Exploring the use of Multi-Agent Systems for Interactive Multi-Actor Spatial Planning

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One of the misconceptions of a PhD research is that it requires years of exile in small rooms with piles of books, notes, papers, and a computer. Perhaps for some this is true. For me, however, an important aspect of "doing a PhD" involves communicating and discussing my work with open minded and motivating people, who have inspiring ideas and unexpected views, and who are not afraid to say that I'am talking double Dutch.

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Chapter 1

Introduction

This research integrates the domains of agent based modelling, artificial intelligence, and software engineering with the domain of spatial planning. This chapter introduces the research, defines the goal, outlines the methodology and sets the scope of the research.

1.1 Statement of the problem

Spatial planning aims at adapting the organization of a spatial environment to meet the demands of society, which continuously change as result of dynamics of society, or dynamics of the physical environment. Societal dynamics originate from changes in policy, in economics, or in the demographic situation of a region. Environmental dynamics are caused by autonomous physical processes or sudden events. In general, spatial planning[1] has changed in a number of aspects during the last decades:

First, space has become a limited resource in many countries. The spatial environment is expected to integrate multiple functions to respond to increasing demands of society. Multiple claims on space lead to increase of conflicting desires of actors i.e. multiple actors compete for the same resources (Valk van der, 2002). Rural areas need to fulfil multiple functions and are under increasing pressure (Cammen van der and Lange de, 1998). They are expected to be attractive for recreation but also maintain an agricultural production function. At the same time claims of expanding cities need to be met. Currently rural areas shift from having primarily a production function, towards areas considered as differentiated residence areas.

Second, interactive multi-actor spatial planning has become subject of increasing interest amongst policy makers. One of the reasons is the shift from central based planning, based on primarily hierarchical principles, towards more decentralized, actor oriented and participatory types of planning (Cammen van der and Lange de, 1998; Geertman, 1996; Woerkum, 2000). In the Netherlands, this trend of decentralized planning is most notable in the most recent versions of The National Spatial Strategy, and the new law for spatial planning in the Netherland (WRO). More decision power is delegated to local authorities. They will be granted a larger mandate, and thus bear a

[1]Often terms like physical planning or land use planning are used in literature. Although, strictly speaking, they might have slightly different meaning they are considered synonyms in this research.

greater responsibility, to create a sustainable[2] spatial planning for their citizens. The central government is less apparent if it comes to regulations and provision of predefined frameworks for spatial developments. Its role shifts towards that of a "process architect" for spatial planning.

Support for interactive multi-actor planning is important to meet the requirements of this modern planning. In practice, however, interactive multi-actor spatial planning[3] is often used to convince citizens of the value of a proposed spatial plan; a level of participation denoted by Arnstein (1969) as "informing" or sometimes "therapy". This indicates that the real objective of participation is to educate or "cure" the participants rather than let citizens genuinely participate in the spatial planning process (Woerkum, 2000). However, an increasing demand for "higher levels" of citizens participation can be noticed amongst both planners and policy makers, as well as citizens. An important argument is the use of local or "indigenous spatial knowledge" (McCall, 2003), which potentially ameliorates the sustainability of spatial planning, and reduces the gap between (strategic) spatial planning at governmental levels and the reality as encountered by citizens (Waard, 2005).

Third, as a result of societal changes, citizens are more demanding regarding their expectations from the authorities, since they expect a communicative and responsive government. This requires an increasing effort by the authorities, at all levels, to enhance their communication skills and channels. Solutions are proposed by "e-ficating" of all kinds of communication. Concepts of *e-government* and *e-governance* are important to develop new channels for maintaining adequate relations with their demanding citizens (Kangas and Store, 2003; Bekkers et al., 2003; Edelenbos et al., 2001).

The above signaled developments in spatial planning accrue the need for "artificial planning environments" in which, interactively, policy can be developed and tested to administer the increasing complexity of modern spatial planning (Cammen van der and Lange de, 1998). Such an artificial environment that consists of, for example, Planning Support Systems (PSS), simulation models, and other tools that support ''ex ante" evaluations of spatial plans, therefore, are a basic requirement for a planner (Geertman and Stillwell, 2003). An "artificial planning environment" can fulfill various functions: it might provide a user insight in the preferences and perceptions of involved

[2]The term sustainability as used here does not "per se" denote environmental sustainability but also social sustainability in terms of citizens genuine agreeing upon a spatial plan.

[3]In this research interactive multi-actor planning is considered synonym for participatory planning, although participatory planning is often considered to be aimed at (actively) involving citizens while interactive planning is associated with multi-disciplinary teams of experts jointly working on an integrative approach to spatial planning.

citizens and indicates its effects and points towards potential solutions. Moreover, users can "play" with various aspects of interactive multi-actor spatial planning, as a research or training, explore reactions of the system, and understand how it works (Axelrod, 2005; Barreteau et al., 2001; Karplus, 1976). The need for artificial planning environments is supported by the trend in (spatial) science that it has become less oriented towards forecasting, but more on the support and structuring of debates, and facilitating the management of new meanings (Batty and Torrens, 2005). Furthermore, the model should be useful to discover what aspects of the system are most in need of further study (Oreskes et al., 1994; Walker and Xuan, 2000). As such the model could be useful for developing theory and generating hypotheses (Carley, 1999; Varenne, 2001), enabling the education of modelers themselves (Vennix, 1996).

Ideally, an artificial planning environment should incorporate behaviour of actors who play a role in the planning process. This implies that many of the current approaches, which aim at modelling and simulating land use change for the purpose of spatial planning, need to be extended or enriched with models of actor decision-making, negotiation, and conflict resolution. In other words, there is a need to include explicitly "the actor-factor" into models of land use. Current land use change models, usually, use implicit and generalized assumptions of human decision-making. Such models are, for example, the CLUE family of models (Veldkamp and Fresco, 1996a; Veldkamp and Fresco, 1996b) or the Land use scanner (Hilverink and Rietveld, 1999), which use statistical techniques. However, the application of statistical techniques is limited in its use to arrive at a better understanding of the explicit effects of human perception, preferences, and decision-making on the change in land use (Costanza and Ruth, 1998).

The inclusion, into existing modelling approaches, of representations of individual actor decision-making is hampered by a number of aspects. The first aspect relates to differences in perceptions amongst actors of the semantics of objects encountered in the spatial environment. A spatial environment is composed of spatial objects like buildings, urban areas, roads, forest, etc. In planning these spatial objects are commonly defined in terms of land use functions. Such land use functions are, for example, agricultural land use, forest, or urban land use. The definition of these functions depends on several factors including the scale of planning (national, regional, or local), the type of planning (strategic or operational), and the actor that considers a spatial environment (a city dweller probably defines a spatial object different than a farmer). This means that there are no clear and uniform semantics for land use functions.

The second aspect relates to the society, which is composed of individual actors i.e. stakeholders, institutions, or authorities. Each actor has his own desires he[4] tries to realize. These desires are based upon an actor's definition of the spatial environment and the demands he has towards his environment. Factors that influence these desires include the social, cultural, economic and political context of an actor and the spatial and temporal scales that are relevant to an actor. For example, the desires of a farmer, who tries to get a living out of his farm, are most likely related to a local scale and a relative short time span. The national government, however, trying to realize an ecological structure, probably considers different spatial scales, and longer time-spans compared to the farmer.

In interactive multi-actor planning, actors meet during a decision-making process, having the mutual target to produce a sustainable spatial plan. Spatial planning is the result of negotiation and decision-making processes between actors having different and sometimes orthogonal views on their environment. The negotiation and decision-making ends, at least in case of a consensus building approach, when all actors involved consider the results of it as righteous (Cammen van der and Lange de, 1998). The latter implies that planning is not a rational process of optimization. It is perhaps better described as a process aimed to "satisfy instead of optimize" (Simon, 1996, page 38).

Interactive multi-actor spatial planning, therefore, can be considered as a complex system where causal relations are difficult to identify and processes often fuzzy (Simon, 1996; Itami, 1994; Couclelis, 1987). In general a complex system comprises a large number of interacting elements that are non-decomposable and may change unexpectedly and in several ways (Batty and Torrens, 2005). In previous research it has been suggested that complex[5] systems have the following characteristics (Richardson et al., 2001; Richardson, 2005):

- current behaviour depends on the history of the system;
- display a wide-range of different behaviour;
- are scale dependent: depending on the scale or level of observation, the system may show different behaviour;
- are often sensitive to initial conditions;

[4]He will be used as an androgynous pronoun including women and men equally in their scope.

[5]It is more precise to speak about complex adaptive system (CAS), which are a special case of complex systems. CAS explicitly considers adaptation and variability of a system and the response of a system on this variability and adaptation (Hartvigsen et al., 1998). Important concepts in CAS are self-organization and emergent properties. Chapter 3 explains these concepts in more detail.

- are incomprehensible, which means that it is impossible to predict all possible system behaviours.

This thesis contributes to the understanding of the complexity of spatial planning, in particular, interactive multi-actor spatial planning, by modelling the characteristics of different actor behaviour in such complex systems. This will be accomplished by exploring Multi-Agent Systems (MAS). It is expected that concepts and techniques found in MAS enable modelers to develop models that avoid the tautology found in many of the mathematical and statistical approaches by avoiding intermediate explanations of phenomena (Goldspink, 2002). Additionally it might help to overcome some of the difficulties found in existing and established analysis and modelling methods, such as shortage of analogies and ideas borrowed from other disciplines, and the lack of theories (Fischer and Nijkamp, 1992; Openshaw, 1992).

1.2 Goal and research questions

The main goal of this research is to explore the use of Multi-Agent Systems (MAS)[6] for its application in simulating interactive multi-actor spatial planning.

The premise is that MAS offer concepts and techniques suitable to handle the complexity found in spatial planning, caused by behaviour of actors, beyond the capabilities of conventional simulation techniques. Therefore the research innovation is towards offering better support for the inference of knowledge and to gain insight into the effects of desires and demands of individual actors upon the organization of space and vice-versa. The research contribution resides in developing a conceptual framework based on the concepts and techniques of MAS for agent based simulation of interactive multi-actor spatial planning. This framework is implemented as a proof-of-concept and demonstrated using three case-studies.

To achieve the main goal of this research, four research questions have been defined as being one of the following:

- How can interactive multi-actor spatial planning be formalized in a conceptual framework based on agent based modelling?
- What modelling metaphors (concepts, architectures and components) can be implemented using Multi-Agents Systems (MAS)?

[6] In the research also the term Agent Based Modelling (ABM) is used. In general these terms will be used interchangeable.

- What are the limitations and potential of agent based approaches to be used as (part of) an artificial environment, and support users to understand the complexity of interactive multi-actor spatial planning?
- What validation approaches are suitable to validate a MAS for interactive multi-actor spatial planning?

The main challenge in the research is to add the “actor factor” to models of spatial planning. It implies finding of a synergy between spatial planning and agent based modelling which goes beyond merely integrating existing approaches.

1.3 Scope of the research

Various research domains are involved in this research; mainly spatial planning, (distributed) artificial intelligence, knowledge engineering, and geographic information science. It is not within the scope of this thesis to provide a detail study on all of these domains. Neither on social processes such as communication, negotiation (group)decision-making, conflict resolution, knowledge reasoning, knowledge representations, or agent approaches. Instead the synergy of existing techniques and methods developed in these domains will be discussed. The focus is on coupling existing theories and techniques of interactive multi-actor spatial planning and agent based modelling to demonstrate the use of MAS as a potential tool. A tool which might help users to understand the complexity of a spatial planning process and, as such, a tool which might be a promising part of an artificial planning environment. The following issues are of interest for this research and will be explored:

- interactive multi-actor spatial planning processes;
- agent modelling approaches;
- representation and acquisition of (spatial) knowledge.

Interactive multi-actor spatial planning processes

Depending on the goal, scale, and nature of planning there are myriad of approaches that have been developed in interactive multi-actor spatial planning; ranging from well described, formal working processes up to and including descriptions of best practices applied on “ad-hoc” basis. In this thesis the research investigates issues related to aspects of interactive spatial planning process itself, such as communication, negotiation, group decision-making, conflict resolution, and knowledge management. Based on a literature review, a conceptual model of interactive multi-actor spatial planning will be developed that describes fundamental concepts of interactive spatial planning processes. This model provides the framework for the development of the MAS. This framework will be applied in three case studies. The case studies mainly focus on aspects such as representation and acquisition of spatial knowledge, decision-making, communication, and sharing of knowledge.

Agent approaches

Many different agent based approaches have been developed in the domains of Artificial Intelligence (AI), Alife[7], and environmental sciences. Many of them are, in theory, suitable to be applied in spatial models. This thesis explores and adapts existing approaches so as to apply them in a MAS for interactive multi-actor spatial planning. Using the case studies, three approaches will be implemented, examined, and discussed. The aim is not to compare the applied agent based approaches but to discuss them in the context of what they might add to the modelling and simulation of an interactive multi-actor spatial planning process.

Representation and acquisition of (spatial) knowledge

The representation and acquisition of (spatial) knowledge is an issue which is particularly relevant to agent based modelling. Even the most elementary agents need somehow a representation of the objects they represent and their environment as well as knowledge to decide about potential actions. Various (spatial) knowledge representations have been developed in the domains of (AI). This thesis focus on approaches which have been already demonstrated and applied in the domain of environmental sciences, such as Cellular Automata (CA), rule based approaches, and utility based approaches. The terms knowledge representation and knowledge acquisition are addressed in a rather loosely manner and do not directly refer to formal definitions employed in AI or knowledge engineering. Knowledge representation and acquisition are referred to as methods to represent facts and rules in a computer, as well as mechanisms to process facts and rules to acquire knowledge necessary to the agents for decision-making. Case studies will be used to explore a number of knowledge representations and their application for simulation of interactive multi-actor spatial planning.

[7] Alife is a subfield of AI studying of the behaviour of complex system (like life) through the use of human-made analogs of living systems (see for example Minsky (1988)). The term was introduced by Christopher Langton during the "International Conference on the Synthesis and Simulation of Living Systems" at the Los Alamos National Laboratory in 1987 (Langton, 1988).

1.4 Structure of the thesis

Chapter 2 frames spatial planning in the context of an interactive multi-actor spatial process. It starts with a definition of spatial planning and next describes spatial planning using a multi-level approach. It presents a general model of interactive multi-actor planning which is used as a reference for the development of the agent based models presented in this thesis.

Chapter 3 presents an overview on the field of MAS. It provides definitions and summarizes the most common general agent architectures. Additionally it explores current applications of MAS in environmental sciences.

Chapter 4 presents a case-study based on a MAS that applies a cellular automata (CA) approach. A CA is implemented to represent spatial information and to enable agents to deduce information from the spatial environment.

Chapter 5 extends the application of Chapter 4 by introducing a rule based reasoning approach along with the concept of observers. This enables agents to apply a more flexible reasoning, not restricted by the neighbourhood paradigm of CA.

Chapter 6 elaborates the decision-making process. A model of knowledge sharing is introduced which provides agents with more advanced decision-making capacities. In addition an extra agent, the facilitator, was added to coordinate the knowledge sharing.

Chapter 7 presents a validation study, mainly for the case study described in Chapter 6. An expert validation methodology is devised based on a face validation amongst subject matter experts, and a validation experiment is carried out together with a group of students playing a role game. The applied validation techniques are regarded as an alternative for traditional methods of validation commonly applied in the domains of spatial modelling.

Chapter 8 concludes the thesis by presenting the main conclusions along with recommendations for further research.

The Chapters 4, 5, 6, and 7 are part of a series of papers that have been published or submitted to internationally reviewed journals.

Chapter 2

Framing spatial planning in the context of interactive multi-actor spatial planning

This chapter defines spatial planning as it is applied in this research. After defining spatial planning it presents a framework that describes multi-actor spatial planning and positions it into a broader scope. Next it presents a conceptual model that was developed to provide the concepts and notions for the design of the multi-agent simulations.

2.1 Introduction

Spatial planning is the process of adapting a spatial environment to meet the needs of society. It is exercised at all levels of administration (Valk van der, 2002) ranging from the national level, where large scale scenarios for nationwide developments are produced, to local levels where individual farmers decide how to use their parcels at the next growing season. In general it can be stated that spatial planning is characterized by the following aspects (see Hidding (1997), Geertman (1996)):

- it is carried out at various spatial levels, sometimes simultaneously and conflicting;
- it involves different temporal scales, ranging from less than 1 year to more than 30 years;
- it needs to integrate different spatial objectives;
- it is increasingly decentralized resulting in an rise of the number of involved actors;
- as space becomes a scarce resource the number of spatial conflicts increase.

The two main roles of spatial planning in terms of processes are: coordination and integration of the above mentioned aspects in order to create acceptable spatial plans (Lammeren, 1994). Acceptability of a plan depends, besides the fulfilment of the objectives, on aspects like agreement amongst stakeholders and the ecological and economic sustainability.

From a procedural point of view, spatial planning can be operational or strategic. Strategic planning is aimed to *search* for possible directions a spatial organization can develop in the future. Operational planning is aimed to *realize* a strategic plan. Operational planning is often procedural while strategic planning has a more explorative character.

An important assumption made in this research is that spatial planning is basically a decision-making process amongst *individual actors*. This assumption seems plausible as spatial planning, at least in the Netherlands and many other West-European countries, tends to decentralize. Therefore, actors are considered key elements in this research. Actors may be individuals, groups or organizations that have means to influence the spatial planning process. Spatial planning is regarded as a process of multi-actor decision-making. Actors use their emotions, senses, brains, communication abilities and memory to analyze and reason about the spatial environment they need to make decisions about. Actors are also part of a society where they meet other actors and where, often unwritten, rules, norms and values exist. This implies that actors are bounded in their individual decision-making by the society they are part of. Moreover actors construct their own definition of reality based on political, cultural and economic factors that are relevant to them and the perceptions they have of the spatial environment (Lammeren, 1994). To structure the relation between society, planning and individual actors, Figure 2.1 presents a, four levelled, view of spatial planning. A detailed description of each level will be discussed in the following sections.

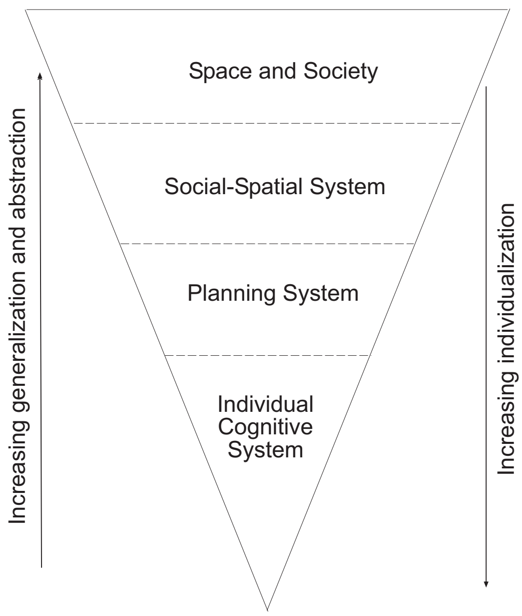

Figure 2.1: Levels of planning.

2.2 Social-spatial system

At the top level of Figure 2.1 a notion of space and society is drawn. These systems contain all entities and processes encountered in the world. The next level, which is of relevance to spatial planning is the social-spatial system.

The social-spatial system is constituted of political, cultural, and economic subsystems; and puts social actions in a spatial perspective (Wisserhof, 1996). It can be used to analyze interactions between developments in a social system and a spatial system. Spatial systems and social systems are strongly intertwined and cannot be analyzed separately (Röling, 2000). This implies that there is a structural coupling between spatial systems and social systems acting upon it. Processes in the social system for example the economic, political or cultural subsystem result in spatial consequences and vice versa. Figure 2.2 portrays this structural coupling, based on a model of the social-spatial system of Kleefmann (1984). Society and the spatial environment are linked to each other through the economic, political and cultural subsystems. Society imposes action upon the spatial environment. The economic, political and cultural composition of society sets boundaries for these actions. Actions might be operationalized through economic rationalities, policy measures or cultural traditions and habits.

Economic subsystems are controlled by norms, values and rules which are present in, what is called here, the culture of a society. A society is in equilibrium when the (mostly functional) processes of economy are harmoniously integrated with the normative processes of the culture. Almost by definition, this is not the case (Röling, 2000). To regulate the economic subsystem, the political subsystem controls economic processes, and provides for the necessary preconditions to function effectively. Moreover, the political subsystem formulates policy that imposes restrictions upon, and opens opportunities to, actors who construct spatial plans. Because the policy subsystem is considered to be driven by democratic processes, policy-making is guided and limited by the legitimacy found in the culture of the society.

Relations between political and economic subsystems are at the side of society (arrow 1 of Figure 2.2) mainly directed to create a sustainable and attractive monetary climate, regulating salary and prices, while stimulating technological development. At the spatial side (arrow 2) the relations between these two subsystems are directed to aspects such as conditioning the spatial environment to, optimally, support economic activities. The relations between the political and cultural subsystem are at the social side (arrow 3) aimed at providing good education, social security, health-care facilities etc. At the spatial side (arrow 4) relations between policy and culture are mainly aimed at providing sustainable, sufficient and pleasant spaces for living and recreation. Not all relations between the economic and cultural subsystems are through policy subsystems. There are also direct relations between them. As a result of decentralization and deregulation in many countries direct relations between economy and culture become increasingly important.

Figure 2.2 shows the relations between society and spatial environment

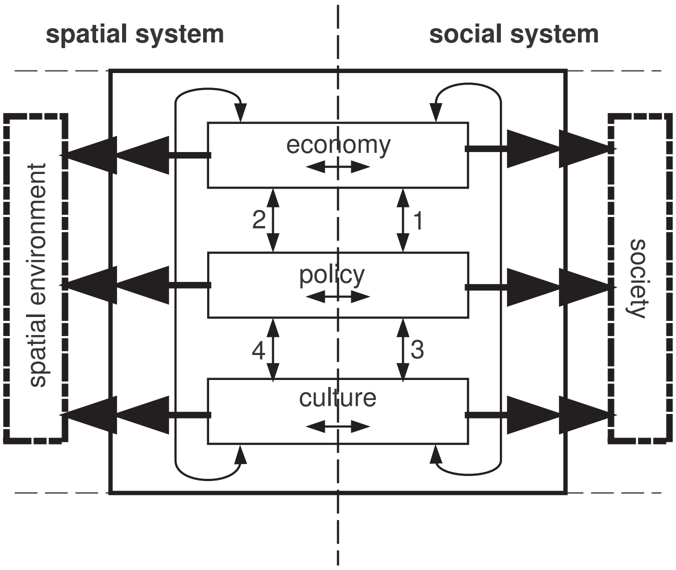

Figure 2.2: The social spatial system (after: Kleefmann (1984)).

using thicker horizontal arrows. Since this research involves modelling relations between actors and the spatial environment, focus is on the horizontal relations between society and the spatial environment.

Although the concept of the social-spatial organization offers a suitable framework for thinking about relations that exist between a spatial environment and society, it does not give any insight in how to plan and model these relations at the pursuit of spatial planning. Therefore the system of spatial planning needs to be considered.

2.3 Planning System

The second level of the pyramid of Figure 2.1 is a planning system which represents the planning process itself. A spatial planning process offers both theoretical notions and “tools” to control and co-ordinate development of new ideas, concepts and solutions for spatial and environmental issues. It is aimed to assist integrating demands of economy, policy, and culture into sustainable spatial solutions[1]. Three prominent approaches that describe spatial planning processes are (Geertman, 1996):

[1]Sustainable here does not only refer to environmental sustainability but also to a sustainability in decision-making.

- decision oriented approach;
- action oriented approach;
- planning as search for direction.

2.3.1 The decision oriented approach

The decision oriented approach has a strong relation with the Strategic Choice Approach of Friend (1994). The central paradigm of this approach is that planning is a process of choice in a situation of uncertainty. Uncertainty is present in the knowledge of the external planning environment i.e. one is not sure about the structure of the physical and social economic systems and its responses upon actions of actors. Also there is uncertainty about what choices are to be expected in related fields, and there is uncertainty about judgements attached to the consequences of decisions. The decision oriented approach discriminates between operational decisions and planning. Planning is defined as temporary support for operational decision-making. Such support is necessary because it is considered impossible to judge instantaneously all operational decisions in the broader context of society and environment. The goal of planning is mainly to inform actors about future decision-making and make future operational decisions interpretable. A main critique on the decision oriented approach is its agency-centred view (Geertman, 1996) which makes it less suitable for an interactive multi-actor approach.

2.3.2 The action oriented approach

The action oriented approach was developed at the Radboud University Nijmegen (Geertman, 1996). The main assumption is that a spatial organization results from actions of, and cooperation amongst numerous actors. This implies that a focus is on relations that exist amongst actors. Their actions need to be compliant to, and embedded in society. Decisions are based upon interactions with other actors. Focus of planning is not "per se" on a critical evaluation of the spatial organization itself but on the analysis of intentional actions and context of actors involved in planning. It also considers the government as one of the actors. This view corresponds with ideas of van Woerkum (2000) who argues that actors should not be considered as entities that need to be informed and convinced of the necessity of planning but as entities that should play an active role in decision-making. As such the action oriented approach strives to a more integrative planning, involving actors at higher participation levels.

2.3.3 Planning as search for direction

Planning as search for direction considers spatial planning as a learning process that aims to investigate new opportunities for establishing social-physical and spatial organization. This approach deviates from the other approaches that focus on realizing an already defined goal or process. The aim of "planning as search for direction" is not directly to prepare operational decisions given a well defined problem, but to reveal alternative and new solutions outside the direct scope of the observed problems. It is meant to "learn and get a bit wiser" i.e. to develop and share knowledge (Kleefmann, 1984). It represents the more holistic, constructivists view on spatial planning. Planning as search for direction gives space to soft-systems thinking (Checkland and Scholes, 1990; Checkland, 1981) and learning (Jiggins and Röling, 2000; Röling, 2000).

In this research, both ideas encountered in the action oriented approach and the search for direction approach have been adopted. The strength of the action oriented approach is that it explicitly considers that the organization of space is the result of actions and reactions of a multitude of actors, including the policy-makers (Wissink, 1982). This implies that spatial planning should explicitly include insight in actions, opinions and ideas of actors and the relations between actors. The relation with society is much stronger developed in this approach than it is in the decision oriented approach. The strength of the ideas captured in the "planning as search for direction" is that planning is considered a knowledge generating process aimed upon searching directions for future development and clarifications of possible states of the social spatial environment and the consequences of policy scenarios (Kleefmann, 1984).

2.4 Individual cognitive system

The two levels described above embed common knowledge of actors about values and norms and the role of communication and negotiation during spatial planning. The assumption is that this knowledge, in principle, is accessible (but not necessarily comprehensible) to all actors involved in the spatial planning. Considering interactive multi-actor spatial planning, however, the basic entities in the process are actors. Actors can be individuals that participate in a planning process on an individual basis, for example, a farmer who sees his farm threatened by urbanization. Actors can also act as representatives of organizations or interest groups. In both cases actors use their knowledge, cognitive and reasoning capacities to actively and intentionally participate.

At the level of individual cognitive systems (see Figure 2.1 on page 13) ideas, desires, and values of individual actors are represented. A cognitive system is defined as the general concept that is concerned with "... acquiring information about the world, representing and transforming this information as knowledge, and using this knowledge to direct our attention and behaviour" (Lloyd, 1997, page 4). Using his cognitive abilities an actor creates his own mental representation of the social-spatial system. This representation depends on what Schutz calls a "stock of knowledge", which is used to put the world into a context of relevance (Lammeren, 1994). To acquire information about the world, an actor maintains relations with other actors in the planning system and the social-spatial system using his communication and learning skills. According to his mental representation of the world and representations of other actors, an actor decides and acts. These decisions and actions result from a perceived difference between the mental representation of the world as it is (a believed world), and a mental representation of the world as it should be (a desired world). Decisions and actions of an actor are therefore assumed to be intentionally oriented towards narrowing the gap between the "world as it is" and the "world as it should be". Habermas distinguishes various intentional models for decision/action-taking (Kunneman, 1983). The models relevant for this research are based on a teleologic and normative understanding of action and decision-making. Teleologic intentional models (Figure 2.3) imply that actors strive to real-

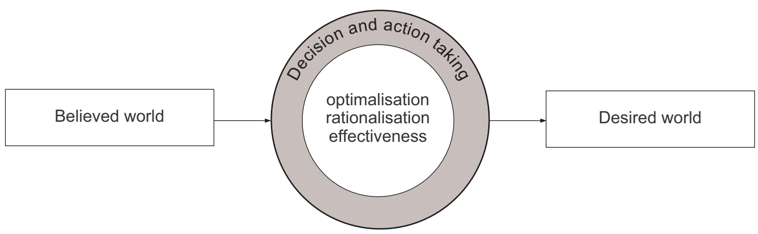

Figure 2.3: Teleologic intentional model.

ize their demands by using adequate means in, what actors considers, an objective reality. The central concept of the teleologic model is that actors choose among alternatives based upon rationalizations like maximization or optimization. The assumption is that actors are situated in a reality about which true statements are possible. The actors aim to realize privately defined goals. Therefore desires and actions of others can only be included into the "calculations" of an actor as objective data. According to Habermas the teleologic view of the world is based upon a one world ontology i.e. that of the believed world.

The normative intentional models (Figure 2.4) takes a social group of actors that comply to a common set of values as a starting point. All actors inside this social group are obliged to comply with this common set of values. Besides a world of objects and events (the believed world), there is also a social reality of obligatory norms and values. Rationality is not only based upon relations between an actor and his objective reality but also on his relations with values of the social group it belongs to. It assumes an ontology based upon two worlds: the believe world, containing objects that are stated true to an actor, and society containing the set of values the actor must comply with.

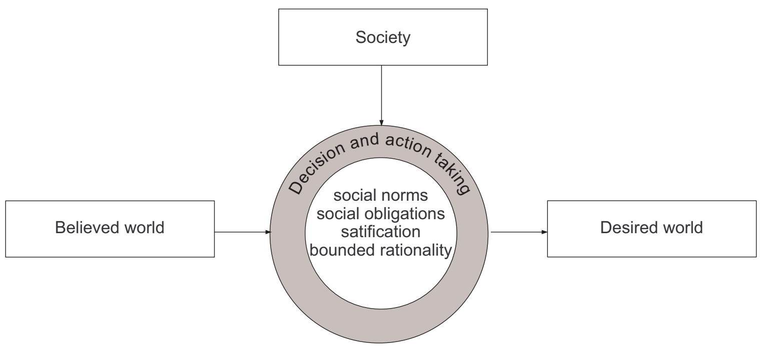

Figure 2.4: Normative intentional model.

The assumptions behind the two-world ontology of the normative intentional model are that actors tell the truth, act according the values and norms of their society, and are truthful in the intentions they show. The judgement (by other actors) whether an action of an actor is valid and acceptable is based upon a shared definition of reality. The latter implies also that there is a shared assumption of how (part of) reality is composed (Kunneman, 1983). It consists of a shared stock of knowledge that makes it possible to understand and act rationally in a given social context. Rationality in this context relates to shared knowledge of values, opinions and ideas of society, known by all the actors present in society. Decision-making therefore cannot be done without explicitly taking into account the believes and desires of other actors.

2.5 Conceptual Framework for an intentional model of planning

So far, the context of an interactive multi-actor spatial planning process has been sketched. This section presents the conceptual framework which is the basis for the case studies presented in this thesis. To devise the conceptual framework, an intentional model of actor decision-making needs to be elaborated. As discussed above, this intentional model should be compliant with the action oriented approach of planning, taking into account a normative notion of action and decision taking.

Such an intentional model can be found in the philosophy of Schutz, adapted for spatial planning by Kleefmann (Kleefmann, 1984; Lammeren, 1994). Figure 2.5 provides a schematic overview. Four types of knowledge are distinguished: desires, beliefs, values and preferences and three intentional interactions with the socio-spatial system: observe, perceive and decide. In the remainder of this section, this model will be explicated taking into account its application in a MAS.

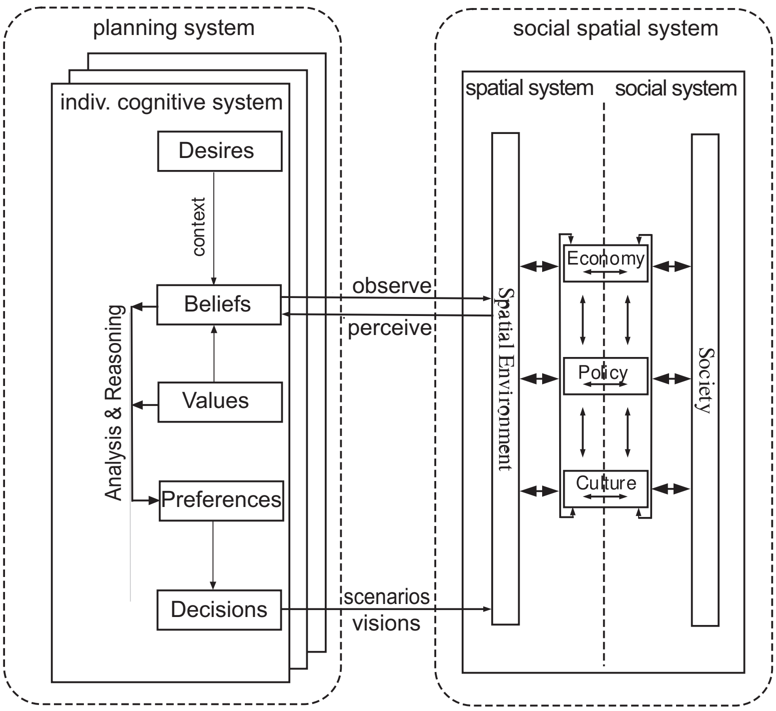

Figure 2.5: Intentional model.

2.5.1 Desires

Being involved in a planning process requires actors to express their desires about the future state of the spatial environment. Desires are considered mental representations of the spatial environment as it ought to be to meet the "needs" of an individual actor. Desires can be viewed as an expression of the functional requirements of a spatial environment according an individual actor. This implies that desires are not generated spontaneously. They are a result of driving forces. Driving forces refer to motivational aspects of the involvement of actors in a spatial planning process. Driving forces themselves are assumed auxiliary to the model. If, for example, demographic growth generates spatial claims for new urbanization, an actor is (probably) motivated to generate desires only if it affects his area of concern. In general terms it can be stated that an actor generates desires if there are driving forces related to his "universe of discourse".

Desires are restricted through structuring forces. Structuring forces are restrictions imposed by (mostly) auxiliary factors (see also Velde van de et al. (2001)). These restrictions limit the set of desires that an actor can possibly realize. For example, at normal circumstances, a desire of an actor to realize new urban areas next to an industrial sector is limited by environmental and safety regulations. An actor, assuming that he has some intelligent reasoning capabilities, will not easily generate such a desire. Restrictions can be hard in terms of physical, legal, or budget constraints or, which is of particular interest of this study, soft, which means that these restrictions are based upon common normative values prevalent in society.

