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Using Bayesian Decision Networks for Knowledge Representation under Conditions of Uncertainty in Multi-Agent Land Use Simulation Models

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Abstract: Land suitability analysis typically involves the assessment of the suitability of land units without knowing the future spatial distribution of land use. Traditional planning techniques have used “algebraic equations” to express land suitability as a weighted function of suitability scores across multiple criteria. However, the existing multi-criteria evaluation methods do not systematically account for uncertainty about the land use in adjacent and other cells. This paper proposes an alternative approach to land suitability analysis that does address the problem of uncertainty. In particular, Bayesian decision networks are suggested as a means of knowledge representation for agents in a multi-agent land use simulation system. Bayesian decision networks model the uncertainty in terms of probabilities specified in the network representing the expertise of specialists with respect to specific land uses. This paper discusses the approach and illustrates its use in the context of a retail agent.

1. INTRODUCTION

1.1 Background

The decision where to locate a particular land use is a key decision problem for urban planners and other location decision makers alike. The location decision problem involves the assessment of the suitability of a particular piece of land (cell, zone) for a particular land use in light of the characteristics of the cell itself and the spatial distribution of a series of land uses. Often, this decision making process is a multi-dimensional and multi-disciplinary activity embracing social, economic, political, and technical factors (Kim et al., 1990). This very nature makes the problem complex, uncertain and subjective (see Yeh et al., 1999).

The most difficult aspect of any location decision problem facing an urban planner/decision maker is uncertainty. Many types of uncertainty can be distinguished, caused by various reasons such as a lack of data, imperfect information, and uncertain future developments. This paper focuses on one type of uncertainty that decision markers are facing: the uncertain spatial distribution of competitive and synergetic land uses.

Over the past decades, land suitability analysis, defined as "finding an appropriate use for the land unit that has the suitability for that desired use" (see Fabos, 1985; Hossain, 1989), has been the focus of much research. The tools that have emerged assist planners to systematically evaluate the suitability of a particular piece of land for different land uses. Typically "algebraic equations" have been used to express land suitability as a weighted function of suitability scores. The widely used Multi-Criteria Evaluation (MCE) techniques are based on a weighted sum of evaluation scores (*i.e.,* Fedra et al., 1990; Carver, 1991; Pereira et al., 1993; Jankowski, 1995; Malczweski, 1996; Lin et al., 1997). The set of criteria is usually divided into criteria that pertain to characteristics of the land unit itself, and to criteria, depicting the accessibility to other land uses in adjacent or more distant cells.

The future land use of other cells is often not or only partly known and hence the suitability of any cell has to be judged under conditions of uncertainty. Decision makers will assess the suitability of any cell partly based on their beliefs about the spatial distribution of land use in the area of interest. Unfortunately, traditional land suitability methods do not consider this type of uncertainty. As an alterative, this paper therefore suggests the use of Bayesian decision networks in land-use decision-making to take into account the problem of uncertainty. The approach described in this paper is part of the development of a wider multi-agent planning support system, called Masque (A Multi Agent System for Supporting the Quest for Urban Excellence) that is currently developed by the authors and their co-workers.

1.2 Structure of this paper

This paper consists of five sections. After this introductive section, the second section shortly presents the Masque framework. The third section introduces Bayesian decision networks. It is followed by a section that describes how these decision networks can be applied in land suitability analysis, explores the approach and provides an illustrative example. Finally, the fifth section summarizes the major conclusions and discusses future research activities.

2. MASQUE FRAMEWORK

Masque is a research program and multi-agent planning support system that aims at supporting decisions related to complex, uncertain and subjective urban planning problems in a user-friendly environment.

This section first presents the components of agents defined in the MASQUE framework. Then, it sketches the functions they need to perform in the MASQUE framework.

2.1 Components of the multi-agent systems in MASQUE framework

Agents have been defined in various ways in the literature (see Maes, 1994; Wooldridge et al., 1995; Dijkstra et al., 2000). This paper defines an "agent" as an entity that has its own knowledge and goals to perform certain tasks. In Masque, a set of agents works together to achieve a set of goals, given an uncertain environment. The framework of the system consists of data structures and protocols to co-ordinate the actions of the agents.

