characteristics of decision-makers and whether or not decisions are made by a group or individual.

The envisioned surplus value of the system, the final question, should also be considered as an element of the system concept. An answer to this question involves a choice which has implications for the system design in a later stage. At a general level, the value of the system is given a priori by the choice of DSS as the type of system to be used. The aim of DSS is to improve the effectiveness of decision making. Stabell (1987) reviews and compares four distinct DSS perspectives and schools which tend to emphasise different aspects related to different views of the nature of the decision making process, as follows:

- the decision analysis school, which is the oldest and best established school, stresses the potential of DSS to reduce uncertainty in choosing among alternative courses of action when there are multiple goals;
- the decision calculus school, which stems from the field of operations research, typically targets the problem solving and choice phases of decision processes;
- the decision research school, which is closely associated with the work of Herbert Simon (wherein "bounded rationality" is a key concept), attempts to increase the effectiveness of how decisions are made by using normative process models;

- the implementation school, which uses adaptive system design as a key concept, is particularly concerned with the implementation stage (satisfied users is the primary goal).

In spatial planning, as will be argued later in more detail, there are two dominant approaches which have characteristics in common with the decision analysis and decision calculus school in business management. The approach related to the decision analysis view considers decision making in multiple goal contexts and stresses the potential contribution of spatial DSS to the reduction of uncertainty in decision making (e.g., Massam 1993; Van der Heijden 1986; Malczewski and Ogryczak 1990). The approach related to the decision calculus view, on the other hand, stresses the potential contribution of spatial DSS to facilitating understanding and formulating the location problem (e.g., Densham 1991; Armstrong et al., 1991). The present study does not make an a-priori choice in this respect but seeks to contribute optimally to all stages of the decision making process.

2.4.4 Functional specification

The functional specification describes two aspects of the DSS: what information the system must be able to generate and the way the system works. These two aspects refer to the information contents of the system and the way this information is structured respectively. Information provision should meet the information needs of decision-makers and the structuring of the information should be compatible with the nature of the decision making process. Therefore, deriving the specification of these content and procedural aspects requires insight in the questions:

- what are the information needs of decision makers/users?
- how is the decision process structured in terms of a sequence of decision steps?
- what are the possibilities and constraints of available methodologies for producing needed information?

In the case of traditional information systems, which deal with well-structured problems, a complete decision theory exists or can be developed so that it is possible to specify both the contents and the structuring of information in a more or less analytic way. In the case of DSS, which addresses poorly structured decision problems, however, a complete decision theory is lacking and deriving a functional specification is more complicated (Sprague, 1989; Rhodes, 1993, p.6). When problems are poorly structured users or decision-makers are not able to make information needs explicit prior to the decision making process. It is the task of the information analyst to derive information needs in interaction with the user/decision maker possibly by using techniques such as prototyping. Rhodes (1993, p.6) pleas for a top-down approach which involves the deduction of information needs from decisions. A deductive approach may be helpful but only to some extent, because a complete deductive theory is in variance with the ill-structured nature of the decisions. The ill-structured nature of the problems also implies that it is not possible to develop one standard method of structuring the information that will suit the variability of decision making processes, as noted earlier. Sprague and Carlson (1982, p.97) argue therefore that to be useful a DSS must be able to support multiple decision making processes (i.e., the above mentioned need for flexibility). This is even more important for a generic DSS.

In the traditional development approach, the design of a DSS is based on a model of the decision making process. The model describes for the decision making field the successive stages of the process and the contents of the information needs. The structure component of the model has strong implications for the organisation of the DSS. The contents component, on the other hand, serves as a basis for the collection or development of the methodology to be incorporated in the analytic component of the DSS (Van der Heijden, 1986, p. 79). Where this approach may work well in the domain of well-structured problems, it has limitations in the field of poorly structured problems. Van der Heijden (1986, p. 65, p.80) comprehensively discusses the conflict between two requirements the model should meet. On the one hand, the model should be sufficiently abstract to be descriptive of a wide variety of decision making processes. Therefore, the model can not be more specific than an abstraction of main lines, which implies a relatively high degree of simplification of the real-world decision making process. On the other hand, the model should be sufficiently specific to have concrete implications for the system design. In Section 2.4.6, we propose a knowledge-based approach to circumvent this problem. In this approach, the method of structuring decision processes is considered knowledge at a higher level. Instead of implementing this knowledge in the design (program code) of the DSS, it will be incorporated as higher-level knowledge in the model base. Thus, it is possible to support multiple decision processes dependent on preferences of the decision-maker and characteristics of the problem.

2.4.5 System design and construction

The system concept and functional specification are input to the stage of developing a functional system design. The functional design can be considered as an abstract definition of the DSS. The technical design and construction that follow are aimed at the implementation of the abstract system in a concrete computer program. Obviously, the appropriate technical design (architecture) of the system depends on the specific functional requirements the system must meet. However, DSS-research has developed the main lines of an architecture which is generally appropriate considering the essential

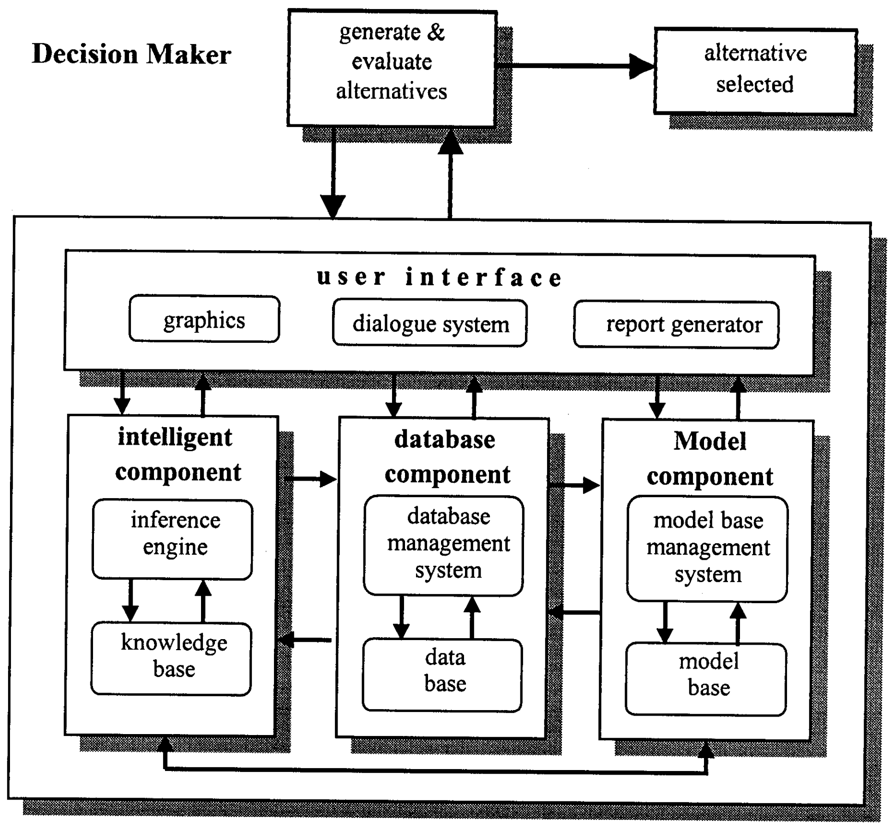

Figure 2.4. The structure of a knowledge-based DSS (source Lolonis 1994).

features of DSS. This study is particularly concerned with the conceptual and functional aspects of DSS design. The technical aspects of DSS building does not receive much attention. Only some comments regarding the main aspects of technical design will be made here.

To support the interactive use of data and models, a DSS should incorporate modules for data management, model management, and dialogue management. Lolonis (1994) proposes an extension of the standard architecture for a knowledge-based DSS. The extended model suits the present purpose and is shown in Figure 2.4. Both GIS and expert system techniques will play a role in developing the spatial DSS. GIS technology is useful for management and display of spatial data. Therefore, GIS tools will have an important role to play particularly in the construction of the data management system and (graphical) user-interface of the spatial DSS. In addition expert system technology will play a role in improving the intelligence of the DSS. As reviewed earlier, these techniques allow one to use expert knowledge for data management (e.g., intelligent data retrieval and management), model management (e.g., specifying models and interpretation of output), user-interface (e.g., explanation) and the overall system (e.g., user guidance). Expert system techniques will also be used for developing qualitative (e.g., heuristic) models as part of the model subsystem.

2.4.6 Developing the spatial DSS

The steps discussed in the sections above provide a research framework for developing DSS. This section discusses the proposed specification of the steps for building the spatial DSS.

Successful embedding of the system in target organisations requires that the system meets information needs and usage requirements of target users. To define the system concept, the present study includes as a first step a survey of the organisational context and practice of decision making in retail planning.

The model base of the system is crucial for the ability to generate required information for decision making. Having identified information needs, the functional specification then involves identification/development of knowledge components for inclusion in the model base. As a general rule, knowledge components are considered relevant for internal modelling if they are:

- generic (not case specific);
- implementable in a computer system;
- internal and external consistent.

The *first* criterion excludes declarative knowledge about the states and events of the (spatial) system under concern which is specific for a specific decision problem. It also excludes heuristic rules applied by decision-makers (e.g., classification) that are too ad hoc or otherwise not useful for generalisation in terms of models in a DSS. The *second* criterion excludes forms of knowledge which can not be formalised in rule-based or mathematical models for example because they are not sufficiently narrowly defined or involve uncertainties to be resolved by human judgement. Finally, the *third* criterion is not used in a strict sense but is meant to exclude knowledge components that do not fit in a coherent and consistent modelling framework. The application of this criterion requires a coherent theory of the problem field (in this case spatial planning).

The present study does not make a-priori choices regarding the sources of knowledge for incorporation in the spatial DSS. The following possible knowledge sources can be distinguished:

- basic research relevant for spatial planning (literature and present study);

- applied research in spatial planning (reports and present study);
- experience of human experts in the field of spatial planning (knowledge elicitation).

The first source refers to theoretical and methodological studies in various disciplines that deal with generic aspects of (spatial) planning problems or the system being planned, such as the spatial sciences, decision analysis, operations research and artificial intelligence. The second source refers to studies conducted for the support of specific cases of retail planning (e.g., analysis of alternative plans put forward by a planner), which may yield generisable methods, theories or insights. Finally, the inclusion of the third source implies the use of techniques for the elicitation, acquisition and structuring of knowledge of human experts. Typically, knowledge from this source has a heuristic and qualitative nature. Heuristic knowledge may play a complementary role to scientific models in dealing with subproblems that are not well-understood or in cases where data, knowledge or computing time required for using scientific models are lacking or too costly.

In this knowledge-based approach the way of structuring the decision process is considered a form of higher-level knowledge that can be incorporated as a higher level layer in the knowledge-base of the DSS (Breuker and Wielinga 1989). The advantage is that various process models can be incorporated so that the DSS-structure as experienced by the user is adaptable to various decision situations. The process models need not be static. That is, by formalising the *competence* to structure decision making processes dependent on characteristics of the decision maker (e.g., style), the decision problem (e.g., planning goal) and available resources (e.g., data), the method of structuring the decision process can be adapted to the problem at hand. Moreover, by incorporating this form of (meta) knowledge in the knowledge-base the system is able to actively support the development of an appropriate problem solving strategy. In sum, rather than developing a single decision process model, which is done in the traditional approach, this study considers multiple decision processes and the conditions for their application. The support of higher-level cognitive tasks is a relatively new field of DSS research known as Adaptive or Active DSS (for an overview see Fazlollahi *et al.* 1997). It is also worth noting that the knowledge-based approach proposed here is similar to the way expert systems are build. The main difference is however that the DSS is designed to support an interactive use, whereby typically the user rather than the system provides the judgmental knowledge for decision making. Although the system incorporates strategic knowledge, it also allows users to determine the way problems are to be structured.

2.4.7 User involvement and development process

The involvement of users in the design of DSS is fundamental for the acceptance and successful embedding of the system in the organisation. A group of potential users has been organised to provide user inputs to the process of building the spatial DSS. The group consists of representatives of local governments, retail companies and consultants in retail planning. The group regularly meets to evaluate steps made in the process of developing the DSS. Several authors (e.g., Keen and Scott Morton 1978; Bahl and Hunt 1985; Sprague 1989) have stressed the importance of user involvement not only in the early stages but throughout the entire system development process.

The analysis, design and implementation steps in DSS development can be combined in a linear or a cyclic way. Sprague (1989) proposes a cyclic (iterative) design process. He argues that, given the poorly structured nature of decision making, it is not possible to define in advance what the functional requirements of the system should be. Therefore, he argues that "a DSS needs to be built with short, rapid feedback from users to ensure that development is proceeding correctly". The development of the Spatial DSS follows this evolutionary approach. The evolutionary process starts with an initial system based on an initial analysis stage. Next, the system functionality is repeatedly evaluated, modified and incrementally expanded. Evaluation will be based on case-studies that show the use of the system in specific decision contexts. Elements of the system concept, functional specification and functional design will be adjusted dependent on the feedback of users. These cycles are repeated until a relatively stable system has evolved. The present study describes the results of this process in terms of the resulting system concept, functional specification, functional design, technical implementation and usefulness of the DSS for retail planning.

CHAPTER 3

RETAIL PLANNING AND A CONCEPT OF A SPATIAL DSS

3.1 Introduction

The last chapter has defined the concept of a DSS for semi-structured decision problems in general. The purpose of this chapter is to specify this concept in terms of objectives for the spatial DSS. Although the DSS intends to support planning of user-attracting systems in general, this chapter focuses on retail facilities only. Retail planning is a distinct field of spatial planning characterised by a distinct body of policy making and methodologies. Arguably, the implied system requirements can be readily generalised to user-attracting systems in general.

First, section 3.2 places retail planning in a historical context and discusses current issues in retail planning. Then, section 3.3 considers the planning objectives and decision making processes. The discussion focuses on retail planning in the context of public sector (local and regional governments) and private sector planning (retailers) respectively. In both contexts, retail research is an important component of plan preparation. The section that follows reviews current research programs with respect to the problems addressed and the methodologies used (section 3.4). Furthermore, the programs are evaluated with regard to the methodologies used, the match with information needs and the integration in the planning process. Finally, the last section discusses implications of section 3.2-3.4 for the spatial DSS in terms of potentials, targets and system requirements. This will provide the next chapters with a definition of the system for further elaboration.

3.2 Retail planning in historical perspective

This section first briefly reviews main lines of Dutch retail planning since the post-war period when government started to develop active retail policies. Against this background, the next section focuses on the current issues in retail planning. The discussion highlights the interaction between consumer markets, the retail industry and governmental retail policies. Much of the material is based on existing historical reviews in Borchert (1988, 1995a, 1995b) and Van der Heijden (1986, 1987) as well as planning documents.

3.2.1 Post-war developments

Before the Second World War there was virtually no case of systematic retail planning. Retail facilities were located in the historical cores and residential areas of towns and cities. The demand and supply of retail facilities were in balance and governments did not feel the need to intervene. This situation changed dramatically in the post-war period. The rapid growth of the industry and population in that time asked for expansion of urban areas. Generally, local and regional government controlled urban developments based on a rational style of planning. Location plans were based on principles of a functional hierarchy, which has its roots in Christaller's theory of central places (Kok 1995). Today the result of this policy is still visible in city areas that were developed in the post war period (Smit 1995). These areas are characterised by many small centres supplying low-order goods (e.g., convenience goods), at the lowest level of the hierarchy, and a single, large centre supplying high-order goods (e.g., comparable goods), at the top of the hierarchy. In addition, there are one or two intermediate levels dependent on city size. The hierarchical model was also used in other European countries, but probably nowhere has the impact been as great as in the Netherlands (see Davies 1995).

The hierarchical system of retail facilities remained unchallenged for a long time. This situation changed, however, in the early seventies when a new type of retailing was introduced in the form of large-scale free-standing stores outside designated shopping areas (usually at the edge or outside towns). This so-called peripheral retail trade was introduced by retailers with the aim to benefit from new opportunities that were created by an increased car mobility and price and quality awareness of consumers. Furthermore, the land price was lower and available land permitted large-scale developments. However, from the point of view of government the peripheral trade formed a threat, because the large stores could have negative impacts on the viability of existing centres, opportunities of the less mobile groups of consumers and the efficiency in use of scarce space (Kok 1995). Furthermore, a shift of shopping trips away from centres in residential areas towards the peripheral locations could lead to an increase in travel demands. In 1976 a change in legislation was implemented that provided an instrument for government to stop further expansion of peripheral trade. The new legislation involved the obligation to carry out retail research for the preparation of physical plans (regional, structure and land-use plans). Government could refuse permission for a new proposed development if retail research had shown that the development would undermine the viability of existing centres. In addition, the new law prescribed in some detail the research methodology to be used. Research had to include an inventory of the existing retail structure, predictions of future population developments and a consumer survey. An expenditure distribution model had to be used to assess the impacts of development proposals.

In the Netherlands the peripheral retail trade has not become as important as in many other European countries such as the UK (see Davies and Howard 1988). It is limited to only a few branches (voluminous and fire hazardous goods) and has a relatively small share (15%) of the total market (Borchert 1995b). This can not be entirely attributed to the restrictive retail policy. Probably, also the compact city policy at that time contributed to this result. This policy was specified in the third bill on physical planning and involved programs for housing, city renewal and revitalisation of the city centre aimed at improving the economic and residential quality of cities. A general movement from city areas towards the edge of cities or towns came to an end. Not only did the city centres become more attractive as shopping areas, also the further decline of the population and economic base of retail facilities in city areas was counter-balanced (Borchert 1995b). The slowing of suburbanisation processes has been a common trend in Europe over the past few decades (Burt 1989).

In the early eighties the obligation to carry out retail research was increasingly subject to criticism from the side of local and regional governments. The core of the criticism stated that the cost-benefit ratio of the model-based research was unfavourable. The time and costs involved in carrying out the model-based research took up too much of the available time and money budgets. Moreover, the external validity of the expenditure distribution models that were prescribed was questioned. In 1983 the regulations that were subject to the criticism were removed and the regulations concerned were withdrawn from the resolution of physical planning in 1985 (Borchert 1995b). From then on retail planning lost its special position and was again subject to the general obligation to carry out research for plan preparation.

The removal of the specific retail research obligation was related to a change in vision what the role of government should be in economic market processes. The emphasis shifted towards a model wherein planning decisions are made through a dialogue between government and the business industry. Furthermore, one realised that a centrally organised collection of data on the retail trade would improve the cost-effectiveness of research for retail planning. In 1984 a start was made with the development of a computerised database, called the distribution trade information system (DIS) (Nijkamp 1990; Nijkamp and Scholten 1990; Mulder 1995). This database stores on a national scale location and attribute information of individual retail stores. The aim of the DIS-initiative is to provide a basis for a cost-effective dialogue between government and the organised business industry. Furthermore, the DIS had to secure the continuity in retail policy and research, after the specific retail research obligation had been removed (Mulder 1995). Although there have been similar initiatives in other countries, a nation wide information system such as the DIS is rather unique (Nijkamp and Scholten 1990). Currently, the DIS and statistics derived from the DIS are widely used for applied retail research.

The change in role of government marked a new period of planning in which research and the planning process are shaped according to new insights (Smilde 1990). The new period represents a shift away from standardised research programs towards a form of research that is more focused on the specific threats and potentials of the retail system under concern. In the post-war period, plans had the character of a blue print of desired developments. In contemporary planning, the ability to adapt plans in response to new developments and insights is stressed. In 1985, a change in legislation reduced existing requirements with respect to the procedures and contents of plan preparation, to make this more flexible form of planning possible (Van Zundert 1993).

3.2.2 Current trends and issues

As a result of the policies reviewed above, many Dutch cities are characterised by a high degree of concentration of stores in centres, a high density of small neighbourhood centres, a hierarchical structure of centres and relatively few large stores at peripheral locations. In 1995 for example, of a total of 110,000 stores in the Netherlands, 35 percent is located in shopping concentrations with less than 25 businesses, 30 percent in concentrations with more than 25 businesses and the remaining 35 percent consists of scattered stores (Borchert 1995a).

Probably, the size of the retail market will remain stable in the foreseeable future. Since the late seventies the rate of population growth has declined and will further decrease in the near future. The predicted increase in per capita retail expenditure is only marginal and can not compensate for the slowing down of population growth (Hendriks 1996; Streefkerk 1996). Although the rate of population growth will decrease, the expansion of residential areas probably will continue as a consequence of a consistent decline of household size. Together with such urban developments, internal retail dynamics may induce a need for reconsidering existing retail structures. Present retail structures are mainly based on post-war period plan concepts, whereas demand-supply relationships have changed since then under influence of recent trends and developments in consumer markets, retail policies and the retail industry.

The consumer market

Probably, the spatial distribution of the population will not undergo major changes in the foreseeable future, as urban policy will continue to give high priority to city development and renewal (the compact city policy). Consumption patterns are less stable, given anticipated demographic, socio-economic and life-style changes. Several trends are commonly observed in retail markets in post-industrial countries (Marganosky 1997). These include an ageing of the population, increasing quality and price awareness, increasing mobility, increasing demand heterogeneity (market segmentation), changing communication and information media (e.g., tele-shopping) and changing lifestyles and activity patterns (demand for new retail formula's). As retailers and planners have experienced, it is no longer possible to understand and predict (spatial) consumer behaviour in terms of simple classifications. Therefore, market research will even become more important in future consumer-oriented planning.

Retail policies

The goal of retail policies has not undergone major changes in recent years. In global terms, governments try to establish and maintain a sustainable and high quality structure of facilities for a local or regional community. Given this goal, a major concern of future planning will be the restructuring of retail systems that were designed in the post-war period (Tetteroo 1989; Leenders and Oskam 1994; Smit 1995; Linders 1996). In the last decade, the constant increases in scale of stores and changed shopping behaviour have threatened the viability of the many small neighbourhood and town centres at the bottom of the retail hierarchy. Plans for restructuring retail facilities have already been implemented in many larger cities in the last decade. However, at present still a considerable proportion of the smaller centres does not have a sufficient economic base for the longer term. Hence, this problem will continue to be an issue in future planning (Smit 1995).

Although basic objectives have remained the same, there are several new elements in recent planning approaches. The increasing complexity of consumer markets has led to a shift towards a consumer-oriented style of planning. Nowadays, many local and regional planners are concerned with matching the supply of services and specific consumer groups using marketing concepts and methodologies (Birkin *et al.* 1996). Another new policy element relates to the decentralisation of governmental power, which has been a constant trend in the nineties. Many municipalities are engaged in a competition to attract economic, recreational and cultural activities to their area (Bouts 1990). In this context, many municipalities have initiated or consider projects for the expansion and revitalisation of inner city shopping areas (Van Dinteren en Tetteroo 1990; Van Dinteren 1990; Treur and Pernot 1994). The approach is characterised by a high public-private partnership nature, the use of marketing concepts and integrative planning of the different inner city functions (recreation, residence, shopping and work). To stress the integrative character of the approach the term centre management has been introduced.

At the same time, the policy of central government towards deregulation and liberalisation has offered regional and local government new possibilities to attain these goals. Specifically, in the early nineties the restrictive national policy regarding large-scale trade outside existing shopping centres has been liberated for the larger cities that have been designated as focus areas for urban development (in the fourth bill on physical planning). Several large cities and provinces are currently investigating the possibilities the new policy offers for improving the quality of the inner city and attracting additional economic activity (Wesselo and Kaptein 1995; Streefkerk 1996). Finally, the reduction of car-mobility is an issue that is receiving much attention since national policies give high priority to the quality of residential environments and the reduction of traffic congestion (Linders 1996; Streefkerk 1996). Co-ordinated by the province concerned, many municipalities are considering more restrictive parking policies aimed at discouraging car-use in the inner city and residential areas. These measures can have far-reaching effects on the accessibility structure of existing shopping facilities. According to one scenario, there will be a large shift in shopping activity away from inner city areas towards peripherally located shopping locations. Given these possible effects, parking policies are generally considered in a broader view of a desirable facility structure.

The retail industry

With respect to the retail industry, the last decade has seen a constant trend towards increasing scale of stores and concentration and internationalisation of businesses. This trend is typical for countries in a post-industrial stage of development (Burt 1989). As a result, in many retail branches, the market structure is characterised by fewer and larger retailers who closely monitor each other actions (oligopolistic competition). Despite the decreasing number of retailers, competition has intensified not only for the demand of consumers, but also for locations to open new outlets. Good locations have become scarcer and rent of floor space has gone up, so that to an increasing extent finding good locations is difficult and failures are costly. Moreover, in developing marketing and location strategies retailers are faced with the increasing heterogeneity of consumer markets and complexity of spatial shopping behaviour, as noted before. Not surprisingly, therefore, in recent years the larger retailers have invested in the expansion of programs for strategic planning and market research.

Retailers have developed different marketing and location strategies to adapt to these changes in retail markets. Burt (1989) distinguishes sales enhancement strategies (e.g., market segmentation and target marketing), cost control strategies and specific direction strategies (e.g., diversification, market penetration, product development, etc.). As a result, new retail formulas have been introduced or are being considered (Hendriks 1996, Marganosky 1997). Examples in the food sector are formulas employing innovations in branch integration (shopping and catering facilities), location types (petrol stations, off-centre retail parks), scale of facilities (large scale, out-of-centre), selling techniques (tele-shopping) or institutional conditions (opening times). In sum, the dynamics of consumer markets and governmental retail policies force retailers to continuously evaluate and reconsider their marketing and location strategies. The success of a chain will depend critically on the ability of management to anticipate on new developments.

3.2.3 Conclusion

It follows from the foregoing that the character of future retail planning will be dominated by the need to restructure retail systems in order to accommodate the changes in demand-supply relationships that occurred in the last decade. The role adopted by the government has shifted away from governing towards facilitating new developments through a dialogue with the industry. The deregulation and decentralisation trend has introduced new goals and instruments for retail policies. Given the increasing complexity of consumer demand, this has led to a style of planning that stresses consumer-orientation, public-private sector partnership and integrated city management. For retailers, the structural changes in consumer markets and governmental policies ask for reconsidering location strategies. Moreover, the saturation of many retail markets has made location decisions both more difficult and more important. Consequently, retailers increasingly acknowledge the need for systematic forms of strategic planning and marketing.

3.3 The retail planning process

Retail planning takes place in the context of local/regional governments and retail companies. This section considers the organisational and decision-making context of retail planning. With respect to the organisational context, the attention is focused on the function of retail plans and the objectives and available options of planning. With respect to the decision making context, the nature of the decision making process in plan preparation is considered. The goal is to identify the various steps in decision making and to describe for each step the decision problem, the difficulties in making decisions and practical solutions. These issues are discussed for the public sector and private sector in turn.

3.3.1 The public sector context

The Physical Planning Context

Physical plans are formulated at the national, regional and local level. In the field of retailing, national bills do not specify objectives in any geographic detail. Regional retail plans provide geographical detail only in as far as retail developments with a regional function are involved. In many cases, this means that regional plans are concerned with the locations of peripheral trade and the conditions under which this form of trade is to be permitted. Furthermore, regional planning is concerned with retail developments in relation to the liveability of town centres in the region (Voogd 1993). The remaining items are covered at the local level by structure and land-use plans. The purpose of structure plans is to translate longer-term policies of the municipality in terms of desired developments in the plan area that allows local government to integrate and co-ordinate the various spatial interests in the area. In addition to this horizontal co-ordination, structure plans serve to co-ordinate policies vertically, i.e. to bring them in line with higher level plans (Van Lohuizen 1989). Land-use plans are obligatory for areas outside the built environment (Van Zundert 1993) and operationalise the structure plan in terms of a zoning of land-uses in the municipality area. The zoning is legally binding so that the plan provides a means to control developments in the area.

In principle, structure and land-use plans are legally valid for a period of maximally ten years. From a strategic point of view, plans at the structural level have a number of functions. First, for the above mentioned action programming function, the possibility to adapt plans when discrepancies with actual developments occur is considered important. Second, the plans fulfil an early warning function. They help planners in detecting in an early stage possible mismatches between anticipated and actual developments. Third and related to the early warning function, the plan facilitates a learning process. An observed mismatch invokes a next cycle in which the plan is brought in agreement with the new information. Due to continuous feedback on actions, planners can improve their knowledge about the dynamics of retail systems and use this knowledge in future planning (Van der Heijden 1986).

It should be noted that a structure plan, in contrast to land-use plans, is not obligatory and not all municipalities develop these plans on a regular basis (Mastop 1989). Especially, in cases where a structure plan is absent, planning may be characterised by ad-hoc decision making. The ad-hoc style of planning involves responding to initiatives of the industry or society on a case-by-case basis. Since the deregulation in mid eighties, structure and land-use plans have become more cost-effective, so that the desired pro-active style of planning has become a feasible option even when budgets are limited.

Objectives and options of retail decision-making

Retail planning is concerned with finding a right balance between the interests of the various groups involved in retail developments (Van der Heijden 1986; Oppewal 1995). The major interests groups are consumers, producers and the community in general. The term producer refers to the supplier of retail facilities, i.e. developers and retailers. Table 3.1 summarises the planning objectives that relate to the interests of the various groups. The table is based on Van der Heijden (1986), Davies (1984) and planning documents. This section first discusses these objectives and next the priorities outlined in latest national bills.

Considering the interests of consumers it is important that retail facilities are easily accessible by public and private transport, provide a wide range of choice opportunities and can be used in a high quality physical environment. On the other hand, it is of the interests of producers that the market and location conditions are favourable for a profitable exploitation of retail facilities and continuation of business. Finally, as Van der Heijden (1986) argues, the interests of the community in general requires that the spatial arrangement of retail facilities meets economic as well as social objectives. Economic objectives refer to various aspects of an efficient use of space. The first aspect concerns the reduction of travel by car for shopping purposes. A second economic principle implies that stores are located at places where other activities benefit from the shopping activity or at least do not experience disadvantages. As an example of this principle, retail location has been widely used as an instrument to revitalise inner cities or to reduce demand pressure on the scarce space in inner city areas. For the latter purpose, large-scale retail trade has been relocated from the core of cities to peripheral areas in many cases. The social objective is perhaps the most salient feature of governmental planning. In a free market, economic developments can lead to a situation in which certain groups of consumers are disadvantaged. Particularly, the spatial opportunities of less mobile consumer groups, such as for example the elderly, are a concern. Similarly, free market processes can also lead to inequity in opportunities for retailers. Although planners are reluctant to interfere in competitive relationships between retailers, they are generally concerned with impacts of developments on the continuity of business particularly of the smaller retailers.

National bills on physical planning and economic affairs influence the relative weights of these objectives. The supplement of the fourth bill on physical planning, which currently is effective, stresses the spatial quality of environments for work, shopping, recreation, transportation and other functions. Bills on economic affairs, on the other hand, highlight the role of government in the economic process. The latest bill stresses that government should facilitate rather than govern developments in the form of co-operation with the (retail) industry. A necessary basis for being a reliable, trustworthy and engaged partner is a long-term vision on how the (retail) industry should develop. Government should promote sustainable economic growth and find a right balance between continuity and flexibility of businesses. Generally, in the area of retailing this has been taken to imply that government should create conditions for an economically viable and profitable exploitation of retail facilities and, at the same time, be cautious not to frustrate market processes (i.e., the natural dynamics of retail systems) (Smilde 1990). Following these national guidelines, planners at local and regional levels nowadays give high priority to the quality of facilities and the internal dynamics of the retail system. In sum, the prevailing criteria on which proposed

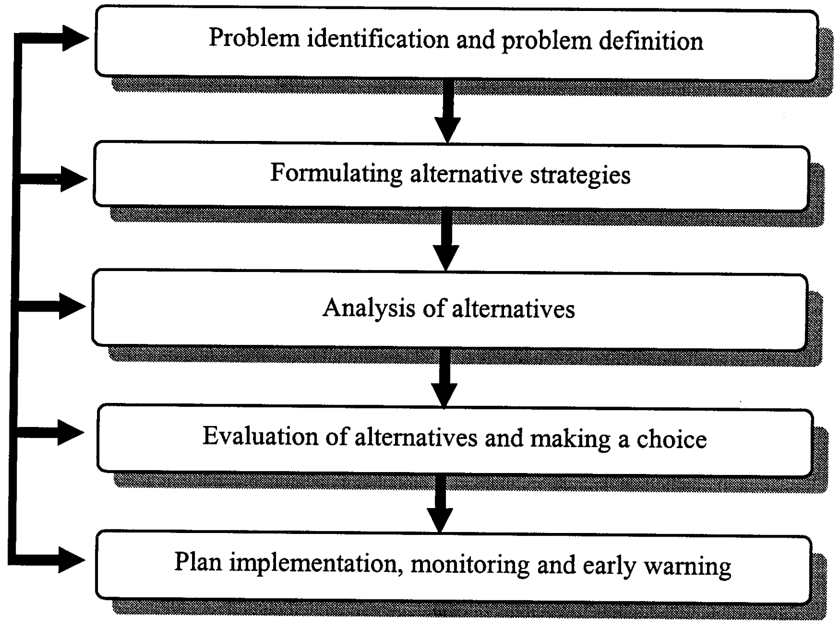

Figure 3.1. A general decision model (free after Simon 1960).

developments are judged are whether they improve the quality of supply and whether or not they have disruptive effects on the existing structure of retail facilities.

The options of retail plan decision making are limited to the physical aspects of the retail system. Van der Heijden (1986 p.15) mentions the following categories:

- the spatial distribution of retail facilities in the study area (where?);
- the amount of floor-space at specific locations and the distribution of branches (how much for what?);
- the accessibility to retail facilities (how to reach?);
- the distribution of population of the study area (for whom?).

Furthermore, as an additional element of retail planning, planners can exert influence on the quality of retail environments (shopping centres), e.g., by means of public investments.

The Plan Decision Making Process

To reconstruct the decision-making process in preparing retail plans, this section uses the general decision model shown schematically in Figure 3.1. The model is based on a rational approach of decision making that was first formulated by Simon (1960). In this model, planning decisions are the result of exploring problems and opportunities, formulating alternative action strategies and making a choice. The use of this model in the present context does not imply a choice for a certain style of planning. In stead, the model is used to reconstruct plan decision making in terms of necessary steps in any decision making process. Argueably, rational plan decision making is also involved in recent forms of planning with emphasis on negotiation and advocacy. To determine a consistent standpoint in dialogues with interests' parties, planners must develop a clear vision of how the retail system should develop. Hence, in the way the term is used here, plan decision-making precedes a negotiation or advocacy stage and serves to formulate a consistent standpoint in discussions. Furthermore, the rational decision model is suitable as a normative method inside a DSS. In major lines, the model corresponds to the models used for describing retail plan decision making by Van der Heijden (1986) and Voogd (1993).

The planning process is not a strictly linear process. Typically, as the scheme indicates, there are numerous feedback loops between steps. Furthermore, the last step that is concerned with monitoring and 'early warning' coincides with the first step of problem identification. In that sense, the model describes a cyclic process. The remainder of this section will discuss for each step the questions, bottlenecks and practical solutions. It may be noted that planning problems are diverse in terms of the interests of the parties that are involved and the meaning and the role of the plan for solving the problem. Given this diversity, the discussion necessarily focuses on main lines.

Step 1: problem identification and problem definition

The goal of this stage is to determine whether there are problems or opportunities in the study area being monitored that ask for updating the current retail policy. There are several possible reasons for raising this question. First, planners investigate this question on a regular basis (i.e., monitoring). A need for intervention may arise when physical conditions no longer match the requirements of changed retail system operations. For example, in recent years many municipalities have investigated the question whether the system of small neighbourhood centres still matches current retail system operations, given the increase in scale of stores and changed shopping behaviour of consumers. Second, a planning process may be initiated as a response to a new policy at a higher governmental level. An example that is currently relevant is the shift towards a more liberal policy regarding large-scale peripheral trade. As mentioned above, several municipalities and provinces are currently in the process of exploring the opportunities this new policy offers for restructuring the current retail system. Third, retail planning may also be an issue in the context of broader urban policies, such as for example the revitalisation of the inner city, expansion of the urban area or urban renewal (Van der Heijden 1986). Finally, planning may be triggered by an external event in the form of a proposal or request of an interest group. In many cases, this concerns a proposal from a retailer or developer to open a store or to develop a centre on a particular location. Then, planners are faced with the question whether or not to give permission or, possibly, to suggest an alternative location.

Table 3.1. Objectives and options of public-sector retail planning.

Consumers	Producers	Community in general
Primary goals		
- improve spatial opportunities	- improve spatial opportunities	- improve the quality of the spatial environment - promote equitability in spatial opportunities - encourage sustainable economic growth
Objectives		
- improve the accessibility of facilities - improve the quality, choice range, diversity and price level of facility supply - improve the quality, safety and comfort of retail environments	- meet locational needs of business activities - provide conditions for continuity and efficiency of business activities	- assist disadvantaged consumers - promote equity in opportu-nities for consumers and producers - reduce negative externali- ties of business activities (e.g., related to car-mobili-ty, land-use conflicts) - improve the cost-effective-ness of public infra-structure for retail and service activities
Options of plan decision making		
- the distribution of population of the study area - the spatial distribution of retail facilities over the study area	- the amount of floor-space at specific locations and the distribution of branches - quality of retail environments - the accessibility of retail facilities	

Irrespective the specific triggering event, the exploration of problems or opportunities is generally based on descriptive-analytic research. This type of research involves an inventory of (i) the size and composition of demand and supply of retail facilities, (ii) the evaluation and use of facilities by consumers and sometimes also (iii) the economic performance of stores. Time-series of these variables should reveal trends and developments over time. Besides monitoring the system in retrospective, planners also try to predict future developments under none-intervention conditions. Particularly, this concerns demographic and socio-economic developments that determine future demand. An analysis of the retail system should reveal the performance of the system in terms of the criteria mentioned earlier (see table 3.1). The core question is whether there are imbalances between demand and supply or opportunities to improve the quality or viability of the retail system. Usually, the identification of problems/opportunities is based on comparing indicators of system performance with planning standards. An indication for intervention exists only if future projections indicate that discrepancies are not resolved by the internal dynamics of the system. For example, current viability problems of particular centres may be solved by a general increase in purchase power.

The problem definition stage follows when problems/opportunities have been detected. This stage involves a more thorough analysis aimed at explaining observed system performance. An indication for intervention exists when underperformance can be attributed to physical attributes that can be controlled by the planner. For example, this is the case when the attractiveness of a centre can be improved by changing the existing branch composition or renovation. In general, the outcome of this stage is a decision whether or not to develop such intervention strategies.

Several categories of uncertainties can be distinguished that complicate decision making in this stage. First, the prediction of trends and developments is often based on uncertain assumptions. One approach to deal with this problem is to explore the sensitivity of different scenarios on outcomes. Second, the identification and analysis of problems is often difficult, due to incomplete knowledge about the causal relationships between the physical and behavioural subsystem: which attributes are responsible for an observed underperformance of a centre? This problem can be characterised as one of diagnosing a system based on symptoms. To deal with this problem, planners typically use planning standards often in the form of national statistics (e.g., average per capita floor space figures).

Step 2: Formulating alternative strategies

The goal of this stage is to formulate a limited and meaningful set of alternative strategies to solve the problem. A set is considered meaningful if it covers the alternatives that are potentially of interest from different political points of view (e.g., social or economic priorities). Action alternatives, such as the opening, closure, expansion, reduction or renovation of centres or stores, have a spatial dimension.

Consequently, decision making in this stage generally involves a search for locations. An initial set of candidate locations is usually identified based on screening criteria such as land availability and physical characteristics of the site. For example, candidate locations for large-scale retail trade may be identified as the sites that can be developed and meet a minimum size. In a general sense, the identification of useful alternatives is based on the degree to which locational characteristics matches requirements imposed by the retail activity under concern. Location characteristics such as the accessibility, parking facilities, visibility of the site and others are often relevant.

In many cases, a strategy requires a coherent set of actions to achieve a balanced configuration of the retail system. For example, the closure or reduction of one centre may require, as a complementary action, the expansion of a competing centre. Hence, in these cases generating alternatives is a design problem. This type of problem recurs in many decision domains and is usually defined as 'selecting a suitable aggregate from a given set of components based on a given set of constraints to satisfy a goal' (Parsaye and Chignell 1988 p.312). Normally, planners make use of design concepts. The overall concept is the functional hierarchy, as mentioned before. In some cases, normative ratios are used to determine the required amount of floor space by centre and branch. In other cases, the generation of alternatives requires creative thinking in combination with subjective judgements of locations.

Step 3: Analysis of alternatives

The goal of this stage is to assess the feasibility and likely impacts of plan alternatives. Feasibility assessment usually involves an analysis of the long-term viability of planned facilities. Only if a proposed centre or store has sufficient market potential compared to investment and exploitation costs, private-sector parties are likely to be willing to invest in the project. Next, assessment of the impacts of a plan alternative usually requires an analysis of the advantages or disadvantages consumers, producers and the community in general will experience under plan conditions. Impact analysis, therefore, focuses on the interests of each of these groups, as discussed above (see table 3.1). Of particular importance is the impact of the plan on the viability of those existing centres that play an essential role in service provision. Furthermore, car mobility, the spatial opportunities of consumers and the attractiveness of the inner city are generally an issue.

Evaluation of these criteria requires insight in how consumers and existing retailers will react to the planned developments. However, it is often difficult to predict with a sufficient degree of accuracy how consumers will re-allocate their expenditure across stores or centres under changed market conditions. Furthermore, it is hard to foresee the ways in which existing retailers, who experience a decline in market share, will adapt their marketing and location strategies. Yet, insight in these dynamics is a prerequisite for assessing the feasibility and long-term impacts of a plan. In most cases, planners or analysts deal with these uncertainties by using information about analogue cases in the past either in the same or comparable plan areas.

Step 4: Evaluation of alternatives and making a choice
The choice of a plan is based on ranking the plan alternatives on the criteria that were analysed in the previous stage. The criteria, which relate to the interests of the different groups, are often in conflict, so that ranking of alternatives requires weighting of these interests. Specifically, the economic interests of consumers and producers are often in conflict with the social and environmental interests of the community in general. This is the traditional conflict between efficiency and equity objectives. Given such conflicts, planners have to make a trade-off between the various interests. Moreover, the choice task is complicated by the fact that the outcomes of alternatives are uncertain, as noted above. In sum, the choice problem can be characterised as a multiple-criteria evaluation problem under uncertainty. Planners may use formal decision-analysis methods, but most of the time the decision is the outcome of negotiations between interest parties or a political process.

Step 5: Plan implementation, monitoring and early warning
The resultant plan describes the planned and predicted developments in the plan period. Often, the planned developments are described in terms of a time path of implementation. By implementing developments in stages planners are able to make adjustments of the original plan, dependent on population developments and reactions of consumers. This flexibility is an important aspect of plans, as the dynamics of the system are hard to predict. Implementation of the plan requires a selection of available policy instruments. Financial or legal instruments are available, but in more and more cases plan effectuation takes place through co-operation with the private sector, as noted before. After implementation, actual developments are monitored with the aim to signal in an early stage mismatches with planned or anticipated developments (i.e., early warning). A mismatch indicates a problem or new opportunity and triggers further research to determine whether adjustments of the plan are needed. The monitoring stage coincides with the first stage of the decision making process, i.e. problem identification and problem formulation. In that sense, the plan decision making process is a continuous process.

Conclusion
Several authors have characterised public-sector-planning problems as being ill structured (Wyatt 1991, Masri and Moore 1993). The above discussion confirms this view. In the various stages of the general decision model, the outcomes are uncertain, because (i) planners have incomplete knowledge about autonomous processes and the causal relations between the physical and behavioural subsystem and (ii) there are

multiple, often conflicting decision criteria with uncertain outcomes. Planners have developed several strategies to deal with the uncertainties. These include assigning an important role to monitoring and research and relying on planning standards, analogue information, expert knowledge, design concepts and the scenario method. Despite these strategies, the decision making process is characterised by many feedback loops. In particular, generating and analysing plan alternatives are iterated. Information about the impacts of an alternative typically raises questions of the kind 'what would happen if ..'. In that sense, the formulation of alternatives is the outcome of a search process.

3.3.2 The private sector context

Under influence of the growing complexity of consumer markets and intensified competition in these markets many retailers have adopted systematic methods of strategic planning. Nowadays, the larger retailers prepare location decisions, such as where to locate new stores or where to close stores, based on market and location research in specialised units of the organisation. For smaller companies, on the other hand, the available resources for research and planning are limited. Usually, in these firms, strategic planning is based on more informal procedures. This section describes locational decision making in the context of a systematic method of retail management, known as the strategic approach. The strategic approach is increasingly used by retailers as a framework for integrating and co-ordinating the various areas of retail management in order to achieve the companies goals (Burt 1989; Jones and Simmons 1990; Moutinho *et al.* 1994; Oppewal 1995; Bennison *et al.* 1995; Birkin *et al.* 1996). This framework has been described in numerous textbooks on retail management (e.g., McDonald and Tideman 1993; Glynn and Barnes 1995; Levy and Weitz 1995; Merrilees and Miller 1996). The purpose here is nòt to review this literature, but rather to place locational decision making in the wider context of strategic retail management.

The strategic retail management context

The general aim of strategic management is to establish an advantageous and sustainable competitive position of the firm. Establishing an advantageous position requires that the retailer has identified the needs of his target markets and is able to satisfy those needs more effectively and efficiently than his competitors. Levi and Weitz (1995) refer to this market orientation of management as the retailing concept. The key-decision areas of retail management are determining a market strategy, a financial strategy and a strategy of managing human resources and information systems. Levy and Weitz (1995) consider determining a location strategy as a separate decision area. Alternatively, Arnold *et al.* (1983) place location decision making at a lower level, as an element of the specification of a market strategy. The latter view is adopted here.

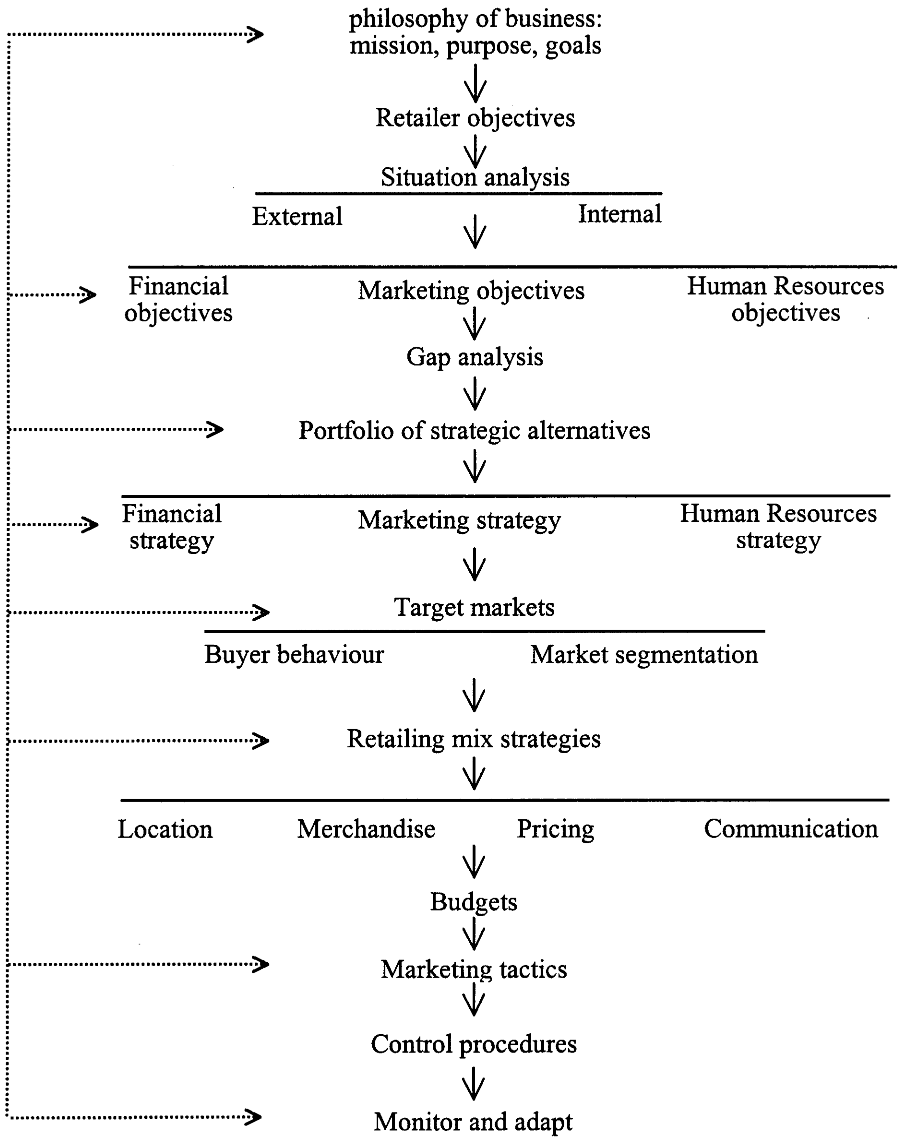

Figure 3.2. *The Strategic Retail Management Process (Arnold et al. 1983, adjusted by Oppewal 1995).*

In this view, the criteria of location decisions are derived from higher level marketing (and also financial) strategies.

The way these decision areas are interrelated in the strategic approach is shown in the scheme in figure 3.2. This scheme stems from Arnold *et al.* (1983 p.2) and was modified and discussed in Oppewal (1995, p.118). The process starts with clarifying the goal (mission) and overall objectives of the organisation. Generally, a goal is a first definition of the target markets and the retail format used to approach these markets. The objective of the stages that follow is to translate this goal into operational retail strategies. First, a situation analysis (situation audit) is conducted that should reveal the attractiveness of potential markets, the strength and weakness of the competition in these markets (external situation) and the opportunities for the chain to attract potential customers (internal situation). Then, strategies to attain the goal are formulated, implemented and monitored. The scheme shows how the various areas of management decision making are co-ordinated into an integrated effort to approach the target markets.

The process results in a marketing plan, which is a written statement specifying (i) the target market, (ii) the format used to satisfy the target market's needs and (iii) the bases upon which the retailer plans to establish a sustainable competitive position (Levy and Weitz 1995). The target market is defined in terms of the market segment the retailer wants to address, for example, as identified by demographic and socio-economic characteristics. The retail format, the second element of the plan, specifies how the retailer intends to approach this target market in terms of available marketing instruments. Usually, these include the pricing policy, type of merchandise, services offered, store design, location type and possibly other variables that can communicate the retail offer to the consumer. This retail mix is the retailing counter-part of the well-known product marketing mix. Having identified the target market and the retail format, there are generally several ways in which an advantageous competitive position can be pursued. A sustainable competitive advantage is an advantage over competition that can be maintained over a long time. The third element of the plan specifies how the retailer plans to achieve such an advantageous position. Generally, this involves a selection between a number of optional policy instruments, such as customer loyalty, image, service, location, merchandise, low cost operations and so on. Generally, several growth strategies may be considered, such as investments in market penetration, market expansion (including new market segments), retail format development (offering a new retail format) or diversification (integration of new branch sectors).

A marketing plan may be formulated at different levels of the organisation, i.e. the chain as a whole, individual stores within a chain and even departments within stores. An explicit plan is considered essential for focusing management activities on specific targets and co-ordinating efforts throughout the organisation. Furthermore, the plan provides a basis for monitoring market developments and strategic control.

Effective strategic control requires that quantifiable objectives are set against which the actual performance of stores can be tested. The plan should be updated on a regular basis, e.g. every two or three year. Thus, like in the public-sector case, monitoring, plan formulation and plan implementation are considered as steps in a cyclic process.

Table 3.2. Objectives and options of private-sector location planning.

Primary goal
- establish an advantageous and sustainable competitive position of the chain in the retail market

Objectives
- marketing objectives: improve market share, market penetration, access to the chain etc.
- financial objectives: improve profits, return on investment, cash flow, etc.

Options of locational decision making
- opening, closure of outlets
- disposal of own outlets, acquisition of competing outlets
- relocating outlets
- resizing, refurbishment, refasciament of outlets

Objectives and options of retail decision making

Store location is generally considered a key-factor for achieving the marketing and financial objectives of a firm. Location determines to an important extent the attractiveness of stores for consumers. Furthermore, location is a powerful instrument for establishing a sustainable advantage over competition (Levy and Weitz 1995). With respect to the strategic meaning of location, Breheney (1988) makes a useful distinction between outlet-dominated and product-dominated types of retailing. The distinction refers to the extent to which either the location or the speciality of the products sold determines the competitive strength of stores. Outlet-dominated stores, such as for example grocery stores, rely heavily on being near to consumers, whereas product-dominated stores can establish an advantage through the specialisation of merchandise. This distinction corresponds to the geographer's classical distinction between low-order and high-order goods. Clearly, the two types of retailing define the begin and end point of a continuous dimension, on which every type of retailing can be positioned. Although different types of retailing have different positions on this dimension, the nature of the location decision problem is largely the same.

The marketing and financial plans determine the objectives and constraints of location strategies. The marketing plan specifies the type of location (e.g., shopping centres, stand-alone) and the geographical regions the retailer wishes to be in.

Marketing objectives are often formulated in terms of market shares and penetration rates of the chain. In addition, the financial plan formulates objectives in terms of the profitability of stores or return on investment. The options of location decisions with which marketing and financial objectives can be achieved include the opening or closure of stores, the disposal or acquisition of stores, expansion or reduction of floor space, refurbishment of stores, and changing the facade of stores (Bennison 1995). Table 3.2 summarises the objectives and options of location decision making.

The location decision making process
For reconstructing the location decision making process this section uses the same general decision model as in the public-sector case (see figure 3.1). There is a considerable overlap with the public-sector case in the way the steps in the model are specified. This section highlights the questions that are specific for the private-sector case.

Step 1: problem identification and problem definition
In contrast to the public-sector case, the study area is not a-priori defined by administrative boundaries. At least large retailers operate outlets throughout an entire region, a country or even internationally. Consequently, the first step in developing a location strategy is the selection of the market area of interest. A market area is loosely defined as the area in which most of the people residing in that area usually shop. Hence, the scale of a market area depends on the type of retailing. For example, a market area may have the scale of a region (for high-order types of retailing) or a middle-sized city area or even a neigbourhood (for low-order types of retailing). Opportunities or problems that ask for a location decision may arise as a consequence of factors that affect the trading potential of existing or potential locations in the market area. Specifically, these include demographic and socio-economic developments in the consumer population, actions of competitors, urban developments, changes in the accessibility structure and the introduction of new sites. In particular, an action of a competitor, such as the opening of a store, generally has a great and sudden impact on existing demand-supply relationships.

In response to a specific event or on a regular basis, retailers explore opportunities for expansion or reorganisation of the chain based on a spatial analysis of the market. Possibly, the retailer already operates one or more stores in the area or wishes to investigate the opportunities to enter the market. In both cases, time-series data are often used, to obtain insight in developments over time (Jones and Simmons 1990). Furthermore, retailers try to predict demographic and economic (available expenditure) developments as well as actions of competitors, to determine future market conditions.

A first indication of opportunities or problems is obtained by comparing the performance of the chain with marketing objectives, e.g., in terms of market penetration and market share. When an underperformance is observed, trade areas are analysed in terms of the characteristics of the consumer market and strengths and weaknesses of the own and competing stores. For example, a low market penetration may be due to suboptimal store characteristics, a low density of target consumers or strong competition. Otherwise, a low market penetration may indicate an opportunity for expanding or reorganising the chain. If there is a positive indication for an expansion or a reorganisation strategy, then a search for candidate sites for opening new stores follows. Generally, candidate sites are identified by matching location characteristics with a target profile.

Just as in the public-sector case, decisions in this first stage are uncertain mainly because of incomplete knowledge about autonomous processes. In other words, it is often hard to predict future market conditions under non-intervention conditions. Furthermore, the identification of the store and market related factors that can explain observed market penetrations or market shares of the chain/store is often uncertain, because knowledge about causal relations between physical and behavioural aspects of retail systems incomplete. Just as in the public-sector case, retailers may deal with these problems by using planning standards often in the form of national statistics or rules of thumb based on experience.

Step 2: Formulating alternative location strategies

This second stage follows only when the former stage has identified ways to improve the market position of the chain through location decisions. For example, this is the case when locations have been identified that provide sufficient trading potential to open a new store or to increase the size of an existing store. If trade areas of individual stores do not overlap, then locations can be evaluated independent of each other. For example, when optional locations for opening a new store are separated by a large distance, then there is no choice involved other than the decision whether or not to open a store on each of the locations. In the general case, however, trade-areas do overlap so that the opening, closure or expansion of one store affects the market potential of competing stores. Particularly, when retailers are planning to enter a new market or to reorganise the chain in an existing market area, e.g. through take overs of competing stores, it is important to view locations dependent on each other (Jones and Simmons 1990). In these cases, there are multiple competing ways in which marketing objectives can be achieved. Different options such as developing a small number of large outlets on the one hand or opening a large number of small outlets on the other may or may not be equivalent in terms of market share. At the same time the performance of the chain depends on the location of the outlets. A few well-located outlets may perform equally well as a larger number of poorly located outlets. A location strategy, therefore, is generally defined as a set of simultaneous location decisions defining a certain configuration of an outlet network.

Formulating alternative ways to configure an outlet network is a design problem. Retailers do not tend to rely as heavily on design concepts as public-sector planners do. More often they may use subjective assessment or heuristics, such as for example 'maximise the distance from existing (own and competing) stores'.

Step 3: Analysis of alternatives

The goal of this stage is to assess the feasibility and impact of alternatives. Traditionally, feasibility assessment is the area on which the greatest part of research efforts in private-sector planning is focused (Breheney 1988). This type of research addresses the question whether a proposed development (e.g., opening, expansion or renovation) is cost-effective (i.e., viable in the longer term) or, more generally, meets the marketing and financial criteria of the firm. Clearly, the market share of the store in the new situation is the critical and uncertain element of the assessment. In the exploration stage, an analysis of the market has already provided an indication of the trading potential at the site (given the proposed development). In this stage, a similar market analysis is repeated more thoroughly using more detailed data with the aim to obtain a more reliable assessment of the market share of the store.

Impact assessment, on the other hand, has received less attention in private-sector planning. The only form of impact that is a concern of retailers is cannibalism between stores, which may occur when the trade areas of own stores overlap. Social and environmental impacts are issues only when the proposed development requires a permission decision of the local authority and retailers have to proof that it will not produce negative impacts.

Just as in the public-sector case, feasibility and impact assessments are uncertain because of a lack of insight in how consumers and competitors will react to new developments. Also, the strategies used to deal with this problem are similar. Like planners, retailers mostly use analogue information. Also, subjective judgements of location analysts play a role in making a final feasibility assessment.

Step 4: Evaluation of alternatives and making a choice

If the previous stages have yielded several alternative strategies, then the goal of this stage is to rank the alternatives on objectives and to decide whether or not to implement the alternative with the highest rank. In many cases, retailers consider decisions for different locations independently of each other, so that there is no ranking problem. In other cases, the ranking involves a comparison of the alternatives on financial and marketing criteria. These two sets of criteria are often in conflict with each other. Strategies involving large expansions of the chain tend to perform highly on marketing criteria, such as market share. However, given the high investment and exploitation costs involved, these strategies tend to perform poorly on financial criteria, such as profitability or returns on investment. In these cases, the ranking of alternatives requires weighting of multiple criteria. Another factor that complicates the ranking task is the uncertainty about the outcomes of the alternatives. As noted above, the feasibility and impacts of an alternative are uncertain because of the incomplete knowledge about how consumers and competitors will react. These uncertainties should be taken into account in ranking the alternatives. In sum, just as in the public sector case, the evaluation of alternatives can be characterised as a multiple-criteria evaluation problem under uncertainty. However, compared to the public-sector the evaluation stage is often less problematic, because the set of evaluation criteria is smaller and less diverse. Having ranked the alternatives, the next question is whether or not to implement the alternative with the highest rank. Usually, the final decision is made at a high level of the company's management.

Step 5: Plan implementation, monitoring and early warning

In contrast to the public-sector case, the choice of instruments to implement the chosen strategy is straight forward and does not imply a choice problem. After implementing the plan, the performance of new stores or existing stores in new market situations is closely monitored. The goal of this monitoring is to identify in an early stage problems, in order to react adequately when adjustments of the plan are needed. In fact, the monitoring stage coincides with the first stage of problem identification (Breheney 1988). In that sense, strategic planning is a cyclic process, just as in the public sector case.

Conclusion

Several steps in the above decision making process are critical for the success of a chain in establishing an advantageous and sustainable market position. First, in the explorative stage, it is important to be informed as early as possible on location decisions of competitors. In contrast to changes in the consumer market, actions of competitors are often hard to foresee and, at the same time, tend to have far-reaching impacts on the existing competitive structure. Consequently, most retailers allocate a substantial amount of effort to monitoring actions of competitors. Second, the success of a chain will depend to a considerable extent on the ability of the location analyst to identify locations with high trading potential earlier than competitors do. Therefore, also the search for new sites is a critical issue. However, whether or not a site will provide sufficient potential for a new store eventually depends on how consumers will react. As shopping behaviour is hard to predict in changed market situations, viability assessment of new stores is a third critical step in the location decision making process. Just as in the public sector case, uncertainties about consumer and competitor behaviour invoke the need to evaluate different scenario's regarding own or competitors' actions.

Such 'what-if' types of analysis can improve insight in the conditional behaviour of the system and the sensitivity of location strategies.

3.3.3 Conclusion

Both public and private sector organisations stress the importance of strategic planning, as opposed to ad-hoc or short-term planning. In the public sector, planners are concerned with the level of service provision for a local or regional population. In the private sector context, the location of retail facilities is one of the instruments to build an advantageous and sustainable position in a competitive market. In both cases, the location decision-making process can be reconstructed in terms of a general decision model. As it turns out, there is a considerable overlap between the public and private sector case with respect to the questions that are raised in the various steps of the model and the strategies used to deal with uncertainties.

Besides the similarities there are, however, also several differences. First, public sector planning is concerned with all stores that constitute the retail system under concern, whereas private sector planning tries to optimise the performance of the subset of stores that belong to the own chain. Second, there is a difference in the choice of the spatial aggregation level. Planners tend to analyse the system at the level of shopping concentrations (centres), whereas retailers typically consider individual stores. Furthermore, planners and retailers often use different ways of segmenting the retail system. Given the available policy instruments, planners typically use a categorisation in broad groups, such as convenience and comparable goods. On the other hand, for retailers it is important to identify the smaller groups of competing stores in a particular demand segment (e.g., grocery stores). Finally, the objectives of the groups differ. Typically, planners use a broad set of criteria including social and environmental criteria, whereas retailers focus on the smaller set of marketing and financial criteria. In a global sense, therefore, one can say that the evaluation criteria used by retailers form a subset of those considered by planners.

Eventually, retail developments are the result of the combined actions of planners on the one hand and retailers/developers on the other. Local/regional government creates the conditions for retail developments mainly by designating shopping locations and developing a public infrastructure for the accessibility of these locations. Retailers and developers, on the other hand, take the initiative of developing retail facilities and are responsible for the operation of these facilities. The feasibility of public sector plans depends entirely on the willingness of private-sector parties to participate. Vice versa, the feasibility of private sector plans depends to a considerable extent on the approval and support of government. Both parties are aware of the importance of creating a match between each other's location plans. As noted before, the dialogue has been chosen as the form to establish such a match. In preparing plans, retailers increasingly take planners' interests into account and vice versa. Given this interaction, differences in planning issues are smaller than the above may suggest.

3.4. Retail planning research and methodology

3.4.1. Introduction

Applied retail research has a long history in public-sector planning. In the sixties and seventies, spatial modelling techniques were developed that provided the tools for applied research. Probably, the use of these techniques culminated in the late seventies and early eighties. Although spatial modelling has lost some of its meaning, research is still an important component in contemporary retail planning. Similar developments have taken place in the UK (e.g., Davies 1984, Birkin *et al.* 1996). In the private sector, the application of systematic forms of research for strategic planning has a relatively short history. For a long time, retailers have relied almost exclusively on the intuition and personal experience of the location analyst (Breheney 1988, Birkin *et al.* 1996). However, in recent years, the role of location and market research has become more important under influence of an increasing need to rationalise the retail management process. Nowadays, the larger retailers have established specialised units for research on a continuous basis.

Potentially, research can improve the quality of decision making in several ways. First, research can reduce uncertainties in decision making through generating information or improving the quality of existing information. Second, research can clarify questionable assumptions made by decision-makers (e.g., a normative turnover-to-floor-space ratio). Finally, systematic forms of generating and evaluating decision alternatives have the potential to broaden the view of the decision-maker and to improve the integration of multiple decision criteria (Brill *et al.* 1990). That is, systematic forms of spatial search / evaluation can lead to the identification of locations that would have been overlooked otherwise. Given this analytic, reflective, creative and synthetic role, research can provide support in the various stages of decision making from exploration of problems, to generating alternatives and making a choice. In practice, research is concentrated in the analytic stages of the planning process and pays little attention to creative and choice stages.

This section reviews research and methodologies used in retail planning. There is a large body of literature on methods and techniques of retail planning research. In this literature, the private and public sector represent different traditions. However, this distinction is not clear-cut in applied research programs. Rather, these programs overlap to a large extent both in contents (i.e., research questions) and the methodology used. For example, consultants in retailing generally apply the same research programs for both groups of commissioners. Therefore, this section will not consider the traditions separately, but rather discuss research in the context of the problem it addresses. The section is organised in various subsections. The first sections consider the current practice with regard to the availability of data (section 3.4.1), the use of information systems (section 3.4.2), methodologies of research (section 3.4.3) and the role of location theory (3.4.4). Then, the last section (3.4.5) gives a critical review of the current practice, in order to be in a position to specify the targets of the DSS in the sections that follow.

3.4.2 Data availability

The last decade has seen an explosive growth in supply of data, not only in the Netherlands, but in most post-industrial countries (Waters 1995). At least three categories of data are relevant for market research and strategic planning. These include data related to demand (demographic data), supply (retail facilities) and spatial interaction (spatial shopping behaviour). Unlike the UK and US, the Netherlands do not collect census data. However, the central office of statistics (the CBS) provides more or less the same information at the level of neighbourhood districts. In addition, there are several commercial information systems that offer nation-wide population data based on five position zipcode areas (28,000 areas with on average 200-225 households). Another group of systems provides areal typologies with a high spatial resolution specifically designed for geomarketing purposes. The typologies are defined in terms of demographic and socio-economic household characteristics, such as age group, household size, income group and the like. Mosaic is a well-known example of this type of system and is based on six position zipcodes (with on average 16 households). In addition, the so-called life-style databases are rapidly gaining popularity (Birkin 1995). These databases store detailed lifestyle information about individuals based on customer registrations.

With regard to the supply-side, Dutch planners and retailers can make use of a nation-wide information system, called DIS (distribution trade information system). The features of the DIS are summarised in Table 3.3. As noted in Section 3.2, DIS is specifically designed for retail planning. The system has a nation-wide coverage, is regularly updated, offers a high spatial resolution (individual stores) and comprises floor space and branch data per outlet (Nijkamp and Scholten 1990). The data collections are organised by geographic region. In recent years, however, the data for some regions have become outdated, because of delays in updates. The decline in quality has forced users of data of the concerned regions to look for other data sources. Hence, there is no longer a case of national coverage in a true sense.

Table 3.3. Features of the DIS (source: Nijkamp and Scholten 1990).