Desires are assumed to be spatially implicit. This means that they are directed to space, but not yet projected at a specific location. Desires consist of general ideas about what is acceptable or preferable and what is not. Desires are commonly expressed in qualitative terms describing functional, spatial, physical, and topological relations between mutual spatial functions.

2.5.2 Observation and Perception

Relating desires to a spatial environment requires an actor to observe spatial objects that constitute the planning area. Observation means processing sensory input, commonly obtained by using eyes and ears. While observing, an actor encounters many objects. Objects of interest are identified by desires in a process of perception. Perception is a cognitive process involved with detection and interpretation of sensory information. Perception requires a direct connection between an actor and the object being perceived (Lloyd, 1997). How exactly the process of perception takes place —in other words, how humans test whether the things they are looking at are the things they are looking for— is not dealt with in detail in this research. It is assumed that perception is a basic associative process that depends on information defined by the desires. It implies that an actor should be able to relate desires to spatial objects in a relative straightforward fashion. If this is not possible, no perceptions can be developed and no beliefs about a spatial environment can be generated relevant to the desires.

2.5.3 Beliefs

Belief refers to the image of the current states of the world that actors consider to be true. Beliefs are only true to an individual actor. Beliefs frame a mental representation of an environment based upon individual perceptions.

The beliefs of an actor are the only references he has to the spatial system. Based upon the beliefs it is possible for an actor to compare, analyze, and reason about a spatial environment. It is possible (and most likely) that various actors have different beliefs about the same spatial objects.

2.5.4 Values and Preferences

Values consists of the set of knowledge used by actors to "confront" beliefs with desires. Using an individual set of values actors analyze a believed situation to identify what spatial functions in a spatial environment are (not) in line with their desires. Referring to the normative notion of decision-making (Figure 2.4 on page 19), values not only include individual values of actors but also values common to a society, and values that result from communication and negotiation with other actors. Based on beliefs and values actors deduce a set of preferences through a process of analysis and reasoning.

2.5.5 Analysis and Reasoning

Analysis and reasoning are at the core of the actor decision-making process. It involves acquisition and analysis of, and reasoning about spatial phenomena. Furthermore, analysis and reasoning involves social processes such as communication and negotiation with other actors. The analysis and reasoning results in preferences about a desired future situation. These preferences determine what changes are possible and desirable to realize the desired world of an actor.

2.5.6 Decisions

Based on preferences actors decide about what environmental states need to be changed to accomplish a desired situation. As a consequence of multi-actor planning, decision-making at an individual level does not actually change any land use function. The question whether the individual decisions are effectuated into actions that indeed change the spatial environment also depend on decisions made by other actors.

2.5.7 Discussion

The above presented outline is a rather abstract notion of actions of actors who are involved in a spatial planning process. The exact methods they apply when defining their environment, do their observations, generate their beliefs and preferences, and make their decisions depend on various factors. Among these factors are the level of planning i.e. operational or strategic (Hidding, 1997), the level of participation and interaction; ranging from just being informed to co-decision-making (Arnstein, 1969), and the level of professionalism of the involved actors. This research focus on regional planning, in which actors are actively involved at the design and decision-making stages. In many European countries active involvement of actors having different backgrounds, different knowledge, and different perceptions on the development of their environment becomes increasingly important. This trend is affirmed by an increasing interest in the development of Planning Support Systems (PSS) (Geertman and Stillwell, 2003), geovisualizations concepts (Al-Kodmany, 2000; Al Kodmany, 2002; Batty et al., 2000; Lammeren and Hoogerwerf, 2003; Lammeren, 2004), and Participatory GIS (PGIS) (Scotta et al., 2006), These developments aspire to support users to achieve a more effective decision-making while facing a semi-structured spatial decision problem (Saarloos, 2006). As mentioned in Chapter 1, it is not the aim of this research to develop a full-fledged system that supports interactive spatial planning but merely to explore and demonstrate techniques that, potentially, support the development of an artificial planning environment.

2.6 Conclusions

In this chapter, spatial planning was explained from the perspective of interactive, intentional human decision-making. It was argued that current spatial planning can be regarded as an activity which is structurally embedded in society; requiring the involvement of actors from a variety of disciplines and interests. The involvement of increasing numbers of actors results in an increasing complexity of spatial planning.

Processes of the planning system are often hard to identify and distinguish, and may occur at various spatial and temporal levels. The strong coupling with the social, economic and political systems often result in hard to predict reactions of the system.

It is difficult to provide a comprehensive description of an interactive multi-actor spatial planning process. Such a description strongly depends on the organization, the level of participation, the number of actors and the goals of the spatial planning process itself.

Nevertheless, it is possible to conceptualize interactive multi-actor spatial planning in terms of desires, observations, perceptions, values, and preferences of the involved actors. These metaphors will constitute the basis to further explore the use of agent based models to simulate interactive multi-actor spatial planning processes.

Chapter 3

Main concepts of Agent Based Modelling

This chapter provides a brief overview of the domains of Agent Based Modelling (ABM) and Multi-Agent Systems(MAS). First, definitions of agents and MAS are provided, and the most common agent architectures are summarized. Next, current applications of ABM in environmental sciences are explored. Finally conclusions are drawn about the application of current agent based approaches for interactive multi-actor spatial planning.

3.1 Introduction

In Chapter 2 it was argued that interactive spatial planning, driven by intentional human actions, result into systems that can be characterized as complex. Conventional deterministic or statistical modelling techniques (like partial differential equations, interaction models, regression models) are only of limited value to modelling these complex systems. Aspects accounting for this include:

- while processes of the physical environment often show well-defined quantifiable processes, mostly behaving according to physical laws, those of the social spatial system typically do not;
- most mathematical approaches require a well-defined description of the interactions between the processes amongst the subsystems. In land use planning this is seldom present;
- causalities occur and vaporize "on-the-fly" depending upon the current state of the system;
- conventional methods often view a system at a macroscopic level thus ignoring that dynamic behaviour is to a large extent rooted in individual behaviour (Phipps and Langlois, 1997);
- conventional methods are based upon computational reducibility of a system. In complex land use systems, however, this reducibility may well be the exception rather than the rule (Itami, 1994).

Agent Based Modelling (ABM) provides means to overcome the above mentioned limitations. The inherent bottom-up concept of an ABM approach offers a conceptual approach to, at least partly, explicitly model representations of desires, beliefs, and preferences of individual actors, and simulating processes of observing, perceiving, analysis, reasoning and decision-making (see fig. 2.5 on page 20).

3.2 Definition of agents

In literature various definitions of agents can be found, see for example Franklin and Graeser (1996), Nwana (1996), Wooldridge and Jennings (1994). Wooldridge and Jennings (1994) consider agents to be (software) systems that represent intentional notions[1]. An agent based system is situated within, and a part of an environment. It senses the environment and acts on it over time, in pursuit of its own agenda (Batty and Jiang, 1999; Franklin and Graeser, 1996).

Generally there are two notions of software agents: a weak notion and a strong notion (Wooldridge and Jennings, 1995). The weak notion considers agents as a software-based computer model with the following properties (Franklin and Graeser, 1996; Mohamed, 2000; Oliveira, 1999; Wooldridge and Jennings, 1995):

Autonomy: meaning that an agent should be able to operate without direct intervention by humans or other agents. Therefore agents need to have control over their own internal states;

Social abilities: meaning that it should be possible for an agent to interact with other agents and humans. Agents can, for example, react benevolent or egoistic;

Reactivity: an agent needs to have the ability to perceive its environment and respond to it;

Pro-activeness: an agent does not simply react to its environment but should also be able to exhibit goal-directed behaviour. Agents that only can perform reactive behaviour towards their environment are often called reactive agents while agents that also are able to develop pro-active behaviour are known as deliberative agents;

Situated in some environment: if the environment changes, the agent no longer exists. There needs to be an environment in which the agent is an agent (Franklin and Graeser, 1996).

The strong notion of agents normally adds concepts like mentality, emotion and sociality to the definition of an agent in an attempt to simulate more human like behaviour (Castelfranchi, 1998). This is particularly relevant when agent based systems are applied to interact directly with humans. For the type of applications pursuing this research it is less important. The main interactions are among mutual agents and not between humans and agents.

Often, agents are distinguished based on the level of intelligence. However, it is not entirely clear what is meant with the term intelligence

[1] Intentional, in this context, should be regarded as behaviour which can be predicted by methods of attributing belief, desires and something like rational acumen.

(Wooldridge and Jennings, 1995). In this research, it is assumed that the notion of intelligence relates to a number of characteristics that an agent possesses at various levels. Intelligence is defined by:

- intentionality;
- autonomy;
- reasoning and learning.

Intentionality addresses the ability of an agent to maintain an intentional state, for example beliefs or desires, attached to an observed phenomenon in its environment. Two levels of intentionality might be distinguished: first order intentional agents only have beliefs and desires about existing objects, while second order intentional agents have beliefs and desires about beliefs and desires (Dennet and Haugeland, 1991; Wooldridge and Jennings, 1995). Most agent systems only deal with first order intentionality directed to an environment composed of identifiable objects i.e. objects that really exist. Generally they are not able to reflect on their own beliefs.

Agents designed to carry out simple tasks do not require sophisticated intentional mechanisms to perform their task. They can be reactive and mechanistic, only relying on direct "input–output" relations. A thermostat can serve as an example; it might be perfectly coherent to notice that a thermostat has a belief about the environment and the desire to change it according to its goal. However, the problem of maintaining a constant room temperature is so sharply defined by laws of nature that perhaps only a few people would attach the term intentional system to it. For more complex systems, there might be the need to implement more stronger notions of intentionality; or as Wooldridge and Jennings (1995) put it:

> ... the more we know about a system, the less we need to rely on animistic, intentional explanations of its behaviour. However, with very complex systems ... a mechanistic, design stance explanation of its behaviour may not be practicable" (page 9).

Autonomy addresses the characteristic of agents to exercise independent control over its own action (full autonomy), or dependent control which means that an agent exercises under external constraints or influences (restricted autonomy) (Mohamed, 2000). For instance, the thermostat is an example of a agent under controlled autonomy. Under normal circumstances a thermostat does not decide autonomously about the desired temperature.

Intelligent agents need the ability to reason about themselves, other agents, and their environment to decide which actions to undertake to achieve their goals. A straightforward definition of reasoning cannot be provided. It depends on the context of the understanding of reason as a form of knowledge. In logical, definitions reasoning is the act of using reason (knowledge), to derive a conclusion from certain premises, using a given methodology. Well-known methods are deductive reasoning, inductive reasoning, abductive reasoning and reasoning by analogy.

In philosophy, reasoning is a mental process informing our imagination, perceptions, thoughts, and feelings by linking our experience with universal meaning. Reasoning requires a representation and reasoning system that includes some kind of language, a way to assign a meaning to knowledge, and procedures that enable an agent to process this knowledge (Poole et al., 1998).

Various techniques of reasoning are developed which generally can be divided into symbolic reasoning and heuristic reasoning techniques. Knowledge presentations that use symbolic systems for reasoning are based on the physical symbol system paradigm of Newell and Simon (Simon, 1996). A physical symbol system consists of a set of entities, called symbols, which are physical patterns that can occur as components of another type of entity called an expression (or symbol structure). Thus, a symbol structure is composed of a number in instances (or tokens) of symbols related in some physical way (such as one token next to another). At any instance of time the system will contain a collection of these symbol structures. Besides these structures, the system also contains a collection of processes that operate on expressions to produce other expressions: processes of creation, modification, reproduction and destruction. A physical symbol system is a machine that produces (over time) an evolving collection of symbol structures. Such a system exists in a world of objects wider than just these symbolic expressions themselves (Ginsberg, 1993) after (Newell and Simon, 1976) using an ontology as a commitment what is present in a particular domain (Poole et al., 1998).

Heuristic reasoning encompasses techniques like Neural Networks, Genetic Algorithms and Simulated Annealing. These techniques are basically optimization techniques, often based upon a hill-climbing approach that enables for the search of local maxima in a parameter-space. Heuristic reasoning does not require an explicit symbolic representation of the environment. Agents that use heuristic approaches to reasoning cannot exhibit intentional notions as they cannot attach any meaning to an observation. Examples are agents that act purely reactively, like the aforementioned thermostat and agents that apply neural networks or genetic algorithms to generate an action.

In general it can be stated that, a stronger notion about intentionality, less controlled autonomy, and self-learning and reasoning capabilities lead to more flexible and intelligent agents.

3.3 Definition of Multi-Agent Systems

MAS can be defined as a set of agents interacting in a common environment, able to modify themselves and their environment (Ferrand, 1996). MAS have their own problem solving capabilities and the agents are able to interact in order to reach an overall goal (Oliveira, 1999). Interaction may occur between agents (agent-agent interaction) and between agents and their environment (Weiss, 1999). Most MAS have the following characteristics:

- each agent has incomplete information to solve the problem;
- there is no system global control;
- data are decentralized;
- computations are asynchronous (Sycara, 1998);
- MAS contain agents that are autonomous and distributed;
- agents in a MAS may be self-interested or co-operative (Huhns and Stephens, 1999).

MAS can be looked at as a problem solving organization that consists of specific and nearly modular agents specialized at solving a particular problem aspect (Sycara, 1998). MAS belongs to the field of distributive artificial intelligence (Green et al., 1997; Nwana, 1996).

In environmental sciences the definition of a MAS is more constraint. The focus is particularly on using multi-agent simulations rather than multi-agent systems, signaling that the interest is in visualization and modelling together. In environmental sciences most MAS are considered as a platform for space-time dynamics (Jiang and Gimblett, 2002). According Bousquet and Le Page (2004) a definition of a MAS meaningful for environmental sciences is a system composed of:

- a spatial environment often defined as a lattice;
- a set of situated objects;
- agents, a subset of the objects, representing the active entities of the system;
- relations between objects;
- operations that enable agents to manipulate objects;
- operators that implement the operations.

In MAS, agents can be rather diverse. They can be cells in a lattice representing pieces of land or representations of human behaviour. Consequently the characteristics of the encountered agents differ also, ranging from simple reactive agents towards more intelligent agents showing (although limited) capacities of reasoning and making deliberate decisions.

3.4 Basic Agent Architectures

To design and construct agent based models, various architectures are developed, mainly in the domain of Artificial Intelligence (AI). This section enumerates the most common ones. According to Wooldridge and Jennings (1995, page 23) an agent architecture is:

> A particular methodology for building agents. It specifies how the agent can be decomposed into the construction of a set of component modules and how these modules should be made to interact. The total set of modules and their interaction have to provide an answer to the question of how the sensor data and the current internal state of the agent determine the actions and future internal states of the agent. An architecture encompasses techniques and algorithms that support this methodology.

Wooldridge (1999) distinguishes four basic agent architectures. These are:

- logic based or deliberative agents;
- reactive agents;
- belief-desire-intention (BDI) agents;
- layered architectures.

These architectures will be described briefly in the following sections.

3.4.1 Deliberative agents

Deliberative agents are based on a rationalists view on cognition and reasoning and generally require a symbolic representation of the environment using logical formulae. The behaviour and desires of agents are based on logical deduction or theorem proving (Wooldridge, 1999; Poole et al., 1998). Logic based reasoning comprise a family of knowledge representations where logic is used to form axioms that describe facts (nuggets of knowledge) and their relations. It assumes an explicit and declarative representation (Lakemeyer and Nebel, 1994). This implies a knowledge base where knowledge is stored using sets of formal entities. Basically there are three aspects to logic based knowledge representations (Singh et al., 1999):

- well formed formulae, used to make statements in;
- a proof theory including axioms and rules of inference (the syntax);
- a model theory giving the meaning of the well formed formulae (the semantics).

There are various forms of logic (see for example Fagin et al. (1995), Halpern (1995)) Most classical (monotonic) logic models are based on a possible worlds paradigm. The idea of the possible worlds model is that besides a true state of affairs there are a number of other states of affaires (possible worlds). Generally, a fact is said to be true if an agent beliefs this fact is true in all the worlds he knows. Most logic adopt a closed world assumption, meaning that everything not known is false.

The above phenomena are often referred to as the problem of logical omniscience (Halpern, 1995; Wooldridge and Jennings, 1995). This logical omniscience hampers the development of so-called “resource bounded” agents; something which is indisputable the case in land use planning. To overcome the problem of logical omniscience non-monotonic type of logic have been developed. Non-monotonic (or defeasible) makes it possible to make tentative conclusions based on the current state of the knowledge. In contrast to the above mentioned monotonic families of logic using non-monotonic logic a conclusion may be withdrawn by new information.

Although very useful for theoretical exploration or descriptive purposes, most logic fails when it comes to their implementation. Eventhough the formalisms are often simple, it is hard to deliver the necessary prove for completeness, soundness and decidability. Therefore, the use of logic based agents in the domain of spatial planning appear to be impractical if not impossible. The complexity of theorem proving, even for small and well described domains, as well as problems of representing information of complex dynamic environments, makes application in a MAS system not very usable (Wooldridge, 1999). Moreover, the assumption of “logical omniscience”, assuming that all agents are “ideal knowers” in terms of knowing all valid formulae as well as the consequences of their knowledge (Halpern, 1995) is by no means realistic to the problem of spatial planning.

Therefore, in practice, most deductive systems take the more syntactic approach of rule based reasoning. Rule base reasoning requires a knowledge base that contains the current state of knowledge to the agents. Knowledge is inferred based upon rules. The structure of these rules are often of the “if ... then” type. The difference between rule based reasoning and logic based reasoning is merely a matter of level: all logic based systems are rule based systems but not all rule based systems are logic based.

3.4.2 Reactive Agents

Reactive agents are developed as reaction upon the, rather rigid, physical symbols paradigm of classic AI. Instead, reactive agents build upon a physical grounded hypothesis. This hypothesis states that:

> ... to build a system that is intelligent it is necessary to has its representations grounded in the physical world ... the world is its own best model. It is always exactly up to date. It always contains every detail there is to be known. The trick is to sense it appropriately and often enough "(Brooks, 1990, page 3).

Although not clearly defined what reactive means, the following characteristics are generally considered to apply to it (Brooks, 1991; Nwana, 1996; Wooldridge, 1999):

- agents are innately linked to their environment. This means intelligence is a product of the interaction with the environment;
- intelligent behaviour emerges from interaction of various simpler behaviour;
- there is no "a-priori" specification of a plan of the behaviour. Reactive agents paradigm is similar to the ideas of individual based modelling found in ecology;
- reactive agents tend to operate on representations which are close to raw sensor data; this implies that no high-level symbolic representations are found;
- reactive agents often only have a partial representation of their environment, relevant to the task they need to fulfil.

One of the drawbacks of the reactive architecture is that it is hard to design and verify the intended behaviour. The emergence of overall behaviour from the interactions of the individual components makes it complicated to engineer agents to fulfill a specific task (Wooldridge, 1999). Especially because it is not specified how the agents might achieve their goals. Furthermore, explicit goal handling is hard to do in purely reactive systems (Nwana, 1996; Nwana and Wooldridge, 1996). Reactive architectures seem to be particulary suitable for real-time robots moving around in a real world environment. Knowledge representations found in reactive architectures are often based on rule based or heuristic reasoning.

Other reasoning approaches found in reactive architectures are based on statistical reasoning techniques. Statistical reasoning deals with descriptions of the real world in terms of probabilities or possibilities. Bayes networks and the Dempster-Shafer theories are amongst commonly used techniques within Artificial Intelligence (AI). Furthermore approaches from mathematical game-theory, and fuzzy-reasoning are common amongst agent based models dealing with co-operative (spatial) economic issues (Otter, 2000; Axtell, 1999)

3.4.3 Belief-Desire-Intention (BDI)

In Belief-Desire-Intention architectures, agents are considered to have certain mental attitudes like beliefs, desires and intentions. Beliefs refer to the information an agent has about its world. Desires relate to the tasks that are allocated to the agent. Intentions are desires that an agent has committed to achieve (Rao and Georgeff, 1995). To achieve its intentions, each agent has a plan library storing plans. Plans are representations of procedural knowledge.

BDI architectures have their foundation in the philosophical tradition of practical reasoning; the process of deciding by moment, which action to perform in the furtherance of goals. In practical reasoning two main processes are distinguished: deciding what goals to achieve, and deciding how to achieve these goals (Wooldridge, 1999). Figure 3.1 shows the basic architecture of common BDI agents. An interpreter takes care of updating beliefs, selecting intentions out of the sets of desires, and selecting actions to perform (Wooldridge, 1996). The interpreter therefore, will be considered the engine that performs the reasoning tasks for the agent. A dilemma in the BDI architecture is always to find a balance between reactiveness and pro-activeness. Agents that show much reactive behaviour perform relatively better in environments that are highly dynamic compared to pro-active agents that do better in more static environments (Wooldridge, 1999).

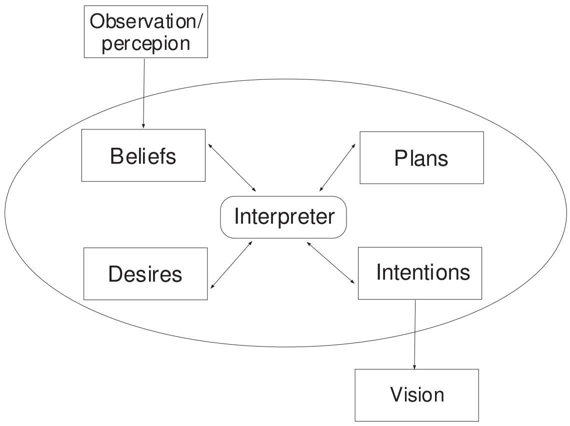

Figure 3.1: BDI Architecture source: after Wooldridge (1996).

The strength of the BDI architecture is mainly the explicit handling of beliefs, desires and intentions. This relates closely to the intentional model for planning. It also provides a clear way of thinking about agents and a usable decomposition to indicate what subsystems might be needed for the design of an agent. A complicating factor, however, is that the formal logics that are developed for BDI agents (see for example Rao and Georgeff (1995), Rao (1991), Wooldridge (1996)) are still difficult to implement in open systems such as spatial planning. It requires substantial formalization of beliefs, desires and intentions (Wooldridge, 1999).

3.4.4 Layered architectures

In layered architectures various layers are designed to deal with both reactive and pro-active behaviourial requirements of an agent. The philosophy of layered architectures is based on the assumption that agents need to produce both simple reactive behaviour (for example to avoid an obstacle in the case of robots) and pro-active behaviour (for example to plan for future actions).

Following Wooldridge (1999) two types of layered architectures exist: horizontal layered, and vertical layered. In horizontal layered architectures (Figure 3.2), each layer is directly connected to a sensory input and action output. This means that each layer in itself is an agent. Horizontal layering has the advantage that it is conceptually simple. It requires just the implementation of one layer for each type of behaviour. The drawback is that the behaviour of the agent sometimes is difficult to control because each layer generates its own actions. A special mediator normally takes care of the prioritization of the various generated actions. In vertical layered architectures input and out-

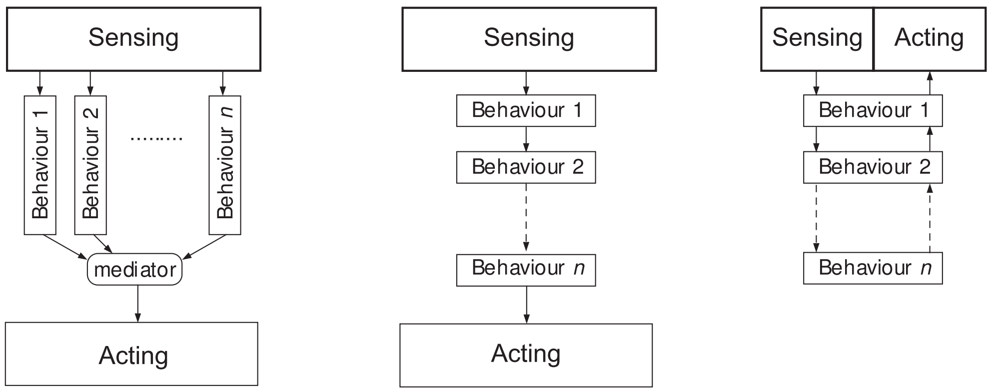

Figure 3.2: Layered architectures: left horizontal, middle vertical (one pass) and right vertical (two pass).

put are dealt with by at most one layer each. The problem of multiple action generation does not exist in the vertical structures. Vertical architectures exists in two flavours. In one pass architectures, sensory input flows from an input layer subsequently through intermediate layers towards an output layer. In two-pass architectures, information flows down through various layers, and next control flows up (see Figure 3.2). Vertical layering overcomes the problem of consistency in behaviour encountered in the horizontal layered architectures. The drawback of the vertical architecture is that it is not fault tolerant. Because information and control need to flow through every layer, failure of one layer will cause failure of the agent.

3.5 MAS in environmental sciences

Definitions and development of MAS for application in environmental science are different than found in the domain of AI. Although some of the architectures mentioned above are found, the origin of the development of agent-based models differs. In AI the development of agent architectures are aimed at constructing intelligent artifacts that reliably pass a Turing test[2] (Ginsberg, 1993). For environmental sciences, agent based architectures are generally aimed at agents that can deal with the complexity of change in geographic environments in a better way than using conventional methods. A principal paradigm adopted by many agent modelers is that of self-organization[3] and emergent properties[4]. This implies that many of the formal AI based architecture are less suitable; which can be explained from the openness, the multiple interactions, and the numerous feedback loop characterizing many spatial systems.

Many of the multi-agent systems found are based on computational organization theory (Carley and Gasser, 1999), Individual Based Modelling theories (IBM)[5] from ecology (Bousquet and Le Page, 2004), and techniques from the Artificial Life (ALife)domain like Cellular Automata (CA) and Markov chains models (Couclelis, 1985; Itami, 1994; Li and Gar-On Yeh, 2000; Li and Yeh, 2002; Parker et al., 2003; Pumain et al., 1995; Torrens, 2003; Wu, 1996). Considering current applications found in environmental sciences roughly 3 types of applications can be distinguished. Applications based on:

[2]The test is named after Alan Turing, an English mathematician who pioneered artificial intelligence during the 1940s and 1950s, and who designed the original test. According the test, a computer is deemed to have artificial intelligence if it can mimic human responses under specific conditions. If the human being conducting the test is unable to consistently determine whether an answer has been given by a computer or by another human being, then the computer is considered to have “passed” the test.

[3]the process in which a system increases in complexity without being influenced by an outside source. Self-organizing systems often show emergent properties.

[4]the process of formation of complex patterns from simpler rules unpredictable from the lower level descriptions

[5]IBM is a computational approach to modelling a system through interaction of individual inhabitants of a system by using atomic models of them (Grimm, 1999).

- dynamically situated agents;
- statically situated agents;
- non-situated agents.

3.5.1 Dynamically situated agents

Models of dynamically situated agents consist of agents that are mobile in their environment. These models, in general, are applied to study the effects of the environment, including other agents, on the locational behaviour of an agent. Models of this type are commonly found in ecology as special cases of individual based modelling (Beecham et al., 2002; Bousquet et al., 2001; Campos, 1998; Dumont and Hill, 2004; Dumont and Hill, 2001). Also models that simulate human behaviour in a spatial environment are present in the work of Batty et al. (2003) who describe movement of pedestrians in large (slow) crowds in order to analyze problems of controlling the crowd, for example, in case of a disaster. Deadman and Gimblett (1994), Gimblett et al. (2000), Gimblett and Itami (1997) describe models that simulate the spatial dynamics of human recreators when roaming in a geographic space. Other models in this category include natural movement and vision in build environments (Turner and Penn, 2002), models for analysis of pedestrian movements through streets (Bruse, 2002; Schelhorn et al., 1999), or traffic-flows control (Bosch van den et al., 2003).

Other applications found are grounded into a connectionist approach and apply heuristic reasoning techniques. Krebs and Bossel (1996) used genetic algorithms to create simple animals that adapt to a changing environment. Dagorn et al. (2000) used a class of neural networks to simulate the behaviour of specific fish in a dynamic environment.

3.5.2 Statically situated agents

Models of statically situated agents consist of agents which are tied to specific locations in the environment. These models are mostly applied to study structural relations between agents and their environment. Based on its location, surroundings, and locations of other agents, an individual agent takes decisions to change its environment in order to accomplish its goals. These decisions, as a consequence of being part of the environment, have an immediate consequence on future behaviour of the agents. Examples are participatory simulation of the effects of farmer households on their environment in: Vietnam (Castella et al., 2005), Senegal (D'Aquino et al., 2003), and Tunisia (Feuillette et al., 2003). Participatory simulation combines role playing with agent based simulations to better explore, understand, and learn from the relations between farmers and their immediate environment in complex dynamic agricultural and natural systems. The same idea originates to the simulation of a social network to explore the viability of an irrigation scheme in Senegal (Barreteau and Bousquet, 2000). Other models deal with the simulation of urban dynamics at a macro-level describing the transitions of one type of city into another (Pumain et al., 1995), development of strategies for natural resource management (Etienne et al., 2003; Janssen et al., 2000; Nute et al., 2004), or micro-level simulating inter-city dynamics of residents changing their residence as a result of economic or cultural-based decisions (Benenson, 1998; Torrens, 2003).

3.5.3 Non-situated agents

In non-situated applications, agents are not tied to a specific location neither they are mobile. In models of non-situated agents the environment and agency are separated. This approach is applied to models that simulate ecosystem management, spatial economics (Lei et al., 2005; Otter, 2000), and stakeholder participation and land use planning (Krywkow et al., 2002; Bennett et al., 1999). The MAS presented in this research belongs to this category.

3.6 Conclusions

The overview of agent based approaches presented in this chapter shows that many of the architectures found in AI are difficult to apply in the spatial planning domain. Agent research in traditional AI focusses on formal methods of reasoning dominated by a physical symbol paradigm. Research in environmental sciences, however, is inspired by concepts and techniques of Alife and IBM research, combined with the concepts of map-algebra proposed by Tomlin (1990).

This implies that agent-based approaches based on a symbolic reasoning are barely found. The construction of a sound and complete logic system for most (if not all) spatial domains is not possible. Most architectures found, are reactive without (sophisticated) reasoning and learning mechanisms, or inspired by an informal interpretation of the BDI approach (see for an example Smith et al. (2002)). Many models apply a (by definition incomplete) rule base that contains the observed or supposed knowledge of individual agents often based on informal interpretations of reality.

Reactive and BDI like architectures, integrated with techniques from A-life research and geo-information sciences are the approaches that further will be explored in this thesis, to develop models that honour the complexity of interactive multi-actor spatial planning.

A comment, which already can be made, is that, although the concept of self-organization and emergent properties deliver, an appealing and sometimes more natural approach to modelling complex spatial systems, it has some shortcomings. A major one is validation. Up till now validation of spatial agent based models remains cumbersome. Traditional validation approaches fail when it comes to dealing with adaptivity, and variability of many of the modelled systems. One could argue that validation of a model of a complex system is almost like a "contradictio in terminus" as the behaviour of such systems is by definition difficult to predict. Nevertheless, to disseminate the agent based models outside the academic domains, methods need to be devised to verify whether the behaviour of the agent based model is acceptable compared to the real world system.

Chapter 4

Multi-actor-based land use modelling: spatial planning using agents

Arend Ligtenberg, Arnold Bregt, Ron van Lammeren
Landscape and Urban Planning (2001); 15: 21-33

This paper describes a spatial planning model combining a Multi Agent Simulation (MAS) approach with Cellular Automata (CA). The model includes individual actor behaviour according a bottom up modelling concept. Spatial planning intentions and related decision-making of planning actors are defined by agents. CA is used to infer the knowledge needed by the agents to make decisions about the future of a spatial organization in a certain area. The innovative item of this approach offers a framework for modelling complex land use planning process by extending CA approach with MAS. The modelling approach is demonstrated by the implementation of a pilot model using JAVA and the SWARM agent modelling toolkit. The pilot model itself is applied to a study area near the city of Nijmegen, the Netherlands.

4.1 Introduction

Controlling the process of land use planning, for example in case of scenario studies, is often hampered by a complex procedure and unexpected behaviour of the process. In general land use planning is considered as complex (Couclelis, 1987; Hidding, 1997; Itami, 1994). Various aspects cause this complexity. The main ones are:

- Actors. Actors are the players (both individuals and groups) in the process of spatial planning. They communicate, negotiate and decide upon the spatial organization of their environment. The intentions of actors initially differ because of different spatial and temporal horizons. They meet in a process of spatial decision-making. This process is characterized by multi-actor, multi-goal, multi-scale and multi-criteria facets (Ferrand, 1996).
- Spatial environment. Not all locations in a spatial environment are equally suitable for the various types of spatial functions (i.e. a defined activity at a location during an uncertain or certain time). A location may show restrictions, opportunities or threats to a specific spatial function.
- Actor based processes. Actors impose their spatial intentions upon their interest in the spatial organization. They are driven by their motivation to narrow the gap between the actor's definition of the current organization and their vision of the future organization. The motives to narrow this gap are driven by their objectives (seen as the derivatives of their intentions), which could be divided into their normative values

and the outcomes of the interpretative and formal models they use to evaluate their environment (Kleefmann, 1984; Lammeren, 1994).

- Autonomous processes. The environment itself hosts processes that change its nature. These processes we denote as autonomous processes and we differentiate them from the intentionally driven actor based processes. Examples of such autonomous processes are erosion, vegetation growth or the flow of groundwater.

The above-mentioned four aspects lead to a spatial planning system that shows non-autonomous, non-linear behaviour, a high sensitivity to initial conditions and hard to determine causal relations.

Cellular Automata (CA) based models are often proposed to offer a technique suitable to model this type of complex spatial system (Couclelis, 1985; Couclelis, 1997; Itami, 1994; Portugali and Benenson, 1995; Wagner, 1997). This proposition is mainly based upon the notion of self-organization i.e. the global structure of the system stems entirely from the interactions between locally defined components (Pumain et al., 1995). The spatial patterns of the systems are entirely generated out of local defined rules applied upon a neighbourhood in a (theoretically) infinite cellular space. For this reason CA have been widely applied as a tool for the simulation of space-time dynamics of relatively autonomous spatial systems, like urban systems emerging in a spatial environment (Batty and Xie, 1994; Couclelis, 1989; Itami, 1994; Lim and Gar-On Yeh, 1998; White and Engelen, 1997). A relaxation of CA based upon the discrete event simulation theory widens the applicability of CA to describe also non-autonomous geographical processes (Couclelis, 1985; Zeigler, 1976). Such relaxed CA can be applied in multi-model approaches like the constrained CA approach of Engelen et al. (1997) or the integration of CA with GIS, Multi-Criteria Analysis (MCA) and Analytical Hierarchy Processes (AHP) (Lim and Gar-On Yeh, 1998; Wu, 1998).