Each individual agent in the system has a set of problem-solving skills and experiences. Four types of agents are distinguished: 1) facilitation agents; 2) interface agents; 3) tool agents; 4) domain agents. The domain agents represent of particular land-uses and are identified based on a commonly used classification of land-use in Dutch planning practice (*i.e.,* the IMRO model). These land uses are business, housing, transportation, recreation, landscape, technical infrastructure, hydraulic construction and service (see Ravi, 2000; Saarloos *et al*, 2001).

2.2 Function of agents

Each agent is autonomous and able to provide (updated) information and to perform different kinds of tasks. The system uses a raster-based representation of the study area. Each agent uses his knowledge (*i.e.,* regulations, requirements, criteria, attributes, constraints, decision rules, techniques, etc.) to develop beliefs about the likely distribution of land uses across space. Based on these expectations, each agent determines his preferences and expresses his claims (*i.e.*, the cells he wants for his land use) and passes this information to other agents. In a cyclic procedure, the initiator of a plan proposal (which can be any one of the domain agents or the planning agent) processes the claims and makes allocation decisions until a plan is fully determined.

A key problem in developing the system therefore is how to represent the domain knowledge that the agents are assumed to use in assessing the suitability of any particular cell in light of their beliefs about the likely (future) distribution of land use in the planning area. In the present paper, we focus on a knowledge representation method (based on Bayesian Decision Networks) for agents to formulate land-use claims.

3. KNOWLEDGE REPRESENTATION IN BAYESIAN DECISION NETWORKS

Knowledge representation refers to the way in which knowledge of experts is modelled. As discussed, for the envisioned planning support system, the knowledge representation format should be able to deal with uncertainty and allow probabilistic reasoning based on beliefs under conditions of uncertainty. Therefore, agent or expert knowledge is represented using Bayesian Decision Networks (*e.g.,* Neapolitan 1990; Ames 2002). In this section, we discuss this means of knowledge representation in which uncertainty is modelled explicitly.

3.1 Structure of Bayesian decision networks

Bayesian decision networks can model uncertainty and provide a framework for representing cause and effect relationships between variables in a decision problem. A Bayesian decision network consists of three types of nodes: decision nodes, nature nodes and utility nodes (see Figure 1). Decision nodes represent the variables on which agents can make a decision. A network may have one or multiple decision nodes. In case of multiple decision nodes, modelers have to decide one the sequential order of these decision nodes. Nature nodes represent the variables over which the decision maker has no control. The outcomes of these nature nodes are typically uncertain to decision makers because nature decides on the value of outcome variables. Utility nodes represent the utility values, reflecting agents' preferences for the possible states of the system being planned. In general, arrows in the network represent cause-effect relationships between nodes. In the envisioned planning support system, they can be interpreted as reasoning relationships and are detailed in a conditional probability table (CPT) in case of a nature node and a conditional utility table (CUT) in case of a utility node. Both decision variables (decision nodes) and nature variables (nature nodes) are represented in terms of an exhaustive set of mutually exclusive states that represent the possible values/outcomes of the variables. This means that if the variables are continuous, they should be discretized.

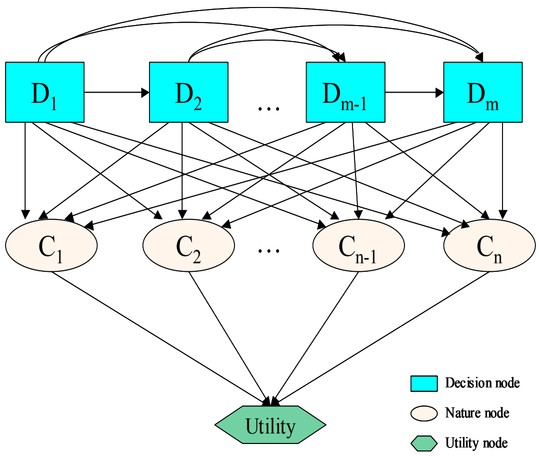

Figure 1. General structure of Bayesian decision networks

3.2 Expected utility

Once the structure of the decision network is defined and the Conditional Probability Tables (CPTs) and Conditional Utility Tables (CUTs) are specified, standard algorithms can be used to reason and determine the expected utility of each decision option. In case of a single decision node, the expected utility of a decision option is calculated as the sum of the products of probability and utility across the possible outcomes of the decision option. In case of multiple decision nodes, the expected utility of a decision option is defined as the expected utility of that decision option under the condition of the best decisions on the next decision variables. To evaluate decision options when multiple decision variables are involved, the following procedure is applied:

1) Calculate the expected utilities of the options of the first decision node;
2) Choose the decision option that maximizes the expected utility;
3) Enter the decision that has been made in the decision networks.
4) Repeat the procedure for the next decision node;
5) Continue this procedure until the last decision is made.

3.3 Conditional Probability Table

A condition Probability Table (CPT) quantitatively defines how an outcome variable (nature node) is impacted by its parent nodes. More specifically, it specifies the probability distribution across the states of the outcome variables for each combination of states of the parent nodes. The rows of the conditional probability table represent all possible combinations of states of the parent nodes and the probability distribution across the states of the nature node under concern. The rows can be interpreted as probabilistic rules, reflecting for example expert knowledge, to determine the state of the nature variables.

Given

1) A nature variable C with a set of states: $\{c^1, c^2, \ldots, c^k, \ldots, c^m\}$ and parent node D_i with states: $\{d_i^1, d_i^2, \ldots, d_i^{n_i}\}$; n_i is the number of states for the parent node D_i.

The probabilities of the states of the nature node can be calculated as:

$$P(c^k) = \sum_S P(c^k \mid S) \qquad (1)$$

where S is the set of all combinations of states of parent node D_i.

The conditional probability table (CPT) represents domain knowledge that can be provided by knowledgeable experts, observational data, results of complex model simulations, written documents or combinations of these knowledge sources depending on the variable under concern.

3.4 Conditional Utility Table

Conditional utility table (CUT) has a similar structure as the conditional probability table (CPT) of a nature node, *i.e.,* the rows of the table represent all possible combinations of states of the parent nodes. However, rather than a probability distribution across all possible combinations of states, the table indicates the utility value of each combination of states of parent nodes. The scale used to measure utility is free to choose, as long as it is metric (*i.e.*, interval scale) and the direction is positive (*i.e.*, a higher value indicates a higher preference).

Given

1) Any set of parent nodes

- C_1 has a set of states: $\{c_1^1, c_1^2, \ldots, c_1^{m_1}\}$;

- C_2 has a set of states: $\{c_2^1, c_2^2, \ldots, c_2^{m_2}\}$;
- …
- C_j has a set of states: $\{c_j^1, c_j^2, \ldots, c_j^{m_j}\}$; m_j is the number of states for the nature variable C_j.

The conditional utility table defines utilities as a set of values:

$$U(c_1^1, c_2^1, \ldots, c_j^1), U(c_1^1, c_2^1, \ldots, c_j^2), \ldots, U(c_1^{m_1}, c_2^{m_2}, \ldots, c_j^{m_j}) \qquad (2)$$

3.5 Order of decisions, non-forgetting links and feasible utility nodes

In the case of multiple decision nodes in a network, the user should define the order in which decisions are made by drawing the arrows from one decision node to another decision node. An arrow is drawn between any two decision nodes D_i and D_j if the decision on D_i is known the moment the decision on D_j is made. Therefore, arrows between decision nodes are called non-forgetting links; they do not present causal relationships but rather define the order in which the decisions are made.

In real decision problems it often occurs that two (or more) options from different decision variables are incompatible with each other. Bayesian decision networks cannot directly represent such incompatibility relationships. A possible way to represent incompatibility indirectly is to add a utility node for each pair of decision variables between which incompatible relations exist. In the conditional utility table of such a utility node, any arbitrary large negative value is specified for each incompatible combination of decision options, whereas the utility for all other compatible combinations is set to zero. Thus, this principle ensures that the expected utility values will be strongly negative for the incompatible option combinations, making sure that the incompatible decision options will not be chosen.