Features of the DIS
- accessibility to the information system
- reliability of relevant data
- up-to-date information (chacked twice a year)
- nationwide coverage at a (de)centralised level
- uniform definition/standards for measuring size
- client-friendly use
- potential for dynamic analysis and monitoring
- aggregation possibility at each spatial and branch level
- flexibility in terms of linkage to other information systems

With regard to interaction data, the third category, planners and retailers still have to rely on collecting data on a case-by-case basis. To date, there has been only one initiative undertaken by the D&P-consultancy to collect spatial shopping behaviour data on a national scale (Brayé and Wapenaar 1995). The data are collected through a survey among a sample of 350,000 passengers in the 200 larger centres in the Netherlands. The passengers were asked to recall the distribution of retail expenditure across centres. The value of this data set, however, is limited, because the remaining 2000 smaller centres were not included in the sample. Therefore, interaction data regarding these smaller centres are only partly available and biased. Since a market for this type of data exists, one may expect that this type of databases will be further developed in the future. In addition, many retailers can make use of customer databases. These data are collected through in-store surveys and increasingly also through automatic registration systems (so-called scanner data). Customer databases provide a rich source of information for mapping penetration rates of stores, but provide only limited information about preferences and spatial choice behaviour of consumers in the market area.

The databases reviewed above provide basic information. In addition, there are several products that represent an added value by integrating different data sets and offering areal statistics. In the Netherlands, such products have been derived from the DIS. The so-called 'Store Atlas' is a geographic information system that integrates DIS, population and geographic information. For each five-position zip code area and for each retail segment the system can display supply-demand ratio's, such as for example 'per capita floor space'. Recently, the Store Atlas has been expanded and integrates in addition the nation-wide interaction database, mentioned above (the D&P, Brayé and Wapenaar 1995). The interaction data are used to delineate catchment areas and to calculate market shares of stores. More detailed forms of location analysis are also supported by the system. For this, the system offers individual retailers the possibility to integrate customer databases. Another DIS-related product, the so-called 'DISpocketbook', provides population and DIS-data in aggregated form. The data concern statistics, possibly desaggregated by area type, describing the size and composition of retail centres in relation to population size across 2400 cities and towns (Nijkamp 1990).

It can be concluded that basic demand and supply data for market research and strategic planning are widely available through nation-wide databases. The databases provide sufficient geographical detail and attribute information for most planning purposes. Also, there is a wealth of summary data describing the structure of retail systems in towns and cities. However, a nation-wide interaction database that provides sufficient spatial coverage and detail is still lacking. Therefore, to date, planners and retailers, who wish to obtain insight in the usage patterns of retail facilities, still have to collect the needed interaction data on a case-by-case basis.

3.4.3 The use of information systems

The management and analysis of the spatial and geographical data require powerful computer software. For this, most organisations in retailing (planners, retailers and consultants) use a combination of general-purpose packages for database management, spread sheets, drawing and charting and statistical analysis respectively. In recent years, geographic information systems (GIS) have become increasingly popular. The Store-Atlas mentioned above is an example of a dedicated GIS for retailing. In the previous chapter, the concept and potential of GIS for spatial planning has already been discussed. The purpose of this section is to review in some detail the implementation of GIS in retail companies and governments in the Dutch context.

Taking the public and private sector together, the adoption of GIS nowadays is characterised by a transition from a stage of stable growth to a stage of declining growth rate (approaching saturation) (Grothe *et al.* 1994). With respect to the public sector, most GIS systems that are now in use by local and regional governments were acquired in the late eighties. Nowadays, in the Netherlands GIS is almost universal among provinces and municipalities above 50,000 inhabitants and in approximately 50 percent of those above 20,000 (Masser and Gaglia 1995). With respect to the private-sector, Grothe *et al.* (1994) describe an inventory among a sample of 2575 private companies in the trade sector and other sectors that are dealing with geographic information. The results suggest that approximately 50 percent of the companies in the trade sector use GIS. Furthermore, 50 percent of the GIS-systems in use runs on a PC-platform. The study further indicates that the adoption of GIS strongly increases through time and is positively correlated with company size. Extrapolation of these trends suggests that in the near future GIS will be generally used by those organisations that use geographical information. For example, at present one of the three largest grocery retailers in the Netherlands is using GIS and the other two are in the process of implementing GIS in their organisation.

It can be concluded that information systems for managing and analysing geographic and spatial databases are available in an increasing number of organisations in retailing. Although the implementation of GIS is widespread, the use of the systems for spatial analysis is still in its infancy. In most cases, GIS is dominantly used for the storage and display of data. The analytic functions currently offered by most GIS-systems are useful for spatial market analysis, and, more specifically, geomarketing (Longley and Clarke 1995a). However, the use of GIS for these purposes is still rare. Therefore, it is safe to say that, at present, the analytic role of GIS in market research and strategic planning is limited.

3.4.4 Research methodologies

Over the last decades, a large body of techniques has been developed in the field that is generally known as 'retail location and market analysis'. We can distinguish three types of studies in applied research: spatial market analysis, store location research and impact assessment. This section discusses approaches in each of these studies in turn. For providing an overview, it suffices to discuss only the main lines. For an extensive review of this field readers are referred to Davies and Rogers (eds., 1984), Ghosh and McLafferty (1987), Wrigley (ed., 1988) and Jones and Simmons (1990).

Spatial market analysis

Studies of this category are normally conducted to evaluate opportunities for opening new stores in given market area. Dependent on the retail sector under concern, the scale of a market area typically corresponds to a city or part of a city. An estimate of market potential is based on an inventory of the demographic and socio-economic characteristics of the consumer population in the area. Usually, the per capita retail expenditure is estimated based on a national mean, possibly, adjusted for the characteristics of the local population (e.g., income level). The calculated retail expenditure should be corrected for the fact that boundaries of the market area are vague. That is, consumers will occasionally shop outside the area and, vice versa, stores will be visited also by consumers residing outside the area. Usually, the size of outgoing and incoming flows is determined based on a consumer survey or rules of thumb. In many cases, a prognosis of population and economic developments is used to estimate future market potential. Normally, the prognosis is based on extrapolation of national trends, possibly, adjusted for local circumstances.

The ratio between (future) market potential and the amount of retail floor space in the area gives an indication of the degree of market saturation. However, the question whether there is an opportunity for expansion does not depend on market saturation alone. Generally, an expansion of floor space increases the market potential through two possible mechanisms: (i) an increase of penetration rates inside and outside the area (increasing inflow and decreasing outflow) and (ii) an increase of the amount of per capita expenditure. The latter mechanism is known as the elasticity of demand for supply. For example, an expansion of the supply of grocery stores in an area may lead to an increase in the amount of expenditure in grocery stores possibly at the expense of expenditures in other sectors, such as for example fast-food restaurants. Estimates of the degree of market saturation and the degree to which the existing market can be expanded are then combined to evaluate opportunities for new stores.

Store location research

Studies of this type involve a more detailed market analysis of the trade area of stores with the aim to estimate the sales potential of a specific location. The purpose of the studies usually are (i) to evaluate sites for opening new stores or (ii) to analyse the performance of existing stores. With respect to the first purpose, store location research is a follow-up of spatial market analysis and is conducted when the latter has indicated that there are opportunities for growth. The sales potential of a new site forms the basis of a cost-benefit analysis that should indicate whether or not financial criteria are met. This financial component of feasibility analysis is beyond the scope of location research and, therefore, will be left out of consideration. With respect to the second purpose, store location research is part of a process of monitoring the performance of existing stores. Comparing sales potential with actual sales of the store or with marketing/financial objectives gives an indication of relative performance. In the case of underperformance an explanation is sought in terms of store or trade-area characteristics, to formulate an appropriate intervention strategy (e.g., closure, expanding floor space etc.). Furthermore, it should be noted that store location research is taken in a broad sense here to include also the type of studies that planners usually conduct to analyse retail system performance. Usually, the latter studies focus not only on the economic performance of stores (or centres), but also on mobility, accessibility and service provision aspects. However, the following will focus on the economic aspect, because this aspect represents the major focus of the studies in both public and private sector contexts.

Birkin *et al.* (1996) give an exhaustive typology of location research techniques and discuss, in addition, their use in British retailing. The following techniques can be distinguished.

The trial and error approach. This approach refers to the absence of a systematic method for evaluating store locations. In stead, the judgement of a location is based on the intuition or 'gut-feeling' of a location analyst who inspects the site. Retailers commonly used the non-systematic approach in a period when locations were easy to find and market growth was a guarantee for a stable market position. Although visual inspection and intuitive judgement still plays a role in any location decision, an increasing number of retailers have established some degree of systemisation of the procedure.

The checklist approach. In this approach, locations are evaluated based on a checklist of location factors that are considered important for the type of retailing under concern. In the literature several generic checklists have been developed. These checklists focus the attention on physical characteristics, accessibility conditions and location type (Snow and Scott 1984). A checklist may be used in combination with methods of sales forecasting in a first stage to identify suitable candidate sites (Mecurio 1984; Ghosh and McLafferty 1987). In other cases, retailers make location decisions based on a checklist alone. In these cases, location decisions are mainly based on the subjective judgement of the location analyst. The checklist is used to make sure that none of the important factors are overlooked.

Analogue techniques. These techniques are very common store-location procedures not only in the Netherlands, but also in the UK and US (Birkin *et al.* 1996). The approach involves estimating sales based on known performance of similar cases in the past. As analogue cases will never completely match the circumstances of the new site, the procedures inevitably involve the judgement of the location analyst to adjust known results to new circumstances. The extent to which subjective judgement plays a role depends, among other things, on the availability of analogue material. Obviously, subjective judgement is dominant in cases where the new development is relatively unique (e.g., new retail formula). On the other hand, most large retailers can select cases, in principle, from a large set of store openings in the past. The major steps in the standard approach are: (i) collect similar cases in terms of store and trade-area characteristics (ii) define component areas of the trade area of the new store, often in terms of drive-time bands and (iii) estimate the drawing power (penetration rate) of the new store in each component area based on the analogues (Drummey 1984). Many retailers (particularly, in grocery retailing) who use this method have established specialised multivariate databases for this purpose.

Regression techniques. Just as analogue techniques, regression analysis makes use of information about comparable cases in the past. However, unlike analogue techniques, it allows the location analyst to model sales volumes or penetrations as a function of one or more explanatory variables. In a usual model specification, the explanatory variables include characteristics of the trade-area (population and competitors), location (e.g., location type) and store (retail format). The model is calibrated on existing stores and is used to predict sales given the store, location and trade-area characteristics at the new site. Regression analysis is used by many retailers at least on an occasional basis.

Spatial modelling. Unlike the previous approaches, spatial modelling is based on a theory of individual or aggregate shopping behaviour of consumers. The models that are useful for retail planning describe and predict shopping trips or expenditure flows, dependent on travel distance and attractiveness of stores or centres. The models are calibrated on observed individual or aggregate shopping behaviour in the existing market situation and are, then, used to predict this behaviour under planned conditions. Given the predicted flows, the market share of the new store and, simultaneously, also the market share of all competing stores, are calculated. Spatial models have been widely used in public-sector planning in the late seventies and eighties. In the private sector, the interest for this technique is more recently and, consequently, the approach does not play a role in current research programs. Birkin *et al.* (1996) describe a number of case-studies that use spatial interaction modelling for retail location analysis. Oppewal (1995) gives a review of case-studies reported in the discrete choice modelling literature.

Impact assessment studies

The aim of these studies is to assess the impact of a proposed development on the performance of the retail system. Traditionally, impact assessment is an important issue in public-sector planning. In private-sector planning, on the other hand, retailers conduct such studies only when a new development requires a permission of local government. In cases where impact assessment is an issue it is integrated as a next step in the above store location studies. In the Netherlands, impact assessment studies are currently relevant in the context of evaluating proposals for developing large-scale off-centre retail trade such as retail parks. Rogers (1979) describes a coherent framework for analysing impacts for environmental, social and economic objectives. Most impact assessment studies, however, have a smaller focus and consider economic performance of stores (or centres) only.

Currently used impact assessment methods were originally developed in the context of superstore appeals in the UK in the eighties (ed., Wade 1983). Two broad approaches can be distinguished, namely spatial modelling and the so-called step-by-step procedure (Davies 1984). The latter procedure is commonly used and involves an extension of the above analogue method. Wade (ed., 1983) gives an extensive overview of the various approaches in step-by-step procedures. In one approach, an estimate of the market share of the new store is taken as a starting point. This estimate is given by the retailer or, otherwise, derived from analogue cases. Then, the losses of market share of competing stores located in the trade area of the new store are estimated. In another approach, the market share of the new store is not given, but is estimated directly from information on the population in the trade-area.

3.4.5 The role of location theory

The above types of studies allow one to assess opportunities for expansion, sales potential of locations and impacts of new developments. This information enables planners and retailers to identify problems and opportunities and to evaluate location plans, but does not offer guidelines how to structure retail systems. Location theories fill this gap and describe either normative or descriptive retail structures based on assumptions about behaviour of consumers and producers.

Already from the beginning of governmental involvement in retail developments, policies are based on the notion of a functional hierarchy of facilities. In this hierarchy, shopping facilities are concentrated in centres of different orders. In the Netherlands, a three-order or four-order system is commonly used for middle-sized and large cities respectively. This taxonomy of centres is based on a micro-economic central-place theory developed by Christaller in the early thirties of this century. Christaller developed this theory to explain hierarchical patterns that could be observed in spontaneous (unplanned) urban systems in Germany at that time. The theory is deductively derived from a set of axioms concerning the nature of demand, supply and the market structure. In Christaller's system, consumers make single-purpose trips and patronise the nearest centre that offer the required goods. Producers choose the location and size of stores based on a profit-maximisation rule. Given these and additional assumptions, the theory predicts a layered system of shopping districts, each with a distinctive scale and mix of retailing outlets (Brown 1990).

Although the hierarchical model was developed to explain spontaneous systems, it has been enormously influential as a normative model for land-use planning in the Netherlands and many other countries. In the post-war period the model was used in a strict sense supported by quantitative guidelines concerning the size and branch composition of shopping centres. However, in the academic literature the model has been heavily criticised for its unrealistic assumptions, logical inconsistencies and inability to explain certain elements of the spatial pattern of urban retailing. Elements such as for example, ribbons of commercial activity alongside arterial routeways and specialised shopping areas supplying a specific category of merchandise could not be explained by the model. The shortcomings gave rise to a variety of modifications and extensions that have led to more realistic typologies of urban commercial structures (e.g., Berries typology, see Brown 1993). An extensive discussion of central place theory, empirical evidence and modifications can be found in Timmermans (1979).

In contemporary planning, the basic hierarchical model is still influential, although the model is subject to discussion (Gantvoort 1993). The concept of large-scale retailing outside existing shopping centres has added a new element to the existing typology. Furthermore, the introduction of new retail formats (e.g., American-style chains), the increasing scale of stores and the changing role of the inner cities have raised the question whether the traditional three or four-layer structure is still adequate. To date, the discussion has not yet resulted in a generally accepted new concept or modification of the old concept. In stead, under influence of the deregulation trend, planners leave more room for the workings of the market in structuring the retail system (e.g., using the concept of 'free enterprise zones').

3.4.6 Evaluation of applied retail research

Applied research and DSS share the same objective, namely supporting strategic decision making primarily through improving the quality of information. For the next section to specify the objectives of the spatial DSS, this section evaluates the effectiveness of current applied research. The three questions considered are: is the methodology adequate? does the output match information needs? and does research support the process of decision making (integration)? These questions refer to the quality, quantity and relevance, and the integration of produced information in the decision making process.

The methodology of applied research

As reviewed above, traditional techniques for predicting sales and impacts of new stores include the trial-and-error, checklist, analogue and regression analysis methods. We argue that these approaches have serious drawbacks for that purpose compared to spatial modelling (Birkin *et al.* 1996, Oppewal 1995 and Timmermans *et al.* 1992). First, the trial-and-error methods and to a lesser extend also the checklist approach have the following potential disadvantages (Birkin *et al.* 1996):

1. judgements depend strongly on the experience of the analyst (typically, the correlation between judgements across experts is low);
2. the knowledge is only available to the analyst under concern (and is lost when the individual leaves the company);
3. the procedure is very time-consuming and expensive;
4. the increasing complexity of retail markets makes it harder to rely on intuition (there are many examples of failures);
5. there is no guarantee of finding the best site, because comparison information is not available (could greater profits have been made elsewhere?).

Given these disadvantages, there is an incentive to systemise the location procedure. Analogue methods provide more sophistication in this respect, but they have several specific drawbacks. First, given the heterogeneity in the sample of stores, the choice of analogue cases is ad-hoc. Second, useful analogue information is missing in cases where the project has novel characteristics (e.g., a new retail formula). Third, the analogue method does not deal with variance in the performance of analogue stores that relates to in-store factors (Birkin *et al.* 1996): the method leads to inaccurate predictions if the analogue store is currently under- or overperforming. Regression analysis is based on a statistical theory and, therefore, is better able to take differences of stores into account (Oppewal 1995). However, for predicting sales and impacts of new stores, a number of problems remains (Birkin *et al.* 1996):

1. the models evaluate sites in isolation, i.e. without considering competing stores in a spatial context;
2. the technique deals with heterogeneity in the sample of stores in an ad-hoc way (as in the analogue method: how easy is it to find a sample of stores with similar characteristics?);
3. correlations between explanatory variables can lead to unreliable parameter estimates (i.e., the problem of multi-collinearity);
4. the models fail to handle customer/expenditure flows adequately.

The latter problem means that market share predictions are not logically consistent, in the sense that the sum of predicted sales does not necessarily equal the sum of available expenditure in the study area (Oppewal 1995).

The above drawbacks follow from the fact that the traditional methods do not model the processes that are responsible for the allocation of demand across stores. That is, they do not model the spatial shopping behaviour that generates expenditure flows between residential locations or work places and shopping locations. Therefore, the ability of these methods to predict impacts of changes in competitive structures and market structures is doubtful. On the other hand, spatial interaction/choice models incorporate such mechanisms and, therefore, have the potential to predict expenditure flows in a way that is consistent with aggregate/individual consumer behaviour in spatial settings.

The information contents of applied research

The question whether generated information matches information needs can be broken down in the following elements:

1. does research shed light on all retail system performance dimensions that are relevant for decision making ?
2. does research support all stages of the decision making process ?

3. is research able to respond to all possible questions related to retail system operations ?

The first question relates to the match between planning objectives on the one hand and the topics covered by the research programs on the other. Van der Heyden (1987) argues that applied retail research falls short in this respect. Although he made this observation in the late eighties, the criticism still holds today. It states that applied studies tend to focus on economic performance of centres and ignore demand-side and public-side issues.

With regard to the second question, we noted in the introduction section that research has the potential to support creative and evaluation stages as well as analytic stages in planning by means of systematic methods. This potential is, however, not fully utilised in current applied studies, as systematic methods of spatial search and evaluating multiple criteria receive little or no attention. This is remarkable because such methods exist and potential gains of systemised search and evaluation are high (Breheney 1988). This means that there is a substantial gap between availability and use of methods of systemisation.

Finally, the third question addresses the responsiveness of research programs to information needs about retail system dynamics (irrespective the specific methodology used). Also, this issue should be considered relative to available methods and techniques. Formulated more precisely the question is whether current research programs fully utilise the potential of available methodologies to be able to respond to all possibly relevant plan scenarios. Answering this question must wait until a detailed overview of the state-of-art in fundamental spatial research is given in the chapters that follow. It is safe to say, however, that current applied research uses methodologies that were developed in the early days of planning. Therefore, also considering the quantity of information, current information provision possibly could be improved by making use of advances in spatial modelling and analysis since then.

The integration of applied research in the planning process

The plan decision making process is inherently iterative in nature, in the sense that in any stage of the process new information tends to invoke new questions. Particularly, information of the impacts of a plan scenario often gives rise to the wish to examine new plan scenarios. In the light of such question-answer dialogues, the time needed to generate information is an important characteristic of research. Traditional approaches perform poorly in this respect. Step-by-step procedures for impact assessment are time-consuming and have to be repeated for each plan scenario.

Regression and spatial choice/interaction models perform better in this respect. The models allow one to analyse the impacts of any plan scenario that can be defined in terms of the explanatory variables of the model. The integration aspect, however, can not be considered independently of the responsiveness aspect. That is, questions raised that lie outside the scope of the model could still be answered, but would require a new cycle of model formulation, model calibration and possibly even new data collections. Such procedures are very time-consuming and, consequently, regression and spatial models with limited responsiveness are either inadequate in terms of information quantity or create delays in information provision to a similar extent as the analogue and step-by-step-procedures.

Time gaps between posing and answering a question hinders the integration of research/models into the planning process. A time gap throws up a threshold for evaluating unanticipated plan scenarios and may imply that such scenarios are not considered at all (Van der Heijden 1986). Hence, the time gaps can have as an effect that the potentials of research for decision support are not fully utilised

3.5 Objectives of the spatial DSS

There are several ways in which a spatial DSS can be specified in terms of target users and intended role of the system. Several choices are made here considering the conclusions that can be drawn from the foregoing sections.

In section 3.3 several factors were identified that create a need for decision support. To summarise:

1. planners/retailers have incomplete knowledge/information about retail system operations and autonomous processes;
2. planners/retailers have incomplete knowledge/information about the causal relationships between the physical and behavioural subsystem;
3. planners/retailers have to deal with multiple, often conflicting decision criteria with uncertain outcomes.

Because of this, outcomes are uncertain in each stage of the decision making process, i.e. defining the problem, formulating alternatives and making a choice. In Section 3.4 it was concluded that current applied retail research only partially comes up to the needs for decision support. The analysis of shortcomings suggests that there are potentials for improvement in the methodology used, the contents of information provided and integration in the planning process. It is the primary purpose of the proposed DSS to avoid shortcomings of current applied research by an approach that:

1. makes advanced methodology available for planning (information quality);
2. extends the range of models to address the creative and choice stages in planning as well as the analytic stages (information quantity and relevance);

3. extends the range of models to address social issues as well as economic and efficiency issues (information quantity and relevance);
4. improves the integration of models in the planning process through a flexible and interactive problem solving environment (information integration).

The latter point is considered particularly important. The proposed DSS intends to make spatial models available for planners/retailers without the need for an analyst as an intermediate agent. Probably, the possibility to evaluate plan scenarios unmediated, easily and without delays reduces the threshold for utilising the potential of advanced modelling/analysis techniques to a minimum and makes a full integration of these techniques in iterative plan procedures feasible.

Besides improving information provision, the proposed DSS intends to facilitate communication between planners and retailers through standardisation of methodologies. In contemporary planning, the importance of the dialogue between government and industry is stressed. Most of the databases in retail planning, such as the DIS, are already standardised and have improved the conditions for a dialogue. However, effective communication requires agreement between parties also with respect to the analytic tools used to generate information for the dialogue. We view that a DSS potentially can offer a suitable platform for that purpose.

As implied by the chosen role, interactivity and flexibility are the key requirements for the proposed DSS. Interactivity in terms of the length of feedback loops and ability to manipulate conditions, is a precondition for attaining the objective of integrating spatial models in the planning process. Flexibility should enable the system to cover information needs and preferences of users across a wide range of applications. Specifically, to be able to support both public and private sector problems, the system should allow users to define:

- the spatial unit of supply (shopping centres or individual stores);
- the set of planning objectives (a broad or a small set);
- the facility network to be optimised (all stores, the subset of stores that belong to a specific chain);
- the segmentation of consumer markets (types of stores or branches).

Finally, we argue for several reasons that the time for introducing a spatial DSS is favourable. First, in both public and private sector planning one can observe an increasing need to rationalise the decision making process. Particularly, retailers are showing an increased interest in what research can offer and have increased the amount of research efforts in location procedures. Section 3.2 pointed at several developments that are probably influential in this respect. Consumer markets have become more diverse and demanding and consumer behaviour harder to predict. At the same time, the saturation of consumer markets and concentration of retail organisation have led to intensified competition in many retail markets. All these developments have led to a situation where there is clearly a potential for a DSS based on the assumptions of a consumer-oriented form of planning. Second, also resources needed for successful integration in the organisations have increased in the last few years:

1. the larger retail companies can utilise specialised units for market research and strategic planning;
2. there is an explosive growth in the supply of data for retail location and market research;
3. within the near future most organisations will make use of a geographic information system for integrating and managing the spatial data.

The availability of rich databases and information technology creates a demand for systems that allow one to utilise the rich source of information for strategic decision making. In that context, several authors have observed a renewed interest in the use of spatial modelling techniques in retailing (Bertuglia *et al.* 1994b, Birkin *et al.* 1996).

PART II

METHODOLOGICAL KNOWLEDGE FOR THE DSS

CHAPTER 4

A LAYERED MODEL OF KNOWLEDGE

4.1 Introduction

In the last chapter, it was argued that retail-planning problems are poorly structured. A characteristic of poorly structured problems is that they cannot be modelled by a single modelling technique. Optimal support of the various steps in the problem solving process requires a set of techniques drawn from various fields such as the spatial sciences, decision analysis, operations research and AI. As was argued in the previous chapter, a DSS provides a suitable framework for the integration and interactive use of such models. The goal of this second part of this study, is to develop a model-base of the spatial DSS that matches information needs described in the previous chapter.

To identify the knowledge components that play a role in spatial planning, this chapter first develops a conceptual model of the knowledge domain. The term knowledge is used to refer to a wide range of resources including data, heuristic expertise and scientific methods. The proposed knowledge model will serve as a theoretic framework for identifying and integrating the models of the DSS in the chapters that follow. It should be stressed that in this stage we are not concerned with a formal and detailed specification of knowledge components. Rather, the goal is to identify in qualitative terms the major knowledge categories. The specification of these categories will be the subject of the chapters that follow. In addition to identifying knowledge categories the framework presents a method of structuring the DSS model-base.

In the previous chapter, the problem area was described in terms of a decision making process model. In this chapter, we will consider the same problem area from a different point of view. Not the decision making process, but the knowledge involved is the central focus. Methods of knowledge acquisition and modelling is a subject that is receiving much attention in the context of Knowledge-Based System (KBS) development. A well-established approach to the acquisition and modelling of expertise is called KADS (knowledge analysis and documentation system) (see Schreiber *et al.* 1993). KADS was introduced in the early eighties as an alternative for the prototyping approach that was prevailing in that time. In the context of KADS a comprehensive set of tools has been developed. In this chapter we will use the conceptual modelling language that represents the core of this set of tools. This language called the KCML (KADS conceptual modelling language) was developed by Breuker and Wielinga in the late eighties and has been used in follow-up studies and KBS-applications in many domains (Breuker and Wielinga 1986).

The KCML is derived from a general theory about flexible expert problem solving. The model is based on the assumption that it is possible and useful to distinguish between several generic types of knowledge according to the roles that knowledge can play in the reasoning process. Furthermore, the model assumes that knowledge can be organised in several layers which have only limited interaction (Wielinga *et al.* 1993). In AI and also in cognitive psychology, it is usual to make a distinction between domain and control knowledge. The KCML also uses this distinction, but makes a further subdivision of control knowledge in three layers. The first layer of control knowledge is the inference layer which contains knowledge about the types of inference that can be made in reasoning about a domain. Second, the task layer embodies knowledge representing elementary tasks. The final layer called the strategic layer provides the flexibility required for solving poorly structured problems.

To specify the layered model for the spatial planning domain, this chapter is structured as follows. The first four sections (4.2 - 4.5) will identify the major categories of knowledge within each of the different layers in turn. An important rationale of organising knowledge in layers is that a layered model makes optimal use of the reusability of common knowledge components in different tasks. The next section (4.6) considers the question how the various layers work together and how reusability of model components can be employed for efficient storage and flexible modelling. Then, section 4.7 discusses the relationship with the model base management approach in the DSS literature. The last section discusses conclusions for developing the model-base in the chapters that follow.

It is useful to clarify on the outset some of the terms used in this chapter. In the following, the term 'planner' is used in an abstract sense to refer to the person (or system) that is preparing spatial plans in a public or a private sector context. Furthermore, the framework is applicable not only to the location planning of retail facilities, but to facility location planning in general. The term 'spatial planning' refers to this broader problem area.

4.2 The domain layer

This layer contains the concepts and the relations between concepts that form a structure for storing facts about states and events in a domain. The domain layer does

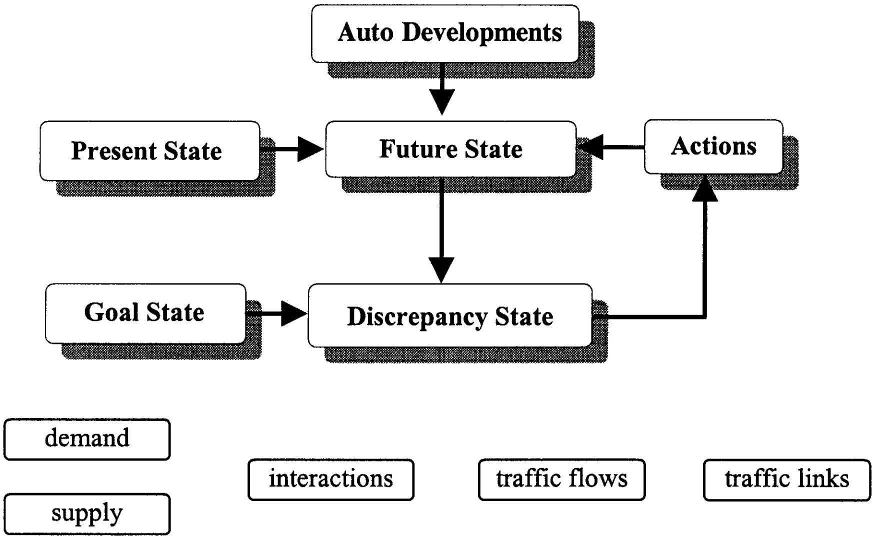

Figure 4.1. The Domain Knowledge Model.

not contain knowledge about how the conceptual structures can be used for performing tasks. The domain layer exclusively stores facts and relations between facts. The way this information is used for achieving problem solving goals is stored in the higher-level layers. The KCML specifies a set of primitives that can be generally used for describing domains. This set involves generic classifications of concepts and conceptual relations (Schreiber *et al.* 1993). Here, we will describe in a similar way the components that are specific for the spatial planning domain.

The proposed method of decomposing the spatial planning problem is shown by the scheme in Figure 4.1. In this method, planning is viewed as the problem of finding the set of actions that reduces discrepancies between an anticipated future state and a given goal state of the system being planned. The boxes in the scheme represent various perspectives on the system that are meaningful for the planning problem. The arrows stand for logical dependencies between perspectives. The scheme as a whole represents at an abstract level the conceptual structure of the domain.

This way of decomposing the problem is consistent with the decision analysis approach. As noted in chapter 2, decision analysis is a well-established DSS-school in business management which is particularly concerned with decision problems that are characterised by uncertain outcomes and multiple goals. According to the decision analysis method, all decision situations can and should be defined in terms of the elements: (i) options/alternatives; (ii) events/states with corresponding probabilities; (iii) outcomes/results with corresponding probabilities and (iv) goals and preferences

(Stabell 1987). These components recur in the proposed model of the spatial planning problem. Based on the discussion in the previous chapter we can now specify the elements of the model as follows.

The present state and the goal state of the system are given. Generally, the goal state represents the desired state of the system at some future moment in time. The future state of the system is the result of two types of anticipated changes of the present state in the plan period. First, there are expected developments in the system that are outside the control of the planner. These changes are referred to as *autonomous* developments, since they occur independent of planner's actions. In spatial planning, we can think for example of demographic and socio-economic changes which are often beyond the control of the planner and yet relevant for the goals pursued. Second, there are anticipated changes that follow from action plans developed by the planner. In spatial planning, possible actions may include changes in the supply of facilities, such as the opening, closing, relocation or upgrading of facilities. The discrepancy state is the result of the comparison between the anticipated future state and the given goal state. It shows in some way the mismatch between future state and goal state and, thus, indicates the extent to which the actions undertaken will be successful in achieving the desired goal state (given the present state and the autonomous developments). Dependent on the specification of the goal state, discrepancies involve either imbalances between demand and supply or opportunities for expanding or otherwise improving a facility network.

Within the various perspectives different sets of spatial objects are considered in the model. In general, the following groups are monitored or planned: (i) demand objects (residential zones), (ii) supply objects (retail or service facilities); (iii) traffic links (the road network); (iv) interactions between demand and supply (trips or expenditure flows) and (v) traffic flows. Traffic links and traffic flows determine the physical accessibility structure of facilities and the externalities of travel behaviour in the form of traffic congestion and environmental effects. The first three groups - demand, supply and traffic links - have a capacity character, as opposed to the latter two groups - interactions and traffic flows - which have a flow character. Given these different groups, we can distinguish different subperspectives, such as for example 'demand objects in the present state', 'traffic links in the future state' and so on.

In addition to categorising spatial objects, the model distinguishes different sets of variables used to describe states and events. Specifically, in spatial planning different variables are used to describe the present state and goal state. First, the present state is normally described in terms of directly observable attributes of objects. For example, with respect to demand these involve the size and characteristics of the population in residential zones. As another example, a useful descriptor of interactions is the size of expenditure flows from residential zones to facility locations. In the model, the directly observable variables are referred to as X-variables, to indicate the fact that they recur as independent variables in models of system performance. Second, the goal state is normally described in

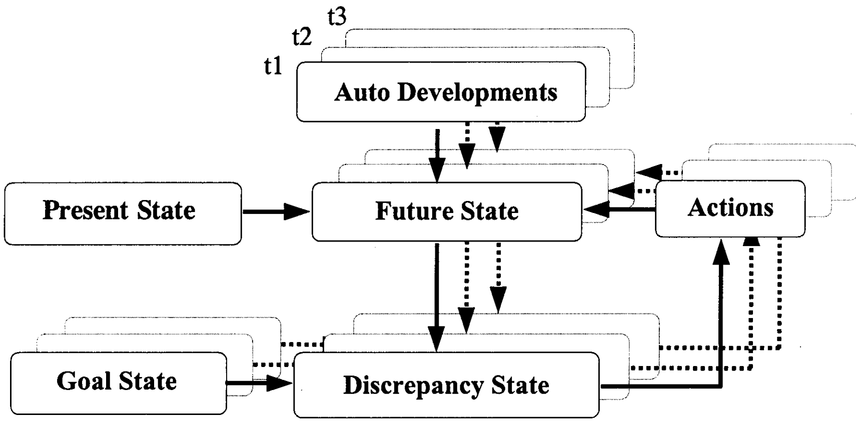

Figure 4.2. The domain knowledge model extended with a discrete time dimension.

terms of goal or criterion variables referred to as *C*-variables. As it appeared in the foregoing chapter, *C*-variables in spatial planning concern aspects of system performance with respect to interests of consumers, producers and the community in general. For example, with respect to consumers, performance variables often include the accessibility of facilities and range of choice opportunities.

An additional set of variables is needed to describe decision situations in which planners do not have the means to change the present state by operating on *X*-variables. This situation is typical for the public sector case. Governmental planners cannot directly control physical aspects of a facility system (let alone, behavioural aspects). In stead, they can only create conditions for developments using financial incentives, zoning regulations, public sector investments or forms of co-operation with the private sector. Then, an action plan is described in terms of the available policy instruments. In the model, these are called instrument or, in short, *I*-variables. Developing plans in terms of these *I*-variables is a complex task since there are usually more ways in which desired changes in *X* can be accomplished by actions in *I*. As was discussed in the previous chapter, the choice of *I*-variables takes place in a separate plan implementation stage, after a plan in terms of *X*-variables has been developed. Here, we will concentrate on the first stage of planning and leave the operationalisation in terms of *I*-variables out of consideration.

Finally, planning has a time dimension, as developments are monitored over time and objectives and actions are specified in a time-path. The scheme in figure 4.2, shows the model extended with a discrete time dimension. In this model, the future state in one time step constitutes the present state in a next time step. Thus, the time layers are connected through an input-output relationship between future states in successive time layers. For each perspective the time layers make up a (discrete) time-path. For example, the series of goal states represents planning objectives specified in successive plan evaluation moments. Finally, it is worth noting that the model describes monitoring as well as planning. In the model, monitoring is a special case in which the action perspectives are 'empty'. When there are no actions specified, the future state represents the predicted state under none-intervention conditions.

Using this model, declarative knowledge elements can be described as specific combinations of a perspective, variable type, object type and time (T) moment. For example, the domain element given by the ordered list '(future state, demand, *C*, T)' would represent factual knowledge about a certain performance aspect of the system with respect to a certain demand object, under conditions of anticipated and planned developments at time T. For example, a specific instance of this category is a measure of the accessibility of facilities for consumers at a certain location, given a planned closure of a facility at time T. The number of elements that can be formed as combinations of distinctions on these dimensions soon becomes very large. However, it should be noted that not all combinations are meaningful. First, planners do not have the means to operate on behavioural aspects of facility systems. Therefore, the perspectives:

(action, j) $\forall j \in$ { traffic flows, interactions }

are not possible. Second, the model treats behavioural objects as endogenous variables. That is, interactions and traffic flows are supposed to be determined by the state of the physical subsystem. Hence, the perspectives:

(auto. developments, j) $\forall j \in$ { traffic flows, interactions }

are not meaningful. As a result, the largest set of relevant domain knowledge categories can be written as:

(present state, j)	$\forall j \in$ { demand, supply, traffic links, interactions, traffic flows }
(auto. developments, j)	$\forall j \in$ { demand, supply, traffic links }
(action, j)	$\forall j \in$ { demand, supply, traffic links }
(future state, j)	$\forall j \in$ { demand, supply, traffic links, interactions, traffic flows }
(goal state, j)	$\forall j \in$ { demand, supply, traffic links, interactions, traffic flows }
(discrepancy, j)	$\forall j \in$ { demand, supply, traffic links, interactions, traffic flows }

This largest set is usually relevant in public-sector planning. Private sector planning is concerned with a smaller set of goals and is necessarily limited to the supply side. Therefore, in private sector planning the following combinations are not considered:

(i,j) $\forall i \in$ { goal state, discrepancy state }, $\forall j \in$ { traffic links, traffic flows, demand }

In this sense, the private-sector case is modelled as a subset of the above largest set of perspectives. Finally, it is noted that additional information, such as probability, accuracy, validity and completeness of declarations, is associated with domain knowledge elements.

The proposed model described in this section is simple but suits the present purpose. The model is nót used as a data model for the DSS - for that purpose a more elaborated scheme would be needed. In stead, the model will serve as a framework for organising the DSS model-base. The dependencies between domain elements (the arrows in the scheme in figure 4.1) are functional relations that are defined by knowledge in the inference layer.

4.3 The inference layer

This layer contains knowledge for reasoning about the domain. The inference layer specifies which inferences are possible given the domain level knowledge. Note that the inference layer does not state when inferences are to be made or in which order. The elements of this layer are modelled as functions that operate on data elements and produces new data elements (Schreiber *et al.* 1993). The KCML identifies a number of primitive functions called knowledge sources, which perform functions such as for example abstraction, classification, matching and so on. Data at the domain level are identified as possible input and output arguments of inference functions through labels called meta-classes (Hamelen and Balder 1993). For example, the labels 'hypothesis' and 'evidence' refer to data-elements that can serve as input of the primitive function 'match'. This function produces as output data of the meta-class 'conclusion'. The goal here is not to review the functional primitives and meta-classes in the KCML. In stead, this section describes inference categories (knowledge sources and meta-classes) at a less abstract level specifically for spatial planning problems.

In the spatial planning model, the inference layer establishes the functional relationships between domain elements. These relationships are depicted as arrows in the schemes in figures 4.1 and 4.2. Thus, the schemes allow us to identify the inference categories that are generally relevant in spatial planning. Table 4.1 summarises these categories. Based on the type of function they perform, we can distinguish the following categories of inferential knowledge.

Causal and associative knowledge. This type of knowledge describes the causal and associative relationships between system events and states. In terms of the planning scheme, it performs the function of (i) predicting autonomous developments based on

Table 4.1. Inference knowledge categories in spatial planning.

Knowledge	Function
- causal knowledge: methods of forecasting trends and developments	- inferring autonomous developments
- causal knowledge: methods of impact assessment	- inferring the future state based on the present state, autonomous developments and actions
- conceptual knowledge: methods of system performance analysis	- inferring the future state in C based on the future state in X
- conceptual knowledge: methods of system performance evaluation	- inferring the discrepancy state based on the goal state and future state
- instrumental knowledge: methods of plan generation	- inferring actions based on the discrepancy state

variables external to the model and (ii) deriving the future state based on the present state, autonomous developments and actions. Schematically:

$\rightarrow$ autonomous developments (X)
present state (X), autonomous developments (X), actions (X) $\rightarrow$ future state (X)

whereby '$\rightarrow$' denotes the implication relationship and X indicates the variable type.

The statistical and spatial sciences have an important role to play in producing knowledge of both relationships. For example, statistical projection techniques can play a role in predicting population developments. Behavioural models are available for predicting demand-supply interactions and traffic flows under the conditions of a plan.

Conceptual knowledge. This type of knowledge defines conceptual relationships between different descriptions of a given system state. In the planning scheme, it performs the function of evaluating the discrepancy between a future state and a goal state. Because a future state is predicted in terms of X-variables and a goal state is specified in terms of C-variables, the first step in determining discrepancies involves translating X into C-variables. For example, to evaluate the accessibility of retail facilities, which is an important criterion variable in spatial planning, distances between locations of demand and supply must be classified or quantified to obtain a measure of accessibility. Schematically, conceptual knowledge performs the functions:

future state (X) $\rightarrow$ future state (C)
future state (C), goal state (C) $\rightarrow$ discrepancy state (C)

Also, for defining these functions the spatial sciences can play an important role. The area is generally known as the analysis and evaluation of system performance, respectively. Various formal methods of measurement and evaluation have been developed, which can improve the quality of planning information.

Instrumental knowledge. This type of knowledge describes instrumental (means-ends) relationships between actions and goals. In terms of the planning scheme, instrumental knowledge performs the function of generating actions that are likely to be successful for solving or reducing an observed discrepancy:

discrepancy state (C) $\rightarrow$ action (X or I)

In spatial planning, instrumental knowledge represents conditional action strategies planners may adopt for achieving their goals. Knowledge elements of this type take the form of rules that specify for each operation the cases it applies to, the conditions for its application and the effects it probably produces (as in the general problem solver SOAR, Laird *et al.* 1987). It should be noted that heuristics seldomly are able to identify useful solutions to a location problem in a single step. In the system, the rules typically are incorporated in iterative procedures for developing location plans. The procedures are defined in the task layer.

4.4 The task layer

The task layer contains knowledge about how elementary inferences can be combined to achieve a certain goal. The components of the task layer are called tasks. A task is a fixed strategy that relate to one or possibly several goals (Schreiber *et al.* 1993). In the DSS, tasks take the form of either algorithms or logic structures that call upon functions in the inference layer and return results together with control messages, for example, indicating the success or failure of an attempt to achieve a goal. The problems addressed by tasks are well-understood elementary problems in planning, which can indeed be solved through algorithmic or heuristic methods.

Potentially relevant task knowledge for spatial planning is developed in the spatial sciences, operations research and AI. A large body of optimisation models are available for solving subproblems in spatial planning that are (now) well-understood. Table 4.2 gives some examples. In accordance to the KCML-method, an optimisation model is defined as a procedure controlling inferential processes at the domain level. To see how this can be done, consider as an example a widely used method of finding optimal locations called the interchange algorithm. For optimising some objective function (typically, minimising aggregate travel distance), the interchange algorithm starts with a random solution and specifies marginal changes of the solution until a stop criterion is met. An iteration of the algorithm involves relocating a facility in the current solution (an action heuristic), allocating consumers to facility locations in the new solution (prediction), calculating the objective function value (measurement) and comparing the objective function with a stop criterion (evaluation). As indicated by the terms between brackets, these steps correspond to elementary inferences in the lower inference layer. In this way, tasks are implemented as control procedures without domain knowledge.

Table 4.2. Examples of tasks in spatial planning.

Goals	Methods
- ranking location strategies on multiple evaluation criteria	- mulitple criteria evaluation methods
- reducing a set of candidate locations based on feasibility criteria	- boolean search methods
- optimising a location configuration based on an objective function and constraints	- mathematical programming, heuristic search methods, or genetic algorithms
- identifying locations with high trading potential	- methods of measuring potentials

As the example illustrates, tasks refer to inferences and do not have a representation of domain layer knowledge. In general, a task is a composition of inference steps or subtasks (e.g., inferences) that when applied to a particular problem results in the achievement of the problem solving goal.

4.5 The strategic layer

Strategic knowledge determines which goals are relevant for solving a particular problem. How each goal is achieved is determined by task knowledge. In other words, strategic knowledge develops a plan of the problem solving process which is executed by task knowledge. An example of a strategic plan at a high abstraction level is the general decision model used in the previous chapter to describe plan decision making. At lower abstraction levels, strategic plans are related to specific spatial planning goals. For example, in relation to the goal to find new locations with high trading potential, a problem solving plan could specify as task level steps the selection of candidate locations first at a regional level, next at a smaller areal level and finally at the level of individual sites. Strategic plans are dynamic in the sense that subgoals are specified conditional upon partial solutions. To return to the example, if the first step of selecting regions would result in a relatively large set of candidates, the plan may specify an extra step in which candidate regions are tested against stricter suitability requirements. In addition to planning, strategic knowledge performs the function of monitoring the process and adjusting plans when impasses occur. For example, when information is not available or contradictory information arises, strategic reasoning comes into play to find alternative routes to a solution.

Just as task knowledge controls inferential processes, strategic knowledge determines when and in which order tasks are to be executed in order to achieve a problem solving goal. This raises the question whether strategic knowledge is indeed a functionally distinct layer or, alternatively, should be regarded as task knowledge of a higher abstraction level. As Breuker and Wielinga (1986) argue, it is useful to make the distinction because the layers differ with regard to the flexibility of the strategies they represent. Where tasks describe fixed compositions of sub-tasks, strategic plans are adaptable to given problem characteristics such as problem type, available data and model sources, and styles and preferences of the decision maker. Furthermore, the plans are flexible in that they specify strategies dependent on obtained results. Thus, strategic knowledge provides the flexibility that is needed for solving poorly structured problems. In that sense, strategic knowledge is typical for human problem solving.

A similar distinction is also made in the spatial DSS-approach proposed by Armstrong *et al.* (1990). In their approach, methods for solving well-defined subproblems and planning the overall problem solving process are offered to users in separate modules. These modules are called subproblem solver and metaplanner and correspond closely to the task and strategic layer in the present model. Subproblem solver typically uses optimisation models to solve well-defined location problems. Metaplanner assists users in achieving a goal by suggesting steps that can be handled by the subproblem solver. Both the subproblem solver and metaplanner link procedures to goals. Armstrong *et al.* discuss the difference between the modules. Their argument corresponds with the assumptions of the four-layered model. As they put it:

> "the subproblem-solver deals with a precisely stated analytic problem and uses an algorithm to solve the problem. On the other hand the metaplanner deals with an ill-specified goal where many important decisionmaking criteria may be implicit or even unknown at a certain point in time."

In a DSS, the strategic layer (or metaplanner) typically provides an intelligent interface between elementary DSS-models and ill-defined problems of users. From the point of view of users, the task and strategic layers behave differently. At the task level the system controls the problem solving process and, when needed, prompts the user for inputs, whereas at the strategic level the system gives guidance to a user-defined process.

Basic and applied studies that contribute to the systemisation of spatial planning can be viewed as sources of strategic knowledge. Here, it is not the place to review methods that have been suggested. In stead we refer to the examples given in Table 4.3.

Table 4.3. Examples of problem solving strategies in spatial planning.

Evaluating a proposal for locating a large-scale retail facility on a broad set of planning goals (see Rogers 1979)
- determine short term and long term effects on goal variables (design and environment, traffic flow, consumer interests, retailers interests etc.) - determine corrective measures for alleviating negative effects (e.g., investments in the road network) - analyze the costs and benefits of the proposal - judge the desirability of the proposal
Developing a location strategy for expanding a retail chain based on optimising economic performance (see Ghosh and McLafferty 1987)
- select a market region (e.g., a city area) based on market expansion potential and degree of market saturation - select suitable market areas (e.g., a sector of a city) based on retail potential and level of competition - select candidate sites based on characteristics of the retail environment and site - generate and evaluate possible network configurations (number, location and size of outlets) - judge the desirability of the optimum configuration
Developing a long term policy for optimising accessibility and economic viability of neighbourhood centres (see Gemeente Maastricht 1988)
- predict demographic, economic and structural developments that affect demand-supply relationships in the convenience good sector - analyse accessibility and economic viability of centres in the future market situation - generate actions (upgrading, closing, opening, expanding centres) to optimise accessibility under constraints of economic viability and branch composition of centres - choose policy instruments (e.g., financial support, zoning regulations) to accomplish the optimal long term retail structure

4.6 Relations between layers

A general observation in modelling knowledge domains is that most knowledge components are not specific for specific tasks, but recur in many tasks within the application (or even across applications). An important rationale of organising knowledge in layers is to allow the model builder (or the user) to make optimal use of model components. To understand the way in which the layered model facilitates the reuse of model components, this section considers the interaction between layers in the model.

Figure 4.3 summarises the knowledge layers and the way they are interconnected. The domain layer describes the system to be planned in terms of states or events (the domain level). The next, inference layer defines the possible inferences in the domain

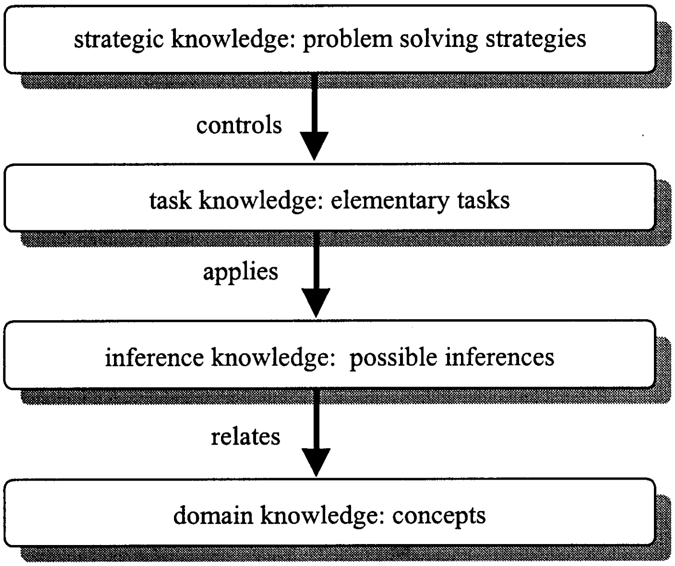

Figure 4.3. Relationships between knowledge layers

layer. The subsequent two layers describe how this knowledge can be used to solve problems at the level of well-structured subproblems (task knowledge) and the poorly structured overall problem (strategic knowledge). The layers work together to achieve problem solving goals within the domain. As Breuker and Wielinga (1986) point out, each layer has an interpretation in a next layer. Data-elements in the domain layer are identified by type in the inference layer, and, similarly, the roles of inference functions are represented in the task layer. On their turn, tasks have a representation in the strategic layer. It follows that the higher layers describe and control processes in the domain layer: the inference layer determines which inferences are possible; the task layer combines inference functions for achieving goals and the strategic layer describes sequences of tasks for solving problems. In that sense, every layer acts as a further constraint to what can take place at the domain level. Since the domain layer represents all possible solutions, the higher level knowledge acts so as to restrict the search of the solution space. The degree to which it does this depends particularly on the extent to which problems are structured at the task and strategic level. For example, in one extreme a brute force problem solving method states that a solution is to be found simply by evaluating all possible actions. In that case, virtually all domain-level processes that are allowed by the inference structure are potentially relevant. Adding intelligence to problem solving methods from this point would result in a meaningful reduction of the search space. In this interpretation, the task and strategic knowledge have the function of restricting the solution space in a meaningful way.

The layered organisation facilitates the reuse of model components. The potential benefits are particularly large in the inference layer (Breuker and Wielinga 1986). Since tasks are defined as (re-)combinations of inference steps, a given inference component need to be defined only once and then can be used in the pursue of many problem solving goals. For example, the same consumer behaviour model can be used in all tasks in which allocating consumers to facility locations is a component, such as for example optimising the branch composition of retail centres or determining optimal locations for expanding a retail chain.

4.7 Model base management

The layered approach is consistent with a method of representing and managing models in DSS that has been proposed on several occasions in spatial planning as well as business management. This so-called Model Base Management System (MBMS) method was introduced in management science in the mid eighties and grew out to an important and ongoing field of study (see, e.g., Ma 1995, Blanning 1993; Hong *et al.* 1991; Krishnan 1989; Alessandro *et al.* 1989; Liang 1985). In the spatial domain, the use of MBMS has been advocated by Densham (1991), Densham and Armstrong (1987) and Densham and Goodchild (1989). As the name suggests, an MBMS performs a task which is analogous to the function of a DataBase Management System (DBMS). Where an DBMS stores components of a database and recombines these components when users query information from the database, an MBMS stores the atomic elements of models and dynamically recombines these elements to achieve problem solving goals.

The MBMS-approach offers several advantages. Densham and Goodchild (1989) discuss the advantages from a model builder (rather than user) point of view. As they argue, storing atomic elements reduces redundancy of code to a minimum which can lead to considerable reductions in storage. Furthermore, the implementation of a new algorithm can simply be realised by developing a formula defining a new recombination of existing elements. Consequently, the researcher can rapidly implement new algorithms and assess the computational properties and suitability of proposed algorithms. Third, modularity facilitates updating the model-base, as individual atoms can be replaced by improved versions without impairing the workings of existing algorithms. From the perspective of users, the method can improve the ability of the system to adapt to problem characteristics, such as available data sources and specific information needs. The number of algorithms that can be composed by making combinations of atomic elements soon becomes much larger than a library of routines normally can contain. The availability of a large number of dynamically defined algorithms means that the system can adapt to a large range of user-defined constraints.

Different approaches have been proposed for model representation and model management (selection and execution of models) in MBMS. Kwon and Park (1996) distinguish three major approaches. The relational approach relies on data manipulation functions developed in the field of relational databases (e.g., relational algebra, query processing etc.). The KBS approach relies on formalisms developed in the field of KBS for the representation (e.g., logic, frames etc.) and execution of models (e.g., inference engine, demons, etc.). Finally, the object-oriented approach draws on the inherent principle of reusability of components in object-oriented systems. Although the KCML has not been introduced in relation to MBMS-methodology, the layered model can be viewed as a particular and powerful knowledge-based MBMS. There are many examples of KBS-applications that demonstrate the usefulness of KCML (although it should be noted that there are less examples of systems that make use of a strategic layer). In the present study, the layered model will be used to specify the above knowledge categories and to organise knowledge in the DSS.

4.8 Conclusion

This section has identified the major categories of knowledge in spatial planning based on the knowledge modelling language called the KCML. The proposed knowledge model organises knowledge in different layers. Because knowledge in higher-level layers are defined as formulas for the combination of knowledge elements at the lower level, the layered organisation optimally exploits the reusability of model components. It was argued that the layered model is a powerful method of implementing an MBMS. The advantages of an MBMS-approach relate to the efficiency of storage, the ease of updating and the flexibility in adapting the model-base. In the present study, particularly the gain in modelling flexibility is pursued.

The chapters that follow will be concerned with the specification of the knowledge categories identified in this section. Hereby, the purpose is not only to integrate existing models, but also to improve existing models when they fall short in matching information needs. The remaining sections of this second part will focus on the latter model development objective. This will involve further development of both inference and task layer knowledge. The resultant model-base will be discussed in the context of the design of the DSS in the third part of this study.

CHAPTER 5

MODELS OF SPATIAL SHOPPING BEHAVIOUR (INFERENCE LAYER)

5.1 Introduction

As discussed in the last chapter, the inference layer forms the basic layer of the DSS-model base. Within this layer, associative /causal, conceptual and instrumental forms of knowledge were distinguished. This chapter is concerned with specifying the associative/causal knowledge component in detail. Inside the DSS, the models of this type serve to predict spatial behaviour of consumers and producers. Thus, the models form the basis for analysing the performance of retail/service systems. The required conceptual component will be considered in the next chapter.

Two fields of modelling can be distinguished on the outset. Spatial shopping models predict and explain the spatial choice behaviour of consumers either individually (discrete choice models) or aggregated (interaction models). Producer models consider the supply-side of retail/service system dynamics and try to predict spatial behaviour of producers. For spatial planning, insights in how producers tend to adjust the spatial configuration of their chain or attributes of individual stores in response to changes in the existing competitive structure are important for evaluating impacts of plans. To be relevant for the DSS, models must have favourable properties for use in applied settings. This means that data needs must not exceed available means for data collection, models must be responsive to the type of scenarios planners/retailers consider and the methodology must be consistent with spatial choice theory. Section 5.2 gives an overview of existing modelling approaches in these fields.

The next section of this chapter describes a proposed extension of existing spatial shopping models to account for multipurpose, multistop behaviour of consumers. This type of behaviour is observed in cases where individuals combine several shopping purposes into a single trip (multipurpose) and possibly visit more than one destination (multistop) to buy the intended bundle of goods. The section discusses the proposed model and an application to test the model. Finally, the last section will conclude with summarising the major conclusions.

5.2 An overview of basic modelling approaches

Modelling spatial shopping behaviour has received much attention in the areas of geography, urban planning, transportation and marketing. The goal of this section is not to give an extensive review of the field. For this readers are referred to Oppewal *et al.* (1997a), Oppewal (1995), Timmermans (1993), Louviere and Timmermans (1990), Barnard (1987) and Timmermans and Borgers (1985). This section will consider the major modelling approaches that are important in current retail/service studies. Following Timmermans (1993) and Oppewal (1995), current approaches will be classified in three broad groups: spatial interaction modelling, discrete choice modelling and decompositional preference/choice modelling. The final section will consider existing approaches to modelling spatial behaviour of producers.

5.2.1 Spatial interaction models

This class of models describes and predicts shopping behaviour at the level of aggregate flows of shopping trips between origin and destination locations. The models are based on the assumption that the size of each flow is proportional to the attractiveness of the shopping location and inversely proportional to travel distance (see, e.g., Wilson 1988 for an overview). In formula:

$$T_{ij} = O_i A_i W_j^{\alpha} f(C_{ij}) \tag{5.1}$$

and

$$A_i = \frac{1}{\sum_j W_j^{\alpha} f(C_{ij})} \tag{5.2}$$

where:

T_{ij} is the flow (either expenditure or trips) between a residential zone i and a shopping zone or centre j;

O_i is some measure of the generation of trips or expenditure from i (e.g., the population of zone i);

W_j is some measure of the attractiveness of stores in zone j (e.g., total floor space in centre j);

α is a parameter to be estimated (or is set to unity);

C_{ij} is travel time or travel distance from i to j;

$f(C_{ij})$ is a function of travel time or distance.

In most applications, the distance function is specified as $f(C_{ij}) = \exp(\beta C_{ij})$ or $f(C_{ij}) = C_{ij}^{\beta}$, where β is a parameter to be estimated and assumed negative. Different versions of the model exist, dependent on whether the flow totals leaving zones (i.e., O_i) and/or arriving zones are taken as given or as variable. The above model is the so-called production-constrained spatial interaction model, in which the flow totals leaving zones (called productions) are given. This model type is commonly used in retail studies.

The size term, W, stems from the early gravity-based formulation of the models. However, later versions of the models acknowledged the fact that in the perception of consumers, the attractiveness of shopping locations may be a multi-dimensional concept. In a more generic formulation, the scale term W is replaced by a multiplicative function of a set of attractiveness factors, such as for example the image of the centre/store, available parking facilities, price level and so on (Nakanishi and Cooper 1982).

Spatial interaction models have been enormously influential in service/retailing since their introduction in the late fifties and early sixties. However, despite their popularity, the models have several drawbacks. As Rushton (1969) argues, the most important drawback relates to the inability of the models to measure consumer preferences independently of the geometry of the study area. The models are calibrated on observed flows, which are the result not only of consumer preferences, but also of available shopping opportunities. The failure to disentangle preferences and spatial structure factors reduces the value of the models for use in spatial planning. First, the parameter estimates cannot be readily interpreted in terms of preferences and, therefore, the models perform poorly with respect to construct validity. Second, the transferability of parameter estimates to areas with a different geometry is limited. Hence, the predictive validity of the models in impact analysis is doubtful. Furthermore, the predictive validity is not only bounded by area geometry, but also by the zoning system used to delineate origin and destination zones. Evidence suggests that predictions tend to be sensitive to the zoning system used (Fotheringham and Wong 1991). Because these shortcomings are related to the fundamentals of spatial interaction models, an important field of research has looked at alternative foundations for shopping models.

5.2.2 Discrete choice models

The second widely used family of models is founded on a theory of individual choice behaviour that originates from econometrics and psychology. This so-called discrete choice theory assumes that individuals compare a limited set of discrete choice alternatives and choose the alternative that maximises a utility value. The set of choice alternatives called the choice-set is determined by the individual's cognition of his environment and, therefore, is individual-specific. In most derivations of discrete choice models, the utility value is decomposed into a structural and a stochastic component, as follows:

$$U_j = V_j + \varepsilon_j \tag{5.3}$$

The structural component V_j is usually defined as an additive function of the attributes on which choice alternatives are compared, i.e., $V_j = \beta' \boldsymbol{x}_j$, where β is an unknown vector of attribute weights and $\boldsymbol{x}_j$ is a vector of attribute values. In retail applications, travel time, size of the retail area, the atmosphere of the retail environment and available parking facilities recur in most models as influential attributes. The ε_j component is commonly referred to as the error or disturbance term and represents variation in perceived utility due to taste variation of individuals and measurement errors.

Different types of models have been formulated dependent on the specific assumption regarding the distribution of the error terms, as reviewed in Hensher and Johnson (1981). The most widely used model type is the multinomial logit model (the MNL-model). The MNL-model is derived from the assumption that the error terms are independently and identically double exponential (or Gumbel, or Type 1 extreme value) distributed. Given this distribution form, the probability that choice alternative j is chosen from a given choice-set $\boldsymbol{J}$ is expressed as:

$$Pr(j \mid j \in \boldsymbol{J}) = P(U_j \geq U_{j'}; \forall j' \in \boldsymbol{J}; j' \neq j) = \frac{\exp(\mu V_j)}{\sum_{j' \in J} \exp(\mu V_{j'})} \tag{5.4}$$

where μ is a scaling factor which is arbitrarily set to unity in single-choice situations. Also other models have been derived. The probit model is the least restrictive model type in terms of the distribution forms of error terms (see Daganzo, 1979). However, these models have not found their way in applied research. The major advantage of the MNL-model over the alternative model types is that it has a closed form so that it can be solved analytically.

In retail applications, the β parameters are usually estimated based on a (representative) sample of consumers residing in the study area. Then, the parameters reflect attribute weights in shopping destination choice of the population as a whole and the error terms represent both intra-individual and inter-individual variance. Heterogeneity in the population can be dealt with by incorporating socio-economic factors as additional interaction terms in the utility function or by estimating a separate model for each distinguished population segment.

In sum, the MNL-model predicts the probability that consumers will choose a particular alternative, given its locational and non-locational attributes, the attributes of its competitors, and possibly a set of socio-economic characteristics of the consumers.

The model is theoretically well founded and is easy to use in applied contexts. Since model estimation is based on observations of *individual* choice behaviour, predictions are less sensitive to the zoning system used. However, when estimated on observed choice behaviour in real-world situations, discrete choice models share with spatial interaction models the potential weakness of limited construct and predictive validity. This potential problem is inherent to model estimation methods based on observed behaviour in actual market situations. However, in practice the models appear to be quite robust for spatial structure effects (Borgers and Timmermans 1987).

5.2.3 Decompositional preference/choice models (conjoint analysis)

A problem of the above modelling techniques is that in real-world situations explanatory variables (the attributes x) are often intercorrelated so that their separate effects are hard to disentangle. The decompositional approach solves this problem of multicollinearity by using choice experiments for collecting choice or preference data in which the explanatory variables can be controlled. In marketing this approach is generally known as conjoint analysis and in transportation studies the term stated preference/choice models is commonly used.

In a conjoint choice experiment, individuals are asked to respond to hypothetical choice situations. Choice alternatives are constructed as attribute profiles based on a balanced experimental design, such that effects of attributes can be measured independently of each other. Respondents are asked to rank or rate the alternatives (preference-based models), make a choice or allocate a given budget (choice-based models). The MNL-model is widely used as a framework to estimate attribute weights (i.e., decompose overall responses into a set of weights).

The major advantage of conjoint choice models over the survey-based models is that the technique allows one to measure consumer preferences independently of the existing structure of the market area (e.g., the geometry of the study area). Consequently, the expected transferability of estimated models to new or changed market situations is larger (predictive validity) and the parameter estimates can be interpreted more equivocally in terms of preferences (construct validity). A potential disadvantage of the conjoint analysis approach relates to the use of predefined discrete levels of attributes and choice sets in the choice experiments. Discrete attribute levels cannot be readily related to the continuous variables (e.g., floor space) that are manipulated in plans. Also, the definition of individual choice-sets in the prediction stage cannot be derived from the results of the estimation stage. Hence, using the models for impact analysis requires several ad-hoc decisions.

5.2.4 Extensions of the basic models

The basic spatial interaction and MNL-choice models have several potential limitations especially when applied to modelling of choice processes in spatial environments. One limitation that has attracted much attention in the literature is related to a property of the models generally known as the independence of irrelevant alternatives or IIA. The second problem relates to the difficulty to define individual choice-sets, i.e. the destination alternatives individuals consider in making a choice.

Relaxing the independence-of-irrelevant-alternatives property
This property implies that the ratio between the choice probabilities of any two choice alternatives is independent of a third alternative. This property is easily demonstrated, for example, in the case of the MNL-model. It follows from equation 5.4 that the ratio between the selection probabilities of any two alternatives, j and k of a given choice-set J equals:

$$\frac{Pr(j \mid j \in J)}{Pr(k \mid k \in J)} = \frac{\exp(\mu V_j)}{\exp(\mu V_k)} \tag{5.5}$$

This ratio is independent of any third element in the choice-set.

As implied by this property, the models can not account for the impact of the spatial structure of destination alternatives on destination choice. As argued by Fotheringham (1985, 1986), spatial relationships between destinations can give rise to agglomeration and competition forces. Spatial agglomeration forces occur when the choice probability of a store increases with increasing proximity of other stores. The positive impacts arise in cases where spatial clusters of stores facilitate comparison shopping (stores of the same type) or multipurpose shopping (stores of different types). In contrast, spatial competition forces are in play when the probability of choosing a store decreases with increasing accessibility of other stores from the location of that store. This occurs when choice alternatives are substitutable for a given purpose and individual. Substitution is likely to occur for example between grocery stores offering comparable assortments.

Spatial agglomeration and competition forces are spatial forms of cross-effects between alternatives that are in variance with the IIA-property. In a broader context, several approaches have been suggested to account for cross-effects between choice-alternatives in discrete choice as well as interaction modelling. Borgers and Timmermans (1987) and Timmermans *et al.* (1992) review these approaches. They distinguish the following strategies:

- Estimate the size of cross-effects in conjoint choice experiments by using experimental designs in which the composition of choice sets is systematically varied. The resultant models incorporate extra terms that represent cross-effects and are known as *mother logit* or *universal logit* models.
- Formulate models which impose more general conditions on the variance-covariance structure of the error-terms. The resultant models no longer assume that error terms are independently and/or identically distributed (see Dellaert 1995 for an overview of this line of research).
- Account for substitution effects by explicitly including some measure of (dis)similarity in the utility function.
- Account for substitution effects by using a hierarchical decision structure.