None of these CA applications provide "support" for typical actor based processes. They all focus on autonomous processes that can be entirely described through the interactions of spatial phenomena. The assumption of self-organization in a spatial context means that CA can only be applied to explicit spatial systems that respond to rules, cells and neighbourhoods that are stationary in space and time. Couclelis (1985) pointed out that these states, rules and neighbourhoods do not necessarily need to be stationary. CA themselves however do not provide methods to assign dynamic characteristic to the states, rules and neighbourhoods and are therefore limited in their use for modelling the human factor in a spatial decision-making process. Various researchers (Deadman, 1999; Openshaw, 1995) emphasize the importance of integrating human system modelling into spatial models.

Multi-Agent Simulation provides means to include human decision-making without losing the strength of the concept of self-organization (Deadman, 1999). Multi Agents Systems can be defined as a set of agents interacting in a common environment, able to modify themselves and their environment (after Ferrand (1996). There are basically two ways of looking at agent technology. The first is to consider agents as an alternative way of designing computer software and in this respect it can be seen as the last generation in the sequence from objects via components up to agents. Another view regards agents as a new kind of modelling paradigm that allows a closer resemblance to the reality to be modelled. In our research we are mainly interested in this latter conception of agents. However constructing agents seem very difficult without building the software "the agents way" i.e. using object oriented programming conventions and environments.

A number of definitions describe the concept of (Multi) Agent Modelling (see Jennings (2000) for an elaboration upon agent programming). In this research we adopt the definition of Maes (1994): "An agent is a system that tries to fulfil a set of goals in a complex, dynamic environment. An agent is situated in the environment: it can sense the environment through its sensors and act upon the environment using its actuators".

In this paper we explore the combined use of Cellular Automata (CA) and Multi Agent Simulation (MAS) techniques to build a spatial multi-actor model that simulates spatial change as result of actor based decision-making. Our main focus is to include the variety of actor based normative ideas related to the allocation of spatial functions that feed a land use change simulation process. In the first part of this paper we propose such a method. Next this method is demonstrated in a case study. We end this paper with a discussion of the approach and formulate some recommendations for further research.

4.2 Proposed method

4.2.1 Conceptual model

To illustrate the integration of MAS with CA we propose a land use simulation model that allocates only one type of land use (urbanization) based upon a-priori defined spatial claim. The allocation is based upon individual preferences of various actors. The set-up of the model does not include predefined local, regional or global constraints like suitability, policy restrictions, price of land etc.

The proposed model mimics a number of actors who by negotiation allocate new locations for urbanization in a study area. To do so, each actor develops a series of preferences through time that depict its ideas about a future organization of the environment. These preferences of the individual actors are translated into a new land use configuration through a process of voting and decision-making on possible allocations.

In the current model we defined two types of actors. The first, the reconnaissance actor, has voting power during a planning process. It means that this actor is only allowed to communicate an opinion about a future land use situation. He doesn't have the direct power to actually change the land use. The second type, the planning actor, has also the authority to change the spatial organization. His decisions are based upon the opinions of the other actors and upon his"personal ideas". This typology mimics a situation in which various actors participate in land use planning leaving the actual authorization of change to a selected group of actors. This is the type of planning often found in very regulated land use planning systems where decision-making is highly decentralized while the actual interpretation, implementation and monitoring of the land use planning process is done by the local, regional or national authorities (Hidding, 1997).

To participate in a land use planning process an actor executes a number of intentional actions. These actions are inspired by the model of intentional decision-making of Schutz (Kleefmann, 1984). The actors go through the following five steps:

1. interpreting the environment and generating an observed definition of it (in terms of a spatial organization);
2. comparing the definition of the spatial organization with their own future objectives and determining the differences between them;
3. prioritizing their wishes depending on a auxiliary imposed set of restrictions and possibilities;
4. adapting the current spatial organization in order to narrow the gap between the desired and the existing organization;
5. effectuating the adaptations by decision-making with other actors.

The intentional actions of actors invoke a number of interactions between the environment and the actors. Amongst these interactions, four types can be recognized (Figure 4.1):

1. interactions between the spatial objects of the environment and actors (O $\rightarrow$ A). These interactions are mainly directed towards a "definition of the situation" by the actors, aimed upon inference of knowledge of the spatial organization;
2. interactions between spatial objects (O $\rightarrow$ O). These types of interactions are mainly related to the autonomous processes;

3. interactions between actors and spatial objects (A → O) . This involves the adaptation of spatial objects by the actors in trying to fulfil their objectives;
4. interactions between actors and actors (A → A). During the land use planning process the formation of one future oriented vision and the related decision-making processes are not only dependent on the observations and objectives of one actor but also on the mutual relations between the observations and objectives of all actors. Often there is a hierarchy amongst the actors based on the decisive power of the individual actors. Interactions of these types include communication, negotiation and co-operation.

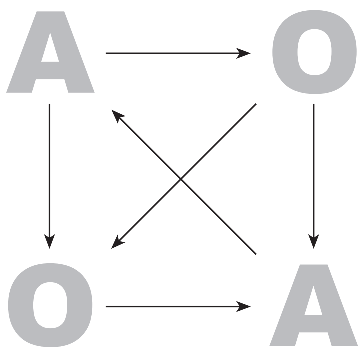

Figure 4.1: Type of interactions between the spatial organization (O) and the actors (A).

Our focus in this paper is mainly upon the interactions between the actor and its environment (A→O), the environment and the actor (O→A) and to a certain extent interactions between actors (A→A).

4.3 Formal description of a MAS model

In the intended approach we use agent technology to simulate actors. These agents mimic the basic intentional actions of actors during a multi-actor planning process, trying to assign a land use claim. They establish interactions with other agents (A → A) and with their environment (O → A and A → O) in order to generate knowledge about it. The model knows two types of entities. The first type of entity forms the spatial organization. This type stores and maintains the state and processes of the environment. The second type stores the characteristics and processes of the actors (the agents).

These entities are equipped with the behaviour that is needed to establish and maintain the interactions that are presented in Figure 4.1. Instead of entities we will use the term objects. The rest of this section deals with a description of these objects and the attached behaviour.

4.3.1 Spatial organization

The environment consists of land use classes (S). These land use classes are described by *BasicCell* objects. Formally *BasicCells* are described as:

$$BasicCell = \{s, i, f\} \tag{4.1}$$

Where: $s =$ the state of the environment, $i =$ a geometric position identifier of the *BasicCell* in the environment, and f = the status of the cell (i.e. should the *BasicCell* be included or excluded from evaluation by the agent).

All *BasicCells* are combined into a Collection object. This Collection object is equipped with methods to spatially reference the *BasicCells* and to generate statistics about the composition of the *BasicCells*. To allow agents to define, store and maintain their own definitions of the environment each, agent in the model maintains its own specific description of the environment, stored in *AgentCell* entities. An *AgentCell* inherits all the characteristic of the *BasicCell* but adds some specific properties needed by the agents:

$$AgentCell = \{BasicCell, x, y, p\} \tag{4.2}$$

Where: $x =$ the x location of the cell in the environment; $y =$ the y location of the cell in the environment and; $p =$ a ranking indicator (explained in the text). Both the *AgentCell* and *BasicCell* are equipped with behaviours that make them respond correctly to requests from other entities of the system.

4.3.2 Agents

Agents evaluate their spatial organization as stored in an agent specific set of AgentCells. Agents base their evaluation upon actor specific knowledge concerning spatial objectives and related claims and characteristics like voting power. In our approach we store the knowledge about the spatial objectives by using the concept of distance based weighted sums (White and Engelen, 1994; White and Engelen, 1997). These weights are comparable with the distance-attraction relations (Engelen et al., 1995). A distance-attraction relation represents the spatial preferences of an actor as a function of the distance from a location currently under review by the agent. Such spatial preference functions need to be drawn for every combination of land use classes. Each agent carries and maintains its own set of spatial preference functions and uses it to evaluate its own specific set of *AgentCells*. The agent can be represented as an entity with the following properties:

$$Agent = \{Ca, Erw, Eaw, Fa, Bi, Be\} \tag{4.3}$$

Where: Ca is the set of agent specific characteristics: $Ca = \{agentname, votingpower, landuseclaims\}$, Erw is the spatial organization: $Erw = \{BasicCells\}$, Eaw is the agent specific instance of spatial organization $Eaw = \{AgentCells\}$, Fa is the agent specific set of spatial preference functions, Bi is the set of methods to perform internal tasks (see below for explanation), and Be is the set of methods to perform external tasks (sensors and actuators).

Each agent is equipped with internal tasks and external tasks. Internal tasks are defined to execute the agent specific things that are related to maintaining, evaluating and updating its specific description of the spatial organization, checking its own integrity, updating its knowledge and preprocessing for the external tasks. External tasks are aimed upon maintaining A → A and A → O interactions (Fig. 4.1) and to dispatch knowledge for the internal tasks. The agents have two key tasks. The first behaviour is related to the construction of an agent specific image of the spatial organization by an individually based definition of the situation. The second task is needed to communicate the ideas and synchronize these ideas with other agents in order to reach a final decision (or end-up at some kind of impasse).

4.3.3 Individual Agent decision-making

The construction of the agent-specific image of how the spatial environment ought to be organized is done following a two step procedure. First the agent evaluates its spatial organization and assigns a ranking indicator (Rs) to every AgentCell object that represents the aggregated land-use potential of each object. CA serve as an engine to carry out this evaluation efficiently. By using CA a simple ranking indicator is generated for a transition according to the distance based weighted sum approach (Engelen et al., 1995; White and Engelen, 1994; White and Engelen, 1997). The distance-based weights are calculated by spatial preference functions. These functions (f) have a general form (see for example (Engelen et al., 1995; Engelen et al., 1997; Wu, 1996), that can be easily applied to objects instead of to a cellular space:

$$f = (AgentCell^{t}_{Sxy}, \Omega_{AgentCell_{xy}}) \tag{4.4}$$

where:$AgentCell^{t}_{xy}$ at time t in state S having location x, y; and $\Omega_{AgentCell_{xy}}$ The neighbourhood for *AgentCell* having location x, y. The neighbourhood consists of the *AgentCell* objects having location properties defined by the extent of the neighbourhood. The extent of the neighbourhood is determined by the preferences of the actor (f). This means that the size of the neighbourhood is dynamic. The assignment of n spatial functions within an environment of s states demands from each agent a set of n spatial preference functions.

The ranking indicator is generated by the following CA rule:

$$R_z = \sum_{i=1}^{n} \sum_{j=1}^{s} p_{jzd} J_{ij} F_{if} \tag{4.5}$$

Where: s is the number of land use classes part of S, n is the number of AgentCells in the neighbourhood, R_z is the aggregated ranking indicator for suitable land use class z, p_{jzd} is the individual ranking indicator of land use class j for land use class z at distance d from the central *AgentCell*, $J_{ij} = 1$ if *AgentCell* i has the state property j otherwise $Jij = 0$; $F_{if} = 1$ if *AgentCell* i has property f set to false, else 0. The aggregated ranking indicator is stored in the *AgentCell* object. Each agent thus owns a "personal" set of ranking indicators. The agents assign the new land use based upon an a-priori defined claim and the ranking indicator present in the *AgentCell* objects. The assigning algorithm is a simple one. A claim n of a land use class is assigned to the AgentCells having the n highest ranking indicators. All the other cells will not be altered. As a result each agent has its own definition of how the spatial organization should be at timestamp $t + 1$.

4.3.4 Synchronized decision-making

After each agent has made up its construct of a desired future spatial organization a decision-making procedure is needed to allocate the new land use classes. A planning agent accomplishes this task. A planning agent is similar to the other agents in the model but has the additional ability to "ask" for the "opinions" of the other agents. The final assignment will be performed in four steps:

1. The planning agent asks every agent in the model to hand over its set of AgentCells. It then determines the locations that are agreed upon by all agents, meaning that for these locations all individual agents intend the same land use class to be assigned. The evaluation is done by simply comparing the land use in the AgentCells of each agent with those of its fellow agents. If the land use situation for a certain AgentCell is not identical for all the agents a reference to its location will be stored in a

conflict list (C). For the non-conflicting AgentCell locations the states of the corresponding BasicCells are updated to represent the consensus reached for that location.

2. For each location stored in the conflict list the agents are asked by the planner agent to vote. The planning agent stores the votes of every agent for every conflicting cell in the conflict list. Each agent has voting power depending on its position in a hierarchy of agents. The voting model is very simple:

$$p_{vote} = V_w i \tag{4.6}$$

where : P_{vote} = the weighted agent vote; V_w = the agent's voting power.

- If the agent specific land use (sa)equals the land use that ought to be assigned according to the scenario (s_{prop}) then it votes in favour of the new land use:

$$i = \begin{cases} 1, & \text{if } s_a = s_{prop} \\ 0, & \text{if } s_a \neq s_{prop} \end{cases}$$

- The other case is when an agent's own assignment does not match with the proposed one. An agent then will vote against it with a strength depending upon his voting power:

$$i = \begin{cases} 1, & \text{if } s_a \neq s_{prop} \\ 0, & \text{if } s_a = s_{prop} \end{cases}$$

3. A subset $Cpro$ of the conflict list (C) is created containing the conflict locations with a majority of votes in favour of the proposed change:

$$C_{pro} \subset \{C \mid p_{vote} > c_{vote}\}$$

where: p_{vote} is the number of votes in favour of the proposed land use and; c_{vote} is the number of votes against the proposed land use.

4. Next the planning agent assigns the remainders of the claims by ranking C_{pro} according to weighted number of votes. Assignment stops after the claim is fulfilled or a situation is reached in which no location exists where the sum of all the votes in favour exceeds the sum of all the votes against.

4.4 Implementation

We have implemented the model using a combination of JAVA and the SWARM library of the Santa Fe Institute (Hiebeler, 1994). The SWARM library is designed to be a flexible toolkit for discrete-event based agent simulations. It provides objects to group activities of agents, schedule activities of agents, probe and visualize agent behaviour etc. The implementation of SWARM is based upon the definition of so-called Modelswarms and Observerswarms. The Modelswarm initiates, groups and schedules the simulation objects including the agents. The Observerswarm defines, groups and schedules all the objects and methods for observing and analyzing the behaviour of agents during the simulation. The characteristics of the actors and their associated spatial preference rules are stored in an Access database. The agents, using the JAVA language can easily access this Access database. A number of additional software objects have been developed to convert data from a traditional relational data structure into the object oriented data structure needed by the agents. An AgentBuilder class takes care of conversion into the object oriented data model of the agents. A ReadGrid class converts a plain ASCII grid (as exported from GIS software, for example Arc/Info) into the BasicCell objects. A Function class stores the spatial transition functions and provide methods to retrieve and store function values and meta-data for these functions. For reasons of performance a CA-engine was entirely written in JAVA without using the SWARM libraries, thus preventing expensive calls upon the objective-C code of SWARM. The agents send their sets of AgentCell objects to the CA-engine to be processed. The CA-engines return the set updated with the ranking indices. Communication between the agents has been implemented by sending messages. The SWARM library provides for classes, which can be used to allow sophisticated message passing, grouping of activities and scheduling of activities. Figure two shows the various objects and agents and the basic interactions of the system.

4.5 Discussion

The presented methodology is a first attempt to model multi actor decision-making in land use planning. Table 4.1 gives an overview of the model components. There are a number of aspects that will need further development in order to provide the user with what sometimes is called “the artificial planning experience” (Portugali and Benenson, 1995).

The first aspect is the assumption that the spatial preferences and knowl-

Conceptual	Formal	Implementation
Entities of the planning process		
Reconnaissance actor	Reconn. agent	Reconn. agent object
Planning actor	Planning agent	Planning agent object inheriting from reconn. agent object
Spatial organisation	Object-oriented data storage in BasicCells	BasicCell object
Actor specific description of the spatial organization	Object-oriented data storage in AgentCells	AgenCell object inheriting characteristics from BasicCell object
Spatial preferences of actors	Spatial preference fucntions	Ca-local rules objects stored in a relational database
Stages of the planning process		
Creating actor-specific spatial preferences	Generating ranking scores based upon spatial organization of a neighbourhood	JAVA CA-engine object scheduled using SWARM
Adapting actor-specific observation of the spatial organization	Land use allocation tasks (based upon ranking scores stored in AgentCells)	Land use allocation method implemented in the agents using JAVA
Synchronizing knowledge of the individual actors	Hierarchical voting tasks	Voting methods implemented in the reconn.agents called upon by the planning agent; SWARM is used to implement the scheduling and routing of messages
Adapting spatial organization	Decision-making upon land use allocation by the planning agent	Methods for comparing and ranking the votes delivered by the reconn. agents and updating BasicCell objects; implemented in the planning agent using JAVA and SWARM
Re-entering the planning cycle	Next time step	SWARM schedule and activity objects are used to invoke and maintain agent activity

Table 4.1: Entities and stages in the conceptual model

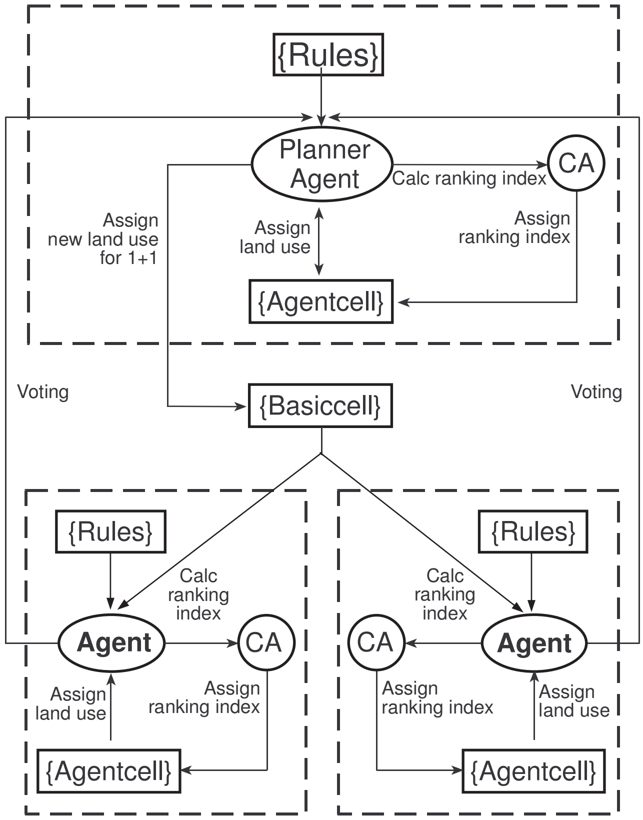

Figure 4.2: Entities and interactions of the MAS model.

edge are static. Through time the planning agent changes neither its spatial preferences nor its collection of certain types of information. The model should probably include learning, co-operation and other feedback mechanisms to elaborate the A → A interactions which are currently rather weakly developed. The second aspect is related to the representation of the spatial organization. At the moment there exists only the notion of discrete entities (objects) storing spatial characteristics and the notion of the neighbourhood that determines the spatial extent of the interaction between the AgentCells. There is clearly a need for refining this concept, for example, to define disjoint neighbourhood, to make use of topological relations and to enhance the recognition of spatial patterns. The last aspect is narrowly related to the implemented decision-making process. Currently a very simple approach has been taken. The actor bases its only decision upon one characteristic of the land use class. No additional information is provided and all agents have access to the same knowledge. Methodologies like game theory, belief-networks, fuzzy set theory, machine learning, etc., perhaps offer a wealth of techniques that should be explored in order to enhance the decision-making procedure. What we have shown so far is that this technique of MAS offers us a new conceptual framework, which could be suitable for integrating various spatial modelling techniques with human behaviour modelling.

4.6 Pilot Application

Three agents were implemented. They where called "Municipality of Nijmegen", "The New Rich" and "Nature and Environment". They serve as the actors in the planning process. The "Municipality of Nijmegen" has been assigned the status of planning actor. The three actors differ in their definitions of the spatial preference functions. The applied preference functions are archetypal for the simulated actors. The "Municipality of Nijmegen" for example prefers a clustering of new urbanization close to existing urbanized areas. "The new rich" prefers to realism new urbanization locations near to existing small villages, natural areas or along the shores of water bodies. Figure 4.3 shows the resulting spatial preference functions for the three actors. Each actor has the task of assigning an a-priori defined urbanization area per year. The spatial organization is constructed out of the Land use Database of the Netherlands (LGN) . The data set was aggregated into a cell size of 100 meter, mainly to speed up calculation.

4.7 Simulation

The simulation runs for two scenarios and 30 time steps each (a time step represents one year). For both scenarios the growth rate of urbanization was fixed for all the actors to 300 hectares/year annually. The decision power of the actors, however, differs. In the first scenario the highest decisive power was assigned to the"Municipality of Nijmegen" while the other agents were assigned equal decision power. In the second scenario all agents had the same decision power. For both scenarios the "Municipality of Nijmegen" was assigned the planning agent while the other agents act as reconnaissance planners The scenarios were not chosen to reflect a potential real world situation but to illustrate the conceptual framework as clearly as possible. Figure 4.4 depicts the results of the simulation for scenario 1. The results for scenario

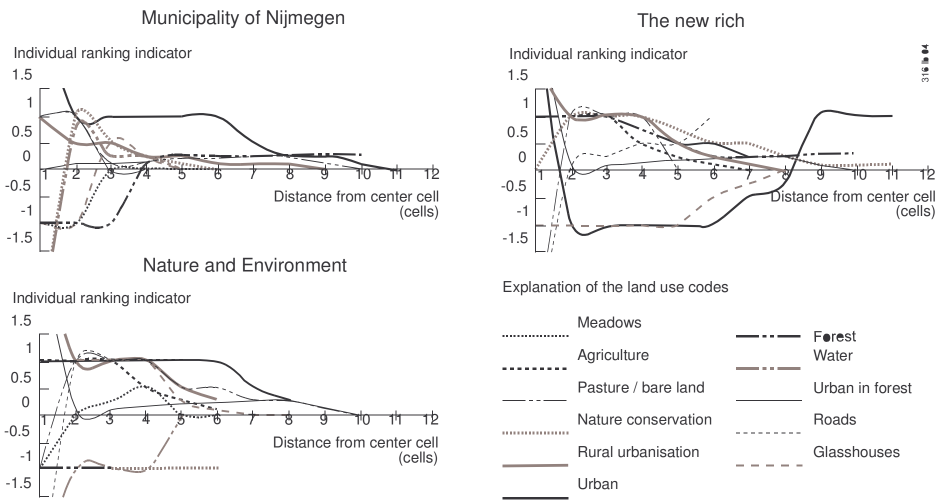

Figure 4.3: Examples of the spatial preference functions implemented in the reactive MAS model.

2 are shown in Figure 4.5.

4.8 decision-making

If we look at the decision-making process in the two scenarios, some interesting observations can be made. In the first scenario the urbanization claim can be assigned at every time step. The simulated dominance of the "Municipality of Nijmegen" pulls the assignment of urban areas into line with this agent's objectives. The other agents are forced to "adapt" their spatial preferences. This process can be observed when looking at the spatial ranking maps. Towards the end of the simulation they show a similar pattern.

The second simulation ends in an impasse after about 8 time steps. The agents do not agree upon the locations where new urbanization claims could be located. None of the agents has the power to dominate the decision-making procedure, so after a while the claims cannot be fulfilled, resulting in a failure to assign new urbanization areas. This process can be traced when looking at the number of conflicts at every time step of the simulation (Figure 4.6). For Scenario 1 the total number of conflicts declines as a result of less area that can be "argued" about. In the second scenario, however, the number of conflicts remains stable after some time. This means that the planning agent could not find locations for new urbanization. The dominance of the "Municipality of Nijmegen" in the decision-making process can be seen in Figure 4.6 where the desired location of the "Municipality of Nijmegen" is fully assigned after 11 years i.e. showed by the absence of conflicts.

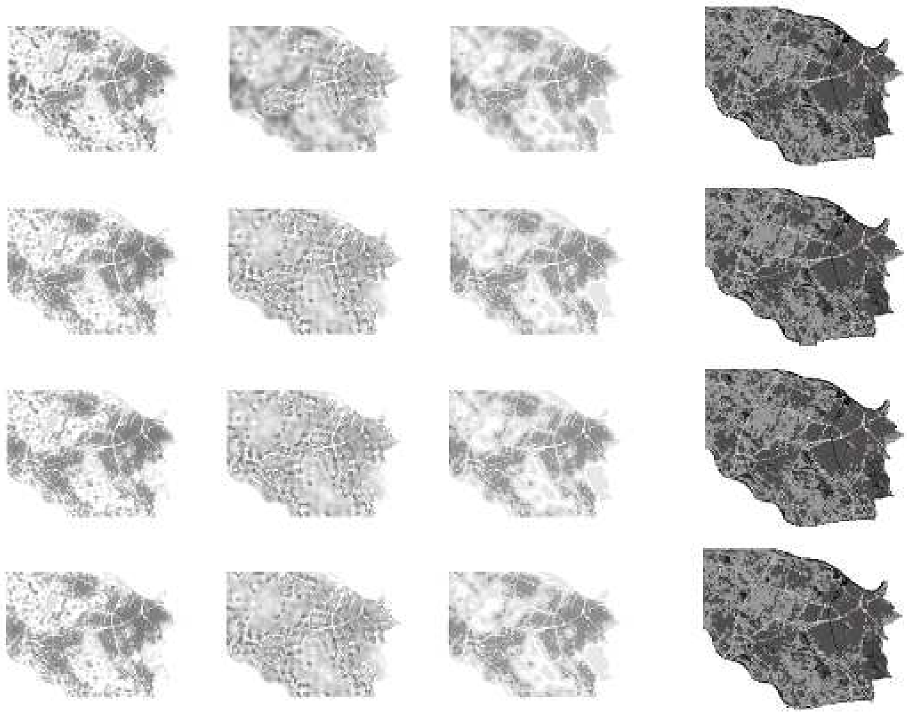

Figure 4.4: Scenario 1, simulation results for $t = 1, t = 10$ and $t = 30$ (from top to bottom), and the actors "Municipality of Nijmegen", "The New Rich" and "Nature and Environment" (from left to right. The rightmost map depicts the spread of the urban areas.

4.9 Land use allocation

The land use allocation depends entirely on the spatial transition functions. The physical conditions of specific location are not taken into account in this experiment. Figure 4.7 shows the changes in land use classes for each of the two scenarios. The growth of the urban area for both scenarios is mainly at the expense of the meadows and crop fields. For all the agents the spatial transition functions are defined such that the existence of meadows or crop fields at the location or in its neighbourhood (see also Figure 8) increases the ranking indicators for that location.

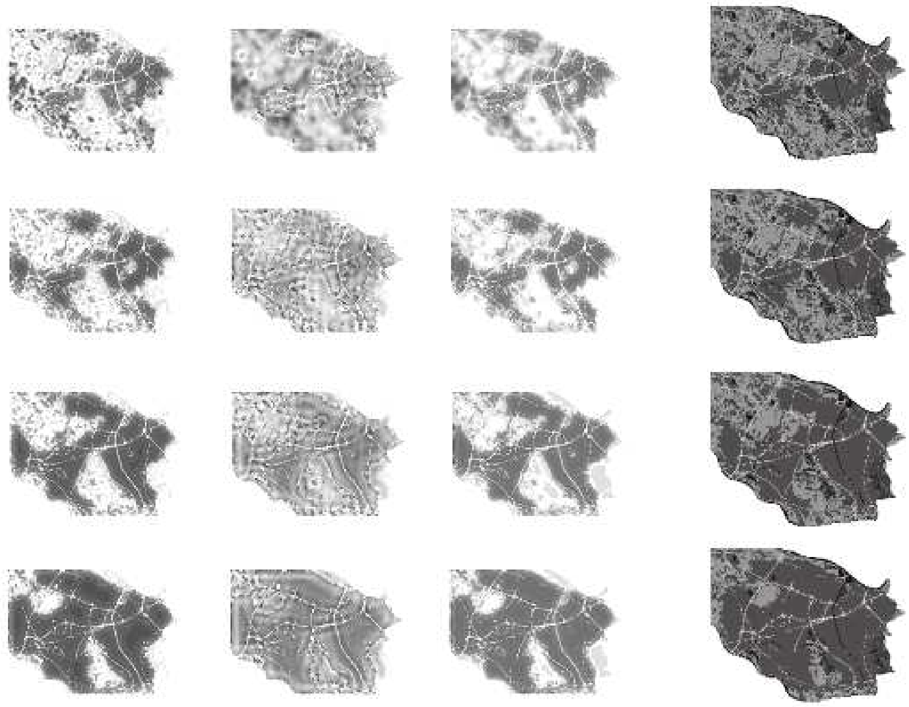

Figure 4.5: Scenario 2, simulation results for $t = 1, t = 10$ and $t = 30$ (from top to bottom), and the actors "Municipality of Nijmegen", "The New Rich" and "Nature and Environment" (from left to right. The rightmost map depicts the spread of the urban areas.

4.10 Conclusions

In this paper the use of Multi Agent Simulation (MAS) for modelling spatial planning is proposed and illustrated. It clearly shows interesting features for the spatial planning domain.

In the first place it provides a platform where various techniques already used in spatial planning and spatial modelling can be integrated. In the pilot study, for instance, CA, a land use allocation procedure and a basic voting algorithm were combined. Secondly it provides for the construction of dynamic models that combines explicit spatial processes and actor interactions.

The work presented here is a first attempt to construct models that show closer resemblance with the real world spatial planning process. This kind of model is not only of interest to run planning scenarios but also, and probably more interestingly, to synthesize knowledge in order to provide a better understanding of the complexity of multi actor driven spatial planning. To reach this ambition an increasing research effort is needed to test alternative

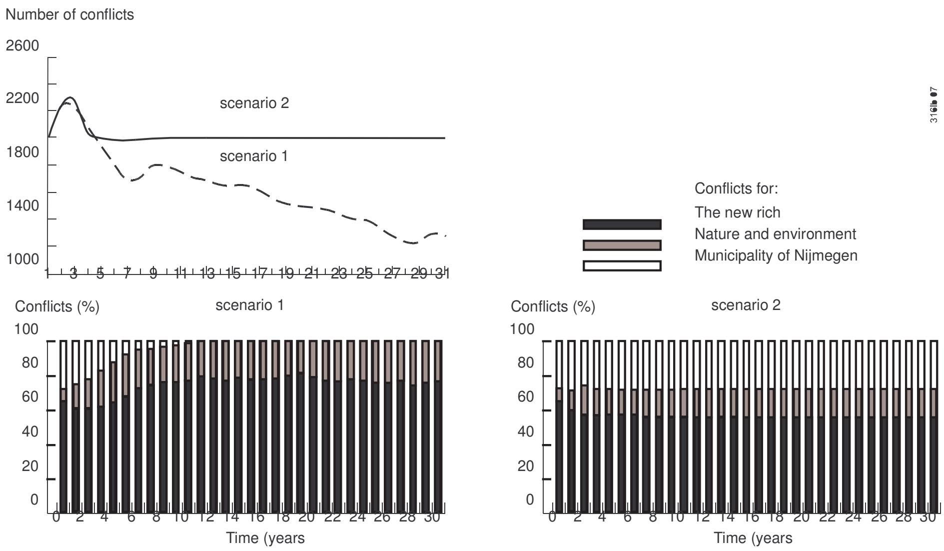

Figure 4.6: Number of conflicts for the two scenarios.

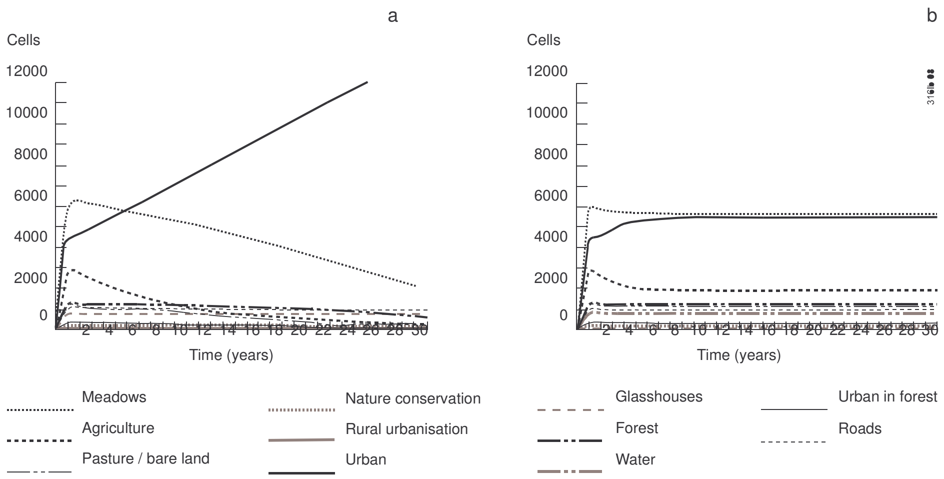

Figure 4.7: Land use change for scenario 1 (a) and scenario 2 (b).

approaches for the processing of knowledge and decision-making by agents. A thorough understanding of knowledge acquisition processes is still a primary requirement. Techniques to describe and implement forms of communication, strategies of negotiation and attitudes of decision-makers are still lacking.

An important question (not touched in this paper) is how to adequately and appropriately “test“ a land use allocation model of the type described in this paper. A suitable methodology to verify and validate these types of models is still lacking. Historical data can be used to see if current patterns can be simulated from the past. A possible other approach is a review of simulated results by domain experts. Improvement of the proposed model and validations of it are challenging for further research.

Chapter 5

A design and application of a multi-agent system for simulation of multi-actor spatial planning

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Multi-agent Systems (MAS) offer a conceptual approach to include multi-actor decision-making into models of land use change. The main goal is to explore the use of MAS to simulate spatial scenarios based on modelling multi-actor decision-making within a spatial planning process. We demonstrate a MAS that consists of agents representing organizations and interest groups involved in an urban allocation problem during a land use planning process. The multi-actor based decision-making is modelled by generating beliefs and preferences of actors about the location of and relation between spatial objects. This allows each agent to confront these beliefs and preferences with its own desires and with that of other agents. The MAS loosely resembles a belief, desire and intentions (BDI) architecture. Based on a case study for a hypothetical land use planning situation in a study area in the Netherlands we discuss the potential and limitations of the MAS to build models that enable spatial planners to include the 'actor factor' in their analysis and design of spatial scenarios. In addition our experiments revealed the need for further research on the representation of spatial objects and reasoning, learning, and communication about allocation problems using MAS.

5.1 Introduction

Spatial planning is aimed at changing the organization of a spatial environment to meet the demands of a society. As space becomes a limited resource the spatial environment is expected to fulfil multiple functions. This cause actors to conflict more often in their desires and expectations about the spatial environment (Valk van der, 2002). Multiple actors from different organizations and interest groups compete for the same resources. Often this leads to conflicting interests. For example, in the Netherlands rural areas are under increasing pressure and need to fulfil multiple functions such as the combination of recreation and agriculture land use (Valk van der, 2002; Cammen van der and Lange de, 1998). At the same time planning shifts from an agency based approach towards a more participatory approach; which includes models that describe multi-actor processes in spatial planning (Valk van der, 2002; Hickling, 1994). The multi-actor based planning approaches enable us to include this 'actor factor' into the development and analysis of spatial scenarios. However, there is still a need to gain insight into the extent to which actor decision-making affects the spatial environment.