3.6 Knowledge representation and uncertainty

Bayesian decision networks can represent expert knowledge qualitatively and quantitatively. The type of knowledge involved depends on the decision problem itself and the type of nodes. In case of a decision node, agents should know the position of the decision in the sequential order of decisions. In case of a nature node, the conditional probability distributions reflect an agent's assessment of the likelihood of outcomes of the variables under each possible combination of decision options, or in general, the influence of parent variables on outcomes. In case of a utility node, agents specify the conditional utility tables to indicate their preferences regarding outcomes in terms of the nature variables.

Bayesian decision networks can model uncertainty in terms of the probability distribution across the states of the nature variables. The degree of uncertainty is reflected by the uniformity of the probability distributions across the states of the outcome variable. The more equal the probabilities are distributed across the possible outcomes, the higher the degree of uncertainty. Uncertainty is inversely proportional to predictability. A perfect uniform distribution (*i.e.,* equal probabilities across alternatives) implies maximum uncertainty, complete unpredictability (random choice), while a deterministic distribution (*i.e.,* 0-100 distribution of hard evidence) means no uncertainty and a deterministic prediction of the outcomes.

4. ILLUSTRATION

To illustrate how a decision network can be used to model expertise and uncertainty in land-use decision problems, we consider a hypothetical medium-sized future district as an example (see Figure 2).

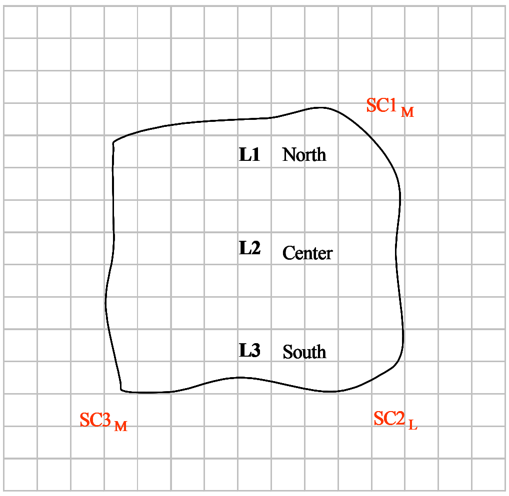

Figure 2. A hypothetical study

We use a raster of cells [i,j] to represent the area. In the present example, the area is divided, on a high level, into three larger regions referred to as: North (L1), Center (L2) and South (L3). In the area, approximately 5000 new houses and all necessary facilities will be located. As an example, we further consider a retail agent that has decided to allocate a maximum of two new shopping centers (a large one denoted as SC_L, a small one denoted as SC_S) in the plan area after he conducted some relevant studies (*i.e.,* market analysis). The decision problems for the retail agent then are: 1) how many (none, one or two) new shopping center(s) should be located in this area? 2) If the number of new shopping centers is not less than one, where should the shopping center(s) be located in the plan area? To reach these decisions, we assume that the retail agent conducts a suitability analysis at two levels: first at the regional level (North, Center and South); second at the cell-based level within that suitable region(s) identified at the regional level.

There are four existing shopping centers in the neighborhood of the plan area (see Figure 2), labeled as medium shopping center one ($SC1_M$), large shopping center two ($SC2_L$) and medium shopping center three ($SC3_M$). The agent is supposed to be aware of this. However, the allocation of land uses in the plan area is not known with certainty until final allocation decisions have been made. The agent only has particular beliefs of land-uses in adjacent cells (and all other relevant cells across the plan area) are represented as probabilities.

4.1 Simplified decision network for the location decision of new shopping centers

Figure 3 shows a simplified decision network to decide where to locate the maximum two shopping centers. This simplified network serves to explain how a Bayesian decision network can be specified to represent knowledge under conditions of uncertainty. It also illustrates how a decision network can be used to address two sequentially related decisions and how to deal with infeasible combinations of shopping center locations. For example, it is not feasible to allocate a small shopping center to the same location where a large shopping center has been allocated. In this simplified decision network, an extra utility node labeled 'feasible' is used to represent these incompatible combinations.