In service/retail studies, model extensions along the third and fourth line have been particularly influential. First, as an exponent of the third approach, the so-called destination competition model developed by Fotheringham (1984, 1985, 1986) takes in a central position. This model is generally derived from the singly-constrained interaction model (equation 5.1) as:

$$T_{ij} = O_i A_i W_j^{\alpha} A_j^{\delta} f(C_{ij}) \qquad (5.6)$$

where A^{δ}_j is an additional term representing the accessibility of other stores from the current destination j. In a usual specification, the term is defined as a Hansen-type accessibility measure (Fotheringham 1985; Guy 1987). For example:

$$A_j = \sum_{k \neq j} W_k^{\alpha'} C_{kj}^{-\beta'} \qquad (5.7)$$

The parameter δ (in 5.6) represents the size and nature (sign) of spatial structure effects and is estimated based on observed shopping behaviour. The sign of the parameter may differ from case to case. A positive value indicates that choice probability is positively related to the accessibility of other stores and, therefore, points at the existence of spatial agglomeration effects. A negative value indicates that this correlation is negative and reflects competition effects. Thus, the model presents a framework for measuring spatial structure effects. Utility-based models such as the MNL-model can be similarly extended by incorporating a store accessibility term in the utility function (Fotheringham 1986). Guy (1987) describes an application of an interaction-based destination competition model specified as above in the area of grocery retailing. He finds a significant improvement in model fit compared to the basic model, but the estimated value of the store accessibility parameter δ is counter-intuitive. The estimated value is positive, whereas agglomeration effects are more likely to occur in comparison-good sectors. Guy argues that a tendency to combine several destinations in single trips is possibly responsible for this result.

Another study that fits in this line of reasoning is Ottensman (1995). He incorporates an extra parameter in a singly-constrained interaction matrix, to represent the degree in which demand is elastic for the scale of (clusters of) facilities. In an application to predict destination choice for leisure activities, the parameter appears to be significant indicating positive agglomeration effects on trip generation for some types of facilities (i.e., library facilities).

In the fourth approach, spatial structure effects are modelled in terms of a hierarchical choice process in which individuals first choose a spatial cluster of destinations (e.g., a shopping centre) and then a specific destination within that cluster. The most influential hierarchical models are based on the general nested-logit modelling framework (see Ben-Akiva and Lerman 1985). An advantage over the conventional MNL-model, is that the nested-logit model can account for the existence of stronger competition, i.e. substitution effects, between stores within clusters. At the highest choice level, the stores compete with each other at the cluster level so that in addition the model can account for positive agglomeration effects. A disadvantage of the models however is that they assume predefined clusters and a predefined order of decision making (Borgers and Timmermans 1987). Probit-models are more flexible in this regard, but they are computationally burdensome.

Ahn and Ghosh (1989) describe and test a nested-logit shopping model. They compare two possible model specifications. In the first specification, individuals first choose a shopping centre by comparing different centres on relevant centre-attributes and next a store within that centre by evaluating store attributes. In the second specification, the order is reversed: individuals first choose a chain based on store attributes and then a shopping centre from the set of centres that has an outlet of that chain. The models are estimated and tested based on a structured choice experiment. The results show that both hierarchical models fit the data significantly better than the basic MNL-model does. The second specification of the hierarchical model (chain, centre sequence) gives the best fit.

Finally, Fotheringham (1984) discusses a related spatial structure effect that results in differences in the size of distance weight in store choice across origin zones. Parameter estimates of origin-specific models suggest that the better accessible origins tend to have less negative distance-decay parameters than peripheral origins indicating a greater readiness to travel to further destinations. On theoretical grounds, Fotheringham argues that the reverse may hold in sectors characterised by agglomeration forces between destinations. To account for such spatial structure effects he suggests using origin-specific distance decay parameters in interaction or choice models. In the same case study mentioned earlier, Guy (1984) describes an empirical test of origin-specific interaction-based models. He finds a considerable improvement in the overall fit in comparison with the conventional model specification in which a distance decay parameter is common to all zones.

Choice-set definition

Another problem that deserves special attention in spatial applications of the basic discrete choice model is the definition of choice-sets. In many studies, choice-sets are simply given exogenously (e.g., Timmermans *et al.* 1984). Other studies report on attempts to incorporate choice-set generation as an endogenous component of destination choice models. This section gives an overview of main approaches in this area. For an extensive review of methods readers are referred to Thill and Horowitz (1997a).

Authors have pointed at various reasons why individuals may not consider the universal set of possible destinations but only a subset. Clearly, individuals do not consider destinations that are not known or familiar to them or not reachable given travel time constraints. Furthermore, individuals may purposely eliminate alternatives from the choice-set to simplify the choice problem. Theoretically, parameter estimates are to some extent sensitive to variation in choice-set definition in particular if the model does not have the IIA property. Several studies have provided empirical evidence that parameter estimates indeed can be sensitive to choice-set definition (Pelligrini *et al.* 1997, Miron and Lo 1997, Thill and Horowitz 1997b, Dai 1998).

Deterministic and probabilistic methods have been proposed to delineate choice-sets. Typically, deterministic methods consider constrained choice situations in terms of limited space-time windows in the context of daily activity patterns. The methods involve eliminating those alternatives that are infeasible given travel time constraints. For example, Golledge and Kwan (1997) use dynamic choice-set definitions in procedures for simulating individuals' choice of activity pattern inside a GIS.

Probabilistic methods attempt to integrate choice-set generation in a utility-maximising framework. Proposed models permit correlations between the random components of a choice-set generation function and the utility function. For example, Miron and Lo (1997) describe a nested-logit model where the choice of a destination is nested within the choice of choice-set. They partition the study area into districts and assume that the individual's choice-set consists of all the destinations in the district selected by the individual (i.e., the district that includes his destination choice). Then, the nested-logit model describes a hierarchical process where individuals first choose a district and next a destination inside that district. Similarly, Fotheringham (1986) argues that the competing destinations model (5.6) provides a flexible framework for modelling such hierarchical choice procedures. This follows if one assumes that individuals perceive choice alternatives in clusters according to their similarities. The Hansen type accessibility measure (5.7) can be interpreted as a measure of similarity in geographic space. In that sense, the competitive destination model predicts the choice of a cluster (choice-set) and destination within a cluster in a hierarchical manner.

5.2.5 Models of producer behaviour

The models reviewed above describe the spatial choice behaviour of consumers and can be used to predict shifts in the distribution of market shares across shopping centres or individual stores under changed market conditions. Producers who experience losses in market share are able to undertake actions to enhance the competitive position of the chain/store in the changed situation. As possible actions, they may consider replacing, expanding, changing the product mix or changing the appearance of stores. Such adjustments imply that consumers again would reconsider which stores to patronise and market share distributions will undergo a change as a consequence. Such cycles of adjusting location characteristics and location choice eventually can lead to a new equilibrium state.

Due to the responsive behaviour of producers, expected impacts of a new development on existing competitive structures will be smaller than in a static situation. This observation demonstrates the significance of producer responsive behaviour models for retail and service planning (Timmermans 1986 and Van der Heijden 1986). Furthermore, in combination with spatial shopping models, producer models close the required loop for predicting the dynamics of retail/service systems. By applying the models in a sequence the model system would describe a process where consumers and producers respond to each other's actions. The output of each cycle can be interpreted as a state of the system in a time path. The predicted time path would allow planners/retailers to anticipate on developments and to adjust strategies when needed.

Although the potential value for spatial planning is clear, modelling producer behaviour has received relatively little attention in the empirical tradition (as opposed to optimisation models). An exception is the stream of studies that has been initiated by the work of Harris and Wilson (1978) in the area of urban dynamics. Harris and Wilson incorporated a equilibrium condition in the standard interaction model (of the Huff type) to predict retail dynamics. The equilibrium condition states that a retail system is in equilibrium if the size of each shopping centre is in balance with the centre's revenues predicted by the interaction model. Assuming profit maximising behaviour of producers and entropy maximising behaviour of aggregate consumer flows, the balancing condition corresponds to a state where neither producers nor consumers have an incentive to change their behaviour. Follow-up studies focused on the behaviour of the model primarily by means of computer experiments (e.g., Beaumont 1981b, Clarke and Wilson 1983, Rijk and Vorst 1983, Lombardo and Rabino 1989, Wilson 1990). To our knowledge, Wilson (1990) is the only study that describes an empirical application.

Oppewal (1995) discusses limitations of the dynamic retail model for application in retail planning. The model is based on the strong assumption that producers exhibit perfect profit maximising behaviour. Clearly, the empirical validity of the deduced equilibrium state is doubtful so that it is difficult to relate the model to the empirical domain. Another more practical drawback of this aggregate type of models is that required data collections make calibration of the model difficult. Arentze *et al.* (1997) describe a case study where the revenue-size balancing condition is incorporated in an MNL model of consumer behaviour to predict shopping centre developments. Simulations show that the predicted equilibrium configurations are very sensitive for the size of the scale parameters. This suggests that for each application the stability of solutions over a range of parameter values needs to be tested. Not only are such simulation procedures cumbersome, but the results are also difficult to interpret in empirical terms.

An inductive approach can avoid these shortcomings and was proposed by Timmermans (1986) and Van der Heijden (1986). These studies present a conceptual framework based on discrete choice theory and tentative empirical tests of the hypothesised relationships. Oppewal and Timmermans (1997) elaborated this model and tested hypothesised relationships in a conjoint experiment under a group of retailers. In the model, retailers react to experienced changes in turnover volumes by choosing a strategy from a given set of options. The options correspond to the elements of the retail mix and include closing, relocating, opening, changing floor space, changing image, refurbishment and changing the retail environment of a store. The results are encouraging, but much further research is required for making the model operational for practical use. First, the level of detail is not compatible with information needs of planners. The model predicts probabilities of responses such as relocations and openings, but does not predict the choice of location where such actions are implemented. Second, the model assumes that retailers' behaviour is merely reactive, whereas at least a minority of (larger) retailers develops active location strategies which can greatly affect existing competitive structures. Finally, combining consumer and producer behaviour into a dynamic model raises the problem how to assess and control the propagation of errors across prediction cycles.

5.2.6 Conclusion

This section has reviewed the basics and proposed extensions of spatial choice and interaction models that are widely used in current retail/service studies. The MNL-model seems the most suitable approach given its favourable features for use in applied contexts. The model is easy to use, is based on sound economic principles and appears to be rather robust. Advantages and disadvantages of experimental and survey-based methods of data collections for calibrating the models were discussed. The ability to measure impacts of attributes independently from each other is an important advantage of the experimental method. However, the method requires analytic expertise in designing appropriate questionnaires and translating estimation results back in terms of an operational model for prediction purposes. On the other hand, survey-based methods of data collection and model estimation can readily be implemented in existing market and location research programs of companies/planners. Therefore, we argue that in the context of a DSS, the survey-based method is to be preferred. With respect to producer behaviour, we conclude that current models are either too restrictive or not operational for use in spatial planning.

As reviewed in this section, extensions of the basic model deal with agglomeration effects on choice-set generation and destination choice. The conclusion that can be drawn form the studies reviewed is that not only distances between origin and destination locations but also distances between destination locations should be represented in spatial choice models. The new model proposed in the next section takes these findings as a starting point. Rather than using an aggregate accessibility term (as the destination competition model), the model intends to describe the multipurpose, multistop behaviour that may be responsible for the agglomeration effects at a more disaggregate level. Moreover, the model is consistent with the survey-based method of data collection and estimation.

5.3 A multipurpose, multistop model of spatial shopping behaviour

5.3.1 Introduction

Shopping trips may involve purchases of several goods possibly at different locations. Empirical studies in the area of retailing or more broadly inter-urban travel suggest that indeed a considerable portion of shopping trips involves multiple purposes and in some cases also multiple stops (Hanson 1980, O' Kelly 1981, Kitamura 1984). Multipurpose, multistop trips allow individuals to reduce the number of shopping trips. Economising travel may be a general objective of individuals, but has probably become more important in the last few years under influence of changes in socio-economic conditions and life-styles. To an increasing extent, shopping activities take place in the context of dual-earner households and active recreational and social out-of-home lifestyles. In the context of high time pressure on activities, the presence of retail agglomerations may become an increasingly valued characteristic of retail/service systems.

This section presents a model of consumer choice of shopping centre that takes into account the degree to which the offered mix of store types matches and determines preferred shopping trip purposes. The model is particularly focused on the effects of retail scale and retail agglomeration on consumer shopping behaviour. The proposed

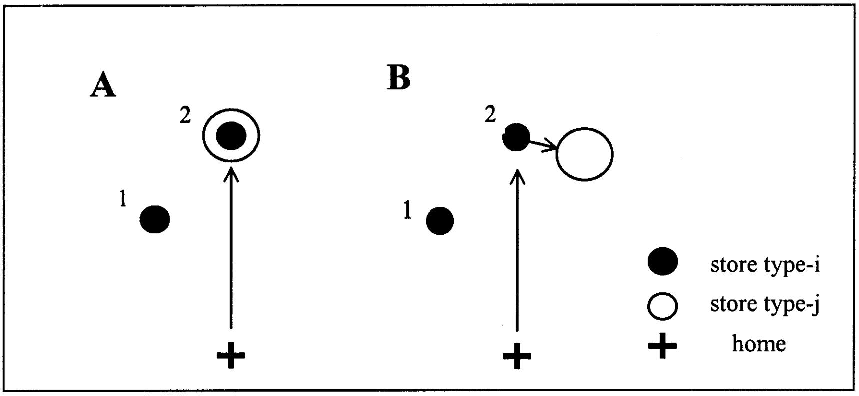

Figure 5.1. *Example: spatial agglomeration effects in the single stop (A) and multistop case (B).*

model distinguishes and quantifies two ways in which retail scale and agglomeration can affect how consumers organise their shopping trips:

1. *Purpose adjustment* refers to the extent to which consumers either have fixed ideas about what combination of products to buy on a single trip or adjust their shopping trips to benefit from the opportunities made available through the particular distribution and qualities of shopping facilities in his/her environment.
2. *Joint attraction* of multiple store types in a centre may be larger than the sum of the attractions of the same stores placed in separate locations. This is because larger retail clusters allow more cross shopping and each store category can appear in multiple purpose-specific destination choice sets.

To illustrate the latter mechanism, Figure 5.1 schematically shows two market situations in which location 2 is more attractive than location 1 for visiting store type i due to the presence of store type j at the same (A) or a nearby location (B). The central *hypothesis* of this paper is that agglomeration effects are significant and, hence, that multipurpose trip models allow better predictions of market share than single purpose models.

This section is organised as follows. First, Section 5.3.2 reviews previous attempts to model multipurpose, multi-stop behaviour. Then, Section 5.3.3 introduces the proposed approach and Section 5.3.4 considers an empirical application. Finally, the last section discusses some conclusions and potentials and limitations of the model in a DSS-context.

5.3.2 Existing approaches

The topic of multipurpose, multistop behaviour is not new. It has received considerable attention in transportation, geography and, though to a lesser extent, in the marketing discipline (Kahn and Smittlein 1989). A review is given in Thill and Thomas (1987). Most studies, however, are only theoretical and make simplifying assumptions about consumer choice behaviour and/or the structure of the market area. Typically, the assumptions concern deterministic and cost-minimising behaviour of consumers (e.g. Kohsaka 1984; Ghosh and McLafferty 1984; Bacon 1984, 1991, 1995; Thill 1985, McLafferty and Ghosh 1986), a strict hierarchy of shopping centres (Papageorgiou and Brummell 1975; Ghosh and McLafferty 1984, Ingene and Ghosh 1990) and/or two-good markets (Ghosh and McLafferty 1984; Bacon 1984; Thill 1985). Therefore, the usefulness of these models for explaining and describing consumer behaviour is limited.

Approaches based on discrete choice models are relevant here. One of the earliest studies in this econometric line of research is Adler and Ben-Akiva (1979). They consider entire trip chains rather than separate destinations as alternatives and model choices between these chains. Using a simple MNL-model, they could estimate the choices between various trip chains. Timmermans (1988) and Timmermans and Van der Waerden (1992) elaborated on this to develop a choice experimental approach to study multistop trips.

The implicit assumption that choice behaviour involves a comparison of all possible trip chains to the available destinations is problematic. The number of possible trip chains soon becomes intractably large. Delleart *et al.* (1995) argues that in reality consumers may evaluate different elements in a trip chain separately. Therefore, attempts have been made to model shopping decision making as a sequential process with interdependencies between present and future destination choices. For example, the utility function of the model proposed by Kitamura (1984) incorporates for any present destination a term that represents the utility of a next possible destination. This so-called prospective utility thus takes into account the accessibility of other destinations from the current destination and is weighted with a coefficient representing a propensity for making multistop trips. In the case of perfect utility maximising behaviour the expected coefficient equals one, whereas when multistop behaviour is absent the coefficient takes a value of zero. The true value within these extremes is estimated based on observed trips.

Kitamuras model offers a framework for modelling trip chaining or multistop trips, but falls short in modelling multipurpose trips. Factors such as the store mix offered by centres are not represented in the model. The model that Arentze, Borgers and Timmermans (1993) introduced deals with the multipurpose element of trips more adequately. They introduced a model that describes shopping centre choices for different categories of goods. Goods are ordered hierarchically on the basis of purchase frequency. The utility of a shopping centre is described as a function of travel distance, the supply of the highest-order good to be purchased on the trip and the supply of lower-order goods adjusted by a propensity coefficient to buy the lower-order goods on the same trip. However, as the authors indicated, the model does not account for multistop trips and is not based on random utility theory.

The purpose of this section therefore is to extend this stream of research with an approach that: (i) allows one to model choices of shopping centre incorporating multiple purposes and multiple stops per trip and (ii) is based in random utility theory. The proposed model assumes a hierarchical choice process in which individuals first choose the purpose of the shopping trip in terms of one or more goods to be purchased and next for each good a destination. A nested logit model structure is used to model this hierarchical choice process. In predicting destination choice, the model accounts for the influence of the accessibility of next destinations (like Kitamura's model) as well as available opportunities for multipurpose shopping in current and next destinations (like Arentze *et al.*'s model).

5.3.3 The multipurpose, multistop model

The problem addressed in this study may be formally stated as follows: Suppose that an individual faces a set of shopping centres, $\boldsymbol{J}$, distributed at discrete points in space at certain distances from his home. Each shopping centre contains a discrete set of stores offering various goods, which are known to the individual. Individuals wish to purchase a set of goods, $\boldsymbol{G}$, possibly with differing purchase frequencies in a given time period. They have the option of making a shopping trip for each purchase separately (single purpose trip) or, alternatively, combine the purchase of different goods on a single trip (multipurpose, multistop trip) to reduce the costs of acquiring the goods. The problem then is to predict simultaneously (i) the purpose of each shopping trip in terms of one or more goods and (ii) the shopping centre(s) that will be chosen for purchasing the good(s).

To represent the two hypothesised agglomeration forces we propose a hierarchical model structure. We adopt the nested-logit framework to parameterise and estimate the model. The model assumes that when they make a trip, shoppers first choose a trip purpose and then select a destination from among the stores or centres that can match the selected purpose. Figures 5.2 and 5.3 show the decision trees for the two cases considered here, i.e. the single stop and the more general multistop case.

The choice of trip purpose

The purpose, $\boldsymbol{p}$, of a trip consists of one or more goods. The choice-set of trip-purposes is defined as the set of all unique and non-empty subsets of $\boldsymbol{G}$ or, formally, $\boldsymbol{P} = \{\, \boldsymbol{p} \mid \forall \boldsymbol{p} \subseteq \boldsymbol{G} \,\}$. In the a three-good case for instance, this definition results in the choice-set $\boldsymbol{P}$ =

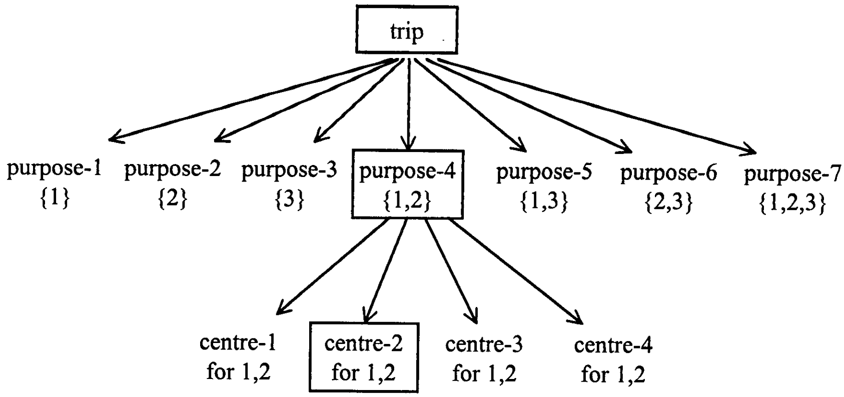

Figure 5.2. The multipurpose, singlestop model structure, given three good types.

{ {1}, {2}, {3}, {1,2}, {1,3}, {2,3}, {1,2,3} } containing 7 elements. In general, the relationship between the number of goods M and size K of $\boldsymbol{P}$ is given by:

$$K = \sum_{i=1}^{M} \frac{M!}{i!(M-i)!} \tag{5.8}$$

The model reduces to the conventional single purpose model when $\boldsymbol{P}$ is defined such that $\forall \boldsymbol{p} \in \boldsymbol{P}$, $\boldsymbol{p}$ consists of exactly one element.

The utility of trip-purpose $\boldsymbol{p}$ is defined as:

$$U^{p} = V^{p} + V'^{p} + \varepsilon^{p} + \varepsilon'^{p} \tag{5.9}$$

where V^{p} is the structural utility of $\boldsymbol{p}$, V'^{p} is the structural utility derived from the available set of destinations for that trip purpose and ε^{p} and ε'^{p} are the stochastic error components corresponding to the two utility components. Based on the nested-logit framework (see Ben-Akiva and Lerman 1985), we assume that the error terms ε^{p} and $\varepsilon^{p} + \varepsilon'^{p}$ follow identical Gumbel distributions and ε^{p} and ε'^{p} are independent. Then, the choice probability of selecting purpose $\boldsymbol{p}$ can be expressed as:

$$Pr(\boldsymbol{p} \mid \boldsymbol{p} \in \boldsymbol{P}) = Pr\left(U^{p} \geq U^{p'}; \forall \boldsymbol{p}' \in \boldsymbol{P}; \boldsymbol{p}' \neq \boldsymbol{p}\right) = \frac{\exp\left(V^{p} + V'^{p}\right)}{\sum_{\boldsymbol{p}' \in \boldsymbol{P}} \exp\left(V^{p'} + V'^{p'}\right)} \tag{5.10}$$

Term V^p in equations 5.9 and 5.10 represents the *supply-independent* and term V'^p represents the *supply-dependent* component of the structural utility of purpose $\boldsymbol{p}$. The first element captures the probability of observing the trip purpose possibly dependent on characteristics of the household, activity program and other context variables. At present, we will represent this set of factors by a purpose specific constant, i.e.:

$$V^p = \alpha^p \tag{5.11}$$

This constant is taken as a parameter to be estimated on observed trips. However, the model can be generalised by replacing this constant by a function of the aforementioned factors. The second component V'^p is expressed as the maximum value of utilities V_j^p associated with alternatives $j \in \boldsymbol{J^p}$, $\boldsymbol{J^p}$ being the set of possible destinations given purpose $\boldsymbol{p}$ has been selected. Assuming Gumbel distributed error terms, this maximum is defined as (see Ben-Akiva and Lerman 1985):

$$V'^p = \frac{1}{\mu^p} \ln \sum_{j \in J^p} \exp\left(\mu^p V_j^p\right) \tag{5.12}$$

where μ^p is the scale value of utilities of choice alternatives $\boldsymbol{J^p}$ relative to the scale value of utilities of choice-alternatives in $\boldsymbol{P}$. Purpose-specific scale values reflect the notion that each purpose may create a distinct destination choice situation.

The hierarchical model structure is only consistent with random utility theory if the scale parameters range between zero and one (e.g., Ben-Akiva and Lerman, 1985). In the extreme case $1/\mu^p$ approximates zero. Then, the probability of selecting purpose $\boldsymbol{p}$ is not influenced by the characteristics of available destinations. That is, it is fully determined by the exogenous factors captured in the constant α^p. Hence, in this case, trip purposes are selected independently of the available retail supply and *purpose adjustment* does not occur. In contrast, if $1/\mu^p$ is larger than zero, the probability of selecting purpose $\boldsymbol{p}$ depends to some degree on the supply available for $\boldsymbol{p}$. The higher the utility of the available stores or store categories for realising that purpose, the more likely it is that trips of this kind are chosen. In the other extreme case, where μ^p equals one, the influence of available destinations on purpose choice is at its maximum and stores or centres compete across purposes proportional to their attraction. Given this interpretation, the scale values can be taken as measures of the size of purpose adjustment effects of supply factors. V'^p thus represents the purpose adjustment effect in the sense that the probability that a trip purpose is chosen increases with the maximum utility of destinations for that purpose across the (purpose-specific) choice-set.

The choice of destination: the single stop case

The second step in the assumed choice process is to select a destination, given the chosen trip purpose. In this stage, we consider two cases. In the *single stop* case, individuals are supposed to select a single shopping centre only to realise the chosen trip purpose (Figure 5.2). In the *multistop* case, this constraint is removed and individuals may select different locations if multiple goods are involved in the trip purpose (Figure 5.3). Thus, the multistop case is a generalisation of the single stop case and will be considered in the next section.

The proposed model predicts the probability of selecting trip purpose and destination combinations as follows:

$$Pr(j,\boldsymbol{p}) = Pr(\boldsymbol{p} \mid \boldsymbol{p} \in \boldsymbol{P}) Pr(j \mid \boldsymbol{p}; j \in \boldsymbol{J}^{\boldsymbol{p}}) \tag{5.13}$$

where $Pr(\boldsymbol{p} \mid \boldsymbol{p} \in \boldsymbol{P})$ is the probability of choosing purpose $\boldsymbol{p}$ from the set of alternatives $\boldsymbol{P}$ and $Pr(j \mid \boldsymbol{p}; j \in \boldsymbol{J}^{\boldsymbol{p}})$ is the probability of choosing j from the set of alternatives $\boldsymbol{J}^{\boldsymbol{p}}$ given purpose $\boldsymbol{p}$. $\boldsymbol{J}^{\boldsymbol{p}} \subseteq \boldsymbol{J}$ is the set of shopping centres known to the individual where $g \in \boldsymbol{p}$ can be bought. This set is empty and consequently $Pr(j,\boldsymbol{p})$ zero, if no such centre exists.

The utility of a shopping centre j for purpose $\boldsymbol{p}$ is defined as:

$$U_j^{\boldsymbol{p}} = V_j^{\boldsymbol{p}} + \varepsilon_j^{\boldsymbol{p}} \tag{5.14}$$

where $V_j^{\boldsymbol{p}}$ and $\varepsilon_j^{\boldsymbol{p}}$ represent the structural and error component of the utility. Assuming Gumbel distributed error terms, the conditional choice probability of selecting a destination is defined as a standard MNL-model:

$$Pr(j \mid \boldsymbol{p}; j \in \boldsymbol{J}^{\boldsymbol{p}}) = Pr(U_j^{\boldsymbol{p}} \geq U_{j'}^{\boldsymbol{p}}; \forall j' \in \boldsymbol{J}^{\boldsymbol{p}}; j' \neq j) = \frac{\exp(V_j^{\boldsymbol{p}})}{\sum_{j' \in J^{p}} \exp(V_{j'}^{\boldsymbol{p}})} \tag{5.15}$$

In these equations the term $V_j^{\boldsymbol{p}}$ is defined as:

$$V_j^{\boldsymbol{p}} = \sum_{g \in \boldsymbol{p}} \beta^{g\prime} \boldsymbol{x}_j^g + \delta^{\boldsymbol{p}} d_j \tag{5.16}$$

where β^g is the vector of parameter values of attractiveness attributes of stores supplying goods g, $\boldsymbol{x}_j^g$ is the corresponding vector of attribute values, $\delta^{\boldsymbol{p}}$ is the purpose-specific travel distance parameter and d_j is the travel distance. As implied by this equation, the attractiveness of a destination for a given purpose $\boldsymbol{p}$ is a summation of part-worth utilities derived for each of the goods $g \in \boldsymbol{p}$ relevant for attaining this trip purpose. Thus, the probability that a destination is selected for a given purpose increases with the utility derived for any store type at the destination that is relevant for

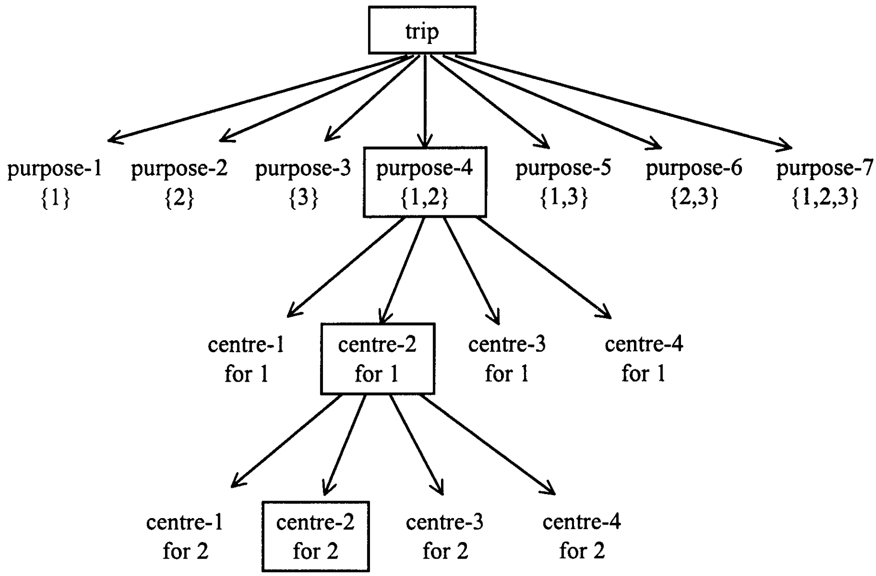

Figure 5.3. The multipurpose, multistop model structure, given three good types.

the trip purpose. Hence, there is a potential *joint attraction* effect in that other stores can contribute to the utility of the destination for making purchases from store of category g, as long as these stores are relevant to the same multipurpose trip.

The choice of destination: the multistop case

In the multistop case, individuals can decide to visit more than one shopping location for realising a selected purpose, e.g., because required store types are not available at a destination location or are more attractive at another location. The above single-stop model can be extended to this multistop case by decomposing the destination choice component into a separate destination choice for each good $g \in \boldsymbol{p}$. Figure 5.3 represents the decision tree for the multistop case. Note that *single-stop* trips represent a special case in which successively the same destination is chosen for each good to be bought on the trip.

To model multiple location choices, the destination choice-set $\boldsymbol{J}^{\boldsymbol{p}}$ is decomposed into a choice-set $\boldsymbol{J}^g$ for each purpose $g \in \boldsymbol{p}$. $\boldsymbol{J}^g \subseteq \boldsymbol{J}$ is the set of shopping centres known to the individual where purpose g can be realised.

To determine a unique sequencing of destination choices for any purpose $\boldsymbol{p}$, we rank the goods in set $\boldsymbol{G}$ such that $g = 1$ is the highest-order good and $g = M$ is the lowest-order good. Then, for a given purpose $\boldsymbol{p}$, the model successively selects destinations from the highest (say, p_1) to the lowest order (say, p_n). Given this ordering, we define ordered purpose-sets $\boldsymbol{p} = \{ p_1, p_2, ..., p_i, ..., p_n \}$ such that $p_1 < p_2 < ... < p_i < ... < p_n$. The choice of a method to order goods should be based on a theory of how individuals perceive and evaluate shopping destinations and is a matter of empirical investigation. Presently, we will assume that goods are ordered on (basic) purchase frequency, such that $g = 1$ is the good with the lowest purchase frequency and $g = M$ the good with the highest purchase frequency.

The introduction of the multistop element has also implications for determining travel distances. The mutlistop model not only allows for trips from home to each shopping destination, but also for trips between different shopping locations. We assume that the disutility of travel associated with a next destination is determined by the extra distance needed to reach that destination. Hereby, the extra distance is calculated based on the optimum route connecting the set of currently selected destinations. The distance attributed to the lowest level choice is calculated as the extra distance required to make the optimum round trip from home that passes through all the selected destinations. The model does not restrict the choice of a method to determine optimum routes. One can think for example of a nearest neighbour or travel minimisation routing method. This choice should be based on a theory of individuals' route choice and is again a matter of empirical investigation.

The multipurpose, multistop model can be formulated by redefining the utilities $V_j^{\boldsymbol{p}}$ of destinations in equation 5.16. In the proposed definition, the utility of the current destination incorporates as an additional component the maximum expected utility of the next destination for the next purpose. Note that this definition is recursive in the sense that the expected utility of the next destination in turn incorporates the expected utility of the subsequent destination and so on. For reasons of explanatory clarity, we will first consider a purpose $\boldsymbol{p}$ consisting of only two goods, p_1 (the highest order) and p_2 (the lowest order). Then, the structural utility of destination j for purpose p_1 is defined as:

$$V_j^{\varnothing p_1} = \mu^{p_1} \beta^{p_1 \prime} \boldsymbol{x}_j^{p_1} + \mu^{p_1} \delta^{p_1} d_j^{\varnothing} + \frac{\mu^{p_1}}{\mu^{p_2}} \ln \sum\nolimits_{k \in J^{p2}} \exp\left(V_k^{\{j\} p_2}\right) \tag{5.17}$$

$$V_k^{\{j\} p_2} = \mu^{p_2} \beta^{p_2 \prime} \boldsymbol{x}_k^{p_2} + \mu^{p_2} \delta^{p_2} d_k^{\{j\}} \tag{5.18}$$

where $V_j^{\varnothing p1}$ is the structural utility of destination j for purpose p_1 given that no locations have been visited for a higher-order purpose, $V_k^{\{j\}p2}$ is the structural utility of destination k for purpose p_2 given that location j has been visited (for a higher-order purpose); μ^{p1} and μ^{p2} are the scale values related to orders p_1 and p_2, $\beta^{p1\prime}\boldsymbol{x}_j^{p1}$ is the attractiveness component of centre j for purpose p_1, $\beta^{p2\prime}\boldsymbol{x}_k^{p2}$ is the attractiveness component of centre k for purpose p_2, δ^{p1} and δ^{p2} are purpose-specific distance parameters; $d_j^{\varnothing}$ is the distance to centre j given that no previous locations have been visited and $d_k^{\{j\}}$ is the extra distance to centre k given that location j and an optimum route have been selected. We stress that the order in which destinations are selected and the order in which destinations are visited are independent. The optimum route condition may imply that a lower-order destination (location k) is visited earlier than a higher-order destination (location j). Furthermore, it should be noted that the extra distance will be zero when $j = k$, i.e. refer to the same shopping centre.

Given this structure, the model can be generalised to any purpose $\boldsymbol{p} = \{ p_1, p_2, ..., p_i, ..., p_n \}$ in recursive form, as follows (5.19):

$$V_j^{Hp_i} \begin{cases} = \mu^{p_i} \beta^{p_i \prime} \boldsymbol{x}_j^{p_i} + \mu^{p_i} \delta^{p_i} d_j^{\boldsymbol{H}} & i = n, j \in \boldsymbol{J}^p \\ = \mu^{p_i} \beta^{p_i \prime} \boldsymbol{x}_j^{p_i} + \mu^{p_i} \delta^{p_i} d_j^{\boldsymbol{H}} + & \\ + \dfrac{\mu^{p_i}}{\mu^{p_{i+1}}} \ln \sum_{k \in \boldsymbol{J}^{pi+1}} \exp\left(V_k^{\{H|j\} p_{i+1}}\right) & 0 < i < n, j \in \boldsymbol{J}^{p_i} \end{cases} \tag{5.19}$$

where $\boldsymbol{H}$ is the set of previous locations and $\{\boldsymbol{H} \mid j\}$ is set $\boldsymbol{H}$ with additional element j. The total utility of a location j for purpose p_i is expressed as:

$$U_j^{Hp_i} = V_j^{Hp_i} + \sum_{i=1}^{n} \varepsilon_{p_i} \tag{5.20}$$

and the choice probability as:

$$Pr\left(j \mid \boldsymbol{H}; p_i; j \in \boldsymbol{J}^{p_i}\right) = \frac{\exp\left(V_j^{Hp_i}\right)}{\sum_{j' \in \boldsymbol{J}^{pi}} \exp\left(V_{j'}^{Hp_i}\right)} \tag{5.21}$$

The *un*conditional probabilities of selecting shopping centre j for purpose p_i can be found by calculating the product of conditional probabilities (equation 5.21) through the paths of the tree-structure.

Finally, the above destination choice component is linked with the purpose-choice component by reformulating equation 5.12 in a straight forward way, as follows:

$$V'^{p} = \alpha^p + \frac{1}{\mu^{p_1}} \ln \sum_{j \in \boldsymbol{J}^{p_1}} \exp\left(\mu^{p_1} V_j^{\varnothing p_1}\right) \tag{5.22}$$

As indicated by the superscripts, the scale values μ^{pi} are good specific rather than purpose specific as in the singlestop model. The values can be interpreted as a hierarchical decomposition of the single-stop equivalents, as follows. μ^{p1} indicates the weight of highest-order destination choice in the utility of trip purpose ***p***, μ^{p2} represents the weight of the second destination choice in the utility of first destinations, μ^{p3} reflects the impact of the third destination choice on the utility of second destinations and so on. Thus, the scale parameters provide information about the impact of available opportunities of a next purpose on the current destination choice.

Summary
To summarise, the nested model structure effectively represents for the single-stop and multistop cases the hypothesised agglomeration effects. First, the purpose adjustment effect is largest if the scale ratios $1/\mu^{p}$ in Equation 5.12 are one. It is absent if the scale ratio is approximately zero. If a scale ratio is between zero and one, the model predicts that destinations that can serve the same purpose compete stronger than destinations that do not match on possible purposes. Second, the joint attraction effect is present if the presence of one store positively affects the utility of a trip on which purchases from another store are also made.

The *multistop* model in addition takes the travel distance between centres into account. Keeping everything else constant, the attractiveness of a shopping location will increase with increasing accessibility and attractiveness of other stores from which goods are bought on the same trip. Scale parameters represent the degree to which a next destination influences the choice of a current destination.

5.3.4 Application

The data used to test the above model were collected in the context of a regional shopping centre impact study in the Brabant region in the Netherlands (Oppewal *et al.* 1997b). The data describe shopping trips of a random sample of 1704 households from a region that contain 386 shopping centres/areas of varying size. The trip data were obtained through a telephone survey in which respondents were asked to recall the last shopping trips to two of the centres randomly selected from the centres that the respondent patronises. The surveys were balanced across days of the week, to avoid possible biases caused by trends in the distribution of trips across days of the week. The shopping trip data that were used in the present analysis include (i) the transport mode used, (ii) the trip destination in terms of a predefined list of the shopping centres in the area and (iii) the items purchased in each of a predefined list of 30 good categories. Furthermore, the respondents were asked whether or not another location was visited before and/or after the reported visit to the centre. The latter information was used to assess the frequency of multistop trips.

Shopping-trip type frequencies

Only a small portion of the shopping trips involved a multistop shopping trip: in 89.5 percent of the trips respondents went directly from their home to the shopping centre, in only 1.8 percent of the cases they first had visited another shopping centre. Furthermore, in 12.8 percent of the trips, a stop was made at another location than the home location after visiting the shopping centre and in 3.5 percent of the cases this concerned another shopping centre. To assess the importance of multipurpose trips, three broader good categories were defined. These correspond largely to the three major levels of the retail hierarchy in most Dutch cities, as follows: grocery goods (neighbourhood centre level); appliances (district centre level) and clothing and/or shoes (city centre level). Higher-order durable goods (e.g., furniture) were not considered, because the low frequency with which they are bought makes them a rather distinct category. Given these three good categories, seven different trip purposes can be distinguished. Table 5.1 shows the frequency of each trip purpose subdivided into two components dependent on whether or not the trip also involved purchases of goods of other categories. As the table shows, if the category 'other' is also taken into account, 882 out of 2802 trips (31.5 %) were multipurpose. If we focus on the three distinguished categories, then 1322 trips involved groceries of which 230 (17.4 %) were bought in some combination with appliances and/or clothing/shoes; 373 trips involved appliances of which 195 (52.3 %) in some combination and 715 trips involved clothing and/or shoes of which 199 (27.8 %) in some combination.

Table 5.1. Observed trip frequencies (SP: singlepurpose frequencies).

Trip purpose			Trip frequency		
Groceries	Appliances	Clothing / shoes	With other	Without other	Total
yes	no	no	203	989 (SP)	1092
no	yes	no	76	102 (SP)	178
no	no	yes	146	370 (SP)	516
yes	yes	no	42	58	100
yes	no	yes	44	60	104
no	yes	yes	28	41	69
yes	yes	yes	15	11	26
no	no	no	459 (SP)	158	617
		Total	1013	1789	2802

Obviously, the frequencies of multistop and multipurpose trips will depend on the definition of the spatial unit of supply and the classification into good categories. In the present case, the shopping centres/areas which were taken as the unit of supply represent relatively large aggregates of stores. Given this definition, the relative frequency of trips involving more than one shopping location is limited to the extent that it may not have a significant impact on shopping destination and purpose choice. Also, the three good categories used represent relatively large aggregates of goods. Yet, a considerable portion of trips involves multiple purposes. We therefore estimate a singlestop model. The trips that involve a purchase of at least one of the three distinguished good categories (including those trips that involved multiple stops) were used for estimation. All trips were considered as being home-based.

Model Estimation

The operationalisation of the model requires a choice of attributes x_j^g. In many retail demand studies, centre size, atmosphere, lay-out and parking facilities emerge as the most influential attributes of centres (Oppewal, Louviere and Timmermans 1997a). Given the present purpose to test the model structure, only centre size was considered. The variable was operationalised for each supply segment as the number of stores available in that segment. Note that, following Equation 5.16, the centre attractiveness component depends on the selected purpose. The component incorporates for each purpose the 'number of stores' variable relevant to that purpose.

Travel times were derived from an existing database of mode-specific travel times between four-position-zip-code areas. For each respondent the travel time corresponding to the reported transport mode (car or other) was used. Choice-sets were derived from aggregated data, as follows. First, for each zone of origin and each good category the centres that consumers are likely to know were identified as the centres available within a certain distance. This distance was derived for each good category separately as the distance within which 95 percent of the respondents' trip destinations for this category are located. We next generated choice sets consisting of four destinations for each reported trip: the chosen destination and one randomly chosen additional destination for each of the three good categories.

An overall full information maximum likelihood estimation of the model was obtained by optimising the multi-layered model in a simultaneous process of estimating the α parameters (purpose constants), the β and δ parameters (location attractiveness) and the μ parameters (the scale values). This was done applying the computer program HieLow developed at the University of Namur (Bierlaire 1995). HieLow is an estimation program that allows one to construct hierarchical model structures and to estimate the structures based on a combined global and regional optimisation procedure to estimate the parameters in the loglikelihood function (Dennis and Schnabel 1983).

Results

The estimation results of the multipurpose, single-stop model are presented in Table 5.2 and some statistics of the analysis in Table 5.3. McFadden's Rho-square was .367

indicating the model fit was satisfactory (a value in the range of 0.2 and 0.4 is generally supposed to indicate a satisfactory level).

Table 5.2. Estimation results of the multipurpose, singlestop model.

Attribute	Parameter estimate	Standard error	t-Value
Travel time (θ)			
- groc.	-0.128 e-03	0.014 e-03	-8.87
- appl.	-2.651 e-03	0.471 e-03	-5.63
- cloth.	-1.323 e-03	0.152 e-03	-8.71
- groc. & appl.	-1.998 e-03	0.355 e-03	-5.63
- groc. & cloth.	-4.805 e-03	0.858 e-03	-5.42
- appl. & cloth	-2.531 e-03	0.518 e-03	-4.89
- groc. & appl. & cloth	-21.67 e-03	1.313 e-03	-16.5
Number of stores (β)			
- groc.	4.383 e-02	0.422 e-02	10.4
- appl.	5.640 e-02	0.902 e-02	6.25
- cloth.	4.565 e-02	0.346 e-02	13.2
Trip-type constant (α)			
- groc.	0	-	-
- appl.	-1.588	0.099	-16.1
- cloth.	-1.267	0.091	-14.0
- groc. & appl.	-2.292	0.115	-20.0
- groc. & cloth.	-1.952	0.110	-17.7
- appl. & cloth	-2.851	0.176	-16.2
- groc. & appl. & cloth	-2.758	0.168	-16.4
Scale (μ) *			
- groc.	0.110	0.0133	-74.2
- appl.	0.205	0.0583	-13.7
- cloth.	0.329	0.0323	-20.8
- groc. & appl.	0.126	0.0456	-19.2
- groc. & cloth.	0.108	0.0265	-33.6
- appl. & cloth	0.188	0.0312	-26.1
- groc. & appl. & cloth	0.054	0.0153	-61.8

*Significance of scale parameters is tested against a value of 1.

Table 5.3. Estimation statistics of the multipurpose, single stop model.

number of observations	1975
number of coefficients	23
Log-likelyhood of the model	-3998.68
Log-likelyhood of the null model	-6356.39
Mc Fadden's Rho bar squared	0.367301

As it appears, all attribute parameters differ significantly from zero (alpha is 0.05) and have signs as expected. To evaluate the interaction between trip purpose and disutility of travel, the purpose-specific travel time parameters (δ) were pairwise compared. As it turned out, for all pairs travel time parameters (δ) differ significantly (alpha is 0.05) from each other except for pairs including 'grocery & appliances', 'appliances & cloths' and 'appliances'. This suggests that, given the spatial structure of our study area, the impact of travel time on destination choice at least partly depends on the selected trip purpose. The disutility of travel is particularly large for the most complex type of multi-purpose trip. The estimates of β parameters indicate for each good that attractiveness of centres increases with increasing number of stores for the concerned good. The α parameters reflect the basic trip frequencies (i.e. the supply-independent component) relative to the frequency of single purpose grocery trips (for which α was set to zero).

All estimates of the scale ratios ($1/\mu^{p}$) fall within the zero-one range and *t*-values are significant at the alpha is .05 level. Note that the t-tests reported in this table report whether the scale ratios differ significantly from unity. Confidence intervals were used and we found that the lower bounds of the 95 percent interval are higher than zero indicating that purpose adjustment effects do occur. That is, available supply does have an influence on trip purpose choice and, therefore, on decisions to combine multiple purposes in trips. Differences in size of scale ratios between trip types indicate the relative sensitivity of trip-purpose choice on supply factors. The influence of supply on purpose choice is largest for clothing/shoes, moderate for appliances and smallest for groceries (the differences are significant, alpha is 0.05). With respect to the multipurpose trips, the influence of spatial opportunities on decisions to combine purposes is largest for 'appliances & clothing/shoes', moderate for 'groceries & appliances' and smallest for 'groceries & clothing/shoes' (the difference between the smallest and largest is significant). This suggests that the associations 'groceries & appliances' and 'appliances & clothing/shoes' depend to a somewhat larger degree on available opportunities than the association 'groceries & clothing/shoes'. In other words, grocery stores have a stronger impact on appliances stores than on clothing/shoes stores and appliances have comparable impacts on grocery stores and clothing/shoes stores.

It can be concluded from the above results that model fit is good and all parameter estimates are consistent with a-priori expectations. Moreover, the hypothesised hierarchical structure is confirmed by the data. The scale ratios reveal the influence of available supply on decisions to combine certain purposes in trips. Being significantly different from zero, the estimated values confirm the trip adjustment hypothesis.

Comparison with the conventional single purpose, single-stop model

The multipurpose model (MP-model) can be viewed as an extension of the conventional single-purpose MNL-model (SP-model), which takes purpose adjustment and joint attraction effects of retail agglomeration into account. The positive scale- ratio estimates indicate that trip adjustment effects occur, i.e. the phenomena that individuals tend to adjust the choice of trip purpose to available supply. Joint attraction effects, on the other hand, refer to the situation where the attractiveness of a destination for a given type of good depends on the availability/attractiveness of other types of stores. As implied by this definition, the size of joint attraction effects can be measured only when we focus on a certain good and measure the beta-parameters related to complementary store types.

Table 5.4. Estimation results of the multipurpose grocery-trips model.

Attribute	Parameter estimate	Standard error	t-Value
Travel time (θ)			
- groc.	-0.124 e-03	0.014 e-03	-8.85
- groc. & appl.	-1.631 e-03	0.290 e-03	-5.62
- groc. & cloth.	-3.967 e-03	1.315 e-03	-3.02
- groc. & appl. & cloth	-4.911 e-03	1.835 e-03	-2.68
Number of stores (β)			
- groc.	4.490 e-02	0.419 e-02	10.7
- appl.	6.278 e-02	1.717 e-02	3.66
- cloth.	5.715 e-02	1.711 e-02	3.34
Trip-type constant (α)			
- groc.	0	-	-
- groc. & appl.	-2.182	0.230	-9.49
- groc. & cloth.	-2.107	0.240	-8.79
- groc. & appl. & cloth	-3.463	0.042	-11.3
Scale (μ) *			
- groc.	0.174	0.1368	-6.03
- groc. & appl.	0.213	0.0939	-8.38
- groc. & cloth.	0.105	0.0486	-18.3
- groc. & appl. & cloth	0.098	0.0478	-18.9

*Significance of scale parameters is tested against a value of 1.

Table 5.5. Estimation statistics of multipurpose grocery-trips model.

number of observations	1250
number of coefficients	14
Log-likelyhood of the model	-2130.40
Log-likelyhood of the null model	-3352.34
Mc Fadden's Rho bar squared	0.360327

This section describes the results of model estimation on a subset of trips, namely all trips that involve grocery purchases either as a single purpose or in some combination with appliances or clothing/shoes. This allows us to measure joint attraction effects in grocery shopping. Under the hypothesis that joint attraction effects exist, the supply of appliances and cloths/shoe-ware affect the choice of grocery trip destination, i.e. the beta parameters related to supply of appliances and cloths/shoe-ware are larger than zero. Second, to evaluate the degree to which joint attraction and purpose adjustment together affect the distribution of market shares of grocery stores across centres, we compare the MP-grocery model with a conventional SP-grocery model. The grocery trips segment is chosen here because it comprises a large number of trips (1250). In principle, the analysis can be performed for every good.

The estimation results and goodness-of-fit statistics of the MP-grocery model are shown in Tables 5.4 and 5.5. Again, all attribute parameters are significant and the values are of the same order of magnitude as in the previous all-trips case. Also, the scale ratio estimates are consistent with the overall model. The β parameter estimates related to appliances and clothing/shoes indicate a significant impact of supply of appliances or clothing/shoes on choice of destination for the grocery trips that also involve purchases in these higher-order segments. Furthermore, it turns out that the travel time parameters of single-purpose trips differ significantly from those of higher-order grocery trips (as in the overall model). The observations that both disutility of travel and centre attractiveness is trip type specific confirm the joint attraction effects.

To evaluate the extent to which the MP-model re-distributes market shares, a conventional SP model was estimated. Goodness-of-fit measures cannot be directly compared in this case, because the loglikelihoods of the null-models differ (the MP model predicts combinations of purpose-destination choices, whereas the SP model predicts destination choice only). We therefore compared the models on the correlation between observed and predicted individual destination choices. As it turns out, the correlation coefficient for the SP model is 0.671 and for the MP model 0.780. The performance of the SP-model could not be measurably improved by extending the utility function with terms representing supply in the clothing/shoes and appliances segments. Therefore, we conclude that at least in this case:

1. The agglomeration forces as predicted by the MP model lead to a substantial shift in market shares in grocery retailing.
2. Being able to account for these forces, the MP model significantly improves the accuracy of market share predictions compared to the SP model.
3. The improvement in predictions must be attributed to the specific structure of the MP model, given the fact that the performance of a conventional SP model could not be improved by incorporating extra terms in the utility function.

5.3.5 Conclusions and discussion

Summary

This section introduced an extension of the conventional MNL-model to account for multipurpose and multistop shopping trips. Following discrete choice theory, a nested-logit framework was proposed to describe a hierarchical choice process in which individuals successively select the purpose and the destination(s) of a trip. Two model variants were considered. In the single-stop variant, destination choice involves selecting a single shopping centre for the purpose of the trip. In the multistop case, destination choice is broken down into a number of consecutive destination choices for each good from high to low order involved in the purpose of the trip. In a case study, a substantial portion of observed shopping trips included more than one purpose, but only a small portion also involved more than one stop for shopping (i.e., a shopping centre). Therefore, the singlestop variant of the multipurpose model was estimated. The estimation results confirm the supposed hierarchical model structure. Moreover, a comparison with a conventional single-purpose-shopping model gives evidence for the significance of the hypothesised agglomeration effects.

Implications for retail planning

The proposed model has favourable features for predicting spatial shopping behaviour in applied contexts. First, the data needs of the model are relatively modest. It only requires data about the purposes and destinations of individual trips. As the case study indicated, the data can be collected against relatively low costs through a consumer survey. Second, existing computer software can be used for full information loglikelihood estimation of the model. Third, probably the most important advantage of the model is that it potentially can improve the predictive ability of existing discrete choice models for predicting market shares of store types within centres. In the case study, the improvement in predictive accuracy was substantial at least in the grocery sector. Furthermore, the model has specific relevance for predicting shopping travel demand. The model is sensitive for the impact of supply on trip type choice and, consequently, can predict shifts in proportion of multipurpose trips in response to changes in location or branch mix of shopping centres. In summary, by predicting destination and purpose choice in interaction the model is sensitive for impacts of mix of store types within centres on both market shares distributions and travel demands. Consequently, it may provide a useful tool for optimising the structure of retail systems not only within retail sectors, but also across sectors (i.e., branch mix per centre).

Future Research

Destination choice-set definition is a critical step in estimating discrete choice models. This is particularly true for the present model where destination choice is nested within choice of trip type and, consequently, the IIA-property no longer holds. Theoretically, the scale-ratio estimates are sensitive to choice-set definition. One may expect that the maximum utility across alternatives increases and hence the estimated scale ratios decrease if irrelevant alternatives are added to the choice-set. In the present case study, a stochastic rule was used to define choice-sets per trip type and no special attention was given to the match with actual choice-sets. There is little known about the extent to which *scale ratio* parameters are sensitive to choice-set definition. Simulation experiments are required to assess this sensitiveness not only for this model type, but more generally for models employing nested location-choice structures.

The present model considers the selection of shopping trips in isolation from other out-of-home household activities. Yet, other activities such as for example work, or bringing and getting child from school may be combined with shopping activities (e.g., shopping on a location on the route from work to home). A possible extension of the present model would be to extend the trip purpose and trip destination choice-sets with purposes and locations related to non-shopping activities. Then, the generalised model would be able to simultaneously predict the purpose and destination selection of various activity types and take into account the interaction between the other activities and shopping activities.

Furthermore, the present model uses a parameter constant to measure the supply-independent factors of trip purpose choice. We may expect on theoretical grounds that the probability of trip type will be influenced by the household and activity pattern in which context the shopping activity takes place. Therefore, it is interesting to replace the constant by a function of context factors such as socio-economic and demographic characteristics of the individual, time of day, day of the week, transport mode and so on. Such a model specification would allow one to predict impacts of a wider range of developments on shopping behaviour.

5.4 Conclusion

This chapter introduced an extension of the MNL-model which fits in the line of previous modelling efforts to deal with spatial structure effects in spatial choice behaviour. The model accounts for spatial agglomeration forces and, thus, can improve accuracy of predictions. At the same time, the model has favourable practical properties. The model can be estimated on survey-data of shopping trips and estimated by means of existing likelihood estimation software. Hence, the procedures can be readily incorporated in existing programs for market and location research in the context of commercial or governmental organisations. For these reasons, the model structure will be incorporated as the central component in the model base of the spatial

DSS. The next chapter will consider complementary models for analysing retail/service performance.

CHAPTER 6

MODELS FOR ANALYSING THE PERFORMANCE OF RETAIL SYSTEMS (INFERENCE LAYER)

6.1 Introduction

The spatial shopping model described in the last chapter allows one to explain and predict retail/service system operations in terms of consumer choice behaviour. However, a description of the retail system in these terms does not readily answer the question which (further) actions are to be undertaken if planning objectives are not met. This chapter focuses on models which perform an intermediate analysis step to relate retail/service system operations to planning objectives. The models form the conceptual component of the inference layer of the DSS model-base. This component is considered crucial for generating required information in the problem identification and plan generation stages. Therefore, this chapter concentrates on models for generating the information. How the information can be used to identify appropriate actions will be the subject of the next chapter. It is considered particularly important that the models are relevant for spatial policy making, conceptually sound, free of measurement bias, precise (i.e., quantitative) and interpretable in non-technical terms (regular planning concepts).

Retail/service system performance analysis has received much attention in the spatial sciences. The models that have been proposed cover the range of issues that are relevant for social as well as economic planning objectives. However, existing models typically assume that consumers make single purpose, single stop trips. In contrast, the case study described in the last chapter as well as other studies suggests that in the area of retailing this assumption is not justified. As it turned out, a considerable portion of shopping trips is multipurpose and may also involve multiple stops. The major objective of this chapter is to extend conventional models to deal with this complex behaviour also in the performance analysis stage. A comprehensive set of models will be proposed to cover a broad range of performance characteristics. Two groups of models are distinguished. The first group considers spatial *opportunities* of consumers offered by the *physical* system, whereas the second group is derived from the multipurpose, multistop shopping model described in the last chapter, to analyse *behavioural* aspects of retail systems.

This chapter is organised in several sections. The first section (6.2) gives an overview of the relevant literature in terms of a classification of issues and modelling approaches. The remainder of this chapter then proposes new models to account for multipurpose, multistop shopping in performance analysis. First, sections 6.4 and 6.5 consider the spatial opportunities of consumers with respect to the two key concepts identified in chapter 3: accessibility of facilities (section 6.3) and the choice range offered by available facilities (section 6.4). As in existing approaches, the model developed in section 6.3 conceptualises accessibility as the minimum amount of effort required to acquire a given set of consumer goods. Unlike existing approaches, however, the proposed model takes into account available opportunities for reducing this effort by making multipurpose, multistop trips. The model developed in section (6.4) evaluates spatial choice range in terms of the effort required to satisfy a criterion for sufficient choice range. In contrast to existing models, which are typically based on a cost-band analysis, the proposed model takes into account opportunities to benefit from the spatial clustering of facilities through multistop travel. In both sections 6.3 and 6.4, we first describe the specification of the model and next an application to assess the performance of the model relative to existing approaches. Then, section 6.5 focuses on the behavioural system. The new models involve an extension of existing models to analyse demand and travel characteristics, given probabilities of multipurpose, multistop trips, e.g. as predicted by the proposed model in the last chapter.

Having developed a coherent set of models for analysing a wide range of behavioural and physical characteristics of retail and service systems, Section 6.6 develops a system for implementing the models in the DSS. The system consists of a collection of atomic elements out of which behavioural and opportunity-based models can be reconstructed. As discussed in chapter 4, this modular approach has advantages related to efficiency in model storage and model management and flexibility in adapting models to specific information needs and data availability. Section 6.6 describes the proposed system in terms of a method of decomposing performance models. Finally, the last section (6.7) summarises the major conclusions.

6.2 A classification of models for analysing performance

Performance characteristics relevant for spatial policy making can be classified into the following categories: (i) internal characteristics of stores, (ii) site characteristics, (iii) the location relative to related types of land-use (e.g., recreation, social, work etc.), (iv) the location relative to distribution centres, (v) the location relative to the transportation network and (vi) the location relative to locations of demand. To make a contribution to the current state-of-the-art, we focus the attention on the last two categories which define the spatial relationships between demand and supply.

Spatial performance analysis has received much attention in geography, urban planning and transportation research. For a recent overview of this field readers are referred to the book edited by Bertuglia *et al.* (1994a). Specifically in the area of retailing, coherent sets of perfomance indicators have been proposed in relation to a specific modelling technique (spatial interaction modelling: Clarke and Wilson 1994; Birkin *et al.* 1994; Birkin *et al.* 1996), private sector planning objectives (Birkin 1994, Birkin *et al.* 1996) or public sector planning objectives (Van der Heijden, Timmermans and Borgers 1984; Van der Heijden 1986). According to which performance dimension they measure, existing models can be classified as follows.

Accessibility

Indicators of accessibility became popular in the 1970s especially in the field of transportation research. According to a widely used definition, accessibility refers to the ease with which any facility location can be reached from a specific location (Dalvi 1978). Usually, this is measured in terms of the travel distance, travel time, monetary travel costs or travel distance required to reach facilities from a specific consumer location. It should be noted that the term accessibility has been used to refer to measures which according to the currently used classification fall in the 'spatial choice range' or 'consumer utility' categories. Reviews of this broader category of models can be found in Dalvi (1978), Wachs and Koenig (1978), Jones (1981), Handy and Niemeier (1997) and Talen and Anselin (1998). Breheney makes a distinction which is useful for the broad as well as the narrow definition of accessibility. He distinguishes (i) measures based directly on observed travel behaviour, such as for example mean trip length or aggregate travel costs and (ii) measures based on the distribution of available opportunities, such as for example distance to nearest facilities. Within the second group, Breheney further distinguishes (i) measures which assume that the effect of distance decays in some fashion and (ii) measures that do not incorporate a distance decay parameter. A well-known example of the first type is the measure proposed by Hansen which uses the balancing condition (A_i, equation 5.2) of the production constrained interaction model as an indicator of accessibility. Nearest-centre distance measures are an example of the last type (no decay of the distance effect). Recent studies have used an extended accessibility concept to take into account limited time-windows for activities in the context of daily activity patterns. An example of this approach is Dijst and Vidakovic (1997).

Spatial choice range

This performance aspect refers to the opportunities the system provides for choosing between alternative destinations (Van der Heijden *et al.* 1984). Obviously, spatial choice range is closely related to accessibility, since choice-sets are restricted by travel distance.

Nevertheless, we feel that it is useful to distinguish the two categories, as they relate to a cost and a benefit aspect. As an operational definition we will consider 'choice range' measures as those measures that in some way quantify the size of a choice-set (as opposed to a travel distance). Well-known examples that fall in this category are (i) the number of facilities of a given type reachable within a given cost band from a specific location (see Breheney 1978) and (ii) a weighted sum of facility size whereby a negative distance function is used as a weight to represent the notion that facilities farther away should have a smaller weight (decay of the distance effect) (see Koenig 1980).

Consumer utility

This performance aspect refers to the utility that consumers can derive from available facility locations. The term 'utility' is used here in a broad sense without necessarily referring to a psychological concept. Under this heading we consider all measures that in some way take into account the trade-offs between travel distance and the attractiveness of facility locations. Koenig (1980) reviews the utility-based approach in performance analysis. The most influential approaches have been based on the spatial interaction model and the MNL discrete choice model. Well-known examples of interaction-based measures are log-accessibility (Leonardi 1978) and consumer surplus (Coelho and Wilson 1976). These measures appear to be equivalent. In global terms, both measures indicate benefits consumers derive from available facilities corrected for the travel costs required to reach them. Alternatively, an MNL-based measure has been derived by Ben-Akiva and Lerman (1978). The measure expresses the expected maximum utility value across a given choice-set, which corresponds to the inclusive value related to nests in nested-logit models (e.g., equation 5.9). This maximum can be interpreted as the expected utility consumers derive from the choice situation if error terms in the utility function are Gumble distributed.

Demand/supply ratios

Measures of this type are concerned with the (quantitative) balance between demand and supply. A distinction can be made between demand-related and supply-related measures. Demand-related measures express for a given demand location the size of supply allocated to that location, possibly, expressed per demand unit. A well-known example is 'per capita retail floor space'. Clarke and Wilson (1994) argue that, when a spatial interaction (or any other consumer model) is used to determine allocations, such ratios measure the effectiveness of a facility system in serving a population. In applied retail studies the ratios are commonly used to assess the balance between supply and demand (under or over provision, see Ghosh and McLafferty 1987). Supply-related measures, on the other hand, express for a certain supply location the amount of demand allocated to that supply location, possibly, expressed per supply unit. A well-known example is 'attracted expenditure per unit floor space'. In the area of public facilities (e.g., schools, hospitals etc.) this type of measure is often taken as a measure of efficiency of service provision, whereas in commercially exploited facilities (e.g., retail stores) the measures are normally interpreted as indicators of profitability (Clarke and Wilson 1994). In applied retail studies demand/supply ratios often play an important role. Commonly used measures include the number of potential customers in the catchment area of a store or centre, market penetration rates, market shares, floor-productivity, per capita floor space and so on.

The above classification summarises the main performance dimensions that are related to the interests of different groups involved. 'Accessibility', 'spatial choice range' and 'consumer utility' are dimensions of consumer interests. Measures of these categories produce a vector of performance scores related to consumer locations in the study area (residential-based scores). Demand-supply ratios on the other hand provide important information in relation to economic interests of producers. These measures produce a vector of scores related to supply locations (e.g., floor productivity) or market areas (e.g., penetrations). Finally, the behaviour-based measures of accessibility are relevant for public interests, as they indicate the amount of shopping related travel in the study area (travel demand).

Another public interest concerns equity in spatial opportunities of consumers or producers across locations. This *social* aspect of public interest does not involve a separate demand-supply measurement dimension. Instead, the variance of performance scores across locations can be taken to indicate equity of opportunities across locations (of consumers or producers). The equity issue has been widely discussed not only in spatial planning but also in welfare economics, social politics and social geography (e.g., McAllister 1976; Morill and Symons 1977; Rich 1979, Mulligan 1991, Talen and Anselin 1998). Generally, equity objectives are in conflict with policies aiming at an efficient allocation of resources. For example, concentrating facilities in densely populated areas promotes efficiency in terms of total travel and profitability, but at the same time tends to reduce equity in terms of the accessibility of facilities for consumers in peripheral locations. Sophisticated measures, such as entropy-based measures, have been proposed to produce non-biased information (Gaile 1977). Examples of simple measures are the minimum, maximum or standard deviation of spatial distributions of performance scores. In the present context it would lead to far to discuss equity measures in detail. For this readers are referred to Gaile (1977) and Mulligan (1991).

A final point of discussion that is relevant here relates to Breheney's distinction between opportunity and behaviour-based models. In this respect, a principle point is made by Rushton (1969). He argues that spatial choice behaviour is the resultant of intrinsic preferences of individuals on the one hand and constraints imposed by the physical system on the other. If behaviour-based measures that fail to disentangle preferences and constraints are used for measuring opportunities, they will produce biased information. For example, this would be the case if the distance decay parameter in interaction-based models confuses physical barriers with disutility of travel and is used in an index of accessibility. Our approach is based on the argument that a *combination* of two sources of information is therefore useful for plan decision making: (i) observed or predicted spatial behaviour and (ii) the physical conditions of this behaviour. The first source is covered by behaviour-based models presented in Section 6.5. The second source is covered by models presented in sections 6.3 and 6.4 for analysing the spatial distribution of facilities with respect to accessibility and spatial choice range. The latter type of models can provide information about what consumers *can* do given physical constraints. This complements the information about what consumers actually (will) do. Thus, the opportunity-based models allow planners to evaluate constraints separately from behaviour.