Tools that support *ex ante* evaluation of spatial planning and spatial plans are therefore a basic requirement to construct sustainable spatial policy. There is a need for a kind of artificial environment in which policy can be developed and tested in order to cope with the increased complexity of reality. A tool extensively used has been Geographic Information Systems (GIS). During the last decade GIS have been developed from relative straightforward systems for storage, retrieval, and presentation of spatial information towards systems that support complex spatial analysis. The increase in computational power and the introduction of Cellular Automata (CA) extended the analytical capabilities of GIS for modelling complex dynamic spatial processes (Batty and Xie, 1994; Engelen et al., 1995; Couclelis, 1997; Couclelis, 1987; Itami, 1994; White and Engelen, 1994). Currently a number of models are available that simulate complex, and dynamic land use change processes. However, none of them explicitly include a representation of the multi-actor planning process (see for example: (Engelen et al., 2003; Ligtenberg et al., 2000; White and Engelen, 2000; Hilverink and Rietveld, 1999; Rijswijk van et al., 1998). Other approaches like Multi-Criteria Analysis (MCA) (see for example: (Beinat and Nijkamp, 1998; Janssen, 1992)) compare only a relative static set of criteria rather then a dynamic exchange of information between owners of the various objectives and sets of criteria. Therefore, an alternative tool is found in Multi-Agent Systems (MAS) that offer a conceptual and methodological approach to include the 'actor factor' into dynamic spatial models of decision-making (Antona et al., 2002; Doran, 2001; Ferrand, 1996; Gimblett, 2001; Otter, 2000; Parker et al., 2003; Sengupta and Bennet, 2003; Torrens, 2003). (Deadman and Gimblett, 1994), for example, carried out research on people-environment interactions using agent based models in which they simulated people deciding on taking a route during recreational trips in a forest area. Moreover, (Deadman, 1999) tried to reproduce phenomena found during common pool experiments according a 'tragedy of the commons' scenario. (Benenson, 1998) simulated the dynamics in residence patterns in a large city using MAS.

The overall goal of our research reported in this article is to explore the use of MAS to simulate spatial scenarios based on modelling multi-actor decision-making within a spatial planning process. In this paper we demonstrate how MAS can be used to simulate land use changes. As an example of a planning process we selected a regional planning situation in the Netherlands. The use of MAS enables us to explicitly include the possible effects of decision-making by multiple actors in a dynamic simulation of land use change. This might lead to an improved insight in the effects that one or more actors have on the global state of a land use system. This in turn might help users of such a simulation system to better assess a plan and get a grip on its feasibility and possible side effects. Our discussion focuses on the use of MAS for developing land use change models by including the process of spatial planning and multi-actor decision-making. To accomplish our objectives we describe a concept and implementation of a prototype of a MAS.

The paper starts with a description of the context of multi-actor spatial planning. It provides a conceptual framework of multi-actor spatial planning and multi-actor decision-making. Based upon this conceptual framework the third section deals with the architecture used to implement a prototype of a MAS. The fourth section reports the results of experimental runs for a case study in the Netherlands. The last section discusses and concludes on the potentials and drawbacks of the followed approach.

5.2 The multi-actor spatial planning process

5.2.1 Conceptual framework of multi-actor spatial planning

Spatial planning involves the study of the psychology, logistics, economics, and sociology of individual and group decision-making processes. In our study actors in decision-making are considered to be organizations or interest-groups that have a common interest to participate in the planning process. These groups or organizations are labelled for example as 'the farmers' or 'the environmentalist'. Decision-making is often organized through interest-groups in co-operation with the more formal administrative bodies such as regional or local authorities (Faludi, 1973); mainly for highly regulated countries such as the Netherlands (Valk van der, 2002). In our study, we assume organizations and interest groups to provide a consistent and stable and well documented behaviour in a spatial planning process, specially about what should be done within a spatial area to be planned. The opinion of actors is assumed to be a result of meetings with and consultations of the individuals represented by the actors. Moreover actors in a planning process have the common goal to produce a spatial plan that is somehow accepted by all involved actors. A spatial plan is the result of a negotiation and communication process between actors with different and sometimes orthogonal views upon the possible scenarios of a spatial environment. Negotiation and communication ends at least in a consensus, when all involved actors accept the selection of some alternatives (spatial scenarios), but not necessarily the selection of optimum ones. We consider spatial-planning a process oriented activity. It is aimed at satisficing rather than optimizing (Simon, 1996). The emphasis lies on heuristic rules and searching for solutions that are good enough (Keen and Scott Morton, 1978).

Finally, the main goal of each actor in a planning process is to perform an *a-priori* defined spatial allocation task. Therefore, an actor evaluates a spatial system, which consists of a spatial environment influenced by dynamic and autonomous processes. Actors also interact with other actors directly involved in the spatial planning. In a real world situation actors are likely to encounter also actors not directly involved in the spatial planning process but who might influence the process. However, our study has limited the complexity of the model by only taking into consideration actors who play an active role in the spatial planning.

Figure 5.1 shows our conceptual framework for modelling a multi-actor spatial planning process. Multi-actor planning is described as having the following characteristics:

- actors who can observe and perceive a spatial environment;
- based upon these observations and perceptions they generate a preference for a desired spatial scenario;
- actors communicate and negotiate their preferences during their interactions with other actors;
- the preferences of the actors serve as input for a final decision-making (the decision-market);
- the final decisions are implemented in the spatial system.

Observations and perceptions are directed by the desires of an actor and, the overall goal of the planning process. In our approach the overall goal is based on auxiliary driving forces that lead to spatial claims for a certain type of land use. Driving forces that lead to these demands are for example, economical, technological, demographical, and social-cultural developments.

During a decision-making process, an actor generates preferences of how the spatial environment needs to be organized in respect to its desires and the overall goal. These preferences are input for the 'decision market'. In the decision market preferences of individual actors are compared. Based upon differences, similarities, and hierarchies, a final decision, acceptable to all involved actors, is made. However, before final decision-making is done, actors communicate and negotiate their preferences with other actors. They try to influence, convince or co-operate with other actors whenever necessary to improve the position of their preferences on the decision market.

5.2.2 The intentional model of multi-actor actor decision-making

To construct a notion of actor decision-making that complies with Figure 5.1 we consider a generic model of intentional decision-making by individual actors in relation to the spatial system. Figure 5.2 presents a simplified version of this intentional model based upon the work of Kleefmann (1984) and the decision theory of Simon (Dillon, 1998; Simon, 1960) Actors are coupled to

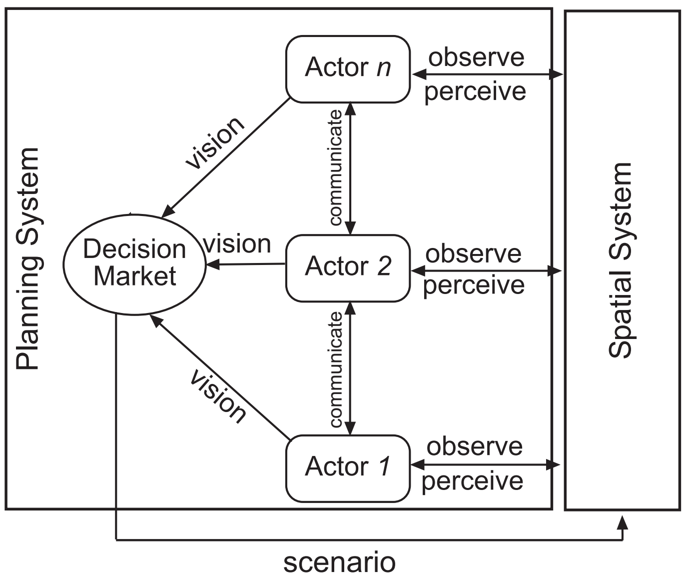

Figure 5.1: Conceptual framework of multi-actor spatial planning.

the spatial system as decision makers. They act and react upon the spatial system. Each actor is assumed to have *desires*. Desires are what an actor wants to be true in a spatial environment in terms of position, location, area, and shape of spatial functions. Spatial functions are, for example, agriculture, forest, nature, or urbanization. How these functions are defined depend on several factors including the scale of spatial planning (national, regional, or local), the type of planning (for example strategic or operational), and the type of actor (the regional authorities probably defines nature differently than the farmers organizations). Desires (box desires) define the context for the *observations* and *perception* of objects in the environment of an actor (arrows 'observe/perceive'). While observing, an actor encounters many objects. Perception in this context is the filtering of observations done by an actor based on the desires. Perception results in *beliefs* about the spatial environment (box 'beliefs'). The term beliefs refers to the current state of

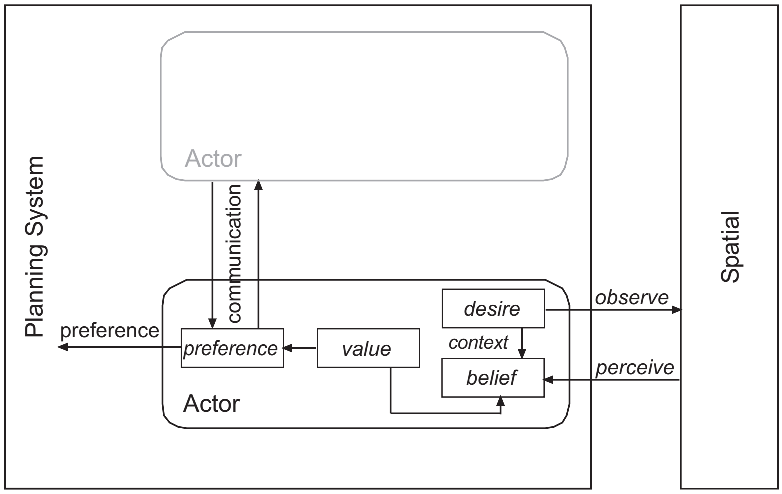

Figure 5.2: Intentional model of actor based decision-making.

the environment an actor considers to be true in the context of its desires.

Analysis of the difference between the believed and the desired land use functions leads to *preferences* (box 'preferences'). Beliefs and preferences are based on the set of values that is part of an actor. Values define the relevance, importance, and acceptability of the differences between the believed and the desired environmental states. Values are based on the social, cultural, economical, and political background of the actor. These values are used to pass judgement on the observations and beliefs. Besides the internal set of values, the preferences of an actor are also influenced by the preferences of other actors. In a conflicting situation an actor might be forced to redefine its preferences to achieve the overall goal of the planning. Finally, a decision-making process (arrow 'prefer') in Figure 5.2 leads to what we call a *vision* representing the individual view upon a future situation. Figure 5.2 describes the process for a single actor situation. In a multi-actor situation every actor generates an actor-specific vision.

The above described process of individual decision-making of an actor comes with a number of assumptions; which can be described as one of the following:

- each actor has full information about its environment. This means, each actor can access the same kind of information;
- each actor has clearly defined desires and values;
- each actor agrees with the planning process as describe above;
- each actor is obliged to fulfil its main task: allocate new land use functions.

We realize that these assumptions are abstractions of a real world multi-actor planning process and the individual decision-making. Actors not always comply with an ascribed process neither they normally have complete information concerning the social spatial system. In our MAS model actors are represented by agents. The agents act upon a representation of the spatial environment; in our case a land use map.

5.3 Description of the MAS model

MAS can be defined as a set of agents that interact in a common environment, able to modify themselves and their environment (Ferrand, 1996). MAS have their own problem solving capabilities and are able to interact in order to reach an overall goal (Oliveira, 1999). Interaction can occur between agents (agent-agent interaction) and between agents and their environment (Weiss, 1999). Agents in a MAS may be self-interested or co-operative (Huhns and Stephens, 1999). Agents themselves are defined as a software based computer model having the following properties (Mohamed, 2000; Green et al., 1997; Franklin and Graeser, 1996; Wooldridge and Jennings, 1995; Maes, 1994):

- goal-directed: an agent tries to fulfill a set of goals in a complex dynamic environment;
- autonomy: an agent should be able to operate without direct intervention by humans or other agents. Therefore, agents need to have control over their own internal states;
- social abilities: an agent interacts with other agents, humans, or both;
- reactivity: an agent need to have the ability to perceive their environment and respond to it;
- pro-activeness: an agent does not simply react to its environment but should also be able to exhibit some goal-directed behaviour;
- situated in some environment: If the environment changes the agent cannot longer exists.

Following the assumptions made in the former section our concept of a MAS is a simulation system that contains a set of agents that have a representation of the multi-actor decision-making process. The agents have a limited ability to reflect upon their own actions and actions of other agents and adjust their behaviour accordingly. The agents, however, are not fully autonomous; interaction with other agents is coordinated by the simulation engine. The architecture is derived from a Belief-Desire-Intention (BDI) architecture (see for example (Rao, 1991; Rao and Georgeff, 1995; Singh et al., 1999; Wooldridge, 1996)). We have not adopted the formal logic that belongs to it.

5.3.1 Information and Tasks

The tasks each agent need to carry out are: observe, perceive, prefer, and generate a vision (see Figure 5.3). To carry out these tasks, agents use information about the objects in the environment, the states these objects are in, their desires, their values and information from other agents. In the next sections the relations between the tasks and the information will be explained in more detail.

The environment consists of a lattice of cells $C = \{c_{ij}, c_{i+1,j}, c_{i+1,j+1}, \ldots, c_{i+n,j+m}\}$; where i, j are indexes that determine the location of the cell in the lattice. Each cell contains information about the state of the environment. The state of the environment is expressed as a vector $s_i = \{a_{i1}, a_{i2}, \ldots, a_{in}, O, P, B, pr_k\}$; where $a_{i1}, \ldots, a_{in}$ are common information of the spatial environment available to all agents (for example land use, soil, and property right), O observations and P perceptions done by the agent, B the beliefs generated over the desires, and pr the preference of a cell for land use k.

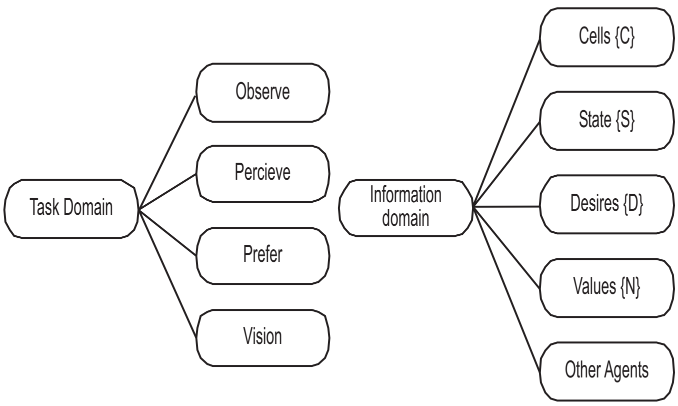

Figure 5.3: Tasks and information domains of the agents.

Observation and Perception

Constructing beliefs is done by perceiving relevant relations between states of the environment and desires. Desires are represented by a set (specific to one agent) $D = \{d_1, d_2, ..., d_n\}$. A desire itself is defined by a tuple $d = \langle C_{subj}, C_{obj}, n_{op} \rangle$. The set $\{C_{subj} \mid \in C\}$ represents cells that the agent needs to generate a belief about. $\{C_{obj} \mid \in C\}$ is the set of cells that is relevant in the context of the desire. The normative rule n_{os} defines qualitatively the relation between the C_{obj} and C_{subj}. An example of a desire is "...close to urban areas". In this example n_o is defined as "close to", the set of C_o contains the cells with state a_{in} defined as "urban areas", and C_{subj} are the remaining cells that need to be qualified according n_{os} . In the current model the following assumptions are made about D:

- D is defined *a priori*;
- D does not change during the planning process;
- D should always have a reference to C_{obj} known to the agent.

A belief is generated using a two-staged process. First the agent observes the relations between C_s and C_o by applying a function on each cell that maps a desire (d) and environmental state of a cell ($s_{c_{i,j}}$) to an observation for that cell ($o_{c_{i,j}}$)

$$Observe : \{d, s_{c_{ij}}\} \rightarrow o_{c_{ij}} \tag{5.1}$$

Relations can be defined, for example by topology, orientation, Euclidean distance, and attributes. Observation is expressed using well defined spatial metrics like m, m^2, or km. In the "...close to urban areas" example the observation is expressed as the distance of a cell (in m) to the nearest cell containing urban land-use areas in its state vector. The observation is added to the state vector as a fact in the form of *distance_to_urban(500)* representing the fact that this cell is at a distance of 500 metres of the nearest urban area.

The second step is to map an observed fact to a qualitative representation of it (named as perception). This mapping is done by applying a normative rule (n_{os}) to an observation $o_{c_{i,j}}$. This leads to the construction of a belief $b_{c_{i,j}}$ of believes. The process of perception is a function according:

$$Perceive : \{o_{c_{i,j}}, n_{os}\} \rightarrow b_{c_{i,j}} \tag{5.2}$$

In our approach beliefs are two valued: *true* if the normative rules applied upon the observations evaluates to true and *false* if not or there is no complete normative rule that can be applied upon the desire. The observations and perceptions are described as plans and stored in a plan library. A plan is a script that describes the required sequence of observations/perceptions that are needed to a belief about a desire. Observations and perceptions are executed by an agent by calling upon *observers.* An observer is a function defined outside the agent, (see Figure 5.4). It is possible (and likely) that different agents generate different believes over the same environmental states; for example if n_{os} or C_{obj} are different for both agents. Various agents

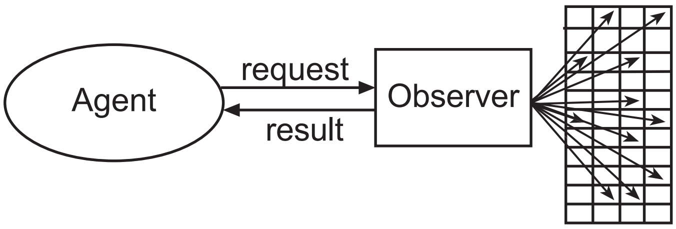

Figure 5.4: The concept of observers.

may share a same belief over different environmental states. A farmer for example, can have a different perception about areas that are valuable for recreation than, a city dweller. The first does probably not consider his farmland a valuable recreational area and thus does not include it in $\{C_{obj}\}$ while for the other actor farmland can be attractive as a recreational area. In this case the following assumptions are made for the observation and perception process:

- the scripts that describe observations/perception processes are defined *a priori* and do not change during the various phases of the planning process;
- the relation between the D and the required observations/perceptions processes is static;

Preferences

Preferences represent the intention of actors to exchange the current state of their environment for another state. Preferences are therefore indicators for the willingness to change the state of the environment at a certain location and at a certain time. Agents base their preferences upon their beliefs B. The plan library stores the knowledge about various combinations of beliefs. These combinations of beliefs map to a preference for a land use at at certain location ($p_{kc_{i,j}}$).

A belief for a certain location $b_{c_{i,j}}$ is assumed to be directly related to a specific desire d through the observation/perception process (see functions 5.1 and 5.2). This knowledge can be expressed as a preference related to a certain combination of desires that are fulfilled or not-fulfilled. The process of generating preferences for a land use (k) can therefore be expressed as:

$$\mathit{Prefer}: \{b_{c_{i,j}}, d\} \rightarrow p_{kc_{i,j}} \tag{5.3}$$

An agent can impose requirements upon the spatial ordering of the preferences, for example, with respect to the minimum size of a cluster with equal preferences. This for example is to prevent small isolated areas having a high preference to be taken into account during the decision-making process.

The preference $p_{kc_{i,j}}$ of an individual agent is influenced by the preferences of other agents in the simulation. Therefore, the agent requests to all other agents in the simulation to send their preferences. The agent then adapts its own preference according to the preferences of the other agents:

$$p'_{kc_{i,j}} = p_{kc_{i,j}} + \sum_{l=1}^{n} \left(\frac{p_{ak_l c_{i,j}} - p_{akc_{i,j}} * w_{a_l}}{N-1} \right) \tag{5.4}$$

where:
$p_{akc_{i,j}}$ = the preference of the agent for land-use k at the location of cell $c_{i,j}$
$p_{ak_l c_{i,j}}$ = the preference of another agent l for land-use k at the location of cell $c_{i,j}$
w_{a_l} = the influence of agent a_l to the calling agent a
n is the collection of agents in the simulation
under the restriction: $p_{ak_l c_{i,j}} \neq p_{akc_{i,j}}$

Considering the preferences the following assumptions are made:

- the relation between combination of beliefs and the preference is static and defined in advance. This means that an agent cannot 'change its mind' about a certain combination of beliefs;
- the set of belief combinations that might generate a preference is defined in advance. This means that if an agent encounters a combination of beliefs at a certain location and time which is not present in p_2, it cannot generate a preference. This means that agents do not have a learning capacity;
- the influence of other agents (the w factor) preferences is also static. No means are implemented yet to update this dynamically.

Decision-making

Decision-making is an activity carried out at two levels: the level of individual agent decision-making and the level of joint decision-making amongst all agents. At the level of an individual agent the decision of what land use is eligible for transition to urban areas is a function:

$$Decide : \{\{P\}, Claim_k\} \rightarrow Vision_k \tag{5.5}$$

This means that the agent creates a vision of where to allocate land use k based on beforehand defined spatial claims for that land use. This function decides based upon a preference order between all the preferences P in the environment:

$$p_{ik} \succ p_{jk} \succ \cdots \succ p_{nk} \tag{5.6}$$

where p_{ik} is the preference at the i^{th} order for land use k and n the number of spatial objects in the environment. The agent effectuates the decision by exchanging cells into the desire land use state until the claim for that land use is met:

$$Transition = \begin{cases} true & \text{if i} \leq claim_k \text{ and } p_{ik} \geq \text{threshold} \\ false & \text{otherwise} \end{cases} \tag{5.7}$$

Figure 5.5 shows a detailed picture of the state sequence of an agent and the flow of information within this agent. A simulation engine handles the transitions of the agent to the different states. Each agent maintains an individual instance of the spatial environment.

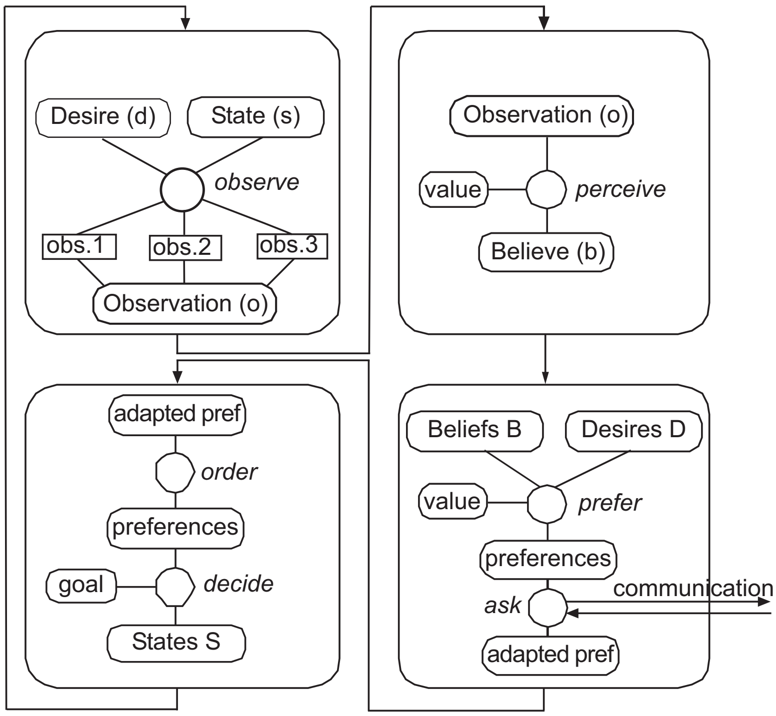

Figure 5.5: Task and information flows for an individual agent.

To accomplish the main task of the MAS for the simulation of land use change as the *result* of multi-actor decision-making, a joint decision still needs to be generated. This implies that decisions made at the level of individual agents need to be compared with the individual decisions of the other agents in the simulation (see Figure 5.6). All agents put their individual generated desired state of the environment into a voting procedure. Various models of collective decision-making are developed and applicable to reach a joint decision (see for an overview Sandholm (1999)). For this study a hierarchical approach to decision-making based upon a weighted voting algorithm was chosen according to (Ligtenberg et al., 2001). To let the agent adapt to the decisions made by other agents we have divided the allocation task into a number of sub tasks. This enforces a frequent shift between individual and group decision-making. For example, if the goal is to allocated 200 hectares of new urbanization in the planning area this problem is solved into a number of allocation steps (e.g. 10 steps of 20 hectares). This allow agents to adapt their view upon the environment regularly, based upon the actions of the other agents.

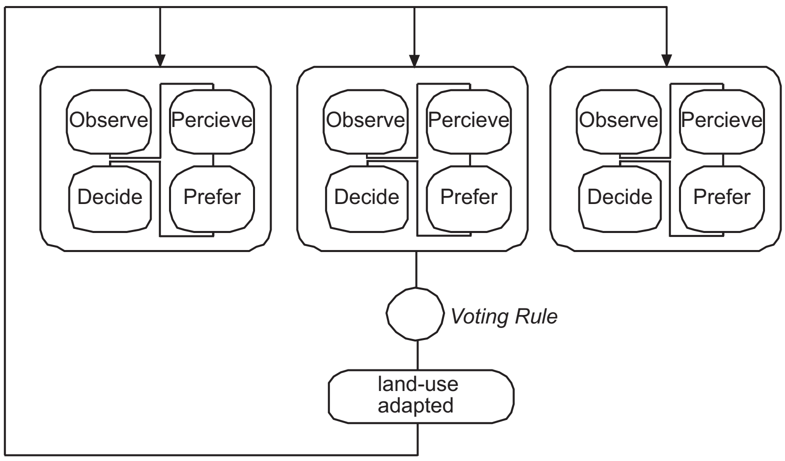

Figure 5.6: The group decision-making process.

5.4 Case study

To demonstrate the above described model a hypothetical land use planning situation was implemented for a part of the 'Land van Maas en Waal'. The study area is located in the Eastern part of the Netherlands (see Figure 5.7). The area consists roughly of 66 % pasture and 26 % agriculture. In addition, orchards are a prominent feature in the area. The "Land van Maas and Waal" has a number of small towns. Parts of the "Land van Maas en Waal" belong to the nodal point Arnhem–Nijmegen. This generates pressure upon the area to supply for new urban areas. Therefore the question where to locate this new urbanization is highly relevant. The involved actors need to allocate 200 hectares of new urbanization to fulfil the future needs of the surrounding cities (mainly the city of Nijmegen) for new housing. This case

Figure 5.7: The study area: "Land van Maas en Waal".

is not grounded onto an elaborated survey, but based on general knowledge of the demographical, economical, and political processes that take place in this area. A number of assumptions are made:

- existing urbanization is considered fixed;
- roads, railways, and water cannot be transformed into urban areas;
- all involved actors have equal information about the area.

To demonstrate the MAS we simulated three scenarios that represent different styles of spatial planning:

- co-deciding: all involved actors have equal decision power. This is a somewhat imaginary situation, not likely to be encountered during a real-world regional planning situation;
- co-deciding with a power player: every actor has different levels of decision power but one has considerably more decision power then the others. This represents, for example, a bottom up type of planning at regional level where various actors jointly come up with a plan but where there is still one actor that might overrule the others;
- consultation: the most common type of planning in the Netherlands. There is one decision-maker (most likely the national or regional authority). Other actors give advice to this actor for his decision-making.

Three different agents are implemented: the regional authorities, the farmers organization and the environmentalists. For each agent a number of desires concerning new urban areas are formulated as follows:

- Regional authorities:
  - as much as possible concentrated around existing urban conglomerates;
  - close as possible to the main roads;
  - within cycling distance of recreational areas;
  - preferably at locations currently having agriculture and pasture.
- Farmers organization:
  - as far as possible from existing agriculture and pasture;
  - nearby existing big cities;
  - keep the existing small villages small.
- Environmentalists:
  - no urbanization in the big open areas;
  - keep the existing orchards;
  - nearby existing urbanization.

5.4.1 Construction of the scripts for perception and preferences

For each desire, scripts for observation, perception and preferences are constructed. If we take, for example, the desire "as much as possible concentrated around existing urban conglomerates" the following steps need to be carried out to generate a belief:

1. an observation action is formulated that correctly allows the agent to invoke an observer that generates urban patches and calculates the sizes of these patches;
2. a perception action applies a normative notion of urban conglomerates on the results of the observation rules i.e. the minimum size the municipality believes an urban patch can be regarded as a conglomerate (in our case they are the urban patches that are bigger then 200 hectares);
3. an observation action is applied that allows the agent to activate an observer able to calculate the distances of all cells to the nearest urban conglomerate;
4. a perception action is applied upon these distances in order to meet the desire "concentrated around" (in our case less then 1500 metres).

To generate the preferences, a binary (true, false) decision table was used that indicates the contribution of each belief to a final preference. Table 5.1 shows a part of the decision table implemented for the municipality of Nijmegen. An agent generates a high preference for urbanization at a certain location if true beliefs are found for the following preceptions: "is agriculture or pasture", "close to an urban conglomerate" and "close to a main road", and "within cycling distance of recreation". As a consequence of the 2-valued

Table 5.1: Part of the decision table of the regional authorities for high, moderate or low preferences for urbanization.

desire	**high**	**moderate**		**low**	
is agricultural or pasture	true	true	true	true	true
close to urban conglomerate	true	true	true	false	false
close to roads	true	true	false	true	false
within cycling distance of recreation	true	false	false	false	false

logic used for the reasoning over the perception the decision table must have a declaration for all possible true–false combinations. If a combination is not present in the decision table, an agent cannot generate a preference over it. The agents then assumes it unknown. As a result the preference is ignored during further decision-making.

5.4.2 Implementation

The MAS was build using the simulation toolbox REPAST. REPAST is a SWARM (Hiebeler, 1994) clone entirely based upon JAVA, which makes it relatively easy to use. REPAST is used to implement the agent structure itself, the schedules and action lists to maintain the state sequence of the agents. The schedule ensures that agents can execute their tasks (see Figure 5.3).

The observers are implemented in Java using basic GIS algorithms for distance, patch, centroid, shapes, and queries. These algorithms can be invoked by the agents to provide for sensory input of the environment during the observation/perception state (see Figure 5.4).

Environmental state and location information of the spatial environment are stored in JAVA objects: the geo-objects. Each geo-object represents one cell of the grid. Results of actions of the agents are also store into geo-objects to facilitate easy visualization and analysis in a GIS. The geo-objects are data objects only equipped with methods to add, update, or remove data. A standard GIS system (ArcView 3.3) is coupled (using a DDE link) to the agent system to present and analyze the data stored in the geo-objects.

The agents can call upon the RETE based rule JESS engine to process the scripts for observing/perceiving and generate preferences. A JESS rule generally consists of a left hand side containing predicates and a righthand side that contains the actions that might be executed when the predicate pattern is matched (see for example Figure 5.8). The execution of an action

```
(defrule observe_urban_conglomerates
    ?ph <- (observe concentrated_around_urban_conglomerates )
    (agent (OBJECT ?agent) )
    =>
    (retract ?ph)

    ;//observation of urban areas
    ;//-----------------------------
    (call ?agent setObserver
        "PatchObserver" ;//name of the observer to be executed
        "Observe"  ;// tell the observer what to do and provide info to the agent
        (create$ "Integer" "Agentfield" "Agentfield" "String" "String" "Integer")
        (create$ ?*urban_area* "env" "agentWorld" "urban_areas" "state" "0")
    )

⋮
```

Figure 5.8: Part of a JESS rule for an observation script

only takes place when the rule is fired. A conflict resolution scheme handles the firing of the rules. All geo-objects are asserted as facts to the rule engine at the moment the agent enters the perception state.

5.4.3 Results

For each scenario 200 hectares are assigned in 20 iteration cycles (10 hectares each cycle). The desires (and thus the rules for beliefs and preferences) were formulated in such a way that several potential conflicting situations are likely to occur. Figure 5.9 shows the result of the 20 iterations. For the co-deciding scenario with equal decision power, we see that the pattern of allocation is relatively scattered with patches of new urbanization allocated in the relative open area in the north-western part of the study-area (there are some small villages in that area). This pattern is the result of each agent having equal opportunities to realize its own desired situation. Figure 5.10 illustrates this behaviour.

The assigned urban areas are equally divided amongst the agents. Only the farmers organization was not able to satisfy its desires as fully as the other two agents. This is due to the farmers organization desire to maintain existing agricultural areas. The farmers are often overruled by the willingness of the regional authorities and (to a lesser extent) the willingness of the environmentalist to exchange agricultural areas for new urbanization. The average relative assigned preference (45.3 % of the desired land use change has been realized) is relatively high when compared with the two other scenarios. The standard deviation (14.8) however is also relatively high indicating a strong fluctuation during the assignment phase.

In the second scenario (co-deciding with a power actor) the voting power of the regional authorities was twice as high as the other agents. This results in a more compact pattern of newly assigned urbanization mainly near existing large urban areas. If we look at the graph in Figure 5.10 we see that the relative assigned preference of the regional authorities is higher throughout the assignment process. As expected the average for all agents (38 %) is lower. The lower standard deviation (10.1) indicates less fluctuation in the system.

For the consultation scenario the farmers organization and the environmentalist had no decision power. We increased however the importance of these agents for the local authorities (the w factor in the equation 5.4. This means that the preferences of these agents are heavily included in the decision-making of the regional authority. The resulting land use pattern (see Figure 5.9) is similar to that of the power actor scenario. We obeserve a bit more new urbanization around the cities of Nijmegen and Wijchen. The average relative assigned urbanization (37.3%) and the standard deviation (9.9) is comparable to that of the former scenario. In Figure 5.10 we can see, however, that the desires of the regional authorities are almost completely met throughout the assignment phase. The environmentalist group is only occasionally satisfied while the desires of the farmers are almost completely discarded. Table 5.2 shows the change in land-use as the result of the three

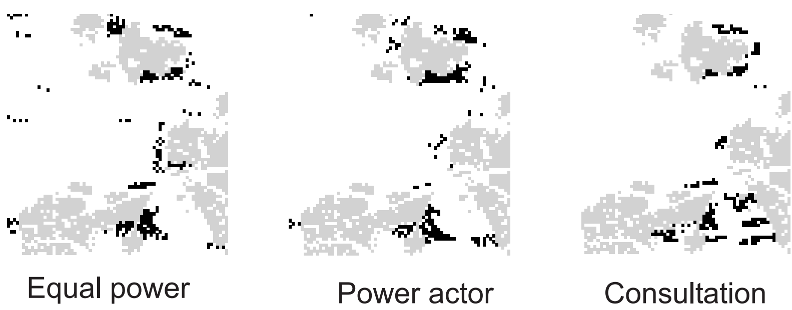

Figure 5.9: Newly assigned urban areas for the 3 scenarios (grey: existing urbanisation, black: newly assigned urbanisation.

scenarios.