The second layer in Figure 3 shows the nature nodes relevant to this problem. It shows that the location decision is assumed influenced by:

1) total minimum travel distance to the nearest shopping center (C_1) and the sum of ratios of the supply of all shopping centers to distance summed across all housing cells (C_2). Both influence consumers' satisfaction;
2) profit of future retailers in the planning scheme (C_3) and profit of other existing retailers outside the plan area (C_4). They have effects on retailers' satisfaction;
3) efficient use of facilities and space (C_5) and total travel distance to all shopping centers (C_6). These variables influence the satisfaction at the level of the community.

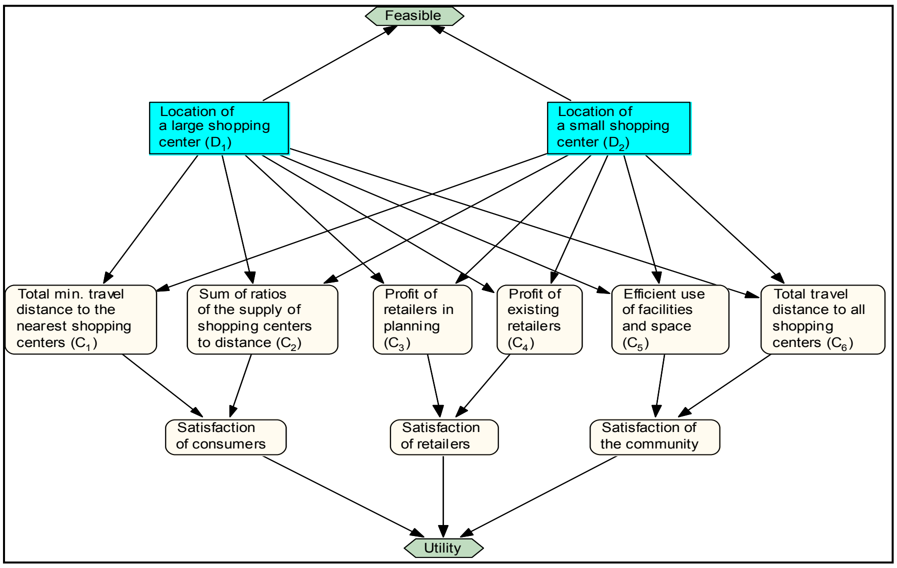

Figure 3. A simplified example of a location decision networks for shopping centers

Each decision variable has four decision options 'North, Center, South and none'. Each of nature variables in this network has three states. The variable C_1 has a set of states 'short, average and long' defined as distance (in meter) intervals: [0~500), [500, 1000), [1000, infinity] respectively. The variable C_2 has states 'high, average, low'. Variables C_3 and C_4 each have states 'high, normal, low'. Variable C_5 has states 'high, normal, low' and variable C_6 has states 'short, average, long'.

The third layer in Figure 3 shows the variables 'satisfaction of consumers', 'satisfaction of retailers' and 'satisfaction of the community'. Each of them has states 'good, normal, poor'. In the following section, we will focus on one nature variable C_1 'total minimum travel distance to the nearest shopping center' to explain how to specify the probabilities for all possible combinations of its parent nodes in a conditional probability table.

4.2 Approach to define the conditional probability table

The retail agent is assumed to make location decisions first at the regional level and then at the cell level within the chosen region(s). The crucial step is how the agent can specify the probabilities in the CPT of for example the nature variables C_1 and C_2 at the regional level and at the cell-based level respectively. Specifying the CPTs requires computing the values of the nature variables, C_i, for each combination of location choices. To determine the values of the variables with certainty, the allocation of the residential land-use must be known, whereas in the planning stage we know only a probability of a residential use for each cell. One possible method would be to use the probabilities as weights in calculations of the measures. However, in that way the notion of uncertainty at the cell level would be lost. To solve this problem, we propose a sampling method to specify the probabilities in conditional probability tables (CPTs).