6.3 A multipurpose-based model for analysing accessibility

6.3.1 Introduction

Models for measuring accessibility have received much attention in urban planning, transportation and geography reflecting the central role of this characteristic of service and retail systems in spatial policy making. In section 6.2., a distinction was made between behaviour-based and opportunity-based approaches. In the present section, we are concerned with the latter approach. As argued by Breheney (1978), the opportunity-based approach has the potential to avoid confounding the effects of preferences and physical hard constraints on spatial behaviour. Furthermore, when properly devised, opportunity-based models have a clear interpretation, are easy to use and have modest data needs.

Existing opportunity-based models measure accessibility in some way as the minimum effort required to reach facility locations for each supply segment (good or trip-purpose) separately. As illustrated by the two hypothetical shopping situations presented in figures 6.1 and 6.2, such studies may lead to biased measurement results. In both

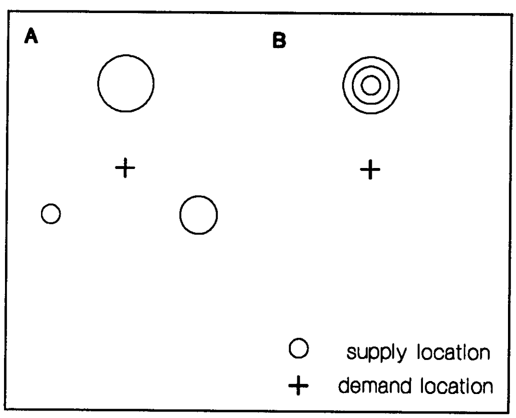

Figure 6.1. Example: spatial agglomeration and destination choice in the multipurpose trip, single stop case.

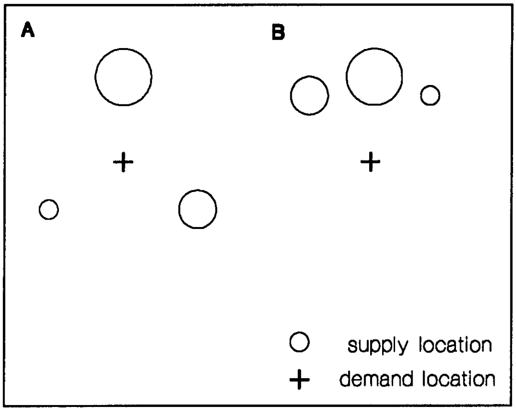

Figure 6.2. Example: spatial agglomeration and destination choice in the multi-purpose trip, mulitstop case.

situations, the distances between the consumer location and the supply locations in a three-purpose case are the same in configurations A and B. Consequently, measured total travel costs are the same when the three purposes are considered separately. In contrast, if consumers can make multipurpose trips, then configurations A and B are no longer equivalent. Then, in both situations, the accessibility of facilities in B is better than in A, because in B consumers can save travel costs by visiting different facilities in a single trip with one stop (Figure 6.1) or multiple stops (Figure 6.2). Existing least travel costs models would fail to differentitate between A and B in the first as well as the second situation. The aim of the new model developed in this section is to account for such agglomeration effects.

6.3.2 Model specification

Assumptions

Following our earlier definitions, we assume a set of L consumer goods which may be categorised into G groups. The categories are ordered such that $g = 1$ represents the highest order good with the lowest purchase frequency and $g = G$ denotes the lowest order good with the highest purchase frequency. Given the purchase frequencies of the good categories the accessibility model determines the minimum travel costs required to purchase the complete set of goods. Thus, in contrast to the behavioural model, the purchase frequencies are given constants.

An imaginary travel-costs minimising consumer will synchronise purchase cycles in such a way that as many as possible purchases coincide in time. Figure 6.3 shows for an example the result of this synchronising behaviour. As the figure illustrates, synchronisation gives rise to different types of multipurpose trips referred to as trip *orders*. A trip of order g is defined as a trip aimed at the purchase of good g and, if possible and beneficial, also the purchase of goods of lower order ($h = g + 1, g + 2, ..., G$). In general, the synchronisation of G goods gives rise to G trip-orders:

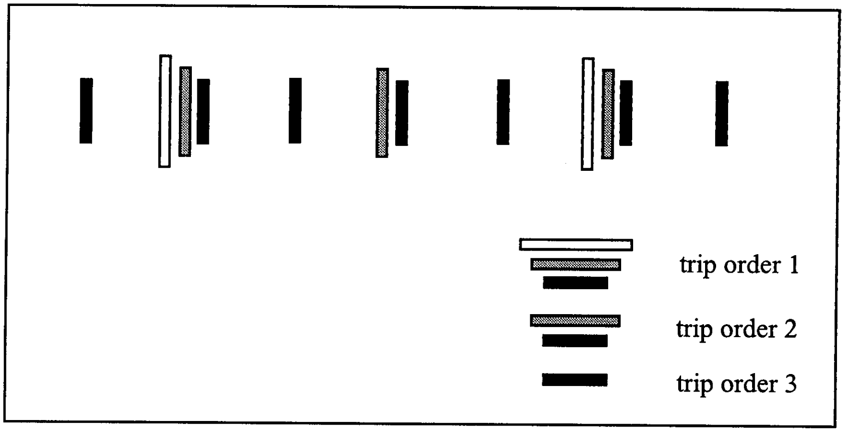

Figure 6.3. Synchronisation of purchase cycles and the hierarchy of multipurpose trips in a three-good case.

- trips of order 1: purchases of 1 and, if possible, also 2, 3,.., G
- trips of order 2: purchases of 2 and, if possible, also 3, 4,.., G

....

- trips of order G: purchases of G

The assumption underlying this way of ordering trips is that at any moment in which goods of order g are needed also goods of all lower order $h > g$ are needed, for all $g < G$. It should be noted that this assumption imposes a constraint on the distribution of purchase frequencies across good orders. That is, the purchase frequency of any order g must be equal or larger than the sum of purchase frequencies of all higher orders:

$$f^g \geq \sum_{h=1}^{g-1} f^h \quad \forall g > 1 \tag{6.1}$$

In practice, the method appears to be rather robust for violations of this synchronisation constraint. If the constraint is not met it is often still possible to order trips in this hierarchical way. The reason is that a higher-order trip often also include a purchase of lower order goods. The resultant reduction in the number of remaining trips of lower orders means that the synchronisation constraint is met even if the lower-order goods are bought with a lower frequency than allowed by constraint 6.1. Hence, violation of the above constraint in a particular case does not necessarily imply that the model is not applicable. Rather, the constraint entails that one should verify for each consumer location whether the trips produced by the model can indeed be ordered in the above hierarchical manner.

The possible destinations of a trip of order g are formed by all the shopping centres in the study area supplying types of order good g. To operationalise travel costs minimising behaviour we introduce a new concept termed *net* travel costs. The net travel costs associated with a trip of order g to centre j is defined as the travel distance minus the savings of travel costs, if any, due to combined purchases of lower order goods at destination j or at the destinations subsequently visited. For clarity of explanation, we will first formulate the model for the *single stop* case and, next, extend the definition to cover the general multistop case.

The single stop model

In the single stop case, the net travel costs of a g-trip from location i to shopping centre j is defined as:

$$C_{ij}^{g} = D_{ij} - \sum_{h=g+1}^{G} \delta_j^h C_i^h \qquad (6.2)$$

where: C_{ij}^g are the net costs of a g-trip from i to j, D_{ij} is the travel distance from i to j, δ_j^h is a binary variable which denotes the presence ($\delta_j^h = 1$) or absence ($\delta_j^h = 0$) of lower order goods h in centre j and C_i^h are the net costs associated with trips of order h originating from location i. Thus, the costs of a lower order trip (the second term on the RHS of equation 6.2) is subtracted from the travel costs of the trip for each of the lower-order purchase realised. This reflects the notion that each lower-order purchase saves a separate trip.

The costs minimising principle implies that a g-trip is allocated to the centre that minimises net travel costs. Formally:

$$a_{ij}^{g} = \begin{cases} 1, & \text{if } C_{ij}^{g} < C_{ik}^{g},\ \forall k \neq j,\ j,k \in \boldsymbol{J}^{g} \\ 0, & \text{otherwise} \end{cases} \qquad (6.3)$$

where a_{ij}^g is an all-or-nothing allocation variable and $\boldsymbol{J}^g$ is the set of shopping centres supplying g. The travel costs associated with a g-trip from location i equals the least net travel costs and can be written as:

$$C_i^g = \sum\nolimits_{j \in J^g} a_{ij}^g C_{ij}^g \qquad (6.4)$$

Since a_{ij}^g is zero for all but the allocated centre, the summation of terms in equation 6.4 results in the net travel costs to the allocated, that is the least-net-costs centre.

Note that the net travel costs of g-trips to j, as defined by equation 6.2, depend on the costs of (lower order) h-trips. Therefore, the equations 6.2 - 6.4, which describe costs per trip, can be solved only from low to high order. The costs of the lowest trip-order simply equal the distance to the nearest centre, since these trips are necessarily single purpose. Given the costs of the lowest order trip, the costs of the subsequent trip-order can be calculated and so on. After solving the equations, the a-variables, which describe the destinations of the G trip-orders, are known. It is worth noting that least-net-costs centres may differ from nearest centres. This may occur if a more distant centre offers better opportunities for multipurpose shopping.

The multistop model

Multistop trips are potentially relevant if not all lower order goods are supplied at the destination of a higher order trip. Then, it may be beneficial to continue the trip to another centre where the purchases not yet realised can be made. The costs minimising principle implies that a trip will be continued if the extra travel costs are compensated by the implied savings of lower-order trips. Consider for example a g-trip from i to centre j which may be continued to centre k. In case centre k supplies lower order goods not supplied in j, the costs of travelling from j to k may be compensated by the costs reductions due to additional purchases in k. To reflect these notions, equation 6.2 must be extended with an extra term representing the *net* travel costs of travelling from the current destination to a next destination (if any). The same reasoning holds also for this next destination k. If other centres can be reached from k which provide lower order goods not supplied in j and k, then the trip may be further continued. Therefore, equation 6.2 must incorporate a next term expressing the net travel costs of continuing the trip further, and so on.

Generally, the travel costs of a g-trip from i to j are recursively defined as the costs of travelling from i to j minus the costs reductions that result from buying goods of lower order in j plus the net travel costs of continuing the trip from j to the next allocated destination:

$$C_{ij}^{g} = D_{ij} - \sum_{h=g+1}^{G}(1-\delta_{i_0}^{gh})\delta_j^h C_{i_0}^h + \sum\nolimits_{k\in J^g} a_{jk}^{g} C_{jk}^{g} \tag{6.5}$$

where i_0 is the home location and δ_i^{gh} is a binary variable indicating whether or not lower order supply h is available at any previous stop of the g-trip starting from i. As in the single stop case, the second term on the RHS represents the costs reductions that result from buying lower order goods in the current centre. Cost reductions are achieved if a lower order good h is supplied at the current stop (δ_j^h=1), while it is not available at any previous stop (δ_i^{gh}=0). The third term on the right-hand side represents the costs of continuing the g-trip. The allocation variable a^g_{jk} is defined by equation (6.3), which was also used to determine first destinations. Thus, the next stop of a g-trip is allocated to the centre that minimises net travel costs. We assume that the home location belongs to the set of optional next destinations and that no costs are assigned to travelling back home. Consequently, the option of continuing a trip from j to the next centre k is considered only if this results in positive savings of costs.

Equation 6.5 reflects the recursive nature of the multistop model in that the net travel costs of a trip to centre j incorporates the net costs of continuing the trip to a next destination k. The next example may clarify the mechanics of this recursive definition. For clarity of presentation, we assume a given allocation pattern (in terms of a-variables) which defines a trip chain from i to j, next from j to k and finally from k to l. Furthermore, we replace the second term on the RHS of equation (6.5) by S_j^g, i.e. the costs savings due to buying lower order goods in the current centre. Then:

$$C_{ij}^g = D_{ij} - S_j^g + C_{jk}^g$$

Replacing C_{jk}^g by its definition (equation 6.5) gives:

$$C_{ij}^g = D_{ij} - S_j^g + (D_{jk} - S_k^g + C_{jl}^g)$$

In turn, replacing C_{kl}^g by its definition results in:

$$C_{ij}^g = D_{ij} - S_j^g + (D_{jk} - S_k^g + (D_{jl} - S_l^g))$$

At this point the recursion (trip chaining) stops, because l is the last destination. In general, the recursion is stopped when either all lower goods have been purchased or the savings of an optimal trip continuation are negative. Thus, the multistop model accounts for the fact that the attractiveness of a centre increases with the accessibility of complementary locations reachable from that centre.

As noted, the proposed measure of accessibility is defined as the *minimum* travel costs required to purchase the complete set of goods from a given consumer location. Solving equations 6.3 - 6.5 for each trip order and for a given location i yields the amount of net costs, C_i^g, for each g. Given the purchase frequency, f^g, of each g, the total travel costs can then be found in a straightforward way by summing the product of f^g and C_i^g across g. Formally:

$$C_i = \sum_{g=1}^{G} f^g C_i^g \tag{6.6}$$

where C_i is the total travel costs which is proposed as a measure of accessibility.

Comparison with single purpose, single stop models

Compared with the conventional single purpose, single stop models, the above multipurpose (multistop) model tends to allocate shopping trips to more distant centres with the aim to reduce the number of trips. The reduction in total travel costs achieved by this strategy will depend on the spatial configuration of the retail system under concern. The reduction will be at a maximum in a perfectly hierarchical structure. A hierarchy is considered perfect if every higher-order centre supplies the goods of that order as well as goods of all lower orders. Then, the (average) length of trips will not increase and the number of trips is at a minimum (in every centre all lower order purchases can be realised). In the other extreme case, store types are not clustered so that gains in number of trips are fully counterbalanced by the required increases in trip length.

To analyse the degree to which retail systems offer opportunities for multipurpose shopping, we will reformulate the above accessibility measure as the sum of trip length and trip frequency products across trip orders, as follows. The length of a (multistop) g-trip starting from i is recursively defined as the distance (travel costs) to the first allocated destination plus the length of the trip (continuation) starting from that destination:

$$D_i^g = \sum\nolimits_{j \in J^g} a_{ij}^g (D_{ij} + D_j^g) \tag{6.7}$$

where D_i^g is the length of a g-trip from i. The frequency of g-trips equals the given purchase frequency of g minus the number of times g is purchased during trips of higher order:

$$T_i^g = f^g - \sum_{h=1}^{g-1} \delta_i^{hg} T_i^h \tag{6.8}$$

where T_i^g is the frequency of g-trips, f^g is the given purchase frequency of g, and δ_i^{hg} denotes the presence of lower order supply g in a h-trip. To determine the frequency of g-trips, the frequency of lower order trips must be known. Consequently, the set of G equations defining trip frequencies can be solved only from high to low trip orders (the frequency of highest order trips equals the given purchase frequency, since by definition these goods cannot be bought in higher-order trips). The measure of accessibility, that is the travel costs required for buying all goods, can now be formulated alternatively as:

$$C_i = \sum_{g=1}^{G} D_i^g T_i^g \tag{6.9}$$

where D_i^g and T_i^g are the length and frequency of *g*-trips.

Further information on the spatial structure of the shopping system can be obtained by comparing the results under the condition of multipurpose, multistop travel (in short the MP method) to results that would be obtained if single purpose, single stop trips are assumed (in short the SP method). The SP score expresses the total travel costs to nearest centres and can be found by determining the sum of products of f^g and the nearest centre distance ($D_i^{min\ g}$) across *g*. Therefore, the reduction in travel costs associated to demand location *i* is:

$$dC_i = \sum_{g=1}^{G} (D_i^{g\min} f^g - D_i^g T_i^g) \tag{6.10}$$

where dC_i is the reduction in travel costs due to multipurpose shopping and $D_i^{g\ \min}$ are the costs to the nearest centre supplying *g*. The reduction of travel-costs is the result of a decrease in trip frequency ($T_i^g \leq f^g$) and an increase in trip length ($D_i^g \geq D_i^{g\ \min}$). Therefore, equation 6.10 can be reformulated as the sum of a trip frequency and a trip length component:

$$dC_i = \sum_{g=1}^{G} \left\{ (f^g - T_i^g) D_i^{g\min} + (D_i^{g\min} - D_i^g) T_i^g \right\} \tag{6.11}$$

The first term represents the (positive) reduction component which is achieved by a decrease in trip frequency and the second term expresses the (negative) component which follows from an increase in trip length.

The costs reduction measure, dC_i, reflects the degree to which consumers at location *i* may benefit from multipurpose, multistop shopping and thus the degree to which spatial clustering of store types contributes to the accessibility of the system. Two levels of clustering can be distinguished, that is clustering of store types within centres and between centres. The effects of clustering at these levels can be separated by determining in addition the travel costs under the multipurpose, *single stop* condition. The difference between the SP condition and the multipurpose, single stop condition indicates the effect of clustering of store types within centres. Likewise, the difference between the multipurpose, single stop condition and the multipurpose, multistop condition represents the effect of clustering at the centre level. The decomposition into a frequency and length component helps to explain the observed agglomeration effects. The size of the trip frequency component indicates possibilities to benefit from trip-chaining and the size of the trip length component the amount of effort this takes.

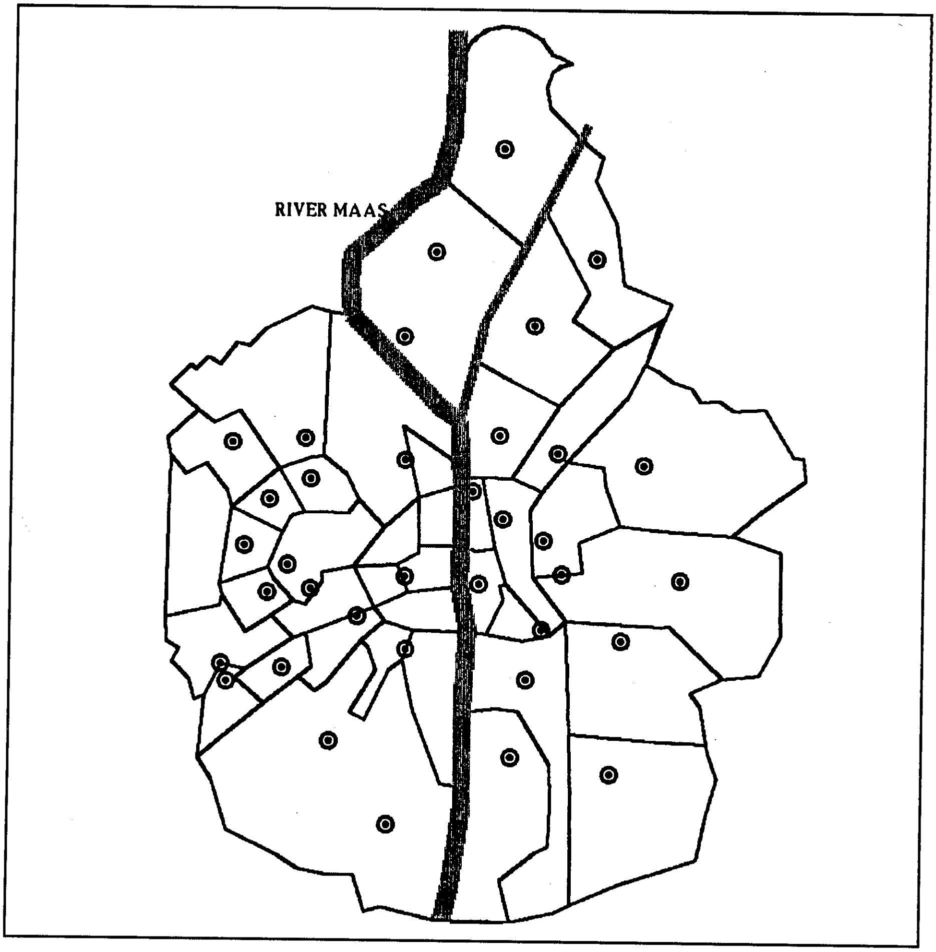

Figure 6.4. Neighbourhoods and shopping areas in Maastricht (source: Oppewal 1995).

6.3.3 Application

To illustrate the use of the model, we analysed the retail system in the city Maastricht, the Netherlands. Maastricht is a middle-sized city with approximately 117,000 inhabitants. Based on the zoning system used by the local authority, the city area was subdivided into 41 residential zones. The supply side consists of 30 shopping centres/areas. The map in Figure 6.4 shows the locations of the residential zones and shopping centres/areas that existed in the early nineties. The retail system is characterised by a relatively dense set of small neighbourhood centres. This reflects the planning concept prevailing in the post-war period in many municipalities in the Netherlands. In addition, there are two larger centres with an above-local service area: the centrally located major shopping centre and a regional centre in the north-west sector of the city. The centroids of residential zones and shopping centres were taken as the origin and destination locations. Travel distance was measured as the travel time in minutes across the road network.

Table 6.1. Reported purchase frequencies per year (N = 676).

Good	Average	Standard deviation
shoe-wear	3.7	3.5
appliances	4.0	7.0
clothing	10.7	10.7
drugs	26.6	25.7
books etc.	35.6	30.8
groceries	140.1	89.5

Six good categories were distinguished based on reported purchase frequencies by a sample of 676 households residing in the area. Table 6.1 presents the average and standard deviation of reported purchase frequencies per good category. Although the standard deviations indicate that a strong variation exists within categories across respondents, the average purchase frequencies were used in the analysis. It should be noted that the frequency distribution across the good categories violates the synchronisation constraint given by equation 6.1. However, as it turned out, this did not lead to any inconsistencies in purchase frequencies produced by the model (see the earlier note).

A multipurpose, multistop analysis (referred to as the MP-analysis) was compared with a conventional single purpose, single stop analysis (the SP-analysis). As it turned out, the average number of shopping trips T_i across zones i is 224 (st.dev. is 0) and 140 (st.dev. is 0.00) in the SP and the MP-case. The corresponding average trip lengths are 4.44 (st. dev. is 2.96) and 4.52 (st.dev. is 2.91) minutes. This means that the average total travel costs across origin locations in the MP-case is considerably lower than in the SP-case (632.83 against 993.73 minutes). Specifically, approximately 36% of the total travel costs can be reduced by multipurpose shopping. The trip-frequency component of this reduction is 400.46 and the trip-length component is -39.56.

It can be concluded from these results, that the retail system in Maastricht allows the average consumer to save a considerable portion of shopping trips through multipurpose shopping. The marginal increase in average trip length indicates that the composition of shopping centres approximates a perfect hierarchy.

As noted earlier, a conventional SP-analysis is insensitive to spatial agglomeration effects and, therefore, may produce biased information. An SP-analysis will fail to identify those consumer groups that can benefit to a larger degree from opportunities to reduce travel costs through multipurpose shopping than others. To test whether an MP-analysis indeed leads to a different ranking of consumer locations in this case, we have compared the rank scores produced by the MP and SP-model. As it appears, the Kendall's rank correlation coefficient is 0.92 indicating that in 92% of all possible pairs the two measures produce the same ranking. The observation that models lead to different rankings in some cases warrants the conclusion that the use of the MP-model may lead to different conclusions concerning the relative accessibility of locations (or, plan alternatives).

In general, shifts in rank scores arise from differences in the degree to which consumers benefit from multipurpose shopping. In the case of Maastricht, the reductions in number of trips appears to be constant across locations and increases of trip lengths are not substantial. A closer look at individual locations reveals that shifts in rank scores arise from differences in the length of saved trips across locations. Locations where long trips rather than short trips are saved benefit to a relatively high degree from multipurpose shopping and vice versa. The small differences in benefits follow from the (approximately) hierarchical structure of the shopping system. In a perfect hierarchy, the opportunities for multipurpose shopping at origin locations are at a maximum and multistop trips are absent. We may expect, therefore, that the agreement between outcomes of the two models will be smaller in cases where the retail system deviates to a larger extent from the perfect hierarchical form.

6.4 A multistop-based model for analysing spatial choice range

6.4.1 Introduction

The last section described a model for analysing the accessibility of retail and service systems in terms of the travel costs minimally required to satisfy the complete set of consumer demands. A complementary aspect of the spatial opportunities of consumers concerns the width and depth of the choice range of goods within a good category offered by available facilities. The aim of this section is to develop a model for analysing this complementary characteristic of retail and service systems. Thus, where the last section focused on travel costs in relation to the complete set of consumer goods, this section is concerned with the spatial choice range in relation to a single good category. The question is to what extent the physical structure of a given retail or service system satisfies the general desire of consumers to be able to choose between alternative opportunities.

The analysis of spatial opportunities is a recurrent subject in urban planning studies. As we have motivated earlier, opportunity-based models as opposed to

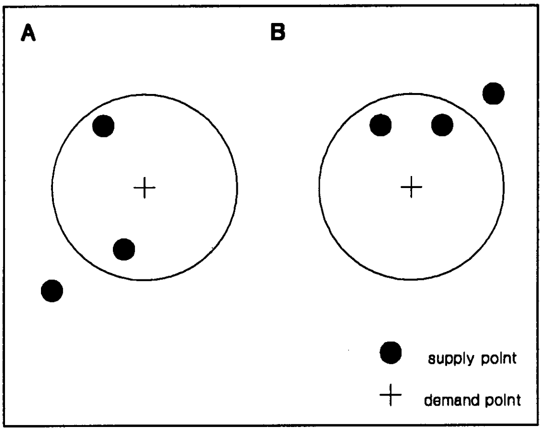

Figure 6.5. Illustration of measurement bias in cost-band models

behaviour-based models are currently of interest. Breheney (1978) has described a system which integrates existing opportunity-based models for analysing spatial opportunities. The system he describes works from a common data set which include the cumulative number of opportunities of a certain type within successive cost-bands away from a demand location. Given these data, three types of measures are calculated: (i) the number of opportunities available at a demand location within a critical level of travel costs (distance or time); (ii) the cost band from a demand location that captures a critical number of opportunities and (iii) the number of consumers having access to a critical number of opportunities within a critical level of costs. Essentially, these measures represent in different ways the relationship between opportunities and travel costs.

These cost-band based models can be criticised for the same simplifying assumption about how people travel that was also made in existing least-travel-costs models of accessibility. Just as the least-travel-costs models, the cost-band models assume that all trips to destinations are home-based and, therefore, they ignore the possibility of chaining together several destinations into trip tours. When trip-chaining behaviour is assumed, not only demand-supply distances, but also distances between supply locations are relevant. In that case the costs of reaching a certain number of opportunities decrease when supply locations are increasingly geographically clustered. This point is illustrated by the two facility systems shown in Figure 6.5. The number of opportunities within the specified cost band in A and B is the same. Consequently, current models would not differentiate between these two configurations, whereas in fact the consumer in B benefits to a higher degree from combining both facilities in a single trip than the consumer in A.

Another drawback of current measures concerns their insensitivity to differences in opportunities at the level of individual facility locations. The cost-band models simply count the facilities captured in the given cost-band and ignore possible differences for example in facility size. Obviously, this is in variance with reality where choice opportunities increase with the size of facilities or the variety of available supply. An adequate model of spatial opportunities must incorporate this factor.

Finally, there is a problem involved in determining the appropriate level of opportunities in order to measure travel costs or, reversely, in determining the appropriate level of costs in order to measure the level of opportunities. Objective criteria for setting the levels of these parameters are lacking, while they may seriously affect measurement results (Breheney 1978).

In this paper we introduce a new approach to analysing spatial opportunities that overcomes the drawbacks of current approaches outlined above. In this approach facilities are characterised by a probability of satisfying a given demand. This probability of success is assumed to be a function of the variety of supply offered by the facility. Then trip routes connecting one or more facility locations are constructed that have an acceptable probability of success. The expected amount of travelling of the optimal trip route is then determined as an indicator of spatial opportunities. This measure is sensitive to both the amount of supply in individual destinations and the distances between destinations. Note that there is only one purpose involved in the kind of multistop trips that are of concern here. Trips are chained not to combine different purposes but to achieve a single purpose.

6.4.2 Model specification

Assumptions

We consider a specific consumer location and a number of available spatially distributed opportunities for satisfying a given demand for goods or services. Each opportunity is characterised by a certain probability that the supply offered matches the given demand. This so called probability of success is supposed to be a function of the variety of supply. For example, the probability of successfully satisfying a demand for clothing in a shopping centre may be estimated based on the total floor space or number of types of clothing stores in that centre. We assume that trip chaining occurs when a purchase fails at a destination. In that case, the trip is continued to another destination where the demanded type of service is supplied. If the purchase also fails at the second destination, then the trip is again lengthened. This chaining of trips continues until the intended purchase is realised. We assume that the probability of success at a next destination does not depend on the supply at previous stops of the trip. However, the probability of success at a location which has been visited during the same trip is assumed to be zero. Finally, the assumption is made that the probability of success associated with a certain supply location is independent of whether or not purchases during previous trips to that location were successful.

Given the location of facilities and the attached probability of success, it is possible to construct for each consumer location chains of trips that have a high (nearly unity) probability of success. From this set of chains the optimum multistop trip, that is the chain with the lowest expected travel costs, can be selected. The costs of this optimum trip indicate the spatial opportunities available at the concerning demand location.

As in the case of the accessibility model described in the previous section, we emphasise that the proposed model must not be interpreted as a model of travel behaviour of consumers. The ideal trips are constructed not to reflect actual behaviour, but to indicate the least possible costs as an indicator of spatial opportunities.

Specification

The costs of the optimum trip from a consumer location is used as a measure of spatial opportunities. In order to establish for each consumer location the optimum route, we allocate trip stops to facility locations in such a way that the expected travel costs are at a minimum:

$$a_{ij} = \begin{cases} 1, & if\ C_{ij} < C_{ik},\ \forall k \neq j,\ j,k \in \boldsymbol{J}_i \\ 0, & otherwise \end{cases} \tag{6.12}$$

where $\boldsymbol{J}_i$ is the set of optional next destinations at the current location i. This choice-set includes the home location (i = 0) and all supply points reachable within a specified level of travel costs away from i, called the Scope parameter. C_{ij} are the expected travel costs assigned to a trip from i to the next destination j (that is the first destination when i is the home location). C_{ij} is formally defined as:

$$C_{ij} = D_{ij} + p_j D_{j0} + (1 - p_j) \textstyle\sum_k a_{jk} C_{jk} \tag{6.13}$$

where D_{ij} are the costs of travelling from i to j (D_{j0} = costs of travelling from j to the home location) and p_j is the probability of success at destination j. In words, the expected travel costs of a trip from i to j equal the costs of travelling to j (D_{ij}) plus the costs of travelling back home when the purchase at j has succeeded ($p_j\ D_{j0}$) plus the expected travel costs of a trip from j to the allocated next destination when the purchase at j has failed ((1 - p_j) $\Sigma\ a_{jk}\ C_{jk}$). Note that the expected travel costs are defined recursively: to determine the expected costs of a trip to the first destination, the expected costs of (continuing) the trip to the next destination must be known, and so on.

The allocation pattern that results from this recursive rule may differ from the allocation to nearest destinations. Differences may occur when other facilities are better accessible from a more distant destination. Another possible reason for bypassing the nearest supply location is that a more distant facility may increase the probability of success to such a degree that the expected costs of visiting that facility (and continuing the trip thereafter) are lower.

The home location is part of the set of optional destinations at every location. The home location is, however, not an attractive option, because the probability of success is zero at that location ($p_0 = 0$, since there are no facilities at home). The same holds for destinations which have been visited before in the same trip, because the probability of success at these locations has become zero.

The probability of success of a (multistop) trip starting from i is found by the following recursive formula:

$$P_i = p_i + (1 - p_i)\sum_j a_{ij} P_j \tag{6.14}$$

In words: the probability of success of a trip starting at i equals the probability of success in i plus the probability of success of (continuing) the trip starting at the next destination when the visit to i fails.

Table 6.2. The a_{ij}-variables of the example

	Destination 0	1	2	3	etc.
Origin 0	0	1	0	0	-
1	0	0	0	1	-
2	0	0	0	0	-
3	0	0	1	0	-
etc.	-	-	-	-	-

The following example serves to explain the recursive nature of equations 6.13 and 6.14. We assume that the set of a-variables, that is the allocation pattern, is already known (Table 6.2). This matrix describes a trip from 0 (the home location) to 1 and from there to 3 and next to 2 etc.. The expected costs of this trip are found by using equation 6.13:

$$C_{01} = \quad D_{01} + p_1 D_{10} + (1 - p_1) \Sigma a_{1k} C_{1k} \tag{6.15a}$$

Substitution of the a-variables results in:

$$C_{01} = \quad D_{01} + p_1 D_{10} + (1 - p_1) C_{13} \tag{6.15b}$$

The same formula, equation 6.13, is used to find C_{13}:

$$C_{01} = \quad D_{01} + p_1 D_{10} + (1 - p_1) \{ D_{13} + p_3 D_{30} + (1 - p_3) C_{32} \} \tag{6.15c}$$

Again, we use equation 6.13 to find C_{32} and so on. The result is (6.15d):

$$C_{01} = D_{01} + p_1 D_{10} + (1 - p_1) \{ D_{13} + p_3 D_{30} + (1 - p_3)\{ D_{32} + p_2 D_{20} + (1 - p_2) \{..\}\}\}$$

This can be rewritten as:

$$\begin{aligned} C_{01} = \quad & D_{01} + p_1 D_{10} + & (6.16a)\\ & + (1 - p_1)(D_{13} + p_3 D_{30}) + & (6.16b)\\ & + (1 - p_1)(1 - p_3)(D_{32} + p_2 D_{20}) + & (6.16c)\\ & + (1 - p_1)(1 - p_3)(1 - p_2)(..) + & (6.16d)\\ & + .. \end{aligned}$$

The equation expresses that costs assigned to a trip from 0 to 1 equal the costs of travelling from 0 to 1 including travelling back home when the purchase succeeds (6.16a) plus the costs associated to a trip from 1 to 3 when the purchase in 1 fails (6.16b) plus the costs of a trip from 3 to 2 when the purchase in 1 and 3 fails (6.16c) plus the costs of a trip from 2 to the next destination when the purchase in 1, 3 and 2 fails (6.16d), etc..

Next, the probability of success from the example trip is found by using equation 6.14:

$$P_0 = p_0 + (1 - p_0) \{ p_1 + (1 - p_1) \{ p_3 + (1 - p_3) \{ p_2 + (1 - p_2) \{..\}\}\}\} \qquad (6.17)$$

This can be rewritten as:

$$\begin{aligned} P_0 = \quad & p_0 + \\ & + (1 - p_0) p_1 + \\ & + (1 - p_0)(1 - p_1) p_3 + \qquad (6.18)\\ & + (1 - p_0)(1 - p_1)(1 - p_3) p_2 + \\ & + (1 - p_0)(1 - p_1)(1 - p_3)(1 - p_2)(..) + \\ & + .. \end{aligned}$$

As long as the successive probabilities, p_0, p_1, p_3, p_2 etc., are higher than zero, P_0 approaches to unity. This means that it becomes more and more likely that a trip succeeds with every successive continuation to a next destination.

In order to calculate the expected costs of a trip, we must define a criterion for terminating the recursion (the chaining of trips). We stop the recursion the moment P_i exceeds the specified level of probability that is supposed to be a sufficient approximation of unity (e.g., P^{lim} = 0.95). This means that the allocation to next destinations is stopped, when the trip, developed so far, is very likely to be successful. However, it may occur at a certain moment of choice that there are no optional next destinations with a probability higher than zero. In that case, the home location will be selected as the next destination (the home location is the most attractive option, because the return distance D_{00} is zero). The allocation of the home location is the second way of terminating a trip (stopping the recursion). Terminating a trip in this way implies that it is impossible to construct a trip with a satisfactory probability of success. This may occur when either the level of opportunities in the study area is too low or the specified scope that defines the set of optional destinations is too restrictive. Trips that fail to reach the specified level of probability cannot be compared to each other or to successful trips.

We conclude that by using equations 6.12 - 6.14 the optimum trip chain from each demand location can be determined. Next, the expected costs of successful trips can be compared to evaluate the relative level of opportunities at demand locations.

6.4.3 Application

To be useful as a measurement tool, the multistop model (in short the MS-model) must be robust for reasonable variations in the specification of the probability threshold and the function for calculating probabilities of success. Furthermore, the model must be sufficiently sensitive to differences in the spatial structure of supply, that is the model must lead to different measurement results compared to the alternative cost-band models. To investigate these properties, we have analysed as a case the retail system of the city Maastricht, the Netherlands, using both the MS-model and the cost-band alternative.

Description of the case

Just as in the case-study described in the previous section (6.2.3): the city area was subdivided into 41 residential zones which are considered the consumer origin locations; a total of 30 shopping centres were identified as the locations of supply and travel distance was measured as the travel time across the road network.

The probability of success of purchasing g at location j is calculated as a function of K indicators of supply, X, using the following general equation:

$$p_j^g = \begin{cases} 0, & \text{if } g \text{ is not supplied in } j \\ \exp(\sum_k \alpha_k^g X_{kj}^{*g}), & \text{otherwise} \end{cases} \tag{6.19}$$

X_{kj}^g is the score of g-type stores in centre j on the k-th indicator for g-type supply. The X-factors (indicators) are normalised to a scale ranging from zero to unity as follows:

$$X_{kj}^{*g} = \frac{X_{k\max}^{g} - X_{kj}^{g}}{X_{k\max}^{g} - X_{k\min}^{g}} \tag{6.20}$$

Where $X_{k\,min}{}^{g}$ and $X_{k\,max}{}^{g}$ are the minimum and maximum level of the k-th indicator. The probability of success is assumed to be an exponential function of (a measure of) supply resulting in a S-shaped relationship. As a consequence of using normalised supply factors, a maximum supply level corresponds to the maximum probability level of unity. The weights, α_k^g, are set to negative values, so that the function values range between infinitely small and unity. The relative level of the weights reflects the relative importance of the factors, whereas the absolute levels determine the slope of the curve (high absolute levels result in a steep curve).

In this case study we have considered the factors floor space, F, and number of shop types, N, as indicators of the variety of supply. Consequently, the general equation 6.19 is specified as:

$$p_j^g = \begin{cases} 0, & if \;\; g \text{ is not supplied in } j \\ \exp(\alpha_1^g F_j^{*g} + \alpha_2^g N_j^{*g}), & otherwise \end{cases} \tag{6.21}$$

Three supply segments (store types) have been analysed. From high to low density of stores, these are the food, clothing and shoe-wear sector.

Results

The length of optimum trip chains depends, among other factors, on the specified probability threshold. When the threshold is set to 0.95, the typical trip involves three to four destinations. Table 6.3 summarises the scores of demand locations of both the MS-model and the costs- band model, respectively. In the cost-band model, the number of opportunities to be captured was set to four different levels, i.e. 1, 2, 3 and 4 facilities (centres supplying g), resulting in four sets of scores. Note that the 1-facility variant corresponds to a least-travel-costs accessibility measure.

Table 6.3. The mean and standard deviation of the expected minimal travel costs (MS, P^{lim} = 0.95, α_1^g = - 0.35, α_2^g = -0.35) and the cost-bands capturing 1, 2, 3 and 4 facilities

	Food		Clothing		Shoe-wear	
	Mean	Stdv	Mean	Stdv	Mean	Stdv
MS	11.39	6.28	20.89	13.72	22.85	17.67
1 fac.	3.32	2.80	7.63	7.14	8.51	8.90
2 fac.	7.44	3.35	11.54	6.13	13.07	8.14
3 fac.	10.66	5.11	15.12	7.59	15.85	7.95
4 fac.	12.71	5.87	17.34	7.33	18.1	7.79

Absolute scores are often not very useful for spatial decision making. Evaluations and decisions are mostly based on the ranking of demand locations rather than exact positions on the concerning measurement scale. For example, the decision maker may wish to identify the 10% worst-off residential zones to decide where to locate additional facilities. Therefore, in the following we will consider rank scores rather than absolute scores. (Note that this implies a stricter test on the performance of the model, since differences in rank scores between models imply differences in absolute scores, but the reverse may not be true.)

Table 6.4. *The mean and standard deviation of probabilities of success for both normal and extreme values (1-4).*

	Norm.	(1)	(2)	(3)	(4)
	$\alpha_1^g = -0.35$	$\alpha_1^g = 0$	$\alpha_1^g = -0.70$	$\alpha_1^g = -0.26$	$\alpha_1^g = -0.46$
	$\alpha_2^g = -0.35$	$\alpha_2^g = -0.70$	$\alpha_2^g = 0$	$\alpha_2^g = -0.26$	$\alpha_2^g = -0.46$
Mean	0.68	0.71	0.74	0.75	0.61
St.dv.	0.14	0.14	0.13	0.11	0.17

Table 6.5. *Kendall's rank correlation coefficients for different probability-of-success distributions.*

	norm.	(1)	(2)	(3)	(4)
norm.	1				
(1)	0.91	1			
(2)	0.85	0.95	1		
(3)	0.87	0.90	0.90	1	
(4)	0.90	0.80	0.73	0.77	1

How sensitive is the MS-model to variations in the specification of the function for calculating probabilities of success? To assess this sensitivity, we have analysed the food sector using four different sets of probabilities, which were obtained by varying the weights α_1^g and α_2^g in equation 6.21. Both the weights relative to each other and the absolute level of the weights were varied. The effects of varying the function specifications on the distribution of probabilities across facility locations are shown in Table 6.4. An increase in the absolute value of both weights results in an increase in the variation of probability and vice versa. The degree to which the measurement results depend on the set of probabilities used is indicated by the rank correlation coefficients in Table 6.5. The degree of agreement between results varies between 73 and 95%. That is to say, 73 to 95% of all possible pairs of demand locations have the same rank ordering when the results based on different probability sets are compared.

The minimum expected costs of a successful trip depend on the threshold probability (the stop condition) specified by the user. How sensitive is the MS-model for variations in this parameter? Table 6.6 shows the rank correlation coefficients between the results that are obtained when the threshold probability is varied between 0.900 and 0.975. As it appears, the degree of agreement between results ranges between 95 and 98%.

Table 6.6. Kendall's rank correlation coefficients for various probability-threshold levels.

	Pl = 0.900	Pl = 0.925	Pl = 0.950	Pl = 0.975
Pl = 0.900	1			
Pl = 0.925	0.98	1		
Pl = 0.950	0.96	0.97	1	
Pl = 0.975	0.95	0.96	0.98	1

To what degree do the results of the MS-model differ from the results of alternative models? First, we have compared the MS-model with the cost-band model. Again, four critical levels of opportunities (1, 2, 3 and 4 facilities) were considered in the specification of the cost-band model. Second, we have compared the MS-model with the results that are obtained when single stop trips are assumed. The single stop alternative includes making different one-destination trips from the home location until the threshold level of probability is reached. The expected costs of the optimum set of trips is a measure of spatial opportunities. Finally, we have compared the MP-scores to scores that result when the probability of success at all supply locations is set to the same level (0.70). The comparison with the single stop and this 'equal probability' alternative yields insight in the separate effects of differences in supply size across facilities and in the spatial structure of supply locations on the measurement results. The tables 6.7, 6.8 and 6.9 show the degree of agreement between the models when they are applied to the food, clothing and shoe-wear sector respectively. (The '1-facility' level in the cost-band model is left out of consideration, since this measure is not comparable to the MS-model, which typically involves more than one facility location.) The degree of agreement between the MS-model and the cost-band model varies from 51 to 56% in case of the food sector, from 67 to 71% in the clothing sector and from 71 to 75% in the shoe-wear sector. The degree of agreement of the MS-model with the single stop alternative range between 91 and 94%. When compared with the 'equal probability' model, we find figures between 63 and 75%.

Further, it is interesting to compare the sets of scores that are obtained when the critical number of opportunities are set to different levels in the cost-band model. In case of the food sector we find correspondence rates ranging from 64 to 83%, in the clothing sector 68 to 84% and in the shoe-wear sector 75 to 96%.

Table 6.7. Kendall's rank correlation coefficients for the MS, the singlestop (SStop), the 'equal probability' (EQ) and the cost-band model, for the food sector.

	MStop	SStop	EQ	1 fac	2 fac	3 fac	4 fac
Mstop	1						
Sstop	0.92	1					
EQ	0.63	0.53	1				
1 fac	0.48	0.41	0.78	1			
2 fac	0.56	0.56	0.50	0.22	1		
3 fac	0.51	0.52	0.40	0.15	0.69	1	
4 fac	0.52	0.51	0.42	0.16	0.64	0.83	1

Table 6.8. Kendall's rank correlation coefficients for the clothing sector.

	MStop	SStop	EQ	1 fac	2 fac	3 fac	4 fac
Mstop	1						
Sstop	0.91	1					
EQ	0.70	0.61	1				
1 fac	0.60	0.52	0.90	1			
2 fac	0.71	0.70	0.64	0.52	1		
3 fac	0.67	0.70	0.55	0.43	0.74	1	
4 fac	0.69	0.69	0.55	0.44	0.68	0.84	1

Table 6.9. Kendall's rank correlation coefficients for the shoe-wear sector.

	MStop	SStop	EQ	1 fac	2 fac	3 fac	4 fac
Mstop	1						
Sstop	0.94	1					
EQ	0.75	0.71	1				
1 fac	0.68	0.62	0.90	1			
2 fac	0.71	0.72	0.62	0.51	1		
3 fac	0.75	0.77	0.65	0.55	0.76	1	
4 fac	0.74	0.75	0.59	0.48	0.75	0.96	1

Interpretation of the results

The relatively high standard deviations of the scores (Table 6.3) indicate that the MS-model strongly differentiates between demand locations. The MS-model appears to be rather sensitive to differences in the used set of probabilities of success (Table 6.5). This means that the results of the model depend to some degree on the specification of the function used to calculate probabilities. On the other hand, the model is not sensitive to variations in the chosen probability threshold within a reasonable range (Table 6.6).

Compared to the cost-band model, the MS-model leads to considerable shifts in the ranking of demand locations. This is particularly apparent in the case of the food sector, where agreement rates of approximately 50% are found (Table 6.7). But even in the sector where the highest degrees of agreement are found, that is shoe-wear, the

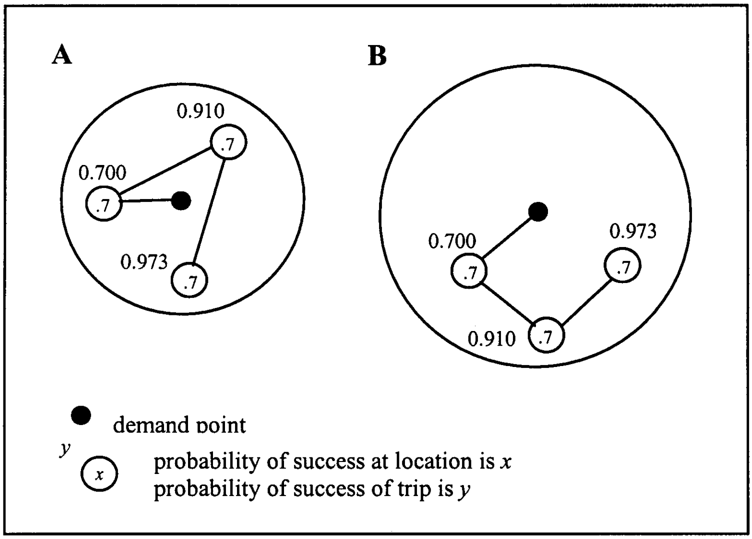

Figure 6.6. *Example 1: the cost-band and multistop model give different rankings of costs: A < B and A > B, respectively.*

shifts in rank scores are significant (r=[0.71, 0.75], Table 6.9). Therefore, the choice of using the MS-model rather than the currently used cost-band alternative, at least in the case of Maastricht, does have consequences for the evaluation of spatial opportunities at demand locations, irrespective of the type of stores considered.

To explain how differences between measurement results may arise, consider the pairs of shopping situations presented in figures 6.6 and 6.7. The pairs are analysed using both the cost-band and the MS-model. In both pairs the MS-model gives rise to a different ranking of the shopping situations, because of its sensitivity to the spatial structure of supply (Figure 6.6) and differences in supply size across centres (Figure 6.7).

Only slightly higher levels of agreement are found *within* the cost-band model when different critical numbers of facilities (2, 3 or 4) are chosen. This finding means that the cost-band model includes arbitrary elements if objective criteria for determining the critical number of facilities are lacking.

The assumption of multistop trips appears to have only a small effect on the measurement results. This follows from the high rates of correspondence between MS and single stop results (r=[0.91, 0.94]). The differentiation of probabilities of success, on the other hand, has a stronger impact on the results as indicated by the agreement rates between the MS and 'equal probability' model variants (r=[0.63, 0.75]). We conclude, therefore, that differences between demand locations are mainly caused by

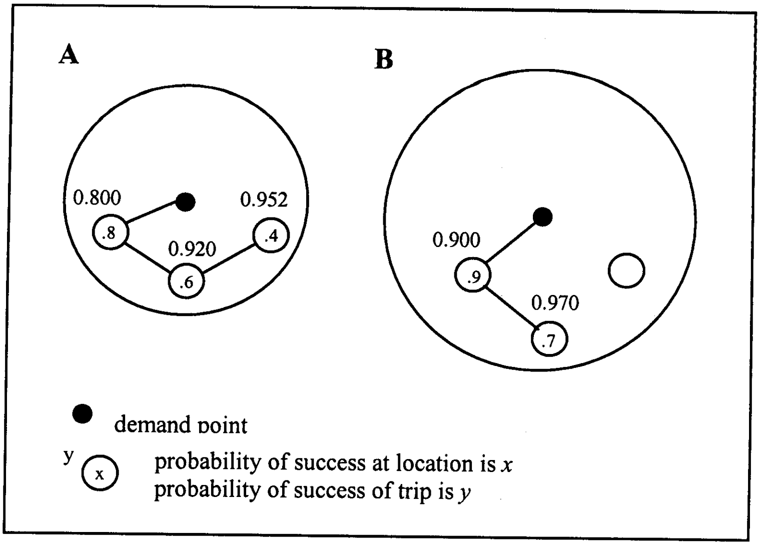

Figure 6.7. Example 2: the cost-b and multistop model give different rankings of costs: A < B and A > B, respectively.

differences in variety of supply at the level of individual facility locations and to a lesser extent by differences in distances between these locations. However, since it does have effect, albeit small, it is worthwhile to include trip chaining into the analysis.

6.5 Behavioural models for performance analysis

Existing interaction-based frameworks for performance analysis described in Clarke and Wilson (1994), Birkin (1994) and Birkin *et al.* (1996) are based on the conventional interaction model. The origin-destination matrices of consumer flows on which these frameworks are based are too restrictive to represent multipurpose, multistop shopping trips. Therefore, this section proposes an extended data structure to represent the more complex trips as well as a set of models required to derive relevant information from these data structures. The first section describes the proposed data structure and considers the question how data in that format can be computed based on the output of the multipurpose, multistop model. The next sections define the proposed models to derive measures of travel demand (an aspect of accessibility), consumer utility and demand-supply ratios (e.g., market shares). A case study to illustrate the application of behavioural models in retail impact studies is described in Chapter 9.

A data structure for describing multipurpose, multistop trips

Conventional interaction/choice models consider different market sectors of a retail/service system either separately or at an aggregate level. Hence, in these models a single two-dimensional matrix of interactions between origin and destination locations suffice to describe shopping behaviour in a given study area. The multipurpose, multstop model considers choice behaviour in different market sectors in interaction and, consequently, requires a more complex data structure. We propose the following set of variables for this purpose:

T_i is the total number of trips leaving consumer location i;

$a_i^{\boldsymbol{p}}$ is the probability of consumers in i selecting trip-purpose set $\boldsymbol{p} \in \boldsymbol{P}$;

$a_{i\boldsymbol{K}}^{\boldsymbol{p}}$ is the probability of consumers in i selecting destination set $\boldsymbol{K}$, given trip-purpose set $\boldsymbol{p}$.

where $\boldsymbol{p} = \{ p_1, p_2, \ldots, p_n \}$ is the ordered set of goods bought on a trip and $\boldsymbol{K} = \{ k_1, k_2, \ldots k_n \}$ is the ordered set of corresponding locations where each good is bought. Note that the following equalities hold:

$$\sum_p a_i^p = 1 \quad \sum_K a_{iK}^p = 1 \qquad (6.22)$$

Furthermore, it is worth noting that single-purpose, single-stop trips can be represented as special cases where both the purpose and destination set contain only a single element, i.e. $\boldsymbol{p} = \{ g \}$ and $\boldsymbol{K} = \{ j \}$. Finally, note that in contrast to conventional models, the T_i terms are not necessarily constant. Rather, the total number of trips may vary under influence of trip-purpose selection. A shift towards increased multipurpose shopping (due to supply factors) may lead to a decrease in the total number of trips and vice versa. Hence, in general the T_i variable is a function of supply-dependent purpose choice probabilities. Models for estimating T_i dependent on assumptions about trip-generation are derived below.

Having defined a suitable data-structure for representing multipurpose, multistop shopping trips, we can now turn to the question how these data can be derived from the multipurpose, multistop model described in the previous chapter. The choice probabilities predicted by the model can be written in terms of the following variables:

$a_i^{\boldsymbol{p}}$ is the probability of selecting purpose-set $\boldsymbol{p} \in \boldsymbol{P}$ (equation 5.10);

$a_{ij}^{\boldsymbol{p}}$ is the probability of selecting shopping centre j given purpose-set $\boldsymbol{p} = \{ p_1, p_2, \ldots, \ldots p_n \}$ in the *single* stop variant (equation 5.15);

$a_{i\boldsymbol{H}j}^{\boldsymbol{p}}$ is the probability of selecting shopping centre $j \in \boldsymbol{J}_i^g$ given purpose-set $\boldsymbol{p} = \{ p_1, p_2, \ldots, g, \ldots p_n \}$ and any arbitrary set of higher order locations $\boldsymbol{H} = \{ k_1, k_2, \ldots, k_{g-1} \}$ in the *multistop* variant (equation 5.21).

The second term represents destination choice in the single-stop specification of the model and the third term destination choice in the multi-stop specification. In the following, we will concentrate on the more general multi-stop case and use the third term only. The single-stop case can simply be computed in the equations below by assuming that the set of previously visited locations $\boldsymbol{H} = \varnothing$ and destination choice-sets are purpose rather than good specific ($j \in \boldsymbol{J}_i^p$ rather than $j \in \boldsymbol{J}_i^g$).

The desired structure a_{iK}^p for describing destination choice behaviour can be derived from the conditional choice probabilities a_{iHj}^p by the model by using the following recursive equation:

$$\begin{aligned} a_{i\varnothing}^{\boldsymbol{p}} &= 1 \\ a_{i\{H|j\}}^{\boldsymbol{p}} &= a_{iK}^{p} a_{iHj}^{p} \quad \boldsymbol{K} = \{k_1, k_2, ..., k_{g-1}\}, j \in \boldsymbol{J}_i^g, g \in \boldsymbol{p} \end{aligned} \tag{6.23}$$

This equation defines for a given purpose-set $\boldsymbol{p} = \{ p_1, p_2, ..., p_n \}$ and a given specification of the trip-chain $\boldsymbol{K} = \{ k_1, k_2, ..., k_n \}$ the probability of selecting $\boldsymbol{K}$ given $\boldsymbol{p}$. Thus, the a_{iK}^p structure is derived by applying equation 6.23 for each $\boldsymbol{p} \in \boldsymbol{P}$ and each possible specification of $\boldsymbol{K}$, given location choice-sets $\boldsymbol{J}_i^{p1}, \boldsymbol{J}_i^{p2} ... \boldsymbol{J}_i^{pn}$.

Finally, we need an expression for the total number of trips T_i leaving consumer location i. The proposed multipurpose model predicts the distribution of trips across trip types. Although it does not predict trip generation in a strict sense, a supply-sensitive trip generation model can be derived if we assume that individuals select multipurpose trips with the aim to reduce the number of trips required for purchasing goods. Note that by definition the purchase frequency of good g equals the total number of trips involving a purchase of g:

$$\sum\nolimits_{p \in P^g} a_i^p T_i = f_i^g \quad \forall i \in \boldsymbol{I} \tag{6.24}$$

where $\boldsymbol{P}^g \in \boldsymbol{P}$ is the subset of purposes including a purchase of g and f_i^g is the purchase frequency of good g. In words, the sum of trips in which g is purchased must be equal to the purchase frequency of g, for each g. Given this constraint, we can distinguish two scenarios of how individuals respond to a change in multipurpose trips. In the first scenario, which is implicitly assumed in conventional approaches, individuals simply keep the total number of trips constant, i.e.:

$$T_i = c \tag{6.25}$$

where c is a given constant, and adjust purchase frequencies according to constraint 6.24. In the second scenario, individuals keep the total frequency of purchases constant and adjust the number of required trips. Then, the total trip frequency can be calculated as:

$$T_i = \frac{c}{\sum_g \sum_{p \in P^g} a_i^p} \tag{6.26}$$

where c is a constant representing the sum of purchase frequencies across goods. Since the same good g may occur in more than one purpose set, $\boldsymbol{p}$, the denominator of the quotient in Equation 6.26 is greater or equal than one, indicating that the number of trips is smaller or equal to the number of purchases. Consider for example a simple 2-good system where $a^{\{1\}}$, $a^{\{2\}}$ and $a^{\{1,2\}}$ represent the choice probabilities of a 1-trip, 2-trip and 1,2-trip. In that case Equation 6.26 becomes:

$$T_i = \frac{c}{a_i^{\{1\}} + a_i^{\{2\}} + 2a_i^{\{1,2\}}} = \frac{c}{1 + a_i^{\{1,2\}}} \tag{6.27}$$

If $a^{\{1,2\}} > 0$, then $T_i > c$. In words, when multipurpose trips occur, the denominator represents the reduction of trips achieved by making multipurpose trips.

The two models 6.25 and 6.26 represent the two extreme cases where individuals either keep purchase frequencies or trip frequencies constant in response to changes in multipurpose trips. In reality, we may assume that consumers adjust both frequencies in response to changes in supply and that, consequently, trip frequency will lie somewhere in between these two extremes. Users can choose the appropriate model for the application at hand.

In sum, the set of variables T_i, a_i^p, a_{iK}^p, which can be derived from the multipurpose, multistop model, gives a suitable description of behavioural aspects of retail/service systems. These variables will be taken as the starting point to derive models for performance analysis in the remainder of this section.

Travel demand models

Travel demand is generally an issue in the context of transportation policies. Travel demand models determine the amount of travel from consumer origin locations to locations of supply for $g = 1...G$. We conceptualise travel demand as the product of trip frequency and average trip length:

$$C_i = T_i D_i \tag{6.28}$$

where C_i is travel demand of consumers at location i, T_i is the number of trips leaving location i, and D_i is the average trip length. As explained above, T_i may be defined either as a constant or a function of multipurpose trips. In the latter case, the travel demand model is sensitive for changes in trip-generation due to supply factors. The average trip length can be found by calculating:

$$D_i = \sum\nolimits_{p \in P} a_i^p \sum\nolimits_{k \in K} a_{ik}^p D_{iK}^p \tag{6.29}$$

where $\boldsymbol{p} = \{ p_1, p_2, ..., p_n \}$, $\boldsymbol{K}$ is the superset of all possible trip-chains given purpose $\boldsymbol{p}$ and location choice-sets $\boldsymbol{J}_i^{p1}$, $\boldsymbol{J}_i^{p2}$ ... $\boldsymbol{J}_i^{pn}$ and D_{ik} is the length of trip-chain $\boldsymbol{k}$ originating from i, given some optimal routing strategy (e.g., shortest path). (Note that in this equation the a_{iK}^p term sums up to unity). The C_i data can be aggregated to obtain a measure of travel demand for the study area as a whole:

$$C = \sum\nolimits_{i \in I} C_i \tag{6.30}$$

This measure of system travel costs may be used to rank alternative retail plans on total travel demand.

In summary, the advantage of the above travel-demand model over conventional travel demand models is that the measure is sensitive to changes in the choice of trip purpose. This has two effects. First, supply induced shifts for example towards higher probabilities of higher-order trips at the expense of lower order trips may lead to larger average trip lengths. Second, an increase in multipurpose trips may lead to a reduction of the number of trips required to realise a given set of purchases.

In a possible extension of the multipurpose, multistop model, the choice of transport mode per trip-type $\boldsymbol{p}$ is included as an additional choice dimension. The extended model would allow one to evaluate impacts of spatial policies on modal split. The case study described in (Oppewal *et al.* 1997b) illustrates the estimation and use of a combined destination and mode choice model in a regional impact analysis study.

Demand-supply ratio models

These models analyse the economic performance of shopping centres. The predicted a_i^p and a_{iK}^p data can be used to allocate available expenditure in consumer locations i for each good g to destinations j and, thus, estimate market shares of centres by store type.

Following common practice in retail impact studies, we assume that for each demand location i the available expenditure for good g is a given constant. Possibly, this constant is calculated as the product of population size and a national per capita expenditure rate possibly adjusted for socio-economic characteristics of the local population. The trip choice probabilities are used to allocate available expenditure across supply locations, as follows:

$$E_{ij}^{g} = E_{i}^{g} \frac{\sum_{p \in P^{g}} w_{g}^{p} \left(1 - a_{i0}^{p}\right) \sum_{k \in K^{j}} a_{ik}^{p}}{\sum_{p \in P^{g}} w_{g}^{p} a_{i}^{p}} \tag{6.31}$$

where E_{ij}^{g} is the flow of g-type expenditure from demand location i to centre j, E_{i}^{g} is the available expenditure for goods g in demand location i, $w_{g}^{\,p}$ is a weight expressing the relative amount of expenditure for g on trips of type $\boldsymbol{p}$, a_{i0}^{p} is a is a given probability of consumers i selecting destinations outside the study area for purpose $\boldsymbol{p}$, and $\boldsymbol{K}^{j}$ is the superset of all possible trip-chains given purpose $\boldsymbol{p} = \{ p_1, p_2, ..., p_n \}$and location choice-sets $\boldsymbol{J}_{i}^{p1}$, $\boldsymbol{J}_{i}^{p2}$ ... $\boldsymbol{J}_{i}^{pn}$ that includes destination j. Usually, the probability of trips to locations outside the study area, a_{i0}^{p}, is estimated based on rules of thumb and specific knowledge of the area. For example, locations near the borders of the study area will have higher shares of external trips than more centrally located zones. The weights, w_{g}^{p}, are specific for the multipurpose trip model. Inclusion of this parameter reflects the notion that the amount of expenditure per trip for a good may be dependent on trip type. For example, we may assume that expenses for a good are less on trips where the good is combined with other goods.

When expressed as a percentage of the totals E_{i}^{g}, the E_{ij}^{g}-flows can be interpreted as penetration rates of g-type stores in centre j in the local market area i. Furthermore, the aggregated value across origin locations:

$$E_{j}^{g} = \sum_{i} E_{ij}^{g} \tag{6.32}$$

provides an estimate of turnover of g-stores in centre j attracted from the study area. In addition the inflows of expenditure from outside the study area must be taken into account. Following common practice, we will assume constant, good-specific and centre-specific inflow volumes. Then, an estimate of turnover volumes becomes:

$$TO_{j}^{g} = \sum_{i} E_{ij}^{g} + E_{j}^{g\ \text{in}} \quad g = 1...G, \forall j \in J_{i}^{g} \tag{6.33}$$

where TO_{j}^{g} is the turnover of g-stores of centre j and $E_{j}^{g\ in}$ is the expenditure component originating from outside the study area. The turnover rates allow one to calculate indicators of profitability such as for example turnover per unit floor space.

As implied by equation 6.31, the method proposed here assumes that both per-capita expenditure and expenditure outflow volumes are supply-inelastic. In a more sophisticated model, these volumes are determined as a function of available supply, possibly by using regression modelling techniques, as suggested by Ghosh and McLafferty (1987) or an interaction model (Ottensman 1997).

In sum, the proposed model makes sure that available expenditure is allocated to centres proportionally to the probability of selecting the centre, while taking into account possible differences between trip types in the amount of goods purchased, purpose adjustment effects, joint attraction effects, expenditure outflows and expenditure inflows.

A consumer utility model

These models measure the utility consumers can derive from available supply. The measure takes into account the disutility of travel and the attractiveness of the shopping centres in the choice-sets of consumers. In that sense, the model is equivalent to the consumer surplus measure that has been derived from spatial interaction models, as noted in Section 2 of this chapter.

Following Ben-Akiva and Lerman (1978), we define consumer utility as the expected maximum of the utility values across elements of the choice-set. In the multipurpose model the error terms are Gumbel distributed, so that the expected maximum can be calculated as (Ben-Akiva and Lerman 1978):

$$U_{i\max} = \ln \sum_{p \in P} \exp\left(V_i^p + V_i'^p\right) \quad \forall i \in \boldsymbol{I} \tag{6.34}$$

where $U_{i\max}$ is a measure of consumer utility and V_i^p and V'^p_i are the structural supply-independent and supply-dependent utility components of trip-types $\boldsymbol{p}$, as defined by equations 5.12 and 5.13.

As this measure has no dimension, the absolute value does not have a meaning without a reference value. In spatial planning, the measure may still be useful, namely for ranking consumer locations on a welfare criterion. Furthermore, when aggregated across consumer locations the measure can be used for ranking plan alternatives. One should keep in mind that the quality of the information depends on the ability of the model to adequately represent preferences of consumers (in terms of estimated scaled attribute weights).

Concluding remarks

The multipurpose, multistop framework for analysing system performance is sensitive for agglomeration forces, as it considers different market sectors in interaction and allows for trip chaining. This increased sensitivity is reflected in the fact that the measures depend on several additional assumptions. First, for predicting travel demand an assumption must be made about how consumers adjust their shopping pattern if frequencies of multipurpose trips change. One may either keep purchase frequencies constant and derive trip-generation from supply-sensitive relative frequency of multipurpose trips or keep total trip frequencies constant and derive purchase frequencies dependent on multipurpose trips. Which assumption is more adequate is a matter of empirical investigation. In future research, it seems interesting to estimate elasticity coefficients of trip and purchase frequencies based on shopping trip data. Possibly, this can be done within the framework of the multipurpose trip model.

Second, for predicting market share allocation across centres, an assumption must be made about how consumers distribute their expenditure for the concerned good across trip types. Users must specify for each good and each trip-purpose a weight indicating the share of trip-type in expenditure. Future research could focus on further refining the model by incorporating and empirically estimating an appropriate coefficient also for this aspect of behaviour.

6.6 A system of performance analysis models

The behavioural as well as opportunity-based models described in the last sections all evaluate some characteristic of the interaction between demand and supply locations. This section describes a system for implementing the models based on the assumption that every instance of this class of models can be decomposed into a number of components, which are characterised by fixed input and output data formats and limited interaction. In the proposed system, the components are implemented as individual computational objects. The retrieval and integration of components is handled by a specialised model management system. Figure 6.8 schematically shows the proposed method of decomposition and functional relationships between the components.