For all scenarios most of the required area for new urbanization is provided by pasture. For the power actor and consultation scenarios the contribution of “deciduous forest in urban areas” and “pasture in in urban areas” to the new urban areas is higher. This probably due to the fact that near to existing urban areas these land uses are relatively more present then in the rural parts of the study area (i.e. the north-west region).

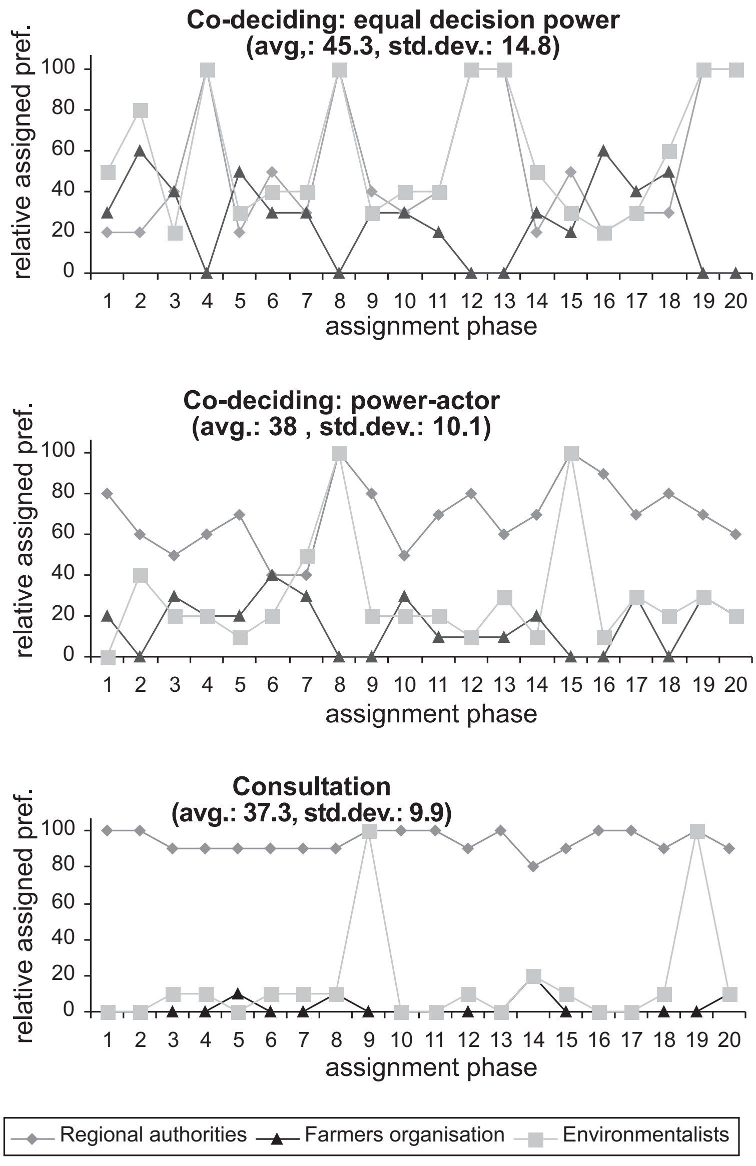

Figure 5.10: Relative assigned preferences for the 3 scenarios.

Table 5.2: Change in land-use for the three scenarios.

land-use	equal power	power actor	consultation
pasture	-87	-90	-75
mais	0	0	0
corn	0	0	-4
bare soil	0	0	0
greenhouse	0	0	0
orchard	-12	-6	0
deciduous forest	-2	-2	-14
coniferous forest	0	0	0
nature	0	0	0
bare soil in nature	0	0	-2
water	0	0	0
urban	190	190	190
urban in rural areas	0	0	0
deciduous forest in urban areas	-5	-3	-11
coniferous forest in urban areas	0	0	0
forest in dense urban areas	-5	-3	-1
pasture in urban areas	-23	-23	-36
bare soil in urban areas	0	0	-1
road and railways	0	0	0
mixed agriculture	-56	-63	-46

5.5 Discussion and conclusion

From our design and implementation of the MAS for multi actor spatial planning model a number of observations and conclusions can be drawn on the concept, implementation, and future research directions‘.

The added value of the concept developed for our MAS can be described as on of the following:

- the use of agents for the represention of organizations or interest groups rather than individual actors provides, according to us, a more realistic modelling of the process. Taking individual people as building blocks of the model does not represent the planning process and unnecessary increases the complexity of the *model.* Organization and interest groups are the decision-makers at the level of multi-actor regional planning;
- it models desires, beliefs, and preferences of actors in the planning process itself and translate them into visions of actors. For spatial planning in the Dutch setting and for land use models in general this is rather unique;
- the outcome is not the result of comparing a relative static set of criteria (like MCA) but of a dynamic exchange of information between actors with different objectives and sets of criteria.
- our experiments showed that effects of hierarchical relations between actors can be made visible to a user of the model (see Figures 5.9 and 5.10);

- calibration and validation seem to be feasible. Goals, visions, desires of organizations and interest groups are normally more stable through time and better documented in. Also the history of decisions taken by organizations and interest groups can be traced better than that of individual stakeholders.

However, the main limitations are:

- no real reasoning about beliefs and preferences is available, only in a rule form. Real intelligence is something that is still far away for such complex land use planning processes;
- we could not make clear the usability of this approach for other applications which do not involve land use changes;
- we only studied a limited form of actor communication. Negotiation and cooperation are still missing in the model.

Although the MAS framework provides a flexible platform to experiment with various concepts and techniques at the level of planning-processes, decision-making, group-dynamics, spatial reasoning, agent interactions, and communication, it still is a research prototype with a number of shortcomings. They are:

- using a rule-based approach like the one implemented in this model, the number of rules rapidly expands with the number of observations, states and desires. This makes it not feasible to to cover all possible combinations;
- all rules are based upon a-priori knowledge concerning the preferences of the actors. Through the iteration phases the preference rules remain static. In real-world situations preferences over desires probably change due to feedback about an action of other actors or other (auxiliary) influences. The current implementation does not facilitate the dynamic changing of the rules by the agent itself and as result of direct agent to agent communication;
- beliefs are expressed using only values (either a belief is true of false). It is not the most appropriate representation for information about fuzzy concepts like close, far, and large. Also the modelling of the preferences is relative basic as the agent only use a static representation of a preference;
- reasoning about relations between spatial objects only contains some basic notions. Reasoning about real topological relations,for example, was not implemented.

Our future research work will focus on:

- the validation of our model. Especially the mapping of expressed desires to rules, observations and beliefs and the effects of interaction and communication between the agents. The main use of this type of models lies in the exploration of solution and problem spaces related to multi-actor spatial planning;
- the application of our approach into different planning situations;
- a more extensive comparison with existing integrated models would be desirable to verify the usability of our approach.

Based on the results of our experiments we draw the conclusion that MAS can generate land use patterns based on a description of a multi-actor planning process. It also can clarify the effects of actors under the regime of different planning styles on the land use, and show how the relations between actors change during a planning process and under various hierarchies of decision-making. The tool enable us to easily add more or different actors and play with the desires and preferences. As such it might provide a user with additional information and insight.

Chapter 6

Simulating knowledge sharing in spatial planning: an agent based approach

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This paper presents a MAS that simulates a multi-actor interactive spatial planning process. The MAS extends an existing approach with the principle of sharing knowledge amongst participating actors while trying to accomplish a shared vision. In the simulation actors are modelled as agents. They have desires and preferences regarding the future development of their environment. Based on this, they develop a view on what areas are eligible for change. A facilitator agent coordinates the exchange of information by indicating possible solutions and conflicts to the actor agents. The simulation is demonstrated by an allocation problem in a pilot area in the South-East of the Netherlands. Four different scenarios are implemented that demonstrate the impact of cooperation and hierarchy during an interactive spatial planning. Although the model is kept limited in terms of input-data the results show that it potentially can be used to provide insight in the relations and interaction amongst actors rather than predicting the results of an interactive spatial planning.

6.1 Introduction

Modern spatial planning often is organized as an interactive decision-making process involving all stakeholders concerned (Mansfeld, 2003). An important driver for this development is the wish to accomplish spatial plans that are broadly supported by the affected stakeholders. To realize such a planning it is important that participating stakeholders are seriously involved in the planning processes (Arnstein, 1969; Woerkum, 2000). In other words: in an interactive spatial planning process, stakeholders are considered actors in the planning process, having a role and certain tasks to fulfill. Interactive planning fits into a development that seeks to replace more traditional sector based spatial planning with an integrated, multi-sectoral ones. Increasing pressure on, mainly, rural areas caused by a multitude of demands, claimed by multiple actors necessitates such an approach. Interactive planning is generally focused on regional scales, with boundaries defined by, for example, a common cultural-historical identity, geomorphology, a comparable language etc. (Mansfeld et al., 2003).

Planning Support Systems (PSS) are developed to support interactive spatial planning. Geertman and Stillwell (2003) defines PSS as "geo-technology related instruments consisting of theories, information, methods, tools, etc. for support of unique professional planning tasks." A PSS can be considered as a special type of model based Spatial Decision Support System

(SDSS). The main task of a PSS is to assist planners and stakeholders to generate and evaluate alternative solutions for, mostly an ill- or semi-structured spatial planning task. A PSS may be implemented as a (spatial) decision support system (Carjens et al., 2003), a collaborative spatial decision system (Jankowski et al., 1997), a game (Duijn et al., 2003), or a simulation system (Hilverink and Rietveld, 1999). Often PSS are based on GIS-technology that provides for necessary data management, analysis, and visualization functions.

Current research shows that Multi-Agent Systems (MAS) are useful to develop PSS that include human action-taking and human decision-making as a driving force of spatial changes (Bousquet and Le Page, 2004; Parker et al., 2003). It proved to be useful for simulation of spatial dynamics (Laine, 2004; Deadman, 1999; Deadman and Gimblett, 1994; White and Engelen, 2000; Wu, 2002), spatial design (Moulin et al., 2003), or recently starting, for the discovery of spatial knowledge (Sengupta and Bennet, 2003; Wachowicz et al., 2005). It is argued that the need to include the "actor factor" into PSS and other GIS-based systems that support spatial analysis lies in the assumptions that (Ferrand, 1996):

- at least for most western countries, the majority of land use changes is induced by deliberate and planned actions;
- an increasing number of actors are playing a role in modern spatial planning;
- which results in multiple claims on the available resources, potentially leading to an increasing number of conflicts.

The proposed MAS extends an existing one (Ligtenberg et al., 2001; Ligtenberg et al., 2004) with the principle of knowledge sharing. It simulates an interactive spatial planning in which a number of actors jointly try to establish a shared perception of potential attractive locations for new urbanization, while minimizing the amount of conflicts. The potential use of such a PSS lies in the exploration of effects that preferences and goals of individual actors have on the results of the interactive planning process. Therefore, it might be used as a tool to provide insight and enable users to learn from experiments as a kind of game. It might also clarify potential routes to a solution for a complex spatial planning problem or to discover unexpected or unexposed relationships (Batty and Torrens, 2005; Goldspink, 2002). The MAS presented and demonstrated in this paper simulates the effects of an interactive regional spatial planning in which a number of aggregated actors jointly develop a spatial plan. The simulation is based on an existing interactive planning approach as applied in the Netherlands but is generic in nature.

6.2 Process Architecture of an interactive planning process

The interactive planning approach, which is simulated by the MAS, is known as the regional dialog approach. The regional dialog approach has been applied repeatedly in the Netherlands during the last years (Mansfeld et al., 2003; Mansfeld, 2003). The core concept of the regional dialogue process reflects the knowledge sharing approach of Nonaka and Takeuchi (1995). It considers a learning process having four iterative phases: socialization, externalization, internalization, and combination. In the initial phase of a regional dialogue, socialization serves to create trust amongst participating actors. Externalization refers to making implicit knowledge explicit while internalization refers to the process of accepting explicit knowledge as part of the joint stock of knowledge of participating actors. Combining means using the internalized knowledge to jointly build new concepts. During a regional dialog approach these phases are specified in a practical set-up for a participatory spatial process (Mansfeld et al., 2003).

The MAS presented in this research focus on the process of externalization, internalization, and combination. In a regional dialogue approach externalization and internalization are referred to as *joint fact finding*. Combination is referred to as developing a *shared broad vision*. Figure 6.1 shows schematically the regional dialogue approach. The scheme is based on interviews with experts in interactive spatial planning and the regional dialogue approach (both scholars and facilitators). In the figure two main sub-systems are distinguished:

- a representation of the social system;
- and a representation of the spatial system i.e. the area under planning.

In the representation of the social system, actors, considered representatives of organizations and interest groups, meet in a process where joint fact finding and developing shared vision are main activities. Based on their backgrounds and interests involved actors are assumed to contribute a number of desires regarding the future organization of the area under planning. These desires define the context for an actor to observe (a representation of) the spatial system. Based on a desire, an actor observes certain aspects of the spatial system. The results of these observations enable the actors to develop a perception about the difference between the current situation and the desired situation. Perceptions can be related directly to the state of the spatial system or be derived from it. To give an example: an actor may consider it undesirable to locate new urbanization near nature-reserves. He will therefore look for locations that are at a far-enough distance of existing nature. Often an actor has multiple desires that even might conflict with each other. The desire not to build near nature, for example, might conflict with a desire to live in quiet rural areas. The process of observation and perception results in a number of preferred locations. These locations are presented to other actors in a process of joint fact finding. Preferences are compared and areas of shared interest or conflicts are identified. In this process a facilitator plays an important role. His main task is to find consensus or conflicts (areas where actors agree or disagree), identify possibilities for solutions, and to keep the process of joined fact finding going. We realize that the above described

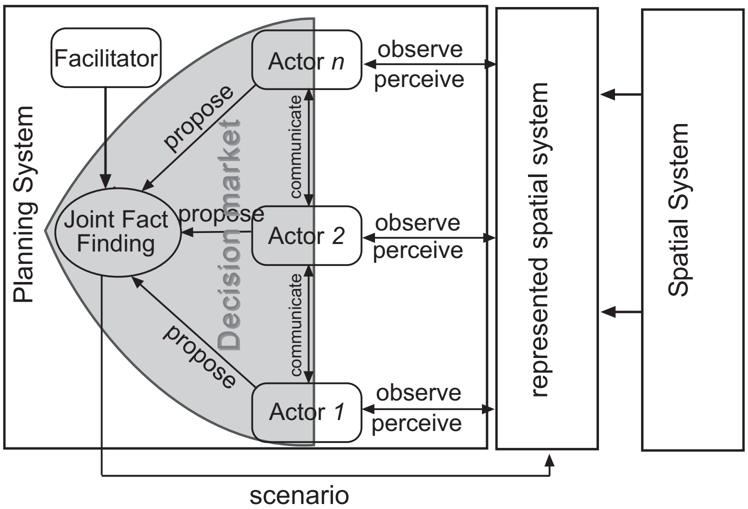


Figure 6.1: Joint fact finding in a multi-actor planning

process is a simplification of how a real-world regional dialogue planning actually takes place. It is based on a limited and stylized representation of the complexity found in processes where humans make decisions. Issues like emotions, personal conflicts, and group dynamics are not considered. The assumption is that the socialization phase has resulted in a situation where the actors are willing to positively cooperate. The main goal of the proposed MAS is:

- generate the contours of a shared vision as the result of a joint fact finding process by presenting maps;
- provide insight into the effects of implicit knowledge of actors (in terms of objectives, desires, and values) on the shared broad vision.

The use of the MAS can be rather diverse. It may support a facilitator to gain insight in the possible directions to search for solutions to a given planning problem. It can also assist a stakeholder to better understand the effects of his desires on the environment and on other stakeholders and vice-versa. The emphasis of the MAS is not to simulate an optimal solution that reliably predicts the outcome of an interactive planning process. It rather will be designed to explore possible directions that provide for solutions that are good enough (Keen and Scott Morton, 1978).

6.3 Model of the MAS

The sketch of the process architecture given in the former section is translated into an agent-based model that simulates the interactive planning process according to the following phases:

- actor agents observe their environment depending of what they considered important aspects for making decisions about a spatial planning problem. These observations results in a set of facts that describe the state of the environment according to an individual agent;
- these facts are evaluated by the agent and combined into an opinion about a preferred solution for a spatial plan. An opinion describes the preferred outcome of the plan according to an individual agent;
- each agent compares its own opinion with the opinions of the other agents in the model. The result is that each agent has valued all opinions of the other agents relative to its own opinion.
- the opinions and the opinions about opinions of other agents are communicated with a facilitator agent;
- the facilitator agent evaluates all contributions of the actors and identifies possible solutions based on analysis of conflicts and opportunities. The contributions of all agents are treated equally. This means there is no centrally settled hierarchy during the planning process;
- the facilitator communicates possible solutions with the actor agents. They include this new information into a revision of their opinions.

The first three stages correspond with the fact finding stages in the regional dialogue approach. The last three stages correspond with developing a shared broad vision. In the remainder of this section we explain the above phases into more detail. As from now on we use the term proposal to refer to the preferred opinion of an actor agent. The base of the agent model consists of the following components:

- a model of the area under planning (the environment);
- agents representing groups of actors (interest groups or organizations);
- one agent representing a facilitator that co-ordinates the process of joint fact finding and generating a shared vision;
- rules that steer observations, perceptions, and preferences.

The model of the area contains environmental information needed by the agents to accomplish their goals. Various information can be included such as, land use data, prices of land, hydrological or soil information, existing policy, and legal restriction on the land use. For the proposed model we assume that all involved agents have equal and full access to all spatial information present in the environment. Besides environmental information, the agents need a model of individual decision-making to enable them to generate a proposal. Figure 6.2 shows the process of an individual agent generating a proposal for its preferences. Based on desires, an agent carries out a number of observations of the environment. An observation is defined as a process of generating beliefs about one or more aspects of the environment. These beliefs can be of a geometric or thematic nature. Examples of observations are measuring the distance between spatial objects, calculating the area or shape of a spatial object, or determining what spatial objects belong to a certain, actor defined, thematic class.

Next, these observed beliefs are perceived based on a utility for that belief. Each agent maintains an individual set of utilities. This process of perception results into a set of percepts about the impact of a belief on the realization of its desire. Such an impact can be positive i.e. raise the suitability of a location for realizing a planning objective or negative. Using the percepts, an agent generates a proposal for the most preferred locations (box preferences) by following a personal decision-taking strategy. In the current model this decision taking is based on combining the total impact of all beliefs under a regime of geometrical requirements or restrictions.

Besides generating individual proposals for the most preferred areas, also proposal of other agents are taken into account during the decision-taking. Each agent rates the most preferred areas of the other agents based on its own percepts. A facilitator agent is involved to stimulate the internalization and combination of the information. Its main goal is to promote an convergence of the individual proposals towards a shared broad vision. All agents are requested to deliver their proposals along with their appreciation of proposals of the other agents to the facilitator agent. Based on this the facilitator agent presents information to the actor agents about areas that appear promising to contribute to the development of a shared vision. The actor agents include

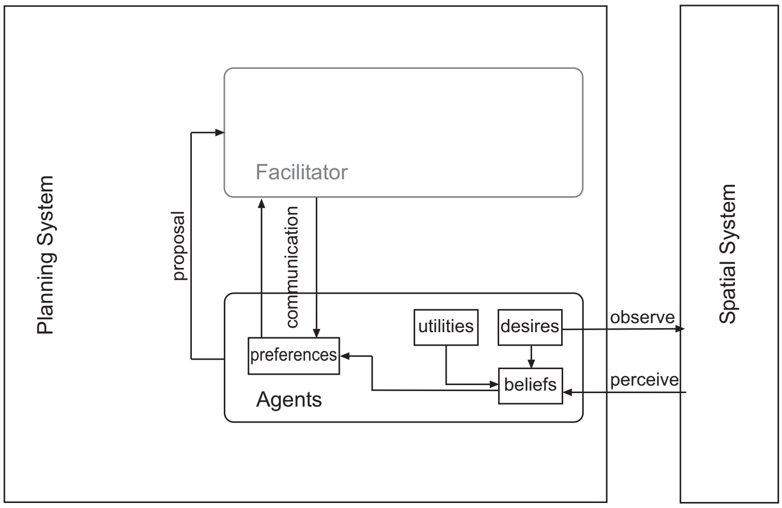


Figure 6.2: The process of generating preferences

this information into a review of their opinion. This process is iterated by the facilitator agent in an attempt to bring together the individual proposals of the actor agents.

The above described concept of the model includes the following assumptions:

- the agency is determined *a priori* and is static during the course of the simulation. This implies that no alternative courses of actions are allowed;
- the type and number of environment states are static. This means that, for example, no new type of land use can be introduced;
- each agent maintains a predefined set of desires. An agent cannot add new desires. It neither can change the utilities. This means that an agent cannot dynamically change its mind;
- the goal of the planning is determined "a priori". Determining a goal is not part of the planning itself;
- each agent is assumed to have full knowledge of and complete access to the environment.

6.4 Implementation of the MAS

The above assumptions lead to a stylized model of the planning process. In real-world planning situations actors not always comply with an ascribed process. Moreover, they usually have incomplete information about the environment and frequently change their minds. At this stage of the research, however, we accept the limitations imposed by these assumptions. In the following sections we describe in detail the formal implementation of the model.

6.4.1 Environment

The environment is formalized as an ordered collection of cells: $C = (c_{ij}, c_{i+1,j}, c_{i+1,j+1}, \ldots, c_{i+n,j+m})$ where i, j are indexes that determine the location of the cell in the lattice. Each cell represents a discrete part of the area and contains information about the state of the environment. The state of the environment is expressed as a vector $s_i = \{a_{i1}, a_{i2}, \ldots, a_{in}\}$ where $a_{i1}, \ldots, a_{in}$ are common information of the spatial environment available to all agents (for example land use, soil, and property right). The next section will elaborate on how agents process the environmental information.

6.4.2 Actor agents

The architecture used for the agent loosely resembles that of the BDI architecture (Rao, 1991; Rao and Georgeff, 1995; Wooldridge, 1996); without adopting the formal logic behind it. Figure 6.3 describes the sequence of tasks and the actions that an agent needs to perform. The agents sequentially carry out these tasks in order to comply with its objective to participate in the planning process. To enable an agent to carry out its task, it maintains a unique worldview. A worldview is formally defined as a tuple consisting of the following information $< D, F, U, P, \mathit{Pref}, \mathit{MPA}, \mathit{MPA}_o, \mathit{PSS} >$. D are the desires of an agent. Recall that desires are defined a priori at the beginning of the simulation. F is the set of observed beliefs for each cell resulting from the observation task, U is the set of utility functions attached to the beliefs. Utilities are static throughout the entire planning process and defined a priori, P is the set of perceptions about the current state of the environment, *Pref* is the set of preferences for realizing new land use, *MPA* are the most preferred locations for realizing a new land use. MPA_o is the the set of valuations of the MPA of the other agents in the play. Finally *PSS* is a possible solution space generated by the facilitator. In the ongoing of this section we describe the elements of the world view in more detail.

Observation Observation of actor agents means mapping desires to beliefs. This implies that the agent needs a set of desires D where each desire $d \in D$ represents a preferred thematic or geometric arrangement of a spatial

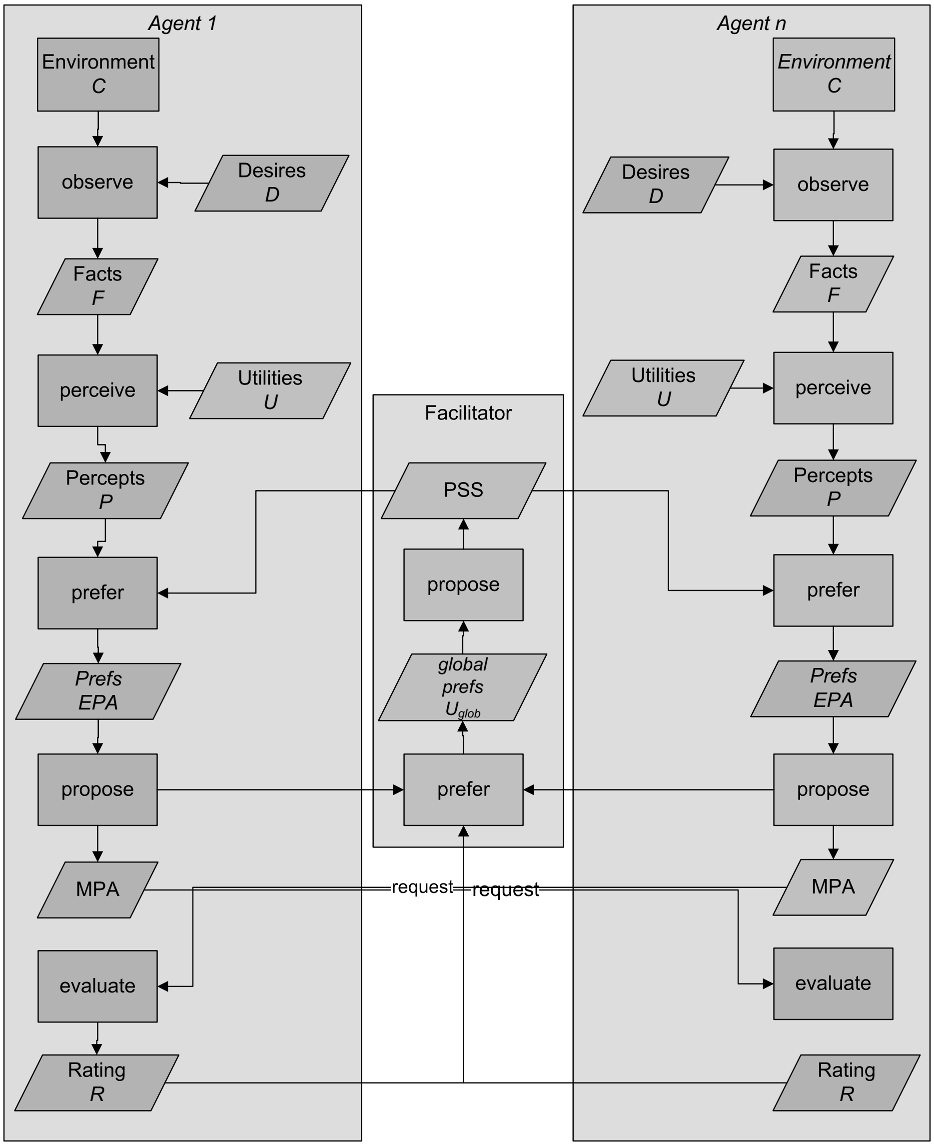


Figure 6.3: Flowchart of the agent tasks.

function. Each $d \in D$ is translated to a quantitative belief $f \in F$ about the environment:

$$observe : D \times F \rightarrow F$$

Which takes desires and, if required, already established beliefs of former observations and maps it to a new belief. The above mentioned rule states that there exists path dependency between observations. To give an example: a desire to realize new urbanization near to existing urbanization requires observation of beliefs about the distance of each cell to existing urbanization. These beliefs in turn need beliefs about urbanized areas.

At the implementation level, beliefs are generated by observers. Observers are predefined functions or algorithms that can be invoked at the request of an agent and that provide for a quantitative measurement of an aspect of the environment. By combining several observers, an agent is able to generate a specific belief. Most beliefs can be generated using a limited set of observers that can analyze distances, size, aggregated, and combined beliefs.

Perception At the next step the agent enters the perception stage. This means that each belief is mapped to a related percept $p \in P$. A percept is a value indicating the worth of a belief. The worth of a belief is a measure of relative contribution of a belief to the realization of the desires of an individual actor. A straightforward rule is currently used:

$$perceive = F \times U \rightarrow P$$

where P is the set of perceptions. The worth of a percept p is calculated according:

$$p_{i,j} = f_{i,j} * u_f$$

Where:
$p_{i,j}$ is the worth at location i, j for the value of belief f at that location, u_f is the utility value for de value of belief f.

Preferences All perceptions are combined into a preference *pref* for each location in the environment according a simple weighted sum:

$$pref_{i,j} = \sum_{i=1}^{n} (p_{f,i,j} * w_f) \tag{6.1}$$

Where n is the total number of beliefs. Thus a preference indicates the worth for an individual agent of a location for realizing a new land use.

Most Preferred Areas Based on their preferences the agent proposes a most preferred solution for the planning problem. Constructing a most preferred solution is basically a problem of selecting, out of the total set of preferences, according to a number of decision rules. For the presented case the decision rules are based on a) the sequence of the preferences and b) geometric restrictions (currently only a minimum and maximum area size). Figure 6.4 depicts the actions that the agents need to undertake to construct a proposal. At the first step the selection problem for the agents is simplified

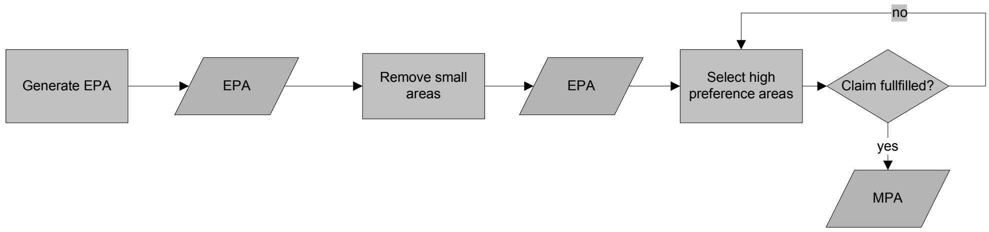


Figure 6.4: The generation of Most Preferred Areas (MPA).

by constructing an Equal Preference Area (EPA). An EPA consists of a set of cells that, according to the agent, have the same preference for realizing the goals of the planning. The idea of EPA is that real-world actors do not reason about a continuous field of preferences as generated by the simulation but tend to group and generalize these preferences in areas that are supposed to have an equal worth to an agent. This process of constructing an EPA, which is basically a generalization, is done by imposing a threshold rule upon the preferences of equation (6.1):

$$EPA = \{c \in C \mid pref_c + t_{pref} \geq pref_c \geq (pref)_c - t_{pref}\} \tag{6.2}$$

where: $pref_c$ is the preference of the actor agent for allocating land us c; t_{pref} is a threshold value "a-priori" defined for each agent. Under the condition that c is an element of a 2 dimensional Moore neighbourhood surrounding an existing cell $c \in EPA$. Secondly, the EPA is checked for its area and potentially other topological rules. Every agent may have a different threshold for the minimum or maximum size of an EPA. This to prevent, for example, small isolated areas to be include into the set of MPA. Next the EPA are sorted according to:

$$pref_{EPA_{ik}} \succ pref_{EPA_{jk}} \succ \cdots \succ ppref_{EPA_{nk}} \tag{6.3}$$

where: $pref_{EPA_{i,k}}$ is the preference of the EPA at the i^{th} order for land use k. Starting at the first EPA in the sorted order a random location is chosen within the EPA as a starting point and labelled as Most Preferred Areas (MPA). Using a 4-way floodfill algorithm the EPA is filled up till the claim is met or the EPA is completely filled. If the EPA is completely filled and the claim is not yet met, this procedure is repeated with the next highest EPA. Actor agents rate also the MPA of all other agents in the simulation according to the following rules:

$$\begin{array}{ll} \text{if} & (c_{i,j} \in MPA_{a,k}) \wedge (c_{i,j} \in MPA_k) \Rightarrow r_{mpa_{a,k,i,j}} = W_{sl} \times Pref_{epa_{k,i,j}} \\ \text{else if} & (c_{i,j} \notin MPA_{a,k}) \wedge (c_{i,j} \in EPA_k) \Rightarrow r_{mpa_{a,k,i,j}} = W_{sr} \times Pref_{epa_{k,i,j}} \\ \text{else} & (c_{i,j} \notin MPA_{a,k}) \wedge (c_{i,j} \notin EPA_k) \Rightarrow r_{mpa_{a,k,i,j}} = W_{ol} \times Pref_{epa_{k,i,j}} \end{array} \tag{6.4}$$

Where: $c_{i,j}$ is a cell at location i, j for the evaluating agent; $MPA_{a,k}$ is the MPA for agent a for land use k; MPA_k is the proposal of the evaluating agent; EPA_k is equal preference area land use k; $r_{mpa_{a,k,i,j}}$ is the rating for the proposal of agent a at cell i, j for land use k. The weights W_{sl}, W_{sr}, and W_{ol} indicate the importance for the evaluating actor agent of the proposals done by the other actor agents at respectively the same location, the same region, or at another region. These rules account for the speed and magnitude of the joint fact finding.

6.4.3 Facilitator agent

After the actor agents completed their tasks the facilitator agent requests all agents for their MPA and the ratings of the MPA of the other agents. Based on this information the facilitator agent selects areas that show a high potential to be positively valued by the joint population of actor agents. After normalizing all MPA's the ratings are combined in a straightforward manner:

$$U_{glob_{k,i,j,t}} = \sum_{a=1}^{n}((pref_{a,k,i,j} \times p_k) + \sum_{b=1}^{n}(r_{mpa_b,i,j,t} \times q)) \tag{6.5}$$

where:
$U_{glob_{k,i,j,t}}$ is a combined utility based at location i, j and iteration t for realizing land use k.
$pref_{a,k,i,j}$ is the preference for location i, j according to agent a for realizing land use k.

$$c_k = \begin{cases} 1 & \text{if } cell_{i,j} \in MPA \\ 0 & \text{otherwise} \end{cases}$$

c indicates that only those areas that are part of an agent MPA are taken into account.
$r_{p_b,k,i,j}$ = rating of the proposal of agent b at location i, j for realizing land use k

$$q = \begin{cases} 1 & \text{if } a \neq b \\ 0 & \text{otherwise} \end{cases}$$

The facilitator agent uses the U_{glob} to create a Possible Solutions Space (PSS) see Figure 6.3. This PSS indicates the area that has a high potential to contribute to a joint fact finding. A PSS reflects the area that has a high preference according to the joint 'opinion' of the actor agents.

The facilitator agent uses a similar procedure as the actor agent generating an MPA. First the facilitator agent creates equal potential areas (EPA) for assigning scenarios of urbanization based on the set of global utilities (U_{glob}) according to equation (6.5).

Next it determines the PSS using mutatis mutandis (6.3). The size of the PSS is determined by $a \times claim$ where a is an overbooking factor. The higher a the larger is the possibility of choice for an actor agent. The drawback of a higher a, however, is that the convergence to a joint solution probably will be slower due to the fact that there is a lower possibility of choosing the same locations. The PSS is rated by the actor agents according to rule (6.6):

$$\begin{array}{ll} \text{if} & (c_{i,j} \in PSS_k) \wedge (c_{i,j} \in MPA_k) \Rightarrow r_{pss_{i,j,k}} = W_{sl_{scen}} \times Pref_{i,j,k} \\ \text{else if} & (c_{i,j} \in PSS_k) \wedge (c_{i,j} \in EPA_k) \Rightarrow r_{pss_{i,j,k}} = W_{sr_{scen}} \times Pref_{i,j,k} \\ \text{else} & (c_{i,j} \in PSS_k) \wedge (c_{i,j} \notin EPA_k) \Rightarrow r_{pss_{i,j,k}} = W_{ol_{scen}} \times Pref_{i,j,k} \end{array} \quad (6.6)$$

Where: PSS_k is the PSS for land use k. $r_{pss_{i,j}}$ is the rating for the PSS at cell i, j for land use k. The weights $W_{sl_{scen}}$, $W_{sr_{scen}}$, and $W_{ol_{scen}}$ indicate the value for the evaluating agent for proposals of others at respectively the same location, in the same region, or at another region. The ratings of the PSS are taken into account by the actor agent at the next step in the simulation (see Figure 6.3).