4.2.1 At the regional level

For the combination of North-North (SC_L in the North and SC_s in the North), the retail agent repeatedly draws a sample from all possible configurations of housing allocations in the plan area by drawing a decision for each cell whether or not the residential land use will be allocated to that cell based on the known probability of a residential land use for that cell. Then the total minimum travel distance from any housing cell to the nearest shopping center is then calculated.

The retail agent repeats to select random samples of configurations of housing allocations, say *n* times, and calculates C_1 for each sample. In doing so, he obtains *n* different values for C_1. Then, he categorizes these results into the distance intervals defined for C_1, e.g.: [0~500), [500, 1000) and [1000, infinity] for three states: short, average and long, respectively. The number of times a value falls in each of these categories can then be counted. Finally the probabilities in the CPT of variable C_1 for the combination of North-North are determined as the number of counts (frequency) in each interval divided by the total number of simulations/samples. This procedure is repeated for each of the remaining fifteen combinations of possible location decisions.

Next, in a similar vein, the agent specifies the CPTs of other variables C_2, C_3, C_4, C_5 and C_6. Note that the CPTs of the satisfaction variables do not require such a sampling procedure as they do not directly depend on land use allocations. Finally the agent specifies the CUT of the utility variable for all state combinations of three variables: ‘satisfaction of consumers’, ‘satisfaction of retailers’, and ‘satisfaction of the community’. After the CPTs for all other variables and the CUT have been specified, the agent “reasons” to derive the expected utility for the decision variables D_1 and D_2 (at the regional level).

There are several incompatible combinations of location of the two shopping centers. To handle these incompatible combinations, a feasible utility node (see Figure 3) is used to make these incompatible combinations infeasible (not to be chosen).

4.2.2 At the cell-based level

To find out where (which cell(s) in that region) the new shopping center(s) should be located, the agent assesses the suitability of each cell, *i.e.*, cells in the North for SC_L and cells in the South for SC_s.

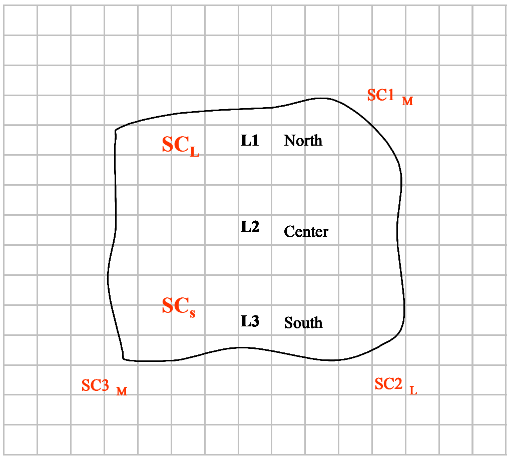

Figure 4. A hypothetical study area

In this example, there is a maximum of 702 combinations of cells for two shopping centers at the cell level (26 cells in the North and 27 cells in the South, see Figure 4). However, this number might be reduced because only cells not closer than a certain distance from any existing shopping center are feasible for the location of the new shopping centers. For each combination of cells, the agent uses the same procedure as explained at the regional level to specify the probabilities in the CPT's and in the conditional utility table. Based on these beliefs, the agent can reason the expected utility of any options of decision variables D_1 and D_2 and decide where to locate the two shopping centers at the cell level.

4.3 Application

This section only analyzes the partial decision network (see Figure 5) discussed in Section 4.0 to show how the technique is applied to a decision problem. The 'feasible' node represents the incompatible location decisions, which are indicated by a large negative penalty. The probability distribution in Table 1 indicates the agent's beliefs of the probabilities of the states of the travel distance variable for each possible combination of the location decisions. The degree of uniformity of the probability distribution indicates the degree of uncertainty. The uncertainty is highest for combinations

"North-South" and "South-North", while lowest for combination "None-None".