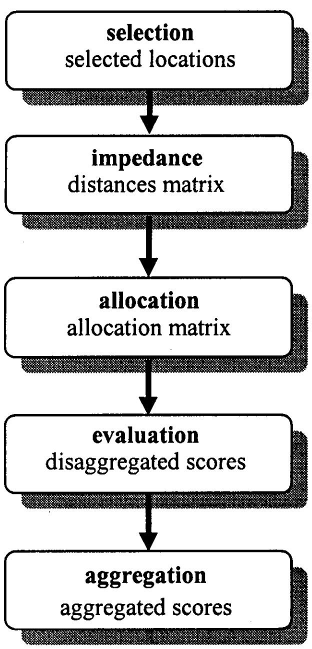

Figure 6.8. Components of performance-analysis models.

The object-oriented approach to implement a model management system has recently been proposed in the context of business-management applications as well (Ma 1995, Kwon and Park 1997). The purpose of this section is not to describe the system in much detail. Instead, we briefly discuss some principles of the object-oriented approach and for each component the function it computes. For a formal specification of the components readers are referred to the general literature in performance analysis (existing models) and the earlier sections of this chapter (new models).

Some principles of the object-oriented approach in structured modelling
As in object-oriented computer programming, the computational objects have an interface and an implementation section. In the system proposed here, the interface section specifies the input-output function the component computes. The system that integrates and manages the components may receive as input user-defined combinations of components. The system links components to each other in the pre-defined way by means of collecting and passing through messages. Moreover, the model management system is able to handle queries of users and derive the appropriate combinations dynamically. For this latter function, the engine incorporates knowledge not only about input-output relationships but also about logical relationships constraining possible combinations. The principle of data encapsulation is employed in the sense that the system communicates through the interface sections of the components and does not need information about the implementation sections.

The selection function
Not all demand or supply locations in the study area may be relevant for analysing given plan alternatives. Given a set of demand locations I and a set of supply locations J, the selection function defines the relevant subsets I^* and J^*. For example, the selection of demand locations may be based on location (e.g., all consumers in a given subarea), a certain target consumer profile or some combination of geographical and sectorial characteristics. Similarly, the selection of supply locations may be defined in terms of facility type (e.g., all food stores), formula characteristics (e.g., all specialist stores or supermarkets), organisation characteristics (e.g., all stores of a particular chain) or geographical characteristics (e.g., all stores in a local market area). It is worth noting that the selection of supply locations is constrained by the purpose of the subsequent analysis. For analysing spatial shopping behaviour, the selection should include at least all shopping centres or stores that occur in the choice-sets of the selected consumer groups.

The impedance function
The impedance function defines the spatial separation between locations. Generally, the function involves (i) a behavioural model of route choice (e.g., shortest path), (ii) a method of determining the generalised costs (e.g., travel time) of the route and (iii) available parking facilities at the destination. Each component can be specified in different ways dependent on specific information needs. Typically, a choice is involved regarding the mode of transport (e.g., public or private transport) one wishes to evaluate. Here, it is not the place to review models of this category. For this readers are

referred to Puu (1997). It suffices to note that the choice of the impedance function is constrained when a shopping model is used in the next analysis step. That is to say, the impedance function should be consistent with the distance parameter of the shopping model.

The allocation function

The allocation function defines the interaction probability between elements of set I^* and set J^* as a function of travel costs (impedance), attributes of competing shopping locations in J^* and, possibly, also attributes of the consumer population in I^*. The following allocation functions are considered relevant for the spatial planning DSS:

1. Allocation to X *nearest* centres, where X is a pre-specified number of centres.
2. Allocation to centres within *cost-band* C, where C is a pre-specified level of travel costs.
3. Allocation based on minimising *net* travel costs (the multipurpose model of accessibility developed in section 6.3).
4. Allocation based on minimising *expected* travel costs (the multistop model of spatial choice range developed in section 6.4).
5. Allocation based on *entropy* maximisation (the class of spatial interaction models, see section 5.2).
6. Allocation based on *utility* maximisation (the class of conventional MNL-models, see section 5.2, and the multipurpose, multistop model developed in section 5.3).

The first two rules employ an all-or-nothing, single stop and single purpose allocation. The third rule applies an all-or-nothing, multipurpose, multistop allocation and the fourth rule a probabilistic, single purpose, multistop allocation. The third and the fourth rule were developed in sections 6.3 and 6.4, as a refinement of the nearest-centre (rule 1) and cost-band based models (rule 2), respectively. Given these refinements the meaning of the first two rules is limited in the spatial DSS. Nevertheless, they are included as easy-to-use additional tools for analysis. The fifth rule and sixth rule, on the other hand, are probabilistic. Arguably, the utility-based rules are to be preferred, as they are based on a sound theory of spatial choice behaviour. The multipurpose, multistop based model, which was developed in chapter 5, represents the most encompassing rule of this class. Since this rule covers the general case and is consistent with discrete choice theory, the use of the entropy-maximisation rule as well as the conventional MNL-based rules is limited. Again, they are nevertheless included in the spatial DSS as easy-to-use alternatives for limited analytic purposes.

The generic data-structure developed in section 6.5 is suitable for storing the allocation information generated by these rules. The data-structure consists of the vector T_i (trip-generation), a two-dimensional matrix a_i^p (trip purpose probability) and a three-dimensional matrix a_{iK}^p (trip-chain probability). The $\boldsymbol{p}$-dimension consists of all the sets that can be formed given the consumer goods distinguished (g = 1...G). The $\boldsymbol{K}$-dimension consists of all trip-chains that can be formed given the destination choice-sets (J_i^g) for each good contained in $\boldsymbol{p}$. Single-purpose trips and/or single stop trips are stored as special cases in which $\boldsymbol{K}$ and/or $\boldsymbol{p}$ consist of only one element. Also, all-or-nothing allocation based on deterministic rules can be stored in this structure, namely as the special case in which the allocation variable takes on a zero or one value only. Finally, it should be noted that the T_i and a_i^p variables are exogenous to all the models except the most encompassing multipurpose, multistop model. In the case of the more restricted rules, these variables are specified by users.

The evaluation function

The evaluation function takes as input the allocation information given by T_i, a_i^p and a_{iK}^p and returns as output either a matrix of performance scores related to interactions (say, C_{ij} or C_{ij}^g) or a vector of performance scores related to demand objects (say, C_i or C_i^g) or supply objects (say, C_j or C_j^g). The format of the output depends on the chosen degree and method of spatial aggregation. The evaluation functions that are relevant for the spatial DSS evaluate the following dimensions of allocation relationships:

1. Travel costs (demand-related accessibility, spatial choice range or travel demand).
2. Available opportunities (demand-related spatial choice range)
3. Total or expected maximum utility (demand-related consumer utility).
4. Demand-supply ratio's (supply related measures of efficiency and demand related measures of effectiveness).

These dimensions correspond to the classification of performance dimensions in section 6.2. The *first* dimension can be handled by a generic function which claculates travel costs as a function of the allocation and impedance variables (see Equation 6.28). At this point the advantage of the modular approach becomes apparent. The interpretation of the function depends on the allocation rule that was used to generate the trips. For example, dependent on the allocation rule used, Equation 6.8 will produce the nearest-centre distance, minimum net travel costs, minimum expected travel costs, total travel demand etc.. Each of these measures highlight a specific characteristic of the retail system.

The *second* dimension can also be handled by a generic function. This function evaluates the weighted sum of opportunities, using the allocation variable as a weight. Measures of this type, such as for example the count of facilities within a pre-specified cost-band, have been influential in public sector planning studies, as noted earlier. However, the stand point taken in this study is that the minimum expected travel costs measure developed in section 6.4 gives a better account of this dimension. Therefore, the meaning of the second evaluation function is limited.

The *third* dimension concerns total utility (weighted sum across facilities) or, in the case of random utilities, the expected maximum utility implied by the given allocation pattern. In these functions the allocation information is used to identify the choice-sets. Equation 6.34 is a particular example of a function which returns the expected maximum utility, if Gumbel-distributed error terms are assumed. Finally, the *fourth* dimension is covered by a class of functions concerned with demand-supply ratio's. These include market penetration, market share, per-capita floor space, turn over per unit floor space etc.. Equations 6.31-6.33 illustrate how this information can be derived from the general format allocation data.

The aggregation function

The aggregation function is a final optional component of performance models which serves to aggregate obtained demand or supply related scores. This component is relevant to evaluate alternative plans at the level of the study area or larger subareas within the study area. In general a given set of scores is summarised by its central tendency and its variance. Therefore, the aggregation component incorporates central tendency and variance statistics using the size of demand or supply as a weight. As noted before, the variance measures have a special meaning in the context of retail planning. The variance of scores across locations is used as an indicator of the equity of spatial opportunities across consumer or producer locations. Useful methods of measuring variance for this purpose are reviewed in Gaile (1977) and Mulligan (1991).

Conclusion

This section has identified the atomic elements of models for performance analysis in spatial planning and proposed an object-oriented model management system. The specific performance models that were proposed in sections 6.2 - 6.4 can be reconstructed out of these building blocks. The behavioural models (section 6.2) result when the multipurpose, multistop shopping model (allocation) is used in combination with functions for evaluating travel costs, maximum expected utility or demand-supply ratios. The accessibility model (section 6.3) results from using the 'minimum net travel costs' allocation rule and, next, evaluating travel costs of the constructed trips. Similarly, the spatial-choice-range model (section 6.4) follows when the 'minimum expected travel costs' allocation rule is used in combination with the same 'travel costs' evaluation function. Table 6.10 gives a summary of existing and proposed models and the used allocation and evaluation components.

As was argued in this chapter, these models cover the most important issues in retail and service planning and, in contrast to existing models, they can account for more complex spatial shopping behaviour. The component functions described in this

Table 6.10. Allocation and evaluation components of existing and new performance models.

allocation function	evaluation function				
	travel cost	available opportunities	utility	demand related ratios	supply related ratios
N nearest-centres	least-travel models of accessibility (e.g., Guy 1977) drive-band distance measures (Breheney 1978)	–	–	proximal area-based floor space per head of the population demand coverage measures	demand in proximal area (applied studies)
centres in cost-band C	–	available supply in cost-band (Breheney 1978)	max. expected utility (Ben-Akiva and Lerman 1978) consumer surplus (e.g., Coelho and Wilson 1976)	costband based floor-space per head of the population	–
minimise *net* travel	multipurpose model of accessibility (section 6.3)	–	–	–	–
minimise *expected* travel	multistop model of spatial choice range (section 6.4)	–	–	–	–
maximise entropy (spatial interaction)	travel demand models (e.g., Jones 1981)	weighted supply measures of accessibility (e.g., Koenig 1980)	–	interaction-based indicators of service-provision effectiveness (Clarke and Wilson 1994)	interaction-based indicators of service efficiency (e.g., Clarke and Wilson 1994)
maximise utility (MNL, nested-logit)	travel demand models (e.g., Jones 1981, section 6.5)	–	–	–	choice-based measures of efficiency (e.g., section 6.3)

chapter allow in addition the reconstruction of other models which have been influential in urban studies. These alternative models (e.g., cost-band based models, spatial interaction models) often represent the more restrictive counterparts of the proposed models. Yet, they may be useful in a DSS-context for specific purposes or when data for the more complex model types are not available.

6.7 Conclusion

This chapter has developed a comprehensive set of models for analysing retail systems in relation to a wide range of planning objectives. The model system accounts for agglomeration effects produced by multipurpose, multistop shopping behaviour and deals with both opportunity and behaviour-based performance analyse. The behaviour-based models are complementary to the proposed multipurpose, multistop shopping model (Chapter 5). They extract from predicted trip patterns information about travel demands, consumer utilities and economic performance of centres. An application in the context of a retail impact study is described in Chapter 9. The oppurtunity-based models were concerned with accessibility and spatial choice range of facilities. The specific advantages of opportunity-based models are that they analyse spatial opportunities independent of actual behaviour, have a clear interpretation and have only modest data needs.

The accessibility model

The proposed accessibility model evaluates spatial structures in terms of the travel costs minimally required to purchase the complete set of consumer goods from a specific location. Unlike existing models, the proposed model is sensitive to variations in distances between locations of supply, since it takes into account offered opportunities for multipurpose behaviour. Consequently, even if distances between demand and supply locations are the same, the multipurpose-analysis may lead to different conclusions on the relative performance at the level of demand locations or plan alternatives. A case study showed that the model indeed may lead to shifts in the ranking of locations. In this case, the observed shifts were relatively small. However, one may expect the model to have a bigger impact when alternative location plans, rather than individual (demand) locations, are considered. For example, the options of either locating new retail developments within existing centres or at off-centre sites may be evaluated quite differently when a multipurpose rather than a single-purpose analysis is conducted. In addition, the comparison of results between these two types of analysis yields useful information about the size of spatial agglomeration effects in a particular configuration of the system.

We should also point at potential limitations of the model. First, the sensitiveness and accuracy of the model will depend on the subdivision of consumer goods into categories. The subdivision should be sufficiently fine and cover the complete set of goods. Second, travelling back home is not considered in determining the optimal route of multistop trips. This means that the model does not differentiate between chains of trips of equal length which differ in distance between the last destination and the home location. This may affect the accuracy of the outcomes.

The spatial choice-range model

This model can provide complementary information about the spatial choice opportunities of consumers. Where the multipurpose model is useful for assessing efforts required to satisfy demands, the multistop model can reveal choice opportunities within supply segments offered by the retail system. Therefore, when used in combination, the models allow planners to analyse the retail system from different, complementary perspectives. The model is applicable to all types of goods or services for which the probability of satisfying consumer demands depends on the diversity or size of supply. Generally, this is the case for comparison goods, such as clothing and shoes, whereby typically purchase decisions are based on comparing different stores.

The proposed model is a refinement of current models that measure the number of opportunities falling within a pre-specified cost-band from demand locations. In contrast to these cost-band based models, the proposed model accounts for distances between supply locations and the variety of supply at these locations, assuming multistop rather than single stop travel behaviour. The results of a case study show that the new model may lead to different evaluations of opportunities in comparing demand locations. Furthermore, the results appear to be practically insensitive for the chosen critical level of supply (the probability threshold). The alternative cost-band model, in contrast, appears to be highly sensitive to the chosen critical number of facilities. This is a serious drawback, since there are no objective criteria available for determining the level of this parameter (Breheney 1978).

The multistop-based model is slightly sensitive to variations in probabilities of success assigned to facilities. This means that measurement results may be somewhat distorted if these probabilities do not accurately reflect the variety of supply across facilities. In order to obtain good estimates, the function used for calculating probabilities of success can be specified based on observed consumer behaviour. General choice modelling techniques can be used to select appropriate independent factors (indicators of the variety of supply) and to determine appropriate levels of the function parameters.

A system of performance models

Finally, it was shown how the general class of performance models can be implemented in a flexible way by applying an object-oriented approach. In the proposed system, performance models are decomposed into atomic elements and defined in terms of formulas for combining these elements. The advantages of this modular structure of a DSS model base were already discussed in chapter 4. An additional advantage follows from another interpretation of the atomic elements. Selection, impedance, allocation, evaluation and aggregation can be viewed, at the same time, as successive steps in performance analysis. The output of each step provides information in itself. The information relates to entities located in space and, thus, can be displayed on a map of the study area. For example, the allocation information can be visualised as trip-chains or flows connecting consumer and shopping locations. Visual inspection of selection, impedance, allocation and evaluation information can enhance the understanding of retail system operations, especially, in the exploration and creative stages of decision making. By splitting up models in elementary components, the system can support each of the successive analysis steps in its own right.

The modular approach is based on the assumption that model components have limited interaction. In the present application, this assumption is valid only to a limited extent. Not every possible combination of functions is meaningful. Particularly, the combination of deterministic allocation functions on the one hand and utility-based evaluation functions on the other does not make sense. Also, behavioural models for allocation impose constraints on the specification of the selection and impedance functions and so on. Such constraints should be incorporated in an engine that is responsible for integrating and managing the components.

The models described in this chapter complete the inference layer of the DSS model-base. The following chapter will be concerned with the task layer in which information produced in the inference layer is translated in possible actions for achieving goals.

CHAPTER 7

A KNOWLEDGE-BASED MODEL FOR DEVELOPING RETAIL LOCATION STRATEGIES (TASK LAYER)

7.1 Introduction

The purpose of inference-layer models developed in the previous chapters is to analyse retail systems and to predict the impact of action plans. However, knowing what the effects of actions are does not readily answer the question which actions are likely to be successful to reduce observed imbalances in the system or to utilise opportunities for expansion. Given the complexity of retail systems and the multiple, often conflicting planning objectives, it is often difficult to obtain a clear view of the problem and possible solutions. This chapter focuses on models for developing location strategies in the plan generation stage of decision making. The models are aimed at translating output of the lower-level inference-layer models into suggestions for actions. Thus, the models specify the task layer of the DSS-model base.

The models that are of interest here focus on optimising or improving the location, size and branch composition of shopping centres or stores in a given market area. The argument of this chapter is that existing optimisation models developed in operations research and spatial sciences are potentially useful for solving relatively well-structured subproblems in retail planning. For structuring the overall problem, we will propose a knowledge-based model. The model incorporates heuristics for the major steps in the planning cycle, i.e. identifying problems, analysing the problem and identifying possible actions. In combination with inference models and in interaction with decision makers, the knowledge-based model supports the development, simulation and analysis of action scenarios.

To develop the task-layer knowledge, this chapter is organised in various sections. First, in section 7.2 we review existing approaches in location modelling and discuss the assumptions of our approach. Then, in the sections that follow we describe the proposed knowledge-based model. Successively, we consider the knowledge representation formalism (7.3) and discuss the proposed model in terms of the basic notions (7.4), a possible specification (7.5) and implementation in an automated knowledge-base (7.6). Then, Section 7.7 describes a case study to illustrate the application of the model in combination with a consumer choice model for developing and analysing action scenarios. Finally, the last section (7.8) discusses the potentials and limitations of the proposed model for use in a spatial DSS.

7.2 Modelling approaches

The concept of user-attracting systems was already defined in Chapter 1. In the context of task-layer models it is useful to elaborate this definition in terms of the roles the different parties play. These are defined by Leonardi (1981b) as follows:

- users travel to facility locations for satisfying their demand or needs (in contrast to delivery systems, where goods and services are delivered by suppliers to locations of demand);
- users choose the destination location (in contrast to systems such as some school systems in the US where the allocation of children to schools is planned);
- transport costs (not necessarily in terms of money) are charged to the users and costs for establishing facilities are paid by local authorities or a private firm.

Hence, models of user-attraction systems must represent two sets of decisions, namely determining the location of facilities and the allocation of demand to these facilities. In the early sixties, location-allocation models became popular as a framework for optimising simultaneously this location and allocation component. To date, it is still an active area of research in operations research, geography and urban planning from which a vast body of literature emerged.

Location-Allocation Models

Following the mathematical programming approach, the goal of location-allocation modelling is to define a set of generic problems and develop standard algorithms to solve them. Problems are defined in terms of an objective function and a set of constraints on decision variables. A basic example is the p-median model. The objective of this model is to find the locations for a given set of p facilities that minimise the aggregated weighted distance from consumer locations to the nearest facility. Another example of a basic model is the set-covering model which finds the set of locations that minimises the number of facilities required to meet a minimum travel distance constraint. Commonly used algorithms stem from the operations research (for an overview see Hansen *et al.* 1995; Densham and Rushton 1992a; Wilson *et al.* 1981). These include linear programming algorithms (e.g., the simplex method), non-linear programming algorithms (e.g., branch-and-bound algorithms) and heuristic methods (e.g., the interchange algorithm, the alternating algorithm). To deal with the large size of many location problems, additional algorithms or extensions have been proposed. Notable examples are genetic algorithms (e.g., Hosage and Goodchild 1986), combined global and regional search (Densham and Rushton 1992b, Horn 1996) and random search combined with an interchange heuristic (Achabal and Gor 1982). Besides this more fundamental research, applied studies have focused on the translation of location-allocation models to location problems in specific areas. For an extensive overview of methods and applications readers are referred to Gosh and Rushton (1987) and Drezner (1995).

Location-allocation models can be classified in many ways. From a problem solving point of view, the assumption of the nature of space - continuous or discrete - is probably the most important (Ostresh 1978). In retail planning, a limited set of candidate locations is usually given. Hence, the discrete-space assumption is most appropriate here. With respect to the objective function, it is useful to make a further distinction between competitive facility problems and central facility problems. In combination with the continuous/discrete space distinction, this dimension seems to divide the major research areas.

The competitive facility problem is typical for private-sector planning and involves optimising the location of the outlets of a retail chain in a competitive market area. Reviews of this area can be found in Ghosh *et al.* (1995), Kohsaka (1989), Ghosh and Mclafferty (1987) and Graig and Ghosh (1984). Two studies have been particularly influential in retail studies. Achabal *et al.* (1982) propose a location-allocation model for a multiple store location problem. The model uses a multiplicative competition interaction model for the allocation step and searches for locations that maximises the profitability of the chain (while accounting for cannibalism between stores). Goodchild (1984) proposes a model for optimising total demand of a chain assuming that consumers patronise the nearest facility and demand is elastic with respect to distance. He describes two model variants. The market-share-maximisation model takes the outlets of competing chains into account, whereas the competition-ignoring model ignores competition (assuming chain loyalty of consumers). The models are illustrated with the case of a restaurant chain (Goodchild 1984) and, in a later study, with the case of locating gasoline retailing outlets (Goodchild and Noronha 1987).

The central facility problem is relevant for planners who are concerned with finding a balance between consumers benefit and the cost of supplying facilities. This class of location-allocation models has a longer history. Beaumont (1987) and Hodgart (1978) give an overview of models that can operationalise central place concepts. Leonardi (1981a, b) describes a unifying framework. The basic models in this field include the p-median, set-covering, maximum covering and the plant location model. When applied to retail planning, these models can be criticised for being an oversimplification of real-world problems. The models fail to represent satisfactorily the multiple objectives of planners, relevant planning variables and the shopping behaviour of consumers. On the other hand, less restrictive models have been developed as extensions of spatial interaction-based shopping models for optimising the size and location of shopping centres. These models are potentially relevant for retail planning. Several approaches deserve attention.

The models developed by Coelho and Wilson (1976) and Leonardi (1978) simultaneously optimise the location and size of shopping centres based on maximising consumer surplus and a measure of accessibility (log-accessibility), respectively. Both models are formulated in the form of a non-linear mathematical program for which standard solution procedures exist. It is shown that in the optimum consumers are allocated to facility centres in accordance to a production constrained interaction model. A closely related family of models is concerned with the dynamics of retail systems given assumptions of consumer and producer behaviour. Harris and Wilson (1978) introduced a dynamic retail model that has invoked a large number of follow-up studies. The model is derived by solving the centre attractiveness term in a production constrained interaction model for which the costs of supplying facilities balance revenues. The costs-revenues balancing condition represents equilibrium in a perfect competitive market structure where producers exhibit profit-maximising behaviour. The model describes a non-linear system in which producers and consumers react to each other's actions. Follow-up studies have focused on numerical properties and extensions of this model (e.g., Beaumont 1981b; Clarke and Wilson 1983; Rijk and Vorst 1983; Lombardo and Rabino 1989; Wilson 1990).

The above mentioned interaction-based location models appear to be equivalent. Leonardi (1978) shows that maximising consumer surplus, maximising log-accessibility and the balancing condition give the same solutions. Roy and Johansson (1984) interpret these solutions as Nash equilibria in a two-player game in which producers and consumers pursue their own interests. They suggest an extension to a three-player game by including the planning authority as an additional player. In their model, the behaviour of both producers and consumers is represented by an entropy-maximisation model. The planner formulates macro-location policies for allocating floor space across locations with the aim to ensure overall efficiency and equity. The efficiency criterion is a weighted sum of the interests of the three groups involved in terms of transaction profits (retailers), travel costs (consumers) and costs of the required public infrastructure (public interests). The equity criterion, on the other hand, is given by multiple objective functions related to profits (retailers) and accessibility (consumers). Roy and Johansson suggest a satisficing approach to solve the multiobjective model.

Limitations and Extensions

A fundamental characteristic of the mathematical programming method in the above location models is the separation of the stage of problem exploration and definition from the stage of problem solution (Lolonis 1994). The potential advantage of this approach is that the problem space is free of biases and personal preferences of decision-makers. However, authors have pointed at several potential problems related to this assumption and have suggested new approaches to overcome these problems.

First, it has been argued on several occasions that the mathematical programming format is too restrictive to be able to represent real-world location problems which are often characterised by uncertainty, multiple objectives and vague definitions (see Brill *et al.* 1990). If the model is too strongly a simplification of the real-world problem it may fail in generating interesting or even relevant alternatives. To make the models more realistic in the face of the poorly structured problems, researchers have advanced multiobjective programming techniques. The general aim of multiobjective programming is to identify non-inferior solutions and to assist decision makers in evaluating these solutions on multiple criteria. The ranking of decision alternatives on multiple criteria has also received much attention in the area known as discrete multicriteria decision making (see Keeney 1980, Voogd 1983, Sawaragi *et al.* 1986, Zimmerman 1991, Massam 1993 and Jankowsky 1995). This research considers the case where a discrete set of choice alternatives is a-priori given (rather than generated by the model). Ghosh and McLafferty (1982) propose an application in the field of retailing where a multiobjective, multiple location model is used to identify the set of non-inferior location strategies given possible uncertain events in the market area. The optimal strategy is then chosen from the set of non-inferior strategies based on either the subjective preferences of the decision-maker or a goal-programming algorithm. A similar two-step procedure is used in the spatial information systems proposed by Chang *et al.* (1982) and Diamond and Wright (1988) in the area of land-use planning.

A second potential problem relates to the absence of an active involvement of the decision-maker in the problem solving process. Several authors have stressed the importance of such an active involvement for the acceptance of solutions even if the model is an acceptable representation of the real-world problem (Malczwesky and Ogryczak 1990; Densham 1991; Armstrong *et al.* 1991, Densham and Rushton 1996). Interactive multidimensional programming for locational decision making was first introduced by Nijkamp and associates (see Nijkamp 1979). This has become an important field of research reviewed by Malzwesky and Ogryczak (1990, 1995, 1996). The interactive approaches do not require a-priori information about the decision-maker's preference structure. Instead, preferred solutions emerge in an interaction between decision-maker and a computer-based location model in two phases. In a judgmental phase, the decision-maker evaluates solutions presented by the system and articulates his or her preferences in terms of the criteria. In a computational stage, a set of (efficient) solutions that meet the specified criteria are generated by the system. The solutions provide feedback on the basis of which decision-makers may re-evaluate criteria values in the judgmental stage. The procedure is repeated until criterion values reach convergence. Malzwesky and Ogryczak (1990) describe an interesting application of an interactive multiple-location model for optimising the location of hospitals in the Warsaw region, Poland, using a set of efficiency and equity objectives.

Suggested Approach

The standpoint taken here is that existing single objective location-allocation models are potentially useful for solving relatively well structured subproblems (i.e., tasks) in spatial planning. For that limited purpose an appropriate selection of models will be incorporated as control structures in the task-layer of the DSS. The primary use of the models is not to generate final solutions to a given problem. Rather, the models are proposed for spatial search in the problem exploration and the plan generation stage. The selected models will include (i) spatial interaction/choice-based models for optimising the location and size of outlets in a competitive environment and (ii) spatial interaction/choice-based models for optimising the location and size of shopping centres. Interactive multiobjective location models are viewed as useful generalisations to overcome some of the drawbacks of the traditional approach.

For the overall-planning problem, we propose a knowledge-based modelling approach. The objective of this approach is to incorporate in a rule-base the concepts and heuristics used by planners. The specific advantages pursued here relate to the open character of such knowledge-based models. When properly designed, a rule-based system can explain the conclusions it reaches in terms of rules and concepts used by planners. Thus, planners can verify the conclusions generated by the model and use this output in a flexible way. They can bring in their own knowledge for example about exceptional conditions in the specific case at hand and adjust generated conclusions. Moreover, the rules themselves are accessible for inspection, modification and updating. This ability to trace the problem solving process and access the rule-base stands in sharp contrast with the algorithmic approach and allows an active participation of the decision-maker in the problem solving process.

Another advantage is that a knowledge-based model can formulate actions based on an identification and diagnosis of problems in the existing retail system. Typically, such actions involve small changes of the existing situation. The optimisation models reviewed above are based on a different principle. These models generate an optimal configuration of retail/service system that can either be accepted or rejected by the user. Although such solutions can be useful in terms of broadening one's view and stimulating creativity, the diagnosis-based approach stands closer to the incremental nature of planning.

As reviewed in Chapter 2, to date there are relatively few examples of knowledge-based systems or expert systems in spatial planning. The applications that have been reported are typically concerned with site selection and land-use planning.

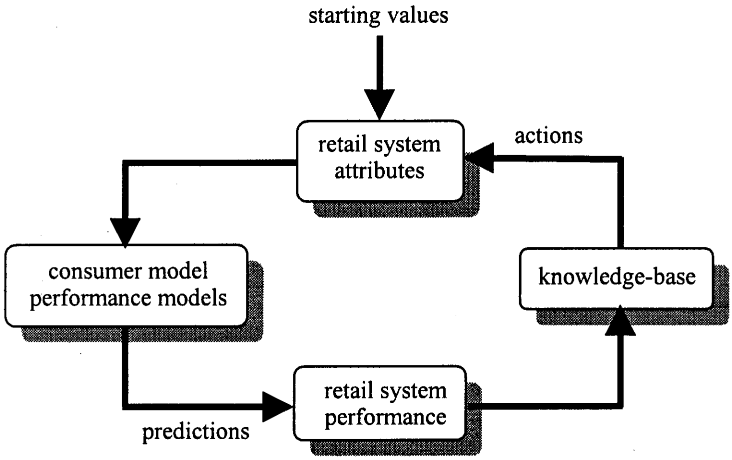

Figure 7.1. Plan generation in the knowledge-based approach.

To our knowledge, applications to the multiple-facility location problem do not exist with only one exception. Lolonis (1994) describes a knowledge-based DSS for service provision problems which is operationalised using a school district reorganisation problem in Iowa City, Iowa. The objectives of his knowledge-based model are similar to the one proposed here. The procedural knowledge in his system corresponds to the task-layer knowledge in our system. Similarly, this part deals, among other things, with diagnosis and plan development.

Retail and service planning problems have characteristics in common with tasks known as diagnosis-repair and design-configuration in the expert system literature (Parsaye and Chignell 1988). Diagnosis-repair refers to the identification of a malfunctioning component of a complex system and the suggestion of a method of remedy or repair. Design-configuration involves the selection of an aggregate from a given set of system components based on one or more constraints to satisfy a goal. Both types of tasks have been handled successfully by expert systems in domains such as medicine and engineering.

The purpose of the remainder of this chapter is to develop a knowledge-based model and investigate the possibilities of such models to represent task-layer knowledge in a spatial DSS. The task layer co-operates with the lower-level inference layer. The inference layer consists of the models developed in the former chapters for simulating and analysing retail systems. The task layer uses this information to identify and diagnose problems in the existing retail/service system and to identify possible actions. Together, the inference and task layer support the following procedure (Figure 7.1):

1. predict and analyse retail system operations using consumer choice and system performance models (inference layer);
2. identify problems or opportunities and formulate possible courses of actions (task layer);
3. select and implement selected actions (user);
4. repeat until a satisficing solution is obtained.

The proposed system corresponds to the knowledge-based DSS-concept discussed in Chapter 2.

7.3 The decision table formalism

To represent the decision rules planners/retailers may use in formulating actions, we propose the Decision Table (DT) formalism. The DT has several advantages over conventional knowledge representations, such as logic, production systems, frames and others. It allows one to systematically verify completeness, exclusivity and consistence of a decision model.

The decision table (DT) is a well-established technique for structuring decision problems. Originally, the tables were introduced as a tool in software engineering for structuring computer programs. Later on, other application domains have been reported including manual decision making, systems analysis and design, representation of complex texts, verification and validation of knowledge-bases and knowledge acquisition (Vanthienen and Dries 1994). The use of the DT for knowledge representation in knowledge-based systems is of more recent date (see Lucardie 1994, Vanthienen and Dries 1994, Witlox 1998, Wets 1998). For an extensive overview of concepts and applications readers are referred to Lucardie (1994) and Wets (1998). Both studies also describe software (AKTS and Prologa, respectively) for developing DT-based knowledge bases that provides significant added value to the DT technique. This section first gives a formal definition of DT's based on the work of Wets (1998) and next discuss some properties of DT's that relevant for the present modelling purpose.

Formal definition

A DT is informally defined by Verhelst (1980) as:

" .. a table representing the exhaustive set of mutual exclusive conditional expressions within a pre-defined problem area"

C1	Distance (meter)	$D < 500$	$500 \leq D < 1000$		$D \geq 1000$	
C2	Parking facilities	-	bad	good	bad	good
A1	bike	×	×	-	-	-
A2	car	-	-	×	-	×
A3	public transport	-	-	-	×	-

Figure 7.2. An example of a decision table.

A simple example of a DT is presented in Figure 7.2. The upper left part of the table lists the condition subjects CS_i for $i = 1, ..., c$ which are the criteria for the decision making process. The universe of discourse CD_i for each condition i is the set of all possible values that the condition can attain. In the example, possible definitions are $CD_1 = \{ 0, 1, ..., 2000 \}$ and $CD_2 = \{$ bad, good $\}$. The condition state set for each condition i consists of the possible states of the condition:

$$CT_i = \{S_{i1}, S_{i2}, ..., S_{it_i}\} \tag{7.1}$$

where S_{ij} determines a subset of CD_i. The condition space of a DT is the Cartesian product of the condition state sets CT_i, as follows:

$$\begin{aligned} \text{SPACE}(C) &= CT_1 \times CT_2 \times ... \times CT_c \quad &\text{for } c > 1 \\ &= CT_1 &\text{for } c = 1 \end{aligned} \tag{7.2}$$

An element of $\text{SPACE}(C)$ is an ordered c-tuple and is called a condition entry (CE). The set of CE's which are present in the DT defines the domain of the DT and is denoted as DOM(DT). In the example, the condition space is defined as:

$$\begin{aligned} \text{SPACE}(C) = \{ &(D < 500, P = \text{'bad'}), (D < 500, P = \text{'good'}), \\ &(500 \leq D < 1000, P = \text{'bad'}), \ (500 \leq D < 1000, P = \text{'good'}), \\ &(D \geq 1000, P = \text{'bad'}), (D \geq 1000, P = \text{'good'}) \} \end{aligned}$$

Note that the symbol '-' represents the entire domain of the concerned condition implying indifference for the state of the condition.

The bottom left part contains the action subjects AS_i for $i = 1, ..., a$, which represent the terms in which decision outcomes are expressed. For each action i, the action state set AT_i contains the possible values action i can attain:

$$AT_i = \{m_{i1}, m_{i2}, \ldots, m_{it_i}\} \tag{7.3}$$

In the example, the definition of the action state sets are $AT_1 = \{ \times, -, . \}$ and $AT_2 = \{ \times, -, . \}$. The value ' × ' indicates that the action AS_i is to be executed, '-' means that the action should not be executed and '.' means unknown. The action space of a DT is defined as the Cartesian product of the action state sets:

$$\begin{aligned} \text{SPACE}(A) &= AT_1 \times AT_2 \times \ldots \times AT_c && \text{for a} > 1 \\ &= AT_1 && \text{for a} = 1 \end{aligned} \tag{7.4}$$

An element of SPACE(A) is an ordered a-tuple called an action entry (AE). The action space of the example DT can thus be written as:

SPACE(A) = { (× , × , ×), (× , × ,-), (× , × , .), ..., (., ., .) }

As Wets (1998) shows, a DT can be defined in different ways as a relation, a function or a matrix. The matrix definition suits the present purpose and can be written as follows. Let n be the number of columns and c the number of conditions. Then, the condition part of a DT can be defined in matrix notation as:

$$D = (d_{ij}), \qquad i = 1, \ldots, c \text{ and } j = 1, \ldots, n \tag{7.5}$$

where $d_{ij} = \cup_{x \in S_{ij}} x$

For the example, this results in:

$$D = \begin{pmatrix} D < 500 & 500 \geq D < 1000 & 500 \geq D < 1000 & D \geq 1000 & D \geq 1000 \\ P = '-' & P = '\text{bad}' & P = '\text{good}' & P = '\text{bad}' & P = '\text{good}' \end{pmatrix}$$

The action part can be written as:

$$E = (e_{ij}), \qquad i = 1, \ldots, a \text{ and } j = 1, \ldots, n \tag{7.6}$$

where $e_{ij} = m_{ij}$

For the example, this yields:

$$E = \begin{pmatrix} \times & \times & - & - & - \\ - & - & \times & - & \times \\ - & - & - & \times & - \end{pmatrix}$$

A DT defines the relation between condition space and action space. Formally:

$$DT = (dt_{ij}) = \begin{pmatrix} D \\ E \end{pmatrix} \qquad (7.7)$$

where $dt_{ij} = d_{ij}$, $\quad i = 1, ..., c$ and $j = 1, ..., n$
$\qquad\quad = e_{(i-c)j}$, $\quad i = c + 1, ..., c + a$ and $j = 1, ..., n$

In this way, the example DT can be written as:

$$DT = \begin{pmatrix} D < 500 & 500 \geq D < 1000 & 500 \geq D < 1000 & D \geq 1000 & D \geq 1000 \\ P = '-' & P = 'bad' & P = 'good' & P = 'bad' & P = 'good' \\ \times & \times & - & - & - \\ - & - & \times & - & \times \\ - & - & - & \times & - \end{pmatrix}$$

The three key-properties of DT's are consistency, exclusivity and completeness. The properties can be formally defined as follows. Let D^j and E^j denote the j-th column of D and the j-th column of E respectively. Then, *consistency* can be defined as:

a DT is consistent $\Leftrightarrow \forall (D^j, D^k)$: if $\forall(d_{ij}, d_{ik})$: $d_{ij} \cap d_{ik} \neq \varnothing$ then $E^j = E^k$ (7.8)

where $i = 1, ..., c$ and $j, k = 1, ..., n$

The example DT is consistent, because there is no intersecting pair of columns in the DT of which the action parts differ. *Exclusivity* can be defined as:

a DT is exclusive $\Leftrightarrow \forall (D^j, D^k)$: if $j \neq k$ then $\exists(d_{ij}, d_{ik})$: $d_{ij} \cap d_{ik} = \varnothing$ (7.9)

where $i = 1, ..., c$ and $j, k = 1, ..., n$

The example DT meets the exclusivity constraint in that for every pair of columns there is at least one condition of which the condition states exclude each other. Finally, a DT is *complete* if it meets the following two constraints:

$$\begin{aligned} &\mathrm{DOM(DT)} = \mathrm{SPACE}(C) \\ &\forall E^{j}: \exists\, e_{ij} \neq \text{`.'} \end{aligned} \qquad (7.10)$$

The example DT is complete since every *CE* is included in the condition part of the DT and in every column at least one action is specified.

Some properties of DT's

DT's allow one to check consistency, exclusivity and completeness of a decision model in a systematic way. This property is an important advantage in the knowledge-acquisition as well as the knowledge-validation-and-verification stages. It helps the expert to consider systematically all possible cases and the knowledge engineer to built a reliable system that will respond univocally in every conceivable case. It is also the distinguishing feature compared to a traditional decision tree.

Furthermore, it is important to note that links between DT's can be defined so that a model can be specified as a DT system. There are at least two different links possible. First, a condition subtable is a DT that defines a condition of a DT that is then called a head table. For example, for the 'parking-facility' condition we could define a subtable that defines the conditions under which parking facilities are classified either as 'bad' or 'good'. Thus, the action of a condition subtable corresponds to a condition of the head table. Second, a table that specifies the action of another table is called an action subtable of that table. For example, the 'choose public transport mode' action of the example DT could be further specified in terms of a subtable defining under which conditions which specifc type (e.g., bus, train) of public transport mode is to be selected.

In many applications, DT-systems are developed in a top-down fashion using these links. In particular, the condition subtable link is important. The table at the highest level contains abstract conditions which are successively worked out in condition subtables. The hierarchical structure reflects the way human experts tend to organise and transfer their knowledge. Conditions in DT's can be thought of as steps in the decision making process and subtables as possible ways to specify the steps. Thus, a DT-system provides a framework for structuring the decision making process at increasing level of operationalisation.

7.4 Assumptions and outline of the model

The goal of the proposed knowledge-based approach is to model the concepts and rules planners/retailers use in analysing retail/service systems and formulating plans. The knowledge sources used for this purpose consist of academic literature, planning documents and personal interviews. A similar, but non-automated method of structuring (part of) the Dutch retail planning domain has been described in SER (1991).

The model is based on various assumptions about how practitioners in spatial planning conceptualise the decision problem. First, the model assumes a subdivision of the study area into zones that correspond to local market areas. The local-market-area assumption states that individuals usually patronise facilities in their own zone and interactions between zones are limited. With respect to the supply side, it states that facilities are typically concentrated in a single centre/street or otherwise recognisable shopping areas. Clearly, the appropriate scale of zones depends on the place of the facility type in the retail hierarchy. For example, in the case of daily good facilities relatively small neighbourhoods may be appropriate, whereas in the case of high-order comparison goods local markets may be as large as city-wide areas.

Although local market areas are far from closed systems, the model further assumes a zone-based type of analysis. That is, the model analyses characteristics of the population, centres and the accessibility structure per zone and formulates possible actions per zone.

The third assumption states that it is possible to define at an abstract level a single set of heuristics that applies to a wide range of cases of retail and service planning. As the main objective, the proposed model attempts to utilise as much as possible opportunities for growth and improvement of the quality and diversity of the retail/service system (or chain) under viability and service provision constraints. This is a maximum strategy in the sense that not necessarily all elements are relevant in every case. For example, service provision constraints are not relevant for marketing or financial objectives.

Fourth, the model is based on an a-priori classification of actions that practitioners may consider to attain this planning objective. The following categories are distinguished:

1. *structural actions*: these actions concern the closure or opening of centres/stores and, consequently, affect the accessibility structure of facilities
2. *non-structural actions*: these actions focus on the functioning and quality of existing centres/stores.

The latter category is further subdivided in:

1. *facility-standard actions*: these are aimed at eliminating unacceptable deficiencies for example in branch mix or state of refurbishment of a centre/store;
2. *provision-level actions*: these attempt to correct a quantitative imbalance between demand and supply in a zone;
3. *facility-performance actions*: these try to utilise opportunities to increase the attractiveness of a centre/store, for example to improve the market share or quality of the retail environment.

In sum, structural actions make sure that the viability and accessibility of the retail system meet planning standards, whereas the other actions are concerned with criteria of branch composition, size and performance of the facilities.

<table>
<tr><td colspan="2">actions of category A</td><td colspan="8"></td></tr>
<tr><td>C1</td><td>performance on dimension A</td><td colspan="7">< norm</td><td>≥ norm</td></tr>
<tr><td>C2</td><td>factor 1 can explain underperformance</td><td colspan="4">yes</td><td colspan="3">no</td><td>-</td></tr>
<tr><td>C3</td><td>constraint 1 is met</td><td>yes</td><td colspan="3">no</td><td colspan="3">-</td><td>-</td></tr>
<tr><td>C4</td><td>factor 2 can explain underperformance</td><td>-</td><td colspan="2">yes</td><td>no</td><td colspan="2">yes</td><td>no</td><td>-</td></tr>
<tr><td>C5</td><td>constraint 2 is met</td><td>-</td><td>yes</td><td>no</td><td>-</td><td>yes</td><td>no</td><td>-</td><td>-</td></tr>
<tr><td>...</td><td>....</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td></tr>
<tr><td>A1</td><td>suggest: take away factor 1</td><td>yes</td><td>no</td><td>no</td><td>no</td><td>no</td><td>no</td><td>no</td><td>no</td></tr>
<tr><td>A2</td><td>suggest: take away factor 2</td><td>no</td><td>yes</td><td>no</td><td>no</td><td>yes</td><td>no</td><td>no</td><td>no</td></tr>
<tr><td></td><td></td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td><td>...</td></tr>
<tr><td></td><td></td><td>R1</td><td>R2</td><td>R3</td><td>R4</td><td>R5</td><td>R6</td><td>R7</td><td>R8</td></tr>
</table>

Figure 7.3. General form of decision tables used in the knowledge-based model.

The model consists of a set of DT's. Each DT is specialised in one of the above action categories and evaluates whether conditions for undertaking that action are met. The general structure of the DT's is shown in Figure 7.3. The structure describes the first stages of a decision-making cycle consisting of the steps:

1. identify the problem by comparing the present state with planning standards (C1);
2. diagnose the problem by evaluating conditions that can explain a detected conflict (C2 and C4);
3. identify possible actions by evaluating whether pre-conditions for possibly effective actions are met (C3 and C5).

In sum, each DT evaluates for the concerned action category whether it can take away an observed under-performance or over-performance and implementing the action does not violate constraints. In some cases, the diagnosis step may be absent. Then, an action follows directly from the identification of the problem. Furthermore, there are often several actions possible for solving a problem. A-priori preferences for action alternatives are expressed in the DT by the order in which they are evaluated. In this example, "taking away factor 1" has a higher priority than "taking away factor 2".

The zone-oriented form of analysis means that the model is to be consulted for each zone separately. For each zone, the procedure consists of the following steps:

1. investigate whether structural actions are needed;
2. if not, then investigate whether facility-standard, provision-level and/or facility-performance actions are needed.

The result is a list of possible zone-based actions. As will be explained in more detail below, interactions between zones may give rise to synergetic or conflicting relations between actions. Therefore, an additional step is required in which suggested actions are integrated in a coherent scenario for the entire study area.

7.5 Model specification: the case of daily good facility centres

This section discusses a specification of a DT system that represents the planning of food retailing in the context of Dutch local government. The figures 7.5-7.8 show for this case the specifications of the DTs related to the different action categories. Figure 7.4 represents an additional DT that derives for a number of performance indicators normative values dependent on location characteristics of facilities. The other DT's for deriving actions use specific outputs of this table to compare actual performances with the normative values.

The DT's discussed here represent rules at a high level of abstraction. Each DT can be further worked out in the form of subtables. We do not go into the specification of subtables, because in the DSS the primary purpose of the model is to structure the overall problem. Although the present specification of the DT system is tailored to this particular case, the DT system at this abstract level intends to provide a framework for modelling other classes of retail/service planning problems as well. The DTs can be easily adapted to represent different planning standards, for example in the context of retail companies, because the overall structure is generic. In this section, we discuss the DT system specification for this particular application and indicate how adjustments/extensions can be realised to suit other applications.

performance norms									
C1	spatial distribution of facilities	scat-tered	centre						
C2	location relative to retail structure	-	unfa-vourable	average					favou-rable
C3	location in zone	-	-	decentral		central			
C4	location of zone	-	-	decentr.	central	decentr.	central		etc.
A1	norm: penetration rate (%)	50	50	60	65	70	75		
A2	norm: min. population base (# persons)	7500	7500	5300	5000	4200	4000		etc.
A3	norm: floor space per 1000 inhabitants	150	150	200	220	240	260		
		R1	R2	R3	R4	R5	R6		

Figure 7.4. Decision table for deriving norms for daily-good sector planning (Dutch context).

structural actions							
C1	there are facilities in the zone	no			yes		
C2	viability perspective for facility unit	unsufficient[1]		dubious OR sufficient	insufficient		dubious OR sufficient
C3	facility unit is essential for service structure	no	yes	-	no	yes	-
A1	close facility unit	no	no	no	yes	yes	no
A2	open facility unit	no	no	yes	no	no	no
A3	open incomplete unit	no	yes	no	no	yes	no
		R1	R2	R3	R4	R5	R6

[1] $\frac{population\_base}{\min population\_base} < 0.90$

Figure 7.5. Decision table for structural actions.

Performance norms (Figure 7.4)

This table derives normative values of performance indicators based on location characteristics of facilities. In global terms, this table states that normative performance levels are high for facilities that are concentrated in centres (as opposed to scattered), centrally located and distant from competing centres. Three performance indicators are considered. Penetration rate (A1) expresses the portion of expenditure available in the zone that is attracted by facilities in that zone. Minimum population base (A2) expresses the population size minimally required for a viable exploitation of a minimum-sized centre/store. Finally, floor space per 1000 inhabitants (A3) represents a balanced ratio between supply and demand. Normative values on each of these indicators vary with location conditions. The normative values on these indicators relate to the attractiveness of a centre that may be expected given its location. The more favourable the location the higher the penetration rate that should be achieved and, consequently, the lower the minimum requirements for minimum population base and the higher the possible size of floor space per head. Particularly, for this DT, the rules will vary strongly from application to application. The rules in this DT typically apply to food-retail planning in the Dutch context. In other contexts, other rules may hold. Furthermore, the DT can be extended to take into account the match between attribute profiles of facilities and the population.

Structural actions (Figure 7.5)
These actions concern the closure or opening of facility units in a zone. A unit can be defined in different ways dependent on the concerned facility type and policy objectives. In daily good facility planning, planners usually define a unit as a centre consisting of a basic mix of stores (as defined in the next table). Retailers may consider the smallest layout of their outlets as a basic unit.

The DT checks whether the facility unit is viable in a longer-term perspective (C2). The minimum population base derived in the former table is used as a norm. A negative answer is an indication for closure, but does not have to lead to a closure decision. Planners may wish to support a unit with doubtful economic base when it fulfils an essential role in serving the needs of the local community. Similarly, retailers may consider maintaining a non-profitable unit for reasons related to the competitive position of the chain. Therefore, this table evaluates as an additional condition whether the facility unit is essential for maintaining a sufficient provision structure (C3). Evaluating this condition is based on measures of accessibility and can be formalised in the form of a subtable. If the population base is not sufficient for a complete unit while facilities are considered essential for serving the local community (R2 and R5), then the table suggests to develop a smaller incomplete centre (e.g., consisting of only one smaller supermarket).

The same considerations play a role in decisions to open a unit. Given the high investments costs involved, a final decision to open a unit will be based on a thorough investigation of the market potential at a potential site. The present table only indicates whether a sufficient population base exists for a new facility unit. Identifying and evaluating specific new locations and sites at a lower scale level requires additional research possibly structured by a subtable.

facility-standard actions								
C1	number of supermarket outlets	none	one				more than one
C2	m2 gross floor space of the supermarket	-	< 700	700 - 800		> 800	-
C3	all fresh products are available	-	-	no	yes	-	-
A1	expand floor space of supermarkets	no	yes	no	no	no	no
A2	open large supermarket	yes	no	no	no	no	no
A3	open complementary specialty stores	no	no	yes	no	no	no
		R1	R2	R3	R4	R5	R6

Figure 7.6. Decision table for facility-standard actions.

over-provision actions							
C1	need for reducing per capita floor space	no	average[1]				large
C2	size of floor space above needed for branche mix	-	nihil			average OR large	
C3	potential increase population density	-	nihil		average OR large	-	etc.
C4	size of floor space above needed for min. unit	-	nihil	average OR large	-	-	etc.
A1	reduce floor space	no	no	average	no	average	
A2	increase density of population	no	no	no	average	no	
		R1	R2	R3	R4	R5	

[1] $$0.7 < \frac{sales\_per\_unit\_floor\_space}{\min sales\_per\_unit\_floor\_space} \leq 0.85 \text{ AND}$$

$$1.15 < \frac{floor\_space\_per\_1000\_inh.}{\text{norm}floor\_space\_per\_1000\_inh.} \leq 1.30$$

Figure 7.7. Decision table for over-provision actions.

Facility-standard actions (Figure 7.6)
Actions in this table are aimed at taking away unacceptable omissions in the branch composition of a unit. The rules are based on a definition of what is generally considered a basic package of daily good supply in the Dutch context. Similar definitions exist in other sectors of retailing. In the case of a retailer, a similar table can be defined for an individual outlet (e.g., standards related to the branch composition, refurbishment level or facade of the outlet).

Provision Actions (Figure 7.7)
Actions of this category are aimed at correcting a quantitative imbalance between demand and supply in a zone. Over-provision is a problem when it leads to insufficient profitability of facilities in the zone given their current size. Under-provision, on the other hand, indicates opportunities for expansion. The normative provision level is defined in terms of 'floor space per 1000 inhabitants' in the performance-norms table (Figure 7.4). Note that the normative value as defined by this table is adjusted to local circumstances. For example, more centrally located facilities obtain a higher value considering the fact that such facilities tend to bind more strongly the available purchase power within and outside their zone.

The table in Figure 7.7 reflects these notions with regard to the over-provision case (a similar table exists for the under-provision case). The need for an over-provision correction (C1) exists only if profitability is below a minimum level and a situation of over-provision can explain this under-performance. As a measure of profitability, this table uses sales per unit floor space. In the present case, the minimum value is set to a pre-specified constant derived from a national mean (i.e., NLG 14 000). In other cases, one may wish to derive the minimum value dynamically from characteristics of the facility, possibly, by using a subtable.

A distinction is made between an average (e.g., 15-30 %) and a large (> 30 %) degree of the needed correction. This degree is defined as the component of under-performance that can be attributed to over-provision. For example, if sales per unit floor space is 20 % below minimum level and 'floor space per 1000 inhabitants' is 15 % above norm level, then an 15 % reduction of the ratio is indicated, e.g., through reducing the amount of floor space. Thus, the level of over-provision sets an upper bound on the required correction. An underperformance that occurs in combination with a balanced provision level, will be handled by the "performance action" DT described below assuming that in that case underperfomance is caused by insufficient attraction relative given locational characteristics of the centre.

The over-provision table describes the following strategy to reduce an over-provision:

1. try to reduce floor space without affecting the existing branch mix (C2);

2. if (1) is not possible or not sufficient, then try to increase the density of the population in the zone (C3);
3. if (1) or (2) are not possible or not sufficient, then try to reduce floor space without affecting a basic supply level (C4).

This strategy reflects a preference for reducing floor space in branches that are over-represented so that the quality of the facility is minimally affected. If this option fails then local governments sometimes have the means to increase the demand-supply ratio through housing policies that increase the population in the area. If the demand-supply ratio cannot be increased without affecting a basic supply level, then the over-provision is structural (i.e., structural actions are required).

performance actions									
C1	penetration rate in zone	≥ norm	< norm[1]			<< norm			
C2	quality of branch mix	-	low OR average	high		low	average		high
C3	quality of retail centre	-	-	low OR average	high	-	low OR average	high	etc.
A1	expand floor space	no	average	no	no	large	average	aver.	
A2	renovate retail centre	no	no	average	no	no	average	no	
		R1	R2	R3	R4	R5	R6	R7	

[1] $0.85 \le \frac{penetration\_rate}{\text{norm}penetration\_rate} < 0.90$

Figure 7.8. Decision table for facility-performance actions.

Facility-performance actions (Figure 7.8)

This table applies only if the facilities in the zone are concentrated in a centre (instead of dispersed). The table evaluates conditions for utilising opportunities to increase the attractiveness or market share of centres. The penetration rate derived by the performance-norm table (Figure 7.4) is taken as the norm. This norm takes into account the location relative to the population and relative to competitors. A lower penetration rate than the norm means that the centre performs less than can be expected given its location. Then, the DT describes the following strategies for remedy:

1. analyse the branch mix of the centre (C2). If certain branches are missing that can (partly) explain the under-performance, then increase floor space in these branches (A1).
2. if (1) does not or can only partly explain under-performance, then analyse the quality of centre characteristics (C3). If the analysis reveals shortcomings that can (partly) explain under-performance, then renovate the centre (A2).

The quality of branch mix is judged based on a definition of what is considered a well-balanced package of branches within or between competing units. The quality of the retail environment is determined by factors such as parking facilities, local accessibility, lay-out, refurbishment, availability of complementary facilities etc.. Subtables can be defined to structure both forms of quality analysis.

The impacts of the two actions A1 and A2 are considered to be additive so that, for example, a two times "average" quality improvement makes a "large" correction of under-performance. If under-performance can not be (fully) explained by shortcomings in the quality of the branch mix or centre characteristics, then an above average strength of competing centres should be hypothesised. Given planner's objectives, it is not desirable to undertake actions for reducing the competitive strength of any centre.

Developing Action Scenario's

To summarise, the above tables are aimed at ensuring a sufficiently accessible network of viable and complete facility units, balanced supply-demand ratios and an optimal performance of facility units. The most important policy variables are the spatial distribution of population growth, location, branch mix, floor space size and qualitative attributes of retail environments. As a general tendency, the model will reduce floor space in zones and branches that are over-provided, add floor space in zones and branches that are under-provided and renovate centres where needed. The tables discussed in this section are customised to planning standards of (Dutch) local government regarding in the food sector. For other cases, the tables should be adjusted in particular with respect to the definition of facility units and performance norms.

Actions that are based on a zone-based analysis can interfere with each other. An obvious example is that an increase in market share of one unit can be realised only at the expense of competing units. On the other hand, there may exist synergetic relationships between actions. For example, an expansion of floor space to correct a local situation of under-provision may at the same time improve the attractiveness of that unit. The model generates a list of proposed actions per zone, but does not take such interactions into account. Developing a coherent action plan is left to the judgement of users.

The zone-based lists of suggested actions can be used to formulate an action scenario for the study area as a whole. The extent to which suggested actions are effective is inherently uncertain given the fact that they are based on heuristic rules. Therefore, a consumer choice model and behavioural performance models are complementary and serve to predict and analyse impacts in terms of the performance dimensions used in the DTs such as penetrations, market shares, sales per unit floor space, per capita floor space and measures of accessibility. The knowledge-based model can then be reconsulted to evaluate whether additional actions are needed in the new situation. This cycle can be repeated until performance levels meet standards.

7.6 Implementation in a KBS

The DT-based model was implemented in a computerised knowledge base using the system AKTS (Advanced Knowledge Transfer System, Lucardie 1994). AKTS provides a graphic environment for editing DT's and an inference engine for consulting the resultant knowledge base. Users can assign a goal status to one or more action subjects. If the knowledge base is consulted, the built in inference engine tries to derive the values of action subjects with a goal status through a backward chaining

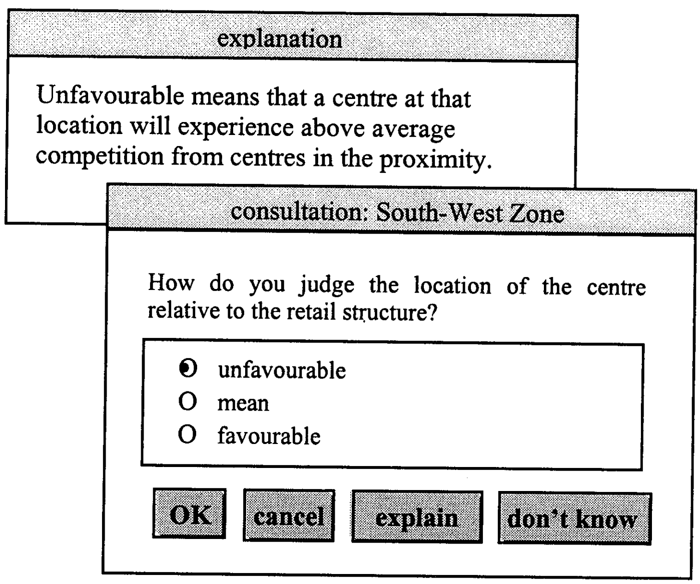

Figure 7.9. Example of a dialogue during consulting the knowledge-base.

mechanism. The engine successively evaluates the relevant conditions. For each condition, different possible sources of information are evaluated in a pre-defined order: retrieve from the fact-base; consult a subtable; execute a specified 'when-needed' procedure or 'ask user'. This order is modified if the condition has been assigned an 'ask user first' status. Then, the engine will first prompt the user for evaluation and, upon failure, use a subtable or 'when-needed' procedure.

AKTS allows one to assign properties to condition and action subjects that determine the behaviour of the system during consultation. These properties are stored together with the tables in the knowledge base. Several properties are relevant here. The 'when-needed' property can be defined in the form of a calculation procedure or a query of a database. In the spatial DSS this property can be used to establish the links between the task layer (the DT-model) and inference layer (the inference models). Prompt texts and explanation texts can be edited in AKTS for use in question-answer dialogues. Figure 7.9 shows an example of such a dialogue. The prompt text is displayed together with the answer alternatives (condition states in the concerned DT). Upon clicking on the 'explanation' button, AKTS activates a window displaying the explanation text. Typically, the explanation facility is used to clarify concepts used in the formulation of the question possibly supported by graphical material. The 'don't know' button is relevant if the condition under concern is defined by a subtable and has an 'ask user first' status. The don't know button allows users to choose between a subjective or a system-based evaluation of the condition. In this example, if users press the don't know button, the system consults the condition subtable to derive the answer. Thus, the 'don't know' option allows users to consult the knowledge base at the level that is considered appropriate for the decision step.

7.7 Application

To test and demonstrate the model, this section considers as a case the food sector in Dordrecht, The Netherlands - a medium sized city with about 115,000 inhabitants. Figure 7.10 shows a map of the area. The city area is subdivided in seventeen residential zones based on the zoning system defined by the municipality. Here, the attention is focused on two zones where changes in demand-supply relationships are to be expected given population developments and impacts of a recent expansion and renovation of competing centres in the proximity. The information used here is based on the research report prepared by the Social Geographic Department of Dordrecht (1995).

Tables 7.1a and 7.1b describe the two zones under concern, Crabbehof and Wielwijk, in relation to two adjacent zones, Sterrenburg and Oud Krispijn. Both Crabbehof and Wielwijk have a shopping centre characterised by a fairly complete mix

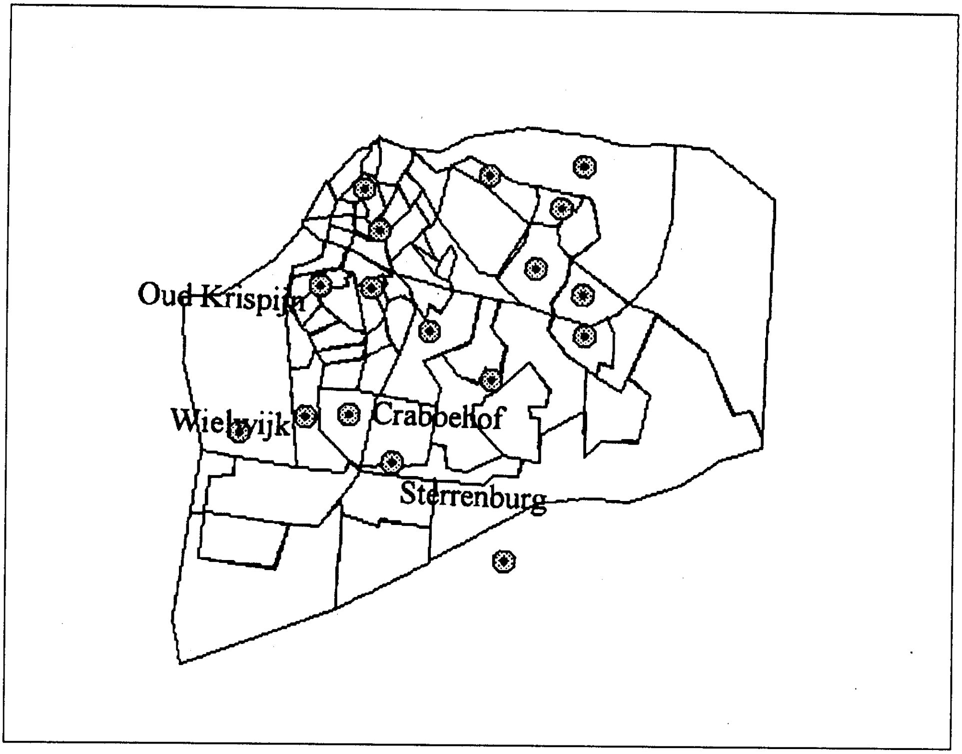

Figure 7.10. Neighbourhoods and shopping centres in Dordrecht.

Table 7.1a. Base scenario: predicted expenditure flows (%) in the daily good sector, given the expansion of Oud Krispijn (+500 m2) (source: social geographic department dordrecht, 1995).

residential zone	shopping zone Crabbehof	Wielwijk	Sterren-burg	Oud Krispijn	other	population in 2000
Crabbehof	60	5	5	12	18	7973
Wielwijk	6	60	3	12	19	7426
Sterrenburg	1.5	3	77	5	13.5	22590
Oud Krispijn	3	3	5	59	30	11990
other	0.5	0.5	2.5	5	91.5	70803

Table 7.1b. Performance of shopping centres in the daily good sector under the base scenario (source: social geographic department Dordrecht, 1995).

	Crabbehof	Wielwijk	Sterren-burg	Oud Krispijn	other
total market share (%)	5.2	5.2	16.9	11.2	61.5
m2 selling floor space	1934	1847	3825	3080	-
m2 selling floor space per 1000 inhabitants	243	249	169	267	-
sales per unit floor space (NLG)	11200	11700	18600	15100	-
major characteristics branche mix	small-sized supermarkets	over supply: 300 m2	well-balanced	well-balanced	-

of food stores. The shopping centres in Sterrenburg and Oud Krispijn are of a comparable scale. Sterrenburg contains a relatively modern and somewhat larger centre attracting to a larger degree consumers from adjacent zones. The renovation and expansion mentioned above concerned the centres in Sterrenburg and Oud-Krispijn, respectively. The tables show the base-scenario, i.e. the expected situation in the year 2000 based on population forecasts and 'no-intervention' conditions. In the scenario, both Crabbehof and Wielwijk are facing a considerable decline in market share. In contrast to Wielwijk, Crabbehof cannot benefit from an increase in population so that it will be most affected by the intensified competition.

The model described in the last section was used to analyse the Wielwijk and Crabbehof zones and to identify possible actions. Structural actions (openings or closures) and facility-standard actions are not needed in this case so that only provision-level and facility-performance actions are considered. As an example, Table 7.2 shows a typical system-user dialogue in the Wielwijk case. Table 7.3 shows the main conclusions. Compared to Wielwijk, the centre in Crabbehof is more centrally located so that it must meet higher norms in terms of penetration rate and floor space per 1000 inhabitants. In both centres a problem is identified because the value of sales per unit floor space is far below norm level. However, different conclusions with respect to causal factors and corrective actions are drawn. In Crabbehof, over-provision actions are nót indicated, because the 'floor space per 1000 inhabitants' is at an about normal level (while accounting for the location characteristics of the centre). Rather, facility-performance actions are suggested given the observation that the penetration rate in the own zone is far below the norm level (while accounting for the location characteristics of the centre). An analysis shows that the needed correction can be achieved by adding floor space in missing branches and by renovating the centre. On the other hand, in Wielwijk the below norm level of sales per unit floor space can be explained

Table 7.2. Example of a system-user dialogue: the Wielwijk case.

System	User
- Are facilities present in the zone (yes/no)?	yes
- How is the viability perspective for a facility (insufficient/dubious/sufficient)?	don't know
- How large is the population size in the zone?	7426
- How is the spatial distribution of facilities in the zone (scattered, centre)?	centre
- How is the location relative to the retail structure (unfavourable, average, favourable)?	don't know
- What is the order of the strongest competing centre (higher, equal, lower)?	equal
- How long is the distance to the strongest competing centre (< 500, 500-750, > 750)?	500-750
⇒ location relative to the retail structure = 'average'	
- How is the location relative to the zone (central, decentral)?	decentral
- How is the location of the zone relative to the whole area (central, decentral)?	decentral
⇒ norm: penetration rate (%) = 60	
⇒ norm: min.population base (# persons) = 5300	
⇒ norm: floor space per 1000 inhabitants = 200	
⇒ structural actions are not needed	
- How many supermarkets are present in the centre (none, one, more than one)?	more than one
⇒ facility-unit actions are not needed	
- How large are the sales per year per unit floor space?	11 700
- How large are the normative sales per year per unit floor space?	14 000
⇒ sales per unit floor space is far below norm	
- How large is the floor space per 1000 inhabitants?	249
⇒ need for reducing per capita floor space is large	
- How large is the floor space above needed for maintaining the current branch mix (nihil, average, large) ?	large
⇒ over-provision actions are needed	
⇒ reduce floor space = large	
- How is the penetration rate in the own zone (%) ?	60
⇒ penetration rate is at about norm level	
⇒ performance-level actions are not needed	

⇒ Conclusions drawn by the system

completely in terms of oversupply in certain branches (the 'floor space per 1000 inhabitants' index). Therefore, a relatively large reduction in floor space (in these branches) is suggested. The attractiveness of the centre in Wielwijk measured as the penetration in the own zone is about normal (given its location) so that performance actions are not indicated.