The MAS has been built using the simulation toolbox REPAST. REPAST is based on the SWARM toolkit (Hiebeler, 1994) and JAVA based. REPAST is used to implement the agent structure itself, the schedules, and action lists to maintain the state sequence of the agents. Furthermore, REPAST is used to implement simple visualization of the results in the form of grid displays (see for a more elaborate description of implementation issues (Ligtenberg et al., 2004).

6.5 Results

6.5.1 Case study

To demonstrate the model we have selected a case in the South-East of the Netherlands. For a study area in the "Land van Maas en Waal" (see Figure 6.5) new urbanization needs to be allocated. The model deals with the question where to allocate urbanization. The "Land van Maas en Waal" is an area under relative high pressure of urbanization. The vicinity of expanding cities like Nijmegen and Arnhem increasingly require additional space to develop new urban areas. Currently the area consists mainly of agricultural areas. The proposed model deals with a spatial planning problem where multiple actors jointly develop a vision of where to allocate new urbanization. Each actor represents an organization or interest group that has own goals and desires. Following the philosophy of the regional dialog approach each actor has an equal status. The outputs are visualizations of the options and conflicts regarding the location of possible new urban areas. The remaining part of this section describes in detail the concept and design of the MAS for the above mentioned case. Although we illustrate the concept with a case study, the concept is generally applicable for spatial problems involving the allocation of a single land use.

Figure 6.5: Study area, the "Land van Maas and Waal".

To demonstrate and discuss the model three actor agents are implemented: an agent representing a farmers organization (farmers), an agent representing the nature conservation lobby (nature-conservationists), and an agent that represents a citizen (citizens). Each agent was assigned a (limited) number of desires they like to have fulfilled. The farmers are assigned the following desires:

- new urbanization should preferably be located around existing urbanized areas;
- not near present agriculture;
- not near small villages.

Similarly for the nature-conservationists the following desires were defined:

- new urbanization not near nature areas;
- new urbanization as less as possible around "historical" villages.

The citizens have been assigned the following desires:

- new urbanization around present urbanized areas;
- near forest and nature.

For each desire a script is designed and stored in the plan library of the agent. A script is a sequence of observations to be executed by an agent that results in a belief about the environment. For example to retrieve beliefs for the first desire the farmer agent need to execute the following plan:

- observe areas that have urbanization based on its definition of it;
- observe which of those areas can be classified as urbanized areas;
- observe for each cell in the environment the distance to the nearest urbanized area.

See Ligtenberg et al. (2004) for a more detailed description of how the observation process is implemented.

Figure 6.6 shows the beliefs resulting from the observation processes. The gray scaling indicates the value for the final beliefs. Figure 6.7 shows the utilities used for the agents to perceive the observed beliefs (note that for the citizens only one utility function is applied to both beliefs). For the purpose of demonstration of the model, these utilities are not based on surveys or other analysis of actor preferences. Rather they are estimations based on generic assumptions about the opinions of actors in the Netherlands. According to equation (6.1) the results of the evaluation of the observed beliefs are merged to a global perception. Figure 6.8 shows the global perception for the actor agents. The dark grey indicates areas which do not have any worth to the actor for realizing new urbanization, the light areas are valuable to an agent. For farmers the best location for new urbanization lies directly around urbanized areas as they strive to protect the existing agricultural areas. For the nature conservationists only "isolated" (most agricultural) and

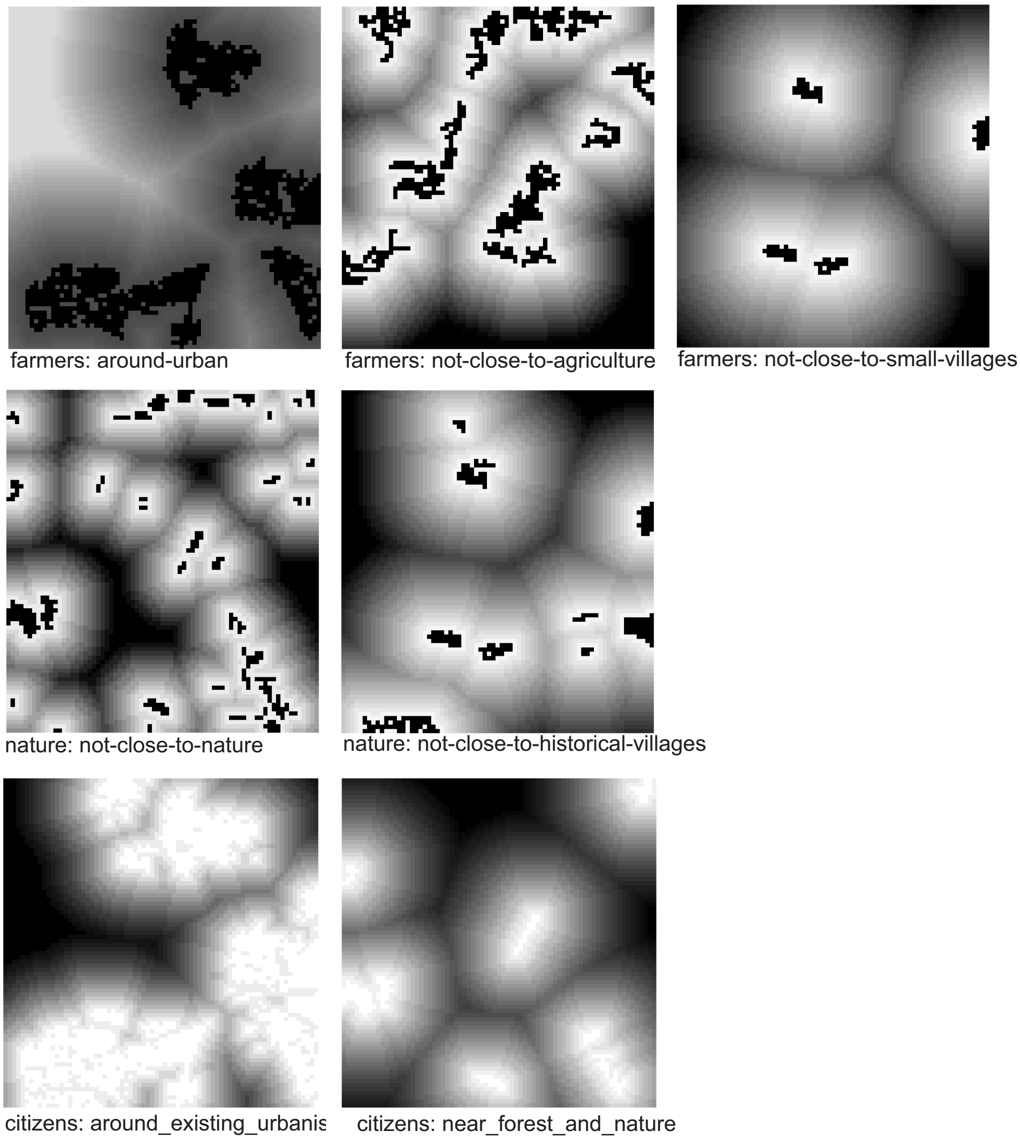


Figure 6.6: Maps of beliefs resulting from the observations by the actor agents. The gray-scale indicates the measured values (white = low, dark-grey = high).

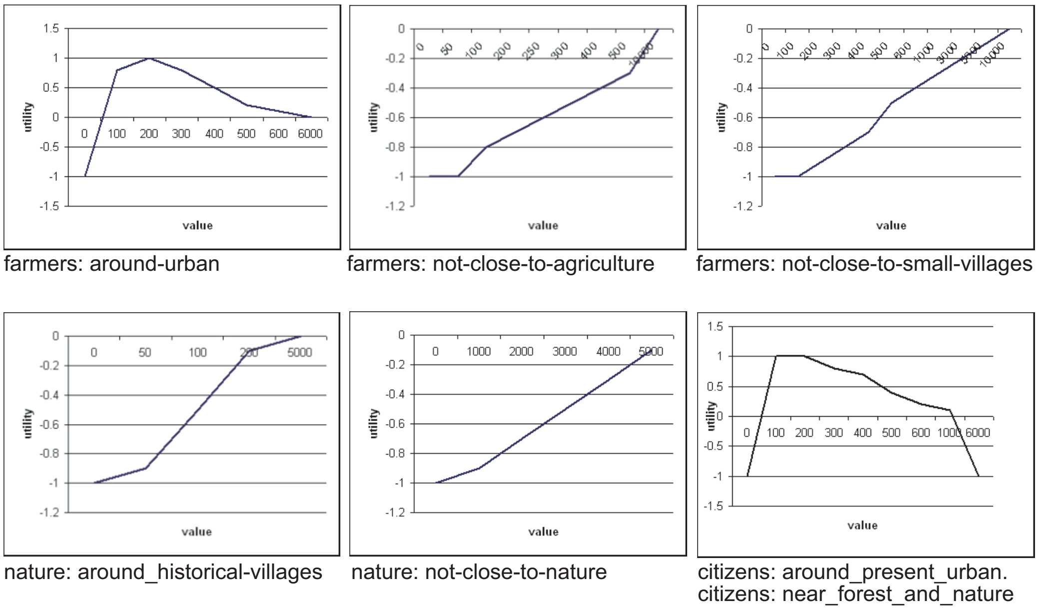


Figure 6.7: Utility functions used by agents to estimate the values for the worth of beliefs that are generated by the observations.

some areas in the south-eastern part are found eligible for new urbanization. This is the result of their striving to protect small villages, forest, and nature areas. The results for the citizens resemble that of the farmers. They only tend to prefer the northern part of the area more than the south.

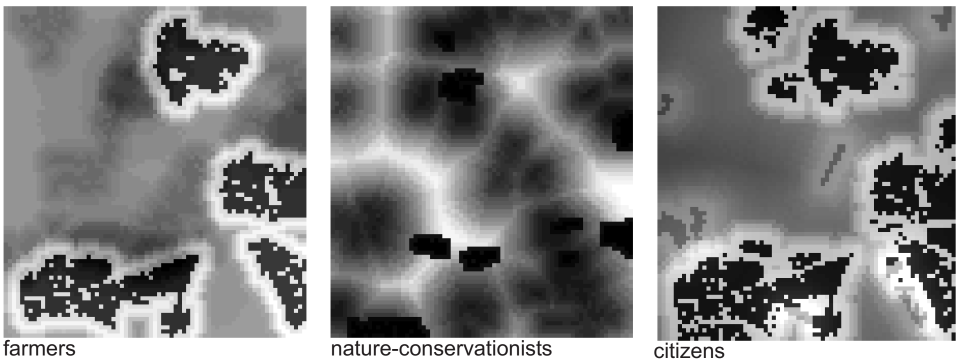


Figure 6.8: Total preference generated by the actor agents (at $t = 0$). Dark-grey indicates low utility, light-grey a high utility.

Figure 6.9 shows the MPA's (black) for new urbanization generated by the agents according to the procedure delineated in (6.2), (6.3), and (6.4).

Existing urban areas are shown in light gray.

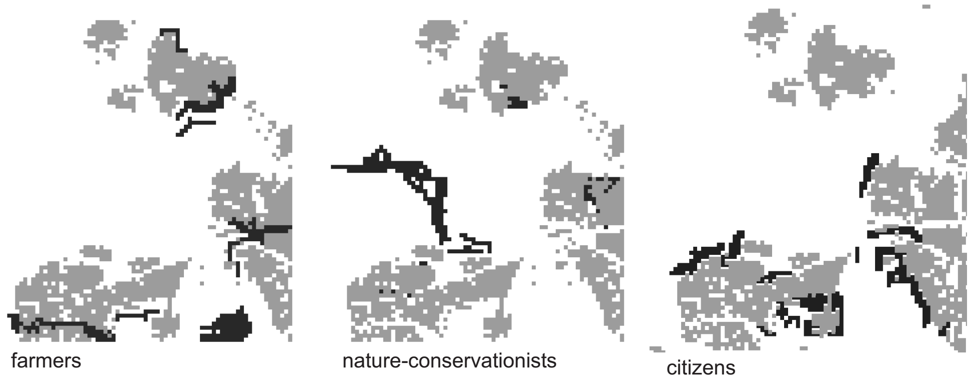


Figure 6.9: Most Preferred Areas (MPA) (black) generated by the agents (at $t = 0$). Grey indicates existing urbanization.

The individual MPA's and the ratings of them by other actor agents are requested for by the facilitator agent to construct a Possible Solution Space (PSS). Figure 6.10 shows the resulting PSS for the first iteration step ($t = 0$).

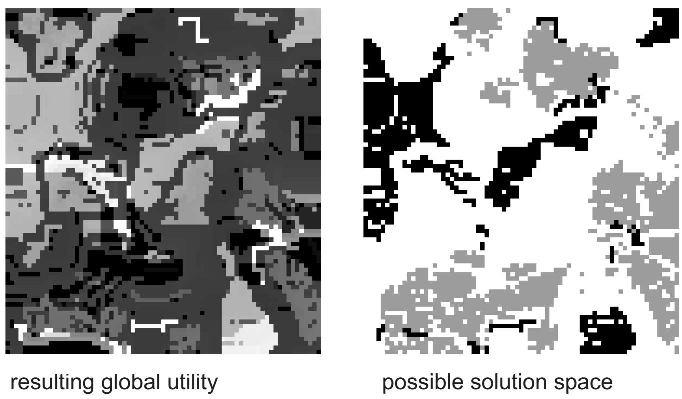


Figure 6.10: The joint utility and possible solution space according to the facilitator (at $t = 1$). Dark grey indicates low utility, light-grey a high joint utility.

Inspired by the work of Hofstede (2001) simulations are carried out for four different scenarios. These scenarios represent four cultures of decision-making:

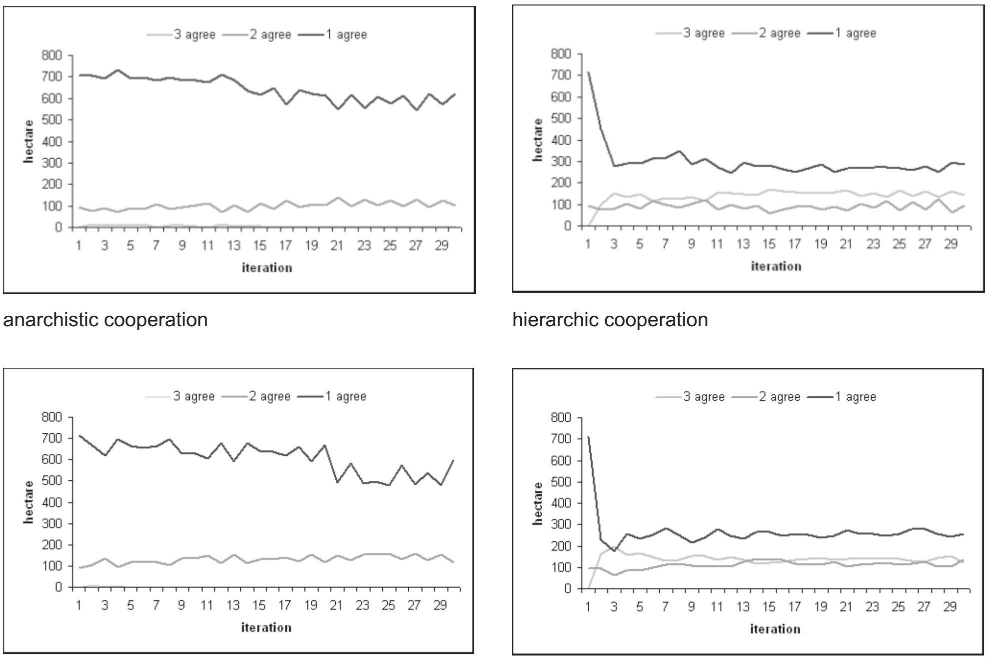
- culture of cooperation and hierarchy (coop-h);
- culture of cooperation and anarchy (coop-a);
- culture of non-cooperation and hierarchy (non-coop-h);
- culture of non-cooperation and anarchy (non-coop-a).

For all four simulations an equal set of desires and utilities was applied. Each scenario was implemented by changing the weights used to evaluate the MPA's of other agents and the PSS of the facilitator (see (6.4) and (6.6)). Changing the weights of (6.4) changes the willingness to cooperate. Similarly for the weight assigned to the evaluation of the PSS (see 6.6) is a measure for the role that a central authority (in this case the facilitator) plays in the process. Table 6.1 shows the values of the weight factors used in the simulations. The weights are chosen based on an evaluation of the sensitivity of the model and demonstrate clearly the four scenarios. They currently are not based on empirical findings. Other parameters like maximum and minimum size of the MPA's and the minimum worth to take into account were kept constant for all scenarios. Each scenario was run for 30 iterations. Figure 6.11 shows the number of agreements during the course of the simulations. It depicts the area for which all 3 actors, 2 actors, or only 1 actor have located their MPA. Most noticeable is the difference between hierarchical and anarchistical scenarios. For the hierarchic scenarios, in early iterations there is a swift convergence towards a relative stable situation. For the anarchistic scenario there is only a slow convergence. The drop around iteration 21 for the non-coop-a scenario is due to the nature actor who was, from that moment on, not able to fulfill its goal of 300 ha of MPA.

The resulting spatial patterns for the MPA (Figure 6.12) also show the difference between the anarchistic (coop-a, non-coop-a) and hierarchic (coop-h and non-coop-h) oriented scenarios. The magnitude of change for the two anarchistic scenarios is limited. The distribution of the patterns changes slightly. The majority of the change is for the nature-agent which MPA became more scattered. Furthermore part of the MPA for the farmers was reallocated around the existing urban area in the south. For the hierarchic

Table 6.1: Parameters assigned to the scenarios (explanation of abbreviations see equations 6.4 and 6.6.)

scenario	w_{sl}	w_{sr}	w_{ol}	w_{sl_scen}	$w_{sr_{scen}}$	$w_{sr_{scen}}$
coop-h	0.5	0.8	1	0.5	0.8	1
coop-a	0.5	0.8	1	1	0.5	0.1
non-coop-h	1	0.5	0.1	0.5	0.8	1
non-coop-a	1	0.5	0.1	1	0.5	0.1



anarchistic non-cooperation hierarchic non-cooperation

Figure 6.11: Number of locations chosen by 3, 2, or only 1 agent for the four scenarios.

scenario simulations, the resulting patterns show a more thoroughly reshuffle of the MPA. The lumped MPA pattern of the nature in the centre almost disappears while there are more MPA agreed upon by two or three agents around the edges of the urban areas.

6.6 Discussion and Conclusion

In this research a somewhat different approach was followed compared to many of the MAS developed to study dynamic spatial processes. A "traditional" MAS applied in geography in general consists of many individual agents competing for the same resources, each agent has its own goal and competes with the other agents in the simulation. The approach presented here, deals with a limited number of agents that try to reach a shared representation of the problem driven by a frequent exchange of information amongst agents. Our motivation to follow this approach is rooted in the nature of the problem. Spatial planning is not a pure competitive process but requires intensive communication and exchange of information and an explicit model of collaboration and decision-making. Moreover in spatial

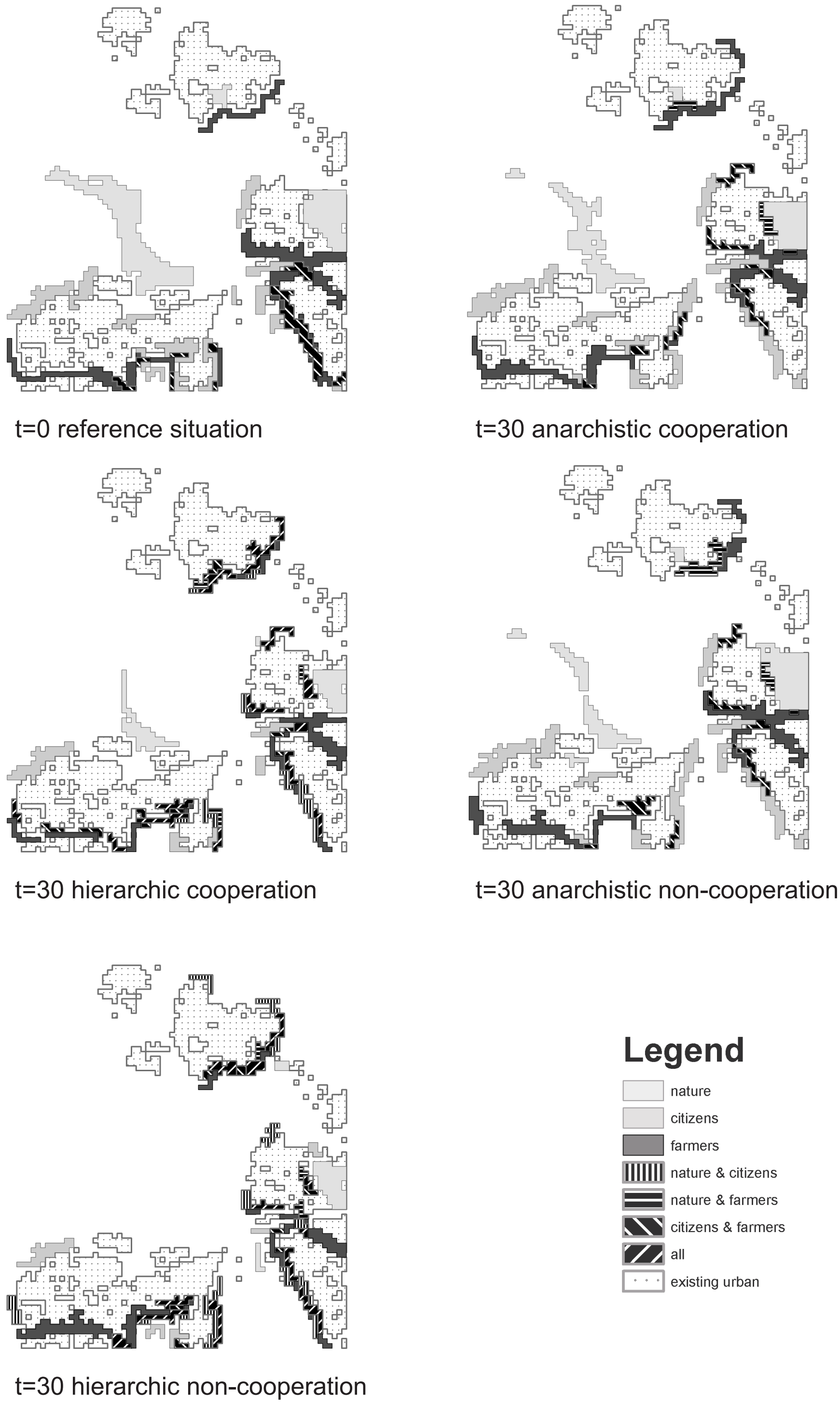


Figure 6.12: Resulting spatial patterns for the Most Preferred Areas (MPA's).

planning often individual stakeholders are not explicitly present during this process but are represented by interest-groups or other organizational bodies that participated on behalf of a stakeholder.

Although the model used to describe the real-world planning process is stylized and only captures the dynamics in a fairly limited way, some interesting phenomena can be observed. One of them is that a high influence of a facilitator (the hierarchic scenarios) leads to a clearly different pattern of agreements than when the suggestions of the facilitator are barely taken into account. The influence of cooperation is shown to be limited. Having a cooperative or non-cooperative culture amongst the agents does not significantly change the rate of convergence to a shared vision. An additional sensitivity analysis showed that a more intensive cooperation only had a limited effect on the number of agreements.

The main question is: what is the relation between the simulated behaviour and the behaviour of a comparable real-world system? We cannot answer this question completely in this paper yet since we have not carried-out a full validation. However we can identify some limitations of the current model:

- the agents have only limited information about the environment compared with real-world actors. In a real-world process additional information is used or needed to make decisions. In the current set-up we assume that the agent can locate their MPA at any location they consider suitable. However, often auxiliary restrictions are imposed on their decisions for example national policy, protected areas, and complicated ownership situations;
- the agent uses a rather primitive spatial reasoning model and do not take into account topological relations. Currently, agents only use size as a measure to define the MPA. However, other geometric and topological information like shape, orientation and relative position is likely to be important in the process of deciding about MPA;
- agents are fully rational in their attitude towards each other. This means that the agent accepts the information requested as sound information. In real life, the rating of information often depends on past experiences with the other. In a regional dialogue approach, trust amongst the participating actors is considered a key-factor for success;
- the algorithms to generate MPA en PSS are rather limited. They are based on the concepts that decisions are based on the positive elements of a former decision. In situations, however, where there is no significant convergence anymore, it can be very beneficiary to explore a fresh situation.

An interesting question, still remaining to be answered, is what to validate. Data driven validation methods are not very useful. Interactive spatial planning processes are aimed to explore new solutions for problematic spatial situations. This implies that existing trends are broken and often solutions are proposed which do not have a direct relation with historical situations. Although a spatial reference can be available which shows the result of a spatial planning, data about the process itself is not. Often it is impossible to trace-back the actors that were involved, their objectives, and their roles in the planning. Even if the objectives and priorities of actors are recorded, for example using MCA like techniques, the causal relations between the objectives and priorities of the individual actors is not known. Moreover, there is often a difference between stated desires and priorities of actors and their real actions.

We think therefore, given the potential use and scope of the model, that validation efforts should be directed not on determining the validity of (spatial) results but on observing and analyzing how the interactions defined in the model relate to interactions observed during a real-world planning. Our future research will focus on developing an approach for validating this class of models.

Chapter 7

Expert Validation of a MAS for spatial planning

This paper presents a qualitative validation of the model presented in Chapter 6. It starts with a general discussion about the pitfalls of validating agent-based models that simulate complex spatial systems. Next it briefly presents a methodology that allows the validation of the MAS model such that it rewards the goal and purpose of the model. The validation focusses on a face validation and a role play. Next the results of a face validation and role play are presented and discussed. The chapter finalizes with conclusions about the validity of the model.

7.1 Introduction

Multi-Agent Systems (MAS) are considered to offer concepts and techniques to develop models of complex organized systems (see for example (Goldspink, 2002). Systems are called complex if they are comprised of a large number of non-linear interacting, non-decomposable elements (Richardson, 2005). Complex systems often generate a surprising behaviour by adapting, mutating or transforming its elements (Batty and Torrens, 2005). An important characteristic of complex systems is its non-closure. In many cases it is difficult to draw a clear boundary around a complex system. Exogenous factors determine to a large extent the behaviour of a complex system and often it is difficult to state which components are part of a system, and which components definitely should be excluded. The main concept of the MAS approach is that it captures observed behaviour of organized complex systems by using (often many) fine grained entities (the agents) representing the main drivers for change of a systems' state. All agents are coupled to an environment and to each other by (often simple) rules. In principle each agent "behaves" autonomously reacting or pro-acting on what it "observes" in its environment. The effects of the individual behaviour of agents is a global change of the state of the environment.

Last decade MAS are increasingly applied in geography and spatial planning to simulate spatial-social systems. This means that effects of social entities (humans, animals) on the spatial configuration of a spatial environment are simulated. Various models have been developed to demonstrate the use of MAS for spatial economics, land use/cover change, spatial planning, ecology, urban spread etc. (Bousquet and Le Page, 2004; Parker et al., 2003).

Validation[1] of agent models of complex dynamic spatial models is currently a concern as it remains underexposed (Batty and Torrens, 2005).

[1]Validation is defined here as: the verification if the accuracy of a model, within its

MAS modelers have difficulties to apply traditional validation techniques upon MAS. Most validation approaches require an existing reference situation. This reference situation can be a historical case or results of other (already validated) models. The requirement of a reference situation makes traditional validation of limited use to validate MAS for spatial-social systems (Batty and Torrens, 2005; Moss and Edmonds, 2005; O'Leary, 1997). For situations that a reference situation is available, various techniques are developed that can deal with complexity issues. Examples are statistical validations (Rand et al., 2003), multi-scale and multi-resolution methods (Pontius Jr. et al., 2004; Kok et al., 2001; Costanza, 1989), cross-tabulation and difference matrices (Petrova and Pontius Jr., 2005), comparison to Null and Random models at various resolutions (Pontius Jr. et al., 2004) and path dependent validation (Brown et al., 2005).

This paper focusses on MAS that simulate a multi-actor interactive regional spatial planning process. (Mansfeld, 2003; Ligtenberg et al., 2004; Ligtenberg et al., 2001). For this type of application it is hard to define a reference situation as a consequence of having one of the following characteristics:

- most spatial planning processes are concerned with exploring new solutions for a problematic spatial situation. This implies that existing trends are broken and often solutions are proposed that do not have a direct relation with historical situations;
- decision-making in spatial planning is driven to a large extent by emotions rather than by ratio. As a result there is often a difference between stated desires and priorities of actors and their real actions. Surveys and interviews therefore are only of limited value;
- spatial planning processes are characterized by intensive iterations, numerous feed-back loops, and parallel processes like negotiations. Consequently, causal relations are hard to define and relations between actors may change continuously;
- already accomplished interactive multi-actor spatial planning processes cannot be repeated due to the the indeterminateness of the relations between the involved actors.

The arguments listed above lead to the conclusion that these types of models cannot be verified or validated in a traditional sense due to a lack of reference and the untestable chains of relations (see also (Batty and Torrens, 2005; Richardson, 2005; Edmonds and Hales, 2003; Sargent, 1999; Rykiel Jr., 1996)).

domain of application, has an satisfactory performance given the purpose of the modelling (Balci, 1997; Pontius Jr. et al., 2004; Rykiel Jr., 1996)

This paper presents and demonstrates an alternative approach to the validation of MAS models, applied for spatial-social process like spatial planning. Although the validation is demonstrated using a specific model it is believed that the approach is of interest to a wider range of models.

The first section briefly describes the MAS used to demonstrate the validation. The second section details with the applied methodology. The third section presents the results of the validation. In the last section the results are discussed and conclusions are drawn about the followed approach.

7.2 Description of the model

The Multi-Agent System (MAS) used to demonstrate the validation simulates an interactive multi-actor spatial planning process inspired by an approach known as the "regional dialogue approach" (Mansfeld et al., 2003). The regional dialogue approach is based on the SECI model of Nonaka and Takeuchi (1995). A regional dialogue meeting is characterized by four phases: socialization, externalization, internalization, and combination. Socialization serves, in the initial phase, to create trust among the participating actors and to get some basic insight of knowledge (desires, preferences) of each participating actor. Externalization refers to the process of making implicit (or tacit) knowledge explicit, while internalization refers to the process of accepting explicit knowledge as part of the joint stock of knowledge of participating actors. Combination means using internalized information to build new concepts together. Externalization, internalization, and combination often are applied according an iterative process, that facilitates continuous development of a shared vision upon the planning problem.

The MAS focus on the externalization, internalization and combination phases. Two types of agents are implemented: agents representing actors, and one agent representing a facilitator. Actors are considered organizations or interest groups rather than individual citizens (Ligtenberg et al., 2001; Ligtenberg et al., 2004). The main task of the facilitator is to co-ordinate the exchange of information by pointing out possible solutions and conflicts. The main input for the model are desires of the actors regarding the future state of the environment, which are expressed in a number of statements. Desires are basic elements that drive the knowledge sharing process simulated by the agents. This process is implemented according the following procedure:

1. actor-agents determine the current state of the environment. Therefore they observe the environment and acquire information about aspects of the environment that are related to a desire. The result of the observations is a set of beliefs describing the state of the environment

according to an individual agent in the context of its desires. For example, a desire to realize new urbanization near existing urbanization requires information about the distance of each location (cell) to existing urbanization. In turn, this information requires information on the areas that are believed urbanized by the actor-agent.
2. the set of beliefs is evaluated by actor-agents and combined into a proposal for the preferred solution to the spatial planning problem. Evaluation of the facts is done, using utility functions describing the relation between the value of a fact (for example a distance to) and the worth it has to an actor. The evaluation results in a perception of the impact of the various desires upon the possible solutions for the planning problem. Based on this perception a proposal for the best solution is selected by the agent.
3. each agent compares its own proposal with proposals of the other agents in the model; resulting into each agent having valued all proposals of the other agents relative to its own.
4. the proposals and the "rating" of the proposals of other agents are communicated with the facilitator agent.
5. the facilitator agent evaluates all contributions of the actors and identifies possible joint solutions based on analysis of conflicts and opportunities. The default settings of the MAS model treats the contributions of all agents equally. This means that no centrally settled hierarchy exists during the planning process.
6. the facilitator communicates the areas that offer possible solutions for the planning problem to the actor-agents. The actor agents include these new information into a revision of their opinions.

The output of the model are maps showing perceptions and preferences of agents and maps showing locations that offer possible solutions for the planning problem. The model is designed and inspired by a Belief, Desire, and Intentions (BDI) architecture (Rao, 1991) without adopting the formal logic behind it. It is implemented in JAVA using the REPAST framework. For a detailed description of the model see Chapter 6.

The goal of this model is threefold. First, it provides insight for users in:

- the effects of individual desires on the perceptions and preferences;
- the preferences and perceptions of other actors;
- the effects of joint preferences and perceptions on potential solutions for a given planning problem.

Second, a user should be able to "play" with it, as a research or training, and explore reactions of the system to understand how it works

(Axelrod, 2005; Barreteau et al., 2001; Karplus, 1976). This idea is supported by the trend in (spatial) science that has become less oriented to forecasting but more towards supporting, structuring debates and facilitating the management of new meanings (Batty and Torrens, 2005).

Third, the model should be useful to discover what aspects of the system are most in need of a further study (Oreskes et al., 1994; Walker and Xuan, 2000). The model should be useful for theory development and generation of hypotheses (Carley, 1999; Varenne, 2001).

7.3 The validation approach

This section outlines the validation approach applied to validate the type of MAS described above. For the greater part, the approach and definitions of validation presented by Sargent (1999) to validate discrete-event simulations are adopted. Sargent (1999) distinguishes three aspects of the validity of a model:

- conceptual model validity;
- computerized model verification;
- operational validity.

Conceptual model validation constitutes the establishment when theories and assumptions underlying the conceptual model are reasonable given the intended purpose of the model. Computerized model verification verifies a correct implementation of the conceptual model into a computer program. Operational validation determines if the model output has sufficient accuracy considering its intended purpose. Accuracy is interpreted in a qualitative fashion.

The remainder of this section elaborates on the methodology chosen to carry out the conceptual and operational validations. Focus is on a conceptual validation of the complete model, and on an operational validation of some of the essential parts of the model. Computerized model verification is not dealt with explicitly in this article; the model is build using the Repast (http://repast.sourceforge.net) agent modelling toolkit which is widely accepted as an operational framework for developing MAS. Furthermore the model has been extensively checked during development using various tests.