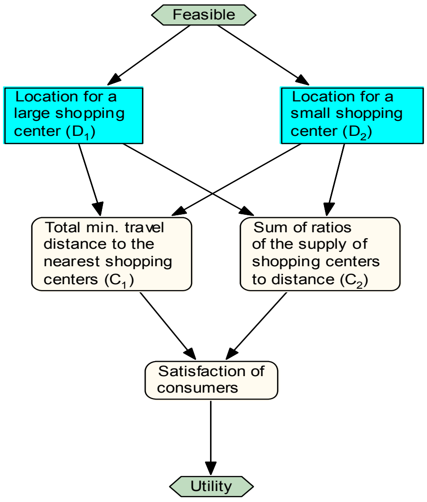

Figure 5. Example of analysis

The degree of uncertainty in Table 2 is rather low because the agent has high confidential beliefs. We assume the agent's preferences are portrayed in Table 3 on a 0-500 scale, where the highest utility receives a value of five hundred and the lowest utility receives a value of zero. These values can be determined from experts' experience or questionnaires.

Table 1 CPT of the total minimum travel distance to the nearest shopping center (%)

Location of a large shopping center	Location of a small shopping center	Total minimum travel distance		
		Short	Average	Long
	North	8	33	59
North	Center	12	38	50
	South	37	36	27
	None	8	33	59
	North	12	38	50
Center	Center	5	30	65
	South	12	42	46
	None	5	30	65
	North	37	36	27
South	Center	12	42	46
	South	8	32	60
	None	8	32	60
	North	8	33	59
None	Center	5	30	65
	South	8	32	60
	None	2	15	83

Table 2 CPT of the sum of ratios of supply of shopping centers to distance (%)

Location of a large shopping center	Location of a small shopping center	Sum of ratios of supply of shopping centers to distance		
		High	Average	Low
North	North	8	62	30
	Center	7	68	25
	South	7	73	20
	None	6	42	52
Center	North	3	77	20
	Center	3	80	17
	South	5	77	18
	None	3	68	28
South	North	7	58	35
	Center	7	53	40
	South	9	48	43
	None	5	42	53
None	North	1	2	97
	Center	2	2	96
	South	2	5	93
	None	1	2	97

Table 3 Conditional utility table

Satisfaction of consumers	Utility
Good	460
Normal	200
Poor	30

Table 4 Expected utility

The large shopping center		The small shopping center	
Decision options	Expected utility	Decision options	Expected utility
North	-816	North	-816
	205	Center	205
	266	South	**266**
	160	None	160
Center	207	North	207
	-821	Center	-821
	216	South	216
	167	None	167
South	249	North	249
	195	Center	195
	-833	South	-833
	154	None	154
None	110	North	110
	97	Center	97
	111	South	111
	-934	None	-934

Given these values, the expected utilities derived from the network at the regional level (see Table 4) indicate that both shopping centers should be planned for the planning area. The maximum expected utility value '266' is generated for the location combination of 'North-South'. Thus the best option for location of the large shopping center is the North while the best option for locating the small shopping center is the South. The expected utility associated with this combination of locations is 266. To decide on locations of the two shopping centers at the cell level, a similar process is followed.

In addition, Table 4 also shows that the incompatible combinations of locations are considered infeasible as reflected by their large negative expected utility.

5. CONCLUSIONS AND FURTHER RESEARCH

This paper argued that most traditional methods of land suitability analysis do not consider the inherent uncertainty in the future spatial distribution of land uses, that is typically assumed to influence the accessibility and hence the suitability of a site. To overcome this limitation, this paper proposes an alternative approach to represent the knowledge and reasoning of multiple agents under conditions of uncertainty. More specifically, the use of Bayesian Decision Networks is advocated. Uncertainty is modelled in terms of conditional probability tables, which represent the impact of particular variables on decision options. The use of this approach is illustrated in the context of a retail location decision example. A sampling method is proposed to maintain the concept of uncertainty across a sequence of decisions. The results of the simple example indicate the potential of this alternative approach.

Further research is required to develop an appropriate support system. First, the knowledge structure should be elicited for every envisioned agent in Masque. This involves the construction of the network, and the derivation of the conditional probability tables and conditional utility table, unless the latter is seen as part of the use of the system where users can specify these tables. Second, the size of the tables can become very large as the complexity of the network increases. For such complex networks, models and standard algorithms that can compute the probability of all possible combinations of parent nodes in the decision network formulated and explored. We plan to report on such development in the near future.

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