Table 7.3. Summary of consultation results for Crabbehof and Wielwijk.

	Crabbehof	Wielwijk
norms daily good sector		
- spatial distribution of facilities	= centre	= centre
- location relative to retail structure	= average	= average
- location in zone	= central	= decentral
- location of zone	= decentral	= decentral
⇒ norm: penetration rate (%)	= 70	= 60
⇒ norm: minimum population base	= 4200	= 5300
⇒ norm: floor space per 1000 inhabitants	= 240	= 200
overprovision actions		
- need for reducing per capita floor space (sales per unit relative to norm and per capita floor space relative to norm)	= no[1]	= large[2]
- size of floor space above needed for branche mix	–	= large[3]
- potential increase population density	–	–
- size of floor space above needed for minimum unit	–	–
⇒ reduce floor space	= no	= large
⇒ increase density of population	= no	= no
performance actions		
- penetration rate in zone	= below norm (60/70 = 0.86)	= norm (60/60 = 1)
- quality of branch mix	= average	–
- quality of retail centre	= average	–
⇒ expand floor space	= average	= no
⇒ renovate centre	= average	= no

[1] 11200/14000 = 0.80 < norm, 243/240 = 1.01 ≈ norm
[2] 11700/14000 = 0.84 < norm, 249/200=1.25 > norm
[3] 300/1847 = 0.16 >> 0.0

This leads to different recommendations for the two centres. For Crabbehof, the system suggests a renovation of the centre and an increase in floor space size in order to improve the competitive strength of the centre. For Wielwijk, the model advises to reduce floor-space in over-represented branches with the aim to improve the centre's profitability. There are no inherent contradictions between these actions. Therefore, all suggestions were adopted in a scenario. The amount of the required expansion (Crabbehof) and reduction of floor space (Wielwijk) was set to 350 m^2 and 300 m^2 respectively. A conventional MNL-model was estimated based on a consumer survey. The model was used to predict the impacts of the intervention scenario. The results are shown in Tables 7.4a and 7.4b. As indicated by these results, the actions have the desired effects. The attractiveness of Crabbehof increases to the desired degree without significantly affecting the performance of Wielwijk or the other competing centres. Also, Wielwijk achieves an acceptable level of sales per unit floor space in the new situation. Hence, reconsulting the model did not give rise to additional actions.

Table 7.4a. *Plan scenario: predicted expenditure flows (%), given the expansion of Oud Krispijn (+500 m2), the expansion of Crabbehof (+350 m2) and the reduction of Wielwijk (-300m2).*

residential zone	shopping zone					population in 2000
	Crabbehof	Wielwijk	Sterren-burg	Oud Krispijn	other	
Crabbehof	70	3	3	10	14	7973
Wielwijk	12	57	4	10	17	7426
Sterrenburg	4	2	76	5	13	22590
Oud Krispijn	7	3	3	59	29	11990
other	1	0.5	2.5	5	91	70803

Table 7.4b. *Performance of shopping centres in the daily good sector under the plan scenario.*

	Crabbehof	Wielwijk	Sterren-burg	Oud Krispijn	other
total market share (%)	7.4	4.7	16.4	11.0	60.4
m2 selling floor space	2384	1547	3825	3080	-
per capita m2 selling floor space (×1000)	299	208	169	257	-
sales per unit floor space (NLG)	12800	12500	18100	14800	-
major characteristics branch mix	well-balanced	well-balanced	well-balanced	well-balanced	-

The actions generated by the model seem to be effective and correspond to the suggestions of experts who analysed this case. It should be noted that the model is fairly sensitive to the specified performance norms. Therefore, in particular the decision table for deriving norm levels deserves special attention in applications (as in common practice).

7.8 Conclusions and discussion

This chapter proposed a knowledge-based model as a specification of the task-layer of the spatial DSS. The decision-table technique was used to represent expert knowledge in terms of a set of decision tables. Each decision table represents for a certain problem area an exhaustive and exclusive set of decision rules to identify problems, analyse problems and formulate actions. The rules are heuristic in nature and, therefore, inference-layer models are used as complementary tools to predict and analyse the impacts of suggested actions. If actions appear to be insufficiently effective or produce unanticipated side effects, the same DT-system can be re-consulted to generate complementary actions. The DT-system was implemented in a computerised knowledge base using AKTS. A case study illustrated the application of the model in combination with a consumer choice model for impact analysis.

The knowledge-based approach was proposed as an alternative to current mathematical programming approaches. Potentially, the new approach is better able to account for the ill-structured nature of the decision problems. The knowledge-based model uses concepts and rules that correspond to the way decision-makers approach the problem. This allows decision-makers to trace and verify the reasoning steps of the model. The decision table has specific advantages as a knowledge-representation method in this regard. Using the decision table, the decision-making process can be structured in the form of a (exhaustive and exclusive) decision tree. While consulting the model, users can choose the degree of support that is considered appropriate for the decision task. By default, the system structures the decision-making process in terms of a sequence of major steps. When indicated by the user (i.e. by pressing the 'don't know' button), the system breaks a step down in more elementary steps that are easier to answer and so on. The openness of the process is considered important in the context of an ill-structured task, because it allows decision-makers to bring in their own judgements to carry out subtasks. Furthermore, being a formalisation of the decision-making process, the DT-system can be used to standardise procedures and thus facilitate communication between planners and retailers and other parties involved in planning.

In the spatial DSS, the primary function of the model is to structure the problem identification, problem analysis and action generation stages. In relation to this function, we point at several problems for future research. First, the knowledge base is generic only to a certain extent. Parts of the tables must be adapted to the planning standards used in the case at hand. The system could be extended by incorporating models for other classes of problems as well. Second, the zone-based analysis means that the ability of the model to account for interactions between zones is limited. Possible conflicting or synergetic relationships between actions must be considered for formulating a consistent action scenario. It is possible to extend the present system and incorporate decision tables for supporting the integration of actions and evaluation of alternatives as well. General methods for composing coherent plans out of action components can be derived from the system developed by Xiang (1997). This system uses a (domain independent) set of if-then rules designed to reduce redundancy, competitiveness and incompatibility between actions.

Finally, we note that in the proposed approach, current location-allocation models are considered complementary to the DT-system. As said in the review section, these models have the potential to generate optimal configurations of a retail/service system that may stimulate ideas for new solutions. Finally, the proposed system, possibly in combination with location-allocation models, supports the generation of plan scenario's, but does not support the choice stage when several functional equivalent alternatives emerge. Hence, also multicriteria decision analysis methods are complementary. The integration of the various components in a DSS will be the subject of the next chapter.

PART III

DESIGN, IMPLEMENTATION AND APPLICATION OF THE DSS

CHAPTER 8

DESIGN AND IMPLEMENTATION OF THE SPATIAL DSS

8.1 Introduction

The models proposed in the last chapters have the potential to improve the quality of information for spatial decision-making. However, integrating the models in the decision making process requires extensive data sets from various sources as well as analytical expertise. In general, the goal of DSS is to integrate domain, inference, task and strategic-layer models into an interactive, flexible and easy-to-use problem-solving environment. This chapter proposes a DSS that incorporates the models described in previous chapters and is designed to meet the requirements and objectives discussed in chapters 2 (general level) and 3 (spatial domain). The proposed DSS is implemented in a windows-application called Location Planner using C++. The application proves that the proposed system design is consistent and feasible given available programming tools.

This chapter is structured as follows. The first section (8.2) reviews existing spatial DSS approaches and discusses the assumptions and objectives of our approach against this background. The intended contribution to the state-of-the-art is to improve the modelling capabilities, flexibility and interactive properties of existing spatial DSS. As distinguishing features of the proposed design, users are able to construct a model of the retail or service system out of available inference model components and use the models for simulation and optimisation through multiple, active and linked views. The sections that follow describe the design and implementation of this system. First, section 8.3 considers the system components that make up the analytic capabilities of the system. Next, section 8.4 describes the user-interface components. Section 8.5 concludes the chapter with a discussion of potentials and limitations of the proposed system.

8.2 Review of spatial DSS approaches

As said in Chapter 2, spatial DSS combines GIS and spatial models with the aim to support spatial decision-making. This section reviews existing approaches. To structure the discussion, a distinction is made between studies reporting on operational systems and studies that are focused on specific aspects of spatial DSS methodology. Within the first category, different types of systems are distinguished dependent on how decision problems are conceptualised and which analytical modelling technique takes in a central position. These include (i) systems based on spatial interaction/choice models for impact analysis; (ii) systems based on mathematical programming for solving multi-facility location problems and (iii) systems based on multi-criteria evaluation methods for (single) site selection. The latter two types of systems have clear counterparts in business management in the decision calculus (mathematical programming) and decision analysis schools (multi-criteria decision making) (Stabell 1987). On the other hand, the methodological types of studies have focused on various aspects of DSS design. These include the visual and interactive properties of DSS, the intelligence of DSS and the ability of the systems to facilitate group decision making (group DSS). This section reviews the different fields in turn.

8.2.1 The spatial interaction/choice modelling approach

The central component of these systems is a spatial shopping model of the interaction or discrete choice type to assess the impact of plans. The systems intend to improve the effectiveness of decision-making by improving the availability and quality of information about the likely impacts of retail plans and lowering existing thresholds for evaluating action scenarios. Considering the latter purpose, the ability of users to manipulate the model easily and intuitively is stressed.

Applications of these systems have been described in Roy and Anderson (1988), Borgers and Timmermans (1991), Grothe and Scholten (1992), Kohsaka (1993), Birkin *et al.* (1994, 1996), and Clarke and Clarke (1995). All systems use a spatial interaction model, except the PEARL system proposed by Borgers and Timmermans (1991) which is based on an MNL-model. Most models use uni-dimensional attraction terms to describe centre/store choice alternatives. More general multi-dimensional models are used in PEARL and the extended version of LAIRD (Roy and Anderson 1988) and in some applications developed by the GMAP consultant group (Birkin *et al.* 1994, 1996; Clarke and Clarke 1995). Moreover, all models are characterised by the IIA-property except the model used in the extended LAIRD system. This model has a nested structure to account for possible substitution effects between stores lying in each others proximity. Furthermore, this model uses income group specific parameters to account for possible differences in choice behaviour between income groups. In all systems the users cannot choose model variables. However, some systems allow users to set or change model parameters (e.g., Grothe *et al.* 1992) or to run a built-in procedure to estimate the model based on observed consumer flows (the LAIRD system).

Typically, the systems also incorporate complementary models for analysing performance characteristics such as demand/supply ratios and travel demand. Spatial opportunities of consumers receive little or no attention. Some GMAP-applications incorporate a set of indicators that can be combined to rank existing or new locations for monitoring purposes. Fewer systems also support location selection actively. The system proposed by Kohsaka (1993) incorporates a steepest descend algorithm to search for locations on a continuous potential surface (predicted by the shopping model). Clarke and Clarke (1995) and Birkin *et al.* (1996) describe applications which incorporate a location-allocation model for developing (competitive) retail outlet networks. None of the systems provide facilities to support the choice stage or group decision-making explicitly (e.g., multi-criteria decision making).

Some systems provide a graphic user-interface. Kohsakas system (1993) uses three-dimensional graphic representations of potential surfaces to visualise trade-areas. The application described in Grothe and Scholten (1992) provides graphic facilities to visualise consumer flows and to implement facility openings and closures on a map. The GMAP applications are developed by linking analytical models with existing GIS software. The graphical abilities of the GIS are considered important particularly for representing model results in the form of thematic maps. Furthermore, in these applications the GIS-component provides the required functions for database management as well as elementary forms of spatial analysis (e.g., geodemographics).

8.2.2 The mathematical programming approach

The core of these systems consists of a (linear) location-allocation program. The earlier problem exploration and problem formulation stages are emphasised. Users are able to formulate the given location problem in terms of an objective function and set of constraints. The system generates optimal configurations of the retail/service network, given candidate locations and sometimes also optional outlet formats. When confronted with a generated solution, users may reformulate the location problem and prompt the system to generate a new solution. By exploring the solution space in this way, users increase their understanding of the problem and eventually converge on an acceptable solution. The DSS seeks to improve decision making by optimally supporting the interactive use of location-allocation models. As Densham (1991) puts it, the objective of spatial DSS (in this approach) is to provide a ‘flexible problem-solving environment in which decision makers can explore a given problem, evaluate the possible trade-offs between conflicting objectives and identify unanticipated, possibly undesirable characteristics of the problem’.

Typically, applications of these systems use a uni-dimensional objective function (i.e., the *p*-median model). A notable exception is the system proposed by Malczewski and Ogryczak (1990). This system allows users to specify aspiration and reservation levels on multiple criteria and generates the corresponding set of non-inferior (efficient) solutions. A prototype DSS illustrates the approach in the area of hospital location selection. Both the uni-dimensional and multi-dimensional models typically use deterministic allocation rules. Therefore, the systems are less suitable for impact assessment in user-attracting facility systems, such as retail systems, where destination choice is a decision of consumers (rather than government, as for example in some school systems).

Densham (1994) reviews applications for location selection. Armstrong *et al.* (1990), and Densham and Rushton (1996) describe spatial DSS applications for reorganising service delivery systems. As a representative example, we will now discuss the system of Armstrong *et al.* (1990) in some detail.

The analysis subsystem of the DSS consists of a shortest-path routine to generate travel distance information, a location-allocation program based on the interchange algorithm and software to reallocate demand. The location-allocation program can solve all objective functions that match the format of Hillsman's unified linear model including the *p*-median, maximum covering and set-covering problems. Existing mapping software (Atlas) is used to display model results in the form of several kinds of thematic maps. Furthermore, a report generator provides users with statistical information about solutions.

A case study concerned with a reorganisation of educational services from central facilities illustrates the use of the system. A group of decision-makers (members of a state government work group) formulated scenarios in terms of criteria and constraints. The scenarios were translated by an analyst into an appropriate model specification. Solutions generated by the system typically evoked discussions leading to re-formulating criteria and constraints. For example, an unconstrained *p*-median solution would evoke suggestions to add a maximum distance constraint to the solution. By making comparisons between solutions the group was able to evaluate trade-offs, for example, whether the gain in performance on one criterion compensates for the loss on another. Through this iterative procedure the group could obtain a better understanding of the problem and reached consensus on a solution. As the authors conclude, this application demonstrates how a spatial DSS can support problem definition, formulation and solution.

8.2.3 The multi-objective decision making approach

The choice of a location for a planned facility or land-use requires finding an acceptable compromise between interests of various parties involved, such as local residents, environmental groups, consumers, producers and the larger community. Environmental and economic interests are typically in conflict in the case of noxious or obnoxious facilities, such as for example solid waste dumps, industrial plants or high-ways, but also the siting of facilities such as for example schools, resort hotels tends to evoke considerable debate among interests groups (Couclelis and Montmonier 1995).

Multi-criteria or multi-objective DSS represents a distinct approach aimed at providing tools for analysing the complex trade-offs between choice alternatives. These systems assume a discrete set of choice alternatives as given and try to improve the quality of decisions by supporting the integration of multiple criteria in the choice stage. For this, the systems offers assistance in identifying location candidates, developing lists of criteria for evaluation, determining weights of criteria, performing sensitivity analysis and alternative ranking (Janssen 1991). A subset of the systems also *explicitly* supports group decision-making. Spatial group DSS typically targets a group consisting of representatives of the different parties involved and offers assistance in identifying and weighting criteria through group discussion. Multi-criteria-evaluation (MCE) or multi-objective programming (e.g., goal programming) techniques are typically integrated with analytical and mapping tools of GIS. There are many examples of such systems reported in the GIS literature (e.g., e.g., Fedra and Reitsma 1990, Carver 1991, Pereira and Duckstein 1993, Jankowski 1995, Lin *et al.* 1997, Malczweski 1996, Jankowski and Ewart 1996, Crossland *et al.* 1995). The spatial DSS for solid waste planning described in MacDonald (1997) combines various techniques including mathematical programming, impact analysis and the Analytical Hierarchical Process. Carver (1991) describes a method for integrating GIS and MCE techniques. As a typical example, we will now consider the system proposed by Carver in some detail.

Carver proposes a two-step procedure. In the first step, area-screening techniques are used to identify all the potentially feasible areas in which to look for suitable sites. For example, feasible areas may be defined in terms of a minimum population density, a maximum distance from a high-way and so on. Standard GIS overlay and buffer analysis tools are well suited for this kind of analysis and also allow decision makers to investigate 'what-if' scenarios. The objective of the second step is to identify within the identified areas the sites that represent a suitable compromise on the set of criteria defined by the decision-maker. Different scenarios can be implemented in terms of different weighting schemes or MCE-techniques (e.g., concordance-discordance analysis, weighted mean etc.). The scenarios may be the outcome of a discussion among the representatives of the involved interests groups. Different specifications of the MCE-model will produce different rankings of alternatives. The outcomes may evoke a re-evaluation of criterion values. Through an iterative procedure group members are supposed to reach consensus about criterion weights and the corresponding solution. If tools are offered for dynamic sensitivity analysis, users can manipulate weights and the system generates the implied ranking of alternatives.

8.2.4 Improving the interactive properties of SDSS: visual interactive modelling

As end-users are normally not familiar with the technical details of decision models, graphic user-interfaces are generally considered an essential feature of DSS. Ideally, the system simulates the environment in which decision-makers operate as realistically as possible, for example, by using images or animation. The objective of the Visual Interactive Modelling (VIM) approach is to supply models with such graphical components not only to display model output, but also to support graphic manipulations of models. VIM was introduced to improve user-interfaces of operation-research models (see Hurrion 1986). Recently, the use of VIM in DSS is an active field of research (see Anthonisse *et al.* 1988, Dror *et al.* 1991, Belton and Elder 1994). Densham and Armstrong (1993) and Densham (1994) have advocated and elaborated this approach for spatial DSS.

In their approach, a decision maker faced with a problem can interact with the DSS in four spaces: the object space consisting of the set of feasible locations; the decision space containing the subset considered feasible by the decision maker; the model space representing analytical relationships between variables and the geographical space representing the spatial context. In the (conceptual) system they propose, the user-interface supports multiple representations of all four spaces. These include maps, graphs and tables. For example, a map is a suitable representation of facility locations and the demand allocated to them, the table can represent attributes of these facilities and graphs may display the distribution on a selected attribute (e.g., size).

The user-interface supports graphic manipulations of the objects and variables in these representations. For example, users can relocate, open or close facilities on a map, change the size of a facility in a histogram and change the value of a model parameter using visual controls. The representations are connected through dynamic links and can be viewed simultaneously in different windows. These links make sure that a change in one window leads to automatically updating the complementary windows. For example, if the user closes a facility on the map, the model would recalculate the allocation relationships and refresh not only the map window, but also the graphs and table representations to display the new state of the system.

Densham and Armstrong (1993) further distinguish two modes of user-system interaction. In the 'intuitive' mode, users define changes (e.g., closing a facility) directly, e.g., through the kind of graphic manipulations described above, and the model determines the consequences, e.g., in terms of reallocations. Clearly, this mode requires that allocation and location components of optimisation models can be run independently. In the 'goal-seeking' mode, users select or change parameters of a model and the system generates an optimal spatial configuration (and updates all windows appropriately). The goal-seeking mode is the normal mode of traditional operation research applications (i.e., systems based on mathematical programming).

The concept of active and linked views has also received much attention in the field of graphics in (spatial) statistics. Examples can be found in Majure and Cressie (1997), Unwin (1996), Beschers and Feiner (1993), Haslett *et al.* (1990) and Cleveland and McGill (1988). The proposed systems allow users not only to view the statistical data graphically, but also to interact with these graphs. Users can have different views (i.e., multiple representations) of the data. These views are active in the sense that users can select and highlight items in each view. The views are linked so that selections in one view are automatically also implemented in all other views. Dynamic graphics facilitate exploratory data analysis and are particularly powerful in spatial statistics. For examples, outliers identified in a scatter diagram representation can be easily located on a map representation due to the dynamic links.

8.2.5 Improving the intelligence of spatial DSS: knowledge-based DSS

Another constant stream of research focuses on the use of expert system techniques (ES) to improve the intelligence of traditional DSS. Zopounidus *et al.* (1997) define Knowledge-Based DSS that emerged from this field as "a computer information system that provides information and methodological knowledge using analytical decision models, data and knowledge bases to support decision-makers in making decisions effectively in complex and ill-structured problem domains". Han, Kim and Adiguzel (1991) identify as possible contributions of ES to DSS: (i) helping users in selecting models, (ii) providing judgmental elements in models, (iii) simplifying building simulation models, (iv) enabling friendlier interfaces and (v) providing explanation capability. The use of ES for the second purpose has already been reviewed in Chapter 7. Other studies both in operation research and spatial planning have focused on using ES to assist users in specifying analytical models and interpreting the results (i.e. the first and third purposes).

A good example is the XPlanner system for military facility management and planning (Han and Kim 1991). The core of the system is a zero-one integer optimisation model. The ES-component consists of a set of if-then rules for formulating the optimisation model and explaining results to the user. Specifically, the ES estimates parameters of a zero-one optimisation, eliminates facilities that are irrelevant for consideration in the optimisation and interprets the output of the model in non-technical terms. Thus, the ES-layer insulates users from the technical details of the mathematical program. Similar applications of ES are described in Krishnan (1989), McGovern and Samson (1989), Elam and Kosynski (1987) and Moser (1986). Rule-based systems are also proposed in the context of model management system (see Zhuge 1998). The KBS proposed by Xiang (1997) advises decision-makers in formulating plans and reduce redundancy, competitiveness and incompatibility between action components.

The knowledge-based DSS-approach proposed by Armstrong *et al.* (1991) goes a step further. As reviewed in Chapter 4 in relation to the multi-layered knowledge model, their system uses an ES component to help users in planning the problem solving process. The so-called Metaplanner module in their system decomposes a given planning problem into subproblems that can be handled by algorithms stored in the analytical model-base (in the module called Subproblem Solver). If the Metaplanner receives a request to achieve a goal, it searches a metaplan library for an appropriate metaplan. A metaplan is a script-like structure specifying a problem solving strategy (rather than an algorithm). If none of the available metaplans matches a given goal or if a selected metaplan fails, the Metaplanner starts a dialogue with the user based on a metaplan at a higher abstraction level (e.g., to reformulate the problem). Thus, the competence of the Metaplanner corresponds to the strategic layer in the four-layered model discussed in Chapter 4. Unfortunately, the study does not provide implementation details or an empirical application of the approach. The support of higher-level cognitive tasks is a distinct field of DSS-research known as active or adaptive DSS. In that broader context, ES technology has specific relevance for DSS (for an overview of the field, see Fazlollahi 1997).

In summary, the role of ES in DSS design ranges from interfacing and management of analytical models to assisting users in high-level cognitive tasks and providing adaptive interfaces. The first role is dominant in operational KBDSS's. The use of ES at a strategic level has been advocated in conceptual studies, but - to our knowledge - has not materialised in operational DSS applications. Recently, Leung et al. (1997a,b) introduced a shell for developing domain-specific intelligent spatial DSS. The system supports the integration of GIS, spatial models and domain-specific knowledge components in a windows environment.

8.2.6 Facilitating group decision making: group DSS

The renewed awareness of the importance of teamwork in organisations has stimulated many studies on group DSS in business management in the nineties (see Chapter 2). Group DSS is also relevant in spatial planning, as decisions where to locate a given facility are often made in the context of multidisciplinary teams or groups consisting of representatives of different interests groups. In recent years, much conceptual work has appeared in the GIS and spatial DSS literature. Couclelis and Monmonier (1995) describe the specific technical needs of groups concerned with defining and structuring problems when there are conflicting interests between parties. They criticise conventional systems for their focus on the decision making stage and emphasise the need for systems for understanding the problem. To emphasise the distinction, they suggest the use of the term understanding support systems for the proposed type of system. Armstrong (1993) identifies the issues Group DSS research should address to account for the needs of multi-disciplinary teams for spatial decision making. Similarly, Jankowsky *et al.* (1997) investigates such issues through a prototype group DSS for habitat site selection named Spatial Group Choice. The latter system consists of several loosely coupled modules including MCE software for decision modelling and voting and interactive map visualisation software.

As styles of decision-making, methods and interests may vary among individuals, the core problem of group decision making is to streamline both divergent and convergent processes, dependent on the stage of the decision making process. In earlier stages, group DSS must stimulate the generation of ideas and arguments by each group member individually (divergence). In later stages, the system must facilitate consensus building (convergence). This requires a local computer network or multi-users system providing both private windows allowing each individual to explore alternatives privately and public windows integrating the inputs of individuals (Armstrong 1993). Appropriate visualisation techniques such as maps are generally considered essential to provide a medium for communicating results and focusing the attention of the group. The extension of conventional MCDSS (or MODSS) with special devices for voting allows groups to set criteria weights and judge alternatives on criteria (Jankowsky 1997).

To conclude, facilitating group processes imposes both additional and higher requirements on DSS capabilities. Additional facilities, such as for example local computer networks and voting devices, are required to handle and integrate inputs from a group. On the other hand, existing features of single-user DSS become more important, as a group brings in a broader spectrum of preferences and styles of decision making. Specifically, flexibility (ability to represent different preferences) and interactive visualisation techniques are highlighted. At present, the specific implications of group decision making for system design of spatial DSS is an ongoing field of research.

8.2.7 Suggested approach

Considering problems in retail/service planning discussed in Chapter 3, none of the approaches reviewed above fully utilises the potentials of available models reviewed or newly developed in chapters 4-7. Moreover, the design proposed here is aimed at integrating visual interactive and knowledge based approaches that were developed independently of each other and, if brought together, would lead to more powerful systems. It should be noted on the outset, however, that every approach entails a specific focus. Although retail/service planning often involves inputs from different parties including the community in general, producers and consumers, the system proposed here does not provide special facilities for group decision making. Instead, the design focuses on what was identified as the most important potential contribution of a spatial DSS in Chapter 3, namely improving the integration of models in the planning process. The intended contribution of our approach to the state-of-the-art can be grouped under the following headings.

Modelling capabilities

Although there are exceptions (e.g., MacDonald 1997), most existing spatial DSS applications are constructed on the basis of a single modelling technique. As every technique has its specific potentials and limitations, such systems master some aspects of decision problems at the expense of others. The spatial interaction/choice modelling (SIM) systems focus on inference-layer capabilities for impact analysis. They offer no or limited task-layer models for solving well-structured subproblems, such as for example generating or ranking alternatives. The reverse holds for existing SDSS based on mathematical programming (MP) or multi-criteria evaluation (MCE) methods. These systems offer task-layer models for multi-facility or multi-criteria optimisation problems. At the inference level, however, the models used fall short in representing the complexity of consumer behaviour that is typical for consumer-attracting systems. For example, built in location-allocation programs typically use the nearest-centre rule to allocate demand to facilities. Similarly, the MCDSS (or MODSS) lack advanced inferential components for impact analysis.

The purpose of our approach is to better utilise the possibilities of available inference and task modelling techniques. In contrast to existing SIM-systems, the proposed DSS uses (i) the generalised multipurpose shopping model for prediction (Chapter 5), (ii) complementary performance models for analysis (Chapter 6), (ii) appropriate task-level models for solving well-structured location problems and (iii) knowledge-based models for structuring the overall task (Chapter 7). The multi-layered modelling framework (Chapter 4) offers a suitable structure to integrate the various techniques. In a layered structure it is possible to use the more advanced inference models as components of task-models. Thus, the proposed system does not only intend to improve the modelling capabilities of existing DSS, but also to improve the integration and flexibility of models.

Interactive properties

This aspect refers to two dimensions of the user-interface: the access to parts of the problem space (openness of the system) and communicative properties. Arguably, existing systems can be improved on both dimensions. In relation to the first dimension, the VIM-based design proposed by Densham (1993) is probably the most advanced design. In this design, there are four spaces of interaction. Yet, considering our earlier knowledge model of planning described in Chapter 4 (Figure 4.1), this seems to be too restrictive. The DSS that we propose, more broadly, offers access to all sections of the domain that are relevant for decision-making. That is, users can view and manipulate not only the contents of an object space (i.e., feasible alternatives) and decision space (i.e., a solution), but also autonomous developments, predictions (future state), goals and discrepancies. Moreover, within each of these spaces users are able to consider demand, supply and spatial interaction objects. We will refer to these spaces as different *sections* of the domain.

To enhance the communicative properties - the *second* dimension of user-interfaces, we use the above discussed VIM and dynamic-graphics techniques much in the same way as proposed by Densham (1993) and Armstrong and Densham (1993). That is, the proposed system supports multiple representation formats (views) of domain sections. These include map, graph and table format. The views are dynamically connected with each other so that changes in one view lead to automatically updating related views.

Flexibility

The ability to adapt to information needs, available data sources and preferences of users is one of the major objectives of DSS. Yet, this aspect has not received much attention in the systems reviewed above. Most operational systems are specifically developed with a certain user and even a particular study area in mind. In chapter 2, a distinction was made between level-1 (adapt to a preferred solution path) and level-2 flexibility (adapt to a problem). The proposed design tries to improve both levels of adaptability of DSS.

With respect to the *level-1* flexibility, existing systems tend to focus on a single interaction mode related to the modelling technique used. Specifically, SIM systems focus on what Densham and Armstrong (1993) call the intuitive mode. In this mode, users can specify scenarios in terms of planned or anticipated developments (e.g., opening a new facility, population forecasts) and the system gives feedback in terms of impacts on criterion variables (e.g., market shares of facilities). On the other hand, DSS based on MP/MCE-methods are designed to support the goal-seeking mode. That is, users can specify the location problem in terms of criterion variables (e.g., criteria weights) and the system generates optimal solutions in terms of decision variables (i.e., optimal configurations or rankings). Where SIM-systems lack the analytical capabilities or an appropriate user-interface for the goal-seeking mode, the MP/MCE systems are weak in supporting the intuitive mode. Hence, the goal of our approach is to provide not only the modelling capabilities, but also the appropriate user-interfaces for both interaction modes. In terms of the layered modelling framework, this means that the system should allow users to *interact* with the same inference models (e.g., shopping models) that are also used as components of task models (e.g., location models).

With respect to *level-2* flexibility, most SIM-systems are highly restrictive. They offer users limited possibilities to change the specification of a shopping model (selection of attributes), the utility function form (e.g., nested logit or MNL) and

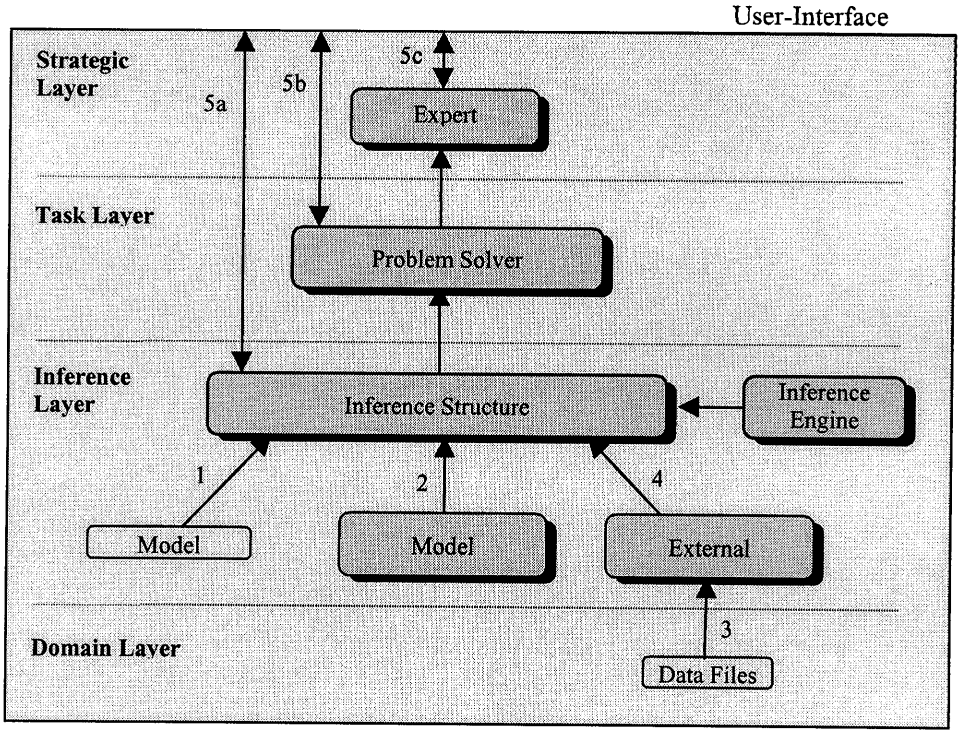

Figure 8.1. Structure of the spatial DSS.

sometimes even the values of model parameters (weights of attributes). The reason for this is that most systems are designed for a specific application. For each new application systems must be re-designed to suit the specific information needs. A generic DSS requires a more fundamental solution. To be able to support problems in both public-sector and private-sector planning, the system must cover the general central-facility problem as well as the competitive-facility problem. Moreover, for both types of problems users should be able to choose attributes, attribute parameters and even the form of the spatial shopping model. To solve this problem, we propose a two-step procedure. In the first step, users construct a model of the retail or service system under investigation out of available inference model components in the model-base. Then, in the second step, users interact with the model to solve the given problem (either at the inference, task or strategic level). In this way, the user rather than the system designer customises the system.

8.3 Location Planner: system components

8.3.1 Overview of the system

Location Planner is best viewed as a shell in which users can specify an inference structure for simulation and optimisation dependent on the given location problem. The components of the system are schematically shown in Figure 8.1. Although the system does not prescribe a procedure, the following list describes a logical sequence of steps:

1. Define exogenous and endogenous variables (e.g., demand and supply attributes).
2. Select and specify for each endogenous variable a model component for computing the variable.
3. Specify the data files constituting the database.
4. Link exogenous variables with appropriate data fields.
5. Use the resultant inference structure for simulation (inference level) or use Problem Solver for finding optimal configurations of a facility network (task level) or use Location Planner Expert for developing problem solving strategies (strategic level).

Steps 1-4 result in an inference structure and step 5 represents the alternative modes of interaction with the model (intuitive, goal seeking, assisted). In the next sections, we first discuss each system component (boxes in Figure 8.1) separately and next the user-interface components related to the above steps.

8.3.2 The inference structure

The multi-layered knowledge-model discussed in Chapter 4 is incorporated in Location Planner as a framework for specifying the inference structure. To suit this purpose, the original model is slightly modified as follows (see Figure 8.2). First, to reduce complexity, the time dimension is omitted (but the model can be easily extended to represent time paths as well). Second, autonomous and planned developments are taken together as a single component referred to as changes (of the present state). Third, an extra component is built in between the future state and discrepancy state. This component represents the future state in terms of goal variables (or C-variables) and is called future-C state. Where the goal state represents normative performance levels, the future-C state displays the measured values. The future-C state is added to derive and display performance characteristics of the future state explicitly before determining discrepancies with the goal state.

As explained in Chapter 4, each box represents a perspective on the system being planned. In addition, three spatial object types are distinguished within each

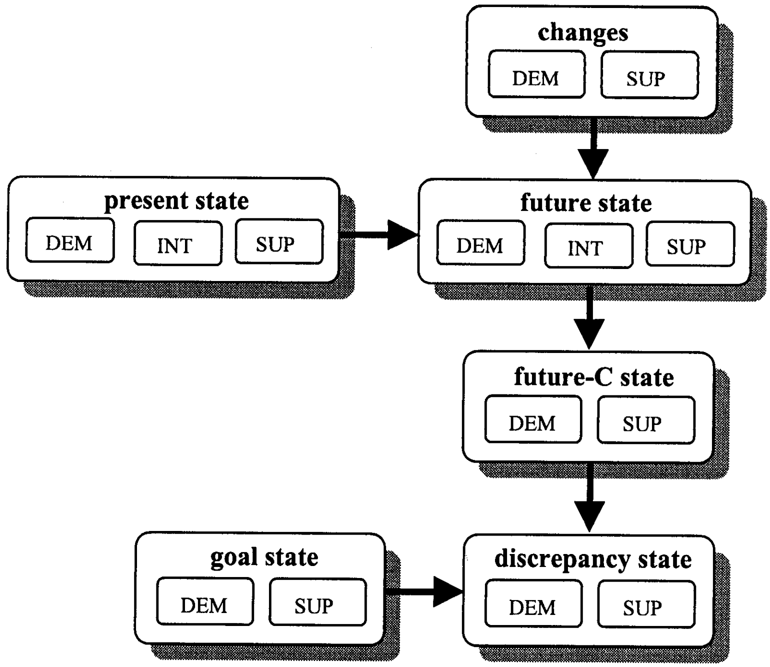

Figure 8.2. The inference structure.

perspective. These include demand objects (residential areas), supply objects (shopping locations) and interactions (consumer flows). In Location Planner a combination of perspective and object type is referred to as a section (of the domain). For example, the section 'future-*C*, demand' reveals demand-related indicators of performance under future conditions. Not every possible combination of perspective and object type is meaningful. For example, the 'goal state – interaction' combination is considered redundant given the assumption that planners do not specify objectives at the level of flows. The sections shown in the figure are enabled in Location Planner.

Internally, a section is a frame-like structure consisting of a collection of slots for holding variables. The variables themselves are complex (dynamic) data structures, dependent on the object type they describe. In demand and supply sections, a variable represents a vector of values related to demand or supply objects. In interaction sections, a variable represents a matrix of flows between demand and supply locations. Regardless variable type, each slot contains subslots for a variable label and a method. A method defines a model for computing the variable. It is useful to distinguish between two types of methods. First, methods available for exogenous variables simply involve a procedure for reading data from a database. Second, methods for endogenous variables refer to internal calculation procedures. The latter methods define inferential links between variables and include the following functions:

1. Arithmetic summation to define the relationships:
   $X_i^{future\ demand} = f(X_i^{present\ demand}, X_i^{change\ demand})$
   $X_i^{future\ supply} = f(X_i^{present\ supply}, X_i^{change\ supply})$

2. Shopping models to define the relationships:
   $X_{ij}^{future\ interaction} = f(\dots X_i^{future\ demand}\dots, \dots X_j^{future\ supply}\dots.)$

3. Demand related performance models to define the relationships:
   $C_i^{future\ demand} = f(\dots X_i^{future\ demand}\dots, \dots X_j^{future\ supply}\dots., \dots X_{ij}^{future\ interaction}\dots)$

4. Supply related performance models to define the relationships:
   $C_j^{future\ supply} = f(\dots X_i^{future\ demand}\dots, \dots X_j^{future\ supply}\dots., \dots X_{ij}^{future\ interaction}\dots)$

5. Arithmetic ratio or difference to define the relationships:
   $C_i^{discrepancy\ demand} = f(C_i^{goal\ demand}, C_i^{future\ demand})$
   $C_i^{discrepancy\ supply} = f(C_i^{goal\ supply}, C_i^{future\ supply})$

where X and C indicate the variable type - attribute or goal variable, the superscripts refer to perspective and object type of the section, and the subscripts denote the dimensions of the variable - demand vector (i), supply vector (j) or interaction matrix (ij). The first and fifth category relates pairs of variables with each other through a simple arithmetic operation. The remaining categories define more complex relationships between sections based on spatial models.

Computationally, an inferential method is an object defining a calculation procedure, identifiers of variables from other sections containing input data, parameter settings and control information for the inference engine (as will be explained below). Thus, the methods establish links in an inference chain (Figure 8.3). Present state, change and goal-section variables are begin points of chains, as they contain exogenous variables whose values are derived from external data sources. Discrepancy state variables represent the end points of chains of input-output links.

8.3.3 Inference model base

This part of the system contains the methods (objects) that can be linked to method slots within sections, as explained above. As said, the incorporated models include elementary arithmetic operations (summation, difference and ratio) and spatial models.

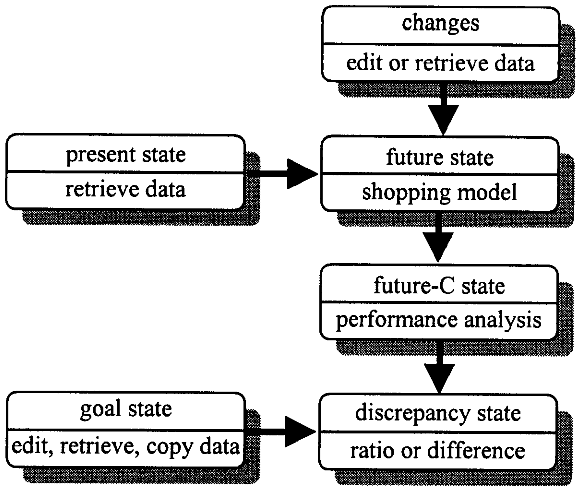

Figure 8.3. Inference links between sections.

Arithmetic operations need no further explanation. Spatial models, on the other hand, will be discussed in more detail and include shopping models and performance models. For a formal description of the models we refer to chapters 5 and 6. This section describes the models at a functional level in terms of input-output relationships.

Shopping Models

These models are used to define interaction variables in the future state section. Recall, that each interaction variable represents a demand × supply matrix of consumer flows. A flow is expressed as a choice probability of consumers (demand) selecting a shopping destination (supply). Flows to locations outside the study area are represented as an extra column in the matrix. As the interaction section contains a collection of slots, in effect users can define either a set of two-dimensional matrices or a single three-dimensional interaction matrix. In a two-dimensional matrix probabilities across supply locations sum to 1 for each demand location, whereas in a three-dimensional matrix probabilities sum to 1 across the supply *and* third dimension. The three-dimensional form allows one to represent trip-type × demand × supply interactions. A set of two-dimensional interaction matrices is relevant in cases where the third dimension does not represent a choice but a segmentation of the consumer population. For example, one may wish to use different specification of shopping models for different segments (e.g., socio-economic groups) of the population that exhibit different shopping patterns.

The number of interaction variables (e.g., number of trip purpose choices or

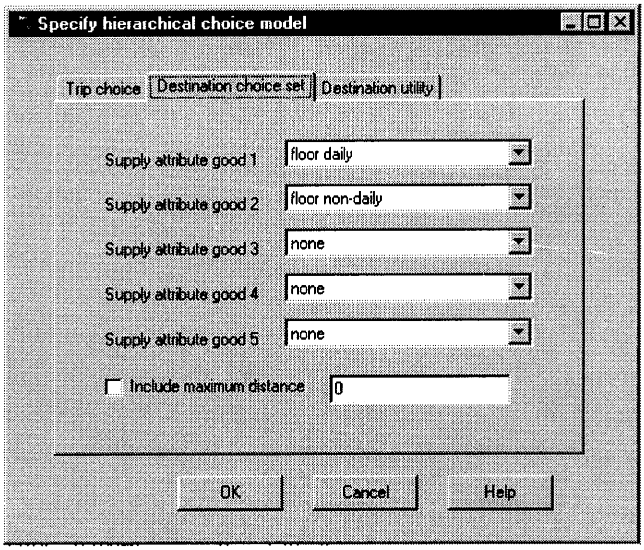

Figure 8.4. Dialogue for specifying a basic shopping model of the MNL-type.

consumer segments) one can consider in Location Planner is bounded only by the maximum number, N, of variables by section, which is a global parameter of the system. Users can specify a shopping model as a method for each interaction variable (i.e. matrix) separately. The available shopping models include the production-constrained interaction model, the MNL model and a two-layered nested-logit model. The more general nested-logit model can be used to define the multipurpose shopping model described in Chapter 5. (Note that the multistop case is not supported in the present system). For the different model types, the same set of parameters is available with which users can specify the utility function and choice-set for the concerned demand × supply interactions. The system automatically creates a three-dimensional matrix in cases where users select the hierarchical model. Thus, users need to specify for each trip type (Figure 8.4):

- for determining destination-choice sets:
  - maximally five $X^{future\ sup}$ variables
  - optionally, maximum travel distance
- for determining the utility function:
  - a constant (α);
  - a scale correction parameter ($1/\mu$);
  - travel time or distance weight (θ);
  - maximally, N $X^{future\ supply}$ variables and related weights (β);

- for determining outflow probability:
  - optionally one $X^{future\ demand}$ variable.
- choice of an allocation function: production-constrained interaction, MNL or hierarchical.

Given these settings, interactions are calculated based on equations 5.1, 5.4 or 5.13, dependent on the chosen model type. A destination-choice set is determined for each demand location based on a deterministic rule. To be included in the choice set, a destination must have a positive value on each specified $X^{future\ supply}$ variable and must be reachable within the specified travel distance, if any. In a typical specification, the $X^{future\ supply}$ variables are set to available floor space for each supply segment involved by the trip type. Supply locations that are not included in the choice-set have zero interaction probability values. If users choose the interaction or MNL type of model, the system ignores the (trip-type) constant and scale correction parameter and determines probabilities for each matrix separately. In summary, the interaction section may represent either a set of two-dimensional or a single three-dimensional matrix. This difference in meaning will come to expression in the way the interaction variables are labelled (by the user) and used for performance analysis in future-*C* sections.

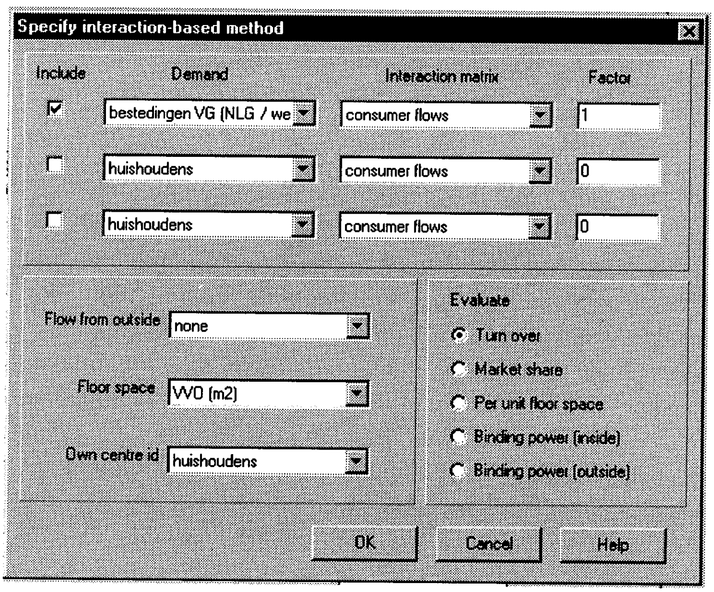

Figure 8.5. *Dialogue for specifying interaction-based supply-related performance indicators.*

Supply-Related Performance Models

These models can be used to determine variables in the supply future-*C* section. The available models calculate (in different ways) a vector representing the amount of allocated demand per supply location (store, centre or area). Interaction-based and deterministic models are available. Interaction-based models use the future state interaction matrices to allocate demand across supply locations. Because these models are based on shopping behaviour, they are suitable for predicting turnover volumes. The parameters depend on the specification of the interaction section, i.e. $n \times 2D$ or $1 \times 3D$. Figure 8.5 shows the dialogue for the two-dimensional case. Here, we consider the three-dimensional case in more detail. For the 3D case users need to specify:

- for determining the available expenditure in origin locations:
  - an $X^{future\ demand}$ variable representing demand in origin locations
  - a weight representing the per-capita-expenditure rate
- for each involved trip type (i.e. interaction variable): a weight representing the relative expenditure-per-trip rate
- optionally, an $X^{future\ supply}$ variable representing inflow from outside the study area
- choice of measure: turnover, market share (i.e. turnover per unit expenditure in the study area) or productivity (i.e. turnover per unit capacity)
- if 'productivity' is chosen: an $X^{future\ supply}$ variable representing the capacity (i.e. floor space)

Given these settings turnover per supply location is calculated based on Equation 6.33.

Deterministic models are available as an alternative to this interaction-based model. The proximal-area based model allocates demand to supply destinations based on the nearest-centre rule. The cost-band based model, on the other hand, allocates demand within a user-specified cost-band from the supply location. For both models, users can define the models by setting:

- one $X^{future\ demand}$ variable representing demand in origin locations:
- choice of a selection function: selected only, deselected only, all demand objects;
- in the case of the cost-band based model: a maximum travel distance
- choice of an evaluation function: turnover, market share (i.e. turnover per unit expenditure in the study area) or productivity (i.e. turnover per unit capacity)
- if 'productivity' is chosen: an $X^{future\ supply}$ variable representing the capacity (i.e. floor space)

Demand-Related Performance Models

These models can be used to determine demand variables in the future-*C* section. The

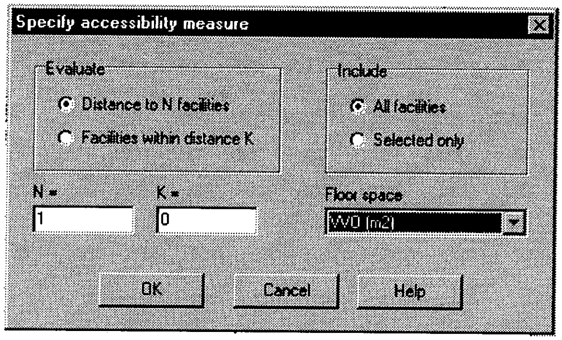

Figure 8.6. Dialogue for specifying cost-band or nearest-centre accessibility models.

available models cover various performance dimensions including accessibility of facilities, travel demand and consumer utility. For analysing accessibility, the following *opportunity*-based models are available:

- a cost-band based model for evaluating either the distance to N nearest facilities or the number of facilities available within cost-band K;
- the multipurpose model for evaluating travel cost, given optimal multipurpose trips;
- the multistop model for evaluating travel cost, given optimal multistop trips.

To specify these models, users need to specify (Figure 8.6):

- choice of an evaluation function: cost-band or nearest-centre rule
- an $X^{future\ supply}$ variable representing supply weights (e.g., floor space).
- choice of a selection function: all supply objects or selected only
- parameters N or K, dependent on the chosen evaluation function

Second, an interaction-based model is available to analyse travel demands. A distinction is made between the multipurpose and single-purpose case. In the latter case, users need to specify:

- for maximally n interaction variables (i.e., segments):
  - an $X^{future\ demand}$ variable representing trip generation per demand location;
  - w representing the relative weight of the i-th interaction variable;

- an $X^{future\ interaction}$ variable representing the distribution of choice probabilities across supply locations per demand location.

The model allocates for each demand location the trips across supply locations and determines the weighted sum of the trips across the segments.

In the multipurpose case, different assumptions are supported with respect to the question whether trip generation is either constrained by a total trip frequency or a total purchase frequency constant (see Chapter 6). Users can specify the multipurpose travel-demand model by setting:

- an $X^{future\ demand}$ variable representing population size
- the total trip frequency (assumption 1) or the total purchase frequency (assumption 2)
- for each trip type (i.e. interaction variable)
  - the goods involved in the trip purpose (a binary n-string in the n-good case)
- choice of an evaluation function: total trip frequency, average trip length, total travel demand (average length times frequency)

The choice between assumptions 1 and 2 determine whether the system keeps the total trip frequency or total purchase frequency constant in deriving trips from the 3-D interactions (see Chapter 6). The system calculates a demand vector of scores using equation 6.26/6.25, 6.29, 6.28, dependent on the chosen evaluation function.

Finally, the consumer utility model evaluates for each origin location the aggregate utility consumers derive from available supply of facilities. Users need to specify the same set of parameters as for shopping models in the future-interaction sections. That is, they must define the choice-set generation function, utility function and model type (MNL or nested logit). Instead of deriving probabilities the utility-model calculates the maximum expected utility for each demand location based on Equation 6.34.

8.3.4 Domain data base

Inferential relationships defined by the above reviewed methods constitute an empty inference structure. Linking data to the inference structure is accomplished by means of an additional generic method which controls a procedure for reading data from an external database. Users can specify the method by indicating the data field from which data are to be read. This method is available for exogenous variables, i.e. variables in the present state, change and goal sections.

The database consists of slots for the following files (Figure 8.7):

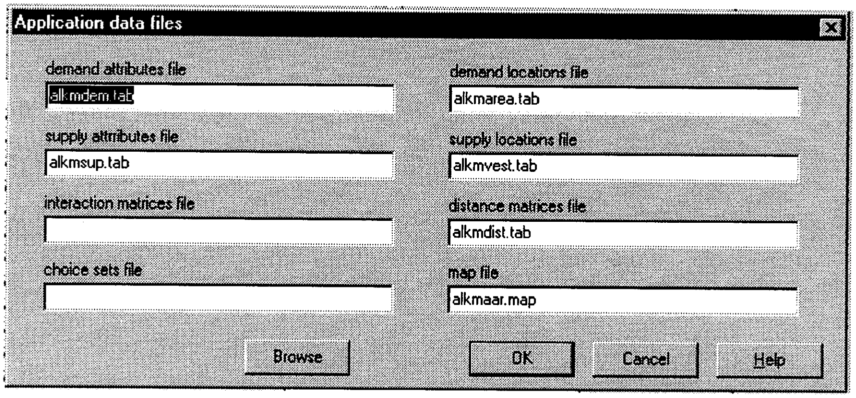

Figure 8.7. Dialogue for specifying a data base.

- demand attribute data file;
- supply attribute data file;
- demand location data file;
- supply location data file;
- travel distance/time data file;
- geographical data file;
- map image data file.

Attribute files are used by the system first of all to read identifiers (either numeric or string type) of demand and supply objects. Second, these files should contain attribute data used to define demand and supply variables at least for the present state and, optionally, also for the change (e.g., population forecasts) and goal sections (e.g., performance standards). The location files should store the location identifiers of involved demand and supply objects. The travel distance/time consists of a location × location matrix. Together, the location and travel distance/time files are used by the system to write a demand × supply matrix and a supply × supply matrix in a temporary random access file. This procedure fails if location identifiers are missing in the location or travel distance/time files.

The geographical and map image data files are optional. The geographical data file stores co-ordinate data for drawing demand and supply objects on a map. The map displays population areas (polygons), centroids of these areas (points), and locations of supply objects (points). Together with co-ordinate data, the file stores demand and supply identifiers used by the system to link geographical and attribute data. If included, the image data file is used by the system to display an image as a background for the map. A possible use of the image file is to display the spatial and functional structure of the study area in terms of the transportation network, physical barriers (e.g., waterways, rail roads etc.) and land-uses.

Location Planner does not provide an editor for creating or modifying these files. Instead, the system supports the use of existing files for example generated by a GIS or other general-purpose software. Supported formats include DBase and TransCad-table files for attribute and spatial data, BNA for geographical data and bitmap for image data.

8.3.5 Inference engine

The inference engine is a central component of the system. This component controls the inference process and guards the internal consistency of the model. Various mechanisms are involved. First, the engine evaluates and resets variables in response to users' actions or task level input from the system. The engine keeps a record of the update status of variables. Initially, the update status of each variable is false. When the engine receives a command to evaluate a variable, it starts a backward chaining inference procedure. First, the engine consults the method related to the variable for identifying input variables. Then, for each of these input variables the engine repeats this procedure to identify the variables which serve as input at the lower level. This is repeated until the begin points of the inference chain are reached. When a method is missing, the engine sends an informative failure message to the user and stops the inference procedure. Otherwise, when the chain has been completely identified, the engine executes the chain. This involves sending an execution command to each method from begin points to the end point of the chain. Upon receiving an execution command, a method runs the appropriate variable evaluation procedure, writes the results to the internal data base and sends a success message to the engine. The engine responds by setting the update status of the variable to true. On the other hand, when execution fails the method sends an error message to the engine. In that case, the engine forwards the message to the user and stops the evaluation procedure. Generally, execution of a method fails when required input data is lacking in the internal database (endogenous variables) or external database (exogenous variables). Since the engine secures internal data supply, missing data in the external database is the only possible cause of a method execution failure. Failure messages are as informative as possible so that users can identify the problem, undertake appropriate action and repeat the procedure.

Second, the inference engine serves to maintain the consistency of the relation between model settings and internal database. Whenever user's action leads to a change in the definition of a variable, the engine responds by resetting the variable (i.e., setting the update status to false). Various user actions can lead to a change of variable definitions. First, re-specifying or deleting a method changes the model used to determine the variable. Second, changing the selection status of supply or demand objects changes the definition of variables which use the selection status for determining the subsets of demand or supply objects to be included in the analysis. Third, changing the specification of the external database and editing data will change inputs of exogenous variables in present state, change or goal sections. If any one of these actions occur, the engine starts a forward chaining procedure. First, it identifies and resets the update status of the variables affected by the action. Next, it repeats the procedure for those variables that use the reset variables as input, as these data are no longer consistent. This procedure is repeated until the end points of inference chains are reached.

Third, to maintain the internal consistency of the inference structure, the inference engine comes into operation also when users add or delete variables. Changing the variable structure in one section generally invalidates method specifications in related sections. Similarly, changing attribute files in the external database will have as an effect that data retrieval methods in exogenous sections are no longer consistent. Consequently, the engine responds to such actions by identifying and resetting affected methods (which in turn invoke a chain reaction of resetting operations).

In sum, the inference engine has general knowledge about the complex network of dependency relationships between the variable structure, external database, selection status of objects and method specifications. The engine uses this knowledge to control data flows in the system and to guard the internal and external consistency of the inference structure when conditions are changed by users.

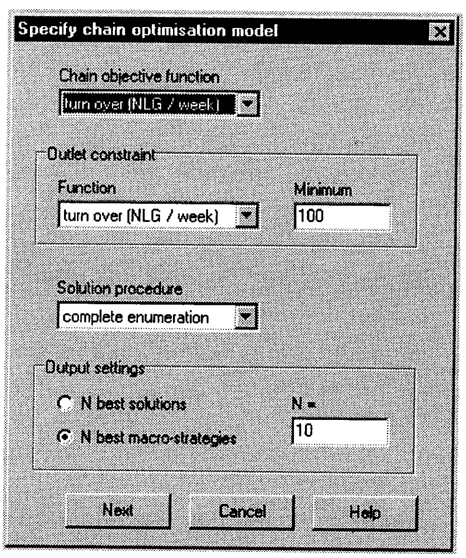

Figure 8.8. Dialogue (1) for defining a location competition model.

8.3.6 Problem solver

This module incorporates task-level models for solving well-defined location problems. In correspondence with the multi-layered knowledge model discussed in Chapter 4, the models are implemented as algorithms controlling processes at the inference level. There are two basic models available. The first model covers the

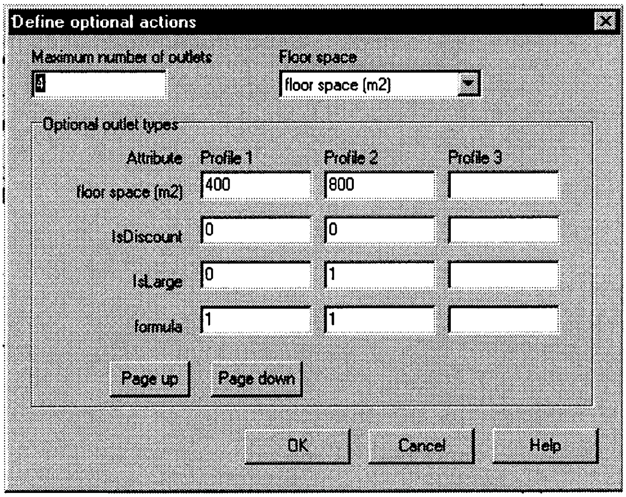

Figure 8.9. Dialogue (2) for defining a location competition model.

generic competitive location problem. This model allows one to optimise the configuration of a retail or service network in a competitive environment in terms of the number, attribute profile and location of outlets. The second model covers the central location problem. This model searches for optimal locations of a given number of facilities to serve a consumer population. The remainder of this section discusses the two models in more detail.

The competitive location model

Users can define the problem by selecting from the inference layer an objective function (a $C^{future\ supply}$ variable), a constraint function (a $C^{future\ supply}$ variable) and a minimum value of the constraint function (Figure 8.8). Furthermore, users can specify maximally three optional attribute profiles of new outlets in terms of $X^{future\ supply}$ variables (Figure 8.9). The system identifies locations of new or existing outlets of the network to be optimised based on the current selection status. That is, selected objects are taken as belonging to the own chain. Candidate locations for new outlets are identified by the system as those locations that have a zero value on the $X^{future\ supply}$ variable selected by the user (normally, floor space).

Next, users can choose between two search algorithms for solving the problem, dependent on the trade-off between speed and accuracy. First, an exhaustive search algorithm is suitable for small sized problems in terms of the number of candidate locations, number of optional profiles and the maximum number of new outlets. The algorithm evaluates all possible combinations of number, profile and locations of new

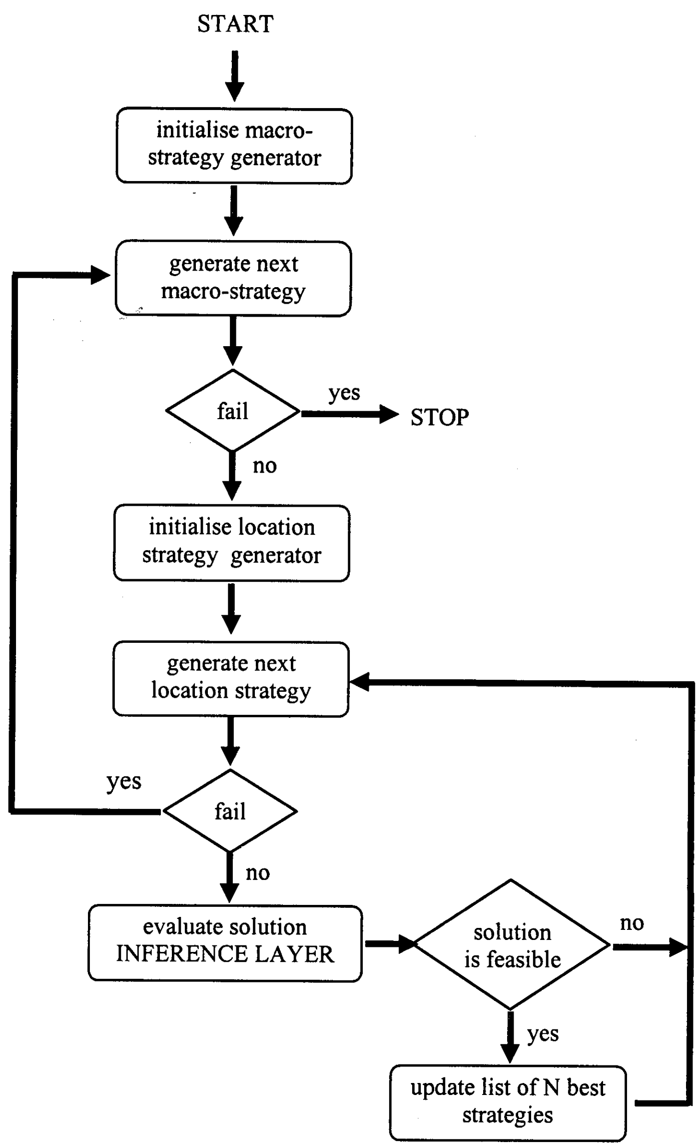

Figure 8.10. The exhaustive search algorithm for solving competitive location models.

outlets as possible solutions of the problem. The system for generating solutions is based on the distinction between macro-strategies and location-strategies proposed by Ghosh and McLafferty (1987). A macro-strategy is a certain combination of number and attribute profiles of new outlets. Given a macro-strategy, the location strategy then specifies the locations of the new outlets described by the macro-strategy. As schematically shown by Figure 8.10, the algorithm generates all possible macro-strategies and for each macro-strategy all possible location strategies. Having evaluated a solution in each step the system updates a list of best solutions. The length of the list is a parameter set by users. Also, the contents of the list depends on the desired form of the output. When users choose to do so, the system can generate a list of the best solution for each macro-strategy.

Second, the interchange algorithm is included for cases where problems are too large to allow exhaustive search. In global terms, the algorithm tries to improve a random initial solution by substituting locations in the current solution with locations not in the solution. The substitution cycle is repeated until the current solution cannot be further improved (by a single substitution). The interchange algorithm is a popular heuristic method designed to solve p-median problems (or more generally all problems that can be formulated in that format). Accordingly, here the method is used embedded in the system for exhaustive generation of macro-strategies. That is, the interchange algorithm serves to find an optimal location strategy given a macro-strategy. The interchange algorithm strongly reduces computing time when problems are large. At the same time, the algorithm appears to be highly robust. It has been shown that the algorithm is able to find optimal or near-optimum solutions under a wide range of parameter settings. Users should keep in mind, however, that performance may be less in highly constrained search spaces (e.g., tight constraints in terms of minimum performance per outlet).

Irrespective the algorithm chosen, the form of the output depends on the chosen output option. Users can choose between displaying the N best solutions or the best solution for each possible macro-strategy. The latter option is considered important specifically for gaining insight in the relationship between macro-strategy and the objective function value (normally market share of the chain). The case study in the next chapter will illustrate how this output provides useful information for trading-off investment and exploitation costs against market share (see also Ghosh and McLaffery 1987).

The central location problem

This model allows users to find the location of p outlets that minimise aggregated weighted travel distance/time to nearest destinations across demand locations. Users need to specify the problem in terms of the size p of the network, the subset of relevant supply locations (all or selected only), the $X^{future\ demand}$ variable containing demand weights and the possibility to change existing supply locations (fixed or replaceable). Again, the system offers both the exhaustive search and the interchange algorithm to solve the problem, so that users can choose the algorithm that suits problem size.

Implementation of the models

As argued in Chapter 4, implementing location models as mere control mechanisms without inference-level knowledge improves modelling flexibility. However, in the central location model, the objective function is a fixed component so that this strategy has no specific advantages. To improve efficiency in terms of computing time, therefore, the task and inference components of this model were both implemented in the same piece of code. In the case of the competitive location model the layered strategy was used. Following this principle, the (interchange and exhaustive) algorithm evaluates solutions by rewriting the change section, triggers the inference engine to update future-*C* variables and updates the current list of best solutions. Thus, the models specified in the inference layer are used as the inference components of the optimisation model. As users can specify these components in the inference layer independent of the location model, a wide variety of model specifications are possible. For example, a complex multipurpose shopping model can be used in combination with sophisticated performance models to evaluate solutions.

8.3.7 Location Planner Expert

This module of the system assists users in structuring a given problem in terms of well-defined subproblems. The module incorporates analytic and strategic knowledge developed in applied retail studies in the form of dynamic scripts. A script is related to a goal and includes suggestions for specifying models at the inference and task-level. A script is dynamic in the sense that suggestions are dependent on characteristics of the problem and available data. A script not only assists in structuring a problem, but also monitors the problem solving process. When impasses occur, a script suggests alternative ways to approach the problem. For example, a script may suggest to re-specify constraints if a spatial search algorithm does not generate useful solutions.