7.3.1 Conceptual validation

The conceptual validation is aimed to verify relations between a real-world interactive spatial planning process and the formalization in the model. More-

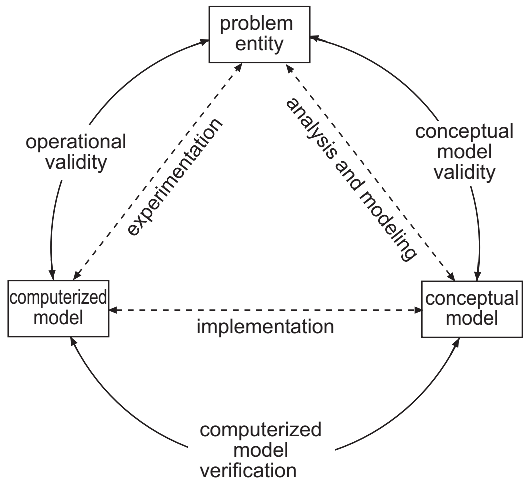


Figure 7.1: The modelling process and the related validation (after Sargent (1999)).

over it gives a clue about the loose-ends, possible research issues, and the potential of the approach to be applied beyond a scientific perspective.

The validation technique used is a face validation. Face validation is a subjective validation method where subject matter experts [2] make judgments about the model. The experts questioned for the validation are either professional planners and facilitators or researchers involved in spatial planning. They were selected to have a profound knowledge about the planning process and able to evaluate the correspondence between processes as they occur in the real world and the way they are modelled in the simulation. Furthermore they can evaluate aspects like the completeness and schematization of information used as input for the simulation.

The experts were asked to evaluate the model on the aspects enumerated in table 7.1. These aspects correspond to the most important components of the model (see Figure 6.1 on page 89). Five domain experts were individually interviewed. Prior to the interview the model was extensively explained using a presentation, and a demonstration was provided. During the presentation information was given on the goal of the model, the type of planning processes modelled, the case study, the modelling approach, its formalization, its various components and the way information was routed through the

[2] an individual who, by virtue of position, education, training, or experience, is expected to have greater-than-normal expertise or insight relative to a particular technical or operational discipline, system, or process, and who has been selected or appointed to participate in development, verification, validation, accreditation or use of a model or simulation (Pace and Sheehan, 2002).

Table 7.1: Aspects used during the expert validation.

Spatial planning process	
1.1	Interactive planning process
1.2	Type amount and role of agents
Actor-Agent	
2.1	Desires
2.2	Observations and perceptions
2.3	Proposals
2.4	Communication
Facilitator	
3.1	Tasks of the facilitator
3.2	Information presented to the facilitator
3.3	Handling of this information
3.4.	Information presented to the actor agents
Spatial System	
4.1	Spatial data: representation
4.2	Spatial data: content

model. No information about specific rules and algorithms was presented. During the introduction it was stressed that the presented model acts as a prototype used to illustrate the principles and should not be considered a final application. After the presentation and demonstration the experts were asked to evaluate the aspects of Table 7.1 (see also Appendix 1). For each aspect the expert compared the representation by the model with that of a real-world situation. For the rating a five point scale was used ranging from "very unrealistic representation" (1) to "a very good representation" (5). For each aspect additional comments could be given by the expert to explain the rating.

7.3.2 Operational validation

The operational validity of the model was evaluated using a role play. In the role play it was tested how agents perform when observing, perceiving and constructing preferences compared to their human counterparts. The role play was performed by a group of 27 students. Because the role play was carried out by students and not by real actors in an interactive planning process not all aspects of the model could be validated. The validation was limited to aspects related to the individual domain of the actors. This implies that only observation, perception, and generating preferences were evaluated. Although not a complete validation, the role play is useful to test whether the assumptions of the model match the representation of the dynamics of the system as experienced by the actors (Barreteau et al., 2001).

The role play was organized by dividing the students into nine groups. Three groups were assigned a role of: the citizens organization, three groups that of a farmers organization, and three groups that of the nature conservationists. The goal was to point out locations to allocate approximately 300 hectare of new urbanization. To each role a number of desires was assigned that should be considered the drivers for the role players to make their choices. The citizens have been assigned the following desires:

- new urbanization around present urbanized areas;
- near forest and nature.

The farmers organization has been assigned:

- new urbanization should preferably be located around existing urbanized areas;
- not near present agriculture, and;
- not near small villages.

Similarly for the nature-conservationists:

- new urbanization not near nature areas;
- new urbanization as less as possible around "historical" villages.

The role play was divided into three stages. At the first stage each group had to sketch, on a paper map of the study area, the most preferred location for new urbanization based on their interpretation of the rules belonging to the role. The information on the map was similar to the input provided to the MAS and contained land use information.

At the second stage the groups were asked to make their perceptions of the rules explicit by:

1. sketching beliefs. If, for example, new urbanization should not be located near existing agriculture, according the desire of the farmers, the group had to sketch what objects in the environment are relevant to fit to their definition of agriculture and;
2. drawing utility graphs[3] that indicate the appreciation for the beliefs. The utility is expressed in a scale, ranging from -1 to 1 in which values

[3]The term utility should be regarded as an ordinal utility only capturing the ranking and not the strength.

below zero indicate a negative appreciation and values above zero a positive. In the example of the farmers the utility is related to valuing the aspect “near existing agriculture” in which, obviously from the context of the desire, a closer distance to existing agriculture will yield a lower utility.

At the third stage each group was asked again sto sketch the most preferred locations for new urbanization, but this time explicitly considering the objects and utility-functions defined at step two. To be able to analyze, and compare results of the role-play with simulated results, the sketches were digitized and rasterized using a GIS at a resolution similar to that of the model. The digitized sketches (defined by the role players at stage 2) were overlayed with the land use data-set to estimate which of the land use classes were considered relevant by the role players to be part of a belief. Additionally the maximum and minimum sizes of these objects where estimated. Using these estimates the agents’ rules are parameterized. Also the utility graphs drawn by the role-players were added to the agents’ knowledge base. Using this information, for each group a simulation was run.

Although the chosen validation approach has some limitations it serves to test the validity of the individual actor processes of observing, perceiving and generating preferences. At this stage the model cannot completely be operationally validated on all aspects because the current version requires considerable knowledge about the internals of the software to be operated. Therefore, operational testing during a real life interactive planning process is at this stage not realistic.

7.4 Results and discussion

This section analyzes and discusses the results of the face validation and the role play as described in the previous section.

7.4.1 Face validation

Figure 7.2 shows the results of the face validation for the aspects mentioned in Table 7.1. Besides rating the various aspects, each expert was given the opportunity to note remarks. Often it was found difficult to only give a rating without explaining its context. Table 7.2 shows the remarks. In case, two or more experts made the same remark this was added to the table as one remark. Furthermore some of the remarks were edited for style and grammar as the noting-down by the experts during the interviews sometimes was done swiftly [4].

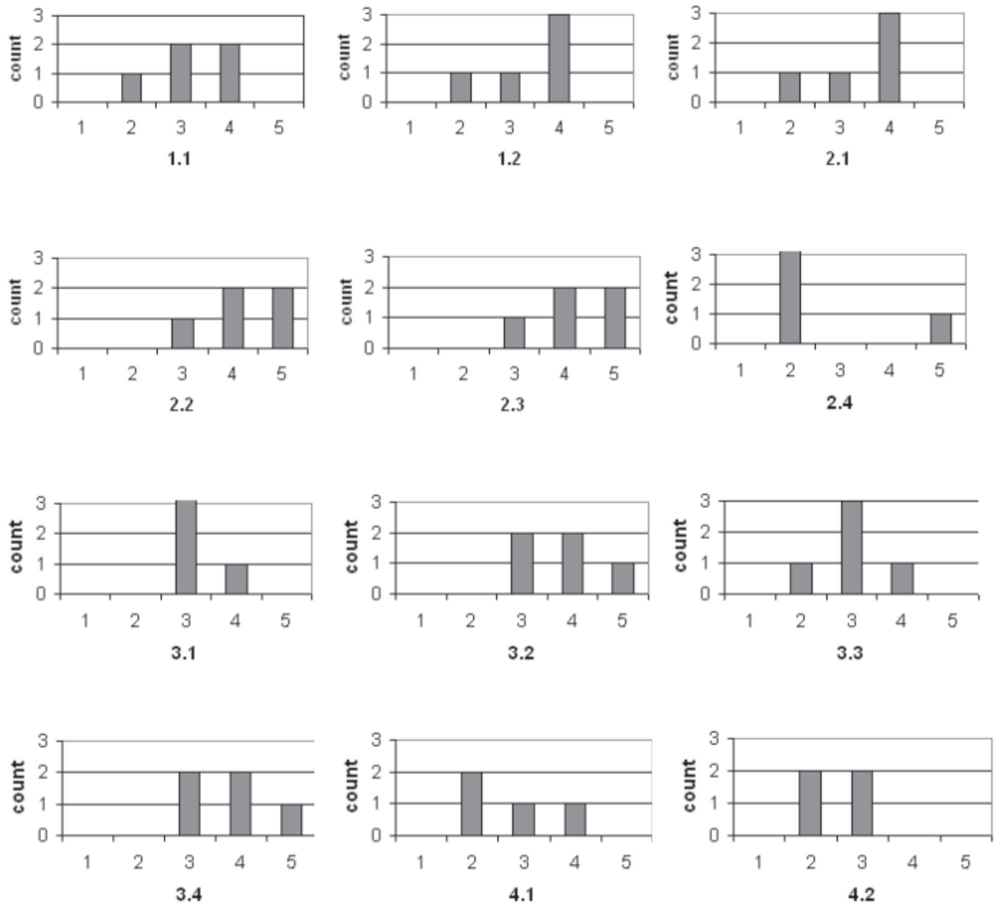


Figure 7.2: Histograms showing the response of the experts on the questions of Table 7.1; The numbers refer to the numbers in Table 7.1.

Spatial Planning Process From the results of Figure 7.2 it appears that the model performs moderate for the aspect of the spatial planning process. From the remarks of Table 7.2 it shows that concerns are: the mono-thematic nature of the planning, and the assumption of rationality. Furthermore, it was addressed that the complexity of real-life policy processes could not be realistically simulated. The model, however, can serve as a useful tool for students and inexperienced citizens to get a better insight in the consequences of various points of view.

[4]the original annotations are still available from the author.

Table 7.2: Remarks made by the experts during the face validation.

Spatial Planning Process:
- actors act often as visionair or supply inspiration rather than rational decisions;
- the model is mono-thematic. For example, only urban areas can be negotiated. Compensating measures, for example extra nature cannot be handled by the model. This limits the application of the model;
- the model only deals with operational planning. Not with strategic plans
- currently the model is a representing a "zuilenmodel" [a] with the premise that the actor represents groups in which all members think alike. In reality agents also have to negotiate with members of the group they represent;
- the model is suitable to provide the actors with more agency. Model might be very well applied in education; Current set-up of the results are fine because the expectations are not to absolute
- the model is a useful eye-opener for situation were students or inexperienced citizens make a first reconnaissance of the problem. The use of the model is to get a better understanding of the consequence of the various points of view;
- the real-life process of decision-making is of such political nature that simulation is not possible.
Actor-Agents:
- the assumption that an actor always has a pre-defined opinion is optimistic. Sometimes an involved actor does not have an explicit opinion;
- desires are broader and ideas of actors are more divers than currently implemented. Design is an important aspect;
- concept of a decision market is good. Elaborate on this in future research. Perhaps use the metaphor of trading;
- sometimes actors are not only actors but also define the rules (for example the authorities);
- what is missing is the ability to form cooperative structures (coalitions) which is an important process during spatial planning processes;
- the model assumes the actors are always open and truthful; in practice this in not always the case (hidden agenda's); also power relations cannot be ignored. They are an important aspect in the planning process;
- the concept of the agent as an organization is good; in practice especially organizations have a clear idea about what they want;
- a restriction is that only geo-related information is used by the agent when formulating their preferences;
- communication is very limited; rating only each others preferences is not realistic.
Facilitator:
- the facilitator processes rather limited information. In reality social type of information are equally or even more important. This involves information about for example(power)relations between actors, conflicts etc;
- a facilitator has a pure facilitating role. He or she should not be involved in issues with respect to the content;
- in reality an facilitator has additional tasks like: introducing new information, introducing a new actor and fuelling the thinking-processes;
- a facilitator also has the task to structure all arguments and not only the spatial information; a facilitator not only identifies certain conflicting or potential areas but especially tries to identify the arguments and criteria behind it.
Artificial Environment:
- maps are difficult to recognize and hard to read;
- important data like ownership and spatial policy is lacking.

[a] the term "zuilenmodel" is a Dutch denotation that refers to the matrix organization of sociopolitical and socioreligious groups that dominated Dutch society during the 50's, 60's and part of the 70's. The political, economic and cultural life was build out of groups with the same political and religious conception.

Actor-Agents The concept of desires is considered reasonable to good representation by most experts 7.2. Main critiques are the assumptions that actors have their desires defined “a-priori”, and are considered to be always open and truthful. Observation and perception is regarded a good representation. The critiques mainly target at the assumption that observations are based only on geo-information which is considered as limited. Generating proposal is ranked as a “reasonable” to “very good” representation. Communication on the other hand is considered rather unrealistic by all experts except one. The main critique is that it only takes into account exchange of factual, information while communication in real life also encompasses the exchange of non-factual messages like emotions.

Facilitator The representation of the tasks of the facilitator by the model is considered reasonable. An important aspect found missing, is the structuring and identification of arguments by the facilitator in addition to structuring spatial information. The information presented to the facilitator and the handling of it is regarded realistic by most of the experts. The remarks are mainly targeted to the rather limited view on the information that is exchanged with the facilitator. In reality the structuring of the spatial information is only of limited interest to a facilitator. Wielding of social information (like conflicts, negotiations, and power-relations) is more important.

Artificial Environment The representation of the environment is, in general, considered unrealistic to reasonably realistic. Most of the remarks are directed at difficulties of interpreting the maps. Mainly this is due to the application being a research prototype rather than it is a conceptual critique. Other remarks are directed at the limited definition of the current environment which only contains land use. There is definitely a need for additional information. However, this is not a restriction of the concept but rather of the limited extent the case has be worked out.

7.4.2 Role play

This section presents the results of the role play. First, for each role, the beliefs defined by the role players are compared with the beliefs generated by the MAS. Next the preferred areas for the new urbanization assigned by the role players are compared with allocations of agents simulating the same role.

Beliefs

Table 7.3 shows for the citizens (groups 4, 6, and 8), the classes of the land use map that constitute for the beliefs of existing urban areas and forest/nature.

Existing urban areas are defined by all groups equally. The definition of forest/nature class is more divers. Group 4 has a narrow definition which only includes deciduous forest, coniferous forest and existing nature. The results of group 8 show the broadest definition including even agriculture and pasture into its definition.

Table 7.3: Land use classes used by the citizen groups to define urban and forest/nature areas. The table derives from the results of the second stage of the role play.

land use	urban			forest/nature		
	4	6	8	4	6	8
pasture (1)						x
cereal (5)						x
glasshouses (8)						
orchards (9)						
dec. forest (11)				x	x	x
con. forest(12)				x	x	
nature (14)				x	x	
bare ground in nature(15)						
water (16)				x		
urbanization (18)	x	x	x			
rural build up (19)						x
dec. forest in build up areas (20)				x		
con. forest in build up areas (21)						
forest in dense urbanization (22)						
pasture in dense urbanization (23)				x		x
bare ground in rural build up (24)						x
main infrastructure (25)						
agriculture (30)						x

Figure 7.3 shows the resulting maps for each group along with the simulated results of the model. From a visual analysis it appears that, for urbanization, there is clear correspondence between role players and model simulation. In general, simulated patterns of urban areas show a more granular pattern than the patterns sketched by role players. The beliefs for forest and nature areas show larger differences. For the groups 4 and 6 the agents assign more areas to forest or nature than the role players. For the case of group 8 the agents fail to reproduce a similar pattern as the role players. This can be explained by including agricultural and pasture areas into the beliefs for forest/nature. The figure clearly shows that the thematic aggregation by the model fails. Clearly a more elaborate reasoning has been applied by the human actors during their decision-making about including agriculture or pasture areas into the definition of beliefs. Table 7.4 shows existing urbanization, existing agriculture, and small villages defined by the farmers. The groups 5 and 9 assign land use class 18 (urbanization) to both urban areas and small villages. The sketches (see Figure 7.4) show that the definition of existing urbanization or small villages not solely depends on the semantics of

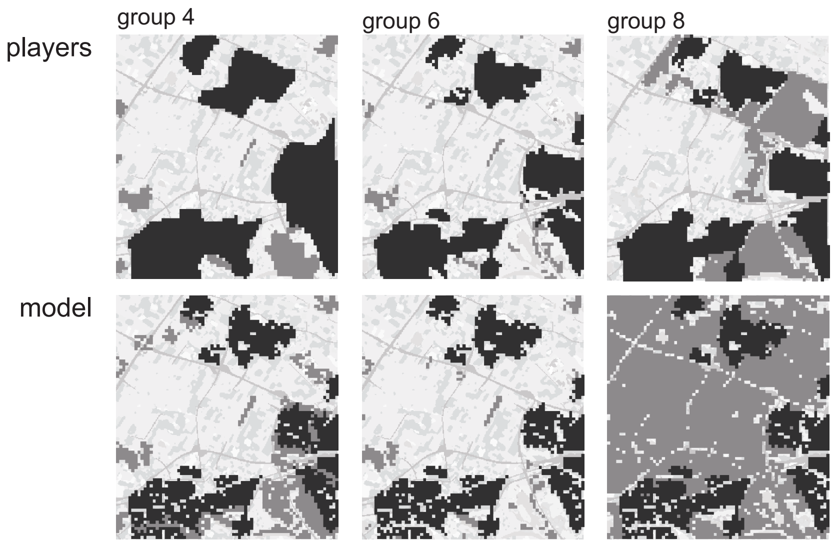


Figure 7.3: Definitions of the beliefs of the citizens (urbanization = black, forest/nature = dark-grey).

Table 7.4: Land use classes used by the farmers groups to define urban, existing agriculture, and small villages. The table derives from analyzing the results of the second assignment.

land use	urban			agriculture			villages		
	3	5	9	3	5	9	3	5	9
pasture (1)				x	x	x			
cereal (5)				x	x	x			
glasshouses (8)				x	x	x			
orchards (9)				x	x	x			
dec. forest (11)									
con. forest(12)									
nature (14)									
bare ground in nature(15)									
water (16)									
urbanization (18)	x	x	x					x	x
rural build up (19)							x		
dec. forest in build up areas (20)									
con. forest in build up areas (21)									
forest in dense urbanization (22)									
pasture in dense urbanization (23)									
bare ground in rural build up (24)									
main infrastructure (25)									
agriculture (30)				x	x	x			

the land use classes but probably also on aspects such as location, size, shape, and topological relations. The agents can, however, besides on differences in land use, only differentiate on the size of objects. This restricts the model in distinguishing between urbanization and small villages for a number of occurrences. Notably this is the case for the village in the north of the area which is defined by the model as existing urbanization whereas the players of group 9 assigns “small village” to it (see Tabel 7.4). For Group 5 the agent assigns “small villages” to the patch in the east, whereas the role players of group 5 assign “existing urbanization” to it.

The delineation of existing urban areas (black) and the agricultural areas (light-grey) are simulated rather well for all the three groups except that the resulting patterns of the agents are more granular.

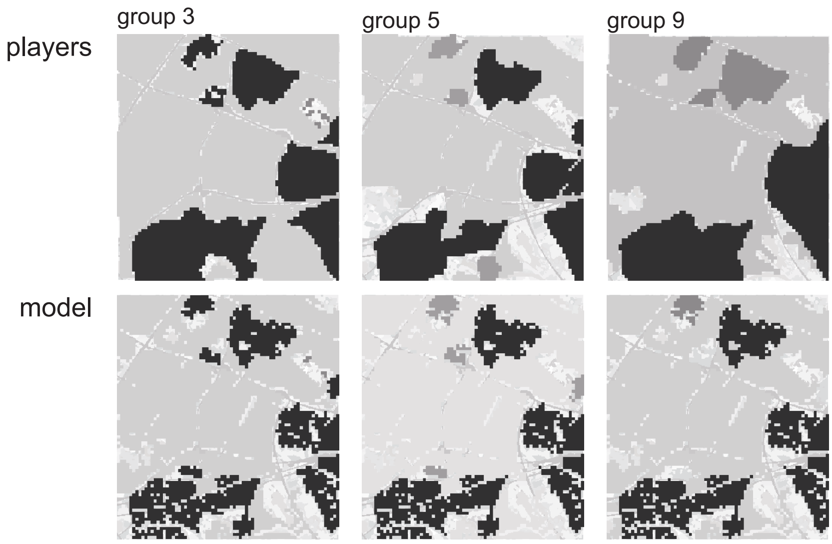


Figure 7.4: Definitions of the beliefs for the farmers (urbanization = black, existing agriculture = light-grey, small village = dark-grey).

Table 7.5 shows the results for the nature conservationist groups. From the table it shows that, if it comes to defining beliefs for historical villages the existing data does not suffice. Currently orchards (group 2) or pasture in dense urbanization (group 1 and 7) are found to be constituent classes of historical villages. However, Figure 7.5 shows that the thematic designation of only the land use, is of limited significance for the beliefs of historical villages. The results of the simulation show a clearly distinct pattern. Also for the beliefs of nature the agents tend to assign more and smaller patches to nature areas than the role players. Based on the results discussed above the following may be observed. From the sketches of the role players it appears that they tend to generalize and aggregate differently than the agents for a number of aspects. First, small pieces of deviant land use i.e. land use which does not fit into the definition of the actors often are considered as noise when encountered within a larger structure of a belief, and as such ignored. Figure 7.6 illustrates this behaviour showing the difference between role players and

Table 7.5: Land use classes used by the nature conservationists groups for the definition of beliefs for nature and historical villages. The table derives from the results of the second assignment.

land use	nature			hist. villages		
	1	2	7	1	2	7
pasture (1)						
cereal (5)						
glasshouses (8)						
orchards (9)					x	
dec. forest (11)	x	x	x			
con. forest(12)	x	x	x			
nature (14)	x	x	x			
bare ground in nature(15)		x				
water (16)	x	x	x			
urbanization (18)						
rural build up (19)						
dec. forest in build up areas (20)	x		x			
con. forest in build up areas (21)						
forest in dense urbanization (22)						
pasture in dense urbanization (23)			x	x		x
bare ground in rural build up (24)						
main infrastructure (25)						
agriculture (30)						

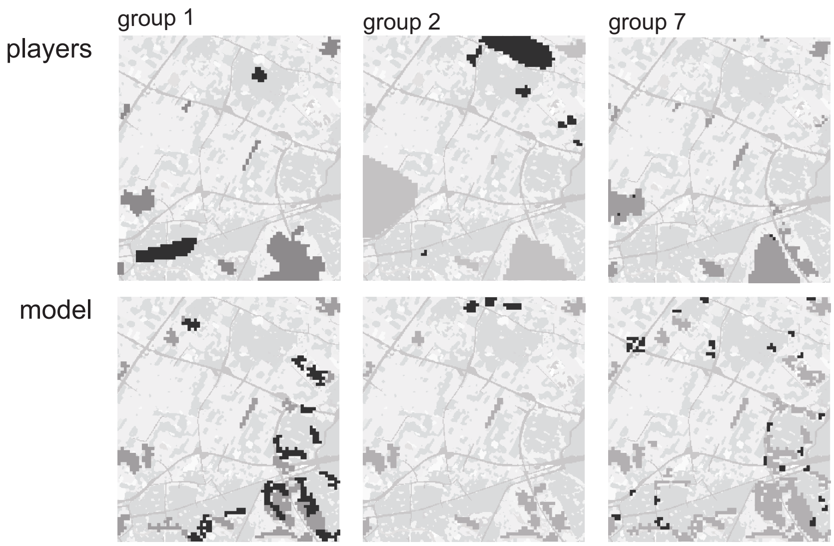


Figure 7.5: Definitions of the relevant spatial objects for the nature conservationists ("historical villages" = black, existing nature = grey).

the agent results for the third group (farmers).

Second, often the role players define beliefs in the context of its surroundings. Based on observed spatial patterns they decide if a land use belongs to the object of interest. Humans use additional clues perceived through various channels to accomplish this (Freksa, 1991). Figure 7.7 illustrates this lack of reasoning capacity of the agents. The upper row shows the assignment of a historical village on the crossing of two highways by an agent whereas the role players do not consider it a historical village (which is probably correct). The second row shows the division of urbanized areas into two objects by the agents due to intersection of a highway whereas the role players consider it as one object.

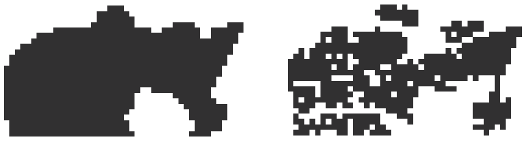


Figure 7.6: Differences in generalization; on the left urbanization defined by role players of group 3 and on the right the results of the model.

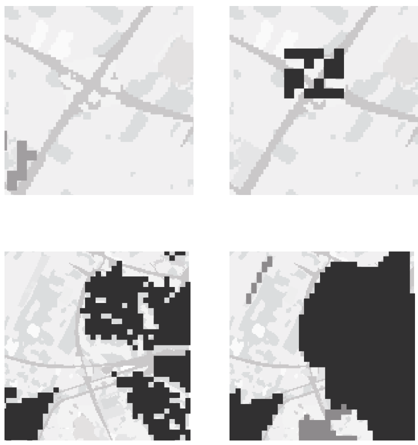


Figure 7.7: Differences in contextualization.

Preferences

Actors generated preferences about potential locations for new urbanization based on beliefs and utilities attached to it. Figure 7.8 shows the results for the citizens. The patterns of urbanization generated by the simulation clearly differ from those sketched by the role players. The role players tend to cluster their most preferred areas into larger patches. Sometimes overriding their preference functions (see figure 7.9) by allocating new urbanization at semi-optimal locations. The same can be observed for the farmers (see Figures 7.10 and 7.11). The most preferred areas for new urbanization tend to be allocated by the model directly around areas defined as urbanization or small villages (Figure 7.4). The model optimizes the allocation strictly according the suitability calculated through the utility functions.

For nature the resulting patterns of the role players and the model show more similarity (see Figure 7.12), although the agents still tend to assign smaller patches than the role players. An explanation for the better correspondence is the shape of the utility functions for the nature. These are both negatively (nearby) and positively/neutral formulated (further away)(see Figure 7.13. In combination with relative small patches of nature and historical villages (figure 7.5) the resulting areas having similar suitabilities are larger, allowing the agents to assign larger clusters without compromising their preference functions.

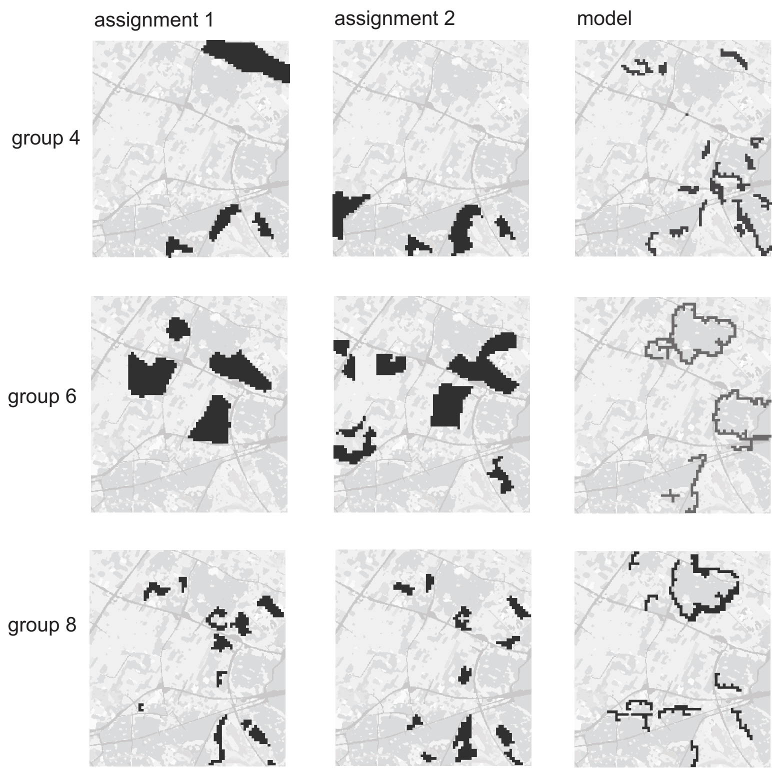


Figure 7.8: Preferences of the citizens for assignment 1, assignment 2 and the results of the model.

7.5 Conclusions

From this validation exercise a number of conclusions can be draw. Considering the first goal of the MAS: “provide insight for users in the effects of

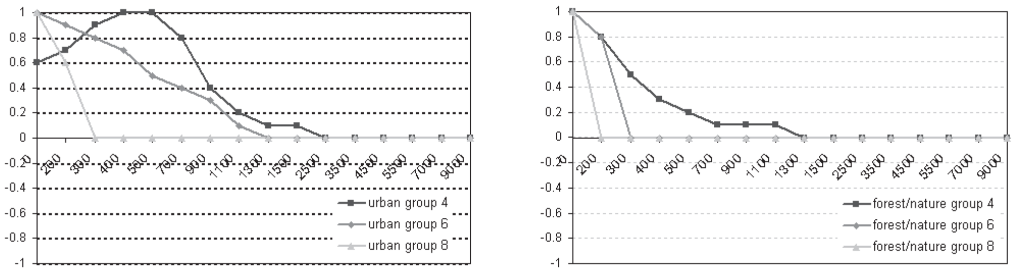


Figure 7.9: Utilities assigned by the citizens role players for “around existing urbanized areas” (left) and “near forest and nature” (right).

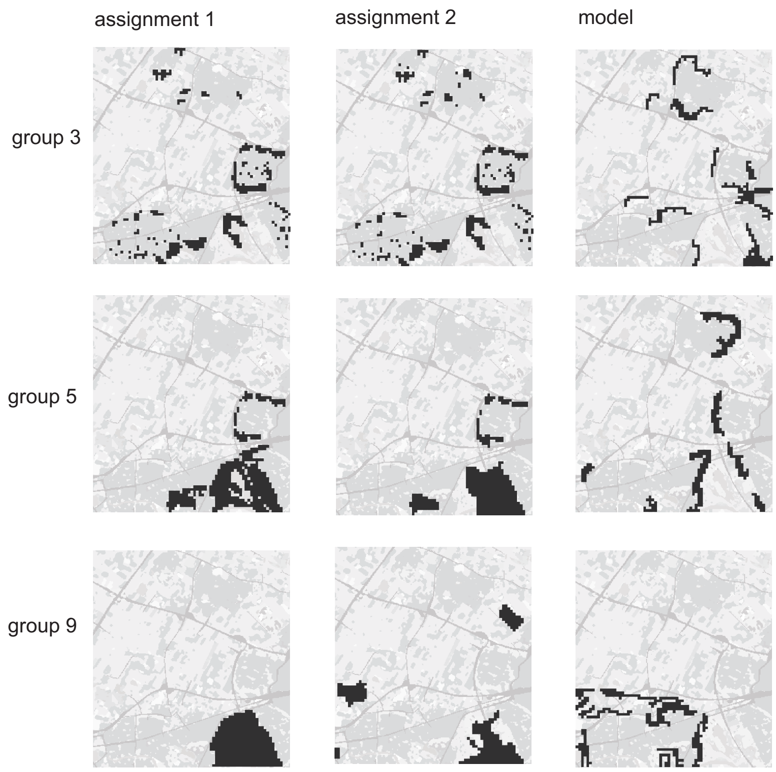


Figure 7.10: Preferences of the farmers for assignment 1, assignment 2 and the results of the model.

individual desires on perceptions and preferences, the preferences and perceptions of other actors, and the effects of the joint preferences on the potential solutions” the following conclusion can be drawn:

- the interactive planning process is modelled rather well. Nevertheless, there are some limitations related to applicability. Currently its use

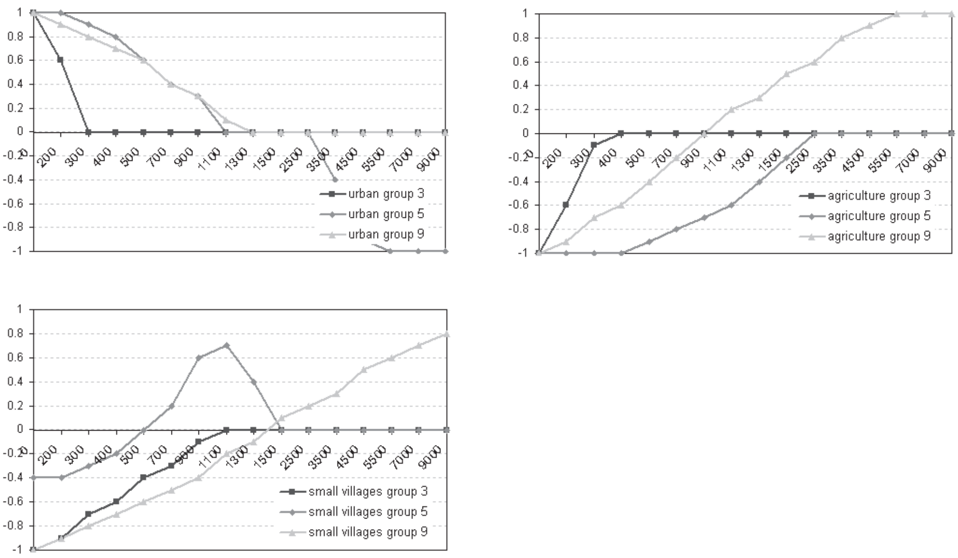


Figure 7.11: Utilities assigned by the farmers role players for "near to existing urbanization" (left), "not near present agriculture" (right) and "not near small villages" (lower left).

is restricted to mono-thematic and operational characteristic of the represented spatial planning process;

- the concept of desires, observations and preferences are generally regarded a realistic representation. However, to adequately provide insight to users the MAS is restricted by a rather limited notion of predefined desires, the use of only geo-information, and the limited communication. Furthermore, the model is rather optimistic for its assumptions regarding the openness and truthfulness of actors;
- operational validation indicates a lack of information processing by the agents. Real actors tend to apply additional information in their decision-making;
- currently, the applied spatial reasoning is to limited to capture the wealth of spatial reasoning applied by human actors. People aggregate or classify based on more than only land use. Somehow, spatial patterns and topological relations are important if it comes to the definition of beliefs and the assignment of the preferred areas.