In sum, Location Planner Expert represents the top layer of the system. The Expert guides users through the options of the system dependent on a given goal. The scripts used by the Expert are more powerful than standard context-sensitive help facilities. Given the dynamic character of scripts, the Expert is better comparable to so-called Wizards in general windows applications. At present, this module of the system is not implemented.

Figure 8.11 summarises the models and the layers of the system. Users are able to interact with each layer. The user-interface components will be discussed in the next section.

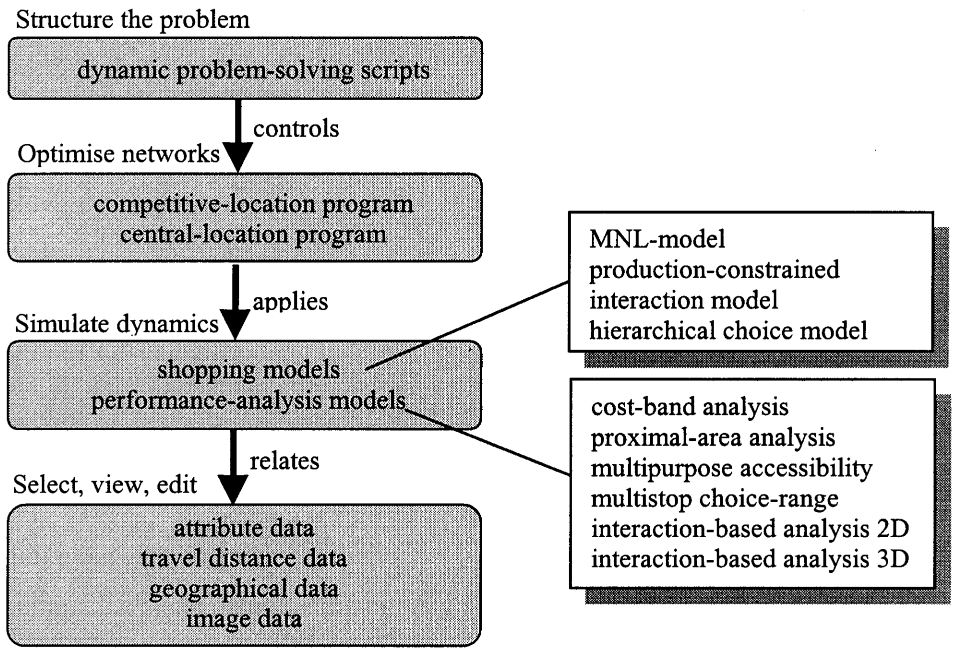

Figure 8.11. Layered organisation of data, models and knowledge in Location Planner.

8.4 Location Planner: user interface components

User-interface components were developed using the C++-Builder library of visual objects called the Visual Component Library. The user-interface includes standard application components such as facilities for file management, data import and export, context sensitive help, window management etc. However, this section focuses on the components specifically for using models and data. The components will be discussed in relation to creating the inference structure, linking domain data to the inference structure and modes of using the model. Figures 8.12-8.13 show some screens of Location planner to give an impression of the interfaces.

8.4.1 Constructing an inference structure

When users open a new application, the system initialises the inference structure with one unknown variable per section. Selecting a section is done by means of speed

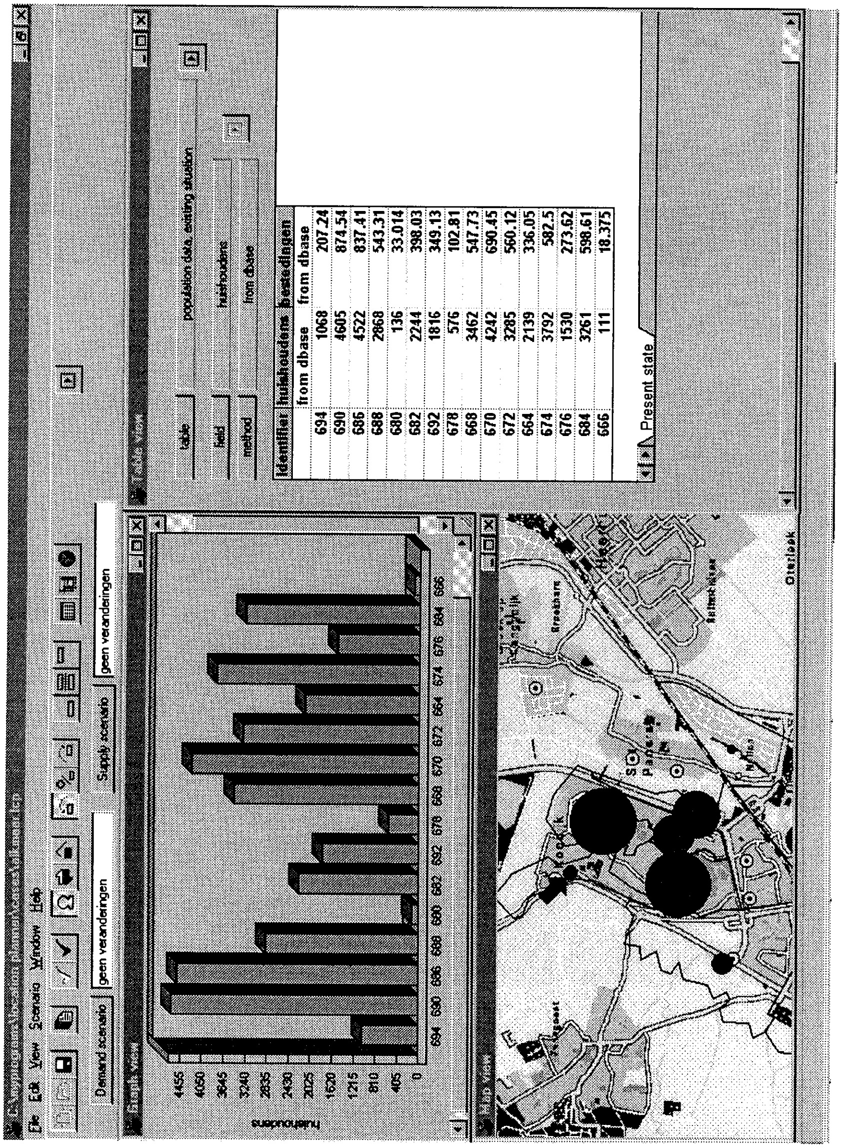

Figure 8.12. *Dynamic and linked graph, map and table views for inference layer interaction.*

buttons arranged on a toolbar. The combination of object type and perspective determines the section. For example, clicking the combination of demand and present state activates the present state × demand section. Undefined combinations are dynamically disabled by the system. For example, when the future-*C* button is down, the interaction button is disabled. Clicking a combination of object type and perspective does not yet result in a visible response of the system. In addition, users must select a representation format. Available formats are table, map and graph. In the system, the combination of section and format is called a view. For example, the goal state × supply × table view is a table representing objective values of supply objects (e.g., centres or stores). Only one section can be opened at a time, whereas multiple views of a section can be displayed. This reflects the idea that users may wish to view the same data set in different representation formats simultaneously.

The table view has a special status. Only in this view actions for manipulating the inference structure are enabled. A table shows the variables in terms of columns for demand and supply sections and overlaid sheets for interaction sections. Sheets are selected through tabs. Through the main menu users can add and delete variables (i.e., sheets or columns). Not necessarily all sections need to be filled. For example, if performance scores related to demand objects are left out of consideration, then the future-*C* state × demand section is simply ignored. Having defined for each section the relevant variables, the next step is to define a method for each variable. To select a method, the user selects the concerned column or sheet and clicks on the method button. This activates a dialogue box displaying a list of methods available for that section. Dependent on the selected method, the system then activates a next method-specific dialogue box for specifying the method's parameters (if any).

When all variables in endogenous sections are defined in this way the inference structure is complete. Note that the inference structure is independent of domain data. As settings can be stored, one can use the same inference structure for different applications (i.e., the same analysis scheme for different study areas or data sets). Also, the reverse is possible: one can develop different inference structures for analysing the same data set. Separating domain and inference components in different layers provides the basis for this flexibility.

8.4.2 Domain-level interaction: linking domain data

The dialogue box for specifying data files is activated by clicking on the database speed button. Having specified the database, the link between domain data and the inference structure is realised by specifying a data retrieval method for each variable in exogenous sections using the same procedure as in the case of endogenous variables. In this stage, the values of variables are still unknown. By clicking on the update button, users activate the execution of methods. Update buttons are available at three levels, i.e.

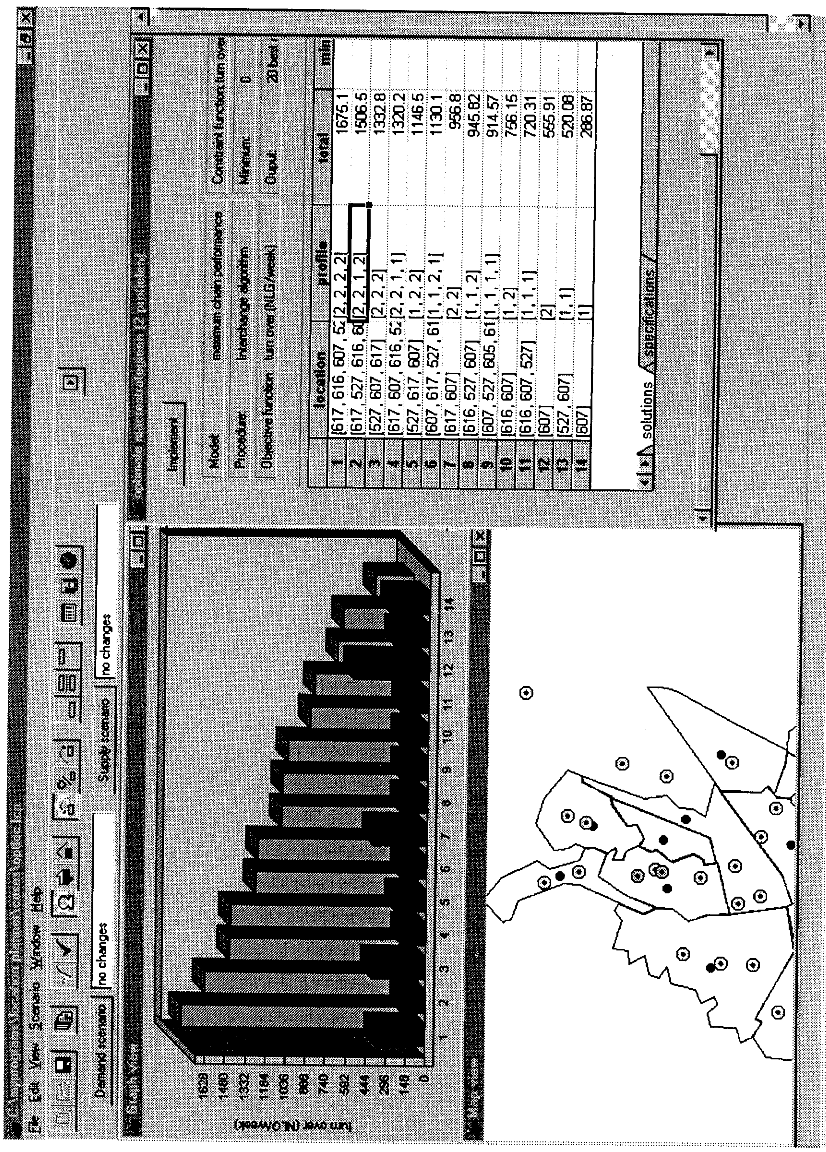

Figure 8.13. Dynamic and linked graph, map and table views for task-layer interaction.

the variable level, the section level and the application level. Only at the variable level, the system displays messages when an evaluation procedure fails. Therefore, this level is suitable for testing data and method settings. The update buttons at the section and application level allow users to evaluate all defined variables of the active section or entire application at once.

At the domain level, the system offers facilities for viewing data, selecting objects and editing data. As said, viewing data is possible in table, map and graph format. The table and map views are bi-directionally linked. When activated, the map window displays demand objects as zones with centroids and supply objects as point locations. By clicking on a map object the object receives focus by means of an arrow pointing at the location. Simultaneously, the corresponding record in the table window is highlighted. Reversibly, by clicking on a table record the arrow moves to the corresponding location on the map. This functionality of the system is considered important, as it allows users to link attribute and geographical data of objects. The use of the map increases when an appropriate image of the study area is available as background. Then, users are able to locate physical barriers between objects.

Furthermore, the system automatically displays thematic information contained in the table view on the map. When users select a column of the table, the map is refreshed by the system to display the attribute in the form of a circle diagram on the map. Thus, the spatial distribution of a quantity such as, for example, population or floor space can be easily assessed. Interaction data, on the other hand, are displayed in the form of lines connecting demand and supply locations. The width of a line represents the relative size of the flow. The map displays the currently selected sheet (matrix). Finally, when activated, the *graph* view displays the selected demand or supply column in the form of a bar diagram. This format gives a visual impression of the distribution of objects on an attribute (e.g., population). Table-graph links are uni-directional from table to graph. Specifically, the graph is refreshed each time the selection of a column changes. There is no graph representation of interaction data.

By selecting objects one can narrow the focus to a subset of demand or supply objects. By default all demand and supply objects are selected. Changing the selection is possible in a dialogue box that is activated by a speed button on the tool-bar. Selection can be based either on identifier (static) or attribute information (dynamic). In the case of static selection, the selection status of objects is unconditional, whereas in the case of dynamic selection the selection status is updated (by the inference engine) each time the chosen selection variable changes (by resetting or evaluation). For example, dynamic selection may be used to highlight and identify the outlets of the own chain or outlets that meet some retail formula characteristic. Note that, when dynamically defined, the selection in the present and future sections may differ.

The selection status of objects plays a role not only in analysis (e.g., to define choice-sets), but also in displaying data. First, in the table view the records of selected objects are highlighted by the system (using bold fonts). Second, themes (circle diagram) are displayed on a map only for selected objects. For interaction data, this means that flows are displayed only between selected demand and supply objects. The selective display feature allows users to concentrate on the objects of interest in assessing the spatial distribution on an attribute. Thus users can asses, for example, the spatial distribution of floor space of a specific chain.

Editing data is possible in the table view of change, future and goal sections. By default, the system sets change variables to zero or 'no change' dependent on the type of the variable - numeric or string. Hence, initially the future state equals the present state. Users can edit changes both directly in the change section or indirectly in the future section. The system updates either future data (in response to new values in the change section) or change data (in response to new values in the future section). Also, interactions are editable so that one can use the system for 'what-if' analysis also when a shopping model is not available. In fact, manual assessment of interaction flows (i.e., purchase binding rates) is common practice in applied retail research. Users must be aware, however, that the system will overwrite edited data when a shopping model is defined and updated for the interaction variable. Therefore, when combined with a shopping model, manual assessments must be repeated after each model update.

8.4.3 Inference-level interaction: simulation

Simulation refers to the interaction mode where the user changes conditions and the system provides feedback. In the system, the contents of a demand or supply change section comprise called a scenario. Note that there are two ways to implement a scenario, namely by editing changes and by retrieving change data from the external database. A simulation cycle consists of implementing a scenario in either one of these ways and next updating variables in the section of interest or at the application level. Typically, users would evaluate impacts by viewing a future-*C* or discrepancy section in table, map or graph format. The future-*C* section represents measured performance on goal variables. The discrepancy state shows these scores relative to the goal state (if any). In addition, users may consider predicted interactions to assess consumer flows under the scenario conditions. In the same way, goal scenarios and consumer flow scenarios can be simulated. Finally, users can also easily vary method settings, for example, to assess the sensitivity of outcomes for specific assumptions.

In many cases, changes in performance rather than absolute performance is considered by planners as the criterion for impact assessment. The system comes up to this information need by allowing users to define the goal state in terms of system performance under some base-scenario. Technically, users can set the goal state by copying the current contents of the future-*C* state. By copying the results of the model under no-change conditions or any other base-scenario condition to the goal section, the

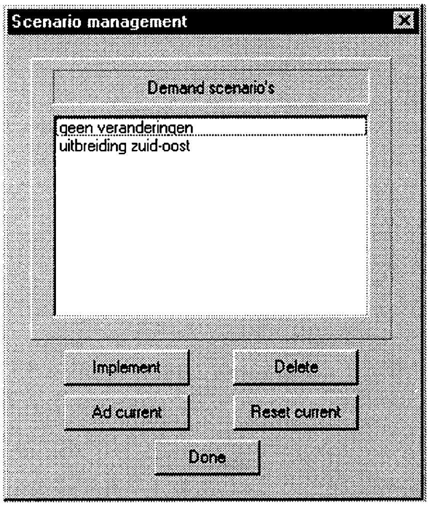

Figure 8.14. Scenario Manager dialogue.

goal state variables will represent base-performance levels. Then, in next runs, the discrepancy state will express performance relative to the base-scenario. Thus, it is possible to evaluate, for instance, economic impacts in terms of increases or decreases in market share. Considering this use, the goal state more broadly represents a reference point for performance scores. The reference point can be easily re-defined by updating and copying the future-*C* under newly defined base conditions to the goal section.

When a scenario, for example, based on population forecasts or a proposed plan have been evaluated, one may wish to store the scenario and evaluate alternative scenarios. The Scenario Manager module allows one to store and manage scenarios. The module is activated through the main menu or by clicking on a speed-button on the tool-bar. When activated, the scenario manager appears as a dialogue box displaying the current list of stored scenarios - which is initially empty. The following options are available (Figure 8.14):

- *Add* the current scenario to an internal scenario database
- *Reset* the current scenario (set the change section to zero or 'no change')
- *Implement* a scenario from the scenario database (i.e., write to the change section)
- *Remove* a scenario from the scenario database

Having developed a scenario database through *add* operations, *implement* allows users to implement a stored scenario in the current inference model for simulation. Thus, the scenario manager facilitates switching between alternative scenarios. Users can easily return to an old scenario or evaluate new combinations of demand and supply scenarios. The labels of the currently implemented scenarios for the demand and supply side are displayed in the toolbar on the screen. Thus, current conditions of model results are always visible on a central location on the program's window.

8.4.4 Task-level interaction: optimisation

At this level, users define objectives and constraints and the system generates optimal solutions of the problem. As said, task-level models are available through the Problem Solver module. Problem Solver not only provides access to task-level models, but also supports the management of generated solutions. Management of solutions is based on the same logic as scenario management. This reflects the idea that every solution represents an optional plan (a system-generated scenario). Problem Solver is activated through the main menu. When activated, Problem Solver appears as a dialogue box displaying the current list of stored solutions, which is initially empty. The following options are available (Figure 8.15):

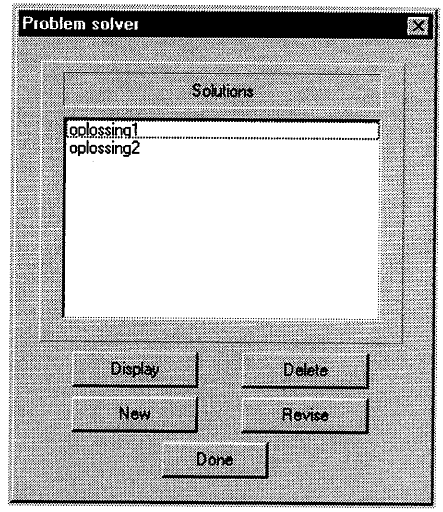

Figure 8.15. Problem solver head dialogue.

- *Generate* a new solution
- *Display* a stored solution
- *Remove* a solution from the database
- *Revise* a stored solution

Generate invokes the standard procedure for selecting a model, setting parameters, running the model and displaying the results. Problem Solver automatically stores a generated solution. When users select *revise*, Problem Solver displays for that solution the existing parameter settings, allows users to revise these settings, re-runs the revised model, displays the new results and updates the database by replacing the old solution with the new solution. The revise option is considered essential for shortening the feedback loop during 'what-if' analysis at the task-level (e.g., model sensitivity analysis or population-forecast sensitivity analysis etc.).

A solution is displayed in a table view. Note that a solution itself is a list generally consisting of *N* best solutions found by the system. The table consists of two sheets. The first sheet shows for each solution both the configuration of the chain in terms of decision variables (number, profile and location of outlets) and the objective function value of the chain as a whole as well as the worst-performing outlet of the chain. In addition, the second sheet displays parameter settings including the used optional attribute profiles. Moreover, the currently selected solution of the list can be displayed also graphically. When users activate the map view, the locations of the solution are highlighted on the map of the area. The map is uni-directionally linked with the table in the sense that the map is refreshed automatically when users select a solution (row) in the table. In this way, users can easily compare the spatial pattern of different solutions. On the other hand, a complementary view is available in the form of a bar diagram. When the graph view is activated, the bar diagram displays for each solution both the total and 'worst-outlet' performance of the chain. This format gives a visual impression of relative performance of solutions. The graph is particularly meaningful in combination with the 'best macro-strategies' output option. In that case, the bar diagram visualises the rate of decline in performance as investment in number or size of outlets decrease.

A solution generated by the system can be easily implemented in the current inference model. When users click on the 'implement' button in the table view, the system implements the currently selected solution as a scenario in the change section view. Then, at the inference level, users can evaluate performance on a broader set of criterion-variables, compare performance with the goal state, store the scenario, combine the scenario with different population scenarios etc.

8.4.5 Reporting results

Typically, the product of inference and task-level analyses is a set of competing scenarios. Each scenario is based on specific assumptions about demographic and economic developments (demand scenarios), consumer choice behaviour (choice model parameters or edited consumer flows) and objective settings (optimisation model parameters or edited goal variables). To prepare political decision making, a report of results should give a comprehensive account of each scenario in terms of these assumptions.

Location Planner offers the material for such reports. The inference model provides an explicit, complete and internally consistent description of the underlying model and data. Change and goal scenarios are explicitly represented and inference model components used to generate each variable are explicitly stored in the form of methods and external data links. Similarly, solution reports generated by Problem Solver describe the used objective function, candidate locations and optional attribute profiles. Moreover, Location Planner offers suitable representation formats of results (tables, thematic maps and graphs) which can be adopted as tables or figures in a report.

Generally, a report generator is the component of DSS which offers facilities for structuring and formatting a report. Location Planner does not offer a report generator, but - instead - facilities for storing views and solutions in appropriate formats. Specifically, users can store results at the application or section level in the form of text files, TransCad table files and Excel spread sheets. In the latter format, not only data values but also format information is preserved in the output files. In general-purpose software like Excel users can easily and intuitively arrange and format the material and print the final report.

8.5 Conclusions and discussion

This chapter proposed a design of the spatial DSS and implementation of the system in a windows-application called Location Planner. The core of the system consists of an inference model-base and a framework for using the models to construct an inference structure of a retail or service system. When linked with an external database, the inference structure can be used for simulating action, population and goal scenarios. In addition, the Problem Solver module offers facilities for using the inference model to find optimal spatial configurations of retail or service networks. User-interfaces of both the inference layer and task layer provide access to data sections through active and linked table, map and graph views.

To potentials and limitations of the spatial DSS can be discussed in relation to the set of requirements for DSS as outlined in Chapter 2, as follows.

DSS supports all stages of the decision making process
The proposed system emphasises the stage of generating and analysing alternative solutions. The preceding stage of monitoring developments and identifying problems (early warning) is only partly supported. When properly specified, the discrepancy section shows the discrepancy between objectives and measured performance. For an optimal support of monitoring, however, the inference structure should represent developments in a time perspective. The present system can be generalised by adding time-layers such that the future state of layer t simultaneously represents the present state of layer $t+1$, and so on. Discrepancy sections across time-layers would provide suitable time-series data for monitoring and models of early warning.

Second, also the identification of candidate locations and formulation of plan/location evaluation criteria receives limited attention in the present system. This reflects the assumption that in (Dutch) retail and service planning, available sites for new developments are often limited in number and are identified based on field inspection by specialised staff personnel. Furthermore, in many cases economic performance and service level provision are the central issues and the formulation of criteria is not critical. Nevertheless, in other cases where identification of new locations or formulating criteria is an issue, the proposed system falls short.

The limited focus of the present system reflects an explicit choice. The proposed system primarily intends to provide a suitable environment for using spatial models to reduce uncertainties in explaining and predicting retail system dynamics. Complementary models are already available by means of existing general-purpose software. Existing GIS tools support the elementary forms of spatial analysis required for identifying candidate locations. Commercially available MCE-software, such as for example Expert Choice (1995), can be used in addition for identifying criteria, deriving criterion weights and judging alternatives on criteria. Hence, Location Planner is explicitly meant to be complementary to existing GIS and MCE (group) software. Communication is realised through data files.

DSS provides a flexible problem-solving environment

As argued in Chapter 3, this ability is important for spatial DSS, as information needs and data availability may vary across applications. Flexibility is a strong point of the proposed system compared to existing spatial DSS. The system does not restrict the choice of independent variables of the consumer choice model or the degree of disaggregating flows into consumer segments or trip purposes. Moreover, the multipurpose model provides a generic form of which simpler model types can be derived as a special case. Also, the available models for performance analysis cover a wide range of goal variables including accessibility, travel demand, consumer utility and economic performance dimensions. For most of these dimensions simpler variants such as cost band-based models as well as more advanced interaction-based variants can be used.

The same properties also hold for incorporated task-level models. Whereas most existing systems are specialised in either public or private sector type of problems, the Problem Solver module offers models for both the competitive and central-location problem. Hereby, the competitive location model covers the most general problem of finding the number, attribute profile and location of outlets under every possible specification of the objective function and the inference model. Furthermore, users are able to choose among different search algorithms to realise an appropriate balance between speed and accuracy. Finally, the output form can be chosen to suit particular information needs.

As another dimension of flexibility, the layered structure of the system offers the possibility to choose between different modes of user-system interaction. At the domain level, the system offers facilities for editing data, highlighting objects and viewing data in different sections and representation formats. This mode is suitable when inference models are lacking or users prefer to use own judgements for predicting consumer flows under new or changed market conditions (as in most applied studies). At the inference level, the system supports systematic impact analysis of plans or market developments. This mode is suitable when a reliable model of consumer choice behaviour is available. At the task-level, the system supports in addition systematic ways of optimising the spatial configuration of retail or service networks. This mode is suitable in cases where also objectives can be defined in terms of an optimisation model. Finally, users can easily switch between levels so that also all combinations of these modes are possible.

DSS provides an interactive problem-solving environment

In Chapter 3, we argued that the potential surplus value of a spatial DSS depends on the ability of the system to simulate retail and market scenarios easily and intuitively. In Chapter 2, the possibility to change relevant conditions (referred to as openness) and the length of the feedback loop were identified as key characteristics in this respect. The present system provides specific facilities for both aspects. First, the available sections of the domain layer allow users to investigate a wide variety of scenarios including demographic/socio-economic developments, action plans, actions of competitor's, interaction probabilities and planning objectives. Moreover, the used type of shopping model is multi-dimensional and, therefore, sensitive to manipulation of different dimensions of attribute data. Finally, the possibility to edit model parameters enables users to simulate economic developments (i.e., per capita expenditure) and parameters of spatial choice behaviour.

On the other hand, there are also some limitations. Changes in the transportation network cannot be implemented other than through the distance data file in the external database. For simulating transportation policies, therefore, the travel distance matrix must be adjusted outside the system. For the same reason, also adding locations or changing co-ordinates of existing locations must be done outside the system. However, the present system can be easily extended by incorporating an extra section which provides access to travel distance information. Then, users would be able to edit transportation policies within the same system as well.

Second, the use of dynamic variable definitions strongly reduces the length of feedback loops. Traditional systems use static definitions, so that users have to repeat a model-based evaluation procedure each time conditions change. Such a procedure is cumbersome when different models have to be executed sequentially to produce results of interest. In the present system, much like spreadsheet systems, users have to specify the inference structure only once and, next, click an update button to derive the implications. The meaning of speed is not just convenience. More importantly, a short feedback loop reduces the threshold for evaluating scenarios and facilitates an understanding of retail/service system dynamics.

Finally, the system's interactive properties are enhanced by using multiple active and linked views on data sections. Table, map and graph views can be open simultaneously, so that users can view the same data set in different formats. Although current GIS-based applications typically do not provide this facility, complementary views are generally considered important for visualising data. Moreover, the views are active and linked to enhance interactive use.

DSS provides a user-friendly problem-solving environment

As an essential feature, DSS intends to make analytic models accessible for decision-makers who are not necessarily familiar with the modelling techniques used (Chapter 2). The present system separates the construction of the inference model and using the model for simulation in different stages. The model construction stage requires an analytic expert who is able to translate the decision problem in terms of a simulation model. However, in the next stage in which the model is used for simulation, users are insulated from technical details as the inference engine controls data flows and guards the internal consistency of the system (by systematically resetting invalidated variable values). The use of conceptually clear measures of retail-system performance, should enable users to relate results of analysis to their problems. An expert or wizard facility can be built in to replace even the human expert in the first stage of model construction.

To conclude, the proposed system shows how different techniques can be combined to enhance the flexibility and interactive properties of spatial DSS. The techniques used include a multi-layered structure of the model-base, inference engine and dynamic variable definitions, and linked and active views. These properties favour the integration of spatial models into the planning process. To demonstrate the use of the system, the next chapter discusses two complementary case studies.

CHAPTER 9

APPLICATION OF THE SPATIAL DSS: SOME ILLUSTRATIVE CASE STUDIES

9.1 Introduction

This chapter describes two case studies that illustrate the application of Location Planner. The case-studies are complementary and relate to the two stages of the decision making processes that were identified in Chapter 3 as the areas in which a retail planning DSS can make an important contribution to the quality of decision making. The first case study is concerned with the inferential capabilities of Location Planner for analysing the impacts of retail plans. The case considers a large-scale expansion of the major shopping centre in Veldhoven - a middle-sized city in the Netherlands. The multipurpose trip model (Chapter 5) and complementary performance models (Chapter 6) are applied to predict and analyse the impacts of the expansion in terms of the economic performance of shopping centres as well as travel demands of consumers. The case study demonstrates (i) how the multipurpose trip model can be specified considering available means of data collection and the information needs of local governments, (ii) the estimation of the model using consumer survey data and existing software for full-information estimation, (iii) the information that can be generated by the model using Location Planner and (iv) the increased sensitiveness of the model for impact analysis compared to conventional MNL-based shopping models.

The second case study illustrates the use of task-level models for generating alternative strategies for developing or optimising a retail chain. The case demonstrates the use of a spatial shopping model in combination with an optimisation model to find for a certain supermarket chain the optimal spatial configuration of outlets in an existing local market area (a middle-sized city in the Netherlands). The location problem considered involves finding the number, attribute profile and location of outlets that maximise the performance of the chain in a competitive environment. The study highlights (i) the specification of the integrated shopping and optimisation model and (ii) the information that can be derived from the model using Location Planner.

The application of spatial models in a DSS environment is not new. Several existing studies in geography and planning have addressed this issue before, as reviewed in the last chapter. Therefore, the intended contribution of the present chapter is to show how the more advanced models, which are available through Location Planner, can be specified to better meet information needs. The advancements concern (i) the extension of conventional MNL-based models to account for multipurpose trips and (ii) the use of shopping models as a component of location models for optimisation. The design of Location Planner has already been discussed in the last chapter. This chapter focuses on the model specification and the information that can be derived from the models. To this end, the chapter is structured as follows. First, sections 9.2 and 9.3 successively discuss the two case-studies. Next, the chapter concludes with summarising the major conclusions.

9.2 The multipurpose trip model and retail impact analysis: the Veldhoven case

The empirical application of the multipurpose trip model in Chapter 5 showed for a realistic case that the extended model was better able to predict shopping centre choice by accounting for spatial retail agglomeration effects. The case study described in this study focuses on the application of the model for analysing the impacts of retail developments. A comparison will be made with conventional models to evaluate the specific properties of the model. Successively, this section describes the study area, the model estimation and the application of the model.

9.2.1 The study area

The study area in this case is Veldhoven - a city in the Netherlands with 41,000 inhabitants in 1996. Veldhoven is located nearby Eindhoven. The map of Figure 9.1 shows the major neighbourhoods of Veldhoven and the spatial distribution of the shopping centres in the area. As is typical for Dutch retail systems, the majority of retail facilities are concentrated in planned neighbourhood centres. The major shopping centre called the City Centre is located in the central district (nr 1). The second centre with an above local function is Kromstraat (nr 3). The major shopping centre of Eindhoven and some shopping centres in the eastern-central part of Eindhoven are the only centres outside Veldhoven that attract consumers from Veldhoven. These centres were identified based on a consumer survey and were also included in the analysis.

In 1997 a large-scale expansion of the City Centre in Veldhoven was realised. The expansion involved an increase in floor space with approximately one halve of the existing floor space in both the daily and the non-daily sector. To analyse the impacts of

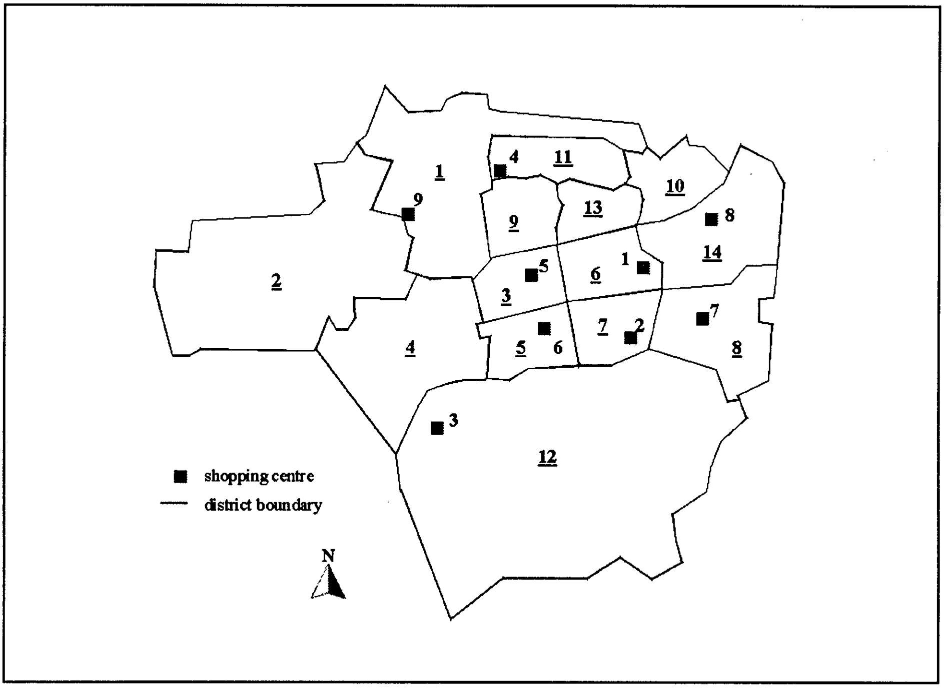

Figure 9.1. The neighbourhoods and shopping centres in Veldhoven.

this development on the shopping and travel behaviour of the Veldhoven population, a consumer survey was held before and after the expansion of the centre. The after-survey provided suitable data for estimating the multipurpose trip model. 498 Households filled out a paper-and-pencil questionnaire. In the part of the questionnaire that was used for estimating the multipurpose trip model, respondents could describe maximally three shopping trips they had made during the last week. A shopping trip was defined as a trip that starts and ends at home and involves at least one visit to a shopping centre. For each trip, respondents could specify the transport mode used and maximally three locations visited on the trip. For each location visited respondents were asked to indicate the purpose of the visit (e.g., work/school, social visit, shopping etc.) and, in the case of a shopping purpose, the items bought and the amount of money spent. Locations could be identified by a zip code or, in the case of a shopping centre, by a reference to a pre-defined list of centres in the area. Thus, the stops as well as purposes were known for one or more shopping trips for each respondent. By using the week as the time frame for recording trips, possible day-of-the-weeks effects on behaviour were controlled for. Hence, we may assume that the resultant sample of trips is representative.

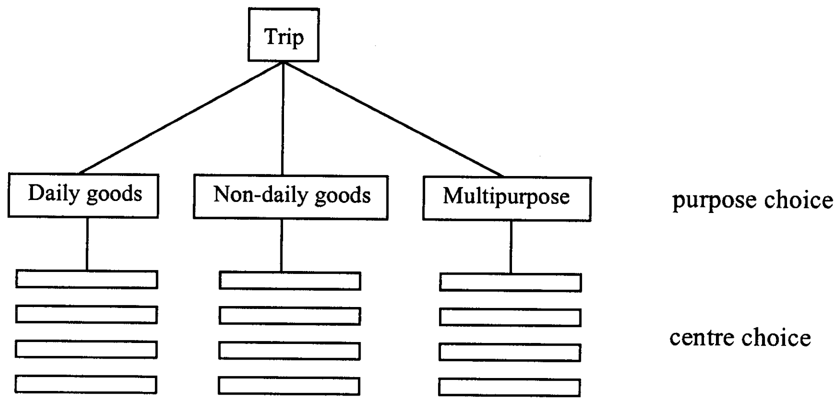

Figure 9.2. Structure of the multipurpose trip model used in the Veldhoven case-study

9.2.2 Model estimation

Considering the general information needs of local government in retail impact studies, the purchased items reported by the respondents were exhaustively classified into daily goods (food and personal care) and non-daily goods (all other goods). Given this 2-good system, three trip types based on trip purpose could be distinguished, namely (i) single purpose daily-good trips, (ii) single purpose non-daily good trips and (iii) multipurpose trips where items of both categories are bought during the same visit to the centre (cf. Roy 1997). Although data were available about multiple trip stops as well, the single stop variant of the multipurpose model was estimated. Figure 9.2 shows the structure of the model used in this case.

The reported shopping trips involved 1369 visits to identifiable shopping centres. These visits were used as observations for estimating the model. In this sample, 53 % involved daily trips only, 27 % non-daily only, and 20 % were multipurpose. This means that, given the used categorisation of goods, a considerable portion of reported trips was multipurpose. The destination choice set for each trip was defined as the set of centres known to the individual where stores required by the trip type under concern were available (daily, non-daily or both). Each destination alternative was described in terms of both travel distance from the home location and a set of attributes of the shopping centre. Distance was measured as the length in meters of the shortest route across the road network. Respondents were assigned to the node of the network that was closest to the 5-position zip code of their home address. Similarly, the shopping centres were assigned to the nodes closest to the centroid of the shopping area (e.g., a street).

The relevant shopping areas in Eindhoven were linked through a major road with the network. The GIS package TransCAD (Caliper Corporation 1996) was used to digitise the geographic data and to generate a demand × supply distance matrix using a shortest path routine. The attributes used to describe shopping centres included the total floor space of stores in the daily and the non-daily sectors, respectively and a binary variable representing the presence of a low-price level image of the centre. Centre atmosphere and parking facilities are generally also influential factors, but were not included as the main purpose of the study was to illustrate the approach.

Table 9.1. Parameter estimates of the multipurpose trip model.

Attribute	Parameter estimate	t-value
Trip constant, non-daily (α_n)	-1.07	-3.03
Trip constant, multipurpose (α_m)	-1.60	-2.56
Trip scale, daily (θ_d)*	0.34	-2.30
Trip scale, non-daily (θ_n)*	0.64	-1.09
Trip scale, multipurpose (θ_m)*	0.53	-1.21
Floor space daily goods (β_d)	17.69 e-05	20.66
Floor space non-daily goods (β_n)	4.38 e-05	11.69
Low price image (χ)	1.35	7.27
Travel distance daily (δ_d)	-5.92 e-04	-14.48
Travel distance non-daily (δ_n)	-4.02 e-04	-12.04

*Significance of scale parameters is tested against one.

Table 9.2. Estimation statistics of the multipurpose model.

Statistic	value
Number of observations	1339
Number of coefficients	10
Log-likelihood model	-3440.47
Log-likelihood null model	-4123.96
Mc Fadden's Rho bar squared	0.1633

The software HieLow was used for full-information estimation of the hierarchical choice model (Bierlaire 1995). The results are shown in tables 9.1 and 9.2. The rho bar squared value of 0.163 indicates a satisfactory goodness-of-fit of the model considering the limited set of variables used to describe shopping centres. All parameter values were statistically significant and had values as expected. First, two distance parameters were used to account for a possible difference in the disutility of travel between low-order trips (daily goods only) and higher-order trips (non-daily single purpose and multipurpose trips). As could be expected, the distance weight is significantly stronger negative for the low-order trips. Second, the trip constants represent the relative frequency of trips independent of the utility of available destinations. The constant for daily good trips was arbitrarily set to zero. Therefore, the negative estimated values of the other constants indicate, as expected, that the base-frequency of the higher-order trips is lower. Finally, the scale parameter for each trip type, θ, captures the trip frequency component that co-varies with the utility of available destinations. The estimated values all fall within the zero-one range indicating that the hierarchical structure of the model fits the data. The *t*-ratio's of the scale parameters refer to a test of the parameters against one. Only, the theta related to the single purpose daily good trips differs significantly from one (alfa is 0.05). As argued in Chapter 5, the scale can be interpreted in terms of the elasticity of trip choice for available supply. Interpreted that way, the scale values suggest that, at least in this case, the relative frequency of single purpose daily good trips is the least sensitive to supply factors. The single purpose non-daily and the multipurpose trips are to a bigger extent sensitive to supply factors.

9.2.3 Using the model for impact analysis

Approach

The model was implemented in Location Planner using the system's facilities for model construction. For predicting shopping trips, the same travel distance matrix as in the estimation stage represented the transportation system. The travel distance matrix was based on a subdivision of the area into 89 zip code areas. However, demographic data were available only at a more aggregated level of 14 districts. The demographic data were disaggregated to the zip code level by assuming that populations within districts are evenly distributed across the zip code areas. Destination choice-sets per trip type and per zone were defined using deterministic rules available for that purpose in Location Planner. Specifically, for each trip type the choice-set was defined as the centres offering the required store types (daily or non-daily or both). Furthermore, an additional rule was used for single-purpose daily good trips, to further reduce choice-sets to centres lying within a distance of 5,000 meter from origin locations.

The multipurpose trip model was used to predict trips in both the before and after situation. Let j denote shopping centre, X floor space, D travel distance and V structural utility, then the equations used in this case to define the structural utilities of trip purpose (9.1-9.3) and trip destination (9.4-9.6) can be written as:

$$V^{\{daily\}} = 0.34 \ln \sum_j \exp\left(V_j^{\{daily\}}\right) \tag{9.1}$$

$$V^{\{non-daily\}} = -1.07 + 0.64 \ln \sum_j \exp\left(V_j^{\{non-daily\}}\right) \tag{9.2}$$

$$V^{\{daily,non-daily\}} = -1.60 + 0.53 \ln \sum_j \exp\left(V_j^{\{daily,non-daily\}}\right) \tag{9.3}$$

$$V_j^{\{daily\}} = 17.69\,10^{-5} X_j^{daily} - 5.92\,10^{-4} D_j \tag{9.4}$$

$$V_j^{\{non-daily\}} = 4.38\,10^{-5} X_j^{non-daily} - 4.02\,10^{-4} D_j \tag{9.5}$$

$$V_j^{\{daily,non-daily\}} = 17.69\,10^{-5} X_j^{daily} + 4.38\,10^{-5} X_j^{non-daily} - 4.02\,10^{-4} D_j \tag{9.6}$$

As the expansion of the City Centre was the only development that had taken place, impacts could be found as the difference between predictions. For comparison, the same analysis was repeated using a conventional impact analysis approach. Assuming single-purpose trips, a conventional approach would assume two independent MNL-type shopping models for daily and non-daily goods. The MNL-models for daily goods and non-daily goods were defined here as the components of the multipurpose model concerned with destination choice for the single purpose cases (Equations 9.4 and 9.5). Because the same equations are used to define structural utilities of destinations, differences in outcomes of the multipurpose and conventional model system can be interpreted unambiguously in terms of predicted agglomeration effects of stores on spatial choice behaviour. It is hypothesised that the increased agglomeration of stores implied by the City Centre expansion leads to a stronger redistribution of shopping trips than would be predicted based on a conventional analysis.

Trip Type Choice

Before comparing the two approaches, this section considers changes in trip purpose choice (the purpose adjustment effects) caused by the expansion, as predicted by the multipurpose model. Weighted with population size, average trip choice probabilities across residential zones are in the *before* situation 51.8 % (daily only), 30.4 % (non-daily only) and 17.8 % (multipurpose trips) and in the *after* situation 51.5 %, 30.2 % and 18.3 %. This indicates a small increase of the probability of multipurpose trips caused by the increased agglomeration of stores in the city centre.

Predicted trip type choice varies not only across time, but also across space. To give an indication: predicted minimum and maximum probabilities across zones in the after situation are 45.9-53.0 % (daily only), 28.3-33.6 % (non-daily only) and 17.9-20.5 % (multipurpose trips). The spread in trip frequency is caused by the spatial differentiation of utilities of available destinations. Generally, zones nearby relatively large shopping centres are characterised by higher shares of single-purpose non-daily as well as multipurpose trips. This reflects the relatively big supply elasticity of higher-order trips compared to daily good trips. For example, relatively high shares of multipurpose trips are predicted for zones nearby the City Centre or the major shopping centre of Eindhoven.

Travel Demand

To predict distance travelled for shopping purposes, the performance model described in section 6.3 was implemented in Location Planner again by using the system's facilities for model construction. As discussed in the last chapter, different assumptions are possible about how individuals adjust travel behaviour in response to changes in trip purpose choice. That is, either the total number of trips across purposes or the total purchase frequency across goods is considered to be constant. Accordingly, Location Planner allows one to specify the number of trips (first assumption) or total purchase frequency (second assumption). In the present case, the latter option was chosen reflecting the assumption that individuals keep purchase frequencies constant and make multipurpose trips in order to reduce the required number of trips. Trips to destinations outside the study area, other than shopping trips to Eindhoven, were not accounted for in the present case. The error is probably small in this case, because Eindhoven is by far the main external attractor, so that the analysis still gives a useful indication of the size of likely travel demand for the new situation.

Table 9.3. Travel Demand after Expansion of the City Centre (Before Expansion is 100)

district	population	total frequency	av. triplength	total travel
1	1560	99.6 (100)	99.0 (99.5)	98.5 (99.5)
2	210	99.5 (100)	98.7 (99.3)	98.3 (99.3)
3	3225	99.5 (100)	97.9 (98.7)	97.6 (98.7)
4	160	99.6 (100)	99.6 (99.9)	99.1 (99.9)
5	3900	99.5 (100)	98.5 (99.2)	98.0 (99.2)
6	4690	99.6 (100)	99.7 (100.0)	99.3 (100.0)
7	3920	99.5 (100)	96.4 (97.6)	95.9 (97.6)
8	2430	99.5 (100)	96.4 (97.6)	95.9 (97.6)
9	5060	99.6 (100)	96.3 (97.6)	95.9 (97.6)
10	560	99.6 (100)	96.3 (97.5)	95.9 (97.5)
11	1500	99.5 (100)	98.1 (98.9)	97.6 (98.9)
12	4800	99.6 (100)	98.6 (99.2)	98.1 (99.2)
13	2975	99.6 (100)	98.1 (98.9)	97.6 (98.9)
14	5985	99.5 (100)	94.8 (96.4)	94.3 (96.4)
average		99.5 (100)	97.5 (98.5)	97.1 (98.5)

Percentages between brackets refer to conventional MNL-model predictions.

The model was run for both the before and after situation. The output generated by Location Planner describes for each zone (i) the predicted trip frequency per capita, (ii) average trip length and (iii) total distance travelled. Table 9.3 shows the after situation when the before predictions are set to 100. Average trip length is calculated as a weighted sum of trip lengths using probabilities of trip types as weights. Then, total distance travelled is simply calculated as the product of trip frequency, trip length and population weights. The figures between brackets show outcomes when the conventional MNL-model system is used. A decomposition in trip frequency and trip length component is trivial in that case, because MNL-models of travel demand implicitly assume constant trip frequencies.

As the figures indicate, the multipurpose model predicts for each zone a small decrease in total trip frequency (on average 0.5 %). Assuming that the sum of purchases of daily and non-daily goods remains constant, the decrease is attributable to the predicted increase in the share of multipurpose trips (on average 3.6 %). Also, the predicted average trip length has decreased for each zone (on average 2.5 %). A closer look at the destination choice probabilities learns that this decrease is the result of two counter-acting effects. First, the City Centre tends to a larger extent attract trips from the local district centres inducing more travel inside Veldhoven. At the same time, the increased competitive strength of the centre is responsible for a decrease of relative long trips to the larger centres in Eindhoven. The net result of these two opposite effects is a decrease of average trip length. Also, the MNL-models predict a decrease in average trip length (on average 1.5 %). However, the predicted change is smaller, probably, due to the fact that ignoring agglomeration effects on spatial behaviour leads to underestimating the increase in competitive strength of the City Centre after expansion.

Market Shares

Location Planner further allows users to determine the market share for each shopping centre and good. In this case, market shares were calculated for daily and non-daily stores in each shopping centre. Recall that in the used market share model the amount of expenditure per head and per good is a given constant independent of available supply. However, the model takes into account that the amount of expenditure may differ between trip types and users can specify the relative weights of trip type. In the present case, the relative weight of multipurpose trips was set to 0.5 for both daily and non-daily goods assuming that the amount of expenditure for each good is twice as much on single purpose trips than on multipurpose trips. Furthermore, users can specify for each shopping centre the amount of expenditure attracted from outside the study area. Because these data were not available in this case, inflows where assumed to be zero. Hence, the calculated market shares cannot be readily interpreted in terms of turnover, but they do give an indication of the competitive strength of centres in attracting consumers from within the study area, which was the primary concern in the present study.

Table 9.4. Market shares after expansion of the City Centre (before expansion is 100).

Centre	size daily (m2)	size non-daily (m2)	low price image	Market share daily %	Market share non-daily %
1. City Centre	8000	10800	0	137.9 (133.7)	131.6 (122.1)
2. Burg van Hoof	1198	1745	0	93.4 (94.1)	94.9 (96.4)
3. Kromstraat	1534	4148	0	94.1 (94.8)	95.1 (96.6)
4. Heikant	775	30	0	93.8 (94.4)	95.0 (96.5)
5. t Look	610	0	0	93.8 (94.4)	
6. Zonderwijk	1340	230	0	93.7 (94.4)	94.9 (96.5)
7. Mariaplein	115	745	0	93.3 (93.9)	95.0 (96.4)
8. Zeelst	657	1146	0	93.2 (93.8)	94.9 (96.4)
9. Oerle	100	0	0	93.3 (93.9)	
10. EH inner city	4273	88273	0	92.6 (94.6)	94.6 (96.5)
11. EH Woensel	7780	12139	0	92.5 ( )	94.0 (96.5)
12. De Hurk	1225	3163	1	92.8 (93.5)	95.0 (96.5)
13. Kast. Plein	1653	2318	0	93.2 (94.3)	94.9 (96.5)
14. Trudoplein	207	2189	0	93.0 (94.9)	95.0 (96.5)

Percentages between brackets refer to conventional MNL-model predictions.

Predicted market shares for the after situation when the before situation is set to 100 are shown in Table 9.4. As expected, the market share of the City Centre has increased considerably in both the daily (38 %) and non-daily sector (32 %). The decrease in market share of competing centres is almost evenly distributed across the centres. Impacts range between 6.9 and 7.5 % in the daily sector and between 4.9 and 6.0 % in the non-daily sector. The competition with the major centre of Eindhoven is also of interest. The loss of market share in Eindhoven inner city is 7.4 % (daily sector) and 5.4 % (non-daily sector).

The MNL-models predict smaller impacts, namely increases in market share of the City Centre of 34 % (daily sector) and 23 % (non-daily) and decreases of market share of Eindhoven inner city of 5.4 % (daily) and 3.5 % (non-daily). Clearly, the MNL-models underestimate the increased competitive strength of the City Centre in the multipurpose trips segment. Differences in predictions would have been even stronger if higher weights of multipurpose trips in expenditure per good were assumed.

Concluding Remarks

As comparisons with the MNL-model system indicate, the multipurpose model system predicts bigger impacts of the expansion of the City Centre both in terms of travel demand and market share re-allocation. The reason for this is that, in contrast to the MNL-based models, the model accounts for the increased competitive strength of the centre in the multipurpose trip segment. The model re-assigns to a bigger extent multipurpose trips away from the other centres in Veldhoven and Eindhoven towards the city centre. This results in bigger shifts in average trip lengths as well as market shares. Although the decrease in trip frequency due to an increase in multipurpose trips is small in this case, the model provides the required information to evaluate also the impact of multipurpose trip choice on trip-generation.

9.2.4 Conclusion

This case study demonstrated the application of the multipurpose trip model for a typical retail impact study. The model was estimated for a two-good system based on shopping trip data. Location Planner was used to predict the impacts of a large-scale expansion of the City Centre of Veldhoven in terms of travel demand and economic performance of shopping centres. For comparison, the analysis was repeated using a conventional model system assuming single-purpose trips. As it turned out, the multipurpose model predicted bigger impacts by accounting for the increased agglomeration of stores implied by the expansion of the centre. We conclude therefore that agglomeration forces as predicted by the model have measurable impacts on retail system operations.

The two-good system assumed in this case suits the data-availability and information needs of local governments. At least in Dutch retail planning, it is usual to analyse and collect floor space data at the level of daily and non-daily goods. Retail plans are normally formulated at this level too. On the other hand, estimating the multipurpose trip model requires data about shopping trips. Although this imposes extra data demands, the required data can be collected relatively easily by extending the consumer surveys that are typically used in retail impact studies. This means longer questionnaires, but on the other hand one should note that the required shopping trip data are useful also for a more general purpose, as it allows one to cross-validate and analyse shopping behaviour at a descriptive level.

The case-study highlighted the extra information that can be derived from the multipurpose model. This includes trip type probabilities and trip frequencies at the level of residential zones. Moreover, the model is sensitive to (i) settings of the relative weight of trip types in predicting market shares, (ii) assumptions about the trip-generation effects of multipurpose trips, (iii) the specific attractiveness of centres as destinations of multipurpose trips (joint-attraction effects) and (iv) supply elasticity of trip choice (purpose adjustment effects). Given our earlier finding in Chapter 5 that the multipurpose model outperforms conventional shopping models in reproducing shopping centre choice, the predictions are probably also more accurate.

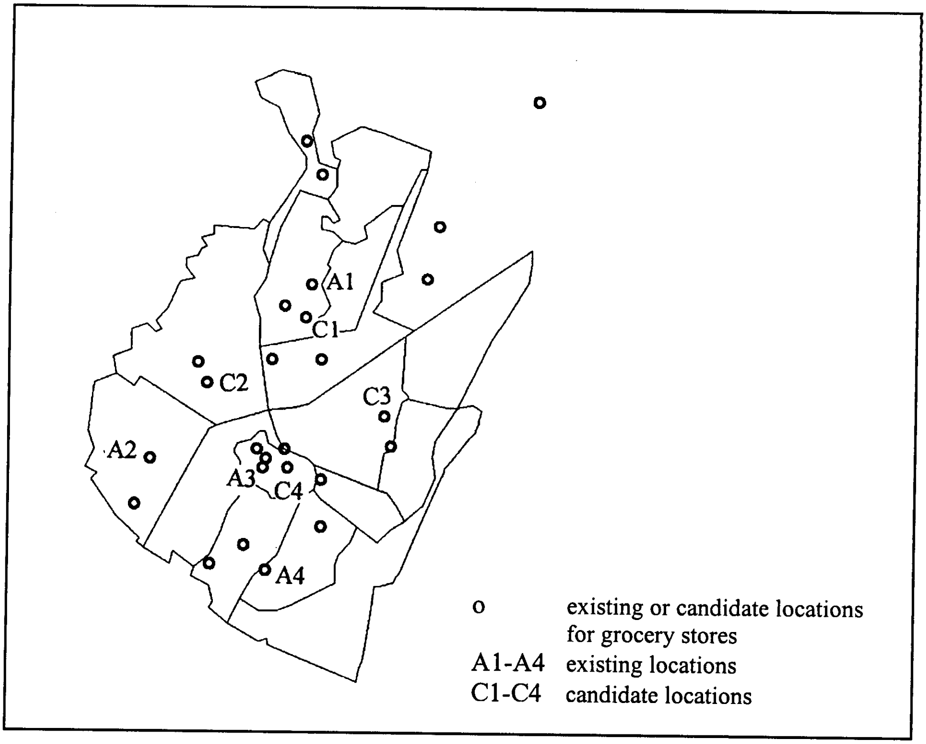

Figure 9.3. *Neighbourhoods and existing and candidate locations of grocery stores in Alkmaar and environment.*

9.3 Optimising retail networks: the Alkmaar case

As noted in the previous chapter, spatial search models typically offered by existing spatial DSS are of limited use for optimising retail network configurations. The offered models typically assume deterministic allocation rules and do not allow one to optimise attribute profiles and locations of new outlets simultaneously. The Problem Solver module of Location Planner is more powerful. At the task level, users can define a model to optimise simultaneously the number, attribute profile and location of retail outlets. At the inferential level, users are able to specify a choice model to predict spatial shopping behaviour under any configuration of the network. The goal of this section is to illustrate the use of Problem Solver for a typical case of developing a strategy for expanding a chain of outlets in an existing market area. We consider a Dutch supermarket chain and a market area in which the chain already operates 4 supermarket outlets. The question considered is whether there are opportunities for increasing the market share of the chain through re-locating, closing or adding outlets. First, section 9.3.1 considers the location problem of the retailer in this particular case. Then, section 9.3.2 looks at the translation of the problem in terms of a spatial choice model and optimisation model. Next, section 9.3.3 discusses the output generated by Problem Solver. Finally, the last section summarises the major conclusions.

9.3.1 The location problem

The grocery retailer considered in this case operates stores throughout the Netherlands. On a regular basis the strategic planning department evaluates existing or new market areas for opportunities to open new outlets or expand existing outlets. The local market areas considered are the urban areas of middle-sized cities or sections of larger cities. The present case study focuses on Alkmaar - a middle-sized city in the Netherlands, with approximately 95,000 inhabitants. Figure 9.3 shows a map of the area.

Table 9.5. Size and market share of grocery chains.

Chain[1]	# outlets	Total floor space (sq.m.)	Market share (%)
ID groceries	4	4470	24.1
G-market	3	1810	7.8
Variomarket	3	4150	19.8
Combi stores	3	1020	5.7
Store next door	4	3350	15.7
Spar market	2	350	4.8
Fresh plus	1	600	4.8
Green store	3	2045	12.9
Comar	1	700	2.4
Vopac	1	275	2.1

[1] Names and numerical data are disguised to secure confidentiality to clients.

There are 25 grocery stores competing for the demand for convenience goods in the area. The outlets are operated by ten different chains. Each chain has its own retail formula in terms of layout of the stores, price setting, product mix and other characteristics. The size and estimated total market share of each chain are shown in Table 9.5. Our case-study retailer, who we will call ID-groceries, operates four outlets in the area (A1-A4 in Figure 9.3). The size and market share of each outlet of this retailer is shown in Table 9.6. Collectively, the outlets have a market share of approximately 24 %. ID-groceries target a wide group of consumers by a formula that is characterised by high quality products and reasonable price levels.

As a general objective, the retailer aims at increasing the market share of the chain by opening new outlets or relocating or expanding existing outlets. For illustration purposes, we assume that management has specified two optional formats for new stores. The formats differ in size of product assortment. Accordingly, the sizes of the stores differ. The smaller outlet requires 750 and the larger outlet 1,500 square meter of gross floor space. Possibilities for expanding the chain are constrained by the requirement set by management that each outlet must generate enough sales to realise normal profits. The retailer considers the amount of sales per square meter floor space as a first indicator of profitability and requires that this figure should at least amount to 13,000 to 17,000 Dutch guilders (NLG). The exact size of this amount depends among other things on the rent price of floor space, which varies across locations. Outlets at more expensive locations, e.g. a major shopping centre, must realise higher levels of sales per square meter to meet the profitability criterion.

Table 9.6. Size and market share of ID-Groceries' outlets.

location	floor space (sq.m.)	sales (NLG[1] × 1000)	sales per sq.m. (NLG)
A1	2490	54,882	22,070
A2	800	8,512	10,650
A3	210	6,831	32,530
A4	980	10,229	10,460

[1] Dutch guilders.

It follows from Table 9.6 that the existing outlets A2 and A4 do not meet the profitability criterion. The underperformance may be caused by in-store factors, such as for example the quality of store layout or store management. However, we assume that market factors, such as an increase in competition in the local market area of the outlets, are responsible. The market conditions of the other outlets, on the other hand, seem to be more favourable. The high rate of sales per square meter realised by outlet A3 suggests opportunities for expansion. To investigate possibilities of re-organising and expanding the chain, the retailer has identified several candidate locations for opening new outlets based on land availability, zoning regulations and site characteristics (C1-C4 in Figure 9.3).

9.3.2 Model specification

The spatial choice model

For illustration purpose, a conventional MNL-model was used to predict outlet choice of consumers. In the model, the following attributes were used to describe outlets:

1. travel distance measured as straight-line distances corrected for the presence of barriers between locations (β_1 = - 0.559);
2. size of stores measured as square meter floor space (β_2= 0.000640);

3. a binary variable indicating whether store type is large (= 1) or basic (= 0) (β_3 = 0.596);
4. a binary variable indicating whether store type features price discounts (= 1) or quality (= 0) ($\beta_4 = 0.318$).

Travel distance for each origin-destination pair is calculated by first determining the straight-line distance and, next, adding an estimate of extra distance incurred by barriers, such as major roads and waterways, if any. This measure was chosen as the best available approximation of real travel distances, given the fact that detailed data about the road network were not available. The size of stores, the second attribute, is a surrogate of the choice range offered by stores. The last two attributes are used to account for different store types on two dimensions. The first dimension refers to the difference between stores offering a wide range of products and basic neighbourhood stores characterised by a small assortment (e.g., no fresh food). As criterion was used 600 m2 floor space. Although this dimension is related to store size, it was nevertheless included to account for an additional qualitative difference between stores. The second dimension refers to a distinction between quality (normal price level) and discount grocery stores (low price level). Attribute parameters, β, were estimated based on recorded outlet choices of consumers residing in the area. The data were collected through a standard telephone consumer survey.

The area was subdivided into neighbourhoods (Figure 9.3) for which population data were available. National statistics were used to estimate the amount of expenditure for daily goods available in each neighbourhood (zone), dependent on number of households, average household income group and average household size. The consumer survey data were used to estimate the amount of outflow per demand zone. It turned out that in this case the amount of daily good shopping trips to locations outside the study area was negligible. Therefore, the outflow term was set to zero for each demand zone. The choice-set for each zone was defined as the stores that lie within a distance of 1,800 meter from the zone's centroid. This distance reflected the maximum radius of most shopping trips recorded in the survey.

The optimisation model

Given the retailer's constraints and objectives, the location problem can be more precisely defined as one of finding the spatial configuration of outlets that maximises market share of the chain while every outlet must meet a minimum profitability and candidate locations C1-C4 and the optional large and small store format of new outlets are given. The minimum profitability level was set to NLG 12,000,- per square meter floor space. The possibility of re-locations and closures were also considered. Hence, the existing outlets of the chain were considered candidate locations. Outlet A1 is an exception. This outlet is significantly larger than the other outlets and attracts consumers from a larger area. Because relocating or re-sizing this outlet is considered undesirable in any solution, the location and size of A1 were fixed. Hence, possible configurations considered by the model consist of all combinations that can be formed as permutations of 7 candidate locations (A2-A4 and C1-C4) and two attribute profiles of new outlets (1,500 and 750 sq.m.).

Table 9.7. *Possible macro-strategies and number of possible location strategies, given 7 candidate locations and 2 optional store formats.*

macro-strategy	number of new outlets	size of new outlets	number of possible location strategies
1	1	small	7
2	1	large	7
3	2	all small	21
4	2	one small, one large	42
5	2	all large	21
6	3	all small	35
7	3	two small, one large	105
8	3	one small, two large	105
9	3	all large	35
10	4	all small	35
...	...	...	...
35	7	all large	21

As Table 9.7 shows, there are 35 possible macro-strategies. The number of possible location strategies, on the other hand, depends on the macro-strategy. For example, there are 35 ways in which '3 outlets, all small' can be located, given 7 candidate locations. If the outlets have different formats (e.g., two small and one large), this number increases to 105. Because the number of candidate locations and store format options is limited in this case, the exhaustive search algorithm was chosen for finding solutions. Figure 8.9 schematically shows the algorithm that is used by Problem Solver. The algorithm systematically enumerates all possible macro-strategies and for each macro-strategy all possible location strategies. Solutions that meet the constraints are further evaluated to determine its objective function value. A list with best solutions is updated in each cycle, dependent on the user-defined format of the output. In this case, the complete list of macro-strategies under optimal location strategy conditions was chosen as the output option. Note that the required inferential models for evaluating the objective function and constraints (i.e., the MNL-model, market share model and floor productivity models) were specified at the inferential level.

Table 9.8. Optimum location strategies generated by the exhaustive search algorithm.

macro-strategy	location of new outlets[1]	total turnover of the chain (NLG × 1000)	%
1	c4	70,818	21.2
2	C4	78,637	23.6
3	a3, c4	83,232	24.9
4	a3, C4	90,091	27.0
5	A3, C4	96,228	28.8
6	a3, c4, c1	93,167	27.9
7	a3, C4, c1	99,910	29.9
8	A3, C4, c1	105,950	31.8
9	A3, C4, C1	110,860	33.2
10	a3, c4, c1, c2	100,790	30.2

[1] Capital letters indicate a 'large' store format.

9.3.3 Using the model for finding the best strategy

The output generated by Problem Solver is represented in Table 9.8. As it turns out, networks consisting of more than 4 outlets are not feasible, given the minimum turnover constraint of NLG 12,000,- per square meter floor space. Moreover, this constraint requires that the 4-outlet network must be implemented by using a small store format for every outlet. The turnover values represent the predicted total turnover of the chain (including the existing outlet A1) under optimal location conditions. As a general tendency and not surprisingly, the total turnover figures increase with the size of the network and the size of the outlets. The functional relationships are visualised in figures 9.4 and 9.5. Figure 9.4 shows the chain's performance as a function of number of outlets, whereas Figure 9.5 represents for three-outlet solutions the relationship between the chain's performance and store size.

The solutions give information about the trading potential of candidate locations. The 1-outlet solutions reveal the best location for adding a single new outlet, given the existing outlet A1. C4, which is a candidate location in the major shopping centre of the city, appears to have the highest potential. Location A3, which is also located in the major shopping centre, is also of interest, as it recurs in all multiple outlet strategies. The occurrence of location C1 in all 3 or 4-outlet strategies is somewhat surprising. C1 lies in the proximity of the existing outlet A1 and will undoubtedly distract market share from that outlet. Apparently, the location has high trading potential so that it can compensate for this cannibalism effect. The more peripherally located sites A2, A4 and

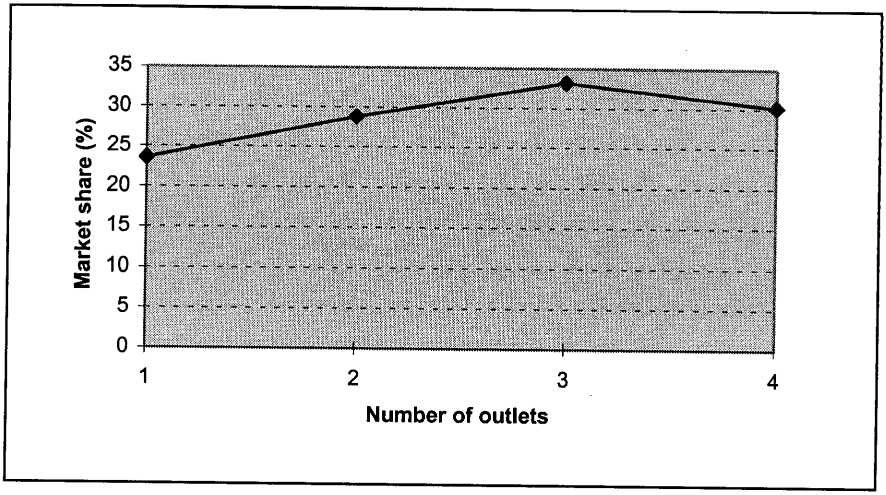

Figure 9.4. *Market share as a function of number of outlets under optimal chain configuration conditions.*

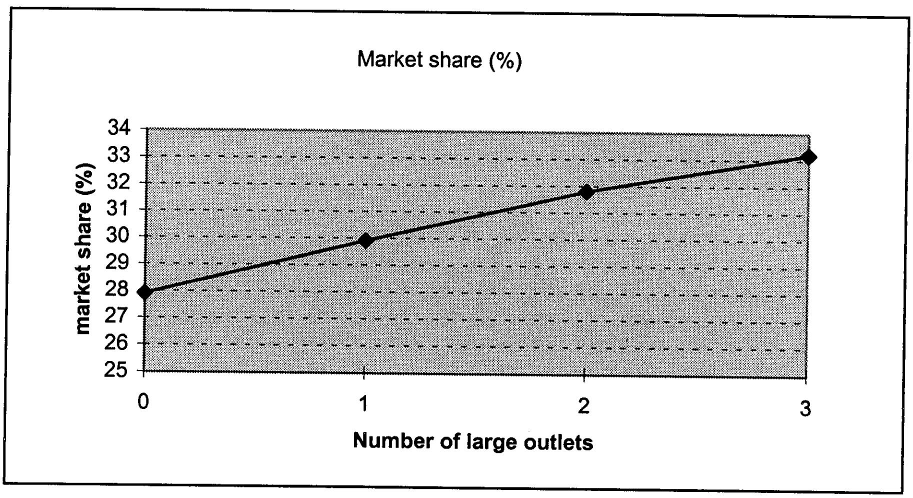

Figure 9.5. *Market share as a function of number of large outlets for optimal three-outlet configurations.*

C3 do not occur in any optimal solution. These sites either have insufficient sales potential or are outperformed by other locations in every macro-configuration.

Given the minimum profitability constraint, it is not feasible to open more than four outlets (in addition to the existing outlet at A1). Comparing networks of different size on market share gives an indication of returns on investment (Figure 9.5). Compared to the best 1-solution (strategy 2) the best 2-outlet solution (strategy 5) gives an increase in market share of 5.2 %. Going from there to the best 3-outlet solution (strategy 9) results in a further increase of 4.4 %. A fourth outlet causes a drop in market share of 3.0 % because of necessary reductions in the size of individual outlets. Also store format appears to have a significant impact on chain performance (Figure 9.6). For example, replacing an 'all small' configuration by an 'all large' one in a 3-outlet network (compare strategies 6 and 9) gives an increase in market share of 5.3 %. Doing the same for a 2-outlet network (compare strategies 3 and 5) results in an increase of 3.9 %.

Table 9.9. Comparison of the chain before and after re-organisation according to Strategy 9

location	existing network			after re-organization		
	floor space (sq.m.)	sales (NLG × 1000)	sales per sq.m. (NLG)	floor space (sq.m.)	sales (NLG × 1000)	sales per sq.m. (NLG)
A1	2490	54,882	22,068	2490	50,385	20,259
A2	800	8,512	10,654	0	0	-
A3	210	6,831	32,529	1500	19,507	13,005
A4	980	10,229	10,459	0	0	-
C1	0	0	-	1500	19,653	13,102
C2	0	0	-	0	0	-
C3	0	0	-	0	0	-
C4	0	0	-	1500	21,316	14,211
Total	4,480	80,454 (24.1%)	17,958.48	7,000	110,861 (33.2%)	15,837.29

It follows that investment in a second and third outlet as well as investment in the large store format yields significant improvements of the market share of the chain under optimal location conditions. From the point of view of market share the 'all large' 3-outlet strategy (solution 9) gives the best results. However, investment decisions will not be based on market share alone but will also depend on costs of operating the network. Clearly, these costs increase with an increasing number and size of outlets. A cost-benefit analysis must be conducted to identify the macro-strategy that yields the highest profits. Whether or not the profit maximising strategy is also the most attractive option depends on the marketing objectives of the retailer. For reasons of increasing the competitive strength of the chain, the retailer may give priority to maximising market share rather than to maximising profits. In that case, the retailer may opt for an additional outlet even if that outlet incurs negative marginal profits.

Having ranked the alternative strategies based on a trade-off between market share, profits and possibly additional criteria, the most attractive strategy can be identified. The decision whether or not to invest in the retail network following this best strategy depends on whether or not profits provide sufficient returns on investment. For illustration purposes we assume that the retailer chooses to implement the market share maximising strategy, that is the 'all large' 3-outlet strategy. Table 9.9 gives an indication of the impact of a re-organisation of the chain following this strategy. Recall that in the starting situation, the retailer operates 4 outlets at locations A1-A4. The re-organisation involves the closure of two outlets (A2 and A4), opening of two new outlets (C1 and C4) and an expansion of one outlet (A3). Although the number of outlets remains the same, the re-organisation results in a considerable expansion (56 %) of the network's total floor space. Just as significant, is the increase in predicted market share (9.2 %) resulting from this expansion.

9.3.4 Conclusions

This case study illustrated the use of Location Planner for solving the competitive location problem. Retail companies face this problem when they are concerned with developing a strategic plan for entering a new market area or reorganising the chain in an existing market area. The Problem Solver module of Location Planner was used to generate and evaluate possible macro-strategies under optimal location conditions. The proposed approach has several potential advantages.

First, the algorithm is able to identify locations with high trading potential that might have been overlooked otherwise. For example in this case, the system selected a location which would cause overlapping trade areas with an existing store and therefore incur cannibalism. Although experts would tend to discard such locations, the system selected the location for its ability to distract market share from competing chains to an extent that can compensate for the loss caused by cannibalism.

Second, the output of Problem Solver in the form of an exhaustive list of possible macro-strategies under optimal location conditions provides the necessary information for management to select a strategy that best fits the longer term objectives of the firm. Specifically, it was shown that the output allows management to trade-off marketing objectives (e.g., maximise market share) against financial objectives (e.g., maximise profits).

Third, by using a spatial choice model for evaluating solutions, the search algorithm is sensitive not only for the location, but also for the attribute profile of outlets. The case study showed that a realistic problem could be satisfactorily represented by an optimisation model. Although a relatively simple choice model was used, Location Planner allows one to implement more sophisticated models as well, e.g. to account for spatial agglomeration effects on choice behaviour. Moreover, there are no limitations to the choice of attributes for specifying optional store formats. The only restriction is that chosen attributes should be represented in the used choice model.

Finally, the study showed that the required data could be obtained from data collections that the case-retailer already performs on a regular basis for general market research purposes. Thus, at least for this particular company, the procedure can be readily integrated in current market research programs, without incurring additional data collection costs. Having said this, the quality of predictions in this case could be improved by collecting more data about the road network as well as attributes of outlets/locations (e.g., parking facilities).

At the same time, we should also point at limitations of the approach. First, the quality of solutions depends on the predictive validity of the used choice model for evaluation. Specifically, the model's assumption of constant relationships between utility and attribute variables limits the range of solutions that can be reliably evaluated. Constraints on decision variables should be set so as to prevent the system from considering solutions that deviate too strongly from the existing market situation on which the model was estimated (e.g., limit the number of new outlets).

Second, it should be noted that optimal solutions are generally sensitive to the choice of the zoning system used to define area units. Fotheringham *et al.* (1995) proved with case material that *p*-median models might suffer from this so-called modifiable areal unit problem. Obviously, the smaller the areal units the less sensitive outcomes will be to the definition of these units. Given the mentioned uncertainties related to the choice model and the spatial search algorithm, the solutions generated by the system should be considered as indicative. Nevertheless, the solutions are useful for identifying alternatives in an exploratory stage of the decision making process.

9.4 Conclusions

The two case studies discussed in this chapter illustrated the potential of Location Planner for improving the quality of decisions in different stages of the decision making process. The Veldhoven case demonstrated the inferential capabilities of Location Planner for analysing retail plans. The case highlighted the specific advantages of the multipurpose trip model. Potentially, the model can generate better quality information, as it allows planners to evaluate trip-adjustment and joint-attraction effects of retail developments. At least in the presented case, the impacts of these effects on retail system performance are substantial. The case-study did not consider complementary models for analysing the accessibility of retail facilities, as this was already covered by the case-studies described in Chapter 6.

The Alkmaar case, on the other hand, illustrated the use of available task level models for generating decision alternatives in the earlier stages of the decision making process where the emphasis is on exploring opportunities for expansion or improving a retail chain. The optimisation model identified interesting alternative strategies and provided the required information for making a choice considering marketing and financial criteria. Both case studies further showed that the models meet user-implied constraints in terms of data-needs and interpretability of outputs. Moreover, the inference engine of Location Planner makes sure that the models can be used without knowledge about the technical implementation of the models.

CHAPTER 10

CONCLUSIONS AND DISCUSSION

The goal of this study was to specify a concept for a generic retail and service planning DSS, develop and integrate the required methodological knowledge and design and implement the DSS. The specification of these three aspects – system concept, knowledge base and design/implementation - were successively considered in the three parts of this book. This final chapter summarises the major conclusions related to each part and discusses potentials of the system and ways of future research.

10.1 Conclusions from Part I

Given the objective of DSS to support ill-structured decision problems, two key characteristics were identified:

1. the ability of DSS to adapt to different solution paths dependent on preferences/styles of decision makers (level-1 flexibility) and adaptability to a wide range of decision problems within the concerned domain (level-2 flexibility);
2. the extent to which users are able to change conditions of problems (openness) and the speed with which the system is able to give feed-back in terms of consequences (length of feed-back loop).

Problems in retail and service planning were investigated in order to specify the objectives of a spatial DSS. An analysis of issues in contemporary retail planning revealed that under influence of saturation and diversification of many retail markets in recent years, location problems in governmental as well as commercial sectors have become both more difficult and more important. More complex because preferences and choice behaviour of consumers are harder to predict and good locations harder to find. More important because location is increasingly considered the key element of the retail mix in establishing and maintaining an advantageous position of a retail chain or promoting high quality residential and work environments. In plan decision making, market research and a dialogue between governmental and commercial sectors are stressed.

An analysis of plan decision making processes in public and private sectors revealed that many uncertainties exist in the problem generation, plan generation and plan evaluation stages. As DSS, applied research attempts to reduce the uncertainties. A closer look at current practice, however, indicated that potentials of research are not fully utilised with regard to the methodology used, the issues addressed and integration in the planning process. The dominantly used analogue (and sometimes regression analysis) technique in feasibility and impact studies fails to adequately take into account competitive structures in market areas and the allocation of expenditure across competing centres/stores. This is due to the fact that the mechanisms – i.e. consumer choice behaviour – by which expenditure is allocated across supply locations are not represented by the models. With respect to the issues covered, it is safe to say that the focus of current applied research is almost exclusively on the economic performance of centres/stores, while social issues are neglected. Moreover, systematic methods for generating and evaluating plans have great potential but receive little attention. Finally, research based on analogue and regression models is often not able to reveal impacts of all actions that planners/retailers may consider, such as for example compensatory measures to reduce negative externalities of new developments. With respect to the integration of research in the planning process, it was concluded that the conventional analysis techniques lack flexibility. The lengthy and costly procedures of analogue and regression techniques may throw up a threshold for evaluating scenarios and questions may remain unanswered.

The objective of the proposed DSS is to improve the integration of spatial and decision models in the planning process. It seeks to enhance the potential contribution of research in planning by (i) providing more advanced methodology (information quality), (ii) addressing the creative and choice stages in planning as well as the analytic stages (information quantity) (iii) covering social issues as well as economic and efficiency issues (information quantity) and (iii) improving the integration of models in the planning process through a flexible and interactive problem solving environment. The wide-spread availability of GIS and spatial databases for research and planning in governmental and commercial organisations favour the cost-benefit ratio of such a system.

Flexibility and interactive properties are essential properties of DSS in general, but prove to be particular important for attainment of the above objectives. Specifically, a highly flexible system is required to accommodate the wide range of retail planning problems across public and private sectors and a highly interactive environment is required to realise the potentials of a better integration of research in the planning process.

10.2 Conclusions from Part II

The fields of methodological research that are relevant for the spatial DSS include diverse areas in spatial sciences, operations research and artificial intelligence. To identify and structure methodological knowledge for the spatial DSS, the conceptual modelling language developed in the context of the well-known KADS methodology in KBS development was specified for the spatial planning field. The knowledge model consists of four layers. The bottom layer represents the basic concepts and conceptual relationships to store facts in the domain (domain layer). The next layers contains control knowledge to reason about the domain (inference layer), attain problem solving goals in terms of inference steps (task layer) and structure ill-defined problems in terms of tasks in flexible ways (strategic layer).

This framework not only helps us to identify relevant knowledge components, but also provides a powerful model management system for the DSS. Models in every layer can be formulated as specific control structures of components in the lower layer. This principle facilitates the reusability of model components, efficient management and flexible use of the models (i.e., dynamic compilations). Moreover, as the strategic layer supports higher-level cognitive tasks decision-makers are faced with, the layered approach is consistent with the objectives of current research in the area of adaptive or active DSS.

Within the inference layer, causal/associative, conceptual and instrumental forms of knowledge were distinguished. To specify the *causal/associative* component, discrete choice models of consumer behaviour were put forward. Research focused on problems that arise when the basic models are applied to the spatial domain was reviewed. Proposed extensions attempt to account for spatial structure in which stores/centres are situated. We argued that even the more advanced models fall short in adequately representing consumers' tendency to make multipurpose trips that may involve multiple stops. Therefore, we proposed a nested-logit model that predicts trip purpose and destination choice in interaction and allows multiple purpose as well as multiple stop choices. The model is designed to account for the two spatial agglomeration effects that may arise from multipurpose shopping:

1. *joint-attraction*: the utility of a spatial cluster of stores may be larger than the sum of attractions of stores at separate locations, because a cluster facilitates multipurpose shopping;
2. *purpose-adjustment*: individuals may adapt the choice between single or multipurpose trips to distances between available shopping facilities.

An application of the model to a large-scale consumer survey data set showed that, at least in that data set, both effects are significant and that compared to a conventional single purpose model, the new model substantially improved the prediction of shopping centre choice. At the same time, the model has specific advantages in applied settings, as it (i) provides useful information for optimising the branch mix of shopping centres/stores (ii) is able to predict impact of spatial structure on consumers propensities to make multipurpose trips and, therefore, has added value for travel demand analysis, (iii) can be estimated on revealed shopping trip data which are relatively easy to collect and (iv) can be estimated using standard full-information likelihood estimation software. The new model is the central component of the inference layer of the DSS model base.

The *conceptual component*, on the other hand, serves to analyse retail/service system performance in the light of given planning objectives. A review of the literature showed that existing models for performance analysis do not adequately account for multipurpose, multistop behaviour. This is problematic for several performance criteria that are important in planning. Extensions were developed here for each identified criterion in turn. First, current indicators of accessibility exclusively consider travel distances between demand and supply locations and, therefore, fail to account for opportunities offered by spatial clusters of facilities to save travel costs through multipurpose shopping. The proposed new model calculates as an alternative measure the minimum travel costs required to satisfy demands while accounting for multipurpose, multistop trips. A case study showed that the new model may lead to different rankings of locations/plans and, consequently, is relevant for spatial decision making.

Second, in current retail/service studies the choice range of facilities is typically measured in terms of the availability of facilities in travel-time-bands away from a consumer location. There are several problems associated with this approach, but the most important problem is the lack of sensitivity for the influence of spatial structure on choice range. The proposed new model determines as a more sensitive measure the minimum expected travel costs for a particular demand while accounting for differences between locations in the probability of satisfying the demand and the possibility of multi-stop trips. A case study showed that compared to the traditional travel-time band approach, the new model may lead to considerable shifts in ranking origin locations due to spatial structure effects and, therefore, has added value for planning.

Besides spatial opportunities of consumers, behavioural aspects of retail/service systems are relevant for planning. Behavioural aspects are considered by planners mainly to evaluate travel demands and economic performance of centres (under plan conditions). In the conventional approach, this information is derived from origin-destination matrices of consumer flows. A two-dimensional matrix, however, is too restrictive to represent the more general multipurpose, multistop case. To overcome this limitation, a new and richer data structure was proposed and new models were formulated to derive information about travel demands, market shares and consumer utilities from these data structures. As the extended data structure can be produced by the multipurpose, multistop shopping model, the new behavioural models are complementary to this causal/associative component of the DSS. The significance of the models for planning was demonstrated in a broader context of illustrating the application of the DSS.

A structured modelling approach was proposed to implement the inference layer. For that purpose, it was shown how the new as well as existing models can be decomposed into a limited number of atomic elements. These include a selection function (defining the relevant subsets of spatial objects), an impedance function (measuring distance between locations), an allocation function (defining trips between locations), evaluation function (defining evaluation scores for locations) and an aggregation function (defining aggregation of scores across locations). In the proposed system, the components are computational (encapsulated) objects. A model management system serves to dynamically link components upon information queries of users, while taking consistency constraints on possible combinations into account. In this way, the system is more flexible in responding to information queries and makes optimal use of the reusability of pieces of code.

The *task layer* consists of knowledge how to control inference processes and attain a particular goal. A review of the literature showed that mathematical programming is the dominant approach in location-allocation models. We argued that this approach is useful for solving well-structured location problems, but falls short in supporting the overall ill-structured problems decision-makers are generally dealing with. To allow active participation of decision-makers in the analysis of the problem and search for solutions, we proposed a knowledge-based approach. In this approach, the decision-table formalism is used to represent the heuristic rules that retailers/planners typically use in problem identification, problem analysis and alternative generation stages in planning. A decision-table system specified for food retailing was implemented by means of a KBS development shell. A case study showed an application of the (automated) knowledge base in combination with inference models (shopping and performance models). The main conclusion was that the system is able to effectively structure the overall task and allows decision-makers to trace, understand and modify or even bypass reasoning steps.

10.3 Conclusions from Part III

The final part was concerned with the design, implementation and application of the proposed DSS. Applications of spatial DSS described in the literature were grouped into systems based on spatial interaction/choice modelling, systems based on mathematical programming and multi-objective decision support systems. We argued that the first type of systems focus on inference-layer support and the latter two types of systems on task-layer support. None of the operational systems is sufficiently generic or fully utilises available methodologies, given our present purpose. The purpose of the design developed here is to improve the modelling, flexibility (level-1 and level-2) and interactive properties of spatial DSS.

The first objective is achieved by including the newly developed shopping and performance analysis models in the model base besides relevant existing models. Flexibility in adapting to a specific application (level-2 flexibility) is realised by a design that allows users to specify an inference structure of the retail/service system dependent on the problem. A wide range of inference models and user-defined parameters are available, so that the system is highly adaptable. Flexibility in adapting to a specific style of decision support (level-1 flexibility) is present in that the system supports different modes of interaction. That is, users can choose between intuitive (inference layer), goal-seeking (task layer) and assisted (strategic layer) modes. With respect to interactive properties, the system offers the possibility to simulate a wide range of scenarios including actions, anticipated developments and planning objectives. Through the working of a built-in inference engine, the system gives immediate feedback. Visual interaction modelling techniques were used to facilitate interaction by means of dynamic graphics (e.g., maps). The system is implemented in a windows-program called Location Planner. This software is considered complementary to general-purpose GIS (generating the spatial and geographic database), multicriteria evaluation software (evaluating alternatives) and logit-model estimation software.

Two case studies were described to demonstrate the application of Location Planner. The first case highlighted the application of the multipurpose models in the context of a retail impact analysis study. The study considered an expansion of the major shopping centre in both the daily and non-daily retail sectors in a middle-sized city in the Netherlands. As it turned out, the spatial agglomeration effects as predicted by the model had significant impacts on travel demands and market shares. Compared to a conventional model, the multipurpose models predicted larger impacts of the expansion on both dimensions, as a consequence of the increased agglomeration implied by the expansion.

The second case study highlighted the use of spatial shopping models in the context of a competitive location model for optimising the configuration of a retail chain in terms of the number, attribute profile and location of outlets. The case showed how objectives of a grocery retailer could be represented in a location model inside Location Planner. The model was applied to an existing local market area and it was shown how the results could be used to formulate an optimal strategy for expansion in the area dependent on a trade-off between financial and marketing criteria. In both studies, the data needs comply with data collection methods in current market/planning research programs in governmental and commercial sectors. Therefore, the procedures supported by Location Planner can be readily incorporated in these programs.

10.4 Discussion

The central problem of this study was two-fold: (i) improve existing models considering information needs in contemporary retail/service planning and (ii) develop a system that makes the (advanced) models accessible for practitioners. With respect to the first objective, the most important contribution involved extensions of spatial choice and performance models to improve their sensitiveness and accuracy for predicting and analysing retail/service system operations. The central aim of the design of the DSS, then, was to integrate the models in a flexible and easy-to-use environment for problem solving.

Ideally, a DSS provides optimal support in every stage of the decision making process. In practice, however, the choice of a system concept inevitably entails that some aspects of decision problems are better covered than others. The present system is strong in supporting the plan generation and plan analysis stages in planning, but relatively weak in supporting the preceding monitoring / problem formulation stages and the next choice stage. Facilities for monitoring would fit well in the present system structure, but requires that a time dimension be added to data and model structures. Then, users could monitor developments over time and models for early warning could be built in (see the next section). Facilities for multicriteria evaluation are available through commercial general-purpose packages (such as for example Expert Choice 1995). Not implementing such tools in Location Planner is an explicit choice. Location Planner is designed to be complementary to the generic decision support software in the sense that it provides tools for generating alternatives and the data required for evaluation.

Obviously, whether the DSS comes up to these goals eventually depends on the integration of the system in existing procedures for plan preparation in companies and local governments. Although customising the DSS to a specific user still requires analytic expertise, it is fairly easy to accomplish. Compared to existing approaches, where systems need to be adapted at the software level, the time involved is reduced to a minimum. The case studies described in Chapter 9 showed that required data for calibrating the models could often be collected through standard consumer surveys in existing market research programs against relatively low extra costs. Furthermore, the system is not connected to any specific GIS package for generating the database for the DSS. It supports data formats that are generally available.

A critical issue, which then remains, is the accuracy of predictions. Although the more advanced models developed in this study represent an improvement in this respect, the quality of predictions will depend to a big extent on data quality. In that context, the argument of this study was that a DSS has added value particularly in explorative stages of planning and impact analysis. For the prediction of turn over of new stores cross-validation with other methods (e.g. analogue methods) is probably advisable.

10.5 Possible directions of future research

Possible improvements of the current DSS could be the subject of future research. Partly, these relate to shortcomings of the current implementation of the system. What remains to be done is to (i) integrate the knowledge-based system as an overall task structure in the task layer of the system and (ii) develop models for structuring and monitoring decision-making processes and integrate the models in the strategic layer of the system. The latter research efforts could be positioned in the context of adaptive/active DSS, which is a recently defined field of DSS-research (for an overview, see Fazlollahi 1997). Furthermore, there remain some fundamental problems for future research that involve extensions of models/system design.

First, empirically estimated models of responsive behaviour of producers are desired to allow planners/retailers to investigate impacts of plans under more realistic conditions. Current predictions of impacts assume that existing retailers do not undertake compensatory actions and, consequently, tend to overestimate market-share losses of existing outlets. The utility-based framework developed by Oppewal (1995) and discussed in Chapter 5, fit well in the current structure of the DSS. When incorporated in the 'change' section, the model would make a dynamic loop complete for simulating dynamics in which consumers and producers react to each other's actions. Research is required to develop and test model specifications that comply with available data sources and information needs in planning.

Second, future research could focus on extending the system with a time dimension. Extended with a time dimension, the system would allow users to monitor, simulate and plan developments through time. Originally, the proposed DSS was designed to incorporate the time as well as the spatial dimension. That this study focused the attention on extending spatial models was only a matter of priority. Adding the time dimension is a logical next step and can be realised in a straightforward way, namely by adding time layers to the current domain layer of Location Planner. The resulting data and model structure would provide the basis for a range of new models that are meaningful in various stages in planning.

First, time series data would provide the basis for an early warning system to support problem identification in the early stage of the decision making process. To this end, statistical methods for time series analysis could be used to identify trends and to project identified trends in the future. Rules could be implemented to identify conflicts between projected future conditions and planning standards. Van der Heijden (1986) already demonstrated with case material the use of such early warning systems for retail planning. Second, the time dimension would enable the system to predict a future time path of developments in a retail/service system. Assuming that there is some time delay between reactions of consumers and producers, every time step would reflect a non-stationary location-allocation pattern. Such a dynamic model system would allow users to experiment with the effects of various hypotheses, such as for example population developments, parameters of behaviour, interventions etc. Third, the time dimension would also open up possibilities to implement dynamic location-allocation models for optimisation of time paths of plans while accounting for costs of relocations and changes of demand over time. These models were already developed in the early eighties as extensions of static location-allocation models (see Beaumont, 1981a), but have never materialised in applied studies or systems. Nevertheless, these models could come up to the desire to investigate longer-term objectives in retail planning and to plan the intermediate stages of developments as well.

Developing the above mentioned dynamic model system would require modelling of more than just responsive behaviour of producers. Producers not only react to changes in market conditions, but also display prospective behaviour. Since retail markets are increasingly dominated by only a few large chains, monitoring the actions of competing chains and learning from past experience are increasingly important for formulating strategies. The utility-maximising framework, therefore, does not seem to be suitable for modelling this behaviour. Instead, specific techniques for simulating intelligent and adaptive behaviour of autonomous agents are currently under development and strongly growing in popularity in information technology and social sciences (e.g., Jennings and Wooldridge 1998). In the DSS-field, MAS is currently receiving attention as a means for dealing with the complexity of developing distributed systems for organisational decision support (examples are Ekenberg *et al.* 1997, Whinston 1997). The purpose here is another one, namely modelling dynamics of the system being planned. Similar applications have been reported in the area of simulating long-term urban processes (Sanders 1996, Sanders *et al.* 1997). In the spatial DSS, MAS could provide the means to simulate retail dynamics under different assumptions on strategic behaviour of particular companies and local authorities. Such simulations would allow one to evaluate robustness of plans and formulate appropriate strategies dependent on strategies of other agents. It seems interesting to investigate possibilities of the new modelling technique in the context of a spatial DSS.

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SUBJECT INDEX

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SAMENVATTING

(Dutch summary)

Achtergrond en doelstellingen van het onderzoek

Decision Support Systemen (DSS) werden eind jaren zeventig geïntroduceerd in de bedrijfskunde met als doel beslissingen in organisaties op een tactisch/strategisch niveau te ondersteunen. Het nemen van beslissingen op dit niveau brengt typisch onzekerheden met zich mee over wat de uitkomsten van mogelijke acties zullen zijn, hoe alternatieve acties kunnen worden geëvalueerd en zelfs welke acties ter beschikking staan. Daarom zijn subjectieve beoordelingen van de persoon/groep die de beslissingen neemt onmisbaar. DSSs zijn ontworpen om besluitvorming te ondersteunen primair door via een gebruikersvriendelijk computersysteem databestanden en analysemodellen toegankelijk te maken voor gebruikers die niet noodzakelijk expert zijn op het terrein van de toegepaste modeltechnieken.

De wetenschappelijke belangstelling voor DSS voor ruimtelijke planning ontstond eind jaren tachtig - ongeveer tien jaar nadat de systemen waren geïntroduceerd in de bedrijfskunde. Recentelijk is deze belangstelling geïntensiveerd in verband met de snel groeiende populariteit van Geografische Informatie Systemen (GIS). Nu GISs op grote schaal zijn geïmplementeerd in overheids- en particuliere organisaties die te maken hebben met geografische informatie, neemt het besef toe dat de systemen tekort schieten in het bieden van de analysemogelijkheden en flexibiliteit die nodig zijn voor een effectieve ondersteuning van ruimtelijke besluitvorming. Tegen die achtergrond hebben verschillende auteurs gepleit voor toepassing van ruimtelijk DSS als een volgende generatie van computersystemen op dit terrein.

De uitgebreide literatuur die bestaat op het gebied van ruimtelijk DSS is overwegend conceptueel van aard. Operationele systemen zijn ontwikkeld maar deze zijn typisch georiënteerd op een specifieke analysetechniek (m.n. keuzemodellen van ruimtelijk consumentengedrag, mathematische programmering of ruimtelijke multi-criteria evaluatie), een bepaalde gebruiker of zelfs een bepaald studiegebied. Geen van de bestaande operationele systemen benut daardoor volledig het potentieel van beschikbare methodologieën of is voldoende generiek om het brede scala van problemen in ruimtelijke planning te kunnen ondersteunen. Deze studie richt zich specifiek op winkel- en dienstenvoorzieningen als onderdeel van zowel lokaal/regionaal overheidsbeleid als het strategisch management van (winkel-)bedrijven. Het doel van de studie is om een ontwerp van een generiek ruimtelijk DSS op dit gebied te ontwikkelen, te implementeren en te laten zien hoe deze kan worden toegepast. De beoogde gebruikers van het systeem zijn zowel lokale/regionale overheden als winkel-/dienstenbedrijven.

De studie is georganiseerd in drie delen die zijn gerelateerd aan de drie subdoelstellingen van het onderzoek. Om te komen tot een specificatie van de doelen en eisen waaraan het systeem moet voldoen, beschrijft het eerste deel de basisconcepten voor DSS en de problemen/methoden/werkwijzen van winkelplanning. Het leveren van een bijdrage aan de 'state-of-the-art' op het terrein van het modelleren van ruimtelijk gedrag/beslissingen met het oog op informatiebehoeften in de planningspraktijk is naast de ontwikkeling van het systeem dat deze modellen samenbrengt en toegankelijk maakt, een tweede expliciet doel van dit onderzoek. Het tweede deel is voor dit doel gericht op het identificeren en verder ontwikkelen van relevante methodologische kennis voor het DSS. Tenslotte beschrijft het derde en laatste deel het ontwerp, implementatie en toepassing van het voorgestelde DSS. Als onderdeel van deze studie is het DSS geïmplementeerd in een windowsapplicatie genaamd Location Planner. In het laatste deel wordt eveneens de toepassing van het systeem geïllustreerd aan de hand van enkele case studies.

Deel I

Het eerste deel is onderverdeeld in twee hoofdstukken. Hoofdstuk 2 bespreekt op basis van de algemene DSS literatuur eerst de doelen en kernvragen van onderzoek voor DSS ontwikkeling. Vervolgens gaat hoofdstuk 3 in op de problemen en werkwijzen in hedendaagse winkelplanning om deze doelen en vragen in te vullen voor dit toepassingsgebied.

Hoofdstuk 2

Om het onderzoek in een breder kader van bestaande benaderingen te plaatsen, gaat dit hoofdstuk eerst in op twee terreinen van onderzoek die nauw verwant zijn aan DSS, namelijk geografische informatie systemen en expert systemen. Geconcludeerd wordt dat beide systemen niet zozeer alternatieve benaderingen representeren, maar eerder dienst kunnen doen als onderdeel van een DSS. Gegevens over vraag en aanbod van voorzieningen hebben een ruimtelijk karakter en geografische informatie systemen bieden technieken voor beheer, analyse en representatie van dergelijke gegevens. Expert systeem-technieken zijn bruikbaar om naast wiskundige modellen ook ervaringskennis onder te brengen in het systeem en om de intelligentie van gebruikersinterfaces te verbeteren.

Centraal in DSS theorie staat de notie dat het nemen van beslissingen op tactisch/strategisch niveau over het algemeen moeilijk is vanwege onzekerheden over doelen, acties en uitkomsten. De eigenschappen waaraan een DSS moet voldoen zijn dan afgeleide van enerzijds het doel om de kwaliteit van beslissingen te verbeteren en anderzijds de constatering dat het niet mogelijk is om het beslissingsproces op voorhand volledig te structureren en te automatiseren. Verschillende auteurs hebben in dat verband als essentiële eigenschappen aangemerkt dat het systeem gebruikers moet toestaan om 1) alle relevante condities van het probleem te variëren, 2) snel feedback te krijgen over de (waarschijnlijke) uitkomsten en 3) verschillende paden naar de oplossing te volgen afhankelijk van voorkeuren en stijlen van besluitvorming.

Om deze eigenschappen te realiseren sluit dit onderzoek met name aan bij twee recente velden van onderzoek in de DSS-literatuur. Het onderzoeksveld dat bekend staat als adaptieve of actieve DSS benadrukt het belang van actieve ondersteuning van gebruikers bij het ontleden van een probleem in kleinere stappen die vervolgens met behulp van (wiskundige) modellen kunnen worden ondersteund. Het door de inrichting van het systeem opleggen van een bepaalde volgorde van stappen is in strijd met het slecht gestructureerde karakter van beslissingsprocessen. Daarom zal ernaar worden gestreefd om gebruikers de mogelijkheid te bieden om elementen van beslissings-ondersteunende modellen te combineren afhankelijk van het probleem en een gekozen pad naar de oplossing. Voor dit laatste is een tweede veld van onderzoek, dat bekend staat als model management systemen, relevant.

Hoofdstuk 3

Het doel van dit hoofdstuk is om informatiebehoeften bij voorzieningenplanning in kaart te brengen en afhankelijk van de bevindingen de doelen voor het DSS verder in te vullen. Detailhandel vormt een duidelijk afgebakend terrein binnen de voorzieningen-planning waarin over de jaren heen een uitgebreide traditie van toegepast onderzoek en beleidsvorming is ontwikkeld. Dit hoofdstuk richt zich specifiek op de detailhandel-sector aannemende dat de problematiek in deze sector model kan staan voor het bredere terrein van voorzieningenplanning. Achtereenvolgens wordt aandacht besteed aan de historische context, het proces van planning en de rol en methodologie van toegepast onderzoek.

De overheid heeft van oudsher het belang van systematisch onderzoek en planning voor locatiebeleid onderkend. Voor veel winkelbedrijven daarentegen is de aanwending van middelen voor locatie-onderzoek en planning het laatste decennium sterk toegenomen. Onder invloed van een constante trend van verzadiging van detail-handelsmarkten en centralisatie van winkelbedrijven is het aantal ketens afgenomen, de omvang van ketens toegenomen en de concurrentie tussen ketens geïntensiveerd. De locatie van vestigingen wordt algemeen gezien als een van de belangrijkste instrumenten om een relatief voordelige marktpositie te bemachtigen en te handhaven. Tegelijkertijd is het locatie keuze-probleem ingewikkelder geworden. Sinds goede locaties schaarser en consumentenmarkten diverser en veeleisender zijn geworden hechten zowel winkelbedrijven als overheden een toenemend belang aan marktonderzoek en een consument-georiënteerde vorm van planning. In uitbreiding-, inkrimping- en herstructureringsvraagstukken onderstrepen beide partijen het belang van samenwerking tussen overheid en bedrijfsleven. De rol van de overheid hierin is niet langer die van planner in een traditionele zin maar die van facilitator van (gewenste) ontwikkelingen.

Hoewel ruimtelijk economisch beleid overwegend het resultaat is van een dialoog tussen de partijen, beschikken zowel locale/regionale overheden als (de grotere) winkelbedrijven over gespecialiseerde diensten/afdelingen voor strategische planning. De stappen en beslisproblemen in het planproces vertonen grote overeenkomsten. Een analyse laat zien dat de belangrijkste onzekerheden bij het nemen van beslissingen het gevolg zijn van onvolledige informatie en kennis over 1) demografische en socio-economische ontwikkelingen 2) voorkeuren van consumenten en locatie-strategieën van winkelbedrijven, en 3) de reactie van zowel consumenten als winkelbedrijven op nieuwe ontwikkelingen. Bovendien is de definitie en weging van criteria voor het evalueren van alternatieve plannen in veel gevallen onzeker met name voor overheden waar sociale en economische doelstellingen vaak met elkaar in strijd zijn en belangen van verschillende partijen tegen elkaar moeten worden afgewogen. De strategieën die zowel overheden als winkelbedrijven toepassen om de onzekerheden te bestrijden bestaan uit: 1) monitoren in de tijd van ontwikkelingen in het plangebied; 2) gefaseerde uitvoering van plannen; 3) gebruik van beschikbare informatie over analoge situaties; 4) in beschouwing betrekken van verschillende scenario's en 5) toekennen van een belangrijke rol aan onderzoek.

De doelen van toegepast onderzoek en DSS zijn vergelijkbaar in de zin dat beiden de kwaliteit van planbeslissingen beogen te verbeteren door het genereren van meer en kwalitatief betere informatie. Voor het beoordelen van de effectiviteit van bestaande onderzoeksprogramma's kunnen daarom dezelfde criteria worden gehanteerd. Ten eerste, met betrekking tot de gebruikte methodologie stellen we vast dat de dominant toegepaste analogie- en regressie-analyse methoden onvoldoende in staat zijn om rekening te houden met concurrentiestructuren in een marktgebied bij de verdeling van bestedingen over winkellocaties. Het DSS beoogt meer geavanceerde modellen die zijn gebaseerd op theorieën van consumenten keuzegedrag beschikbaar te maken voor verklaring en voorspelling van gedrag. Ten tweede, met betrekking tot de volledigheid van informatie constateren we dat de programma's eenzijdig op de analysefase en daarbinnen de economische effecten van plannen zijn gericht. Het DSS wil het bereik vergroten zodat systematische methoden ook voor de creatieve (genereren van plannen) en keuze fasen (evaluatie van planalternatieven) kunnen worden benut. Daarnaast kan een DSS meerwaarde bieden in de analysefase met modellen die een breder spectrum van planningsdoelen en criteria afdekken. Tenslotte, beoogt het DSS de integratie van modellen/methoden/technieken in het planningsproces te verbeteren. Onderzoeks-procedures veroorzaken vaak lange en kostbare feed-back loops. Door automatisering van procedures kan het systeem snel antwoord geven op 'wat-zou-er-gebeuren-als...' vragen en zo de integratie van modellen in een iteratief planningsproces bevorderen.

Deel II

Het doel van het tweede deel is de ontwikkeling van modellen die beantwoorden aan de vastgestelde doelen voor het DSS. Voor dit doel, is dit deel als volgt opgebouwd. Ten eerste, ontwikkelt Hoofdstuk 4 een conceptueel kader voor het identificeren en integreren van relevante modellen. De hoofdstukken die volgen zoomen in op specifieke onderdelen van dit conceptuele kader, namelijk ruimtelijk consumentengedragsmodellen (Hoofdstuk 5), systeem prestatie-modellen (Hoofdstuk 6) en planningstaak modellen (Hoofdstuk 7). Elk hoofdstuk geeft voor het betreffende onderdeel eerst een overzicht van bestaande literatuur op dat gebied en stelt vervolgens een aanpak voor om bestaande modellen te verbeteren in relatie tot informatiebehoeften.

Hoofdstuk 4

Modellen, technieken en methoden die zijn ontwikkeld in de ruimtelijke wetenschappen, operations research, besliskunde en artificiële intelligentie zijn mogelijk relevant voor ruimtelijke planning. Dit hoofdstuk beschouwt de vraag hoe deze kenniscomponenten in een samenhangend kader kunnen worden geclassificeerd en geïntegreerd. We gebruiken hiervoor de 'KADS conceptual modeling language' (KCML) dat in de jaren tachtig is ontwikkeld en sindsdien veel is toegepast voor de ontwikkeling van kennisgebaseerde systemen. Het KCML onderscheidt vier kennislagen. De basislaag bestaat uit de concepten en conceptuele relaties die nodig zijn voor het representeren van feiten in het betreffende domein (domein laag). De hogere lagen bevatten procedurele kennis voor redeneren (inferentie laag), het bereiken van doelen (taak laag) en het structureren van een gegeven probleem (strategische laag).

Na uitleg van aannames/principes die ten grondslag liggen aan het KCML, beschrijft het hoofdstuk vervolgens een voorstel voor invulling van de kennislagen voor het domein van ruimtelijke planning. In het voorgestelde model is de domein laag opgebouwd uit perspectieven op het voorzieningensysteem (de huidige staat, de toekomstige staat, acties, doelen etc.), objecten (vraag, aanbod, wegverbindingen, bestedingsstromen enz.), variabelen voor het beschrijven van objecten (attributen, criteria) en de stappen in een tijdspad. De inferentie laag bestaat dan uit de modellen waarmee nieuwe feiten uit bestaande feiten kunnen worden afgeleid op basis van causale/associatieve (voorspellen), conceptuele (analyse en evaluatie) en instrumentele (actie heuristieken) verbanden. Bestaande algoritmen voor het oplossen van bepaalde optimalisatieproblemen en andere goed gedefinieerde subproblemen in ruimtelijke planning kunnen nu in de taak laag worden gepositioneerd. Tenslotte, bestaat de strategische laag uit methoden voor het structureren van planningsproblemen.

Het voordeel van deze laagsgewijze opbouw van kennis is dat modellen in een hogere kennislaag slechts kunnen bestaan uit regels voor het combineren van de componenten uit de laag er direct onder. Zo hoeft een component maar een keer te worden gedefinieerd terwijl het in vele modellen kan worden gebruikt. Het structureren en flexibel hergebruik van modelcomponenten vormt sinds de jaren tachtig een actief terrein van algemeen DSS-onderzoek. Ook op het terrein van ruimtelijke DSS is deze zogenaamde 'model management' benadering door verschillende auteurs bepleit. Het hier uitgewerkte vier-lagen systeem gaat verder dan de bestaande (conceptuele) systemen waarin slechts twee niveaus zijn onderscheiden. Verder merken we op dat het opnemen van een strategische laag beantwoordt aan doelen in de lijn van de eerder genoemde actieve/adaptieve DSS. In de hoofdstukken die volgen worden elk van de componenten van het gelaagde model in detail ingevuld.

Hoofdstuk 5

De causaal/associatieve component van de inferentie laag heeft in het DSS de functie om het gedrag van consumenten en producenten te voorspellen afhankelijk van (voorgestelde) planmaatregelen. Planmaatregelen kunnen betrekking hebben op, bijvoorbeeld, openen van een winkelcentrum, uitbreiding/inkrimping van vloeroppervlak, renovatie maar ook veranderingen in de bereikbaarheid van winkellocaties etc. Dit hoofdstuk geeft eerst een overzicht van modellen die voor deze doelen in de literatuur zijn ontwikkeld en die relevant zijn voor het DSS.

Modellen van ruimtelijk consumentengedrag gaan ervan uit dat individuen een keuze maken uit de voor hun beschikbare alternatieve winkellocaties op basis van reisafstand en de aantrekkelijkheid van de locatie en soms ook van kenmerken van het individu. De aantrekkelijkheid van een winkellocatie kan op verschillende wijzen worden gemeten, maar de meeste modellen die zijn ontwikkeld onderscheiden de grootte van het winkelaanbod, parkeermogelijkheden, het prijsniveau, de sfeer/aankleding van het winkelcentrum en andere attributen. De relatieve gewichten van de verschillende attributen zijn niet a-priori bekend maar dienen te worden geschat op basis van het waargenomen keuzegedrag (in het betreffende studiegebied) voor de uitgangssituatie (d.w.z. voor implementatie van het plan).

Verschillende typen van modellen die op dit principe zijn gebaseerd zijn ontwikkeld/toegepast in geografie, marketing, stedelijke planning en vervoerskunde, namelijk ruimtelijke interactie modellen, discrete keuzemodellen en decompositionele preferentie/keuzemodellen. Beargumenteerd wordt dat het discrete keuzemodel het meest geschikt is voor toepassing in het DSS. De rest van het literatuuroverzicht gaat daarom in op de uitbreidingen van dit type model die zijn voorgesteld in de literatuur om het model te verbeteren voor toepassing in een ruimtelijk context. De meer uitgebreide modellen houden rekening met ruimtelijke substitutie-effecten bij de afbakening van keuzesets en afweging van alternatieven.

Modellen van producentengedrag voorspellen de reacties van producenten op veranderingen in hun marktgebied/concurrentiepositie bijvoorbeeld als gevolg van veranderd winkelkeuzegedrag van consumenten. Reacties die een ruimtelijke effect hebben zijn bijvoorbeeld aanpassing van het uiterlijk van de winkel, re-locatie, uitbreiden/inkrimpen van vloeroppervlak etc. Hoewel de ontwikkeling van dergelijke modellen aandacht heeft gekregen in de literatuur, wordt geconcludeerd uit het literatuuroverzicht dat geen van de voorgestelde empirisch getoetste modellen voldoende operationeel is voor toepassing in een DSS. Verder fundamenteel onderzoek is hiervoor noodzakelijk.

Het tweede deel van dit hoofdstuk beschrijft vervolgens het 'multipurpose trip' model van consumentenkeuzegedrag dat in deze studie is ontwikkeld. Het basismodel van consumentenkeuzegedrag gaat ervan uit dat consumenten uitsluitend 'single purpose trips' maken. Een single purpose trip is een trip waarop slechts inkopen uit één artikelgroep wordt gedaan zoals bijvoorbeeld dagelijkse of huishoudelijke artikelen. Het voorgestelde multipurpose model daarentegen houdt rekening met de mogelijkheid dat individuen meerdere artikelgroepen combineren. Als dit in hetzelfde winkelcentrum gebeurt dan spreken we van mulitpurpose, *single stop* trips en als meerdere locaties worden bezocht van multipurpose, *multistop* trips. We beargumenteren dat multipurpose gedrag hetzij multistop of single stop, de aantrekkelijkheid van locaties kan beïnvloeden op grond van tenminste twee ruimtelijke agglomeratie-effecten:

1. *joint attraction*: het nut van ruimtelijk clusters van winkels kan groter zijn dan het gezamenlijk nut van ruimtelijk geïsoleerde winkels doordat zij betere mogelijkheden bieden voor multi-purpose inkopen.
2. *purpose adjustment*: individuen kunnen de keuze tussen het maken van single of multipurpose trips aanpassen aan de mate van ruimtelijke clustering van beschikbare winkels.

Hoewel het modelleren van multi-purpose trips ruim aandacht heeft gekregen in de literatuur, laat een overzicht zien dat bestaande modellen ofwel deze ruimtelijke effecten veronachtzamen of niet zijn gebaseerd op discrete keuzetheorie (m.n. random utility theorie).

Het voorgestelde, nieuwe model veronderstelt een hiërarchisch keuzeproces waarin individuen eerst de 'purpose' en vervolgens één of meerdere winkelcentra kiezen om de gekozen artikelen te kopen. De 'purpose' keuzeset bevat zowel de enkelvoudige als de mogelijke combinaties van artikelgroepen. Welke artikelgroepen er worden onderscheiden is niet vastgelegd in de algemene specificatie van het model. De winkelcentrumkeuze bestaat uit verschillende stappen, namelijk één bestemmingskeuze voor elke betrokken artikelgroep. Door gebruik te maken van een nested-logit model structuur kunnen zowel de joint attraction als de purpose-adjustment effecten in het model tot uitdrukking worden gebracht.

Om het model empirisch te toetsen is het geschat op basis van een grootschalige consumenten survey. Dagelijkse goederen, huishoudelijke artikelen en kleding/schoeisel werden als drie representatieve artikelcategorieën onderscheiden. Omdat slechts een marginaal deel van de gerapporteerde winkeltrips multi-stop was, werd alleen de single stop variant van het multipurpose model (full-information) geschat. De resultaten ondersteunen de hypothese dat join attraction en purpose adjustment effecten beiden optreden. Verder toonde een aanvullende analyse aan dat de agglomeratie-effecten bovendien een significante invloed hebben op winkelcentrumkeuze. De verbetering in voorspelling van winkelcentrumkeuze t.o.v. een (uitgebreid) conventioneel model is substantieel.

Naast de verbetering van de accuraatheid van voorspellingen heeft het model nog andere voordelen met name voor toepassing in het DSS: 1) het model is beter in staat om verplaatsingsbehoeften voor winkelen te voorspellen, 2) het model kan ook worden toegepast voor het optimaliseren van de branche samenstelling van winkelcentra en 3) het model kan worden geschat op relatief eenvoudig/goedkoop te verzamelen data en met standaard (full information) loglikelihood procedures.

Hoofdstuk 6

Op basis van de in het vorige hoofdstuk beschreven modellen kan het effect van planmaatregelen op ruimtelijke keuzegedrag van consumenten worden voorspeld. De vertaling van wat de implicaties zijn voor planningsdoelen is daarmee echter nog niet meteen duidelijk. Het doel van dit hoofdstuk is om modellen in de conceptuele laag in te vullen die de implicaties voor planningsdoelen met betrekking tot bereikbaarheid van voorzieningen, keuzemogelijkheden voor consumenten en economisch functioneren van voorzieningen expliciet kunnen maken. Voor dit doel is de literatuur op het gebied van (ruimtelijke) prestatie indicatoren relevant. Na een overzicht gegeven te hebben van deze literatuur, beschrijft dit hoofdstuk een aantal nieuw ontwikkelde modellen om tekortkomingen van bestaande modellen op dit gebied te ondervangen.

Het eerste model meet de bereikbaarheid van voorzieningen rekening houdend met multipurpose, multistop gedrag. Het model berekent de minimale benodigde totale reisafstand om een gegeven pakket van artikelen in te kopen bij een gegeven aankoopfrequentie voor elke artikelgroep. Het model houdt hierbij rekening met de mogelijkheid om door multipurpose, multistop trips de totale reisafstand te verminderen. Zodoende is het model, i.t.t. bestaande modellen, gevoelig voor de mate van ruimtelijke clustering van voorzieningen. Een case-studie laat zien dat het model significante invloed kan hebben op de rangschikking van locaties naar bereikbaarheid en dus op de beoordeling van planalternatieven.

Bereikbaarheid verwijst naar de moeite die mensen moeten doen om locaties te bereiken. Het tweede model meet als aanvulling daarop de range van keuzemogelijkheden tussen beschikbare alternatieve locaties. In bestaande studies wordt keuzemogelijkheid typisch bepaald op basis van het aantal voorzieningen dat binnen een bepaalde reistijdband vanaf een (woon-)locatie beschikbaar is. Een reistijdband houdt echter geen rekening met de mogelijkheid om via multistop trips het actiebereik te vergroten bij een gegeven reisafstand. Het voorgestelde nieuwe model biedt een alternatieve aanpak door te veronderstellen dat de kans van slagen van een gegeven tripdoel op een locatie afhankelijk is van de omvang van het aanbod van aanwezige voorzieningen op die locatie. In het geval van niet-slagen wordt de trip verlengd naar een volgende locatie enzovoort. Het model berekent op basis van deze veronderstellingen de minimale verwachte reisafstand bij een gegeven minimale kans op slagen van de gehele trip-keten (bijv. 95 %). Deze afstand geeft een indicatie van de ruimtelijke keuzemogelijkheden voor een consument rekening houdend met de ruimtelijke structuur van de beschikbare voorzieningen. Een case studie laat zien dat ook in dit model de ruimtelijke structuur-effecten op de rangschikking van locaties/-planalternatieven significant kan zijn.

De bovenbeschreven twee modellen hebben betrekking op mogelijkheden die de fysieke omgeving biedt ongeacht het feitelijke gedrag van consumenten. Het derde deel van dit hoofdstuk ontwikkelt een reeks van aanvullende modellen die op basis van gegevens over (voorspeld) keuzegegedrag in het studiegebied informatie genereert over de winstgevendheid van voorzieningen, de reisbehoeften van consumenten en het nut dat consumenten ontlenen aan voorzieningen. Het voordeel van de nieuwe modellen is dat zij, in tegenstelling tot bestaande modellen, rekening houden met multipurpose, multistop gedrag.

Tenslotte werkt het laatste deel van dit hoofdstuk een model management systeem uit voor de inferentie laag. Het voorgestelde systeem ontleedt de modellen in een aantal elementaire componenten. De componenten bestaan uit functies voor de selectie van objecten, berekening van afstanden tussen objecten, allocatie van vraag aan aanbod, evaluatie van vraag-aanbod relaties en aggregatie van evaluatie scores. Door modellen op te bouwen als combinaties van deze elementaire functies kunnen de eerder genoemde voordelen van model management systemen worden gerealiseerd in het DSS.

Hoofdstuk 7

Nadat de inferentie laag is ingevuld beschouwt dit hoofdstuk modellen voor de taak laag. Deze hogere laag heeft in het DSS de functie om inferentiemodellen aan te sturen voor het oplossen van bepaalde (sub)problemen in voorzieningenplanning. Het eerste deel van dit hoofdstuk geeft een overzicht van de literatuur op dit terrein. Bestaande modellen zijn overwegend gebaseerd op mathematische programmering. De voorgestelde modellen optimaliseren de ruimtelijke configuratie van een voorzieningennetwerk op basis van verschillende doelstellingsfuncties, zoals bijvoorbeeld bereikbaarheid of winstgevendhevendheid van het netwerk.

We beargumenteren dat bestaande optimalisatiemodellen weliswaar bruikbaar zijn als componenten van de taak laag, maar dat zij onvoldoende in staat zijn om ook op een hoger strategisch niveau planningsproblemen te ondersteunen. Dit hoofdstuk stelt daarom een kennisgebaseerd systeem (KBS) voor als alternatieve aanpak. In tegenstelling tot wiskundige optimalisatiemodellen sluit een kennisgebaseerd systeem direct aan bij de concepten, werkwijzen en heuristische regels die planners in de praktijk hanteren. Bovendien is een KBS in staat om de adviezen die het geeft over te ondernemen acties te onderbouwen met redenen voor dat advies. Dit stelt gebruikers in staat om actief deel te nemen aan het zoekprocess naar een oplossing. Hoewel toepassing van KBS al sinds de eind jaren tachtig ruim aandacht krijgt in de ruimtelijke planning-literatuur, is een KBS voor voorzieningenplanning zoals hier wordt voorgesteld nieuw.

Na het literatuuroverzicht en bespreking van de doelen van de nieuwe aanpak, beschrijft de rest van het hoofdstuk de specificatie en toepassing van het KBS. De beslistabel wordt gebruikt als formalisme om heuristische beslisregels te representeren in het systeem. De regels zijn gespecialiseerd in 1) het signaleren van eventuele problemen/mogelijkheden in de bestaande of een geanticipeerde situatie, 2) het vinden van de waarschijnlijke oorzaken van een gesignaleerd probleem en 3) het vinden van adequate acties voor het oplossen van het probleem. Als optionele acties beschouwt het systeem het openen/sluiten van centra, ingrepen in de branche samenstelling van centra, verkleinen/vergroten van vloeroppervlak en renovatie van een centrum. De regels beschouwen als doel de situatie waarin aan bereikbaarheidscriteria is voldaan, de omvang van het aanbod in evenwicht is met de omvang van de vraag, en elk van de centra voldoen aan eisen van rendabiliteit, aantrekkelijkheid en evenwichtige branche samenstelling. De modellen in de inferentie worden toegepast om de regels van de benodigde informatie over prestaties van voorzieningen en de waarschijnlijke effecten van acties te voorzien.

Het systeem is geïmplementeerd in AKTS – een op beslistabellen gebaseerd systeem voor het ontwikkelen en consulteren van kennisbanken. Een case studie laat zien hoe het systeem in combinatie met de inferentie laag-modellen kan worden toegepast in de dagelijkse goederen-sector. We concluderen op basis van de studie dat het systeem beantwoordt aan de gestelde doelen.

Deel III

Het doel van dit derde en laatste deel is ontwikkeling van een ontwerp van een DSS dat de in Deel II beschreven modellen samenbrengt en bovendien voldoet aan de in Deel I geformuleerde doelen en eisen. De programmeeromgeving C++Builder is gebruikt om het systeem te implementeren in een windows-applicatie (genaamd Location Planner). Het eerste hoofdstuk van dit deel beschrijft het voorgestelde ontwerp. Hoofdstuk 9 bespreekt vervolgens de toepassing van Location Planner in twee illustratieve case studies.

Hoofdstuk 8

Dit hoofdstuk geeft eerst een literatuuroverzicht van toepassingen en onderzoek op het terrein van ruimtelijk DSS vanaf eind jaren tachtig toen de systemen werden geïntroduceerd. Beargumenteerd wordt dat bestaande systemen eenzijdig zijn opgebouwd rond slechts een bepaalde analysetechniek. Het hier beschreven DSS wil door middel van de gelaagde structuur een bredere range van modellen integreren. Verder stellen we vast dat bestaande operationele systemen vaak specifiek zijn ontworpen voor een beperkte range van locatieproblemen/gebruikers/studiegebieden. Het hier voorgestelde ontwerp wil een generieker en flexibeler systeem realiseren binnen de randvoorwaarden van gebruikersvriendelijkheid.

De rest van dit hoofdstuk is vervolgens gewijd aan een beschrijving van het voorgestelde ontwerp eerst met betrekking tot de kerncomponenten van het systeem en vervolgens de gebruikersinterfaces. Het systeem biedt een structuur dat in overeenstemming is met het conceptuele model van Hoofdstuk 4 en waaraan gebruikers aanwezige modellen en eigen databases kunnen koppelen, afhankelijk van de betreffende toepassing. De ingevulde structuur voorziet in een dynamische omgeving waarin gebruikers op een gemakkelijke en intuïtieve manier bevolkings- en planscenario's kunnen invoeren en doorrekenen op criteria die van belang zijn voor het specifieke planningsprobleem. Bovenop deze inferentie laag biedt het systeem de mogelijkheid om aanwezige modellen van de taak laag toe te passen. Beschikbaar zijn algoritmen die modellen in de inferentie laag aansturen voor het optimaliseren van de configuratie van voorzieningennetwerken afhankelijk van een door de gebruikers gedefinieerde doelstellingsfunctie. Het aantal voorzieningen, locatie en attributen kunnen gelijktijdig met de aanwezige algoritmen worden geoptimaliseerd. Hoewel het ontwerp daar ruimte voor open laat, zijn het KBS en de strategische laag niet geïmplementeerd in de huidige versie van Location Planner.

Het gebruikersinterface biedt verschillende formats voor het weergeven en bewerken van data, namelijk de tabel-, grafiek- en kaartvorm. Deze zogenaamde 'views' zijn dynamisch aan elkaar gekoppeld zodat veranderingen/selecties aangebracht in het ene view (bijv. tabel) direct ook zichtbaar worden in eventuele andere views (bijv. kaart) die tegelijk geopend zijn. Alle relevante condities kunnen door de gebruiker worden gevarieerd en de resultaten worden onmiddelijk doorgerekend door een ingebouwd inferentie mechanisme. Het mechanisme zorgt er niet alleen voor dat gebuikers onmiddellijk feedback krijgen, maar ook dat zij zijn afgeschermd van de technische details van de onderliggende modellen. De resultaten van optimalisaties kunnen op dezelfde wijze via multiple, dynamisch gekoppelde views worden bekeken. Het systeem biedt verder gespecialiseerde modules voor management (opslag, bewerking, weergave) van gebruiker-gedefinieerde scenario's en gegenereerde oplossingen.

Het laatste deel van dit hoofdstuk bespreekt tenslotte sterke en zwakke punten van het voorgestelde systeem. We benadrukken dat het systeem zelfstandig werkt. Bestaande databases die in de praktijk veelal al voor marktonderzoek zijn ontwikkeld en zijn opgeslagen in een GIS kunnen eenvoudig aan Location Planner worden gekoppeld voor gebruik van de data voor ondersteuning van de planningsfase. Daarnaast is bestaande MCE software complementair voor het evalueren van planalternatieven in de keuzefase. De flexibiliteit, interactieve eigenschappen en de modelcapaciteiten zijn met name sterke eigenschappen van het DSS in vergelijking tot bestaande systemen.

Hoofdstuk 9

De twee case studies die in dit hoofdstuk worden beschreven illustreren de toepassing van Location Planner voor twee planningsproblemen die representatief zijn voor overheden en detailhandelsbedrijven. De eerste case studie heeft betrekking op de voorspelling en analyse van de effecten van een grootschalige uitbreiding van het hoofdwinkelcentrum in Veldhoven. Om de effecten te voorspellen is het multipurpose model (Hoofdstuk 5) geschat voor het gebied. De studie laat verder zien hoe met aanwezige modellen (Hoofdstuk 6) effecten in termen van reisbehoeften en marktaandelen van het betreffende en de concurrerende winkelcentra kunnen worden geanalyseerd rekening houdend met multipurpose gedrag. Een vergelijking met een conventioneel (single purpose) model-systeem toont aan dat voorspelde effecten in marktaandelen en reisbehoeften groter zijn als met multipurpose gedrag rekening wordt gehouden. Dit toont aan dat de voorgestelde uitbreidingen van de modellen significant (kunnen) zijn voor de planningspraktijk.

De tweede case-studie is eveneens in Location Planner uitgevoerd en is met name relevant voor strategische planning in de context van een winkelbedrijf. Voor een grote Nederlandse supermarktketen wordt met behulp van de combinatie van een consumentengedragsmodel en een optimalisatiemodel voor het gekozen studiegebied – Alkmaar – de optimale configuratie (aantal, grootte, locatie van supermarktvestigingen) van de keten bepaald rekening houden met bestaande concurrenten in het gebied. De studie laat zien hoe op basis van genereerde informatie, marketing en financiële doelen tegen elkaar afgewogen kunnen worden om tot een keuze van een optimale strategie te komen. Ook in deze studie is uitsluitend gebruik gemaakt van beschikbare data uit marktonderzoek.

Chapter 10

Dit laatste hoofdstuk geeft een samenvatting van de belangrijkste conclusies en bespreekt mogelijkheden voor toekomstig onderzoek. Met betrekking tot de gestelde doelen in het eerste deel beargumenteren we dat het DSS met name krachtig is in de fasen van plangeneratie en plananalyse, maar relatief zwak in de fasen van probleemsignalering en het maken van een keuze. Voor een deel is dit toe te schrijven aan een expliciete keuze. Het is met name in de fasen van plangeneratie/-analyse dat een DSS de kwaliteit van beslissingen in ruimtelijk economische vraagstukken kan verbeteren. Bovendien zijn voor de overige fasen bestaande software in de vorm van GIS en MCE algemeen beschikbaar. Vervolgonderzoek kan zich richten op verdere uitbouw van het DSS in twee fundamentele richtingen. Ten eerste opent toevoeging van een tijdsdimensie aan de model- en datastructuren betere mogelijkheden voor monitoring en het simuleren van dynamische processen. Ten tweede is het interessant om de mogelijkheden te verkennen die 'multi-agent systemen' bieden om dynamische processen verder te simuleren in de vorm van interacties tussen de verschillende partijen (overheid, aanbieders, vragers) die zijn betrokken in het proces.

CURRICULUM VITAE

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A spatial decision support system for the planning of retail and service facilities

Decision support systems for spatial decision making (spatial DSS) have attracted research interests since the late eighties. Generally, the systems combine geographic information systems (GIS) and spatial models for "what-if" type of analyses. The extensive literature in the area of spatial DSS is largely of a conceptual nature. Operational systems have been reported, but these are typically oriented on a specific modelling technique, a specific user or even a specific study area. This means that none of the existing systems fully utilises the potential of available methodologies or is sufficiently generic to be able to support the broad spectrum of problems that exists in spatial planning. This study focuses on retail and service planning in the context of both local/regional government and strategic management of companies. The objective of the study is to develop, implement and apply a generic spatial DSS for decision making in that field.

The study is organised into three parts that relate to the three elements of this objective. To specify objectives and requirements for the DSS, the first part discusses basic DSS concepts and problems/methods/approaches in retail planning. Having identified information needs, the second part, then, develops a model base and model management system for the DSS. It is argued that existing models of consumer behaviour fall short in representing multipurpose, multistop shopping trips. To overcome this shortcoming, we propose and empirically test extensions of existing models to take multipurpose, multistop shopping behaviour into account in predicting shopping centre choice and analysing performance characteristics of the system. Besides economic and travel related aspects, the accessibility of facilities and available choice range for consumers receive attention. In addition, this part develops a knowledge-based system to assist planners/retailers in solving planning problems based on these models.

The last part describes the design, implementation and application of the proposed DSS. The system is implemented in a windows '95 program called Location Planner. The system is adaptable to a wide range of problems. Users can construct a model dependent on the application, using the available model components as building blocks. Once linked with a database, a built-in inference engine allows users to analyse the impacts of anticipated or planned developments and optimise the spatial configuration of facility networks. Multiple and dynamically linked views allow users to view and edit data in table, map and graph format. The application of the DSS is illustrated using two case studies as examples.

Stellingen

1. Het is mogelijk om een generiek DSS te ontwikkelen dat de kwaliteit en integratie van informatievoorziening in winkel- en dienstenplanning kan verbeteren (dit proefschrift).

2. Het KCML ('KADS conceptual modelling language') biedt een geschikt instrument om procedurele en declaratieve vormen van kennis op het gebied van winkel- en dienstenplanning op een flexibele en efficiënte wijze te integreren, beheren en toe te passen in een DSS (dit proefschrift).

3. De ruimtelijke structuur van winkelvoorzieningen heeft invloed op zowel de winkelcentrumkeuzen als verplaatsingsbehoeften van individuen. Deze effecten zijn betekenisvol voor planning en kunnen tenminste voor een deel met het in dit proefschrift voorgestelde model van 'multipurpose' winkelen worden verklaard en voorspeld (dit proefschrift).

4. De ruimtelijke structuur van winkelvoorzieningen heeft een voor planning betekenisvolle invloed op zowel de bereikbaarheid van voorzieningen als de effectieve keuzemogelijkheden voor consumenten. De in dit proefschrift voorgestelde modellen van 'multipurpose' en 'multistop' trips maken het mogelijk om tenminste een deel van deze effecten te meten (dit proefschrift).

5. De beslistabel biedt een geschikte techniek om beslisprocessen in winkel- en dienstenplanning te structureren en beslisregels voor het genereren van planmaatregelen te representeren en toe te passen in een DSS (dit proefschrift).

6. Het centraal stellen van geografische informatie systemen als thema van wetenschappelijke congressen of tijdschriften is weinig effectief omdat deze systemen niet het object maar een instrument van ruimtelijk onderzoek vormen.

7. Bestaande speculaties – inclusief serieuze – over de mogelijkheid van reizen in de tijd gaan er impliciet vanuit dat de persoon (of het ding) die de reis onderneemt zelf níet evenredig ouder of jonger wordt en zijn daarom logisch inconsistent.

8. Het feit dat voor verkiezingen in het algemeen de totale populatie in plaats van een representatieve steekproef wordt uitgenodigd om een stem uit te brengen weerspiegelt een impliciet wantrouwen in de wet van de grote aantallen.

9. Philips zou haar geloofwaardigheid vergroten als zij de slogan 'let's make things better' zou veranderen in 'let's make better things'.

10. Het gezegde 'de uitzondering bevestigt de regel' is een logisch geldige gevolgtrekking van het feit dat een uitzondering niet kan bestaan zonder regel. Het geeft te denken dat de even geldige uitspraak 'overspel bevestigt het huwelijk' nooit in zwang is geraakt.