Focussing on the second goal of the model: "enable users to play with the model to gain some insights into the reactions of the systems"; the interviewed experts consider the MAS as a very useful tool for educational purposes, or as a model to provide agency to actors, especially to non-experts,

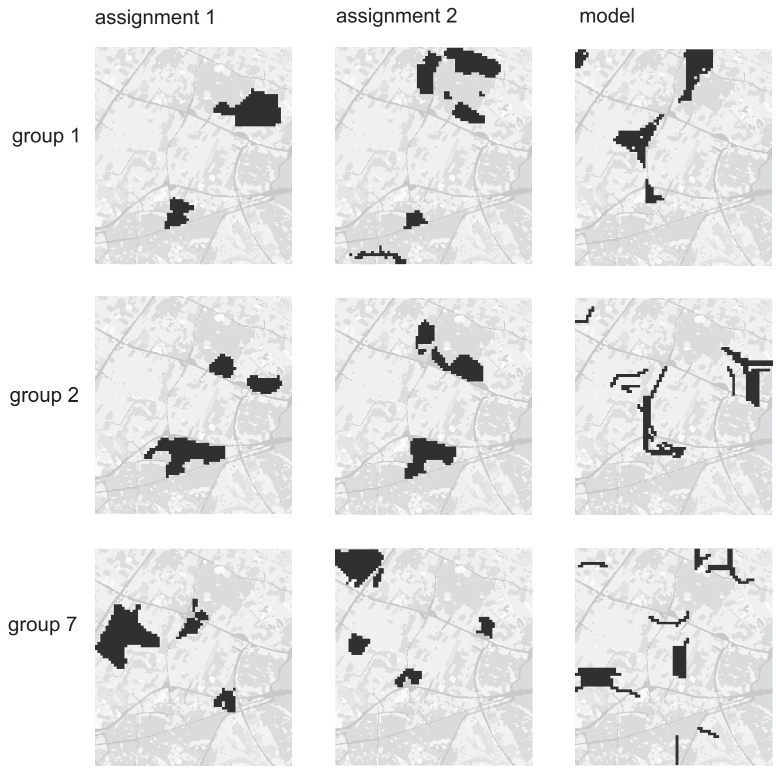


Figure 7.12: Preferences of the nature for assignment 1, assignment 2 and the results of the model.

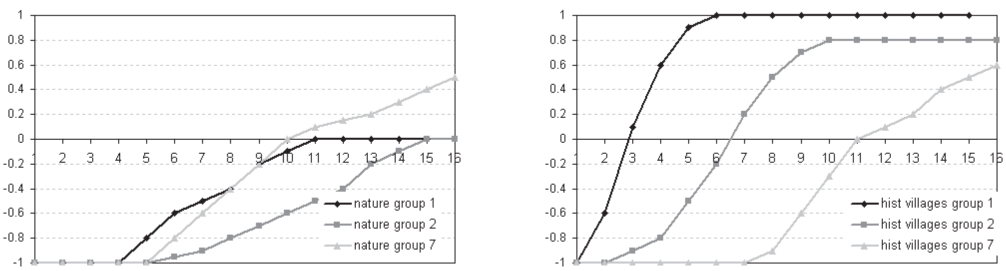


Figure 7.13: Utilities assigned by the nature role players for “not near nature areas” (left) and “less as possible around historical villages” (right).

at the beginning of a spatial planning process. Although the experts signaled a number of insufficiencies (see above) the explicit representation of actors in a simulation of interactive planning was considered innovative and of added value, because it provides information beyond that of most current models used in spatial planning.

Chapter 8

Conclusions and further research

In the preceding chapters the use of MAS to simulate interactive multi-actor spatial planning was explored and discussed. This chapter draws the final conclusions of the thesis structured by the research questions stated in the first chapter. Furthermore, suggestions for future research will be given.

8.1 Introduction

The main objective of this thesis is: explore the use of Multi-Agent Systems (MAS) for its application in simulating interactive multi-actor spatial planning. To structure this exploration, a number of research questions raised. This chapter will provide the answers to these questions. Moreover, suggestions for further research will be given.

8.2 Conclusions

In the first chapter the following research questions were stated:

- How can interactive multi-actor spatial planning be formalized in a conceptual framework based on agent based modelling?
- What modelling metaphors (concepts, architectures and components) can be implemented using Multi-Agents Systems (MAS)?
- What validation approaches are suitable to validate a MAS for interactive multi-actor spatial planning?
- What are the drawbacks and potentialities of agent based approaches for the use as (part of) an artificial environment, and support users to understand the complexity of interactive multi-actor spatial planning?

The next sections will summarize the answers to the questions.

How can interactive multi-actor spatial planning be formalized in a conceptual framework based on agent based modelling? This question was mainly explored in Chapter 2. The planning process is analyzed from a perspective of various systemic levels: the social-spatial system, the planning system and the individual cognitive system (see Figure 2.1 on page 13). This leads to the argumentation that spatial planning should be considered an activity which is structurally embedded in society, requiring active involvement of actors from various disciples or interests.

Furthermore, it is argued that due to structural relations between political, economic and cultural subsystems, it is difficult to provide a single comprehensive description of an interactive multi-actor planning process. This conclusion is affirmed by the interviews held with spatial planning experts (Chapter 7). The question, how spatial planning is composed depends strongly on the organization, the required or desired level of participation, the number of involved actors, the goal of the planning, and the spatial scale.

The overview given in Chapter 2 elucidates that modern spatial planning ought to be regarded as a decision-making process grounded into intentional behaviour of individual actors. Based on this, a model of an actor is proposed that distinguishes four types of knowledge: desires, beliefs, values and preferences. These types of knowledge are the basis for a conceptual model of an interactive multi-actor spatial planning process, presented in Chapter 2 (see figure 2.5 on page 20).

Subject matter experts, interviewed during the validation of the model, addressed that the conceptual model is a representation of a type of spatial planning of which many variations are possible. The presented model represents a planning situation supposing a high level of participation, which not has been widely applied in the Netherlands yet. Currently, many interactive spatial planning processes restrict participants in the level of participation. The participants are for example consulted or asked for alternatives (co-designing). The decision-making itself is often done during a more centralized process organized amongst policy makers. There is, however, a trend to involve actors at participation levels that allow them also to have a stake in the decision-making process itself. The presented model anticipates on this development.

What modelling metaphors (concepts, architectures and components) can be implemented using Multi-Agents Systems (MAS)?
In Chapter 3 various agent based concepts and architectures are discussed. It was argued that, as a consequence of the complexity of interactive multi-actor spatial planning, formal approaches used in traditional AI are difficult to be implemented for the model described in Chapter 2. The inherent openness of the spatial planning system and the inability to construct sound and complete representations of knowledge decisions impede the application of deliberate, logic based approaches.

Reactive agent architectures are amongst the most common ones found in environmental sciences. Concrete MAS implementations are generally are founded on CA or rule based approaches. Based on sensory input a mathematical or expert rule is fired to generate a response to these sensory input. To improve the pro-active and reasoning behaviour "Belief, Desires, and Intention" (BDI) architectures offer an alternative for purely reactive architectures, although the formal BDI logic (Rao and Georgeff, 1995; Rao, 1991) is not often found to be applied.

Additionally heuristic approaches are found. These are not particulary suitable to simulate interactive spatial planning because the main interest lies in the analysis of actor based intentional processes and their effects on spatial patterns. Not in generating spatial patterns representing optimal or suboptimal points in a search space. Therefore explicit access to the "black box" is a requirement.

The main conclusion is that currently only reactive architectures offer enough flexibility to be applied in a MAS for interactive multi-actor spatial planning. Additional concepts of BDI architectures possibly offer techniques to add some pro-active behaviour to a MAS. The case studies (Chapters 4, 5, and 6) focus on various components of the conceptual framework. The first case study applied a Cellular Automata (CA) approach to represent spatial knowledge. A major restriction of this approach is that agents only had a limited "view" as consequence of the neighbourhood concept of the CA. For decision-making in spatial planning this entailed that disjoint spatial reasoning is difficult to accomplish. Including environmental states outside the extent of a neighbourhood is only possible for dispersion like processes, where the current state of an environment depends on its former states. This restricted the CA based approach in being applied for planning conditions that required a more holistic view on the area, for example in case of spatial planning motivated by design considerations rather than solely process oriented planning.

To overcome restrictions of the CA approach, the second case study implements a MAS based on a rule-base, and introduces the concept of observers. The rule-base maintains knowledge about the desires of the agents, knowledge of the required observations, and knowledge to interpret the results of the observations. Instead of only a CA-engine, agents can invoke various other methods to infer knowledge from their environment. Based on the type of observations, agents can fire various observers to produce beliefs. In turn, these beliefs fire rules that account for the knowledge to assign new land use satisfying the desires of agents. The advantage of the rule based approach combined with the concept of observers was that it, in principle allows more flexibility in defining methods that agents can apply to observe and perceive their environment.

A disadvantage of the rule-based approach is the amount of rules, rapidly expanding, when the number of desires or number of environmental states increase. Even a limited amount of desires already required considerable effort in formulating rules to cover all possible combinations. From various experiments with the model it appeared that for some locations agents were not able to generate a belief or preference because a situation was encountered not covered by a rule. If the number of agents, the number of environmental states, and the size of the area increases, the definition of a rule base will become a challenging exercise. A second restriction is related to the two valued logic used (true, false); the agents only were able to generate true of false statements. For fuzzy expressions of desires, like "close to ..." or "far away ...", it is not an appropriate representation.

Sofar, communication amongst agents is rather limited. This implies that sharing of information is also rather limited. In the third case study the MAS is enriched with the ability to share knowledge, based on the approach of Nonaka and Takeuchi (1995). Moreover, to overcome the limitations in reasoning and representing desires of the first two case studies, the concept of spatial preference functions is combined with the use of observers. This enable agents to produce a continuous representation of their preferences. As such, this case study integrates a number of approaches of the first two cases.

To simulate knowledge sharing, agents were equipped with the ability to judge, and communicate preferences of other agents. A facilitator agent was added to co-ordinate the communication and assist in finding joint facts; for this case, identification of areas that show potential to provide solutions acceptable to the majority of the agents.

What validation approaches are suitable to validate a MAS for interactive multi-actor spatial planning? This question is explored in Chapter 7. It was argued that conventional types of validation, commonly applied to validate spatial models, are not particulary suitable for MAS developed in this research. The main argument is the absence of a reference situation to compare the model results. Moreover it was not the main goal of the MAS to simulate spatial results as accurate as possible, but to provide insight to the user in various aspects of interactive multi-actor spatial planning. Expert-based validation is found to be a better alternative. Two validation exercises are carried out. The first is based on structured interviews with subject matter experts. The second on a role play with students. Particular the interviews with the experts are very valuable. It provide clear insight into the weak and strong points of the MAS from the context of a potential user.

What are the limitations and potentialities of agent based approaches to be used as (part of) an artificial environment, and support users to understand the complexity of interactive multi-actor spatial planning? Based on the validation study presented in Chapter 7 a number of limitations have been identified: The first relates to the assumption that knowledge is static during the pace of planning. This means that desires and values of agents do not change as consequence of a changing environment or changing desires of other agents. Interviews with subject matter experts suggest that many of the real world interactive multi-actor spatial planning processes are more dynamic in terms of actors regularly changing their minds than currently can be simulated. Also negotiation and co-operation processes are implemented rather limitedly in the MAS. This complicates the inclusion of compensating measures or other "tit for tat" like processes.

A second limitation is related to availability and representation of knowledge. In real-world planning processes more and different information is used during the reasoning and decision-making of actors. Especially representations of social type of knowledge are only limitedly implemented in the MAS, whereas it plays an important role during real world planning processes. Furthermore, additional spatial information need to be included in the MAS, for example, information of existing policies, ownerships, suitability, and accessibility.

A third limitation relates to limited spatial reasoning. As shown during the role play (see section 7.3.2 on page 116) the reasoning of humans showed more complexity than could be simulated by the current implementation of the MAS. This restriction especially applies to heterogeneous spatial environments where complex spatial patterns are present. As appeared from the role play, humans tend to apply different reasoning to classify and generalize the spatial complexity.

Final conclusion. Despite the limitations summed above the potential of simulating interactive multi-actor planning using MAS has clearly been shown. The various cases explored in this thesis are amongst the few approaches that explicitly simulates an interactive multi-actor spatial planning process. It showed that MAS enables modelers to deal with the complexity of multiple actors trying to realize their desires in a process of multi-actor decision-making. The following aspects classify MAS as a potential tool to be applied in an "artificial planning environment":

- the principle of perceiving spatial information in the context of individual desires and preferences;

- the sharing of knowledge about preferences and;
- the explicit simulation of interactive multi-actor decision-making.

These aspects are barely found in existing techniques that might be applied to learn and gain insight in the behaviour of spatial planning system based on interactive multi-actor planning.

8.3 Reflection

This section tries to answer the questions: what is the research innovation, and what is its contribution to the research domain of spatial planning?

The innovative aspect of the thesis resides in modelling the spatial planning process itself as a dynamic system consisting of interacting agents. To accomplish this an explicit representation and formalization of an interactive multi-actor spatial planning process needed to be devised, beyond that commonly found in spatial planning theory. Spatial planning theory usually does not include analysis of individual aspects of individual actors such as: individual decision-making, communication, negotiation, and knowledge sharing.

To be able to devise a MAS capable to represent a model of interactive multi-actor spatial planning, existing representations of spatial planning processes needed to be expanded with notions of these individual aspects. Concrete the following contributions to the domain of spatial planning can be listed:

- the development of a generic framework which provides:
  - an operational model of interactive multi-actor spatial planning;
  - a representation of individual decision-making of actors;
  - methods to represent knowledge of desires and values of actors;
  - means to infer the knowledge necessary to generated preferences and make decisions;
  - a model of communication and exchange of knowledge amongst actors.
- it was showed that agent based modelling offers concepts and techniques that enable modelers to implement models that offer a more natural representation of a spatial planning process and the components it consists of;
- consequently, it enables planners to study the planning processes itself by means of computer models.

This research dedicated considerable effort in finding synergy between the domains of spatial planning and computer sciences. Although slowly changing, such synergy is not natural. Planners traditionally depend on creative and social skills which enable them to design, present, and communicate spatial plans and policies. They have learned to handle the dynamics, complexity and sensitivity of spatial planning processes, and know how to deal with soft, often ill defined knowledge. Soft systems thinking and wicked-problem solving are typical task of a planner. Computer scientists, on the other hand, are used to eliminate unexpected events as much as possible as they are difficult to handle. Traditional system engineering is still a dominant paradigm. It depends on clearly defined goals and domains which enables the formulation of crisp specifications and requirements.

The added value of this research is that it showed to planners that MAS based simulations are useful and valuable to gain insights that otherwise are difficult to obtain. It can prepare planners for complex planning tasks by allowing them to carry out "ex ante" evaluations of various scenarios.

A drawback of the exploratory type of research, and the focus on finding a synergy is that a number of issues, as identified in the conclusions, could not be covered. The next section will suggest a number of research topics that will contribute to the advance of the "artificial planning environment".

8.4 Further research

Based on the above, a number of issues are identified for future research. These are related to:

- spatial representation and reasoning;
- decision-making process;
- validation;
- coupling with other models.

Spatial representation and reasoning. As concluded above, the demonstrated approaches would benefit from a better spatial reasoning. Qualitative Spatial Reasoning (QSR) about topological relations, shapes of objects, and size and distance would improve the abilities of the agents deal with the dynamics of complex spatial objects and patterns. QSR probably also requires a different spatial representation. The current grid-based representation of the spatial environment probably does not very well facilitate QSR. Spatial representations are required that enables representation of the different (dynamic) attributes of (spatial) objects that are important for making decisions in a planning context. An important question that arises is: can current spatial reasoning approaches, such as constraint based reasoning or reasoning based on composition tables, handle the abundant inferences required for interactive spatial planning (Cohn and Hazarika, 2001; Freksa, 1991)? Till now QSR has only been applied on finite and well defined domains. Alternative techniques probably need to be searched or developed, that enable spatial reasoning beyond the traditional inductive or deductive methods. Abductive reasoning[1], reasoning by analogies, or other types of defeasible reasoning are probably worthwhile to be explored.

Decision-making process. The conceptual model as presented in Chapter 2 allows a more elaborate treatment of the decision-making process than currently implemented. As pointed out in the conclusions processes like formation of dynamic coalitions and negotiation are not explicitly implemented in the current models. The predominant assumption in all 3 case studies is that the best solution for the planning problem is the one that causes as less "friction" as possible. As such it simplifies to an optimization problem. In reality, as pointed out also by the experts, the process is more diverse. Issues such as dynamic change in desires or beliefs, or formation of coalitions amongst agents having more or less similar preferences, have not been investigated yet. Questions such as: how many concessions are agents prepared to make in order to join a coalition that can hold off more "threatening" scenarios, have not been explored nor experimented in a MAS. A similar issue relates to negotiation and offering of compensating measures. Especially the latter is important in spatial planning. Often a desired spatial situation is only realizable if opposing actors are compensated for their "losses".

An additional aspect is that of learning. In real-world situations, interactive multi-actor planning learning is an important process. Actors adjust their desires and preferences according to previous experiences. Currently the agents of the explored models cannot changes their desires or preferences as their rule-sets are fixed.

Enrichment of the agents by applying more enhanced negotiation and learning mechanisms would not only add more realism to simulating the effects of interactive multi-actor decision-making on the spatial environment but would also add the possibility to study the way agents affect each other. This allows for the study of the more social aspects related to spatial planning in terms of conflict resolution, group decision-making, formation of cooperations etc.

[1] Abductive reasoning is the process of reasoning to the best explanations. This means that it starts from a set of facts and derives their most likely explanations.

Validation of MAS As indicated in Chapter 7, validation of MAS is currently an important issue. Depending on the goal of the model different validation requirements are needed. In this research a start was made with alternative approaches to validation, based on expert validation and a role playing game. The presented approach requires to be broadened. There is a need for additional insights to assess whether the model really provides insight to a user and enables him to play with the model and explore the reactions of the system. Therefore, it is necessary to improve the MAS itself, so it becomes available to common users; but more important, methodologies need to devised that can measure not only if the model provides additional insights, but also determines to value for the an actual interactive multi-actor spatial planning process.

Coupling with other models. The case studies are currently designed as stand-alone simulation models. For the purpose of exploring and demonstrating this suffices; spatial claims were defined beforehand and the required spatial data was kept at a minimum. However, coupling MAS with models that simulate land use change at different scales would allow for a more elaborated or complete "artificial planning environment". Processes that occur at different scales, like demographic change, social-economic behaviour, or climatological changes can influence the decision-making at the levels of the individual actors and "vice-versa". A MAS can simulate the effects of these "macro level" changes upon individual behaviour of actors while the effects of individual behaviour might affect processes external to the MAS.

Another approach would be to couple MAS with group-ware systems or with a serious-gaming approach. This might allow users to operate the MAS interactively, as part of the simulation. It would enable to combine both human actors with agents.

Appendix 1: Face validation MAS model

Name:
Date:

We like you to answer the following questions:

I consider the aspect mentioned in the table as a:

1. Very unrealistic representation
2. Unrealistic representation
3. Reasonable representation
4. Good representation
5. Very good representation

of the aspect as I, in my perception, encounter them in real-world situations

Answer the question both from the focus of the conceptual model and the model implemented in the computer (computerized)

aspect	rating	comment nr
Spatial planning process		
1.1 Interactive planning process	1 2 3 4 5	
1.2 Type, amount and roles of the agents	1 2 3 4 5	
Actor-Agent		
2.1 Desires	1 2 3 4 5	
2.2 Observations and perceptions	1 2 3 4 5	
2.3 Proposals	1 2 3 4 5	
2.4 Communication	1 2 3 4 5	
Facilitator		
3.1 Tasks of the facilitator	1 2 3 4 5	
3.2 Information presented to the facilitator	1 2 3 4 5	
3.3 Handling of this information	1 2 3 4 5	
3.4 Information presented to the actor-agents	1 2 3 4 5	
Environment		
4.1 Spatial data: representation	1 2 3 4 5	
4.2 Spatial data: content	1 2 3 4 5	

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Summary

Spatial planning has become increasingly complex. Factors that contribute to this increasing complexity include the fact that space becomes a limited resource in many countries, the increasing interest amongst policy makers for interactive multi-actor planning, and the increasing expectations of citizens if it comes to communicating with their authorities. These developments accrue a need for “artificial planning environments” in which, interactively, policy can be developed and tested.

Multi-Agent Systems (MAS) are thought to offer concepts and techniques to understand the complexity of interactive multi-actor spatial planning processes, and as such, contribute to the “artificial planning environment”. The objective of this research is to explore the use of MAS for its application in simulating interactive multi-actor spatial planning.

This thesis includes three case-studies that demonstrate various concepts and techniques of MAS to simulate an interactive multi-actor spatial planning process. The basis for these simulations is a conceptual model which relates intentional actions of individual actors in a planning system to a representation of a spatial system. This intentional model of spatial planning is based on four types of knowledge: desires, beliefs, values, and preferences and three intentional relations with the spatial system: observe, perceive, and decide.

For each case-study, agents are implemented to represent actors in an interactive spatial planning process. An actor is regarded as a representation of an organization or interest group rather than an individual citizen. The goal of the planning process explored in the case-studies was to decide on locations for new urbanization in the pilot area “Land van Maas en Waal”, in the south-eastern part of the Netherlands.

The first case-study (Chapter 4) demonstrates a MAS that applies agents implementing a Cellular Automata (CA) to infer knowledge from their environment. A set of rules that describe distance-attraction relations are applied

on neighbourhoods. Based on these rules the agents generate preferences for locations of new urbanization, and generate a proposal of new urbanization. A voting procedure is applied to combine all individual proposals into a final decision. A drawback of using CA was that the inclusion of parts of the environment which are outside the scope of a neighbourhood, was only possible for dispersion-like processes, where the current state of an environment depends on its former states. This restricts CA in being applied for planning situations that require a more holistic view on the area, for example in case of spatial planning motivated by design considerations rather than solely process oriented planning.

Chapter 5 presents a second case-study, which tries to overcome the restrictions of CA. It introduces the concept of observers, and uses rule-based reasoning. The rule-base stores knowledge about desires of an agent, knowledge of required observations, and knowledge to interpret the results of the observations. The MAS is inspired on a Belief Desires Intentions (BDI) architecture. This enables the agents to use various other methods to infer knowledge from their environment. Based on the type of observations an agent invokes various observers to produce beliefs about its environment. In turn, these beliefs fire rules accounting for the knowledge to assign new land use according the desires of the agents. The advantages of the rules-based approach combined with the concept of observers is that, in principle, it allows more flexibility to define methods that agents can apply to observe and perceive their environment. An important drawback of the rule-based approach is the rapid expansion of rules when the number of desires or environmental states increases. Even a limited amount of rules made it difficult to cover all possible combinations.

Chapter 6 presents the third case-study, that focuses on sharing knowledge and communication amongst agents. The intentional model of spatial planning is extended with a model of knowledge sharing. Moreover, to overcome the limitations in reasoning and the representation of desires of first two case studies the use of spatial utility functions is combined with that of observers. This enables the agents to produce continuous representations of their preferences. As such this case study combines a number of approaches of the first two cases. To simulate knowledge sharing, agents can appraise and communicate preferences of other agents. A facilitator agent coordinates the communication and assists in targeting areas that provide potential solutions for the planning problem that is acceptable for the majority of the agents.

Chapter 7 elaborates on validation of the MAS developed in this thesis. It focuses on the MAS presented in Chapter 6. In general, it is difficult to apply traditional validation techniques upon MAS. Most validation approaches require an existing reference situation. This reference situation can be a historical case or the results of other (already validated) models. The requirement of a reference situation makes traditional validation of limited use to validate MAS for spatial-social systems.

An alternative validation approach is suggested, aiming at validating the conceptual model validity and, to a limited extent, the operational model validity. The conceptual validation verifies the relations between an interactive spatial planning process as found in the real world and the formalization of it by the model. The operational validation was limited to observation, perception, and generating preference by the agents.

For the conceptual validation five expert were individually interviewed and asked to evaluate various aspect of the model. The questioned aspects were related to the spatial planning process, the agents, and the representations of the knowledge.

For the operational validation, a group of 27 students were engaged in a role play in which they were asked to play the role of an actor having a number of predefined desires. In a number of rounds the role players sketched on a map their beliefs, and defined "utility functions" indicating the appreciation for these relevant objects. Next they were asked to sketch the most preferred locations for new urbanization.

The sketches of relevant objects and utility function are used to parameterize the rules of the MAS. Based on these rules the role play was simulated by the MAS and the results visually compared to the original results generated by the role players.

The main conclusion drawn from the validation exercises are:

- the interactive planning process is modelled rather well. However its use is restricted to mono-thematic and operational characteristic of the represented spatial planning process.
- the desires, observations and preferences are generally regarded a good representation. However, to really provide insight to users, the model is hampered by: a limited notion of desires, the predefined nature of the desires, the use of only geo-information, and the shortage in communications. Furthermore, the model is rather optimistic in its assumptions regarding the openness and truthfulness of the actors;
- the operational validation indicates a lack of information processing and reasoning capacities for the agents. Real actors tend to apply and combine additional information in their decision-making;

Chapter 8 presents the final conclusions and gives recommendations for further research. The overall conclusion is, that despite the limitations listed above, the potential of simulating interactive multi-actor planning using a MAS has been shown. The various cases explored in this thesis are amongst the few approaches that explicitly simulate interactive multi-actor spatial planning. It is demonstrated that agent based modelling offers concepts and techniques which enable modelers to implement models applying a more natural representation of a spatial planning process and the components it consists of. This means it requires less generalization and aggregation. Moreover it has the potential to enable planners to study the planning proces itself by means of computer models. The generic framework developed in this study offers a suitable basis for the realization of A MAS for interactive multi-actor spatial planning.

Samenvatting

Ruimtelijke planning is een complexe aangelegenheid. Aspecten die bijdragen aan deze complexiteit zijn onder andere: de steeds schaarser wordende ruimte, een toenemende belangstelling van bestuurders voor interactieve vormen van planning en de toenemende verwachting van de burger ten aanzien van de communicatie met overheden. Deze aspecten stimuleren de ontwikkeling van modellen waarmee, op interactieve wijze, beleid kan worden ontwikkeld en getoetst.

Multi-Agent Systems (MAS) lijken een bijdrage te kunnen leveren aan het beter modelleren en begrijpen van de complexiteit van een interactief multi-actor ruimtelijk planningsproces. De belangrijkste doelstelling van dit onderzoek was daarom het verkennen van MAS ten behoeve van toepassing in de simulatie van interactieve multi-actor ruimtelijke planning.

Deze verkenning in uitgevoerd middels drie case-studies. Als basis voor deze case-studies dient een intentioneel model voor ruimtelijke planning. Dit model relateert intentionele beslissingen van individuele actoren aan een representatie van een sociaal-ruimtelijk systeem. Het model is gebaseerd op vier soorten kennis ten aanzien van de ruimtelijke omgeving: wensen, opvattingen, waarden en preferenties. Daarnaast onderscheidt het model drie intentionele relaties met het sociaal-ruimtelijke systeem te weten: observaties, percepties en beslissingen.

In elke case-studie worden agents toegepast om actoren in een interactief multi-actor ruimtelijk planningsproces te simuleren. In dit onderzoek worden de actoren gezien als representanten van overheid- of belangenorganisaties. De planningsopgave voor de case-studie is het alloceren van ruimte voor nieuwe stedelijke ontwikkeling in het land van Maas en Waal, nabij Nijmegen.

In hoofdstuk vier wordt de eerste case-studie uitgewerkt. Voor deze case wordt gebruikt gemaakt van Cellulaire Automata (CA). Via de toepassing van CA kunnen de agents kennis uit de ruimtelijke omgeving vergaren en classificeren naar gelang de geschiktheid voor nieuwe stedelijke ontwikkelingen. In regels wordt de geschiktheid voor een locatie aangeven op basis van de afstand tot objecten in de omgeving. Op basis van deze regels genereren de agents een preferentie voor locaties voor nieuwe urbanisatie, en doen een concreet voorstel voor de nieuwe locaties. Een belangrijk nadeel van het gebruik van CA is dat gebieden die buiten de analyse omgeving (neighbourhood) van het CA vallen alleen betrokken kunnen worden voor het modelleren van processen die volgens principes van dispersie kunnen worden beschreven. Dit beperkt het gebruik van op CA gebaseerde agents voor planning situaties die een meer holistische kijk op het gebied vereisen. Dit is typisch het geval voor ruimtelijk planning die tevens een duidelijke ontwerp component kent.

Hoofdstuk 5 presenteert een case-studie die bovengenoemd nadeel tracht te ondervangen. Dit MAS is gebaseerd op een “Beliefs, Desires and Intentions” (BDI) architectuur. Het past een “expert-base” toe, waarin kennis van de agents over de wensen, de benodigde observaties en de interpretaties van observaties zijn opgeslagen. Daarnaast is het concept van “observers” geïntroduceerd. Dit concept geeft agents de mogelijkheid om, op basis van de kennisregels, alternatieve technieken toe te passen om kennis over hun omgeving te verwerven en vervolgens de verworven kennis te beoordelen. Het voordeel van het gebruik van expert regels in combinatie met het concept van “observers” is dat agents op een meer flexibele wijze hun omgeving kunnen observeren en waarderen. Een nadeel is het snel groeiend aantal regels bij een toenemend aantal wensen en omgevingstoestanden.

Hoofdstuk 6 presenteert de derde case studie. Deze studie richt zich op het delen van kennis tussen agents. Om dit te kunnen realiseren is het model van intentionele planning uitgebreid met de “knowledge sharing” benadering van Nonaka and Takeuchi (1995). Daarnaast wordt het concept van “observers” gecombineerd met “utility functions”. Dit maakt het mogelijk voor de agents om een continue representatie van hun preferenties te genereren. Om het delen van kennis te kunnen simuleren zijn de agents voorzien van methoden waarmee ze in staat worden gesteld om de preferenties van andere agents te kunnen beoordelen en de eigen preferenties te kunnen communiceren. Daarnaast is er een facilitator agent toegevoegd die als taak heeft ondersteuning te bieden aan het process van gezamenlijke identificatie van gebieden die acceptabel zijn voor de meerderheid van de betrokken agenten.

Hoofdstuk 7 richt zich op de validatie van het MAS zoals dit in hoofdstuk 6 is gepresenteerd. In het algemeen is het moeilijk bestaande validatie technieken toe te passen voor het valideren van MAS. De meeste validatie methoden vereisen een referentie. Deze referentie kan een al bekende case zijn of kan bestaan uit resultaten van gevalideerde modellen. De eis van een bestaande referentie situatie beperkt echter de geschiktheid van veel validatie methoden om toegepast te worden om een MAS voor sociaal ruimtelijke systemen te valideren. Een alternatieve methode wordt voorgesteld met focus op een conceptuele validatie en een beperkte operationele validatie. De conceptuele validatie heeft als doel de relatie tussen een reëel interactief ruimtelijk planningsproces en de formalisatie ervan in het MAS model te beoordelen. De operationele validatie beperkt zich tot de aspecten observatie, perceptie, en het genereren van preferenties door de actor.

Voor de conceptuele validatie zijn vijf experts individueel geïnterviewd en gevraagd om verschillende aspecten van het model te beoordelen. Deze aspecten zijn gerelateerd aan het ruimtelijke planningsproces, de agents en de representaties van verschillende soorten kennis.

Voor operationele validatie is een groep van 27 studenten ingeschakeld voor een rollenspel. Gedurende dit rollenspel werden de studenten gevraagd om een van te voren gedefiniëerde rol te spelen met slechts een beperkt aantal wensen. De spelers dienden allereerst de objecten te definiëren die relevant waren voor het nemen van de beslissingen. Vervolgens definiëerden ze de "utility" functies die de waarde voor deze objecten vastlegden, om uiteindelijk die gebieden op een kaart te schetsen met de hoogste preferenties voor nieuwe urbanisatie.

De kaarten, getekend door de spelers, werden gebruikt om identieke regels voor de model te parameteriseren. Gebaseerd op deze regels werd het rollenspel gesimuleerd door het MAS. De resultaten werden vervolgens vergeleken met de originele resultaten van het rollenspel. De belangrijkste conclusies die hieruit te trekken zijn:

- het model is beperkt tot monothematische en operationele planning.
- het gebruik van wensen, observaties en preferenties zijn een goede representatie van de kennis die door actoren wordt gebruikt in een interactief planningsproces. Echter, om inzicht te geven in een daadwerkelijk planningsproces is het te beperkt. Dit komt doordat de huidige definitie van deze kennis beperkt is. Daarnaast wordt het model gelimiteerd doordat de wensen van te voren zijn geformuleerd en preferenties, beslissingen bijna uitsluitend op geo-informatie worden gebaseerd. Daarnaast is er sprake is van een te beperkte communicatie en is het model optimistisch als het gaat om aannames die worden gedaan wat betreft openheid en integriteit van de agent's;
- de operationele validatie indiceert beperking in het proces van ruimtelijk redeneren. De spelers van het rollenspel lijken aanvullende informatie te gebruiken voor hun besluitvorming;

- het concept van "utility" functies zoals dit in de huidige versie is geïmplementeerd voldoet niet in alle gevallen als model voor de wijze waarop de spelers in het rollenspel hun preferenties bepalen.

Hoofdstuk 8 presenteert de conclusies en geeft een aantal aanbevelingen voor toekomstig onderzoek. De algemene conclusie is dat, ondanks de genoemde beperkingen, de bruikbaarheid van MAS voor het simuleren van interactieve ruimtelijke planning is aangetoond. De case studies hebben duidelijk gemaakt dat het gebruik van agent concepten en technieken het mogelijk maakt om modellen te realiseren die een ruimtelijke planningsproces op een meer natuurlijke wijze kan representeren. Daarnaast geeft het gebruik van MAS aan planners de mogelijkheid het ruimtelijke planningsproces zelf te bestuderen. Het "framework" dat in deze studie is ontwikkeld biedt daarvoor een goede basis.

Curriculum Vitae

Arend Ligtenberg was born on December 1968 in Almelo, The Netherlands. He holds a BSc as an irrigation engineer from Larenstein, and a MSc in environment planning and design from Wageningen University which he finished 'cum laude' in 1996, majoring in spatial planning and GIS.

From 1996 until 1997 he worked as a GIS consultant for a consultancy agency. He developed GIS applications for provinces, municipalities and water boards. Moreover his function was to acquire projects and organize GIS training for new employees.

From 1997 till 2000 he was employed at the Agricultural Economics Institute in the Hague. During this period for the greater part of his time he was detached as a researcher to the Laboratory of Geo-information and Remote Sensing of Wageningen University. He continued working for the Centre of Geo-information of Alterra from 2000 onwards.

He participated as a researcher in various national and EU-projects on participatory spatial planning, gaming, mobile technologies, web applications, open standards, and geo-visualizations. He wrote more than 50 scientific publications in the fields of spatial planning and geo-information science. His current research interests is associated with spatial modelling, geo-visualization, and the development of methods and tools that support interactive spatial planning.

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